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Article

Comparing Human Versus Machine-Driven Cadastral Boundary Feature Extraction

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Abstract: The objective to fast-track the mapping and registration of large numbers of unrecorded land rights globally, leads to the experimental application of Artificial Intelligence (AI) in the domain of land administration, and specifically the application of automated visual cognition techniques for cadastral mapping tasks. In this research, we applied and compared the ability of rule-based systems within Object Based Image Analysis (OBIA), as opposed to human analysis, to extract visible cadastral boundaries from Very high resolution (VHR) World View-2 image, in both rural and urban settings. From our experiments, machine-based techniques were able to automatically delineate a good proportion of rural parcels with explicit polygons where the correctness of the automatically extracted boundaries was 47.4% against 74.24% for humans and the completeness of 45% for machine, as against 70.4% for humans. On the contrary, in the urban area, automatic results were counterintuitive: even though urban plots and buildings are clearly marked with visible features such as fences, roads and tacitly perceptible to eyes, automation resulted in geometrically and topologically poorly structured data, that could neither be geometrically compared with human digitised, nor actual cadastral data from the field. These results provide an updated snapshot with regards to the performance of contemporary machine-drive feature extraction techniques compared to conventional manual digitising.

Keywords: Cadastral boundaries; Automation; Feature extraction; Object Based Image Analysis.

1. Introduction

The emergence of Artificial Intelligence (AI) concepts, methods, and techniques in the 1950-1960s [15]; [39]; [59]; [64], ushered in a new era of the longstanding philosophical debate and technical competition between the merits of 'man' versus machine [7]; [13]; [23]; [28]; [46]; [50]; [52]; [62]; [66]; [73]. The optimistic perspective saw machine as unavoidable: as people become more intelligent, they can prescribe precision and program performance of a high quantity task to automation [73]. Moreover, the strength of machines is they exhibit computation capabilities capable of handling complex issues not quickly solved by humans.

For the domain of land administration, where only around 30% of land ownership units worldwide are covered with the formal cadastres and land registration systems [11]; [26], automation could be a supportive tool used to generate parcel boundaries, enabling faster registration and mapping of land rights. In this vein, the current study aims at measuring the ability of machine-based image analysis algorithms, against human operators, in relation to extracting cadastral parcel boundaries from VHR remotely sensed images.

1.1. Cadastral intelligence

Our definition of cadastral intelligence draws on the 1983-Howard Gardner's theory of multiple intelligences in the area of spatial intelligence [16]; [27]; [35]. Howard Gardner defines spatial intelligence as the ability to perceive the visual-spatial world [27]. More specifically, perceiving the visual spatial world includes the ability to localise and visualise geographic objects [35]. From a remote sensing perspective, spatial intelligence ranges from visually discriminating geographic objects upon reasoning, and then drawing and manipulating an image [16]. In the cadastral domain the ability to acquire and apply spatial intelligence in detecting cadastral boundaries is referred to as cadastral intelligence [9], [10].

Recently, developments in AI have reshaped spatial intelligence into "automated spatial-intelligence" [17]; [20]. From an AI perspective, spatial-intelligence is constituted by the procedural knowledge exhibited through computational functions represented by a set of rules[1] and structural knowledge which allow the establishment of the relationship between image-objects and real-world geographical objects [12]. AI has implied that there are many algorithmically trained perception-capable computing models, that beside human operators, can perceive, and recognise geographically referenced physical features [20]. In the contemporary era we can witness substantial progress in remote sensing where automatic image registration allows for the handling of huge volume of remote sensing images [2] efficiently [47], [56]. Regarding feature extraction from remotely sensed images, automation, though difficult to configure and implement, is the eventual solution to the limitations of manual digitisation [41], and this is with no exception in cadastral mapping [9], [10]. For these reasons, the use of AI and automation is gains traction within geoinformatics and land administration research domain generally [36].

1.2. The quest of automation in cadastral mapping

The cadastre is a foundation for land management and development [21],[68-70],[75]. An appropriate cadastral system supports securing property rights and mobilising land capital, and without it, many development goals of countries can either not be met, or are greatly impeded [68]. A major issue, however, is that only around one-third of land ownership units worldwide are covered with the formal cadastre [11], [26]. The full coverage of cadastre is argued to be impeded, in part, by procedural and costly conventional surveying approach. The latter suggests that all cadastral boundaries must be 'walked to be mapped' [49], [77] making it resource intensive. Surveying is thus the costliest process when registering landed or immovable property [58]; incurring 30-60% of the total cost of any land registration project [14], [51]. The consequence is a growing aversion towards land registration, lest the benefits of it would not compensate money spent [76].

Emerging geospatial technologies have made it possible to democratise mapping and registration activities, conventionally undertaken by high level surveying experts. Mobile devices equipped with simple web mapping apps, incorporating the ever increasing amount of high quality aerial imagery, and connected to the cloud, has seen the rise of the 'barefoot'[2] surveyor and more recently the 'air-foot' surveyor [9], [10], in the context of Unmanned Aerial Vehicles (UAVs) applications. The latter; in substitute to the use of ropes, groma, tape measure, theodolite, total stations and walking outside in the field [71], allows detection of visible cadastral boundaries based on their patterns with respect to appearance and form from a distance [18], [36]. Owing to advances in remote sensing, image-based cadastral demarcation approaches have been proposed and have been experimented with in countries including Rwanda, Ethiopia and Namibia. Experimentation

[1] 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 [29].

[2] Also referred to as 'grassroots surveyor' and 'community mapper'

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shows effectiveness of remote sensing image-based demarcation in delivering fast-track land registration [32].

Meanwhile, recent developments in the field of computer vision and AI have led to a renewed interest for cadastral mapping where machine algorithms, able to mimic humans in exhibiting spatial intelligence, could potentially be used to automate boundary extraction. The latter approach could allow tapping existing opportunities of having VHR remote sensing images and LIDAR[3] data, from various sources and wide coverage. Contemporary satellites, besides manned airborne photography, have offered sub-metre spatial resolution images, since the late 1990s [33], [55]. Far better, with UAV, it is now possible to acquire centimetre-level image resolution and point cloud data, allowing to uncover features occluded by vegetation [24], [30], [36].

When compared with manual on-screen digitisation, automation offers many potential advantages. These include removing inconsistency errors resulting from different users performing digitisation. Automation also allows coverage of wide areas with minimum labour, and supports cheap and up-to-date fit-for-purpose solutions that aim to target existing societal needs [11], [53], [66]. Automation could assist with the massive generation of digital property boundaries. Visible[4] boundaries are marked by extractable physical features like fences, hedges, roads, footpaths, trees, water drainages, building walls and pavement [1], [41]. Being visible, they are detectable by remote sensors and can be extracted from remote sensing data, to generate boundaries of the features they represent [18]. Such cadastral boundaries features can be detected based on their specific properties like being regular, linear-shaped or with limited curvature in their geometry, topology, size and spectral radiometry or texture [18].

Machine-based image analysis approaches, applicable for automated cadastral boundaries extraction, can be grouped into two categories: (i) Pixel-Based Approaches [PBA] and (ii) Object-Based Approaches, also well known as Object-Based Image Analysis [OBIA] [18]. The first approach only considers spectral value or one aspect for boundary class [4]. Thus, PBA algorithms, with exception to state-of-the-art Convolution Neural Network [CNN] [5], [18], [54], [74], may result in a “salt and pepper” map when applied to Very High-Resolution images [34]. Due to the lack of an explicit object topology that might lead to inferior results than those of human vision, PBA falls short of expectations in topographic mapping applications [13]. Unlike PBA, objects resulting from OBIA are features with explicit topology, meaning they have geometric properties, such as shape and size [50]. This makes OBIA suitable for extracting cadastral boundaries [18], [31], [48].

In brief, it appears there are many potentialities for automation of feature delineation using AI tools such as state of the art CNN models and OBIA. However, the major problem remains how to make automation an operational solution [25], especially in cadastral mapping, where properties need to be delineated with high precision specification geometrically and topologically. This infers there lies a compelling need to research more on the usability and applicability of AI-based cadastral intelligence in land administration [37]. Therefore, our study is built on the necessity to explore the potentialities of machine-based image analysis algorithms to extract cadastral parcels. While, theoretically some automation tools could even outperform human operators to extract features from images [12], little is said on their performance compared to humans within a cadastral domain-specific application. The focus of this research is therefore to investigate the extent to which automatically captured cadastral boundaries align with existing geometric standards of cadastres.

2. Materials and Methods

3 Light Detection and Ranging

4 Despite the two-sorted ontology of boundaries, implying that some of the property boundaries are invisible [57-58], the majority of cadastral boundaries are believed to be self-defining and can be extracted visually [48].

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This study applied a comparative approach using two case sites, one an urban setting and the other a rural setting within Kigali city in Rwanda[5]. The sites were selected based on the availability of VHR satellite images, the hypothesised visual detectability of cadastral boundaries, and convenience of accessing reference datasets for comparison. The study used pansharpened, by fusing the 2 m resolution multispectral with 0.5 m-resolution panchromatic WorldView-2 satellite images, tiles of 280 x 560 m and 320 x 400 m respectively, for extracting rural parcels and urban plots with building outlines. The study involved three main steps: pre-processing of the image, boundaries extraction (automation and human digitisation) and geometric comparison.

2.1. *Pre-processing*

Pre-processing concerned preliminary operations: (1) subsetting the image to eliminate extraneous data and constrain the image to a manageable area of interest and (2) pan-sharpening to fuse the high-resolution panchromatic image with a low-resolution multispectral image for enhanced visual interpretability and analysis. For pan sharpening, the Nearest-Neighbour Diffusion algorithms available within the Environment for Visualising Images [ENVI] software, was applied owing to its advantage of enhancing the salient spatial features while preserving spectral fidelity [60].

[5] The country is recognised globally to be among the first countries where image-based demarcation was applied to build a nationwide cadastre system at a low cost.

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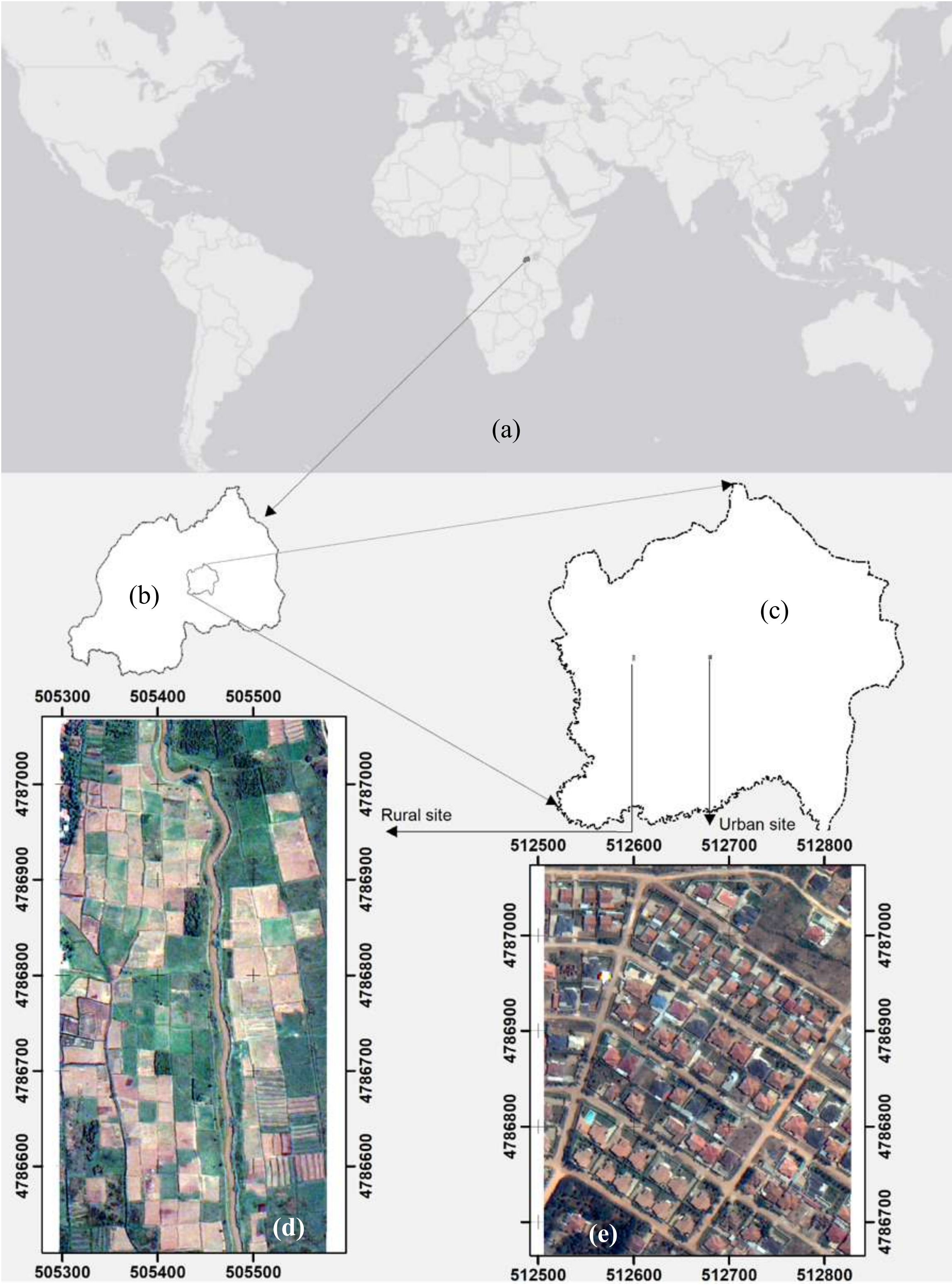

144 Figure 1: Case study location: (a), (b), (c), (d) and (e) show respectively, the study area on global
145 scale; Rwanda; the city of Kigali; rural site and urban site.

2.2. Parcels and building outline extraction

2.2.1. Automatic process

The extraction parcels and building[6] outlines were based on spectra, texture, geometry and contextual information. OBIA, used approach, can combine spectra, texture, geometry and contextual to delineate objects with explicit topology, shape and size [43] which are key aspects of cadastral index map. Rule-based expert systems within eCognition software were developed to allow the segmentation of the image (Figure 2). Getting an optimal segmentation where maximum numbers of segments matched parcel boundaries or buildings outlines was crucial. Initially, the automated Estimate Scale Parameter [ESP2] tool described in [22] was applied. 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 and it is fully automatic. But ultimately, the study used expert knowledge for parameterisation for boundaries [22]. The selection of parameters such as scale parameter in MRS is an objective an objective decision [22] requiring reasoning of the user who can instruct the machine. After segmentation, to classify candidate objects into parcels, geometry information such as polygon area, compactness, asymmetry, density, elliptical fit and shape index was used. But not all targeted parcels could be extracted whole and correctly immediately: several iterations were needed. İn most cases, automation resulted in so-called jagged lines, however, cadastral boundary edges have standard properties of linearity or limited curvature, and smoothness. To improve and smooth ragged boundaries, the morphological operator within eCognition was considered.

[6] In this research it was important to compare the ability of machine against humans in extracting building outlines with correct shapes, as it could help for solving the incomplete cadastre database in Rwanda [11].

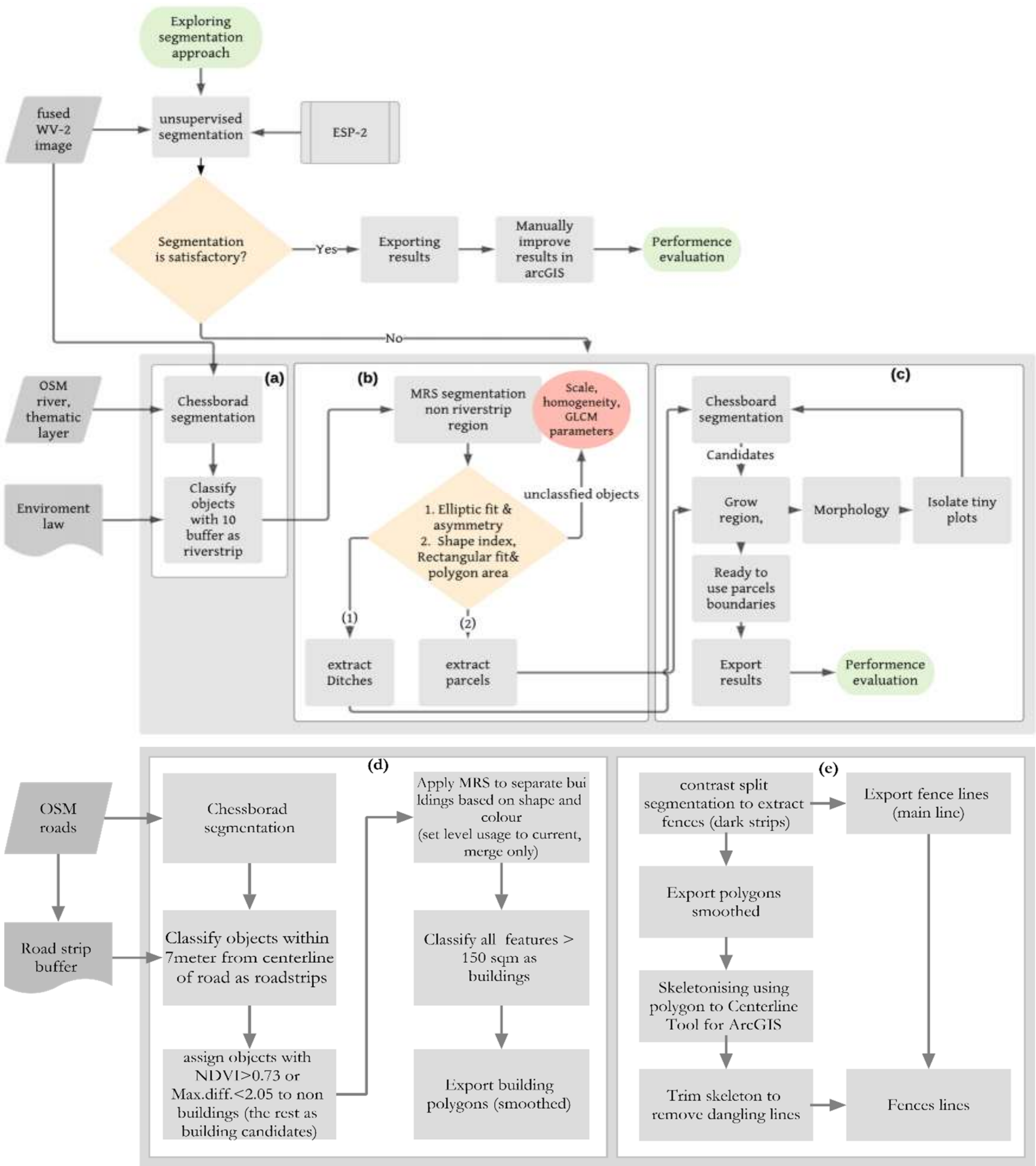

Figure 2: Applied automated boundaries extraction workflow

2.2.2. *Manual digitisation*

Five[7] human cadastral experts were tasked to individually hypothesise and manually digitise cadastral boundaries using the same dataset as used in automation. In accordance with [6], experts were identified based on cadastral domain professional qualifications, experience, and memberships of the recognised surveying professional body (Table 1). The domain experts had extensive knowledge and expertise and were familiar with the subject at hand and analyses the issue by automatic, abstract, intuitive, tacit, and reflexive reasoning can perceive systems, organise and interpret information [38]. The team was provided with an extraction guide that clearly describes cadastral objects to be extracted, input dataset with clear digitising rules.

[7] Using more than one person allowed to assess human consistency

Table 1: Human operators

Expert ID	Qualification	Professional body	Experience
A	Master in Geoinformation and Earth Observation	National cadastre	8 years
B	Bachelor of Science in Geography	National cadastre	8 years
C	Bachelor of Science in Geography	National cadastre	8 years
D	Bachelor of Science in Land Surveying	Organisation of surveyor	5 years
E	Bachelor of Science in Geography	National cadastre	5 years

2.2.3. Geometric comparison of automation versus humans

In our study, geometric precision, that is usually more important than the thematic accuracy for spatial features delineation [48], was considered the key aspect in measuring the performance of machine against human operators, for parcels and building outlines extraction. Considering that an important aspect of developing systems for automated cartographic feature extraction is the rigorous evaluation of performance, based on precisely defined characteristics [40], we decided to use accurate reference boundaries measured[8] out in the field rather than current legal boundaries. While the later are not accurate enough (with an estimate shift of 1 to 5m) to not serve as reference data, they provide shapes that helped surveyors to know the parcels that need to be precisely measured following existing boundaries features. In fact, it would be practically impossible to survey reference parcel for each of the parcels extracted, with the presence of respective owners and owners of neighbouring parcels to show the limit of parcels, as required by the conventional surveying approach in Rwanda.

In an ideal case, a one to one relationship is obtained where desirably one parcel in the reference is explained by one parcel in the extracted data set (Figure 3: i, ii, iii and v). In other cases of one to many or many to one correspondence (Figure 3, iv) omission errors and commission errors called false negatives and false positives metrics were determined. (i) The False Positives (FP) are parcels, which were erroneously included by either machine or human experts; (ii) the False Negatives (FN) are parcels not detected by either human or machine but they exist in the reference dataset. The performance of machine versus humans could be also estimated as the portion of extracted parcels that could match their corresponding references (correctness) or the portion of reference parcels that could be reproduced by extraction (completeness) [18].

Mathematically,

$$\text{FN (omitted)} + \text{TP (detected)} = \text{Reference,} \tag{1}$$

$$\text{FP (Committed)} + \text{TP (Correctly detected)} = \text{Extracted,} \tag{2}$$

$$\text{Correctness} = \frac{\text{Extracted} \cap \text{Reference}}{\text{Extracted}} * 100, \tag{3}$$

$$\text{Completeness} = \frac{\text{Reference} \cap \text{Extracted}}{\text{Reference}} * 100 \tag{4}$$

A framework for comparing extracted and reference parcels was developed in the esri ArcGIS environment (Figure 4). To be able to compare each individual parcel in the reference set with the corresponding parcel in the extraction set, the splitting by attributes tool was used to split the index cadastral map into individual parcels. Then the batch intersect tool for each parcel in the reference data with each corresponding parcel in the extraction set. Resulting intersects were then merged to have one attribute table containing area of intersection of extracted parcels and reference parcels. Other input data like shape index values were computed using esri ArcGIS geoprocessing calculate field tool.

[8] Field survey used precision survey tablet running Zeno field mapping software with access to GNSS RTK CORS instant corrections. A network of Continuously Operating Reference Stations (CORS) with Real Time Kinematic (RTK) positioning techniques provides instant corrections to measurement taken using Global Navigation Satellite System (GNSS) to allow centimetre accuracy.

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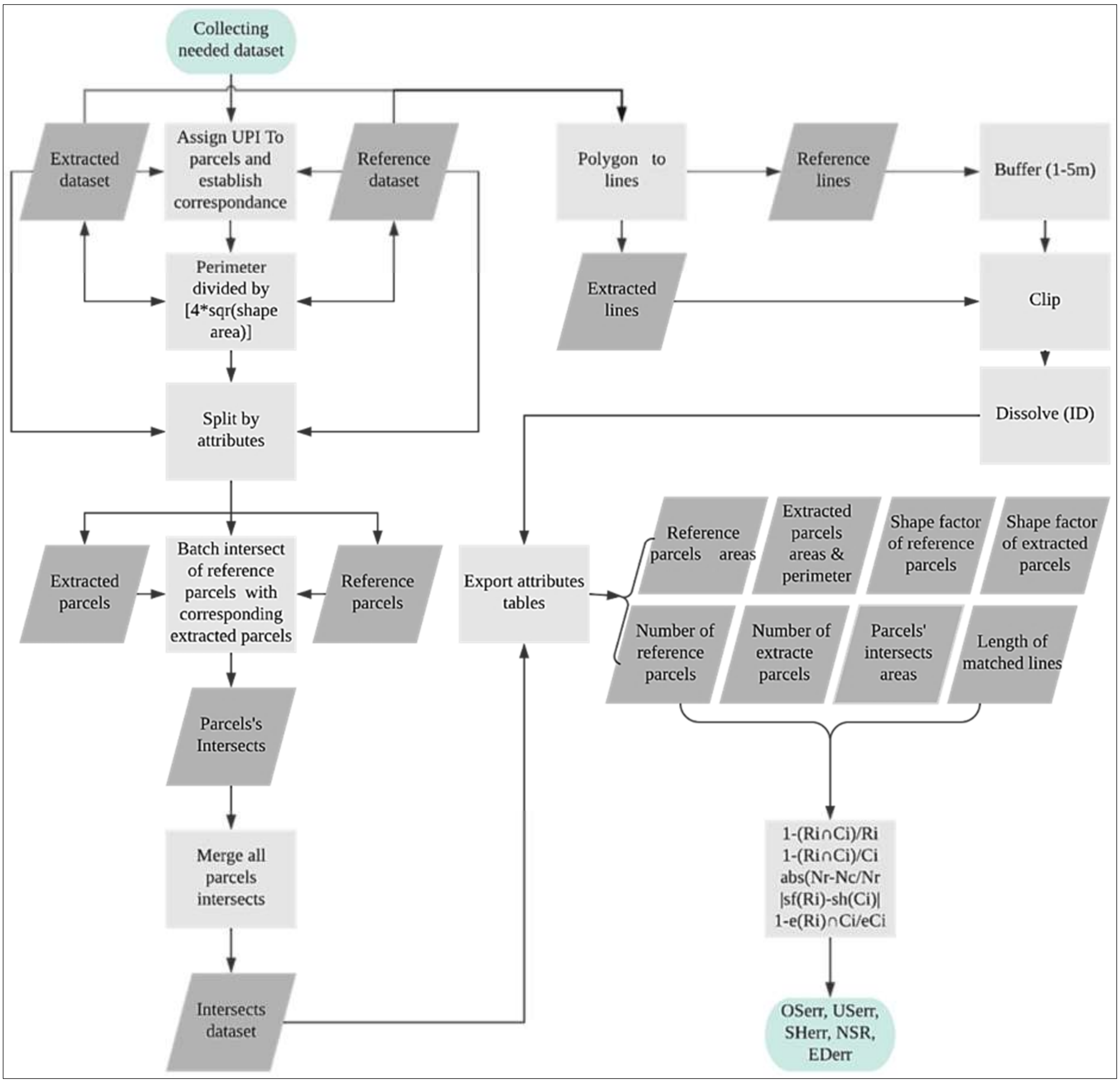

Figure 4: Implemented framework for computing geometric discrepancies

For edge shifting computation using ArcGIS a model (Figure 5) was built to automate the process.

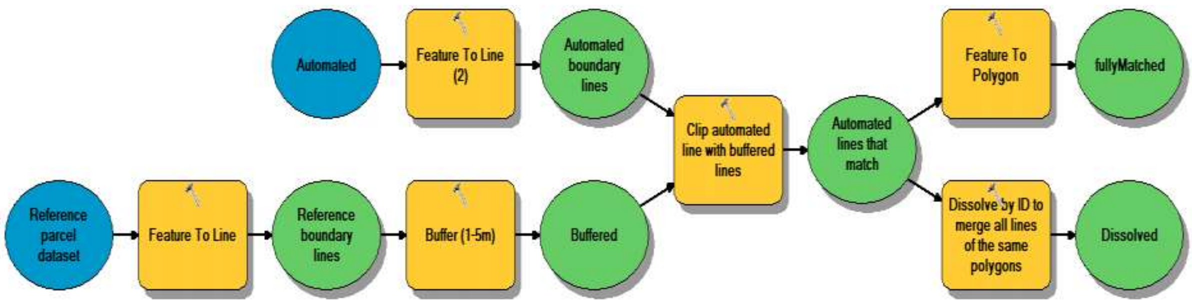

Figure 5: Model for assessing edge error between reference and automated boundaries lines

3. Experimental Results

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This section presents parcel and building extraction results by humans and automation means, and the performance of human operator against machine operator. Extraction results were disaggregated by sites: rural versus urban.

3.1. Extraction of parcel boundaries in rural area

In the rural area, cadastral professional hypothesised and digitised parcels following visible features such as ditches according to their expertise. From (a) to (e), Figure 6 below presents manually digitised rural parcels. On the same figure in (f), we have legal boundaries from the national cadastre.

Figure 6: Manually digitised rural parcel boundaries (a-e) and legal boundaries from the national cadastre (f).

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The automated OBIA approach, on the other hand, resulted in ragged and highly inaccurate segments [Figure 7 (a)] when using the fully automated Estimate Scale Parameter (ESP-2) tool with the shape factor of 0.1 and the compactness of 0.5 for the segmentation. The results were improved by modifying the shape factor and compactness to 0.5 and 0.8 respectively [Figure 7. (b)]. As indicated in Figure 7 (c), much better results were obtained by using the user-developed rule set based on experts ground knowledge since it is more adapted to context than the ESP-2 tool.

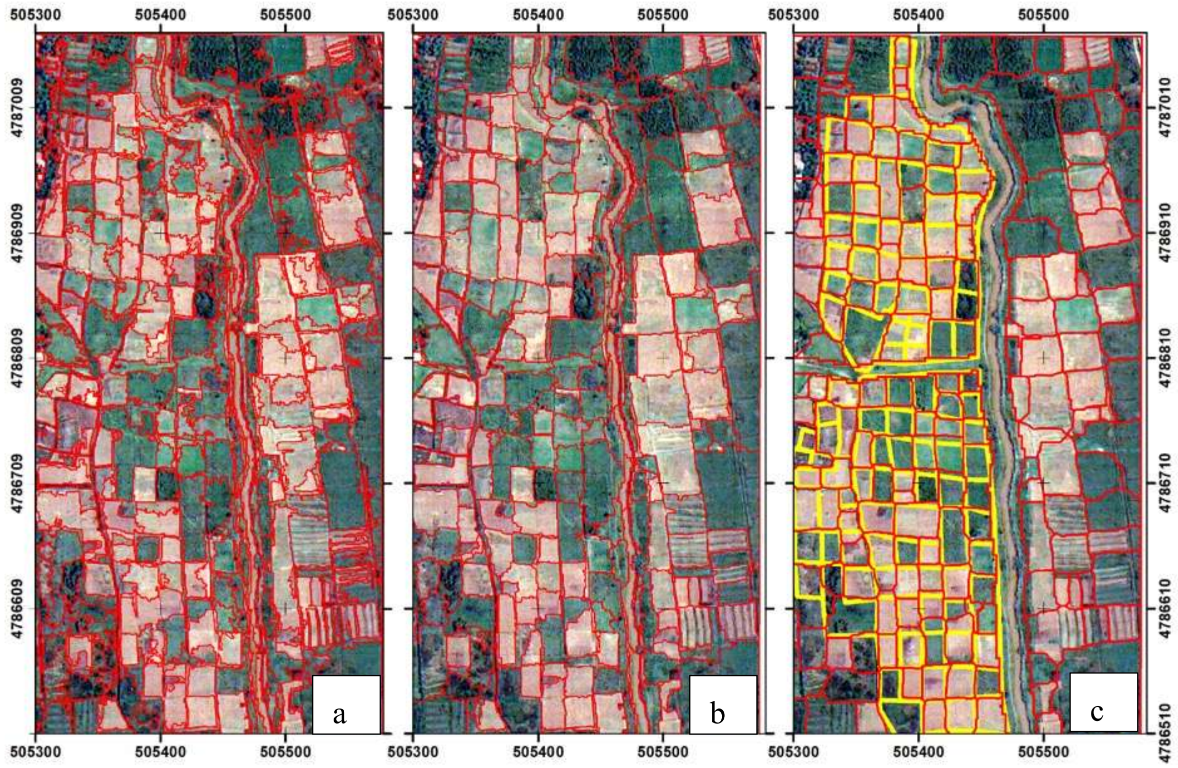

Figure 7: Automatically extracted parcels boundaries. in (c), automated parcels are overlaid with reference (in yellow) parcels.

During automation, resulting boundaries presented dangling features that do not meet cadastral geometry and topology requirements. On Figure 8 (a), the parcel in red has a dangling area that need to be trimmed off, but also ditches, dark strips that separate parcels need to be represented as line and not as polygons. The morphology operator within eCognition was used to improve the boundaries. In (b), the pixel-based binary morphology operation is used to trim dangling portion off the main parcels. An opening morphology operation to define the area of extracted parcel that can completely contain the mask and the area, that cannot contain the mask completely is trimmed off the parcel. Morphology setting was done based instructions from eCognition reference manual. In (c), ditches and other loosely extracted features are sliced into smaller image objects using chessboard segmentation. For smoother 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.

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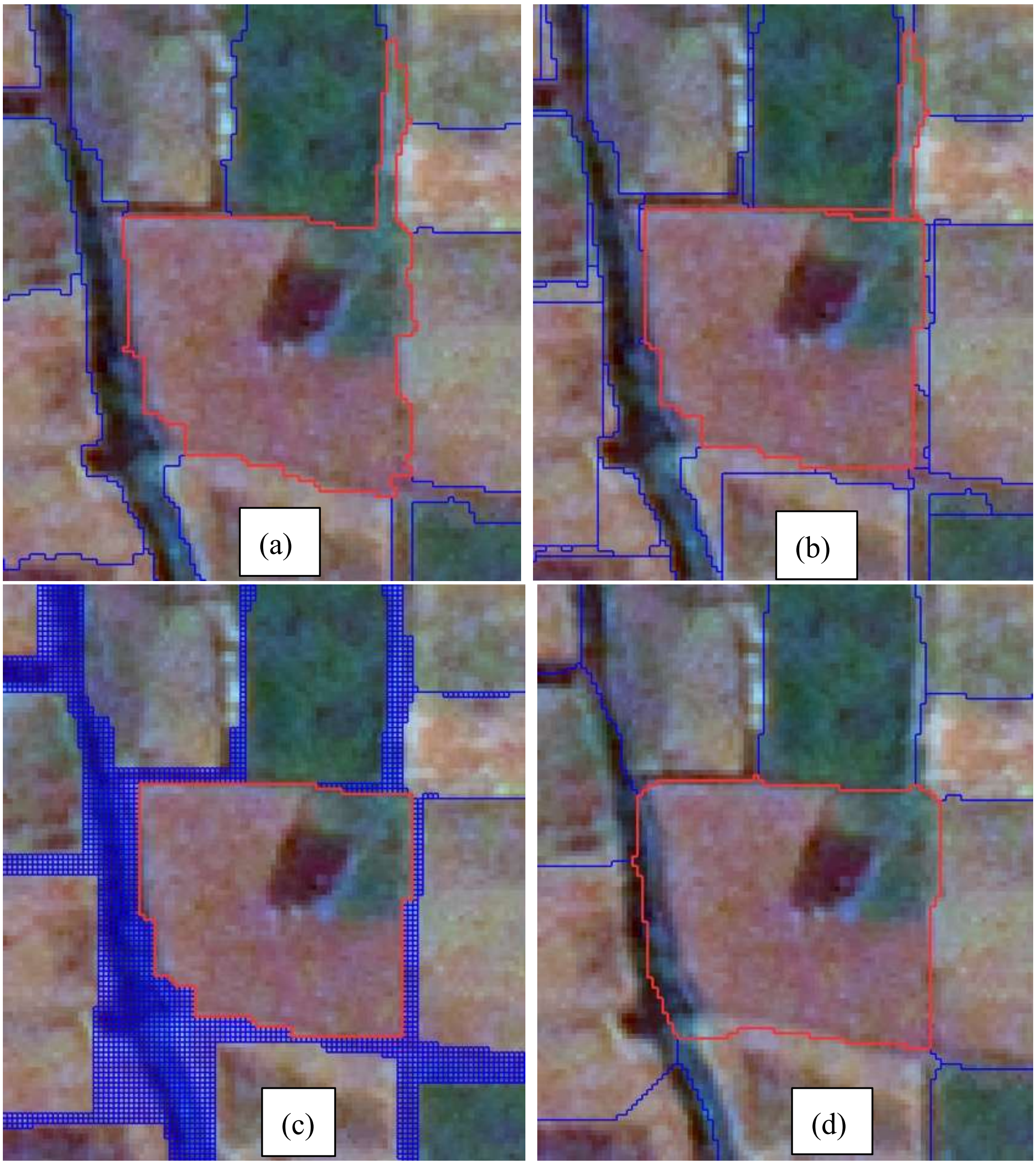

Figure 8: Boundaries line enhancement

3.2. Extraction parcels in urban areas and building outlines

The extraction of parcel and building in urban area relied on visible fences, roofs and roads. From (i) to (v), Figure 9, presents reference parcels (in red) overlaid with manually extracted urban plots (in yellow).

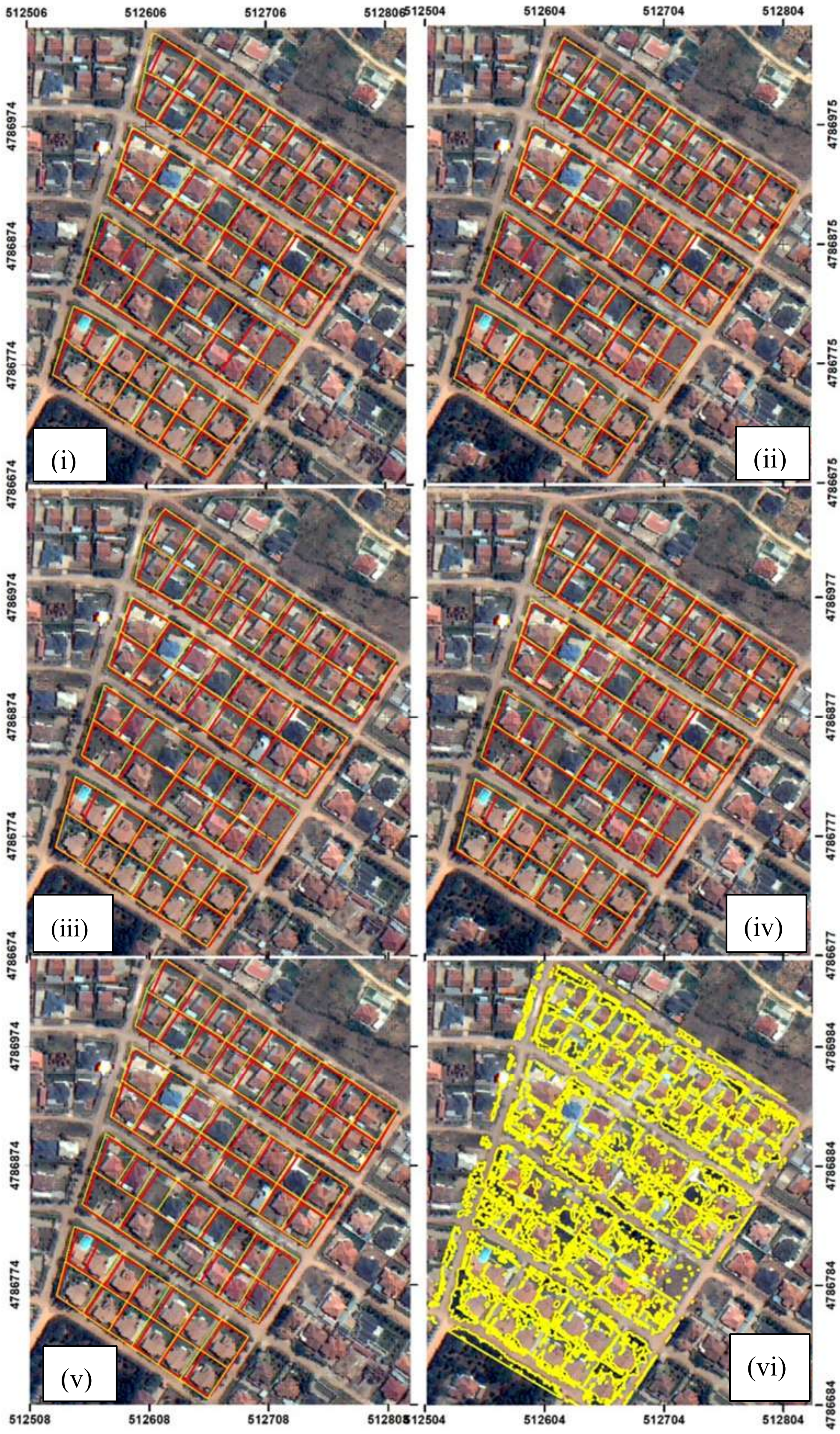

Figure 9: Extracted building plots by experts (i-v) overlaid with reference parcels and machine (vi).

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Other than building plots we also applied both automatic and manual techniques for the extraction of building outlines. Presented in Figure 10 are results from expert team manual digitisation [a-e] and automatically extracted building outlines[f].

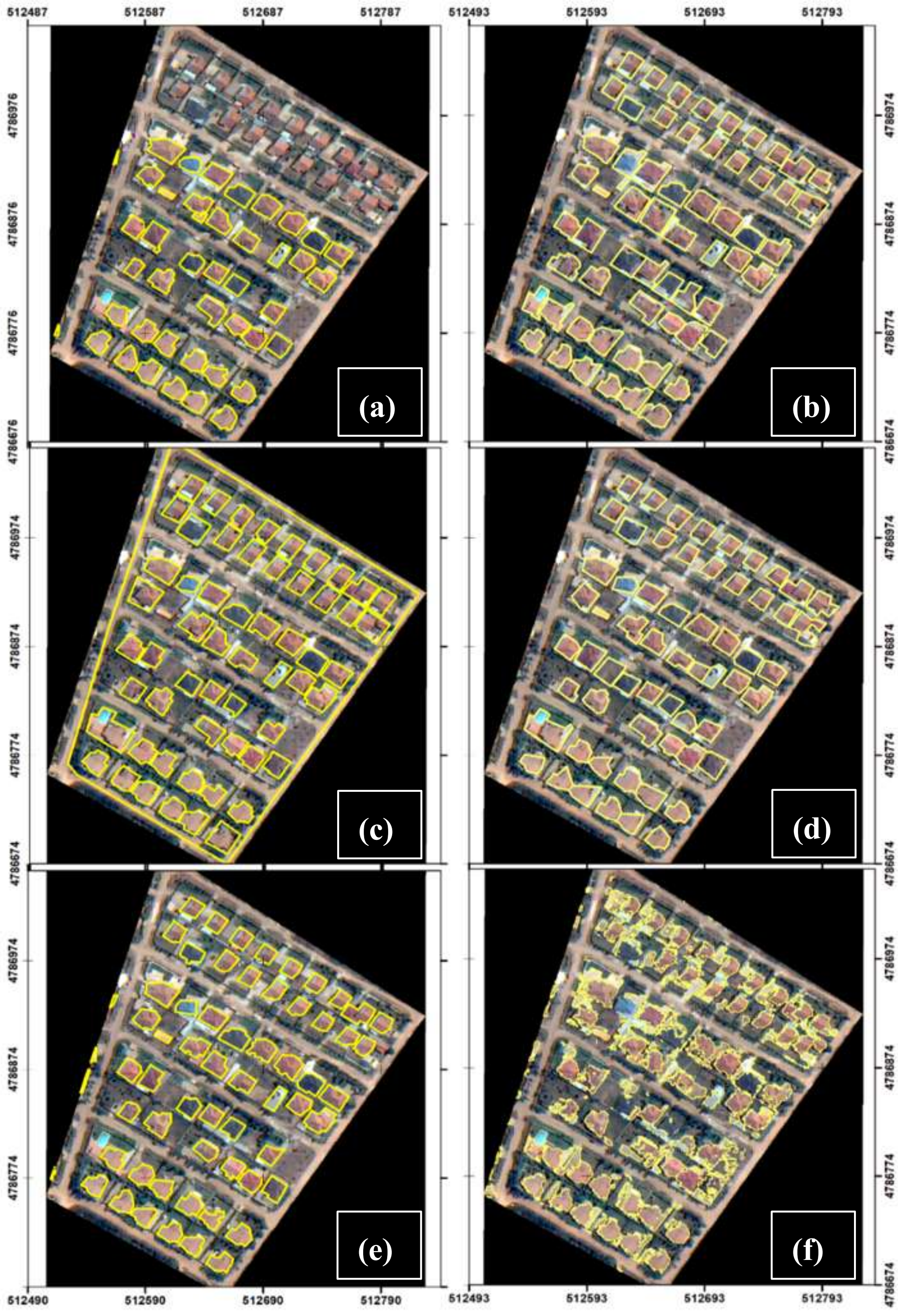

Figure 10: Extracted buildings plots by manual digitisation and automation

The automation output in the urban area was counterintuitive, at least compared to human visual interpretation. As it can be remarked, automation resulted in poorly structured parcel boundaries compared to the manually digitised parcels. As shown on Figure 10 (f), the machine faced difficulties to trim pavements and tiny structures from the main buildings. Blue and black roofed building were omitted as they spectrally appear like vegetation. On the contrary, humans were more precise and concise.

3.3. Geometric comparison of automated against manually digitised boundaries

Geometric discrepancies between each reference parcel and the corresponding extracted parcel were determined by overlaying automatically produced parcels with manually digitised and field

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surveyed parcels. A distance tolerance buffer of 4 m was applied considering the shift of boundaries inherent in the source image. Note that the comparison was done only for the rural site, where automation results were geometrically comparable with manual and reference parcel polygons.

In Figure 11, violin graphs are shown, on which white dot marks the median, illustrating the full distribution of discrepancies between reference parcels and automated and manually digitised parcels.

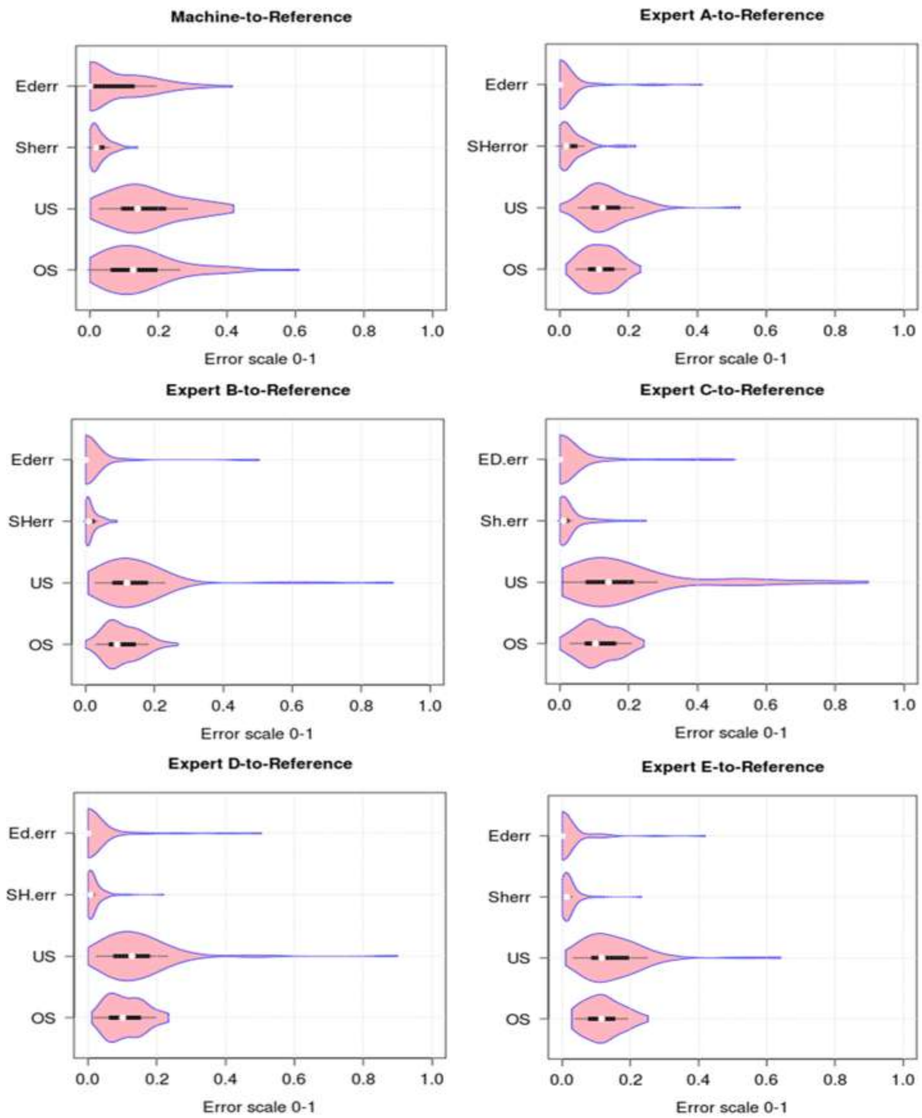

Figure 11: Clustering of geometric discrepancies

The wider section of the violin plot[9] in Figure 11 indicated higher number of extracted parcels with given error value whereas the skinnier section shows a reverse case. The graphs allow examination of the behaviour for all instances, that is, the variation and likeness in the full distribution and the pattern of responses for machine and human can be visualised and compared.

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 did not necessarily consider the correctness of detection i.e. the degree of coincidence of extraction with cadastral boundaries. The focus is the ability to detect visible boundaries features on the image. As it

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[9] see https://mode.com/blog/violin-plot-examples for interpretation of violin graph

can be observed in Figure 12, the pattern of distribution of discrepancies corroborated with Figure 11 with respect to shapes of extracted parcels.

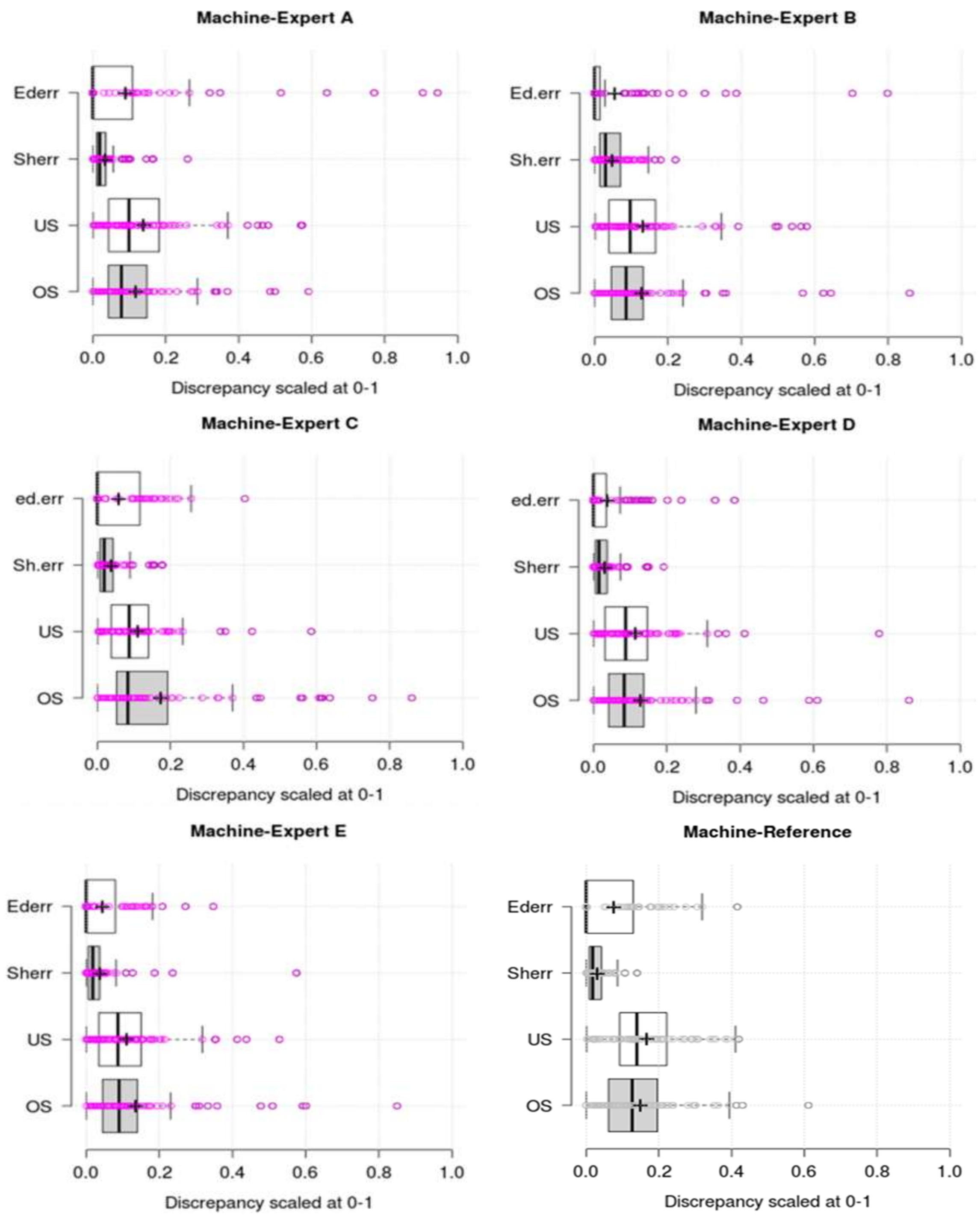

Figure 12: Discrepancies between automated boundaries and manually digitised parcels

Table 2 presents the global error for each metric considered: over-segmentation, under-segmentation, shape and edge shifting. Since an optimum and error-free segmentation where OSerr, USerr, SHerr and EDerr equal 0 is the ideal case and rare to have, we can simply define an error tolerance range within which extracted parcels are maintained as acceptable.

Table 2: overall detection (*) error by machine against humans

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	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%

(*) Reference= 100 parcels; automation=95 parcels; expert A=96 parcels; expert B=94 parcels; Expert C=90 parcels; expert D=99 parcels and Expert E=95 parcels

4. Discussion

4.1. Manual extraction creates quality issues

In general, manual digitisation of rural parcels resulted in slight inconsistencies among users. Not all parcels could be extracted equally the same, despite having the extraction guide provided to support the cadastral experts. The results show a commonality of approximately 60% in detected parcels by humans, however, 40% are perceived quite differently amongst the experts. The findings raise questions regarding cadastral updating: arguably if human operators update boundaries with only imagery as support, they may introduce different non-systematic errors. Machines may introduce less error during cadastral updating: the algorithms used, if not changed, will follow the same logic. Therefore, beyond issue of higher costs and time usually associated with human users, the issue of quality is significant to consider also.

4.2. Semi-automated is more feasible than fully-automated

The findings of this research suggest that a semi-automated rather than a fully automated approach is more applicable for cadastral boundaries extraction, for ready-to-use data that can be exported as a vector file, for example, to esri ArcGIS or other GIS. Semi-automated approaches with a user-developed rule sets, based on experts' ground knowledge, generate better 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 that do not require manual post-processing and editing. For instance, knowing the setback distance, a user can extract parcels within a defined distance from specific roads or river. Also, since it is not possible to have all parcels with same morphological conditions, to adapt to variation in size and shape, semi-automated approaches allow for a subsequent segmentation and classification.

4.3. Invisible social boundaries: a challenge to both machines and humans

4.3.1. Rural area

While colour is the primary information contained in image with which objects are extracted and separated [63], individual parcels are not reflected by different colours. In addition, parcel boundaries shown on images, some are social constructs making it rather challenging to extract them. Some parcel boundaries are visible on image whereas others are invisible and cannot be detected.

In our study, the separability of rural parcels was influenced by the extractability of features marking boundaries, parcel size and shape. Most of the parcels in rural sites were marked consistently by visible ditches. Ditches were extractable by machine as separate elongated narrow strips (Figure 8) or otherwise it would be difficult to separate two parcels with same texture. In

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eCognition, such elongated features like ditches are characterised by very low elliptic fit values and or being very highly asymmetric. The ditches being extractable as separate entities from parcels facilitate separating parcels from their neighbours. Experiments show that a parcels' layout, size and fragmentation affect the extraction of boundaries. With regard to shape and size of parcels, it could be observed that having regular shaped parcels eased the automation whereas highly fragmented parcels prompted to omission and commission errors due to variation in shapes and size of parcels. As was experienced, when classifying segments with shape indexes like rectangular fit, shape index, border index, elliptic fit, compactness - the over-segmentation error was likely. To avoid this error, a parcel area threshold value was defined that would remove small (likely committed) parcels from classification. But also, screening small polygons to prevent over-segmentation resulted in under-segmentation error as there exist very tiny plots reflecting the level of land pressure in the country. Not only extracting highly fragmented parcels was a challenge to automation, but also to humans. Some of the hypothesised boundaries by human experts could not necessarily match references parcels. This means that the physical line is not enough to define a boundary. This leads to human subjectivity, because of individual differences in image interpretation [65], in parcel delineation. Inconsistencies, where it is likely for one human expert not to produce same parcels nor uniformly digitise the same boundaries for repeated times, present a weakening feature of image-based demarcation.

4.3.2. Urban area

Major challenges were encountered in the urban area owing to higher heterogeneity and diversity with respect to form, size, layout, and material constitution of urban structures. For instance, one roof surface may display varying spectral signatures, making it very difficult for automated building extraction. In the studied case, buildings roofs are mostly hip and valley and prone to spectral reflectance variation. In fact, depending on the position of the sun at the time of image acquisition, some parts of the roof are not illuminated which affect the extraction, raising requirement concerns over the quality of image required for cadastral mapping purposes. Not only roofs, but also the material composition of fences and marking of plot boundaries varies, making it difficult for parcel extraction. Fences are very relatively and typically narrow objects, hard to detect with a 0.5-metre resolution image. In some cases, building roofs, the fences marking parcels, building shadows and garden had almost the same spectral signatures making it almost impossible to separate these features.

Generally, from the experiments it can be assumed that the extraction of buildings and urban plot boundaries using spectral information of roofs and fences is challenging due the complexity of urban fabric and the quality of the remotely sensed data used by the machine, as opposed to humans. Looking at the image, buildings and fences are very able to identified with eyes, and we can also see good results from digitisation by experts. Counter-intuitive results obtained from automation confirm observations made in [43].

4.4. Both strengths and weaknesses between human and machine

From the comparison of manually digitised boundaries against automatically generated rural parcel boundaries (Figure 11), the most striking observation is the likeness of the degree of deviation of automatically and manually extracted parcels shapes from the real (reference) parcel shapes. This demonstrates that the deviation of automated parcel shapes from manually digitised parcel shapes were too small. Figure 11 was corroborated by Figure 12, in showing that nearly all extracted parcel polygon areas by experts have less than 20% of their areas committed or omitted from automated parcels polygon areas. In general, human operators were geometrically a more precise than machine algorithms when drawing and reproducing parcel geometries from images but the performance of machine is auspicious in the rural context. On the contrary in urban areas, humans outperformed automation. In fact, automated parcels and building outlines were topologically and geometrically poorly structured and not comparable to manually digitised parcels and building outlines.

4.5. Corroboration with previous studies

Our study findings corroborate with some of previous studies [37], [67] where obtained automation performance was 24-65%. In contrast to findings by [3],[19], [25], [61], however, automation performance was lower due to focus on geometric precision rather than thematic accuracy. Different from previous studies, with exception to the study of [37]; this study focused on automated extraction of whole-parcel boundaries. 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 [31] and [67], 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 in rural areas. In urban area, however, while an unambiguous ontology status of buildings, with shapes that are clearly detectable to humans, would to ease their delineation [8], results can be counterintuitive.

4.6. Implications for practice and research

Our method for comparison is implementable in esri ArcGIS. It is quantitative and hence reproducible and replicable. As for implications, first, the study instils future researchers to use geometric accuracy metrics in compliance with cadastral standards.

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

Third, from reviewed previous proponent works in 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 inferences made in this work are based on simple case studies using smaller tiles of images which do not represent the complexity on the ground. The research problem is aligned to a real-world problem, but the presented solution primarily considers methodological matters, not the broader set of pollical, legal, organisational, and administrative challenges. Added to that, using automation in a small area might not be a wise idea, it terms of gaining critical mass and economies of scale. The implication of this is a need to apply automatic tool to a large area in simulation to real-world practice than using smaller and subjectively selected area. In general, the conclusion is that the tool can be successfully used for large scales in support to the current surveyors as a preliminary step before undertaking final map creation. After cadastral professionals have automatically extracted boundaries, they can overlay them on an image and discuss with the owners, to be eventually fixed and legally accepted.

Generally, beyond the requirement to understand the data, the experimentation suggests that automated extraction of cadastral boundaries, requires in addition, knowing the social contexts that shape landholding structures in a given area. During automation, the user must integrate this knowledge within the rule sets. Fully automated approaches could not be fruitful compared with the user-developed rule set, since it limits user intervention, if not ignores it, and does not integrate expert ground knowledge.

5. Conclusion and Recommendation

This study compared machine driven techniques, using rule sets within OBIA, and human abilities in detecting and extracting visible cadastral boundaries from VHR satellite images. From the results, automation was able to correctly extract 47.4% of visible rural parcels and achieved 45% of completeness, whereas in urban areas, it failed to generate explicit polygons owing to urban complexities and spectral reflectance confusion of cadastral features. As was elaborated, machines are meant to increase human performance in production and service delivery. In the cadastral field, this will be achieved if human cadastral intelligence; knowing where boundaries are results of social constructs and more perceptible to humankind; is integrated with computational machine power to allow the extraction of many parcels to support land registration. With the obtained results in rural settings, land registration service coverage can be taken farther than it is today.

Despite rigorous methods applied, the study does not, however, claim the full-fledged experimentation with automation tools. Thus, more studies are needed using other tools and other case studies in search of the tool that best fits the concrete purpose. In this study, automation was applied on relatively small area but it is suggested it could also be scaled up on large areas. Finally, in urban areas, the study encountered limitations since the colour (i.e. spectral signatures) was the primary information contained in image data in segmentation. As an implication, the incorporation of LIDAR information may improve obtained results and hence is suggested for application to the same case and other studies. The goal is to identify and apply user-friendly and learnable automation tool that allow having precise and GIS ready cadastral boundaries on a large scale possible.

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