THE BATTLE OF CADASTRAL INTELLIGENCE: MEASURING THE RESULTS OF COMPETITION BETWEEN PEOPLE AND MACHINE IN CREATION OF CADASTRAL BOUNDARIES

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February, 2018

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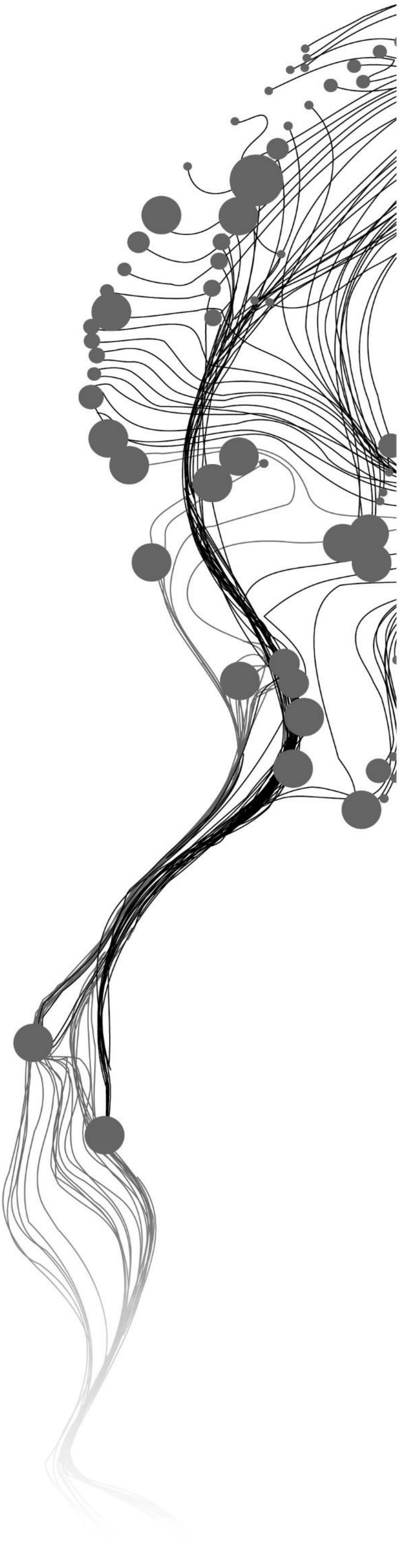

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EMMANUEL NYANDWI
Enschede, The Netherlands, February, 2018

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-Information Science and Earth Observation.
Specialization: Land Administration

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ABSTRACT

Today, more than ever before, the world of technology is inclined towards the use of artificial intelligent systems for improved performance in service delivery. State of the art spatial-visual intelligent algorithms able to detect patterns from image are finding their applications in different fields and potentially in cadastral mapping. To test how these new smart agents could work in cadastral mapping, the current study measured and compared the performance of machine-based image analysis algorithms versus human operators in extracting cadastral boundaries from VHR image. Specifically, the study used OBIA rule-based expert systems within eCognition environment. In parallel, a team of five land professionals were tasked to hypothesise and manually digitise cadastral boundaries using the same image dataset used for automation. Both automation and manual digitisation used a WorldView-2 image that was pansharpened using Nearest Neighbour Diffusion-based algorithms that preserves spectral information while allowing for high visual interpretability. Two sites, one rural and the other urban within Kigali City in Rwanda were used. A rough cadastral map from automation and hypothesised and manually digitised boundaries were validated using surveyed data out in the field. To compare automated boundaries against manually digitised boundaries the study used quantitative geometric metrics to determine over-segmentation, under-segmentation, edge and shape errors from reference data. Arithmetically, the Number-of-Segments Ratio, completeness, correctness, false positive and false negative metrics were used to determine the overall performance of automation versus manual digitisation. Qualitatively, a focus group discussion was conducted to elicit experts perspectives on the legitimacy of machine-based image analysis algorithms for generating cadastral boundaries. The core themes of the discussion was automation and cost-effectiveness, ease of use and alignment with longstanding surveying values and surveyors vested interests.

In rural area, results indicate that machine was able to produce topologically and geometrically well-structured parcels. Automation achieved a completeness rate of 45% versus 70.4% for human operators. İn urban areas, automation results were counter-intuitive. It was so challenging for machine to extract fences and building footprints while it was really not a problem for human operator to digitise. From experts perspectives, automation could make the life of surveyors more easier while allowing them to deliver more services to landowners in short time with less cost. However, they suggested that the automation tool has to be learnable and simple to manipulate. The challenges raised by experts are that automation inaccuracies and inabilities of local people to validate automation results might cut back support from landowners. According to experts, it seems to be very challenging for automation to fit in current survey procedures that involve not only the landowners and surveyors but also local authorities and all neighbours. Thus for automation to work, some of the procedures will have to be suppressed. Experts suggested the use of locally acquired and accurate data. They further recommend a participatory mapping approach for validation of automation results after local people are trained to interpret and read spatial maps. Importantly, opinions from the focus group reflect both experts own views and experience and reality with image-based demarcation and fit for purpose approaches that have been implemented in Rwanda.

In conclusion, the study achieved its objective and attained automation performance is sufficient enough to reduce the cost incurred in field surveying by nearly a half. As for recommendation, in line with experts views, automation will require highly accurate data and skilled operators. For automation to be successful, a fully fledged involvement of spatially literate landowners and surveyors is needed.

Keywords: Automation; feature extraction; cadastral intelligence; visible boundaries; OBIA; geometric accuracy; technology legitimacy.

ACKNOWLEDGEMENTS

I would like to thank ITC Excellence Scholarship Programme team and the Government of Rwanda through Rwanda Land Management Authority for financially supporting my studies.

Special gratitude goes to my enthusiastic supervisors, exceptional instructors of good hand "*M.N.koeva*" and "*D.Kohli*". My Research journey has been a fantastic experience, and I thank you wholeheartedly, for tireless guidance and motivation.

I acknowledge the entire ITC community for kindness, internationalisation, advise and accommodation. Especially, I am thankful to Land Administration professors, lecturers and administration staff for their expertise and facilitation of all kind throughout my studies.

And most of all I am thankful to my dearly loved people;

For my lifelong wife "*Antoinette*" who unremittingly in faith and love took care of my son all alone, endured my absence and has been caring for me despite being far apart;

For, my first son "*Shimmel*", it took your angelic heart melt smile to break my silence and re-energise my brain and clear away rough times;

For "*my mum*", I know behind successful son is an "*intelligent mum*"; for your nugget of wisdom and instructions right all along my life, I became who I am and I've got to know what I know and what I will know. I am proud of myself and proud of you.

I love you all and I dedicate my success to you

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1. INTRODUCTION

Traditional approach uses mainly field survey and manual digitisation of remotely sensed images by humans to map cadastral boundaries. Alternatively, machine-based image analysis algorithms could be used to automatically extract visible cadastral boundaries from Very High Resolution [VHR] remotely sensed data. This chapter introduces research which compared the performance of human and machine in extracting cadastral boundaries from VHR satellite images.

1.1. General background

The cadastre is the foundation for land management and development in the long now (Donnelly, 2012; Williamson, 1985, 1997, 2000; Yomralioglu & Mclaughlin, 2017). An appropriate cadastral system is an essential part of the legal and institutional infrastructure that supports securing property rights and mobilising land capital, and without it, many of the "challenges of development" in a developing country will not be met (Williamson, 1997). Unfortunately, till today, only around 30% of land ownership units worldwide are covered with the formal cadastre (Bennett et al., 2017; Sophie Crommelinck et al., 2017; GLTN[1], 2015). The smaller coverage of cadastre is due mainly to procedural and costly traditional surveying approach. The latter suggests that all cadastral boundaries must be walked to be mapped (Rizos, 2017; Zevenbergen & Bennett, 2015) making it human intensive. Surveying is thus the most costly process when registering property (Rogers, C.Ballantyne, & B.Ballantyne, 2017); incurring 30-60% of the total cost of any land registration project (Burns, Grant, Nettle, Brits, & Dalrymple, 2007; Rogers et al., 2017). The consequence has been a growing aversion towards registering land. Many persons holding interests in land are not really looking for registration because the benefits of it would not compensate for the time and money they will have to invest (Zevenbergen, 2004).

With the advancement in remote sensing, it is now possible to acquire VHR data with which visible cadastral boundaries could be detected based on their patterns with regards to appearance and form (Crommelinck et al., 2016; Luo, Bennett, Koeva, & Lemmen, 2017). Satellites, in addition to manned airborne photography, can offer sub metre spatial resolution images since 1999s (Lennartz & Congalton, 2004; Salehi, Zhang, Zhong, & Dey, 2012). With Unmanned Aerial Vehicle [UAV], it now possible to acquire centimetre-level image resolution and point clouds data allowing to uncover features occluded by vegetation (Gao, Xu, Klinger, Van Der Woerd, & Tapponnier, 2017; Koeva, Muneza, Gevaert, Gerke, & Nex, 2016; Luo et al., 2017). The ability to acquire VHR remotely sensed data had given birth to image-based cadastral mapping. The latter has been experimented in Rwanda, Ethiopia and Namibia and proved effective in delivering fast-track land registration (Lemmen & Zevenbergen, 2014). However, despite the effectiveness of image-based parcel demarcation, the method is still human intensive. The non-trivial issue is then how to demarcate as many as possible land units based on VHR data while maintaining the accuracy and time requirements with minimum manual labour (García-Pedrero, Gonzalo-Martín, & Lillo-Saavedra, 2017). This question calls for resorting to automation.

Theoretically, it is believed that some of states of the art machine-based image analysis algorithms are as good as human perceptions for feature extraction (Blaschke et al., 2014; Xie & Tu, 2015) presenting the potential for automated cadastral boundaries extraction. Eventually, if succeeded, automation could eliminate substantial inconsistency errors resulting from the manual digitisation of imagery by draftspersons and could support in solving the issue of incomplete cadastre (Sahar, Muthukumar, & French, 2010). As put forward by Wassie, Koeva, Bennett & Lemmen (2017), automation could support cheap and up-to-date fit-

[1] Global Land Tool Network

for-purpose technologies targeting on existing societal needs, fast-track cadastral mapping to make land sector play its underlying role in ensuring sustainable development.

1.2. Prior studies and research gap

As mentioned in the general background, both cadastral surveying out in the field and manual digitisation of boundaries on VHR image are time and labour intensive. Specifically, manual digitisation is prone to inconsistency errors and it is impotent to handle remote sensing data covering huge area with minimum labour making it technologically less appealing. In response to that, the use of machine-based image analysis algorithms for automation of boundary delineation is gaining traction within geoinformation and land administration research arena (Luo, Bennett, Koeva & Quadros, 2016). This section summarises some of the previous studies and research gap.

1.2.1. Reviewed works

Among previous studies in field of automation of cadastral boundaries include the prominent work by Wassie et al. (2017);Crommelinck et al. (2017); Luo et al. (2017); García-Pedrero, Gonzalo-Martín & Lillo-Saavedra (2017); Suresh, Merugu, and Jain (2015); (Djenaliev, 2013)and Alkan and Marangoz (2009).

Wassie et al. (2017), applied mean shift based algorithms for automated delineation of parcels from WorldView-2 image. The study used buffer overlays to measure the accuracy of automated parcel boundaries to reference parcel boundaries. The study also used interviews method to land professionals to capture perceived achievement and deficiencies of automation tools. As claimed by authors, for three different sites, the automation was able to achieve 82.8%, 62.1% and 44.2% of completeness and 34.3%, 33% and 24.1% of correctness. This performance was obtained by applying a 2-metre buffer from reference lines. According to the same study, professionals perceived that if automation could extract up to 40-50% of all boundaries, it will significantly reduce the cost of land registration. Some of the major concerns with automation raised by professionals include invisible boundaries lines due to occlusion from high vegetation.

Crommelinck et al. (2017), tested the use of Simple Linear Iterative Clustering [SLIC] superpixels to extract visible boundaries from VHR UAV imagery. specifically, their study tested the ability of the SLIC tool to delineate roads and roof outlines. The study claims to have achieved promising results with a completeness rates of up to 64% using a buffer of 0.3m around reference data.

Luo et al. (2017), studied the extraction of cadastral boundaries from LIDAR data in urban and suburban areas using α-shape, canny edge and skeleton algorithms. During automation, clouds points were classified into planar object outlines like roads and buildings and then centerlines were fitted to fences to obtain building plot (parcel) boundaries. The study involved manual post-refinement where gaps among line segments were manually filled based on visual interpretation. Authors claim to have achieved promising results, with around 50% of parcel boundaries successfully extracted with a tolerance of 4m from references boundary lines.

García-Pedrero et al. (2017), investigated machine learning approach by way of combining superpixels and supervised classification for agricultural parcel delineation through agglomerative segmentation. The study applied to highly fragmented agrarian landscapes with high spatial heterogeneity produced by the diversity in sizes, shapes, and crops of the different agricultural parcels. The study used an extended version of SLIC algorithm to over-segment the image generating superpixels. A supervised classification was then used to determine superpixels to be merged. The obtained results showed to be nearly 90% accurate.

Suresh, Merugu and Jain (2015), studied the use of an edge detection technique and object-based classification to extract the land information automatically from satellite imagery. In their work, a modified directional Sobel edge detection was applied to improve the quality of segmentation results. The objects boundary was defined by merging edge detection results with the original image and applying the Multi-Resolution Segmentation [MRS] in eCognition. By using colour and shape information features like forest, river, roads, agriculture fields and buildings were extracted. An error matrix was used to evaluate the performance of the automation and the study claim to have attained 95% of accuracy for agriculture field.

Djenaliev (2013), examined object-based image analysis for building footprints delineation from WorldView-2 satellite imagery. The author used cany edge detectors to delineate contour lines of buildings from panchromatic image and then applied contrast split segmentation for separating detected lines fro the rest. The result of contrast split segmentation was exported to ArcGIS. Exported vectors together with manually digitised road lines were used as the thematic layer for multiresolution segmentation process. Different features could then be classified based on geometry and colour information. The classification achieved an overall accuracy of 80% using a confusion matrix.

Alkan and Marangoz (2009), studied the automatic object-based classification and manual approach for delineating buildings and parcels in built up and non-built-up contexts using the e-Cognition v4.0.6 software. In their research, the original image was first pan sharpened and segmented using MRS. Then the classification of segments into parcels and buildings was done by using different parameters available within e-cognition for features extractions. A confusion matrix was used to evaluate the performance of automation and on the screen manual digitisation based reference field dataset. In a built-up area, it was found that 10% versus 15% of the parcels and 85% versus 90% of buildings could be extracted by automation and manual digitisation respectively. In a rural area, up to 85% versus 90% of parcels, could be obtained by automation and manual digitisation respectively.

1.2.2. Research gap

From the reviewed works, with exception to the work of Crommelinck et al. (2017); Luo et al. (2017) and Wassie et al.(2017), performance a evaluation of machine performance used thematic accuracy with little attention on geometric properties of cadastral boundaries. There is lack of research evidence of how obtained cadastral boundaries fit well with existing cadastral geometric standards. Many of the researchers claimed to have achieved higher performance while non-geometric accuracy metric may not adequately inform on the number of parcels that were extracted wholes and geometrically and topologically correct. Thus, the current study, aimed at substantiating the prominence of machine intelligence exhibited by image analysis algorithms with both qualitative and quantitative indicators within a cadastral domain-specific application. The need to compare the performance of machine algorithms to the ground truth of cadastral expert emphasised on geometric properties and user perspectives on legitimacy of automation serve the primary motivation for the current study.

The other issue which evolved the passion for the current research derives from incomplete cadastre in Rwanda, as it for many other developing countries according to Sahar, Muthukumar & French (2010). Relevant property and topological information about building and physical utilities which is fundamental to planning and development are still missing in the Rwanda national cadastre (Ho, Biraro, Muvunyi & Wayumba, 2017 cited in Rohan Bennett et al., 2017). Thus, the researcher was passionate to test the possibility for automation to delineate buildings which could support completing the cadastral database.

1.3. Aim of the study

1.3.1. General objective

Setup and measure the results of competition between human operators and emerging machine-based approaches for creating and extracting cadastral boundaries from high-resolution satellite imagery.

1.3.2. Specific objectives

1.3.2.1. Identify and apply automated and manual approaches to extract visible cadastral boundaries.
1.3.2.2. To compare the performance of machine against human operators in creating cadastral boundaries based on geometric metrics.
1.3.2.3. To assess professionals' perceived legitimacy of artificial cadastral intelligence exhibited by machine-based image analysis algorithms

1.3.3. Research questions

Objective 1:
1.3.3.1. What are traditional approaches for image-based cadastral boundaries extraction?
1.3.3.2. What are image analysis algorithms for automatic cadastral boundaries extraction?
1.3.3.3. How to extract cadastral boundaries from imagery manually and automatically?

Objective 2:
1.3.3.4. How precise is machine algorithm in reproducing geometries and shapes of cadastral features?
1.3.3.5. What are precision and recall rates of machine algorithms in extracting cadastral boundaries?

Objective 3:
1.3.3.6. What are cadastral experts' perceptions towards machine-based approaches regarding their ease of use, cost-effectiveness, alignment with existing cadastral surveying procedures?

1.4. Research outline

Chapter 1. Introduction
General background. Prior studies and research gap. Aim of the study. Research outline
Chapter 2. Theoretical and Conceptual Framework:
Epistemology of automation. Ontology of boundaries and cadastral intelligence. Exhibiting cadastral intelligence by way of image analysis algorithms. Performance of image analysis algorithms in cadastral mapping. The legitimacy of image-based cadastral intelligent algorithms. Conceptual framework. Summary.
Chapter 3. Methodology
Research Strategy. Case study sites. Imagery dataset. Automated cadastral boundaries extraction. Set up cadastral expert team for manual cadastral boundaries extraction. Framework for comparing automated against manually digitised boundaries.
Chapter 4. Results
Introduction. Rural site. Urban site. Edge enhancing. Geometric comparison of automated against manually digitised boundaries. Summary of results
Chapter 5. Automation Legitimacy Perspectives
Introduction. Acquaintance with automation tool and perceived user-friendliness. Perceived deficiencies of automation. Automation and surveyors interests. Experts recommendation
Chapter 6. Discussion and Conclusion
Automation process. Machine versus Human performance. Legitimacy perspectives. Implication for practices. Limitation of the study
Chapter 7. Conclusion and recommendation
Reflection to objectives and questions. Final remark. Recommendation

2. THEORETICAL AND CONCEPTUAL FRAMEWORK

The previous chapter defines research problems and objectives to be addressed. This chapter goes on to discuss and interpret the study's underpinning theories. Specifically, the first section gives an epistemology of machine intelligence justifying and giving the rationality and necessity of machine-human integration. The second section provides an ontology of boundaries i.e. description of nature and characteristics of cadastral boundaries and their recognition. The third section offers approaches for exhibiting automated cadastral intelligence using image analysis algorithms. The fourth section goes on to discuss the performance theory to understand requirements, standards, direction and methods for assessing the accuracy of automated boundaries. The fifth section gives a conceptual framework that is built on an interpretation of underlying study theories to provide a schematic model that guided the empirical study. Finally, a summary of the main points is given in section six.

2.1. Epistemology of automation

Machine emulates human to perform specific jobs. This furtherance of machine intelligence has been a longstanding philosophical battle. In general, there are two major schools of thoughts of technology. In Franssen, Lokhorst, & van de Poel (2015); Swer (2014); Waelbers (2011) the two schools are labelled as "technological instrumentalism versus determinism". In Swer (2014); Winner, (1997) the two opposing views are described as "technology myopia or utopia versus dystopia" or "technological idealism versus materialism". In Sacasas (2015) the term "Humanist technology criticism is used to describe pessimistic viewpoints of technology while to the opposite in González (2005) the term "technology voluntarism" is used. There many opinions for utopia as well as for humanist technology thinkers. To get an insight of the debate, a few examples of prominent thinkings are cited in the next paragraphs.

For determinists, with the most proponents being Heidegger, Marcuse, Ellul and Karl Jasper, technology engulfs humanity due to automation and use of highly productive machinery that lead to the dismissal of labourers and loss of social value (Brey, 2003; Peter-Paul Verbeek, 2005). Technology thus holds a controlling power over society culturally, politically and ecologically (Franssen et al., 2015; Swer, 2014). Contrary, instrumentalists believe that technology is merely the concretisation of scientific thoughts in our daily life (Swer, 2014). For them, technology is just like a bare physical structure that serves human goals thus it is value-neutral and a controllable mean by people (Franssen et al., 2015). İnstrumentalists believe machine is a tool usable upon user's complete free will (George, 2017).

There are critical views of the technological prospect from both utopia and dystopia worth mentioning. One highlighted in literature came from Bernhard Irrgang philosophy. Bernhard Irrgang philosophy rejects both technological determinism and autonomy (George, 2017). According to Bernhard Irrgang, technical power arises from the management of everyday life. Therefore, it would not make sense to separate technology from human life since technology is embodied in human. Irrgang thoughts suggested that technology improves the old and advance new human capabilities and social organisation, the working and life conditions of human, increasing wealth and introduced new lifestyles. Emphasising Irrgang thoughts, Winner (1997) stated that whether taken in optimistic or pessimistic variants, modern technology had certain essential qualities, for instance, relentless search for efficiency, optimisation, efficiency, safety, and sustainability. While supporting technology optimism, Winner also criticises ironic voluntarism that denies humans being swept up by unstoppable technology-centred changes.

Another most influential thought in technology came from Lyotard (Balke, 2016), whose philosophy was neither framed in utopia nor dystopia (Roberts, 2013). Lyotard prophesied the exteriorisation of knowledge to enable the continual sharing of thoughts even after the demise of whom they are credited to. According to Balke, Lyotard's thought is being implemented by computerisation that creates a new performance, new potential for machine along human to create new emergent orders and socio-technical connections. As foreseen by Lyotard, since 1950s, with the emergence of artificial intelligence (Bush, 1945; McCarthy, Minsk, Rochester & Shannon, 1955; Smith, McGuire, Chris, Huang & Yang, 2006; Turing, 1950), humans discovered that computers could be instructed to learn to perform certain tasks without being explicitly programmed (David, Craig & Ragu, 2015). According to Winston (1993), the artificial intelligence has made people become more intelligent and force precision and can perform quantity task tirelessly.

In geoscience, automation has revolutionised geospatial intelligence by allowing to efficiently deal with huge image data covering wide area (Quackenbush, 2004; Schade, 2015). For instance, automatic image registration whereby machine establishes the correspondence between two images and determine a geometrical transformation that aligns the image pair is the substantial progress in remote sensing due to increasing volume of remote sensing images (Alkaabi & Deravi, 2005). For features extraction, automation is considered the holy grail of remote sensing that has been quested for a long time (O'Neil-Dunne, 2011). Today, some of the machine-based approaches are argued to outperform human operators to extract features from imagery (Blaschke et al., 2014). Practically, however, an optimised human capacities and artificial intelligence integration in which human ground truthing feeds into self-learning algorithms and vice versa is recommended (Schade, 2015). In this integration, humans are believed to be good at scanning large areas and recognising objects whereas computers are good at optimisation, detailed delineation, and repetition (Quackenbush, 2004) with minimum consistency errors.

In cadastral surveying field, throughout history technology has made it possible to move from barefoot to air-foot surveying, from archaic tools that require multiple operators in the field to robotic total station with a single operator (Bennett, 2016; Bennett, Asiama, Zevenbergen & Juliens, 2015). Today GNSS PPP[2] RTK[3] services and UAV-Based survey, 3D laser scanner and LIDAR have improved the accuracy and speed at which surveying can be done (Windrose, 2017). As it was spelt in the introductory part, today, VHR images have made image-based surveying possible though there approach is still human intensive. A more compelling need for accelerated land registration call for resorting to machine intelligence exhibited by machine-based image analysis algorithms for automatic extraction of cadastral boundaries. Automation for delineating parcels, building and other cadastral features could contribute to fast track and cheap land surveying in the course of land registration. The appeal of just pushing a button and having all the features of interests such as boundaries identified on an image would be understandably appealing (O'Neil-Dunne & Schuckman, 2017).

2.2. Ontology[4] of boundaries and cadastral intelligence

Geometrically, a boundary is a set, a line of geographical features representing limits of an entity or metaphorically the transitional zone between an object and the rest of its domain of disclose (ISO 19107:2003). İn real-world life, spatial problems connected with the notions of adjacency, separation and division can be dealt with intuitively by recognising two-sorted ontology of boundaries, bona fide (or physical) boundaries on the one hand, and fiat (arbitrary) boundaries on the other (B. Smith & Varzi, 1997, 2000). İn the first case, there is spatial discontinuity such as holes, fissures, slits or qualitative heterogeneity

[2] Point Precision Positioning
[3] Real-Time Kinematic
[4] An ontology is an explicit specification of a conceptualisation (Stubkjær, 2001)

of material constitution or texture. İn the latter case one may speak of a boundary even in the absence of any corresponding physical discontinuity or qualitative differentiation like property line or a country. Generally, a boundary is conceptual construction and a matter of the convention (Varzi, 2015). Due to that some anthropogenic entities in the geographic world are immaterial with no visible boundaries and others are self-defining and can be extracted visually (Radoux & Bogaert, 2017).

In cadastre domain, a boundary is either the "limit at law" of any estate or a "physical feature" designated to mark the limit at law (Dale 1976). FGDC (2008), defined cadastral boundary as the "geographic extent of ownership" while Donnelly, (2012) used the term the "extent of the legal limits of ownership" of any parcel of land. Zevenbergen & Bennett, (2015) provide a theoretical and practical extent of cadastral boundaries. Theoretically, a boundary surface divides one land parcel from another extent from the centre of the earth vertically upwards to the infinite in the sky. However, more practically, people simply use an imaginary line to mark the confines or line of division of two contiguous parcels. By the agency of man or naturally, visible boundaries are marked by physical features fences, hedges, roads, footpaths, trees, water drainages, building walls and pavement (Ali, Tuladhar & Zevenbergen, 2012; Mumbone, Bennet, Gerke & Volkmann, 2015; Rijsdijk et al., 2013). These features are intuitively recognisable by humans at first glance based on visual cues learnt over time and had been firmly ingrained in our brain.

Cadastral boundaries can be classified as fixed boundaries when they are precisely measured or general boundaries in case no precise spatial measurement is determined (Lemmens, 2011; Zevenbergen & Bennett, 2015). Depending on the use and purpose, either type of cadastral boundary may apply (Enemark, Bell, Lemmen, & McLaren, 2014). Cadastral boundaries can be measured using direct or indirect survey technique (Sophie Crommelinck et al., 2016). Normally, fixed boundaries are measured with higher accuracy by direct techniques in the field while indirect techniques apply to extractable general boundaries. However with VHR remotely sensed data, the indirect survey can also apply to delineate fixed boundaries (Crommelinck et al., 2016).

Indirect survey technique relies on remotely sensed data and visibility is a sine qua non of boundary extractability and for proceeding to any application. Cadastral boundaries features can be detected from remotely sensed data based on their specific properties like "being regular, linear-shaped or with limited curvature in their geometry, topology, size and spectral properties such as tones or colour or texture"(Sophie Crommelinck et al., 2016). Extracting these features can be done manually by human or machine operators both exhibiting cadastral intelligence.

To understand cadastral intelligence one could refer back to 1983 Howard Gardner's theory of multiple intelligences; the work of Linn & Petersen (1985); Campbell, Campbell, & Dickinson (1996); Castilla and Hay (2008) and Blaschke (2010). In multiple intelligence, spatial intelligence is defined as the ability to perceive the visual-spatial world (Goldstein & Naglieri, 2011). Linn & Petersen (1985), defined that ability as being able to perceive spatially, localise and visualise geographical objects. According to Campbell et al. (1996), the visual-spatial intelligence refers to a range of abilities including, to visually discriminate upon reasoning, to draw and to manipulate an image.

From an Artificial Intelligence [AI] perspective, geo-intelligence denotes the procedural and structural knowledge exhibited by a machine (Castilla and Hay, 2008). Procedural knowledge is concerned with specific computational functions and can be represented by a set of rules[5]. Structural knowledge is concerned with

[5] Rule-based system or production system or expert system is the simplest form of artificial intelligence that encodes human expert's knowledge in a fairly narrow area into an automated system (Grosan & Abraham, 2011)

the relationship between image-objects and real-world geographical features. Therefore, geo-intelligence is concerned with "geospatial content in context" where features are detected based on rule sets and some level cues in association with neighbouring features (Hay and Blaschke, 2010). As put forward in Chen, Haya & St-Onge (2011); (Dold & Groopman, 2017) the advent of the artificial intelligence has reshaped geo intelligence into "automated geo-intelligence". As stated in Dold & Groopman (2017) today there exist a range of algorithmically trained perception-capable computing models capable of perceiving, recognising geographically referenced physical features.

In cadastral mapping, machine does also have the ability alongside human to acquire and apply spatial knowledge in detecting and extracting cadastral boundaries (Bennett, 2016; Bennett, Asiama, Zevenbergen, & Juliens, 2015). While human use brain machine applies artificial intelligence embedded in the algorithm to do the same job as humans do. As defined by McCarthy et al. (1955) artificial intelligence is the ability of machine to simulate functions of the human brain. In the framework of this research, we focused on cadastral intelligence applying on VHR data. Referring to Crommelinck et al. (2016); Xianghuan, Bennett, Koeva, & Nathan (2016); (Grosan & Abraham, 2011) the current study tested how far we can go with the artificial cadastral intelligence exhibited by machine-based image analysis algorithms. These algorithms encode and mimic human visual perception to extract cadastral boundaries from RS image. Such machine-based image analysis algorithms constitute artificial cadastral intelligence since they can do as human cadastral experts but they are not humans.

2.3. Exhibiting cadastral intelligence by way of image analysis algorithms

Crommelinck et al., (2016) group machine-based image analysis approaches applicable for automated cadastral boundaries extraction into two categories: i) Pixel-Based Approach [PBA] also referred to as data-driven approach ii) Object-Based Approach called model-driven. The latter is famously known as Object-Based Image Analysis [OBIA] or Geographic Object-Based Image analysis[GEOBIA] (Blaschke et al., 2014).

2.3.1. Pixel-based approach

Pixel-based approach only considers spectral value or one aspect for boundary class making it more easy and fast (Aryaguna & Danoedoro, 2016). When applied to Very High Resolution Remotely Sensed [VHRRS] data, the pixel-based approach results in salt and pepper map (Li & Shao, 2014). Therefore it falls short of expectations in topographic mapping applications due to the lack of an explicit object topology that might lead to inferior results than those of human vision (Hay at al., 2003). However, recently, the pixel-based approach is gaining much attention with the renaissance of Convolution Neural Network [CNN] (Sophie Crommelinck et al., 2016). For instance, holistically-nested edge detection algorithms are argued to approach the human ability (Xie & Tu, 2015) to identify boundaries from imagery. Some of the most recent publications (Audebert et al., 2016; Saito & Aoki, 2015) consider CNN-based segmentation algorithms state-of-the-art for predicting the shapes of the buildings and roads and hence could be potentially useful for cadastral mapping as well. However, these methods are rather not popular and suffer from being computationally intensive as they are challenging to train and requires programming skills.

2.3.2. OBIA approach

OBIA employs rule-based expert systems (O'Neil-Dunne, Pelletier, MacFaden, Troy & Grove, 2009) and is still the most popular and has been suitable for VHR image analysis in recent years (Blaschke et al., 2014; Lu & Weng, 2007). An in-depth perusal by Ma et al. (2017), of 173 publications proved the popularity of OBIA claimed by Blaschke et al. (2014) and Lu & Weng (2007), where the mean overall accuracy was found to be above 80%. In fact, by applying geo-intelligence with both procedural and structural knowledge OBIA partitions an image into semantically meaningful spatial objects with results equalling or better than human perception(Blaschke, 2010; Blaschke et al., 2014). In fact, human use contextual information to identify features from image. This intelligence can be replicated in OBIA by building context through an iterative process in which the identity of some features is used to inform classification of others (O'Neil-Dunne, Macfaden & Pelletier, 2011). Thus, results from human and OBIA can be assumed to be comparable.

OBIA aims at automating feature extraction (Blaschke, 2010). However, it is important to note that its performance depends on the quality of low-level features as actually high-level features are extracted from low-level features (Babawuro & Beiji, 2012). While high-level objects are target features and end products, low-level features are extracted directly from the raw image of possibly noisy pixels by edge detectors (Babawuro & Beiji, 2012) or segmentation algorithms (Ma et al., 2017). In other words, OBIA involves segmentation and the classification of segments (low-level features) into meaningful objects (high-level features). Thus, getting segments representing meaningful objects is critical. Another thing to note is that while OBIA serves a tool for automation, it cannot operate on its own. Quackenbush (2004), asserts that automation with OBIA provides an efficient way to analyse VHRRS data over a larger area while still taking advantage of input from human operator. In other words, automation by no mean necessitates incorporating expert knowledge (Blaschke et al., 2014).

Unlike pixel-based approach, objects resulting from OBIA are polygons with explicit topology, meaning that they have geometric properties, such as shape and size (O'Neil-Dunne & Schuckman, 2017). This makes OBIA suitable for extracting cadastral boundaries (Crommelinck et al., 2016; Radoux & Bogaert, 2017). OBIA appears highly promising than pixel-based approaches for automated cadastral boundaries extraction as it mimics the human interpretation process to detect geographic entities from an image (Kohli et al., 2017). The only problem remains that there is no transferable method between contexts owing to topographical peculiarities and diverse and complex social constructs that shape land holding size and shape and hence complex boundary morphologies across regions as noted Kohli et al.(2017).OBIA workflow (Blaschke et al., 2014), follow a stepwise process where segments are classified and enhanced iteratively based on procedural and structural knowledge.

2.3.2.1. Pre-processing

Pre-processing in concerned with preliminary operations that aim to enhance image interpretability and analysis. These include for instance subsetting, pansharpening and edge enhancement. Subsetting consists of eliminating extraneous data and constrain the image to a manageable area of interest. Pan-sharpening is an operation of fusing the high-resolution panchromatic image with a low-resolution multispectral image for enhanced visual interpretability and analysis. Another preprocessing operation is edge enhancing to ensure proper segmentation and easy detection of cadastral boundary lines.

While the first operation is straightforward by clicking specific buttons, the last two require user expertise. For pan sharpening, Pohl & Van Genderen (1998) suggested that the application very much drives the decision on which technique is the most suitable. For commercial multispectral satellite datasets, such as WorldView-2 and Geoeye-1 images with the use other than visual assessment, the Harris Geospatial Product Documentation Centre and Sun, Chen & Messinger (2014) propose the Nearest-Neighbour Diffusion [NND]. The latter enhances the salient spatial features while preserving spectral fidelity. Other techniques are suggested in Li, Jing & Tang (2017) such as the Haze and Ratio-based [HR], adaptive Gram-Schmidt, Generalized Laplacian Pyramids [GLP]. For edge detection, while Canny's edge detection algorithm is computationally more expensive compared to Sobel, Prewitt and Robert's operator, it performs better than all these operators under almost all scenarios (Maini & Aggarwal, 2009).

2.3.2.2. Segmentation and feature extraction

Segmentation uses visual cues such as brightness, colour, texture to sequentially partition an image (Shi & Malik, 2000). It is a method that was developed in the 1970s, to delineate or build readily usable objects from imagery (Blascke, 2010). Since then till now there are several segmentation algorithms. The most popular segmentation algorithm include Object Background [Threshold Model], Neural Model, Markov Random Field Model, Fuzzy Model, Fractal Model, Multi-Resolution and Transformation model [Watershed model and Wavelet model] (Dey, Zhang, & Zhong, 2010). Crommelinck et al. (2016) and O'Neil-Dunne & Schuckman (2017) classified these techniques into (1) unsupervised approaches and (2) supervised methods. Supervised methods consist of machine learning and pattern recognition. Unsupervised approached apply parametric methods using colour, texture, spectral homogeneity, size, shape, compactness, and scale of image segments.

Of the listed methods, scholars such Baatz & Shape (2000); Belgiu & Drăguţ (2014); Gupta & Bhadauria (2014); Saba, Valadanzouj & Mokhtarzade (2013) highlighted the pre-eminence of MRS in GEOBIA framework. MRS is suitable for shape analysis and allows coping with variability in sizes for different physical structures (Aksoy & Akçay, 2005). Different from the classic spectral analysis, MRS aggregate pixels starting with the one-pixel object and merge smaller image objects into increasingly larger ones in the subsequent segmentation steps thus constructing a semantic hierarchy, to find desired single objects of interest identifiable by colour or shape (Barrile & Bilotta, 2008).

As for automation of parcel extraction, since theoretically, a parcel is defined as a single land area under homogeneous real property rights and unique ownership (UN ECE 2004 and WG-CPI, 2006 cited in Kresse & Danko, 2012; Oosterom & Zlatanova, 2008) we assume that a parcel is also homogeneous in terms of land cover as in Hu, Yang, Li & Gong (2016). On the assumption that we have homogeneous land cover parcels, we can extract them using spectral information. For automation of buildings extraction, with their unambiguous ontological status (Belgiu & Drăguţ, 2014), we assume they are easily detectable by remote sensing technique and hence extractable. However, in practice, it is important to note that features extraction require highly accurate data and skilled personnel (O'Neil-Dunne & Schuckman, 2017). According to Zhiyong, Zhang & Benediktsson (2017), parameters tuning in segmentation is time-consuming and highly dependent on experience. These authors caution about unpleasant results that may arise from image data source. In their experimentation, O'Neil-Dunne and Schuckman (2017) have observed that even small change in tone and the direction of shadows that may have little to no effect on a human operator, can wreak havoc on automation.

2.3.2.3. Post processing

Post-processing operations aim at improving automation output by optimising shape, following properties of cadastral boundaries: linearity or limited curvature, connectedness and smoothness (Crommelinck, 2016). Post-processing employ algorithms such Ramer-Douglas-Peucker line simplifier or morphological operators to smooth the contour of generated cadastral lines. Further topology analysis may be performed to assess geometric relationship and connectedness of boundaries lines.

2.4. Performance of image analysis algorithm in cadastral mapping

Performance theory[6] is most associated with the work of Turner (1988) and Schechner (1985). Turner and Schechner drew attention to how a code of performance governs events and rituals and daily human life. Performance is hence multidimensional and dynamic (Sonnentag & Frese, 2001) implying different

[6] https://www.history.ac.uk/1807commemorated/about.html

meanings. In the framework of this study, a task-oriented definition of performance defined in Borman and Motowidlo (1993 cited in Borman & Motowidlo, 1997; Motowidlo & Van Scotter, 1994; Sonnentag & Frese, 2001), is underlined. According to Borman and Motowidlo (1997) performance is related to ability, more prescribed and constitutes in-role standards.

In practice, it might be difficult to describe the action aspect of performance without any reference to the outcome aspect (Sonnentag & Frese, 2001). In fact, not any output from a task is relevant. Thus, one needs criteria for evaluating the degree to which the performed task meets the prescribed code and acceptable standards. In remote sensing, evaluation of classification performance uses standard accuracy metrics, where the deviation by classified objects from the reference is due to the classification error (Lu & Weng, 2007).

For assessing the performance of machine and accuracy of automated features extraction, scholars like Persello & Bruzzone (2010); Crommelinck et al. (2016); Möller, Birger, Gidudu & Gläßer (2013); Gruen, Baltsavias & Henricsson (1997) and Radoux & Bogaert (2017) emphasise the need to consider the geometric quality of classified objects in addition to the thematic accuracy. Specifically, Radoux & Bogaert (2017) stressed that for spatial features delineation, the geometric precision is usually more important than the thematic accuracy. Therefore, for the focus of our study will be comparing machine and human performance to reference dataset based on geometric precision than the thematic accuracy.

In literature, quite many frameworks for geometric accuracy assessment are provided. Those which fall in line with this research include, among others (1) the novel protocol for accuracy assessment which included five geometrical indices elaborated by Persello & Bruzzone (2010). (2)The Polygons and Line Segments [PoLiS] metric for polygon comparison developed by Avbelj, Müller & Bamler (2015). (3)The framework for the geometric accuracy assessment of classified object elaborated by Möller et al. (2013). Of these methods, geometric indices elaborated in Persello & Bruzzone may be easily implemented in ArcGIS and have been applied in Belgiu & Drăguţ (2014) and elaborated further in (Liu et al., 2012).

Geometric accuracy assessment may also use some other planimetric measures like True Positives [TP], False Positives [FP], False Negatives [FN] and True Negatives [TN] described in Crommelinck et al. (2016) and Radoux & Bogaert (2017). The TP are features that are correctly detected by the method. The FP are incorrectly detected objects. The FN are features that are not detected by either human or machine but they exist. The TN are truly undetected features by one method but falsely detected by another method. False positives and false negatives, results from over-segmentation where the classifier predicts more than one image-segment for one spatial entity and under-segmentation where the classifier predicts more than one features encapsulated inside one image-segment. These two FP and FN inform the degree of omission and commission error by the classifier (Crommelinck et al., 2016; Persello & Bruzzone, 2010).

Two global metrics, completeness and correctness (Crommelinck et al., 2016), also referred to as precision and recall (Estrada & Jepson, 2009) are suggested to avoid biases of under-segmentation and over-segmentation. Correctness or precision measurement of the percentage of correctly extracted data, i.e. the proportion of the extraction which is in accordance with the reference data. Completeness or recall measures the percentage of the reference data which is explained by the extracted data, i.e. the proportion of boundaries in the reference dataset that was detected by automated extraction. Estrada & Jepson argue for two metrics being an attractive metric of segmentation quality because they are not biased in favour of over- or under-segmentation.

2.5. The Legitimacy of image-based cadastral intelligent algorithms

Talking of machine performance in cadastral boundaries extraction from VHR images, its legitimacy becomes an important aspect as well. Ho (2017) argued that while land information is a technology-driven field, thinking that only cost-benefit efficiency determines a given technology adoption would be wrong, instead it is worth considering performance needs while also fitting with contemporary values.

The term legitimacy dates back to the dawn of organisation and social theory introduced by Weber (Deephouse & Suchman, 2008; Roth & Wittich, 1978). In 1995s, Suchman came up with the most widely accepted definition of legitimacy (Cruz-Suarez, Prado-Román & Prado-Román, 2014; Suddaby, Bitektine & Haack, 2015). Suchman defined legitimacy to be "the generalised perception or assumption that an entity's actions are desirable, proper or appropriate within some socially constructed system of norms, values, beliefs, and definitions". Since then, legitimacy is used in many directions to denote the conformity with both general social norms and formal laws (Deephouse & Suchman, 2008). In technology, legitimacy refers to the perceived alignment or misalignment of a focal technology with technical design rules, business models or consumer expectations as defined by institutional structures (Markard, Wirth & Truffer, 2016). As stated by Markard et al. (2016), technology is said to misalign if does not conform to the norms and to formal rules, laws and regulations performance criteria of established technology and the larger sociotechnical regime it is embedded in. Thus, for it to grow and thrive, a new technological venture need to be legitimised to mobilise resources or regulatory support (Payette, 2014).

Legitimacy is a matter of perspective and vested interests (Markard et al., 2016). As for implication, different stakeholders: professionals and citizens are likely to have different motivation towards new technology. For instance, it was noticed that professional codes are used to resist against innovative approaches in land administration fearing these changes may obstruct their interests and their values (Enemark et al., 2014). To measure the legitimacy of technology as perceived by different users fall into three dimensions: 1) cognitive, 2) normative or moral or regulatory 3) pragmatic (Johnson, Dowd & Ridgeway, 2006; Markard et al., 2016; Payette, 2014; Suchman, 1995). Cognitive is based on comprehensibility, the degree to which an entity is known, understood and taken for granted. Normative relates to professional accreditation regarding the level of conformity with established professional values and widely shared principles, formal rules, laws and regulations. Pragmatic rests on self-interested calculations.

For our study, assessment of the legitimacy of automation tool for extracting cadastral boundaries from remotely sensed data involved mainly land professionals. It was important for the study to assess how professionals perceive the usefulness of machine intelligence for automated cadastral boundaries extraction, how they understand it, observance to survey charter and legality of automated boundaries, the readiness of users to embrace the tool and the perceived ease of use. The latter, following Burns et al. (2007) was captured by perceptions of professional on time and cost it takes and complexity indicators for surveying a property.

2.6. Conceptual framework

In reflection to previous sections and the introductory part, a quantitative and qualitative framework for comparing machine abilities against draftsperson to perform boundaries extraction was developed. Three central assumptions were made. (i) a)Rural parcel boundaries are physically manifested through visually detectable features such as ditches, hedges made of traditional tree line, walkways. Parcels are homogeneous in terms of land use and hence spectrally homogeneous. b) Urban parcels can be delineated based on visible fences. Building are ontologically well distinguishable by their colour of roof materials. (ii) Using cadastral intelligence with contextual cues learned over time, professionals can hypothesise and digitise boundaries on image. (iii) Since boundaries are visible and hence detectable by remote sensors, machine with minimum input of human knowledge can discern these boundaries features based on spectral and geometric information as people do. Both human and machine performance can be evaluated and compared based on predefined accuracy metrics and reference data. The perceived performance and deficiencies of machine will play a greater role towards its legitimacy. A conceptual diagram is presented here below:

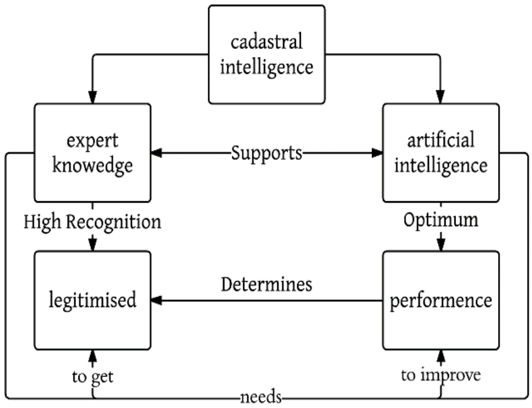

Figure 1: Conceptual framework for measuring cadastral intelligence exhibited by humans and machine.

As for interpretation of Figure 1, cadastral intelligence can be exhibited using (human) spatial reasoning and expert knowledge or using machine algorithms. People are believed to have high ability to recognise boundary features than machine since boundaries are social constructions and hence more perceptible to human. But also, the machine is known for its relentless computational power and hence we need it for improved performance. Table 1 summarises operationalisation process.

Table 1: Operationalisation of concepts

Concept	Dimension	Variables	Indicators
Cadastral	1)Human	Geometry	Geometric indices allow quantifying the spatial quality of
intelligence	2)Technology	Correctness	extracted cadastral boundaries
		Completeness	Number of correctly extracted cadastral boundaries
		Omission	Number of reference features extracted
		commission	Number of omitted features from references features
Performance	Task-oriented		Number of commits features to reference features
Legitimacy	1)Regulatory	Perceptions of	Alignment to survey rules, standards; ease of use and
	2)Cognitive	experts	cost-effectiveness regarding time and money
	3)Pragmatic		

2.7. Summary

In this chapter, a thorough discourse of technology and machine intelligence was given. Essential points worthy of consideration emphasised that machine is unavoidable in our daily life. The reason was given being that machine intelligence results from exteriorisation of our brain functions allowing to share, optimise and immortalise the knowledge. The most point to note was the implication and innovation brought about by automation in remote sensing and ptentially to cadastral applications. This chapters went on to discuss possible approaches by which machine intelligence to automate boundaries extraction can be exhibited. Different evaluation methods to assess the performance of machine to the ground truth of experts were discussed. Apart from mathematical performance evaluation, the intriguing issue of legitimacy of automation tool based on user perspective with regard to norms and practices was discussed. Ultimately, from theories, a conceptual framework to compare quantitatively and qualitatively machine and human performance for extracting parcels and building shapes from image was laid down. The next chapter will elaborate a methodology that was used to operationalise the conceptual diagram.

3. METHODOLOGY

This chapter describes applied methods to operationalise the concepts to address the research problem and objectives. The chapter presents the general workflow (Figure 2), research strategy (section 3.1), case study sites (section 3.2), imagery dataset (section 3.3), implemented approach for automation (section 3.4) and manual boundaries extraction (section 3.5) and comparison framework (section 3.6).

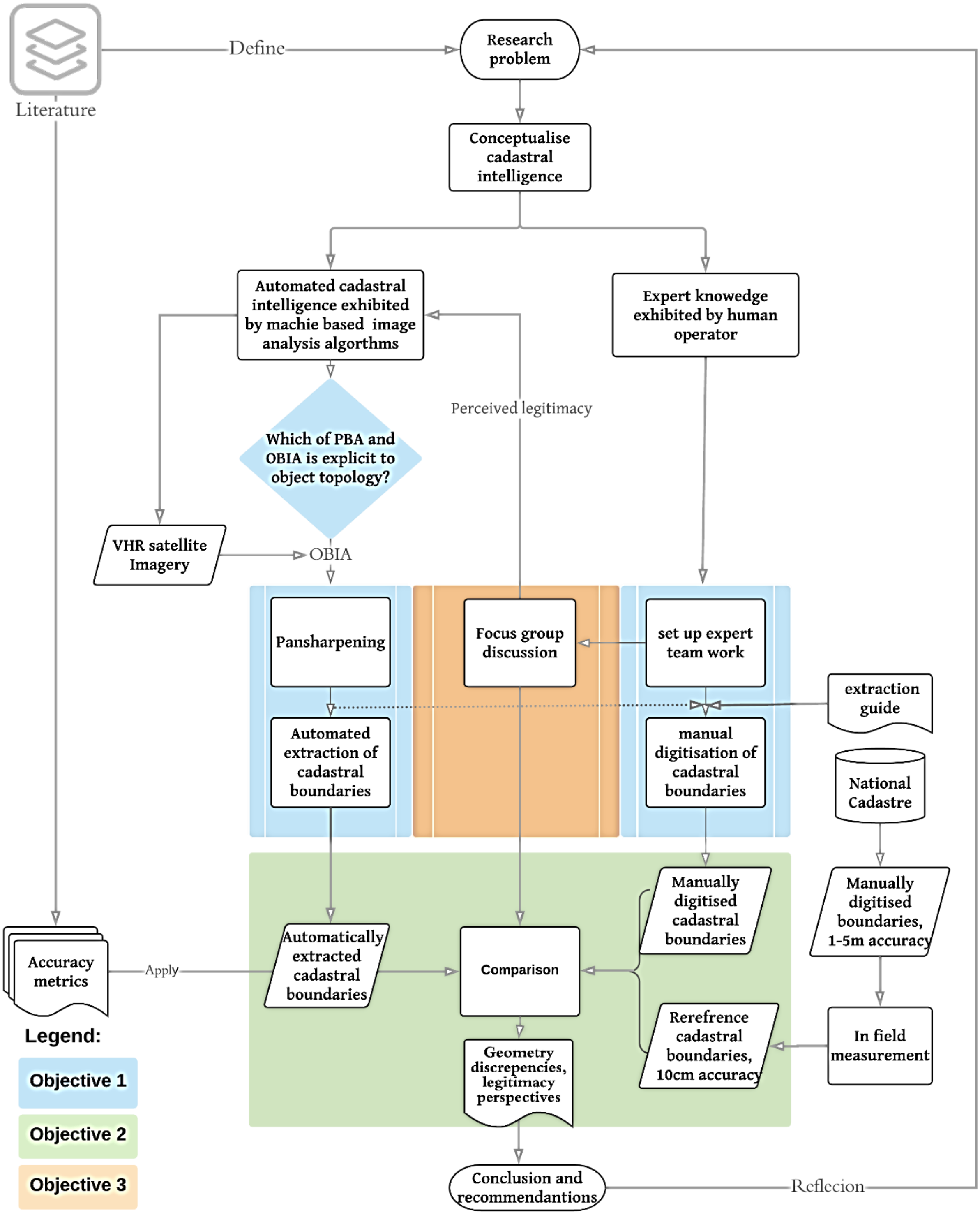

Figure 2: Research workflow

3.1. Research strategy

The study applied a comparative approach using a case study. Referring to Bhattacherjee (2012); Miller & Brewer (2003), a case study was found useful and adapted for testing whether using machine-based features extraction algorithms could actually apply for automated cadastral boundaries extraction in the specific real-world setting.

3.2. Case study sites

Two sites, one representing urban setting and the other one rural setting within Kigali city in Rwanda were selected based on the availability of VHR satellite images, visual detectability of cadastral boundaries, and convenience of accessing reference datasets for comparison. The selection of testing sites followed a visual interpretation as pre-step to automation as suggested in Kohli, Bennett, Lemmen, Kwabena, & Zevenbergen (2017). After hovering over Kigali city and intuitively trying to quantity boundaries that are identifiable through visual interpretation, areas with maximum visual interpretability of cadastral boundaries were selected. The rural site is located in Nyamugali cell, Gatsata sector and the urban site is located in Gibagabaga cell, Kimironko sector within Gasabo districts. A map of the study sites is given below (Figure 4).

Rwanda is renown globally to be among the first countries where image-based demarcation was applied to build a nationwide cadastre system at a low cost. Since one of the objectives of the study is to gather experts and user perspectives, Rwanda would serve the best case study. Opinions from the focus group not only reflected experts' own views but also experience and reality with image-based demarcation and fit for purpose approaches.

3.3. Imagery dataset

The research used ortho-rectified, 2m-resolution multispectral and 0.5m-resolution panchromatic WorldView-2 satellite images. This imagery, according to DigitalGlobe (2010), has shown significant improvement in object-oriented classification and automation. The 0.5m-resolution panchromatic image offers a much higher spatial resolution with which features marking cadastral boundaries like ditches and fences are clearly visible. The 2m-resolution multispectral (RGBNIR) image provides high spectral resolution where features can be separated based on their colour. To take advantage of both high spatial resolution of the panchromatic image and high spectral resolution of the multiresolution image a fused image was produced. For this operation, the Nearest-Neighbour Diffusion (NNDiffuse) pansharpening algorithms available within the Environment for Visualising Images [ENVI] software was applied, owing to its advantages discussed in section 2.3.2.1. The resulting image i.e. pan-sharpened image provides higher spatial and spectral resolution (Figure 3).

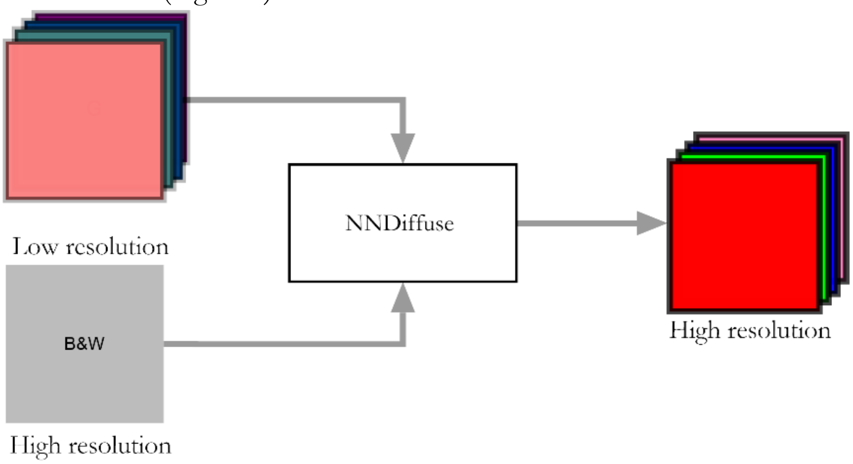

Figure 3: Illustration of pansharpening operation

To avoid lengthy computation, the original image was subset to eliminate the extraneous data and constrain the image to a manageable area of interest, i.e., test sites. The rural site was restricted to an area of 280x560m and the urban site to an area of 320x400m. Then, subset images were fused as illustrated in Figure 3. The outputs of sharpening are presented in Figure 5.

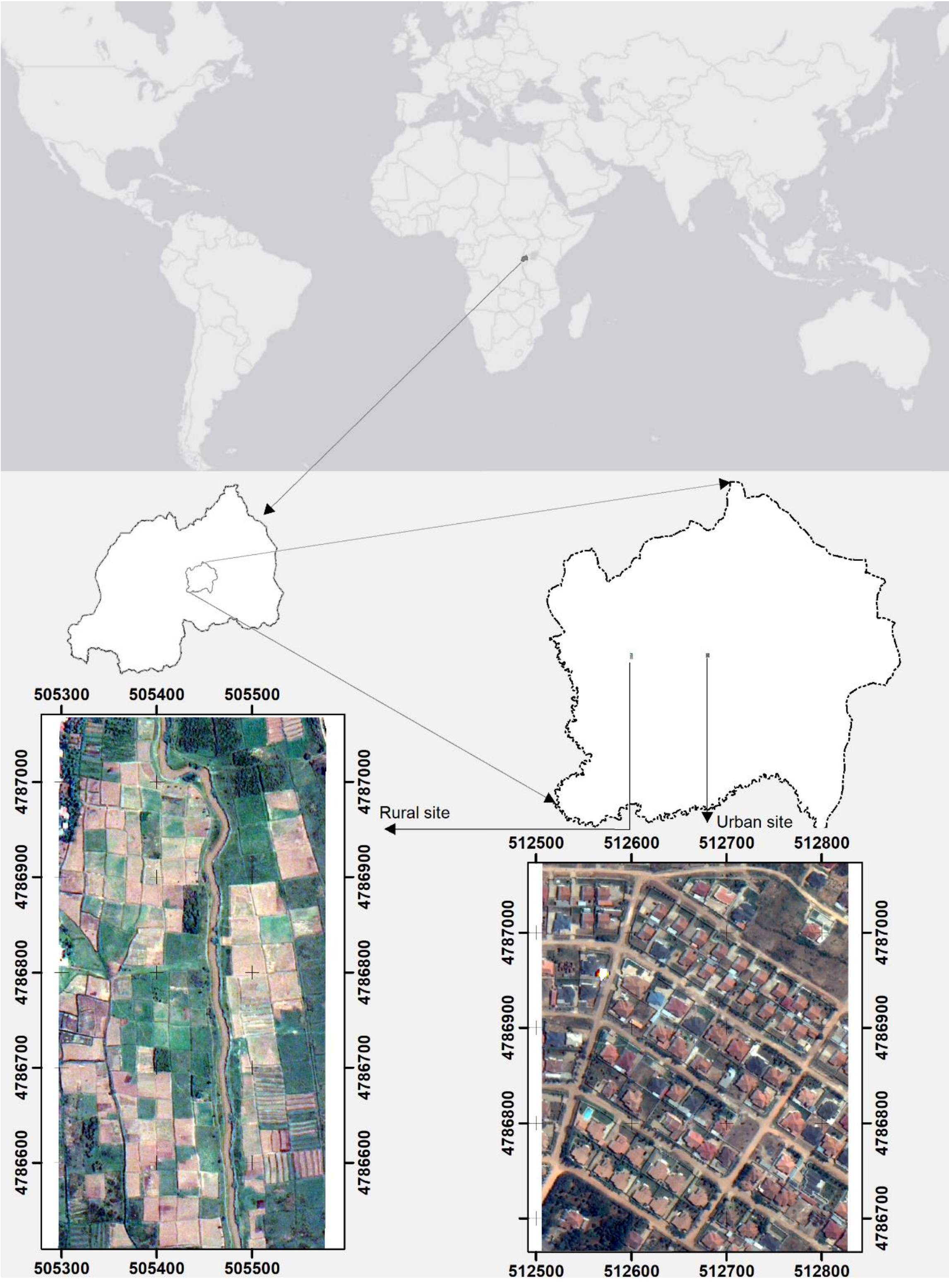

Figure 4: Case research sites

On the map (a) shows the location of the study area on global scale; (b) Rwanda & (c) Kigali City.

The comparison of the pansharpened image and low-resolution image could reveal very significant difference as it can be observed in Figure5.

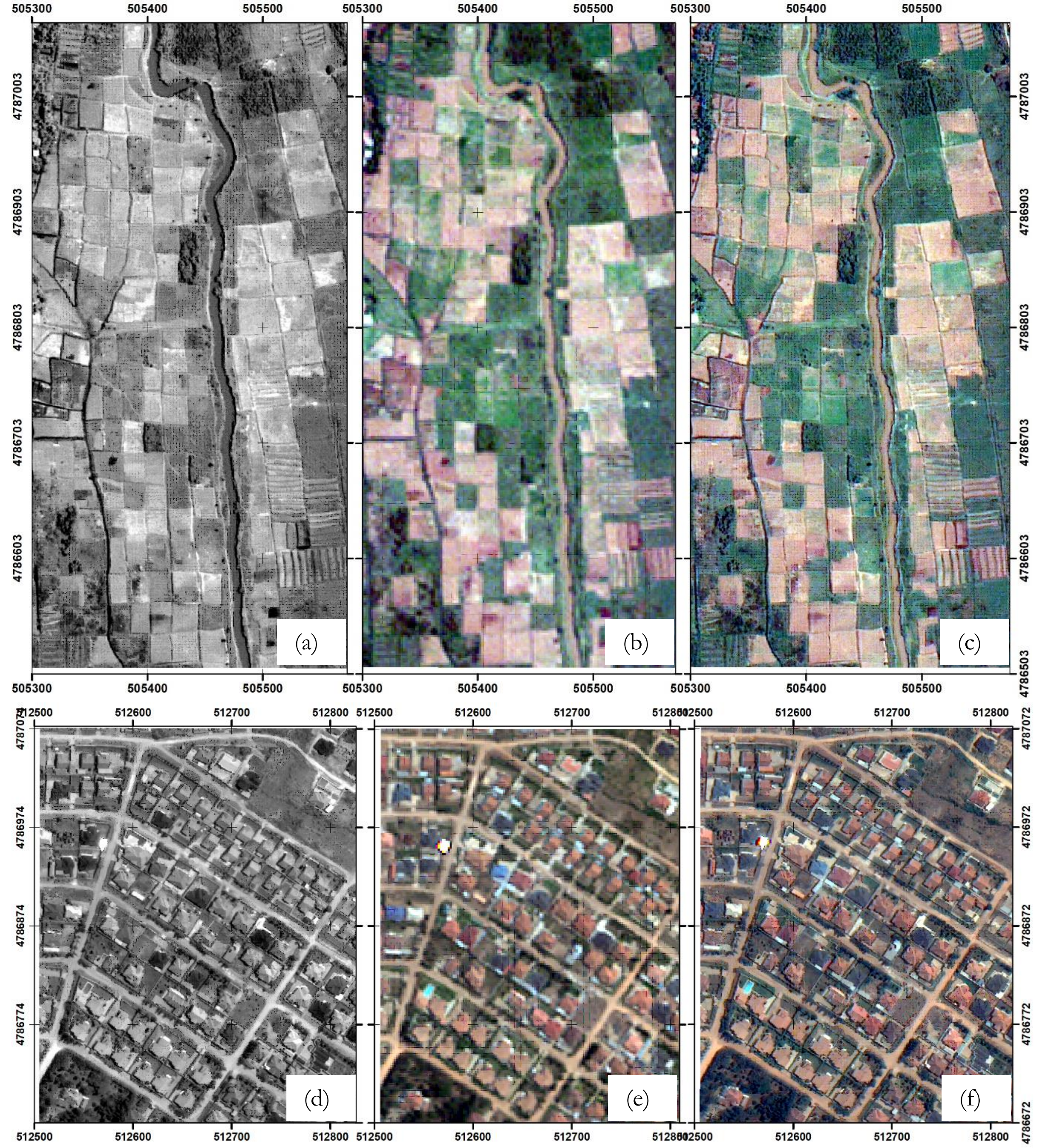

Figure 5: Comparison of panchromatic, multispectral and pan-sharpened images

On the left of Figure 5, (a) and (d) are a black and white images on which features shape can be seen but really somewhat challenging to get land cover information on parcels or buildings. İn the middle (b), (e), the coloured images look coarse. On the right (c) and (f) are other coloured images on which shape and colour of features are well displayed. Features such ditches, river, bare soil and vegetated parcels; red, black, blue roof and pavement are clearly discernible. With the first image, despite being a high spatial resolution image, it would be difficult for people and machine to delineated parcels or building by only considering the morphological pattern. Thus combining it with the coarse colour image in the middle provided an image(c), (f) that is both spectrally and spatially rich enough for the user to identify boundaries by combining both shape and spectral signatures of features.

3.4. Automation process

Automated boundaries extraction built on the description of visible boundaries elaborated in section 2.2 and assumptions made in section 2.6 and experts ground knowledge as indicated in Figure 6. İn the rural site, visible ditches mark most of the parcel boundaries making them extractable. İn urban site, buildings and plots are discernible by looking at shape and colour. Rule-based expert systems within eCognition were developed to allow the segmentation of the image and extract parcels and building shapes based on spectra, texture, geometry and contextual information. As discussed in section 2.3.2.2 getting an optimal segmentation where maximum number of segments match parcels or buildings is crucial and was primarily beseeched. Initially, the automated Estimate Scale Parameter [ESP2] tool (Drăguţ, Csillik, Eisank & Tiede, 2014) was tried. The appeal of this tool is that it supports for automated optimisation of scale parameter SP which is the key control in MultiResolution Segmentation [MRS] process. It produces fully automatically three scale levels, based on the concept of Local Variance on one push of the button that if succeeded would fit best the purpose of the study. But, mainly, the study used expert knowledge for parameterisation for boundaries are results of social constructs and more perceptible to human as it has been discussed in section 2.2. In fact, the selection of parameter like scale parameter in MRS is a more objective decision (Drăguţ et al., 2014) requiring more reasoning of the expert.

The semi-automated process involved different techniques such as chessboard and multiresolution segmentation. The chessboard segmentation with the size smaller than river in rural area and the size smaller than road in urban area were applied. Open Source Map (OSM) river and roads dataset were used as thematic layers in chessboard for rural and in urban areas respectively. In rural area, based on expert ground knowledge, the distance to vectors contextual information was used to remove river strips of 10-meter buffer along river shores. In urban, a 7-meter buffer from the central line of streets was applied to remove road strips from image objects. MRS was applied to the rest of the image to generate candidates objects classifiable into parcels or building. Unlike in ESP-2, manual scale parameterisation was a trial and error process and involved iterative tuning of scale and homogeneity. To enhance the detectability of parcel boundaries, the texture after Haralick derived from the Grey Level Co-occurrence Matrix (GLCM) which is known to be the best for localising texture boundaries (Al-Kadi, 2011) was used as a temporary image layer. The scale was used to control the size and homogeneity based on visual assessment. A single parcel was hypothetically considered homogeneous. It could be observed that a higher scale caused many parcels to merge and boundaries to disappear and hence results were considered heterogeneous. The homogeneity could be determined by balancing colour and shape (smoothness + compactness) weights. İt could be observed that a high value for either shape or colour criterion operated at the cost of homogeneity of the objects i.e. as the value of the shape increased, the less the spectral information played a role in delineating parcels. Since ultimately, the colour is the primary information contained in image data (eCognition Developer, 2014), the value of compactness was always higher than the shape value. Mathematically parameter tuning considered that Colour=1-shape; Shape=smoothness+compactness; Compactness=(1-βcompactness)*shape and Compactness= βcompactness*shape.

Geometry information such as polygon area, compactness, asymmetry, density, elliptical fit and shape index was then used to classify candidates objects into parcels. But also, not all targeted parcels could be extracted whole and correct at one go but in a stepwise manner. The process required subsequent segmentation and classification of fitting objects into parcel until results were satisfactory i.e. visually most of the extracted parcels matches boundaries lines on image. As it was elaborated in the theoretical and conceptual framework part, cadastral boundaries have standard properties of linearity or limited curvature, and smoothness which is not the case for automated boundaries. İn most case, automation result into jagged lines. To improve and smooth ragged boundaries morphological operator within eCognition were considered.

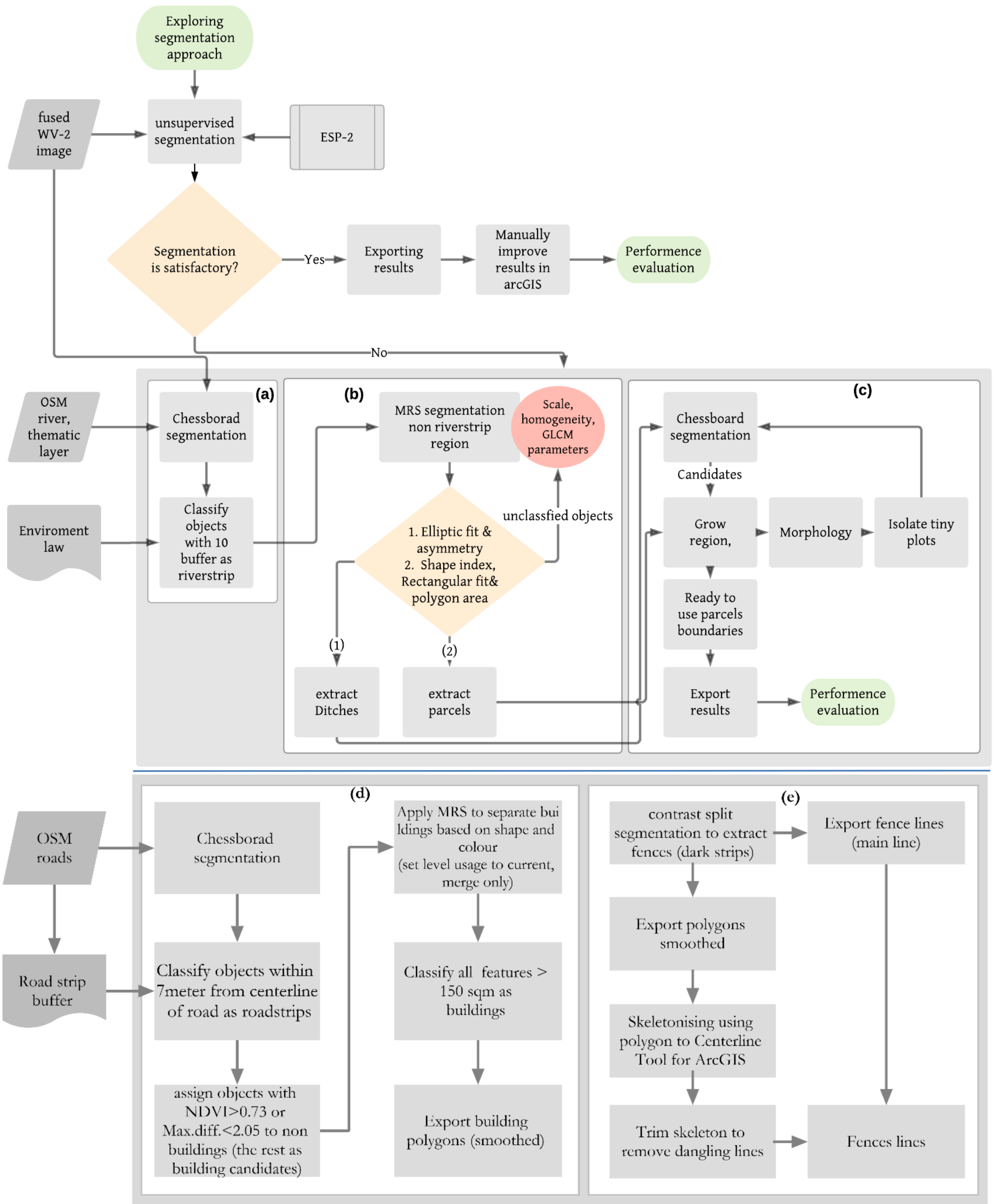

Figure 6: Applied automated boundaries extraction workflow

İn (a) chessboard segmentation is used to incorporate contextual information from Open Source Map (OSM) layer. A 10 m buffer zone is applied to remove rivers trip from parcel candidates. In (b), subsequently, the image is segmented and segments classified with the elliptic fit, asymmetry shape index, rectangular fit and polygon area threshold values. İn (c), boundaries are enhanced. By applying chessboard segmentation, tiny plots size resulting from over-segmentation are split into small parts to merge with neighbouring parcels using grow region rule set. In (d) after applying chessboard segmentation roads strip and garden were removed based on NDVI and Max.Diff. [(which refer to maxim difference between an image object and its neighbour image objects, regarding their mean layer intensity values, (eCognition reference book, 2014)] value. The rest of the image was segmented using MRS to generate individual buildings based on colour and shape. In (e), since fences appear dark, we tempted to extract them using contrast splits.

3.5. Manual digitisation

Apart from automated cadastral boundaries extraction; a group of five human operators were tasked to hypothesise and manually digitise cadastral boundaries using the same dataset as in automation. Since the team comprised many people, a precise description was required. The team was provided with extraction guide. The guide was developed with the aim to give a clear description of cadastral objects to be extracted, input dataset and set clear digitising rules. Before actual extraction exercise begun, users were instructed on smallest interpretation unit, appearance in the image, geometric type and attributes, aggregation rules and level of details.

As automation included the expert knowledge, for comparison purpose, it was thought to make sense to use cadastral experts for manual extraction of cadastral boundaries as well. According to Ayyub (2001), an expert is identified on the basis of professional qualifications, experience, and memberships of the recognised professional body. Such person has acquired extensive knowledge and expertise that allows to perceive systems, organise and interpret information (Perera, 2011). A domain or substantive expert is familiar with the subject at hand and is responsible for analysing the issue by automatic, abstract, intuitive, tacit, and reflexive reasoning. In the same vein, cadastral expertise was considered when selecting participants and only people with more than five years of work experience in cadastre or being a member of chartered surveyor professionals were selected.

3.6. Framework for comparing automated against manually digitised boundaries

3.6.1. Quantitative geometric accuracy metrics

Adapted from Persello & Bruzzone (2010) and Liu et al. (2012), to measure the precision of machine classifier in reproducing the correct geometry and the shapes of cadastral objects,
Given;

- A reference map of n objects constituting a set R= {R1, R2, …, R_n}; each object with assumedly exact shape, structure, and position
- Thematic map of extracted and topologically connected cadastral objects forming a set C = {C_1, C_2, . . ., C_s};

The geometric error measure is computed by an intersection of each polygon R_i in the cadastral reference map and the corresponding segment in thematic map Ci;

For a pair (R_i, C_i), the following scenarios can outline in the figure below:

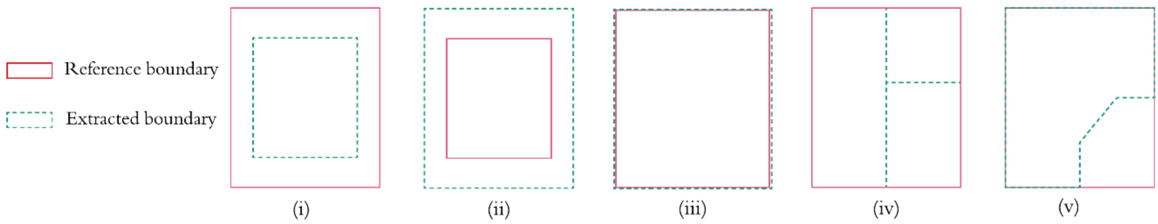

Figure 7: Geometric error scenarios

In (i) the areas that fall outside the green zone are called over-segments, i.e. the areas omitted from the reference polygon. (ii) The area beyond the red line is under segment and committed to the reference. (iii) edge error where boundaries of extracted object mismatch boundaries of the reference object. (iv) Fragmentation error, where a classifier has split the object into several fragments. (v) the shape in green has deviated from the reference shape in red.

Geometric error measures Over-segmentation error [OS_{err}], Under-segmentation error [US_{err}], Edge Location [ED_{err}], Fragmentation error or Number-of-Segments Ratio [NSR] and Shape error S_{err}] that evaluate the degree of mismatching between the reference cadastral object and the corresponding extracted cadastral object on the map can be computed as follow:

$$\mathrm{OS_{err}}(\mathrm{R_i}, \mathrm{C_i}) = 1 - \frac{\mathrm{R_i} \cap \mathrm{C_i}}{\mathrm{R_i}} \tag{1}$$

$$\mathrm{US_{err}}(\mathrm{R_i}, \mathrm{C_i}) = 1 - \frac{\mathrm{C_i} \cap \mathrm{R_i}}{\mathrm{C_i}} \tag{2}$$

$$NSR = \frac{abs(N_{r-}N_{c)}}{N_r} \tag{3}$$

Where, N_r is the number of polygons in reference dataset and N_c the number of corresponding segment

$$\mathrm{ED_{err}}(\mathrm{R_i}, \mathrm{C_i}) = 1 - \frac{\varepsilon(\mathrm{R_i}) \cap (\mathrm{C_i})}{\varepsilon \mathrm{C_i}} \tag{4}$$

where $\varepsilon(R_i)$ denotes a tolerance introduced to extracts the set of edge area from a generic region R_i in the recognition of the object borders. Since in Rwanda most legal boundaries were manually digitized within 1-5m of the 'true' position (Koeva et al., 2017), $\varepsilon(R_i)$ can take value up to 5 metres.

$$\mathrm{SH_{err}} = \|\mathrm{sf}(\mathrm{R_i}) - \mathrm{sf}(\mathrm{C_i})\| \tag{5}$$

Where, a shape factor sf could be one of several geometry indices like asymmetry, border index, compactness, density, elliptic fit, main direction, radius of largest enclosed ellipse, rectangular fit, roundness, or shape index (eCognition Developer, 2014). The latter was used for ease of computation. It is calculated from the border length of the object divided by four times the square root of its area:

$$\text{Shape index} = \frac{\text{Perimeter}}{4\sqrt{Area}} \tag{6}$$

Knowing the geometrical error of individuals classified objects (Err_i), a global geometric error (Err_n) for n classified objects can computed as:

$$Err_n = \frac{1}{n}\sum_{i=1}^{n}(Err_i) \tag{7}$$

For all (1), (2), (4), (5) and (6) the optimum value is 0 and 1 as the worse performance. For (3), the zero indicates a preferred one-to-one relationship between reference polygon parcel or building and corresponding extracted parcels or buildings while a substantial value would show a dominant one-to-many relationship due to excessive fragmentation or omission.

The above formula (1), (2), (4) and (5) were applied for one to one relationship where desirably one parcel in the reference is explained by one parcel in the extracted data set. In other cases of one to many or many to one correspondence omission error and commision error referred to as false negatives and false positive were applied. (i) The False Positives (FP) are instances, in the context of the study parcels or buildings, which were erroneously included by either machine or human experts; (ii) the False Negatives (FN) are parcels or buildings that are not detected by either human or machine but they exist in the reference dataset.

$$\text{FN (Ommitted)} + \text{TP (Detetcted)} = \text{Reference}; \tag{8}$$

$$\text{FP (Committed)} + \text{TP (Correctly Detected)} = \text{Extracted} \tag{9}$$

FN results from many to one reference-extracted relationship and FP results from one to many relationships

From there, the two global accuracy metrics, namely correctness and completeness rates and were computed a follow:

$$\text{Correctness} \quad = \frac{\text{Extracted} \cap \text{Reference}}{\text{Extracted}} * 100 \qquad (10)$$

$$\text{Completeness} \quad = \frac{\text{Reference} \cap \text{Extracted}}{\text{Reference}} * 100 \qquad (11)$$

The formulas were implemented in ArcGIS and required mastery of GIS overlay and proximity analysis. (1), (2) were performed first by splitting by attributes both extracted and reference to generate individual parcels. Then we applied batch intersect for each parcel in the reference with each corresponding parcel in the extracted data set and then merge intersects to have one attribute table containing area of intersection of all parcels. (3) was implemented by counting the number of references and extracted parcels to get the value of Nr and Nc and then use them into the formula. (4) was implemented with model (Figure 8). (6) was implemented using calculate field in attributes tables. The overall framework is given in Figure 10.

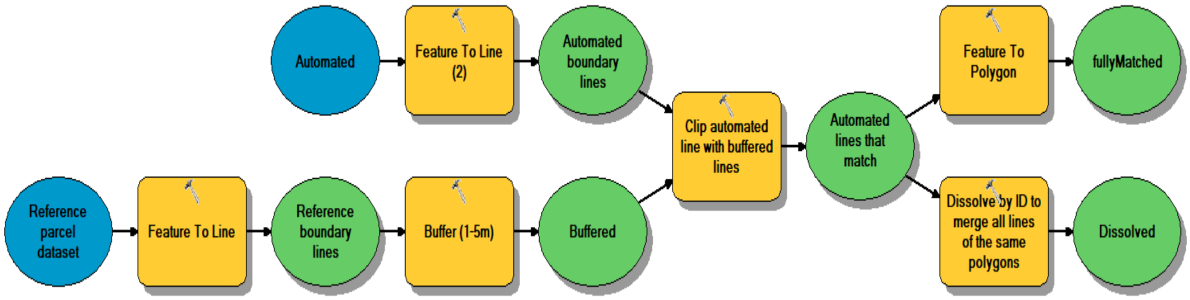

Figure 8: Model for assessing edge error between reference and automated boundaries lines

For visualisation, violin and box plots were used. Specifically, the violin plot, according to (Burkhart, 2015; Statgraphics, 2018) it is a useful tool for summarising and comparing samples of quantitative data by combining box-and-whisker plots with nonparametric density estimators. The commonalities and interpretation of box plot and violin plot are elaborated in Hintze and Nelson (1998) as in Figure 9.

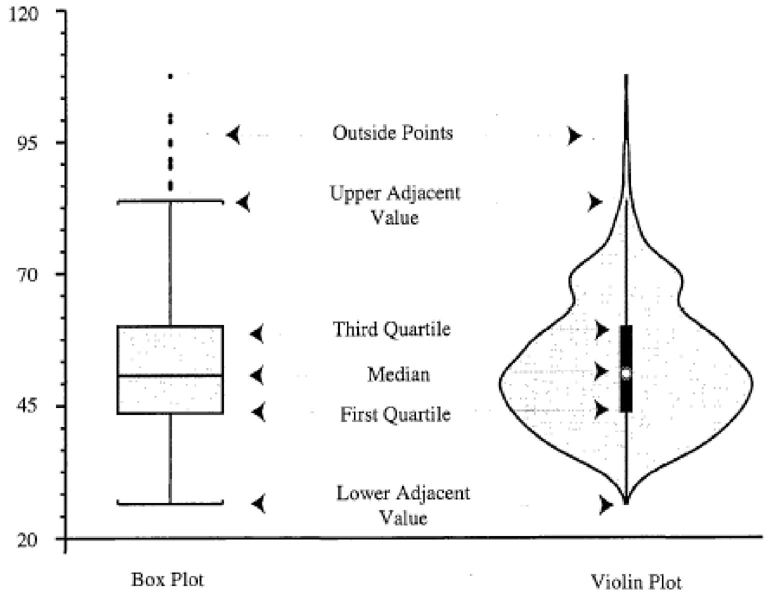

Figure 9: Interpretation and commonalities of box plot and violin plots. Hintze and Nelson (1998)

As it could be seen in the above figure, violin plot can show the full distribution of data behaviour for all instances and the pattern of responses for machine and human can be compared.

3.6.2. Reference [validation] dataset

According to Mckeown et al. (2000), an important aspect of the development of systems for automated cartographic feature extraction is the rigorous evaluation of their performance in the sense that it has to base on precisely defined characteristics. İn implementing Mckeown et al's suggestions, reference dataset to which the performance of machine and human cadastral intelligence were evaluated was obtained using state of the art Zeno mapping software embedded in a lightweight survey tablet with instant access to GNSS[7] RTK[8] CORS[9] corrections via GSM[10] built-in modem allowing gather centimetre accuracy data.

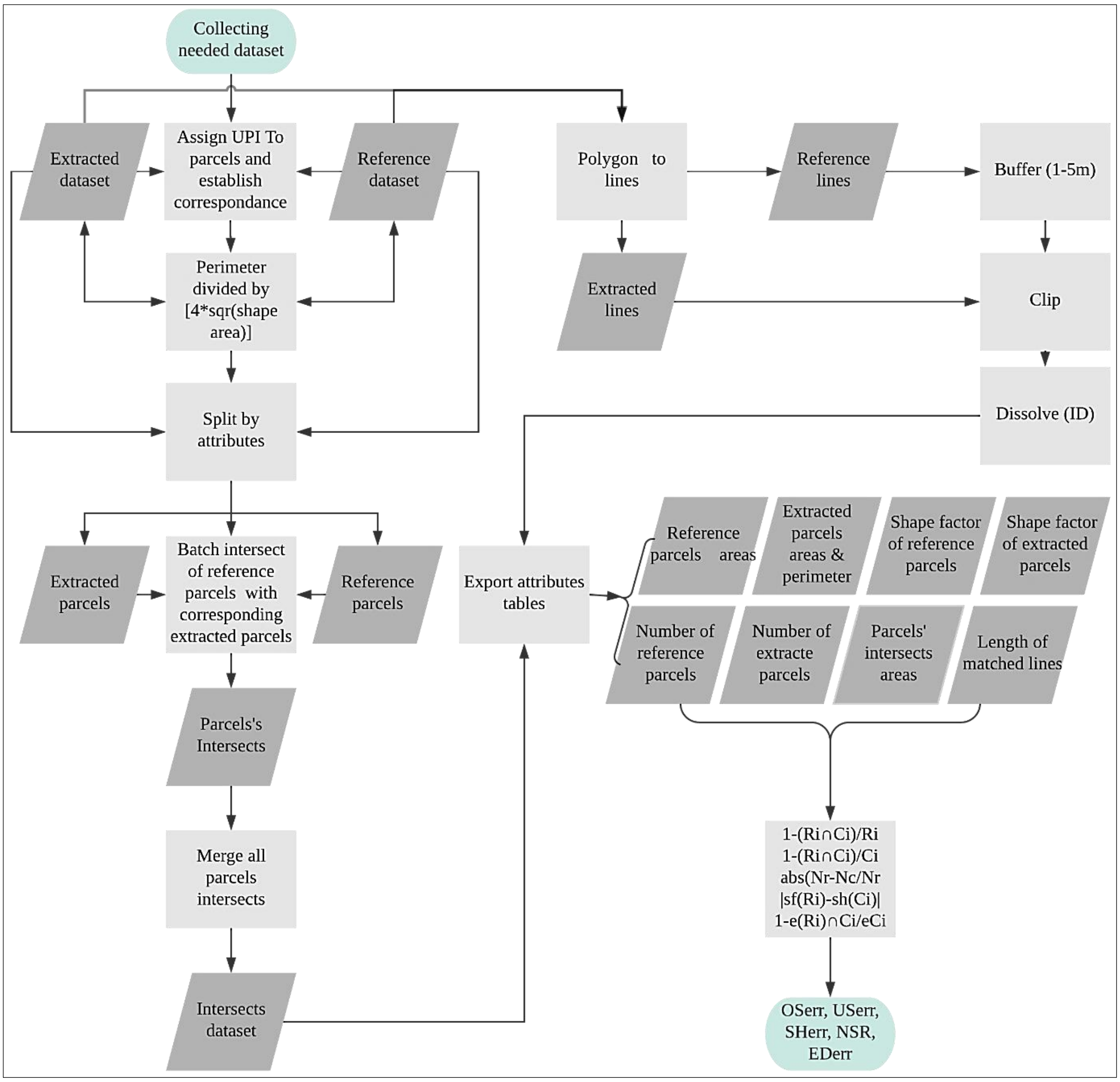

Figure 10: Implemented framework for computing geometric discrepancies

[7] Global Navigation Satellite System
[8] Realtime Kinematic
[9] Continuously Operating Reference Station. Rwanda has 8 stations, each one with a coverage radius of 30km
[10] Global System for Mobile [originally Groupe Speciale Mobile. https://www.lifewire.com/definition-of-gsm-578670

3.6.3. Qualitative evaluation: legitimacy perspectives on automation

To assess the legitimacy of machine-based cadastral intelligence, as perceived by human cadastral experts, a focus group discussion was used. Normally, Bhattacharjee (2012) proposes a group comprising six to ten people with a moderator to discuss a theme of interests for about a period of 1.5 to 2 hours. But, for this study, a mini focus group of four was rather preferred. According to Anderson & Arsenault (2005), a mini focus group of four to six people having long and substantial experiences can be used when the topic needs to be explored in greater depth.

Accordingly, an expert sampling was applied where referring to Bhattacherjee (2012) respondents are chosen in a non-random manner based on their expertise on the phenomenon being studied leading to glean more credible data than a sample that includes both experts and non-experts. Experts were selected based on expected their strong linkage with the cadastre. The team comprises three cadastral maintenance officers with more than five years of work experience with the national cadastre and one charted surveyor and the moderator and an assistant. The team discussed automation and the expert's acquaintance, the readiness of experts to use automation tool, learnability of automation tools, adherence to standards practices in land demarcation, perceived gain and loss to surveyors in favour of automation and what could be the role of surveyor automation process.

4. RESULTS

4.1. Introduction

The primary objective of the study was to set up and compare automated against manually digitised cadastral boundaries. Manual digitisation, using human cadastral intelligence, was performed by five experts. Automation, using machine-based image analysis, used OBIA which applies rule-based experts systems in eCognition. Reference and validation dataset to which the machine and human experts'performance was evaluated was obtained using high precision surveying tool in the field based on the general boundary from the national cadastre. Quantitatively, the performance valuation used geometric metrics to measure discrepancies between automated, manually digitised and reference boundaries. In next sections, parcels and building outlines obtained from manual digitisation and automation and field collection and comparison results are presented. Specifically, results from rural site are presented in section 4.2; results from urban in section 4.3; boundaries enhancement in section 4.4; results of the comparison of machine and manual digitisation in section 4.5 and finally section 4.6 gives a summary of results.

4.2. Rural site

Rural site is made of tiny, highly fragmented but well-structured plots regarding their shapes and arrangement (Figure 11). The size ranges from 90 to 1375sqm. Ditches and river strip delimit most of the parcels. Grasses cover some parcels other are bare land.

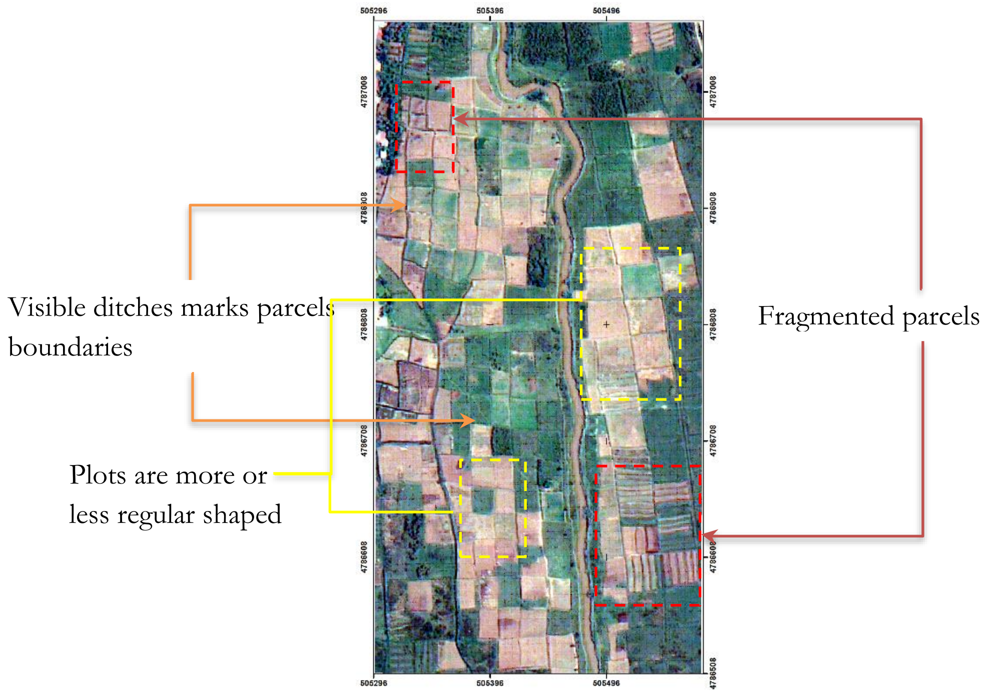

Figure 11: Description of rural parcels

4.2.1. Manually digitised cadastral boundaries by expert team

As it was introduced in the previous section, one of the tasks required to address objective (one) is to apply human intelligence to hypothesise and manually digitise cadastral boundaries from VHR image. The human cadastral intelligence comprises human brain ability to identify parcel and other landed property limits based on ingrained cues learnt over time. From (a) to (e), the Figure 12 below presents manually digitised rural parcels by five cadastral experts. On the same Figure, (f) shows boundaries extracted from the national cadastre and that have been digitised based on orthorectified aerial imagery of 2008.

Figure 12: Manually digitised rural parcel boundaries

What stands out from Figure 12 is that manual digitisation resulted in slight inconsistencies among users. Not all parcels could be extracted equally the same despite having the extraction provided to cadastre experts. Significant discrepancies can be observed in (c) and along the river shore for all the experts.

4.2.2. Automated parcels and validation

The second task under objective one was to apply rule-based intelligence in OBIA to extract cadastral boundaries automatically from image over the same area used by the expert team. Getting to have desired boundaries meeting all cadastral properties at one go was really a difficult process. In reality, parcels that appeared and purportedly imagined to be straightforward to identify with human eyes were tricky for machine to delineate. More difficulties were experienced when trying fully automated approach.

As it can be observed in Figure 13 (a), fully automated approach using Estimate Scale Parameter (ESP-2) tool for segmentation resulted into ragged and highly inaccurate segments. However, remarkable improvements were noticed after slight modification of scale parameters [Figure 13. (b)]. Much better results were obtained by using tailored experts rule sets (c). This semi-automated technique described in Figure 6 involved integration of experts ground knowledge and the trial and error tuning of parameters until image segments best approximate reference parcels boundaries (in yellow) as it can be seen in Figure 13 (c).

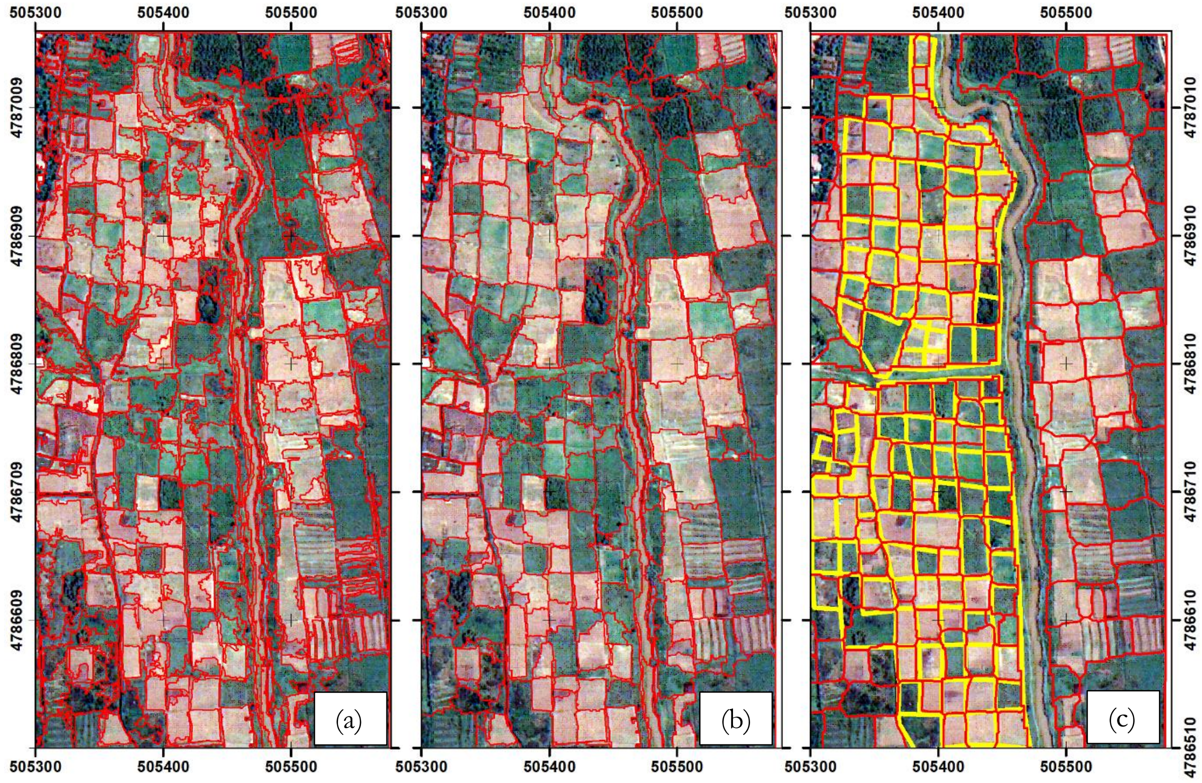

Figure 13: Automatically extracted parcels boundaries

(a) presents ESP-2 results when the shape factor is set 0.1 and 0.5 compactness. (b) shows results of ESP-2 after the shape criterion is modified and increased to 0.5 and the compact set to 0.8. The (c) presents the results of supervised segmentation layered with reference dataset (in yellow) obtained from field measurement. Reference data set permissible range of precision and hence it was collected using precision survey tablet running Zeno field mapping software with access to GNSS RTK COR instant corrections. Presented results were surveyed with less than 10-centimetre accuracy. Surveying a reference parcel for each of the parcels extracted would require the presence of respective owners in the field which was found practically impossible. Thus manually digitised and legal boundaries from the national cadastre was used. Existing cadastral data could not serve reference due to low accuracy ranging from 1-5m but it could help in acquiring high precision boundaries with only the presence of few landowners where it was needed.

4.3. Urban site

The urban site comprises well-structured and planned urban houses. Plots are well delineated and visually distinguishable on image by fences. Even where fences were occluded or do not exist, plots could still be hypothesised and delineated following the plan.

Figure 14: Appearance of building roof and fences on image

4.3.1. Extracting buildings plots

From (i) to (v), the Figure 15, presents reference parcels (in red) overlayed with manually extracted urban plots (in yellow). Automation results are presented in (vi). As it can be clearly spotted, automation resulted in poorly structured parcel boundaries than manually digitised parcels. Another point from observation is that experts were more consistent and precise.

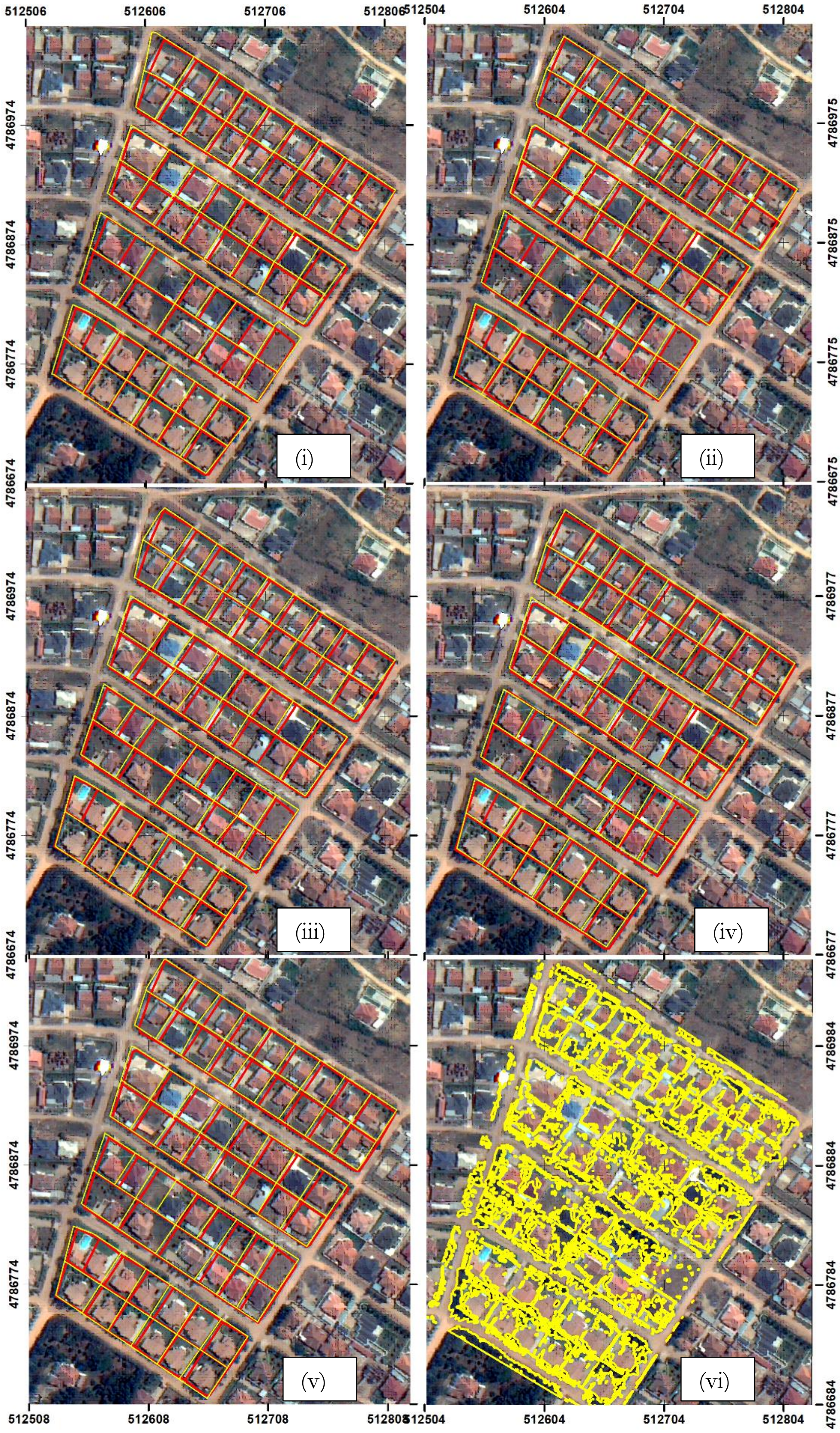

Figure 15: Extracted building plots by experts and automation

Automated parcels were obtained using contrast segmentation considering that fences appear as dark strips. Resulting boundaries were topologically and geometrically chaotic. The reason is that machine could not spectrally differentiate fences and buildings shadows and some other dark green objects.

4.3.2. Extraction of buildings

Apart from delineated rural parcels and building plot, the author was passionate to test the ability of machine in extracting building outlines with correct shapes comparative to manual digitisation as it could help for completing the cadastre database where buildings are still missing. Presented in Figure 16 are results from experts team [from (a) to (e)] and automation (f). As it can be noticed, machine face difficulties to trim pavements and tiny structures from the main buildings. Blue and black roofed building was omitted as they spectrally appear like vegetation.

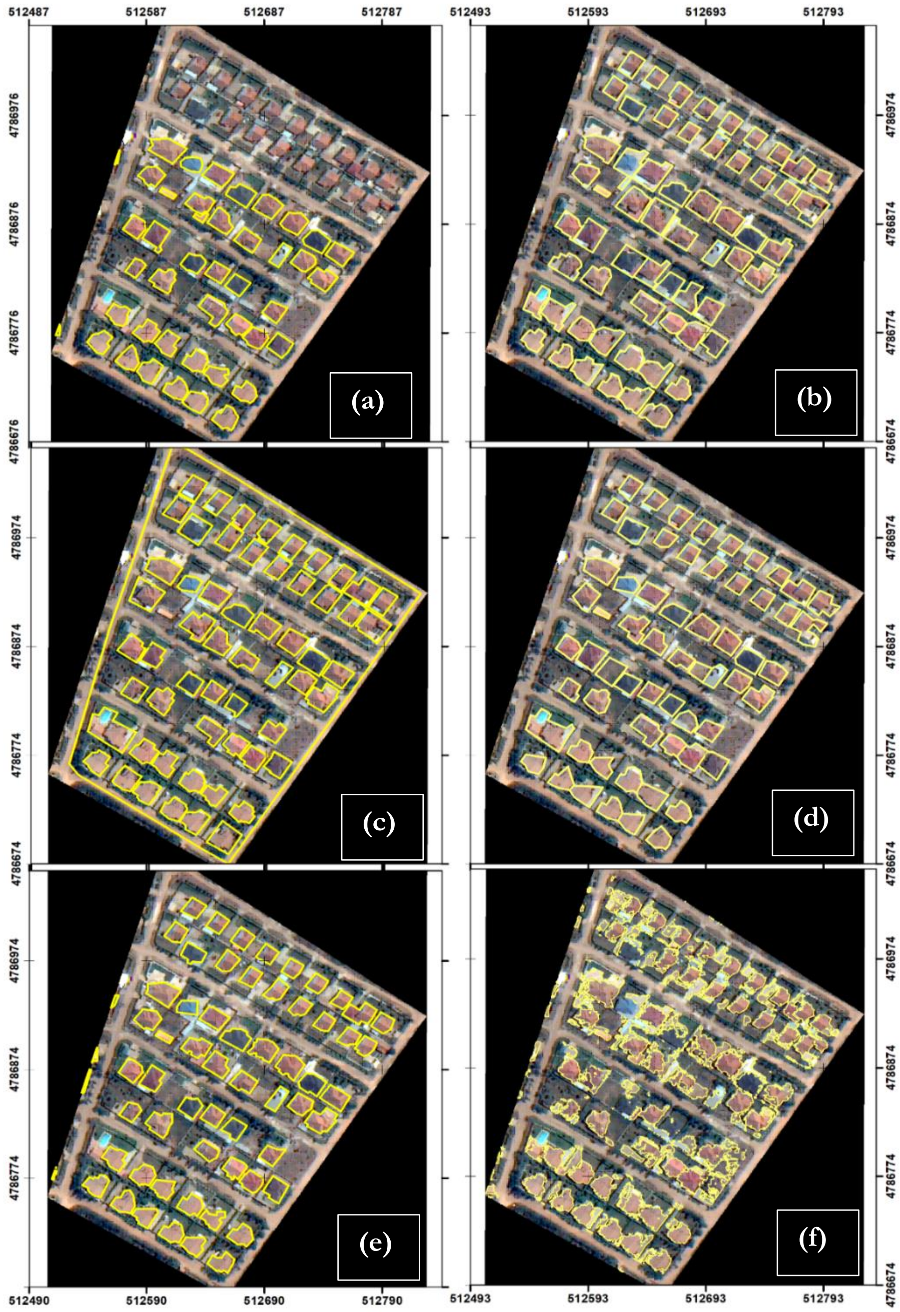

Figure 16: Extracted buildings plots by manual digitisation and automation

Automation results were obtained using chessboard segmentation to split an image into equal smaller objects of 0.5x0.5m and buffer of 7m from the central line of roads to eliminate road strip. Afterward NDVI and Max.Diff. information was used to removed vegetation and non-roof objects.

4.4. Boundaries enhancing

Resulting boundaries from segmentation and classification may present some unpleasant shapes that do not fit with cadastral boundaries standards like the one highlighted (in red). Ditches (dark strips) needs also to merge with main parcel polygons. Morphology operator within eCognition was used to do the job. The process is illustrated in Figure 17.

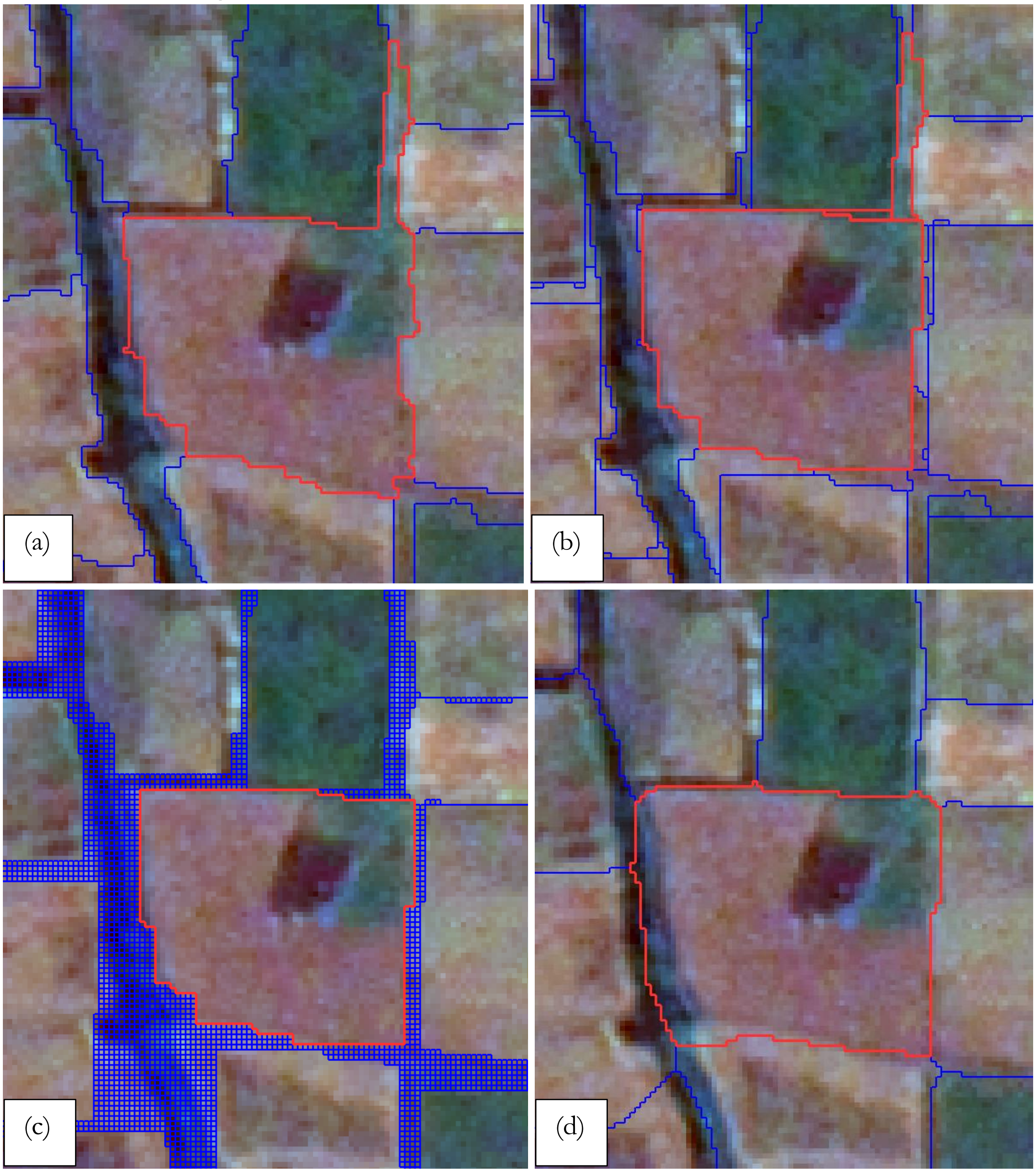

Figure 17: Boundaries line enhancement

In (a), parcels present some dangling areas. Also ditches strips need to merge main parcels polygons. in (b) to smooth the border of parcels the pixel-based binary morphology operation is used to trim dangling portion off the main parcels. In so doing, an opening operation is chosen. An Opening is defined as the area of an image object that can completely contain the mask. The area of an image object that cannot contain the mask completely is trimmed off the objects. Morphology setting is done based instructions from eCognition reference manual. In (c), ditches and separate parts from the main parcels are split using chessboard segmentation. For better and smooth results, the object size is set to the smaller size possible, in our case to 1. In (d), split segments are set to merge neighbouring parcels and parcels boundaries are improved.

4.5. Geometric comparison of automated against manually digitised boundaries

Comparison of machine performance vers human operators constitutes the core aim of the study. A comparison was worth considering only for rural site where results were meaningful as presented earlier. The comparison was performed by layering automated with manually digitised and field surveyed parcels. Geometric discrepancies between each reference parcel and the corresponding extracted parcel (automated or manually digitised) were computed as described in Figure 10. Mainly batch intersection, buffer and clip, calculate field and model tools in ArcGIS were used. These tools allowed to get geometric attributes that were inserted in formulas elaborated in section 3.6.1 to compute over-segmentation, under-segmentation, edge and shape errors.

To find out the tolerance distance that should be used for assessing the discrepancy between reference boundaries lines and extracted boundaries lines, the base image was overlaid with reference surveyed data. The shift of boundary lines, ditches on image from surveyed lines, could be measured using measuring tool in ArcGIS. İt was found that there was a shift of 0 to 4.5 meters of boundaries on image from the actual boundaries position as measured on the ground. This range is nearly the same with the current error range of 0-5m in the national cadastre database. For that matter, a buffer 5m would still be acceptable as many shifts will not be due to inaccurate detection but rather some error will be inherent in the source image.

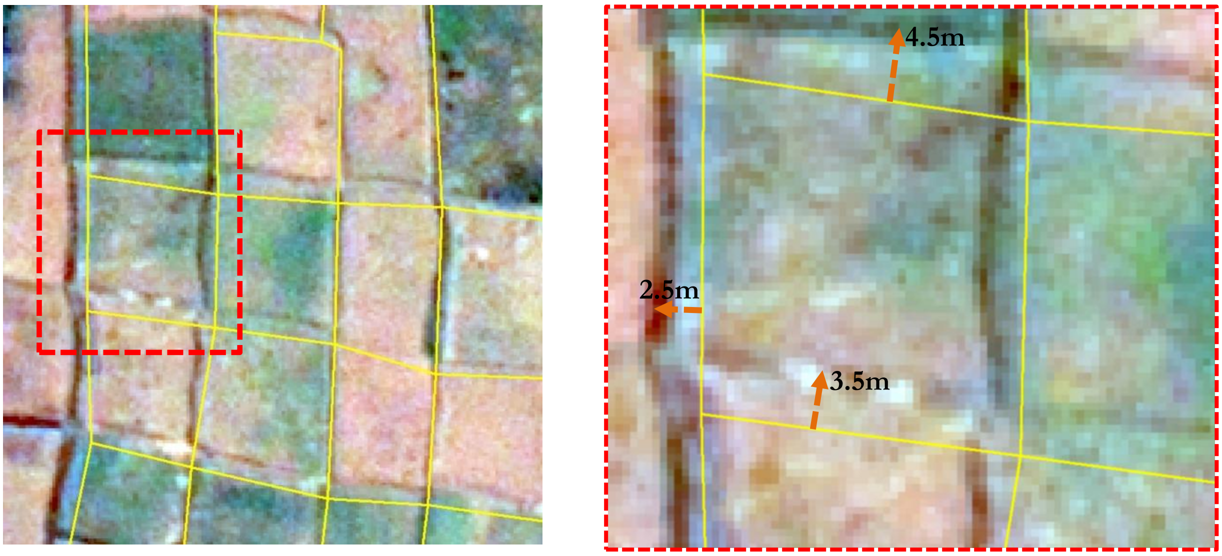

Figure 18: Shift of boundaries on image from the measured boundary lines on the ground

In Figure 19, violin graphs show the full distribution of discrepancies between reference parcels and automated and manually digitised parcels. The graphs allow seeing variation in the distribution patterns and skewness within the dataset. The white dot marks the median. The single most striking observation to emerge from the comparison is the likeness in the distribution of shape error for the machine and human meaning that automation was able to delineate parcels in good shape as human experts. As it can be seen by comparing Machine-to-Reference versus Expert A-to-Reference graphs, for shape error the machine at some point could beat humans. However, it is difficult to conclude whether it is due to inaccurate perception or just a blundering mistake on the side of human operator. The results of comparison allow seeing that under segmentation error for expert C was far big than machine and somewhat the same for machine and experts B, and expert D.

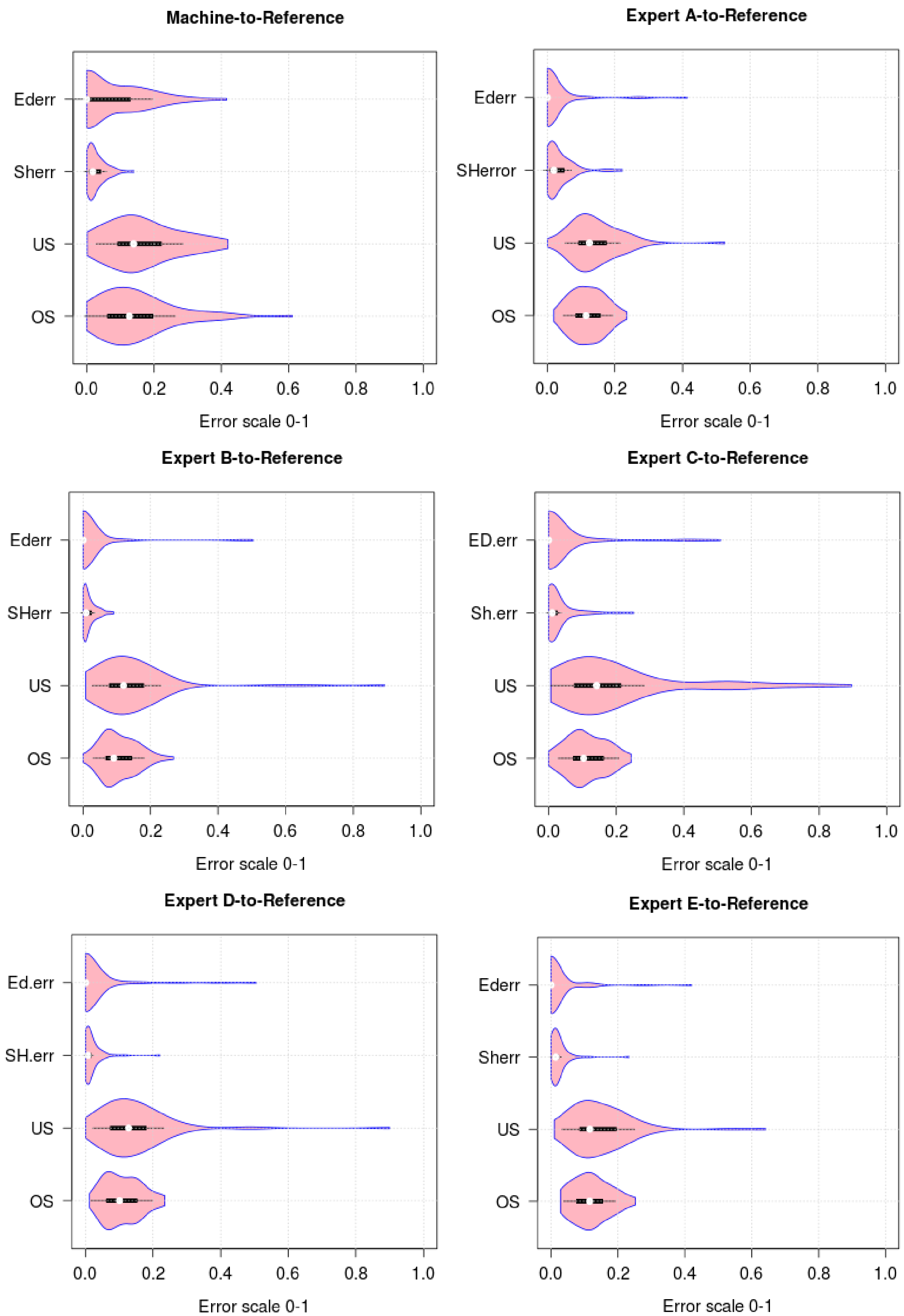

Figure 19: Geometric discrepancies between extracted parcels and reference parcels

The comparison of machine intelligence to expert knowledge was also done by comparing automated parcels with hypothesised and manually digitised parcels. Unlike in the previous comparison, the analysis of automated parcels against hypothesised parcels by experts doesn't necessarily consider the correctness of detection. The focus is the ability to detect visible boundaries features. As it can be observed in Figure 20, the pattern of distribution of discrepancies corroborated with Figure 19 with respects to shapes of extracted parcels.

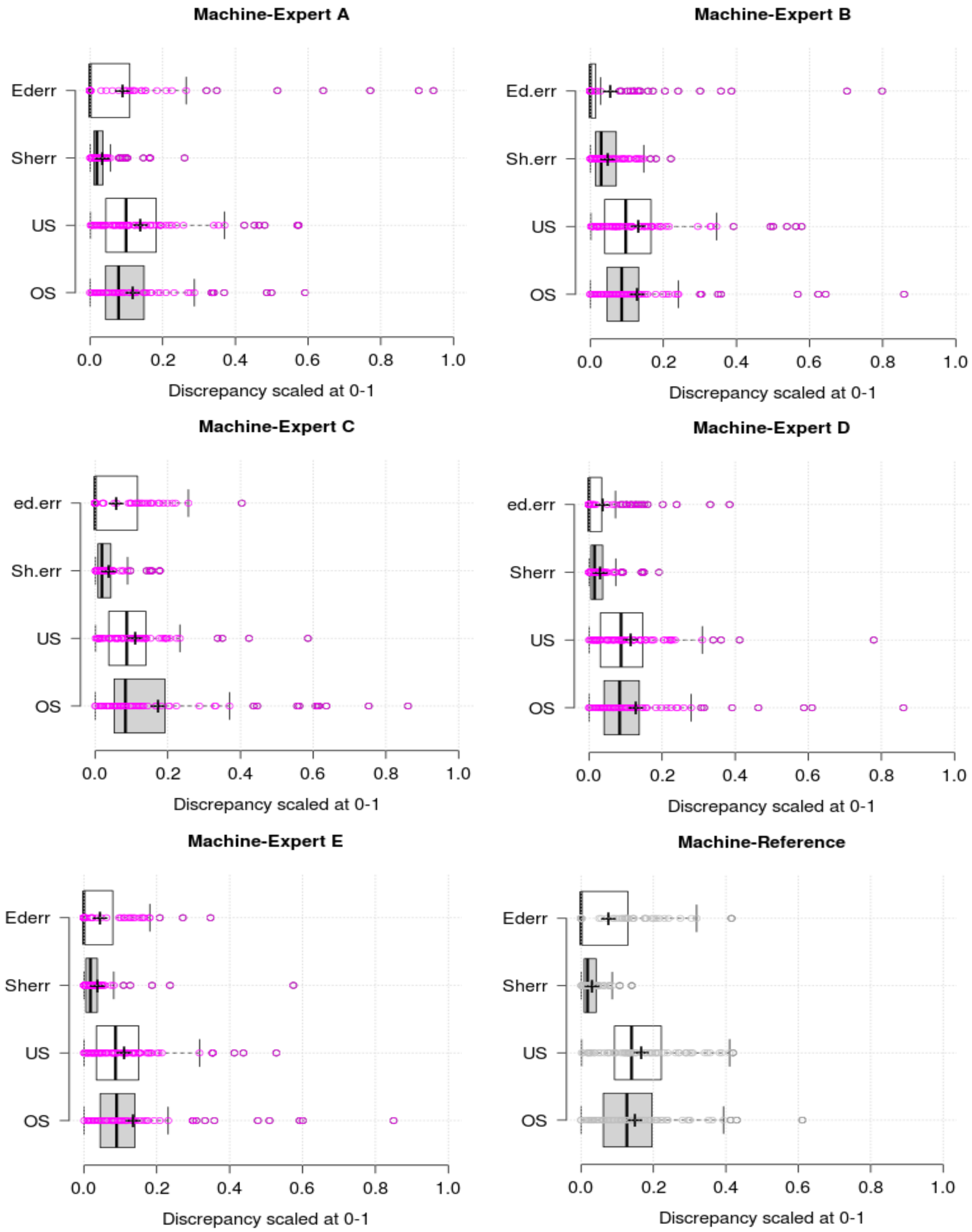

Figure 20: Discrepancies between automated boundaries and manually digitised parcels

The above figures, on the whole, demonstrate that the deviation of automated parcel shapes from manually digitised parcel shapes were too small. It can also be noticed that nearly all extracted parcels have less than 20% of their areas committed or omitted from automated parcels polygon areas as read the over-segmentation and under-segmentation boxes.

Visually, parcels, where both human and machine had difficulties and where discrepancies were spotted, are zoomed in allowing seeing how each of the operators behaved. In Figure 21, (a) are automated parcels layered with reference parcels and from (b) to (f) the same area but with experts work overlayed with reference parcels. Interesting patterns to note is that for both machine and experts were facing similar difficulties with invisible boundaries.

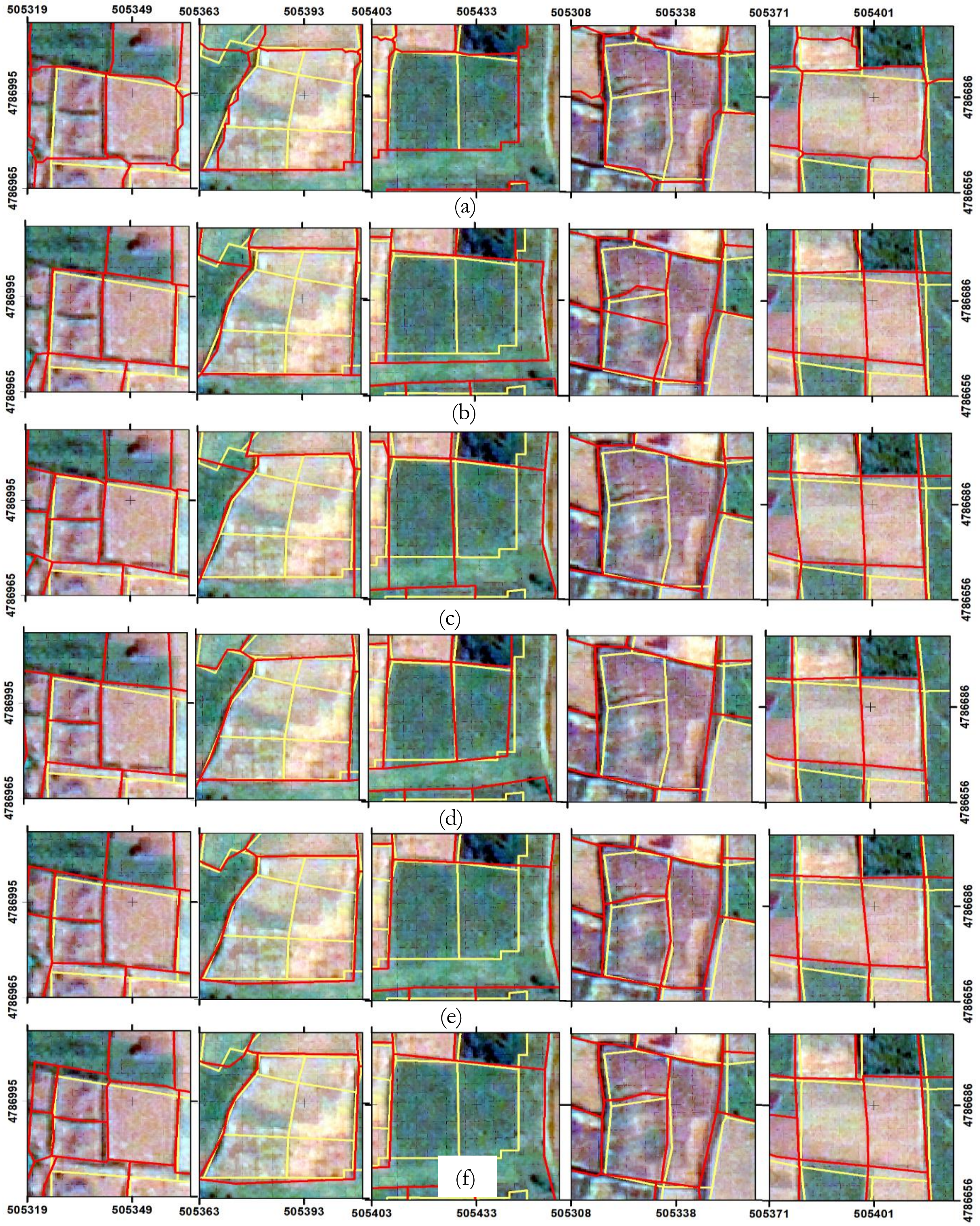

Figure 21: Visual comparison of automation and experts' performance

The results in Figure 19 and Figure 20, allowed to compute a global error that will lead to having an overall performance. The table below shows the mean over-segmentation, under-segmentation, shape and edge errors. The table also includes other metrics like the number of segmentation ratio (NSR), FP (committed parcels) and FN (omitted parcels) and the correctness rate and completeness.

To compute the correctness and completeness, we can combine all the metrics. Since an optimum error value is 0, a parcel that is correctly delineated will have all OSerr, USerr, SHerr and EDerr equals 0. This is the ideal case and rare to have. Simply, we can define an error tolerance range within which extracted parcels are maintained as acceptable. The advantage of using all metrics is to make sure all aspects were considered. For ease of computation this study will consider only the edge metric. The reason is that the shape error is relative too small and under-segmentation and over-segmentation errors are by default edge errors. Only the difference is that edge error is computed including a distance tolerance from the reference boundary line. By using formulas (10), (11), we computed the completeness and correctness rates. For numerators of the equations we sort and count all EDerr rows with value 0.0 in the tables of comparison (see appendices).

Table 2: Global geometric error of parcel delineation between machine and humans

	Machine	*Expert A*	*Expert B*	*Expert C*	*Expert D*	*Expert E*
OS.err	0.15	0.12	0.13	0.11	0.11	0.12
US.err	0.17	0.14	0.13	0.20	0.15	0.15
SH.err	0.03	0.02	0.05	0.03	0.03	0.02
ED.err (buffer=4m)	0.07	0.02	0.06	0.03	0.03	0.02
NSR	0.063	0.049	0.069	0.108	0.020	0.059
FP	14.74%	12.5%	9.57%	12.22%	12.12%	13.68
FN	14.85%	15.84%	16.83	25.74%	13.86%	19.80%
Correctness	47.4%	76%	67%	77.8%	77.8%	72.6%
Completeness	45%	73%	63%	70%	77%	69%

Number of parcels:
Reference=100; Automated=95; expert A=96; expert B=94; Expert C=90; expert D=99 and Expert E=95

As it can be apparently spotted, from Table 4, the FN rate (omission error) is significantly high for expert A, expert B, expert C and expert E compared to machine. Contrary, geometrically humans operators were more precise than machine as read the OS.err, US.err, ED.err values. The error of commission for automation was also high than for human operators.

4.6. Summary of results

This chapter presented the results of manual digitisation and automation of parcels boundaries and building footprints. Ultimately it presented geometric discrepancies resulting from a comparison of (1) extracted parcel polygons with reference parcels and (2) automated parcels polygon with manually digitised parcels polygons. An interesting general aspect of results is that machine could extract parcels in good shape as human operators. The omission error of automation is relatively low when compared to human operators. Results indicate that human operators were geometrically a little bit more precise than machine algorithms when drawing and reproducing parcel geometries from images. In conclusion the performance of machine is auspicious. The issue remains to know how this automation approach will be accepted and incorporated in current survey framework. Therefore, the next chapter will present experts (as proponent users) views on legitimacy of the automation tool we have tested.

5. AUTOMATION LEGITIMACY PERSPECTIVES

5.1. Introduction

The previous chapter demonstrated the capability of machine against human in extracting parcel boundaries. However, making automation a legitimate tool goes beyond its ability to extract physical line from image. As it was explained in Chapter-2, a boundary has a two-sorted ontology: (1) arbitrary (socially constructed/immaterial) versus (2) real (physical) nature and understandably more perceptible to humans than machine. It is then important to assess how the ability of machine to detect physical lines from image will fit in cadastral survey values. In that context, this chapter offers opinions reflecting experts views on automation. The text summary is a result of transcription of a group discussion after the short movie on automation process within OBIA environment using Trimble eCognition software. The transcripts were analysed in Atlas-ti. The leading themes of the discussion were acquaintance of experts with automation and perceived user-friendliness of automation tools, perceived benefits and deficiencies and impacts of automation to community and land surveying practitioners.

5.2. Acquaintance with automation tools and perceive user-friendliness

The majority of participants stated that it was for the first time to hear about automation in cadastral mapping. Some of the experts know its application in other domain, but its use in the cadastre was far to believe. Others asserted to have thought about it, due to a heavy workload in their daily activities but practically, it was very surprising to hear that what they thought is now possible.

When asked if they feel ready to adopt and use cadastral automation mapping, some of them replied that they do not feel like having that skills since it would require them specialised training. They advanced that operator of automation will need to have additional knowledge in photogrammetry and photo interpretations. Other were too optimistic towards the automation tool. From demonstration, they perceived the tool learnable. The only problem they said would be developing such a tool from scratch which would require advanced programming skills.

5.3. Perceived usefulness of automation

Regarding the benefits of automation, a common view amongst experts was that automation would make life of land professional easier. “A programmer would understand it better”: said one of the participants. Among the benefit of automation as perceived by experts will be to enable land administration service provider to serves many people in short time. Experts think automation tools will help in registering land very quickly and reduce time landowners spend on waiting for land documents. For them automation will help to get boundaries without undertaking long procedure.

5.4. Perceived deficiencies of automation

Concerns surfaced regarding limitations and possible weaknesses of automation. Participants on the whole, pointed out the issue of invisible and haphazard boundaries limiting the applicability of machine-based image analysis algorithm for extracting boundaries. They perceive automation may only apply in areas where subdivision plans were implemented, in row plantation farms and in planned urban settlement. The issue of difference in morphology according to contexts like rural versus urban was raised. Concerns were expressed about inaccurate results that could be challenging and costly to maintain. Problems linked with social constructs which are hard to be mapped were advanced. An example was given for visible features like ditches and hedges which do not necessarily correspond to boundaries and where boundaries are marked differently by different landowners. The participants were critically concerned about the trust and acceptability of automated boundaries by landowners. Participant believes that due to automation inaccuracies relations between land professional and landowners will be loosened.

Talking of trust and acceptability, experts were referring to existing survey procedures. Usually, a deed plan serve a triggering document based on which change in the registry are made. To be accepted a deed plan has to bear the signatures of landowners and neighbours and the seal of the district and chartered surveyors. This requires landowners to undergo through a process that involves the owner him/herself, neighbours, local authorities, district land officer, surveyors and Land Information System [LIS] staff in charge of cadastre (Figure 22). According to experts, the sealed and signed deed plan by officials, landowners and neighbours not only it confirm boundaries extent but also it confirms the ownership information. Linked to that, experts recurrently raised the issue relates to validation. From expert's point of views, it very challenging to validate and link automated boundaries with ownership information. For them asking lay people to identify their parcels and confirm whether they were correctly delineated or not it is nearly not feasible. Owing to that, experts think, validation and corrections may incur the cost almost equalling to the cost of field surveying and will be more a burden to landowners.

5.5. Automation and surveyors interests

Participants were asked to describe surveyor and his role in land administration. Experts described surveyor as a trusted person by landowners and land governance institutions whose product (sealed deed plan and survey report) serves a triggering document in land transaction process. According to participants surveying is a hot cake as currently, a chartered private surveyor can earn a monthly payee that is twice higher than a central government land officer. When questioned about how they perceive automation will impact on surveyors interests, two divergent discourses emerged. Some, the optimists of machine performance, feel that automation will take over the work of surveyors, while others, pessimists towards machine, asserted that automation would create more jobs for surveyors during maintenance. For the first group, exchanging field survey for automation will work at surveyors' disadvantage. This subgroup argues that automation will reduce labour and benefit the government, however at the cost of land surveyors. For them if the government accept automation it will have to be acquiring images on its own and not acquired from other commercial producers and its where surveyors could find their job. They asserted that the quality of commercial image could be called into question as they are not purpose driven. The second subgroup argued that, the undermined trust of automated boundaries will prompt landowners to contact private surveyors to verify the correctness of their boundaries and giving more work to them.

5.6. Experts recommendations

Experts provided different suggestions for automation to be applicable. First there a need to have a commonly agreed way of marking visible boundaries for landowners. Also for it to work, will require change in the land administration workflow and legal backing. They will need to be complementarity between machine and surveyors. According to views of experts, surveyors will mainly be involved in images acquisition and maintenance. Before it could be introduced, experts require the government to have well-trained staffs.

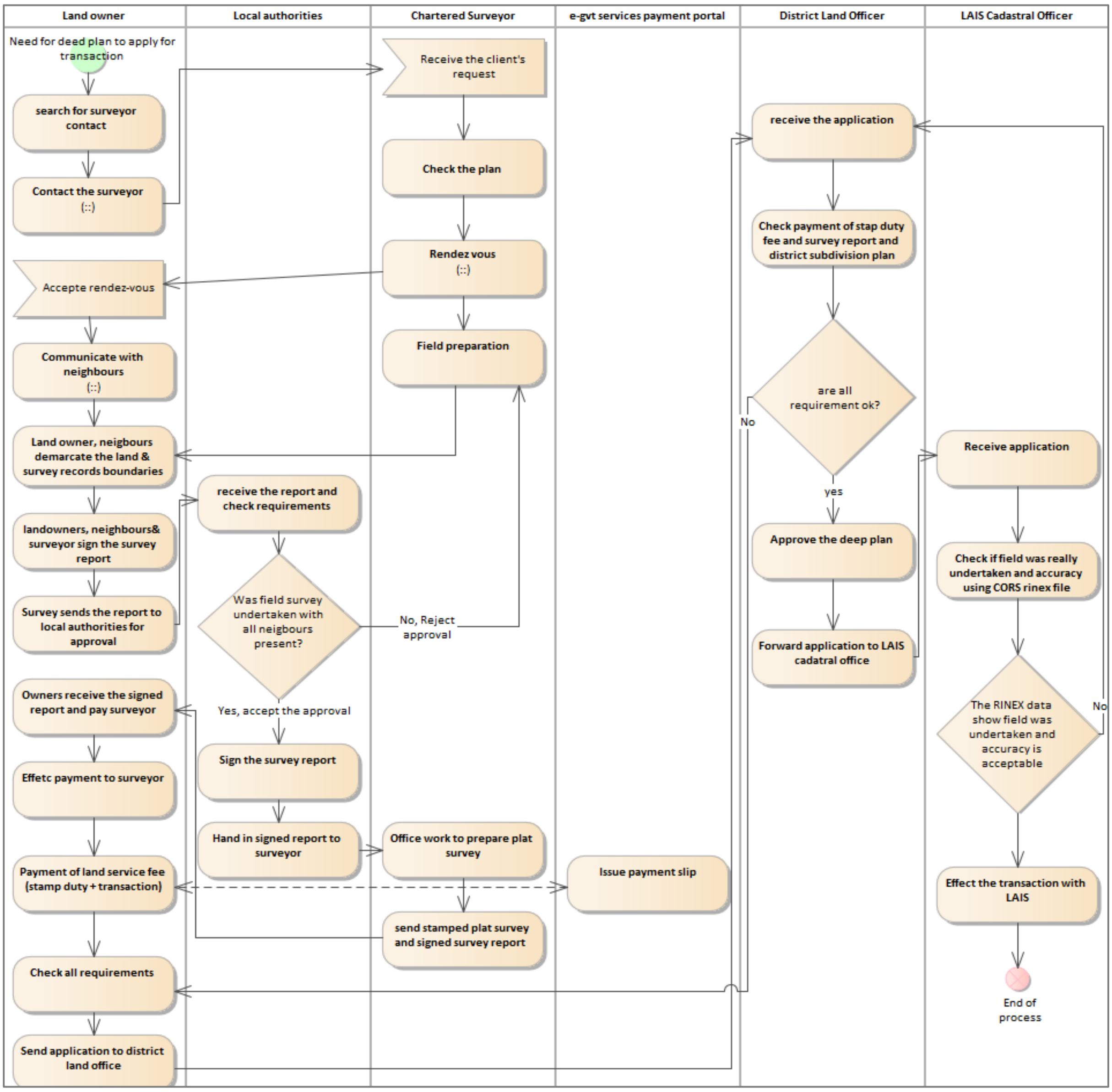

Figure 22: Land survey process as described by experts team

Survey process begin with landowners who need to get the deed plan (plat of land survey). Landowners need a deed plan for different uses but mainly to complete the file when applying for land transaction. The landowners will contact a surveyor, in most case the private surveyor. The surveyor must have authorisation to survey issued by Land Management Authority upon applying for it and have followed surveying courses. The surveyors will carry a field work to delineate the land. İn the field, the presence of neighbours (owners of the land next to the parcel to be surveyed) is mandatory. After demarcation the surveyor prepares a field survey report to be signed by landowners and neighbours, surveyors and later by local authorities. Afterward the surveyor will prepare a deed plan and seal it. Upon payment the landowner will pick the deed plan and survey report and deposit it with stamp duty fee and other application documents to the district land office. After checking all procedures and requirements the district land officer approves the deed plan and forward the application to LAIS cadastral office. The latter, will check if the field was undertaken using archived Receiver Independent Exchange (RINEX) file from CORS. After the deed is inspected and found correct the transaction is effected in LAIS and the process ends here or otherwise the deed plan is rejected and surveyor will have to resume fieldwork.

6. DISCUSSION

In this chapter, results are discussed, compared and contrasted with previous findings. Key points reflecting users, i.e. experts' views towards making automated feature extraction a legitimate tool for extracting cadastral parcels are elucidated further. In the end, the significance of findings and implication for practices and contribution to the cadastral field of knowledge is highlighted. Specifically, Section 6.1 discusses the automation process. Section 6.2 discusses results of comparison of automated and manual work using geometric metrics. Section 6.3 discusses experts perspectives on acceptability and applicability of automation tools. Section 6.2 discusses the implications for practices as it derives from findings.

6.1. Automation process

The findings of this research suggest that fully automated approach such as the Estimate Scale Parameter-2 (ESP-2) in extracting cadastral boundaries may pose many challenges considering a number of factors. As it was presented earlier on the Figure 13 the ESP-2 tool may result in ragged parcels boundaries which will be improved only after modification of size and scale parameters. Also, it could be observed that obtained results with the modified Estimate Scale Parameter tool are not topologically well structured requiring for manual post-processing editing.

The study findings suggest that using semi-automated approach with own-developed rule set based on experts ground knowledge may generate more improved results since it is more adapted to context than the ESP-2 tool. By improved results here, we mean topologically and geometrically well-structured parcel boundaries vectors that don't require manual post-processing editing. In the current study, own-developed rule set combined chessboard segmentation and subsequent multiresolution segmentation and classification and morphology operation. An important observation from our experimentation is that chessboard allows extraction of features in association with existing thematic layer from the open street map and could also be another publicly accessible repository to be able to extract other features. For instance, knowing the set back distance, user can extract features within a defined distance from specific roads or river. In our study, the tool was used to remove rivers trip and road strips from image objects but it could also be used for removing any other linear features. By way of multiresolution segmentation, user can get features and approximate segments to boundaries lines which are classified with geometry indexes threshold values. Since it is not possible to have all parcels with same morphological conditions, to adapt to variation in size and shape, a subsequent segmentation and classification method is rather used. To be ready to use, segments classified as parcels may need to be to geometrically and topologically improved as it can be seen in Figure 17. This is where morphology operators find their applications. The final results are ready to use and can be exported to ArcGIS as vector file.

Consistent with Zhang & Benediktsson, (2017); O'Neil-Dunne and Schuckman (2017), the study findings allow assuming that boundaries extraction is not a straightforward operation but tricky. Thus, it can be argued that automation may not be worth considering for a small area where manual digitisation takes relatively short time than setting up automation process. As it is generally required for features extraction (Blaschke et al., 2014; Quackenbush, 2004), our experimentation indicate the need for automation of cadastral boundaries extraction process to integrate contextual information with machine algorithms. Beyond the requirement to have a thorough understanding of the data, it was found that the extraction of cadastral boundaries, requires in addition, knowing the social contexts that shape landholding structures. During automation, the user will have to integrate this knowledge within the rule sets. For that matter, fully automated approach could not be fruitful compared with the own developed rule set systems, since it limits user intervention and the integration of expert ground knowledge. In the study by Belgiu & Drăguţ (2014) where both fully automated and supervised approach generated similar results, the reason could be that they focus was on delineating buildings with unambiguous ontological status. In our study, parcel and exhibited significant spectral variation.

From our experimentation with automation, two critical factors that should be considered before proceeding to boundaries extraction are discussed: 1) the separability of parcels as social objects 2) spectral reflectance of parcel.

6.1.1. Separability of parcels as social constructions

Normally neighbouring features made of different materials would have distinct spectral signatures based on which they can be delineated separately. In cadastre, as outlined in the theoretical framework, cadastral features are separated by lines. On the ground, these lines are marked by features like ditches, hedges or stones or otherwise they are invisible. It is important to recall the two-sorted ontology of boundary which suggests that some boundaries are real other immaterial in nature. The implication of this is that some of the boundaries may not be visually detectable in nature and some other visually detectable may not correspond with cadastral boundaries. Features marking boundaries might be inconsistently placed unless there are standards that have been established. In other words, having ditches marking a boundary for one landowner doesn't mean it is so for the neighbour. Another implication of the social nature of boundaries is their morphology. Land holdings structures like size and fragmentation affect boundaries detectability.

For the current study, it was fortunate, for rural area but not in urban area, to have parcels boundaries in most cases marked by visible ditches. Ditches were extractable by machine as separate elongated narrow strips as in Figure 23(a) or otherwise it would be difficult if not impossible to separate two parcels with same texture. In eCognition such elongated features like ditches are characterised by very low elliptic fit values and or being very highly asymmetric. The isolation of ditches from main parcels facilitate separating parcels from their neighbours. Normally we were interested in demarcating parcel not the ditches. For that, isolated ditches could be split using chessboard segmentation [Figure 23 (b)] and set to merge with parcels using grow region rule set as Figure 23 (c).

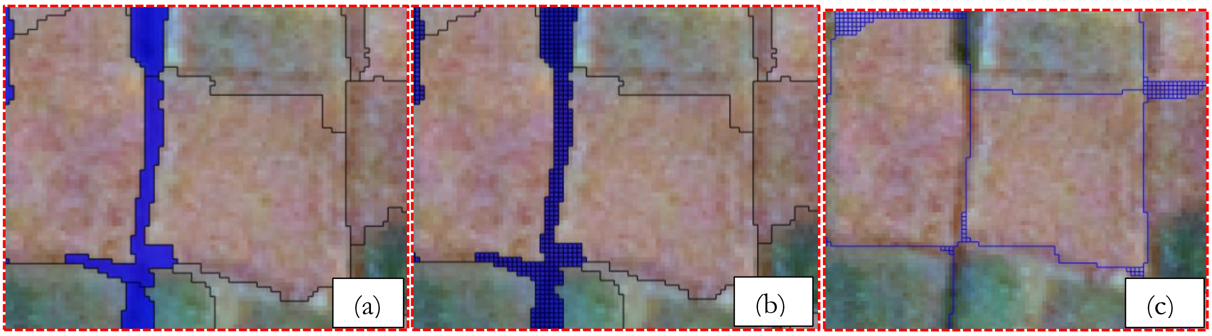

Figure 23: Two spectrally similar parcel but separable by ditches

In (a), ditches are extracted based on spectral information. in (b) chessboard segmentation rule set is used to slice the ditches strip into small equal grids. In (c) a grow region algorithm is used to merge ditches with neighbouring parcels

The effect of landholding structures parcels's layout, size and fragmentation on detectability of boundaries was apparent. It was observed that having a regular pattern in way parcel are arranged to ease the automation. Fragmented parcels under one ownership were sources of omission and commission errors. As experienced, when classifying segments with geometry threshold values like rectangular fit, shape index, border index, elliptic fit, compactness over-segmentation error is likely. To avoid it requires using a parcel area threshold value to remove small parcels. But also, screening small polygons to prevent over-segmentation may lead to under-segmentation. As it was noted, challenges linked with fragmentation were not constrained to machine but also teased the experts. it was observed that some of the hypothesised boundaries by experts could not necessarily match references parcels. Some fragmented parcels were found to be under one homogeneous ownership. This means that the physical line is not enough to define a boundary. It could be observed that likely and possibly one human expert would not produce same parcels nor uniformly digitise the same boundaries for repeated times.

6.1.2. Spectral reflectance of the parcels

In addition to peculiarities in marking property boundaries, there comes the issue of spectral reflectance of parcels and building roofs which complicate automation approach. We recall the assumptions of homogeneity of parcels and building land cover (section 2.6). Since a parcel is defined as portion of land under homogeneous ownership (UN ECE, 2004; WG-CPI, 2006 cited in Kresse & Danko, 2012; Oosterom & Zlatanova, 2008), we assumed the parcel would be homogeneous in function of land use (Hu et al., 2016). Eventually, we hoped to see homogeneous parcels in terms of land cover on image. We also believed that the assumption of unambiguous ontology status of buildings would hold water the same as in Belgiu & Drăguț (2014). However, on the ground, according to our findings, the homogeneity of ownership is rarely reflected by land cover. Further, appearance of boundaries features as perceived by human eyes differs from spectral reflectances information usable to machine. It is so while, as it was elaborated in the methodology part section 3.4, colour is the primary information contained in image with which objects and eventually parcels, fences, roofs can be extracted. To understand how difficult it was challenging for machine to extract individual parcels and buildings we reflect back to observations made by O'Neil-Dunne & Schuckman (2017) where experiments revealed that very little change in spectral reflectance values lead to unstructured results from automation.

In rural areas, some plots were covered by grass other were bare soil and another one partly bare and vegetated (Figure 11) but relatively not too complex. Parcels could be separated based on ditches that were extractable as discussed in the previous section. Major challenges were encountered in urban area owing to higher heterogeneity and diversity with respect to form, size, layout, and material constitution of urban structures. For instance, one roof could have different spectral reflectances, making it very difficult for automation of building extraction using spectral information. Building were covered by hip and valley roof and depending on the position of the sun, some part of the roof will not be well exposed to the sun (Figure 14). Apart from heterogeneous reflectance of dark roof, the fences, building shadows and garden had almost the same spectral signatures making it challenging to extract fences as plot boundaries automatically.

Generally, from our experiments it can be assumed that the extraction of buildings and urban plot boundaries based on roof material and fences spectral information is challenging. If one looks at image, buildings and fences are very clear to identify with eyes and we can also see goods results from digitisation by experts. For any type and geometry of roof, fences was really not a problem for human operator to digitise (Figure 15; Figure 16). But, experience with automation was counter-intuitive confirming O'Neil-Dunne & Schuckman (2017) observations. Urban plot fences extraction stands a big challenge for automation since it is very rare to see a fence with similar texture along its entire length. In most case, fences are very thin objects, and their material composition varies but extractable by integrating height with spectral information, according to Xianghuan et al. (2016). Especially UAV data which are known for their high resolution will find their application in here.

6.2. Human and machine cadastral intelligence compared based on geometric metrics

The comparison of automated with manually digitised and reference rural parcel polygons evidence that automation could generate topologically and geometrically well-structured parcels as human operators. At a glance, as indicated by the EDerr and SHerr plots in Figure 19, the patterns of distribution of discrepancies measures indicate comparable responses of machine and human experts in drawing geometries of parcel from images. Automation was able to achieve 45% of completeness and 47.5% of correctness. Discrepancies observed between automated parcel polygons and reference parcel polygons could be linked in part to inaccurate detections of machine. But, in other part shifts in edge are also linked with problems inherent in the source image (Figure 18).

Obtained automation performance rate is in the range of reported accuracy rates of 24-65% in some of reviewed studies (Crommelinck et al. (2017); Luo et al., 2017; Wassie et al., 2017). On the contrary, the current automation performance is lower to the one reported in Alkan & Marangoz(2009); Djenaliev (2013); García-Pedrero et al. (2017) and Suresh et al. (2015). In these studies, automation performance is claimed to be beyond 80 and up to 95% the reason being probably different methods of accuracy assessment. Contrary to our study, these studies used thematic accuracy while generally geometric accuracy is imperative for featured delineation as stated in Radoux & Bogaert (2017). Different from previous studies, with exception to the study of Luo et al.(2017); this study focused on automation of whole-parcel extraction. The study strongly took note of Mckeown et al. (2000) recommendations for assessing performance with rigour. Cadastral mapping application actually requires the performance assessment to be rigorous with geometry aspects. The accuracy is based on quantitative indicators and not on operator's judgments when a particular parcel is correctly delineated nor on thematic accuracy. Here the importance would not be to consider only higher automation rates but also more emphasis on providing information that fit with acceptable cadastral standards. According to Kohli et al.(2017) and Wassie, Koeva, Bennett & Lemmen (2017), even with automation performance 30-50% will significantly reduce the cost incurred in land demarcation. Therefore, it can be concluded that, the current study achieved promising results.

6.3. Automation legitimacy perspectives

Experts perceptions suggest that machine-based image analysis could be a potential smart agent in land demarcation that could allow millions of unregistered land to be registered but with its own cost with respect to skills required for users, accuracy, trust by the landowners and validation process. The study elicited user views for automation to be accepted as legitimate tool for cadastral boundaries extraction. Key point emerging from experts views is that machine-based image analysis could be one intelligent cadastral operator that could allow fast demarcation, registration and issuance of titles in short time and with little cost. However for it to work successfully, views of experts emphasised the need to have highly-trained experts and acceptable quality data stressing the suggestions in O'Neil-Dunne & Schuckman (2017). Another important point to note from experts views is the learnability aspect of the tool. The automation tool requiring advanced programming skills might not work best. The reason automation tool has to be learnable to land professionals is that it is eventually their responsibility and duties to institutionalise new tools that intend to ensure cadastre respond to society's need. Another possible explanation for this might be that extra skills beyond cadastral knowledge of land professionals will incur more costs to pay for external experts which would make automation not flexible nor a pro-poor tool.

Considering views of land professionals, imagery data will have to be taken considering intended purpose. Data will have to allow extracting boundaries as accurate as possible. An implication of this is the necessity to acquired data during cloud-free season and during the time boundaries lines are not covered by grasses or when parcels can be separated based on vegetation covers otherwise many boundaries will invisible. Apparently this is an ideal condition that is far to be met.

Another most intriguing question emerging from experts views is the legality and trust, validation process of automated boundaries. As it can be seen in Figure 22 survey goes beyond taking physical lines. In the context of study area context, the main importance of field survey is to correct evidence about who owns which land and who else can testify it. This stands a big challenge for automation. Only the issue of validation can be tackled using participatory mapping approach. Automation could be very useful in areas with no reliable cadastral maps- so even if 50% of the boundaries are mapped correctly, they can be used as a base. This also requires a spatially literate community. Landowners will have to e able to interpret automation results during validation process. Other aspects like issue of trust is not straight to answer and required further study to analyse land owners perceptions which is beyond the scope of this study. We recall that Rwanda is renown globally to be among the first countries where image-based demarcation was applied to build a nationwide cadastre system at a low cost. Many of the participants fully participated in the whole process. Therefore, opinions from the focus group reflect both experts' own views and experience and reality with image-based demarcation and fit for purpose approaches.

6.4. Implications for practices

The study aimed at providing research evidence on the ability of machine-based image analysis algorithms to extract ready to use cadastral boundaries from VHR image. As part of our work we made a critical review on previous studies. Reviewed studies can be grouped into two categories. The first category of reviewed studies (Alkan & Marangoz, 2009; Djenaliev, 2013; García-Pedrero et al., 2017; Suresh et al., 2015) claim high automation performance of 80% and higher but it provides little information or none information about the geometric aspects of extracted parcels. The second category including the works of Crommelinck et al. (2017); Luo et al. (2017) and Wassie et al.(2017) attempted to use geometric metric for performance assessment. In these studies, the completeness rate of extracted boundaries ranges between 24 and 65% in the same range as the current study findings. In the same vein with the second category the current study used more rigorous accuracy assessment geometric metrics to provide more suitable vectors data usable for cadastral application. Our method is straightforward to implemented in ArcGIS and quantitative and reproducible and replicable. Therefore, the implication of our study is to instil future researchers to use more rigorous test of automation tool in compliance with cadastral standards.

The second implication of our study derives from the spatial quality of the obtained automation results leading to, potentially, transferability not of the rule set but the approach we used. It was noted, in experimentation with ESP-2 tool, that the rule set might not be transferable instinctively. It is because the rule set includes parameter values that are set to fit a specific context and not the general context. Likely, we believe that our approach is designed in such a way that with small adjustments of the rule parameters depending on the context of the concrete case, is definitely replicable which makes our work highly beneficial for future researchers and other case studies.

Thirdly, from reviewed previous proponent works in the field of automation of cadastral boundaries extraction (as it is also for the current study as limitation) emerge the issue of scalability. In common, many of the inference are made based on simple case studies using smaller tiles of images which do not represent the complexity on the ground. In fact, there is still a huge gap between research problem and real-world problems. Added to that, it was also discussed that using automation in a small area might not be a wise idea. The implication of this is a need to apply automation tool to a large area in simulation to real-world practice than using smaller and subjectively selected area. The future focus suggests to be on fit-for-purpose automation approaches that provide scalable solutions to a real-world problem.

7. CONCLUSION AND RECOMMENDATION

7.1. Reflection to objectives and question

The primary purpose of the study was to apply and compare human by way of manual digitisation versus machine using image analysis algorithms to extracted parcels and buildings from VHR image. In so doing, a group of five lands professional with substantial knowledge in cadastral data mining was tasked to hypothesise and manually digitise boundaries from a pan-sharpened WorldView-2 image, on the one hand. On the other hand, automated extraction of parcels and buildings was performed using rule-based expert systems developed within eCognition. using two sites, one rural the other in urban, the study tested both fully automated approach using ESP-2 and semi-automated approach using own developed rule set for segmentation and extraction of rural parcels and urban plots and buildings. Difference in automation results was apparent with respect to approach used whether fully automated or semi-automated and context be it rural or urban. With regard to approach, the study findings show that fully automated approach is not adaptive to variations of changing contexts as it resulted in highly ragged boundaries. Unlike a fully automated method, the developed rule set within using experts contextual knowledge provided promising results. Regarding the context, obtained automated rural parcels were topologically and geometrically well structured. Whereas, in urban areas, due to the spectral heterogeneity of urban features, results were unstructured.

The performance evaluation of machine against human applied geometric metrics to determine the error of segmentation, under-segmentation, edge shifting, shape deviation and fragmentation errors. The geometric errors were computed for rural area where results were meaningful. The comparison used very high precision surveyed reference data in the field from which discrepancies were computed using documented geometric comparison framework. Distribution of discrepancies measures indicate comparable responses of machine and human experts in drawing geometries of parcel from images. The correctness and completeness rates of automation was found to be 47.5% and 45% respectively.

In addition to evaluating the performance of machine with mathematical figures, the study elicited experts perspectives on legitimacy of machine to generate cadastral boundaries from imageries. The main point worth noting with respect to legitimacy of automation tool as perceived by experts is the requirement for the tool to be learnable by land professional without necessarily having to use advanced programming skills. Remote sensed data will have to be more accurate. An automation tool will need to have been tested for its robustness to offer accurate results. Eventually, the performance of the tool will determine its acceptability and will make it thrive.

Specifically, the study addressed the underlying objectives and questions as follow:

I. Identify and apply automated and manual approaches to extract visible cadastral boundaries.
   - What are traditional approaches for image-based cadastral boundaries extraction?
   - What are image analysis algorithms for automatic cadastral boundaries extraction?
   - How to extract cadastral boundaries from imagery manually and automatically?

The traditional image-based demarcation use mainly in (a) field surveying where boundary lines are drawn on paper sheets as they are walked. Back in the office, papers are scanned and then digitised to generate vector data. (b)Alternatively, draftspersons draw hypothetical boundaries from the image and hypothesised boundaries can be validated in the field. Innovative technique by way of image analysis algorithms that could potentially apply for cadastral boundaries extraction includes mainly (c) pixel-based approach using machine (deep) learning and (d)object-based approach which use rule-based expert systems. The latter is a simple form of artificial intelligence that mimics human reasoning and perception in extracting features from image. Our study involved (b) for manual digitisation and (d) for automation of boundaries from image. Out in the field, reference boundaries were walked and mapped using GNSS high precision surveying tools. Manual boundaries digitisation based on extraction guide. Automation combined spectral and geometric information to extract parcels and buildings from image.

II. To compare the performance of machine against human operators in creating cadastral boundaries based on geometric metrics.
   - How precise is machine algorithm in reproducing geometries and shapes of cadastral features?
   - What are completeness and correctness rates of machine algorithms in extracting cadastral boundaries?

In rural area, the comparison of automated parcel polygons with reference parcel polygons indicates that machine was able to produce topologically and geometrically well-structured parcels. The correctness (precision) and completeness (recall) rates of automation were 47.5% and 45% respectively using 4-meter buffer tolerance. The buffer used related to shifts of 0-4.5 metres between boundaries on the source image and exact boundaries as measured in the field. In urban areas, results were highly unstructured and of little use due to the spectral heterogeneity of features. It was very challenging to separate fences from garden. It was also difficult for machine to trim ground pavements from building roof using spectral information.

III. To assess professionals' perceived legitimacy of artificial cadastral intelligence exhibited by machine-based image analysis algorithms
   - What are cadastral experts' perceptions towards machine-based approaches regarding their ease of use, cost-effectiveness alignment with professional surveying procedures, rules and regulations in cadastral mapping?

Experts perceive automation as the ultima solution to procedural and expensive land surveying but with its own cost. For that matter automation has to be institutionalised with caution. On the one hand, if it succeeds automation could support fast-track demarcation, registration and issuance of title in a short time and on reduced cost. On the contrary, automation may create inaccurate boundaries difficult for maintaining and causing more burden to landowners who in turn may averse land services. Added to that automation may be confronted with existing procedures abiding survey process. In case it is adopted, there will need to have highly trained staff who will also need to use high-quality data, preferably taken for the purpose of cadastral mapping. Automation tool will have to be learnable by land professional and shall require few manoeuvre. Experts views generally reflect their experience with fit for purpose techniques as Rwanda is renown globally to be among the first countries where image-based demarcation was applied to build a nationwide cadastre system at a low cost.

7.2. Final remark reflecting

In general, the study was able to compare machine and human cadastral intelligence. Despite rigorous methods applied, the study doesn't, however, claim the full-fledged experimentation with automation tools. More studies would be needed using other case studies and using other tools in search of the tool that fit the purpose the best. Such a tool will have to be able to allow achieving an acceptable accuracy while also being more user-friendly and learnable. In this study, automation applied on relatively small areas but could also be scaled up on large areas. With automated cadastral extraction, land registration service coverage can be taken farther than it is today. As it was elaborated in theoretical framework part, machine is meant to make human more intelligent and increase our performance in production and service delivery. In cadastral field, this will only be captured if human precision is integrated with computational machine power to allow the extraction of many parcels at time. As suggests views of land professionals, this will require various actors including landowners, surveyor and programmer. Some of the requirements in surveying process will have to be suppressed. Surveyor will have to be willing to abandon surveying dogmatism and embrace new smart, innovative, responsive, pro-poor and fit for purpose approaches. The programmer will have to be smart enough to be able to produce robust tool able integrate human intelligence with computational power.

7.3. Limitation of the study

The study, despite it was able to demonstrate the capability of machine alongside humans in extracting parcels from VHR images it was limited on using rule-based expert system within OBIA environment. However, full experimentation of machine intelligence will have to test different approaches. Assessing the ability of deep learning approach would be as important as OBIA approach we have focused on. Also the legitimacy of machine is extracting boundaries from images were limited to experts views. As discussed earlier in section 6.3, one critical concern raised from expert group discussion is the trust of automated boundaries by landowners the actual beneficiaries. An extended study to captures land owners perspectives is worth considering. Finally, in urban area, our study encountered limitation of lacking height information which could potentially improve our results. We believe better results could be found by integrating height with spectral information to extract fences and building geometries.

7.4. Recommendation

In sections 6.2 and 7.3 we highlighted some of the limitations and challenges of the current study calling for further studies.

(1) Comparison of deep learning algorithms and human in extracting cadastral boundaries. Artificial cadastral intelligence may be displayed through different approaches including state of the art deep learning techniques as a pixel-based approach. Automation in the current study was limited to the use of OBIA. As for recommendation, further investigations could delve into the use of deep learning for automating cadastral boundaries extraction, preferably over the same dataset and performance accuracy assessment method as the current study.

(2) Integrating height information with spectral information in extracting fences and building geometries in urban area using OBIA. In urban area, material composition for different objects varies. Consequently, spectral reflectance for roof, pavements, garden and fences exhibit variations. This stands a limitation for automation to extract fences that mark building plots and geometries of buildings roof. Next studies could investigate the use of height information together with spectral information in extracting fences and building in OBIA environment.

(3) Model for multiple parcel polygons comparison. In ArcGIS the model builder tool allows for batch processing in an automated fashion without necessarily having to use programming codes. For ease of computation of geometric performances of automation or manual digitisation, research to develop such a model is worth considering.

(4) Finally, assessment of landowners' views on legitimacy of automation in generating parcels boundaries. Our study was limited to experts' views, but next researches could be extended to captures landowners' views and to whom the tool will serve. The focus should be put on involving landowners during validation process and capturing their ability to interpret automation results and how they perceive and trust machine algorithms to offer accurate boundaries.

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APPENDICES

Appendix 1: Rule set for cadastral boundaries extraction

1. Rural parel extraction

```
01:37.204  Parcel extraction
  0.454    chess board: 5 creating 'New Level'
  05.406   unclassified with image object distance to River (outline) <= 22 Pxl at  New Level: Riverstrips
  0.453    Riverstrips at  New Level: merge region
  0.328    with image object distance to Drainage (outline) <= 10 Pxl at  New Level: Drainage
  0.031    Drainage at  New Level: merge region
  0.110    unclassified at  New Level: merge region
  08.156   unclassified at  New Level: 10 [shape:0.1 compct.:0.5]
  03.781   at  New Level: create temp. image layer 'temporary' using 'GLCM Entropy (quick 8/11) R (all dir.)'
  08.031   unclassified at  New Level: 20 [shape:0.4 compct.:0.8]
  0.079    unclassified with Elliptic fit = 0  or Asymmetry > 0.92  at  New Level: Ditches
  0.015    unclassified at  New Level: merge region
  07.188   unclassified at  New Level: 70 [shape:0.5 compct.:0.9]
  0.140    unclassified with Shape index < 1.2  and Rectangular fit >= 0.88  and Area (including inner polygons) > 300 m² at  New Level: Parcel 1
  0.016    unclassified at  New Level: merge region
  11.531   unclassified at  New Level: 70 [shape:0.6 compct.:0.8]
  0.141    unclassified with Rectangular fit > 0.9  and Shape index < 1.3  and Area (including inner polygons) >= 200 m² at  New Level: Parcles 2
  <0.001s  Ditches at  New Level: unclassified
  0.015    unclassified at  New Level: merge region
  08.141   unclassified at  New Level: 35 [shape:0.4 compct.:0.8]
  0.047    unclassified with Rectangular fit >= 0.93  at  New Level: Parcels 3
  0.156    unclassified with Shape index <= 1.345  and Rectangular fit >= 0.88  and Area (including inner polygons) >= 425 m² and Border index <= 1.3
  0.016    unclassified at  New Level: merge region
  10.703   unclassified at  New Level: 35 [shape:0.5 compct.:0.8]
  0.141    unclassified with Rectangular fit > 0.9  and Shape index <= 1.35  and Area (including inner polygons) >= 400 m² at  New Level: Parcels 5
  <0.001s  unclassified at  New Level: merge region
  08.218   unclassified at  New Level: 70 [shape:0.5 compct.:0.9]
  0.063    unclassified with Shape index < 1.4  and Area (including inner polygons) >= 360 m² at  New Level: Parcels 6
  <0.001s  unclassified at  New Level: merge region
  08.031   unclassified at  New Level: 60 [shape:0.5 compct.:0.8]
  0.109    unclassified with Rectangular fit > 0.9  and Shape index <= 1.4  and Area (including inner polygons) > 300 m² at  New Level: Parcel 7
  <0.001s  unclassified at  New Level: merge region
  07.641   unclassified at  New Level: 70 [shape:0.6 compct.:0.9]
  0.016    unclassified with Rectangular fit >= 0.85  and Shape index <= 1.4  at  New Level: Parcel 8
  0.015    unclassified at  New Level: merge region
  06.938   unclassified at  New Level: 90 [shape:0.5 compct.:0.8]
  <0.001s  unclassified with Density >= 1.6  at  New Level: Parcels 9
  <0.001s  Parcel 1, Parcel 4, Parcel 7, Parcel 8, Parcels 3, Parcels 5, Parcels 6, Parcels, Parcels 8, Parcels 9, Parcles 2 at  New Level: Parcels
  0.234    Parcels at  New Level: opening
  0.235    Parcels with Area (including inner polygons) <= 100 m² at  New Level: unclassified
  0.234    unclassified at  New Level: chess board: 1
  0.391    loop: Parcels at  New Level: <- unclassified <not found> = 0
```

Removing river strip and drainage using chessboard segmentation and OSM river shapefile

MRS subsequent segmentation and classification of parcels with geometry indexes values

Boundary smoothing using morphology operator, chessboard and region grow algorithms.

2. Building extraction

- Segmentation
  - chess board: 1 creating 'New Level'
  - unclassified with image object distance to OSM Roadset (outline) <= 7 m at New Level: Roadstrips
  - Roadstrips at New Level: merge region
  - unclassified with NDVI > 0.73 or Max. diff. < 2.05 at New Level: Non buildings
  - Non buildings at New Level: merge region
  - unclassified at New Level: 70 [shape:0.8 compct.:0.9]
  - unclassified with Area (including inner polygons) > 150 m² at New Level: Buildings

3. Fences (building plots boundaries) extraction

Auto name: edge ratio split B [0-255:+5] :30-> [creating 'New Level', unclassified,Fence]

Setting	Value
Condition	---
Map	From Parent
Algorithm parameters	
Settings	
Chessboard Tile Size	30
Level Name	New Level
Overwrite existing level	Yes
Minimum threshold	0
Maximum threshold	255
Step size	5
Stepping type	add
Image layer	B
Class for bright objects	unclassified
Class for dark objects	Fence
Advanced Settings	
Contrast mode	edge ratio
Execute splitting	Yes
Variable for best threshold	
Variable for best contrast	
Minimum relative area dark	0.1
Minimum relative area bright	0.1
Minimum contrast	0
Minimum object size	1
Loops & cycles	
Loop while something changes only	Yes
Number of cycles	1

The small the tile, the more precision

We kept as default

the Blue layer Pansharpened image

The values were kept as default

Appendix ii: Assigning UPI to reference parcels and extracted parcels

Appendix iii: Comparison of extracted parcels to reference parcels

Machine -reference

ID	OS	US	SHerr	EDerr	ID	OS	US	SHerr	EDerr
1	0.113	0.188	0.048	0	71	0.028	0.121	0.014	0
2	0.393	0.019	0.010	0.175	72	0.092	0.130	0.048	0
6	0.108	0.048	0.002	0	73	0.087	0.139	0.023	0
7	0.191	0.134	0.006	0.144	74	0.010	0.193	0.007	0.175
9	0.127	0.122	0.054	0	75	0.082	0.132	0.001	0
12	0.173	0.166	0.020	0	76	0.024	0.130	0.046	0
14	0.019	0.211	0.064	0	77	0.220	0.001	0.030	0
15	0.413	0.305	0.023	0.215	78	0.191	0.023	0.034	0
16	0.110	0.291	0.003	0.127	79	0	0.341	0.003	0.097
17	0.362	0.151	0.027	0.126	80	0.187	0.388	0.140	0.087
18	0.034	0.074	0.001	0	81	0.207	0.356	0.024	0.142
20	0	0.124	0.018	0	82	0.610	0.181	0.065	0.319
21	0.280	0.410	0.020	0.242	83	0.430	0.270	0.001	0.207
22	0.023	0.206	0.002	0	84	0.301	0.054	0.013	0.131
23	0.210	0.290	0.004	0.106	85	0.127	0.145	0.061	0.113
24	0.205	0.018	0.037	0.071	87	0.239	0.239	0.007	0.121
25	0.124	0.064	0.017	0	88	0.139	0.191	0.016	0
27	0.237	0.349	0.007	0.230	89	0.061	0.419	0.086	0.180
28	0.200	0.035	0.000	0	90	0.076	0.118	0.004	0
29	0.036	0.129	0.046	0.050	91	0.152	0.095	0.009	0.091
30	0.030	0.308	0.019	0.178	93	0.166	0.109	0.020	0
32	0.158	0.038	0.014	0	94	0.045	0.205	0.039	0.415
33	0.062	0.197	0.010	0.056	98	0.124	0.152	0.106	0
34	0.058	0.300	0.042	0	99	0.126	0.288	0.007	0.122
43	0.114	0.018	0.042	0	100	0.298	0.382	0.014	0.274
44	0.043	0.096	0.014	0	101	0.114	0.129	0.006	0
45	0.135	0.028	0.008	0					
46	0.121	0.134	0.078	0					
47	0.154	0.213	0.078	0					
48	0.127	0.080	0.014	0					
49	0.051	0.176	0.076	0					
50	0.351	0.026	0.078	0.201					
51	0.295	0.074	0.016	0.127					
54	0.225	0.229	0.001	0.305					
55	0.175	0.261	0.024	0.195					
57	0.063	0.005	0.011	0					
59	0.115	0.165	0.010	0					
61	0.029	0.132	0.039	0					
63	0.061	0.205	0.047	0.146					
64	0.159	0.270	0.012	0.115					
65	0.137	0.176	0.041	0					
66	0.103	0.090	0.041	0					
67	0.071	0.115	0.010	0					
68	0.137	0.093	0.023	0					
70	0.060	0.091	0.015	0					
71	0.028	0.121	0.014	0					
72	0.092	0.130	0.048	0					

Expert A-reference

ID	OS	US	SH.err	ED.err	ID	OS	US	SHerr	EDerr
1	0.147	0.124	0.001	0	60	0.094	0.213	0.047	0
2	0.199	0.068	0.001	0	61	0.062	0.102	0.039	0
5	0.070	0.070	0.001	0	62	0.087	0.166	0.002	0
6	0.114	0.066	0.017	0	63	0.176	0.218	0.001	0
7	0.134	0.189	0.026	0.117	64	0.224	0.161	0.006	0
9	0.104	0.164	0.008	0	65	0.088	0.121	0.000	0
10	0.156	0.138	0.060	0	66	0.104	0.121	0.007	0
11	0.178	0.309	0.222	0.272	67	0.087	0.124	0.001	0
12	0.169	0.237	0.014	0.101	68	0.142	0.141	0.018	0
13	0.163	0.103	0.004	0	69	0.033	0.090	0.017	0
14	0.119	0.194	0.079	0	70	0.142	0.000	0.003	0
15	0.203	0.274	0.003	0.089	71	0.107	0.070	0.007	0

16	0.102	0.234	0.007	0.026	73	0.053	0.103	0.009	0
17	0.105	0.134	0.009	0	74	0.089	0.104	0.024	0
18	0.094	0.092	0.031	0	75	0.071	0.079	0.013	0
19	0.093	0.099	0.004	0	76	0.105	0.072	0.003	0
20	0.112	0.126	0.006	0	77	0.150	0.091	0.011	0
21	0.169	0.215	0.022	0	78	0.019	0.145	0.014	0
22	0.157	0.161	0.000	0	79	0.207	0.024	0.007	0
23	0.157	0.096	0.011	0	80	0.048	0.123	0.006	0
24	0.159	0.101	0.020	0	81	0.082	0.089	0.011	0
25	0.189	0.103	0.009	0	82	0.042	0.121	0.009	0
27	0.162	0.258	0.014	0.023	83	0.048	0.154	0.009	0
28	0.077	0.159	0.004	0	84	0.094	0.177	0.009	0.058
29	0.055	0.086	0.069	0.014	87	0.235	0.240	0.005	0.047
30	0.141	0.182	0.062	0	89	0.190	0.166	0.008	0
32	0.086	0.106	0.034	0	90	0.134	0.106	0.002	0
33	0.067	0.154	0.046	0	92	0.102	0.137	0.019	0
34	0.066	0.231	0.003	0.024	93	0.113	0.077	0.009	0
43	0.157	0.003	0.009	0	94	0.066	0.138	0.050	0
44	0.063	0.041	0.007	0	95	0.139	0.232	0.050	0
45	0.121	0.015	0.006	0	97	0.198	0.062	0.042	0
46	0.050	0.099	0.046	0	98	0.073	0.524	0.057	0.414
47	0.154	0.160	0.048	0	101	0.141	0.130	0.004	0.035
48	0.132	0.072	0.007	0					
49	0.139	0.213	0.059	0					
50	0.115	0.075	0.024	0					
51	0.177	0.103	7E-05	0					
53	0.119	0.215	0.023	0.264					
54	0.143	0.102	0.001	0.037					
55	0.176	0.142	0.010	0					
57	0.130	0.096	0.007	0					
58	0.032	0.247	0.007	0					
59	0.058	0.179	0.032	0					

Expert B-reference

ID	OS	US	SH err	ED err	ID	OS	US	SH err	ED err
1	0.134	0.144	0.002	0	61	0.054	0.107	0.055	0
2	0.230	0.023	0.003	0	62	0.137	0.192	0.003	0.050
5	0.076	0.089	0.001	0	63	0.183	0.212	0.002	0
6	0.148	0.042	0.031	0	64	0.184	0.174	0.008	0
7	0.122	0.184	0.004	0	65	0.050	0.154	0.001	0
8	0.143	0.169	0.024	0	66	0.104	0.126	0.001	0
9	0.110	0.143	0.010	0	67	0.040	0.109	0.005	0
12	0.137	0.212	0.020	0	68	0.163	0.150	0.010	0
13	0.199	0.102	0.011	0	69	0.016	0.071	0.000	0
14	0.117	0.230	0.008	0	70	0.109	0.017	0.034	0
15	0.196	0.214	0.003	0	71	0.074	0.030	0.026	0
16	0.089	0.224	0.008	0	72	0.051	0.033	0.037	0
18	0.055	0.137	0.057	0	73	0.064	0.048	0.014	0
20	0.079	0.161	0.015	0	74	0.003	0.097	0.000	0
21	0.160	0.154	0.024	0	75	0.064	0.065	0.003	0
22	0.130	0.139	0.003	0	76	0.067	0.089	0.001	0
24	0.066	0.120	0.003	0	77	0.078	0.085	0.001	0
27	0.129	0.208	0.021	0	78	0.159	0.059	0.002	0
28	0.086	0.101	0.010	0	79	0.103	0.121	0.006	0
29	0.057	0.073	0.078	0	80	0.046	0.150	0.006	0
30	0.091	0.199	0.039	0	81	0.077	0.102	0.009	0
32	0.124	0.080	0.003	0	82	0.051	0.105	2.3E-05	0
33	0.037	0.104	0.045	0	83	0.080	0.126	0.009	0
34	0.080	0.251	0.043	0	84	0.080	0.187	0.012	0.019
41	0.076	0.032	0.024	0	85	0.133	0.047	0.058	0
42	0	0.089	0.009	0	87	0.179	0.239	0.004	0
43	0.097	0.011	0.005	0	88	0.152	0.179	0.004	0
44	0.060	0.007	0.007	0	89	0.149	0.209	0.032	0
45	0.068	0.034	0.007	0	90	0.098	0.117	0.018	0
46	0.084	0.074	0.050	0	92	0.121	0.153	0.004	0
47	0.074	0.182	0.028	0	93	0.149	0.083	0.000	0
48	0.080	0.051	0.002	0	94	0.088	0.037	0.019	0

49	0.177	0.165	0.053	0	98	0.049	0.671	0.076	0.457
50	0.157	0.057	0.012	0	101	0.185	0.143	0.012	0
51	0.232	0.104	0.003	0.122					
52	0.132	0.107	0.007	0					
53	0.148	0.259	0.012	0.108					
54	0.183	0.092	6E-06	0					
55	0.143	0.196	0.007	0.101					
56	0.267	0.124	0.011	0.014					
57	0.080	0.053	3.1E-05	0					
58	0.079	0.103	0.030	0					
59	0.071	0.165	0.012	0					
60	0.058	0.261	0.047	0					

Expert C-reference

ID	OS	US	SH err	ED err	ID	OS	US	SH err	ED err
1	0.163	0.499	0.086	0.430	69	0.051	0.060	0.023	0.000
2	0.176	0.050	0.005	0.000	70	0.098	0.006	0.002	0.000
5	0.075	0.072	0.010	0.000	71	0.149	0.049	0.037	0.000
6	0.118	0.057	0.014	0.000	72	0.105	0.064	0.027	0.000
7	0.171	0.205	0.011	0.129	73	0.036	0.063	0.010	0.000
9	0.094	0.186	0.005	0.000	74	0.011	0.131	0.000	0.000
10	0.174	0.145	0.063	0.000	75	0.063	0.109	0.000	0.000
11	0.189	0.326	0.251	0.298	76	0.089	0.064	0.007	0.000
12	0.143	0.197	0.007	0.000	77	0.097	0.053	0.003	0.000
13	0.162	0.109	0.012	0.000	80	0.062	0.071	0.001	0.000
14	0.103	0.188	0.078	0.000	81	0.056	0.077	0.002	0.000
15	0.243	0.296	0.002	0.089	83	0.046	0.143	0.000	0.000
16	0.124	0.280	0.002	0.129	84	0.083	0.135	0.020	0.000
18	0.081	0.092	0.005	0.000	85	0.119	0.076	0.043	0.000
19	0.083	0.100	0.001	0.000	87	0.160	0.249	0.004	0.175
20	0.104	0.117	0.013	0.000	88	0.179	0.211	0.001	0.030
21	0.211	0.294	0.005	0.000	89	0.168	0.169	0.010	0.000
22	0.168	0.188	0.003	0.011	90	0.130	0.076	0.025	0.000
24	0.105	0.109	0.002	0.000	92	0.068	0.161	0.004	0.000
25	0.171	0.072	0.003	0.000	93	0.113	0.072	0.012	0.000
27	0.174	0.272	0.000	0.000	94	0.049	0.144	0.032	0.000
28	0.070	0.190	0.003	0.010	98	0.089	0.484	0.070	0.397
29	0.018	0.062	0.000	0.000	101	0.156	0.147	0.002	0.037
30	0.113	0.187	0.017	0.000					
32	0.087	0.082	0.009	0.000					
33	0.025	0.136	0.042	0.000					
34	0.081	0.181	0.001	0.000					
41	0.014	0.037	0.015	0.000					
42	0.092	0.052	0.003	0.000					
44	0.102	0.016	0.007	0.000					
45	0.081	0.047	0.010	0.000					
49	0.198	0.158	0.013	0.000					
51	0.236	0.157	0.003	0.083					
52	0.199	0.141	0	0.000					
53	0.189	0.112	0.011	0.000					
54	0.148	0.114	0.009	0.000					
55	0.132	0.210	0.011	0.069					
56	0.225	0.131	0.013	0.000					
57	0.073	0.076	0.014	0.000					
58	0.122	0.214	0.026	0.000					
59	0.087	0.214	0.006	0.000					
60	0.077	0.245	0.035	0.000					
61	0.087	0.139	0.047	0.000					
64	0.184	0.123	0.009	0.000					
67	0.139	0.090	0.025	0.000					

Expert d -reference

ID	OS	US	SH err	ED err	ID	OS	US	SH err	ED err
1	0.128	0.154	0.003	0	58	0.044	0.186	0.021	0
2	0.209	0.034	0.008	0	59	0.069	0.159	0.016	0
5	0.063	0.063	0.012	0	60	0.073	0.202	0.039	0

6	0.100	0.063	0.017	0	61	0.059	0.126	0.039	0
7	0.146	0.180	0.010	0.068	62	0.098	0.196	0.000	0
9	0.097	0.154	0.003	0	63	0.200	0.167	0.000	0
10	0.182	0.149	0.049	0	64	0.154	0.129	0.004	0
11	0.160	0.304	0.219	0.269	65	0.054	0.118	0.002	0
12	0.137	0.203	0.014	0	66	0.112	0.112	0.001	0.020
13	0.160	0.073	0.000	0	67	0.060	0.104	0.003	0
14	0.145	0.216	0.060	0	68	0.114	0.167	0.012	0.028
15	0.229	0.275	0.017	0.040	69	0.037	0.069	0.018	0
16	0.132	0.242	0.000	0.070	70	0.094	0.013	0.006	0
17	0.011	0.479	0.115	0	71	0.078	0.045	0.004	0
18	0.079	0.086	0.014	0	72	0.050	0.054	0.044	0
19	0.105	0.098	0.000	0	73	0.060	0.059	0.004	0
20	0.131	0.151	0.005	0	74	0.054	0.087	0.002	0
21	0.221	0.250	0.010	0	75	0.086	0.056	0.001	0
22	0.154	0.197	0.005	0	76	0.084	0.074	0.007	0
24	0.101	0.122	0.002	0	77	0.065	0.089	0.006	0
25	0.174	0.086	0.004	0	78	0.058	0.131	0.003	0
27	0.154	0.294	0.010	0.143	79	0.051	0.095	0.003	0
28	0.072	0.156	0.009	0	80	0.053	0.119	0.006	0
29	0.017	0.084	0.021	0	81	0.095	0.077	0.004	0
30	0.133	0.206	0.045	0	82	0.050	0.096	0.007	0
32	0.079	0.069	0.009	0	83	0.048	0.135	0.001	0
33	0.028	0.120	0.032	0	84	0.117	0.161	0.004	0
34	0.063	0.159	0.030	0	85	0.134	0.073	0.043	0
43	0.048	0.006	0.004	0	87	0.191	0.243	0.007	0.166
44	0.061	0.000	0.007	0	88	0.161	0.221	0.003	0
45	0.059	0.016	0.008	0	89	0.165	0.158	0.015	0
46	0.085	0.052	0.051	0	90	0.111	0.135	0.006	0
47	0.149	0.176	0.035	0	92	0.088	0.162	0.005	0
48	0.040	0.063	0.013	0	94	0.066	0.136	0.051	0
49	0.225	0.139	0.014	0	95	0.116	0.191	0.026	0
50	0.156	0.057	0.009	0	97	0.157	0.050	0.009	0
51	0.203	0.099	0.009	0.082	98	0.081	0.496	0.084	0.399
52	0.163	0.075	0.001	0	99	0.162	0.899	0.006	0.505
53	0.140	0.209	0.003	0	101	0.143	0.146	0.000	0
54	0.144	0.098	0.006	0	58	0.044	0.186	0.021	0
55	0.120	0.201	0.010	0.067	59	0.069	0.159	0.016	0
56	0.234	0.098	0.017	0	60	0.073	0.202	0.039	0
57	0.052	0.059	0.003	0	61	0.059	0.126	0.039	0

Expert E -reference

ID	OS	US	SHerr	EDerr	ID	OS	US	SHerr	EDerr
1	0.130	0.110	0.013	0	67	0.161	0.109	0.026	0
2	0.190	0.087	0.022	0	68	0.126	0.140	0.016	0
5	0.081	0.074	0.009	0	69	0.047	0.076	0.002	0
6	0.114	0.071	0.001	0	70	0.107	0.021	0.020	0
7	0.155	0.171	0.016	0.110	71	0.076	0.076	0.013	0
9	0.113	0.116	0.004	0	72	0.055	0.062	0.033	0
10	0.191	0.202	0.037	0	73	0.052	0.057	0.000	0
11	0.233	0.315	0.233	0.275	74	0.029	0.113	0.012	0
12	0.121	0.227	0.007	0.119	75	0.092	0.092	0.010	0
13	0.179	0.106	0.006	0	76	0.074	0.079	0.002	0
14	0.147	0.196	0.112	0	77	0.111	0.014	0.030	0
15	0.221	0.291	0.019	0.086	78	0.031	0.178	0.010	0.012
16	0.113	0.243	0.002	0.110	79	0.027	0.062	0.001	0
18	0.100	0.109	0.015	0	80	0.065	0.103	0.012	0
19	0.118	0.114	0.005	0	81	0.097	0.061	0.009	0
20	0.132	0.144	0.023	0	82	0.029	0.110	0.008	0
21	0.207	0.263	0.052	0.016	83	0.051	0.146	0.017	0
22	0.135	0.165	0.019	0	84	0.097	0.145	0.019	0
24	0.124	0.099	0.021	0	85	0.066	0.108	0.019	0
25	0.184	0.083	0.002	0	87	0.178	0.217	0.007	0
27	0.154	0.305	0.022	0.010	88	0.174	0.200	0.011	0
28	0.116	0.127	0.002	0	89	0.175	0.177	0.028	0
29	0.030	0.060	0.008	0	92	0.124	0.171	0.015	0
30	0.092	0.201	0.021	0	93	0.098	0.098	0.009	0

32	0.122	0.078	0.010	0	94	0.093	0.169	0.057	0
33	0.047	0.115	0.033	0	95	0.124	0.194	0.021	0
34	0.056	0.237	0.053	0	96	0.095	0.155	0.010	0
44	0.070	0.009	0.006	0	97	0.207	0.066	0.015	0
45	0.103	0.029	0.006	0	98	0.146	0.531	0.080	0.420
50	0.145	0.054	0.030	0	99	0.126	0.641	0.063	0
51	0.251	0.113	0.005	0.123	101	0.178	0.193	0.003	0
52	0.160	0.151	0.002	0	67	0.161	0.109	0.026	0
54	0.151	0.094	0.010	0	68	0.126	0.140	0.016	0
55	0.145	0.192	0.006	0.101	69	0.047	0.076	0.002	0
56	0.238	0.114	0.015	0	70	0.107	0.021	0.020	0
57	0.123	0.051	0.019	0	71	0.076	0.076	0.013	0
58	0.056	0.230	0.013	0	72	0.055	0.062	0.033	0
59	0.060	0.231	0.021	0	73	0.052	0.057	0.000	0
60	0.077	0.226	0.045	0	74	0.029	0.113	0.012	0
61	0.048	0.098	0.031	0	75	0.092	0.092	0.010	0
62	0.080	0.193	0.003	0	76	0.074	0.079	0.002	0
63	0.198	0.200	0.002	0	77	0.111	0.014	0.030	0
64	0.192	0.198	0.023	0					
65	0.077	0.137	0.037	0					
66	0.115	0.114	0.002	0					

Machine-expert A

ID	OS	US	SHerr	EDerr	ID	OS	US	SHerr	EDerr
1	0.028	0.135	0.046	0	54	0.120	0.165	0.003	0.515
2	0.341	0.085	0.012	0.153	55	0.063	0.194	0.035	0
3	0.149	0.084	0.007	0	57	0.126	0.107	0.019	0
3	0.147	0.042	0.014	0	59	0.109	0.036	0.042	0
4	0.020	0.370	0.024	0.320	61	0.021	0.086	0.000	0
4	0.074	0.072	0.004	0	63	0.092	0.189	0.048	0.641
6	0.075	0.062	0.014	0	64	0.013	0.208	0.018	0
7	0.127	0.003	0.019	0	65	0.086	0.094	0.042	0
9	0.109	0.040	0.045	0	66	0.120	0.091	0.033	0
10	0.021	0.452	0.260	0.030	67	0.075	0.081	0.011	0
12	0.118	0.031	0.006	0	68	0.081	0.037	0.004	0
13	0.047	0.570	0.100	0	70	0.004	0.173	0.018	0
14	0.014	0.134	0.014	0	71	0.023	0.151	0.006	0.000
15	0.231	0.001	0.019	0.142	73	0.148	0.152	0.033	0.119
16	0.017	0.082	0.003	0	74	0.064	0.225	0.031	0.209
17	0.276	0.005	0.017	0.118	75	0.080	0.123	0.011	0
18	0.066	0.107	0.033	0	76	0.005	0.145	0.042	0
20	0.094	0.193	0.011	0	77	0.168	0.004	0.018	0
21	0.121	0.238	0.001	0.124	78	0.287	0.011	0.048	0.225
22	0.015	0.196	0.002	0.078	79	0	0.465	0.010	0.264
23	0.066	0.217	0.006	0.100	80	0.193	0.340	0.146	0.100
24	0.155	0.024	0.017	0	81	0.209	0.353	0.013	0.152
25	0.047	0.079	0.026	0	82	0.591	0.063	0.055	0.348
26	0.076	0.182	0.079	0	83	0.369	0.091	0.007	0.140
27	0.088	0.122	0.021	0	84	0.336	0.012	0.022	0.904
28	0.269	0.032	0.004	0.094	87	0.074	0.067	0.001	0
29	0.043	0.106	0.022	0.044	88	0.068	0.073	0.011	0
30	0.007	0.257	0.081	0.112	89	0.042	0.424	0.095	0.944
32	0.167	0.027	0.020	0	90	0.027	0.101	0.007	0.771
33	0.079	0.132	0.035	0	93	0.078	0.054	0.011	0
34	0.107	0.194	0.038	0	94	0.026	0.122	0.011	0
35	0.073	0.004	0.007	0	98	0.486	0.031	0.164	0.109
41	0.013	0.016	0.004	0	101	0.036	0.064	0.010	0
43	0.043	0.104	0.032	0					
44	0.016	0.092	0.006	0					
45	0.071	0.068	0.014	0					
46	0.079	0.043	0.031	0					
47	0.043	0.104	0.030	0					
48	0.152	0.165	0.022	0					
49	0.051	0.099	0.016	0					
50	0.334	0.043	0.102	0.184					
51	0.186	0.019	0.016	0					
52	0.498	0.574	0.088	0.061					

53	0.065	0.480	0.165	0

Machine expert B

ID	OS	US	SH err	ED err	ID	OS	US	SH err	ED err
1	0.037	0.110	0.045	0	57	0.058	0.028	0.029	0
2	0.303	0.113	0.014	0	59	0.095	0.050	0.080	0
3	0.114	0.055	0.027	0	61	0.029	0.080	0.036	0
3	0.136	0.020	0.011	0	63	0.078	0.191	0.039	0.016
4	0.045	0.071	0.009	0	64	0.031	0.169	0.002	0
6	0.021	0.070	0.179	0	65	0.141	0.080	0.005	0
7	0.149	0.020	0.004	0	66	0.124	0.090	0.005	0.013
9	0.069	0.028	0.127	0	67	0.096	0.072	0	0
10	0.178	0.067	0.061	0	68	0.077	0.045	0.000	0
12	0.102	0.007	0.021	0	70	0.047	0.165	0.028	0.027
13	0.021	0.578	0.036	0.080	71	0.005	0.140	0.022	0.798
14	0.037	0.113	0.125	0	72	0.116	0.169	0.040	0
15	0.240	0.080	0.220	0.157	73	0.081	0.148	0.031	0
16	0.054	0.115	0.020	0	74	0.053	0.148	0.023	0
17	0.623	0.022	0.017	0.120	75	0.053	0.105	0.073	0
18	0.107	0.063	0.164	0	76	0.013	0.099	0.026	0
20	0.113	0.147	0.092	0	77	0.232	0.009	0.027	0
21	0.132	0.294	0.032	0.137	78	0.131	0.062	0.050	0
22	0.014	0.191	0.140	0	79	0	0.328	0.132	0.118
24	0.238	0.001	0.035	0	80	0.207	0.330	0.056	0.132
26	0.077	0.004	0.004	0	81	0.215	0.345	0.008	0.171
27	0.102	0.158	0.110	0	82	0.567	0.035	0.029	0.357
28	0.198	0.016	0.013	0	83	0.357	0.134	0.003	0.129
29	0.031	0.109	0.067	0	84	0.349	0.004	0.001	0.240
30	0.020	0.206	0.091	0	85	0.052	0.156	0.105	0.101
32	0.114	0.035	0.096	0	87	0.091	0.019	0.016	0
33	0.093	0.166	0.011	0	88	0.028	0.057	0.025	0
34	0.118	0.194	0.017	0	89	0.086	0.391	0.104	0.204
35	0.070	0.016	0.009	0	90	0.044	0.068	0.018	0
41	0.010	0.500	0.133	0	93	0.103	0.111	0.050	0
43	0.085	0.075	0.040	0	94	0.004	0.215	0.013	0
44	0.009	0.113	0.038	0	95	0.061	0.026	0.022	0
45	0.083	0.005	0.088	0	98	0.644	0.002	0.009	0.300
46	0.044	0.069	0.122	0	99	0.858	0.018	0.004	0.386
47	0.089	0.043	0.068	0	101	0.047	0.109	0.007	0.702
48	0.156	0.137	0.047	0					
49	0.046	0.183	0.085	0					
50	0.300	0.060	0.023	0.110					
51	0.131	0.020	0.022	0					
52	0	0.562	0.033	0					
53	0.109	0.493	0.146	0					
54	0.071	0.169	0.002	0.085					
55	0.054	0.097	0.061	0					
56	0.095	0.538	0.029	0					

Machine expert C

ID	OS	US	SHerr	ED err	ID	OS	US	SH err	ED err
1	0.436	0.138	0.038	0.187	63	0.636	0.063	0.153	0.130
2	0.331	0.063	0.005	0.153	64	0.016	0.205	0.002	0
3	0.561	0.060	0.150	0	67	0.059	0.152	0.035	0
3	0.169	0.037	0.003	0.199	68	0.555	0.021	0.088	0.144
4	0.057	0.073	0.010	0	70	0.018	0.139	0.017	0
6	0.061	0.062	0.017	0	71	0.000	0.191	0.051	0
7	0.117	0.014	0.004	0	72	0.121	0.194	0.076	0.256
9	0.130	0.027	0.049	0	73	0.095	0.122	0.013	0.003
12	0.080	0.009	0.013	0	74	0.069	0.137	0.007	0.177
14	0.016	0.127	0.014	0	75	0.108	0.114	0.001	0
15	0.223	0.012	0.020	0.114	76	0.008	0.141	0.038	0
16	0.023	0.054	0.006	0	77	0.181	0.001	0.026	0
17	0.615	0.039	0.156	0.118	78	0.607	0.100	0.046	0.212
18	0.070	0.099	0.003	0	80	0.144	0.350	0.141	0.098
20	0.073	0.176	0.004	0	81	0.201	0.337	0.022	0.158

21	0.123	0.196	0.026	0.099	83	0.369	0.102	0.001	0.137
22	0.033	0.195	0.001	0.091	84	0.329	0.038	0.034	0.221
24	0.204	0.011	0.035	0	85	0.054	0.118	0.018	0
25	0.032	0.077	0.013	0	87	0.115	0.009	0.002	0
26	0.069	0.184	0.076	0	88	0.041	0.062	0.017	0
27	0.103	0.132	0.008	0	89	0.069	0.423	0.097	0.126
28	0.286	0.012	0.002	0.109	90	0.011	0.112	0.021	0
29	0.056	0.107	0.046	0.052	93	0.074	0.055	0.008	0
30	0.014	0.233	0.037	0.059	94	0.036	0.109	0.006	0
32	0.133	0.014	0.004	0	95	0.052	0.042	0.049	0
33	0.096	0.128	0.031	0.020	98	0.446	0.053	0.176	0.097
34	0.069	0.224	0.040	0.023	99	0.860	0.008	0.009	0.403
35	0.052	0.008	0.010	0	101	0.049	0.075	0.008	0
43	0.752	0.004	0.068	0.173					
44	0.002	0.140	0.006	0					
45	0.082	0.005	0.018	0					
46	0.611	0.074	0.040	0.121					
49	0.031	0.198	0.089	0					
51	0.166	0.007	0.019	0					
53	0.085	0.585	0.178	0.152					
54	0.100	0.139	0.007	0.022					
55	0.069	0.084	0.013	0					
57	0.079	0.019	0.025	0					
59	0.126	0.043	0.017	0					
61	0.040	0.090	0.008	0					

Machine-expert D

ID	OS	US	SHerr	ED err	ID	OS	US	SHerr	ED err
1	0.066	0.120	0.044	0	64	0.019	0.173	0.016	0
2	0.314	0.093	0.002	0.137	65	0.118	0.097	0.039	0
3	0.147	0.081	0.014	0	66	0.119	0.107	0.040	0.010
3	0.128	0.059	0.005	0	67	0.084	0.085	0.013	0
4	0.071	0.066	0.002	0	68	0.126	0.024	0.010	0
6	0.074	0.050	0.014	0	70	0.034	0.143	0.022	0
7	0.122	0.021	0.004	0	71	0.033	0.155	0.018	0
9	0.095	0.029	0.051	0	72	0.146	0.178	0.093	0.239
12	0.105	0.022	0.006	0	73	0.105	0.156	0.028	0.117
14	0.032	0.151	0.004	0	74	0.056	0.204	0.009	0.202
15	0.223	0.022	0.005	0.130	75	0.058	0.138	0.000	0
16	0.024	0.11	0.002	0	76	0.001	0.120	0.038	0
17	0.610	0.015	0.143	0.126	77	0.239	0.000	0.036	0
18	0.057	0.090	0.016	0	78	0.242	0.007	0.038	0
20	0.114	0.205	0.012	0	79	0.000	0.309	0.000	0.019
21	0.085	0.221	0.010	0.113	80	0.183	0.339	0.146	0.102
22	0.028	0.168	0.007	0.072	81	0.197	0.361	0.019	0.150
24	0.212	0.003	0.035	0	82	0.588	0.088	0.073	0.331
25	0.051	0.083	0.012	0	83	0.391	0.142	0.000	0.144
26	0.083	0.012	0.150	0	84	0.307	0.013	0.018	0.160
27	0.114	0.094	0.003	0	85	0.037	0.120	0.018	0.000
28	0.259	0.017	0.009	0.086	86	0.067	0.227	0.014	0
29	0.058	0.088	0.024	0.013	87	0.068	0.003	0.000	0
30	0.018	0.235	0.064	0.092	88	0.042	0.030	0.012	0
32	0.125	0.011	0.004	0	89	0.041	0.412	0.070	0.000
33	0.087	0.138	0.021	0.007	90	0.033	0.052	0.002	0
34	0.063	0.224	0.011	0.008	93	0.080	0.073	0.015	0
35	0.066	0.010	0.003	0	94	0.024	0.122	0.012	0
41	0.001	0.023	0.003	0	95	0.040	0.778	0.026	0
43	0.104	0.049	0.038	0	98	0.463	0.052	0.191	0.101
44	0.011	0.123	0.006	0	99	0.860	0.056	0.000	0.384
45	0.100	0.032	0.016	0	101	0.055	0.068	0.006	0
46	0.046	0.092	0.026	0					
47	0.026	0.065	0.043	0					
48	0.155	0.087	0.001	0					
49	0.005	0.222	0.090	0					
50	0.279	0.031	0.088	0.064					
51	0.158	0.021	0.026	0					
54	0.091	0.142	0.004	0.049					

55	0.067	0.079	0.014	0
57	0.084	0.021	0.015	0
59	0.084	0.043	0.026	0
61	0.031	0.066	0.000	0
63	0.035	0.215	0.048	0.013

Machine-expert E

ID	OS	US	SHerr	EDerr	ID	OS	US	SHerr	EDerr
1	0.012	0.116	0.035	0	64	0.029	0.150	0.011	0
2	0.332	0.043	0.011	0.161	65	0.096	0.077	0.003	0
3	0.136	0.106	0.037	0	66	0.104	0.092	0.038	0.005
3	0.132	0.024	0.006	0	67	0.075	0.171	0.036	0
4	0.028	0.140	0.011	0	68	0.084	0.022	0.006	0
6	0.085	0.068	0.004	0	70	0.021	0.137	0.035	0
7	0.106	0.024	0.009	0	71	0.042	0.133	0.000	0
9	0.058	0.050	0.050	0	72	0.153	0.182	0.082	0.271
10	0.029	0.437	0.236	0.047	73	0.095	0.142	0.023	0
12	0.164	0.041	0.028	0	74	0.078	0.178	0.019	0.179
14	0.008	0.154	0.048	0.003	75	0.081	0.131	0.011	0
15	0.231	0.000	0.003	0.126	76	0.015	0.118	0.049	0
16	0.011	0.077	0.000	0	77	0.135	0.001	0.000	0
18	0.083	0.112	0.017	0	78	0.299	0.002	0.024	0
20	0.083	0.186	0.005	0	79	0.000	0.317	0.005	0.062
21	0.099	0.205	0.031	0.110	80	0.175	0.352	0.127	0.096
22	0.020	0.176	0.021	0.020	81	0.171	0.353	0.033	0.153
24	0.192	0.030	0.016	0	82	0.592	0.064	0.074	0.347
25	0.039	0.087	0.019	0	83	0.358	0.086	0.015	0.135
26	0.081	0.005	0.025	0	84	0.308	0.010	0.033	0.208
27	0.095	0.059	0.015	0	85	0.114	0.092	0.042	0.037
28	0.208	0.033	0.002	0.024	86	0.112	0.019	0.000	0
29	0.038	0.103	0.038	0.018	87	0.098	0.053	0.000	0
30	0.013	0.200	0.041	0.111	88	0.014	0.044	0.005	0
32	0.114	0.035	0.003	0	89	0.052	0.412	0.057	0.159
33	0.077	0.150	0.022	0	93	0.119	0.059	0.011	0
34	0.077	0.151	0.011	0	94	0.047	0.135	0.018	0
35	0.082	0.011	0.004	0	98	0.477	0.079	0.187	0.101
41	0.012	0.031	0.003	0	99	0.509	0.026	0.056	0.121
43	0.600	0.002	0.005	0.166	101	0.114	0.113	0.003	0.023
44	0.009	0.122	0.007	0					
45	0.047	0.011	0.015	0					
46	0.849	0.041	0.574	0.130					
50	0.299	0.047	0.108	0.180					
51	0.115	0.018	0.022	0					
54	0.094	0.155	0.012	0.140					
55	0.062	0.110	0.017	0					
56	0.102	0.528	0.001	0					
57	0.064	0.082	0.030	0					
59	0.143	0.012	0.031	0					
61	0.025	0.079	0.007	0					
63	0.073	0.213	0.049	0.007					

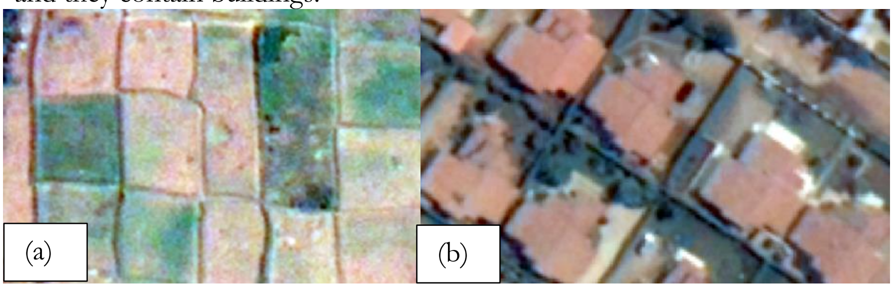
Appendix iv: Manual Cadastral Boundaries Extraction Guide for cadastral experts

Introduction

This exercise consists on interpreting the image with an eye-brain system by experts to reconstruct, digitise cadastral structures. As experts, you will apply the cadastral intelligence and visual interpretation cues: scene knowledge, tone, texture, pattern, shape, size, location, association to delineate parcels, buildings and roads. One of the attributes (description) will allow describing applied knowledge. Kindly, read this extraction guide and complete the exercise.

Extraction guide

This extraction guide aims to provide a clear and precise description of cadastral objects to be delineated, requirements on input data/information, description of objects appearance on the image, delineation criteria and digitisation rules.

<table>
<tr><td>Input data</td><td>For this exercise, you will use the pan-sharpened image of the ortho-rectified, 2m-resolution multispectral and 0.5m-resolution panchromatic WorldView-2 satellite image. You will hypothesise and apply your expert knowledge to digitise cadastral boundaries for the two sites: Nyamugali site for a typical rural setting and Kibagabaga as a sample for the built-up area.</td></tr>
<tr><td>Set up digitisation</td><td>
You will use the geodatabase file provided by the facilitator (with ITRF-2005 coordinates system) and name the feature dataset in your name as below:
⊟ Expert_Digitisation.gdb
  ⊟ Expert_name
    Buildings
    Parcels
You will need to fill in the attribute table especially the description column to justify applied knowledge to delineate features
<table>
<tr><th>Field Name</th><th>Data Type</th></tr>
<tr><td>OBJECTID</td><td>Object ID</td></tr>
<tr><td>SHAPE</td><td>Geometry</td></tr>
<tr><td>Label</td><td>Text</td></tr>
<tr><td>Description</td><td>Text</td></tr>
<tr><td>SHAPE_Length</td><td>Double</td></tr>
<tr><td>SHAPE_Area</td><td>Double</td></tr>
</table>
</td></tr>
<tr><td colspan="2">Object class (1): Parcels</td></tr>
<tr><td>Definition</td><td>A cadastral parcel is a single area of Earth surface, under homogeneous real property rights and unique ownership.</td></tr>
<tr><td>Appearance</td><td>
Farmland parcels appear some green and bared soil colour when displayed in BGR order. Mostly parcels delimited by visible narrow ditches.
In the built up area, parcels are bounded by fences and roads in regular pattern, and they contain buildings.

(a) (b)
</td></tr>
</table>

Identifying features	• Farmland parcels (a): ditches, watercourse • Urban parcels: fences around buildings
Extraction	• Delineate the perimeter of the visible extent of the parcel • Use polygon data type • For urban parcel include any associated structure even when it qualifies for separate extraction such as building (Parcel can contain buildings) • Make sure you fill in the column description in the attribute table
Object class (2): Buildings	
Definition	A walled and roofed structure designed for residential use by people, or other use
Appearance	Buildings are seen from above based on their shape, hip and valley roof in tiles or iron sheets
Identifying features	Roof design and shape and colour, fence
Extraction	• Delineate the perimeter of the visible extent of the building, i.e. digitise building footprint • Do not remove indents or protrusions • Use polygon data type • Consider any associate structure that qualifies for separate extraction • Make sure you fill in the column description in the attribute table
Object class (3): Roads or streets	
Definition	Roads are open ways for the passage people and vehicle, person or animals. These refer to streets in a built-up area with buildings on one side or both sides
Appearance	Roads have a well-defined width (8-16m), and straight edges, arranged in a regular pattern, a feature of the planned built up area.
Identifying features	Fence of parcels on one side or both sides, elongated open spaces between building blocks
Extraction	• Delineate the edges line of the extent of visible roads • Use ITRF-2005 coordinates system • Make sure you fill in the column description in the attribute table

Appendix v: Focus group discussion guide

Introduction

This discussion is part of the study that aims to measure the results of competition between humans and machine in creating and extracting cadastral boundaries leading to a thesis to be submitted to the Faculty of Geo-information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the award of the degree of Master of Science in Geo-Information Science and Earth Observation for Land Administration. The discussion aims to capture experts' perspectives on the legitimacy of machine-based image analysis algorithms to extract parcels and buildings usable in cadastre. Your acceptance of participation is duly acknowledged, and your views will be treated in complete anonymity and confidentiality and used merely for the academic purpose stated hereinabove.

Themes of discussion

1. Automation and ease of use, comprehensibility
2. Automation and alignment to existing survey practices
3. Automation and self-calculated interests

i. Automation and ease of use, comprehensibility

a. Have ever thought of automation in cadastral boundaries extraction?
b. Have you ever heard of it?
c. Have you ever used some algorithm to automate cadastral boundaries delineation? How easy was it?
d. How do you think it will revive your work?
e. How easy do you see or think it is?
f. What do you think are required skills? Do you feel ready for it if your institutions decide to introduce it?
g. What do you think will be challenges for its implementation regarding to skills, ease of use?
h. What are advantages?

ii. Automation and alignment to existing survey practices

a. What are existing survey procedures
b. Can we discuss challenges and opportunities for automation vis a vis outlined procedures?
c. Where do you find the application and usefulness of automation could be useful to land administration community?

iii. Automation and expert interest

a. What are benefits of being chartered surveyors?
b. Can you estimate monthly income from surveying services?
c. How do you think automation will enable you to earn more money than before?
d. What do you think automation could bring as obstructions to your values as land surveyors?

Appendix vi: Cadastral Survey Form (*Trasnlated From Kinyarwanda By Author*)

Date: … /…/20…

Names of landowners and ID number • …………………………………………… • …………………………………………… • …………………………………………… • ……………………………………………	**Location of the land** District: …………………..………………… Sector: …………………...……………..… Cell :……..……………………………..… Village :……...……………………………
UPI : ………………………….…….. Current use :…………………………………. Planned use: …….…..…..…………………… The area in words and figures: …………….... Lease/title ID no (for registered land): ……..…	**Requested service [11]:** -Subdivision -First registration -Rectification of boundaries -Building permit (auto-batir)

Demarcation process[12]

- Equipment used:
  1. *Type of GNSS rover:*
  2. *Serial No:*
  3. *Rwanda Geonet User-ID:*
- Access to CORS:
  1. Network ☐
  2. Single phase ..☐ Mountpoint: ……………
- Accuracy in (Cm): .... Cm
- Date (year-month-day): ............-...........-...........
- From (hours-minutes-seconds) to (hours-minutes-seconds) …
- Challenges accounted in the field:

Number of children parcels :…………...
Area of each children parcel:

Surveyor observations:[13]

- What exists on land ……………………………………….
- Mode of acquisition…………………………………….

[11] Select accordingly; Multiple answers are allowed
[12] Annex extra page for more explanation if required
[13] Add extra page or write on the back page for additional information

• Reason for subdivision if intended service is subdivision[14]: ……………………… • If the client (landowner) is requesting boundaries rectification provides all neighbouring parcels IDs and consents of respective owners whose parcels area will be affected: • If the client, intends to apply for registering the parcel he/she should explain why the land is not yet registered: • Provide information about existing liens, mortgage and disputes on land (ford mortgaged land provide the name of lender/bank): • Report challenge accounted during fieldwork[15]:
UPI, names, ID numbers, telephone number and signatures of landowners who whose land share boundaries with surveyed land:

Declaration: I, the surveyor, hereby declare that I have effected fieldwork and surveyed the land in accordance with survey procedures, ethics and rules and that any incorrect measurement, upon request by authorities for adjustment, will incur my own cost.

SIGNING THE SURVEY REPORT

Owners of the land (names, signatures and telephone number)	**Land surveyors** (names, signatures and telephone number)

Name and signature and stamp of the executive secretary of the cell

[14] Selling shares, donating a portion of the land, or parcels developments
[15] In relation to surveyed land, neighbouring parcels and, reported by local authorities any other one having interests on that land.