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Object Based Image Segmentation Algorithm of SAGA GIS for Detecting Urban Spaces in Yaoundé, Cameroon

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Abstract: Present study is focused on the satellite image processing by means of SAGA GIS. The objective of the study is assessment and analysis of the core urban areas and its spatial distribution in the limits of the city and suburbs. The study area includes Yaoundé and its surroundings, Republic of Cameroon. The methodology includes Object Based Image Segmentation (OBIS) approach by SAGA GIS. The paper presents a methodologically structured workflow used in SAGA GIS for segmentation of the Sentinel-2A image. The segmentation techniques includes adjusting technical parameters, performing neighborhood approach and post-processing procedures (unsupervised classification, number of clusters). The OBIS model and SAGA GIS were used as main methods and machine learning techniques for image segmentation. Data include Sentinel-2A satellite image with high resolution (10 m). The image was analyzed by two approaches of cell neighborhood analysis: Moore and Neumann. The results showed following numerical parameters of the computed area: the perimeter of 1,060,560 km and an area estimated for the Yaoundé city 191,745,000 km^2. The Neumann approach demonstrated better results for image clustering. The results presented automatically detected and separated segments of the city areas and other land cover types (savannah, forests, mountains). The spectral reflectance of various land cover types on a satellite image enables to group pixels of the image into classes using segmentation technique which has an important impact on the conceptual methodology of the urban mapping. The results of the image segmentation show the average values of the Neumann approach more correct in urban area than Moore approach. The accuracy assessment demonstrated 74.63% for the core urban area by using the Neumann method. The applicability of SAGA GIS for automated methods of image processing using machine learning algorithm of OBIS is presented and the advantages are discussed. The study demonstrated the effectiveness of the high-resolution Sentinel-2A for socio-economic studies, exemplified by urban mapping where remote sensing data serve as reliable sources of geoinformation. The advantages of the OBIS are discussed with detailed explanation of the SAGA GIS workflow.

Key words: Sentinel-2A, object based image analysis, segmentation, machine learning, SAGA GIS

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1. INTRODUCTION

The Object Based Image Analysis (OBIA) or Object Based Image Segmentation (OBIS) approaches applied for satellite imagery is an effective tool to analyze contours of the urban districts using objects geometry and spectral brightness of the pixels on an image. This is especially actual in urban mapping where city spaces and suburbs should be separated from other land cover types. An OBIS approach enables to classify image into clusters by grouping pixels of the original image into homogenous, similar regions on a final map. Such a detection of urban spaces on a satellite scene can be performed using the

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machine learning approaches by a variety of existing GIS-embedded segmentation algorithms, reviewed, compared and analyzed in the existing literature [1–4].

The most important feature of OBIA that differs it from the standard image analysis consists in the algorithm approach. While the traditional pixel-based image classification separately groups each pixel into classes, the OBIA automatically groups multiple neighboring pixels into one polygon based on similar spectral characteristics of these pixels, using the machine learning algorithms [5–7]. The applications of the computer techniques in cartography have an indisputable value nowadays, due to the increased speed and precision of cartographic workflow. Machine learning plays a significant role in contemporary cartography – and especially in image analysis. Satellite image analysis have become an increasingly important part of the environmental studies. Image analysis presents new information on the Earth's surface derived from the machine based algorithms of image processing. Examples of the machine learning applications in cartography include background modeling, human tracking and extraction, 3D reconstruction moving target detecting [8], marine geological studies [9–11].

As a result of the application of the machine learning methods, the OBIA has a more meaningful semantics to the human eye, since image is classified into groups of objects, rather than standalone pixels, e.g. it can be ‘tree’, ‘forest’, ‘agricultural field’, ‘building’, ‘car’, or ‘city’, depending on classification scale. The OBIA utilities the phenomena of spectral brightness that differs for pixels on an image representing various land cover types [12–14]. That is, the differentiation of pixels and grouping them into objects is based on the machine-based analysis of their spectral brightness. The OBIA is available in a wide variety of geospatial applications. Among others, these include both socio-economic and physio-geographic studies, for instance, geomorphological mapping [15], detecting road networks [16], agricultural mapping [17], vegetation mapping [18–20], detecting buildings using geometry of roofs and spectral reflectance [21–23], soil studies [24], marine mapping [25], built-up regions [26].

There are many factors that explain the advantages of the machine-learning methods of image segmentation over the human-made classification. These include (but are not limited to) the significantly increased speed and precision of data processing. Thus, the traditional classification can produce errors in the most complex landscape patterns due to the wrong recognition of pixels on an image and result in misclassification. The approaches of geodata processing and spatial analysis are diverse and may include laser scanning point clouds using panoramic images [27], neural networks, regression and relevance analysis, cluster analysis [28–30], data analysis and modelling in geological studies [31–33] and scripting methods in cartography [34] as well as ArcGIS and GRASS GIS based thematic mapping, spatial analysis and overlay [35–40], to mention a few.

Comparing to these studies, the use of OBIA method of detecting clusters presents prospects in urban studies, given rapid development of the machine learning algorithms than traditional semi-automated GIS mapping. Using OBIA presents new horizons which open up due to the capabilities of the machine learning in cartography. An automated OBIA method that selects information from the satellite images forms the applications that enable to solve the tasks of monitoring in urban studies and agriculture, in water resource management and forestry. This study aimed to detect urban space of the Yaoundé, Cameroon, and evaluate two neighborhood grouping methods (Moore and Neumann) for the Sentinel-2A high-resolution (10 m) multispectral image based on the OBIS approach in SAGA GIS.

2. STUDY AREA

The study area is located in Cameroon, Yaoundé (Figure 1), in western coasts of central Africa with spatial extent 3°47’N and 3°56’ N and 11°10’E and 11°45’E. The precise coordinates of the study area in a Sentinel-2A image include the following extent: 10°8’E, 3°5N’–11°8’E, 4°5N’ (Figure 2). It covers an area of 100 km^2 according to the technical specification of the Sentinel-2A tiles in UTM/WGS84 projection. The study area is rectangular, with a visible flow of the Sanaga River. For the purpose of urban segmentation, this research cropped a rectangle that contains the entire extent of the Yaoundé city and its suburbs (Figure 2). The regions containing other land cover types, such as savannah, tropical rainforests, deserts and mountains, were excluded to focus on the city space of Yaoundé and suburbs (Figure 2).

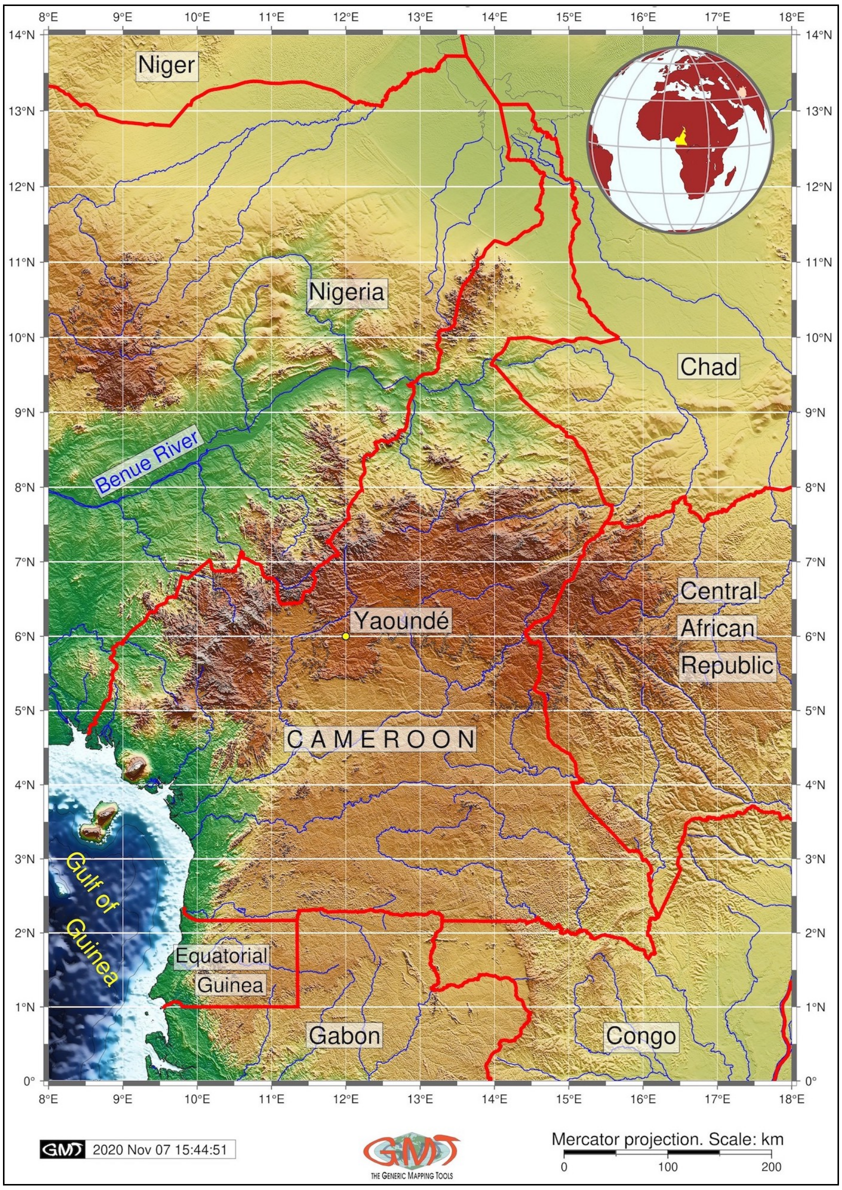
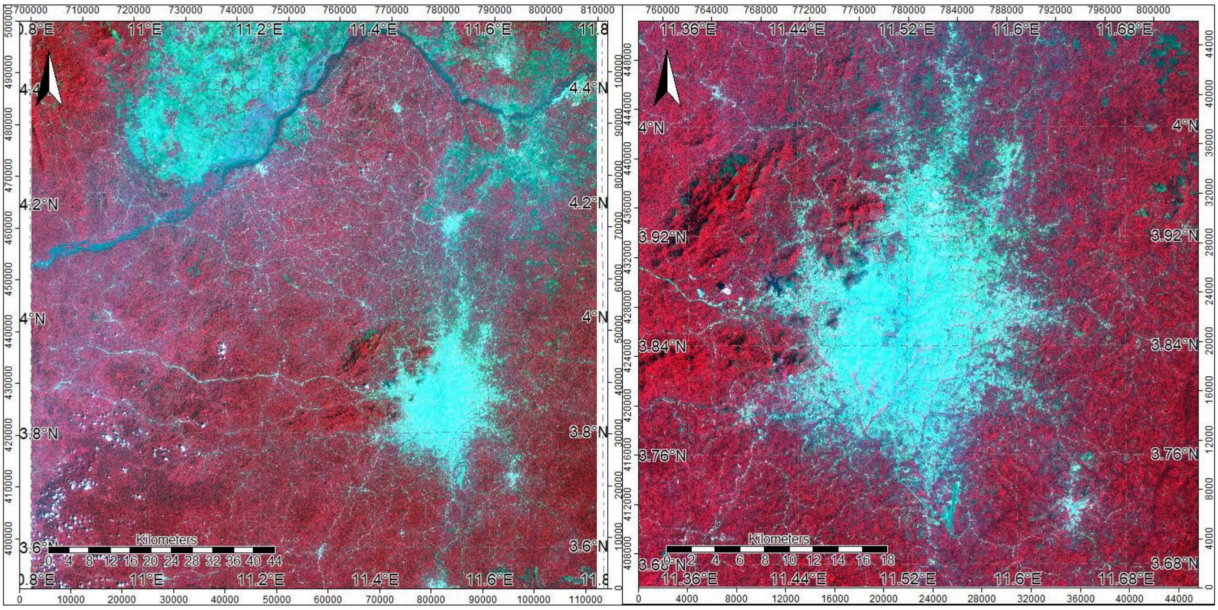


Figure 1. Topographic map of Cameroon based on SRTM/GEBCO grid
Cartography: Generic Mapping Tools (GMT)
Source: author

The exploitation of natural resources in a context of poor governance quality creates conditions for rapid urbanization and urban concentration [41]. As a result, Cameroon nowadays faces up serious problems including economic growth, urbanization, and soil degradation [42]. The environmental degradation can be illustrated by the deforestation in Cameroon with forests reduced to 1/3 after 90 years of land cultivation. For instance, agricultural activities resulted in the reduction of the area of Zamai forest reserve from ca. 50% in 1970 to ca. 30% in 2016 [43].

In recent years, Yaoundé is experiencing rapid urbanization [44]. The urbanization process is as essential as its economical and ecological outcomes. On the one hand, it facilitates dwellers to achieve the intended career plans, gives an access to education and medicine, and provides living conditions. On the other hand, it increases the burden on the landscape environment. The population of Yaoundé grew from 318,700 inhabitants in 1976 to 2.8 million by 2020. The population doubled after every decade since the 1970s: grew by 90% in the 1970s, doubled in the 1980s, and grew by 91% in the 1990s [45]. These processes are especially intensive in the peripheral areas, such as Mbalngong and Nkozoa, with high urbanization rates. The Bamenda city faced rapid and unplanned urbanization that happened since 80s.

The growth of population necessarily involved urbanization processes in the cities of Cameroon and its capital Yaoundé. Some cities in Cameroon change in functionality from the traditional agriculture villages to the complex heterogeneous cities [46]. The processes of urbanization in turn involve changes in ecosystem service provisioning areas related to the current land tenure system which are reflected in the land management of Yaoundé and urban spaces [47]. For instance, a gradual increase in population is often accompanied by the construction of the unplanned buildings, which resulted in changed geometric contours of the city.



(a) **(b)**

Figure 2. Sentinel-2A image Map of Yaoundé in false colour composite of Sentinel-2A: Red as 8, Green as 4, Blue as 3. North: river Sanaga. Mapping: SAGA GIS. **(a)**; Enlarged fragment Yaoundé city and suburbs: clipped image in false colour composite of Sentinel-2A: Red 8, Green 4, Blue 3. Mapping: SAGA GIS **(b)**
Source: author

The unplanned urban expansion necessarily resulted in land surface change. The increased urban spaces in various city districts including suburbs can influence urban development of the country in general and may have environmental consequences in particular, because new urban spaces are modified in their unit boundaries and structure. Besides, the location of the suburban often becomes a part of the city, transforming from the fenced farms or unfenced agro-pastoral small-holdings with crop cultivation covered by the semi-natural savanna vegetation, used as livestock or wildlife ranches to the urban cities [48]. Besides socio-economical dynamics, other concerns of Cameroon include environmental industrial and market waste management, pollution and poor town planning [49], as well as the progressive deterioration in the environmental quality. Changes in vegetation cover are caused by farming, grazing land and de-bushing. For additional info and a comprehensive overview of the current knowledge on urban planning challenges and prospects in Cameroon, the reader is referred to the literature [50–55].

3. METHODS AND DATA

3.1. Data and Software

The changed city dimensions and increased urban spaces can be visualized and calculated through the OBIS image segmentation method amongst others. The Sentinel-2A satellite image was processed by SAGA GIS, for a case study area of Cameroon. The selected region has contrasting land cover types including urban spaces, bare soils and various types of vegetation (grasslands, savannah, tropical rainforests). The visualization of study area via the Sentinel-2A displays a shift in the urban spaces. Due to the open source availability and regular uploads to the GloVis repository, the Sentinel-2A imagery can easily be received by the end-users. Thus, a period of receiving imagery by a Sentinel-2A mission enables frequent surveys repeating every 5 days at the equator and occurring every 2-3 days at mid-latitudes.

Another important parameter of the Sentinel-2A image is its high spatial resolution, which was considered while selecting the data for this research. The 10-m resolution of the Sentinel-2A presents an excellent source of data both for environmental and urban studies. As a general rule, the finer resolution of the input data (e.g. a 10-m Sentinel-2A satellite image), the more accurate is the resulting OBIA segmentation. Conversely, a coarser resolution of the input data (e.g., the 30-m Landsat TM satellite image) may show the effect of the over-generalization. For instance, using coarse resolution imagery might result in a simplified boundary of the urban districts and buildings, as well as merging of the small patches with the smallest pixel area into one class. Therefore, the value of the resolution of the input data increases the overall precision of the map. The original Sentinel-2A image has the selected coordinate extent (10°8'E, 3°5N' – 11°8'E, 4°5N') taken in 2020 (Figure 2).

The image has the 13 spectral bands with various spatial resolution and no cloudiness (0%). It was sensed on January 27 2020 at 10:45 by Sentinel-2A satellite, sensing orbit number 136, WGS-84 coordinate system in European Petroleum Survey Group (EPSG) Geodetic Parameter Dataset. The downloaded Sentinel image bands were loaded into GIS, opened in a UTM coordinate Grid System and displayed as colour composites RGB. The Sentinel-2A image processing and segmentation were completed using the OBIS algorithm in the open source GIS software SAGA GIS [56].

From the total 13 bands of Sentinel-2, only bands 2,3,4,8 were used for the OBIS classification. These bands were selected due to the spectral properties of the Sentinel bands and spatial resolutions. The Band 1 contains information on coastal aerosol which was not necessary for this study. The bands 2, 3 and 4 were selected, since they contain spectral information for Red (Band 2), Green (Band 3) and Blue (Band 4). The bands 5 to 7 contain red edge and were not appropriate, while the Band 8 has an infra-red, which enables to detect vegetation. The Band 9 is useful for detecting water vapor, Bands 10 to 12 contain Short-wave infrared data (SWIR), which were not necessary for this study. The Band 8 was displayed as red with composition bands 4 for Green and 3 for Blue. The image was then prepared for segmentation by clipping necessary area from the whole image using the following SAGA GIS path: 'Gris> Grid System > Clip Grids interactive' and then applying a 'Clip to Extent' menu for the selected square capturing the Yaoundé city and its suburbs (Figure 2, a). A new grid with a smaller extent (11°32'E, 3°67N' – 11°72'E, 4°1N') was used for further image processing. This square area now corresponds to the city of Yaoundé, the capital of Cameroon, and its suburban surroundings (Figure 2, b).

3.2. Workflow

The algorithm of OBIS module in SAGA GIS utilizes the chain of tool functions that allow several modules to be linked together into one process of the automatic image segmentation. The theoretical methodology of the segmentation algorithm of OBIA/OBIS implemented in eCognition software is described in a variety of works, [57–60] while applications of SAGA GIS are mainly focused on spatial analysis, vegetation mapping, terrain modelling and geomorphometric analysis [61–63]. In this study, a workflow included a chain of seven techniques in the methodology of OBIS image processing in SAGA GIS:

1) Loading the Sentinel-2A original image in false colour composite, bands 8-4-3 (Figure 2);
2) Clipping the study area using a mask for the city space from the original image (Figure 2);
3) Visualizing the clipped study area in false colour composites;
4) Detecting city area using OBIS approach by von Neumann and Moore approaches;
5) Performing automated image classification with 12 classes as a subtask (Figure 3);
6) Separating the city from the other land cover classes (forests, grasslands, savannah, water, roads) and deleting the unused contours (Figure 4);
7) Merging the machine-selected contours of the city into the one contour (Figure 5, a);
8) Computing the square and perimeter of the area (Figure 5, b)

The cropped part of the original Sentinel-2 image was processed using the segmentation clustering techniques by the following path in SAGA GIS menu: Geoprosessing> Imagery> Segmentation> Object Based Image Segmentation.

Using the pointer tool a box was dragged across the polygons of the Yaoundé city area. This automatically selected all polygons of the same class of the city and suburbs which resulted in all the selected squares and districts of the city. Afterwards, the selection was inverted and all other areas of 'not-city': forests, wetlands, savannah, mountains, etc. (Figure 4, b). This result in all the not-city area polygons was first selected and then deleted, to leave only the polygons of the city of Yaounde. by 'clear Selection' in the SAGA GIS menu. This resulted in only the city area polygons remaining were visualized to enable calculation (Figure 5). After the processing of the image, a post-processed unsupervised classification of the image was applied with identified 20 clusters. The square area and perimeter of the Yaoundé city and its suburbs have been calculated using the SAGA GIS path: Shapes> Polygons> Polygon Properties.

3.3. Algorithms

The technical details regarding the segmentation algorithm implemented in SAGA GIS are well described with reviewed OBIA algorithms, their strengths and weaknesses [64]. The workflow of SAGA GIS methodology of OBIS was applied according to the SAGA GIS documentation [65]. The two methods used by SAGA GIS analyse cells on an image using an approach similar to the lattice network. The two algorithm approaches tested in this study include von Neumann approach with Neighbourhood 4 and Moore approach with Neighbourhood 8. The algorithms determine the most effective object features in OBIA that ensure high separability among landscape features [66]. The Moore neighbourhood is one of these methods, based on a 2D square lattice with a central cell and the eight cells around it. Another method is the contrasting von Neumann method, which uses a central cell and four adjacent cells.

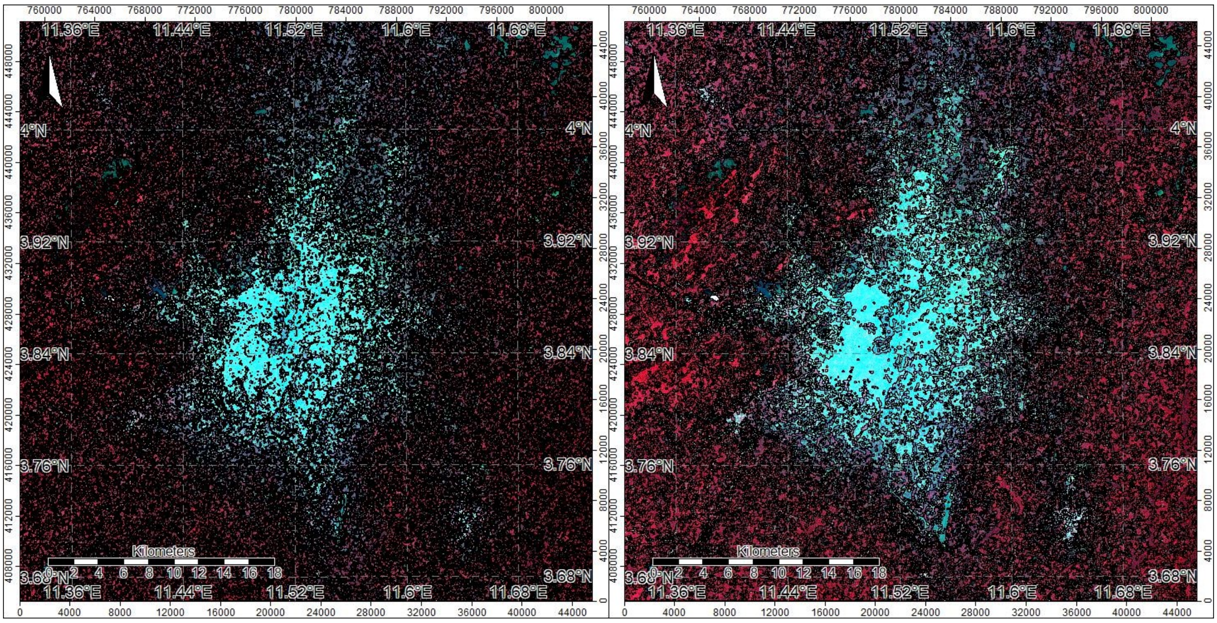
Besides, it allows four more cells as 'neighbours of neighbours' as extended neighbourhood of cells. Using approach of neighbourhood analysis approved for pixels on an image, the machine can easily group pixels based on the similarity of the spectral brightness of their neighbours (that is, other pixels surrounding the target one). Both methods of neighbourhood analysis are a well-known technique used for analysis of the pixels in cell automata of the object based image segmentation [67,68]. The OBIS merging technique detects groups of pixels from the pool of pixels on an image in an iterative process. In this case, the bandwidth for seed generation was selected as 10 for the both approaches. The segmented outputs are controlled by a post-processing with includes an unsupervised classification of the output image, performed automatically by the machine. The 12 classes were used with split clusters to complete the procedure. The high-resolution SRTM topographic data was used for mapping study area (Figure 1) to visualize the extent of Cameroon.

The Google Earth imagery was used for detecting urban spaces to assess the quality of the segmentation and filter the natural and urban areas. The open-source availability of the Google Earth imagery was applied for validation of the results with comparative analysis of the Moore and Neumann methods derived from the two approaches of OBIS in SAGA GIS. A confusion matrix [69,70] was computed to present the classification accuracy, a useful technique for the accuracy and validation assessment in remote sensing data analysis [71]. The workflow included the input image (Sentinel-2A) OBIS data, and Google Earth Engine (GEE) classifier (https://earthengine.google.com/) with reference points for testing. The GEE was selected, as it provides a cloud-based opportunity to perform a variety of the advanced geospatial analysis, such as those based on the spectral imagery and object-based methods (https://developers.google.com/earth-engine/guides/image_objects).

4. RESULTS

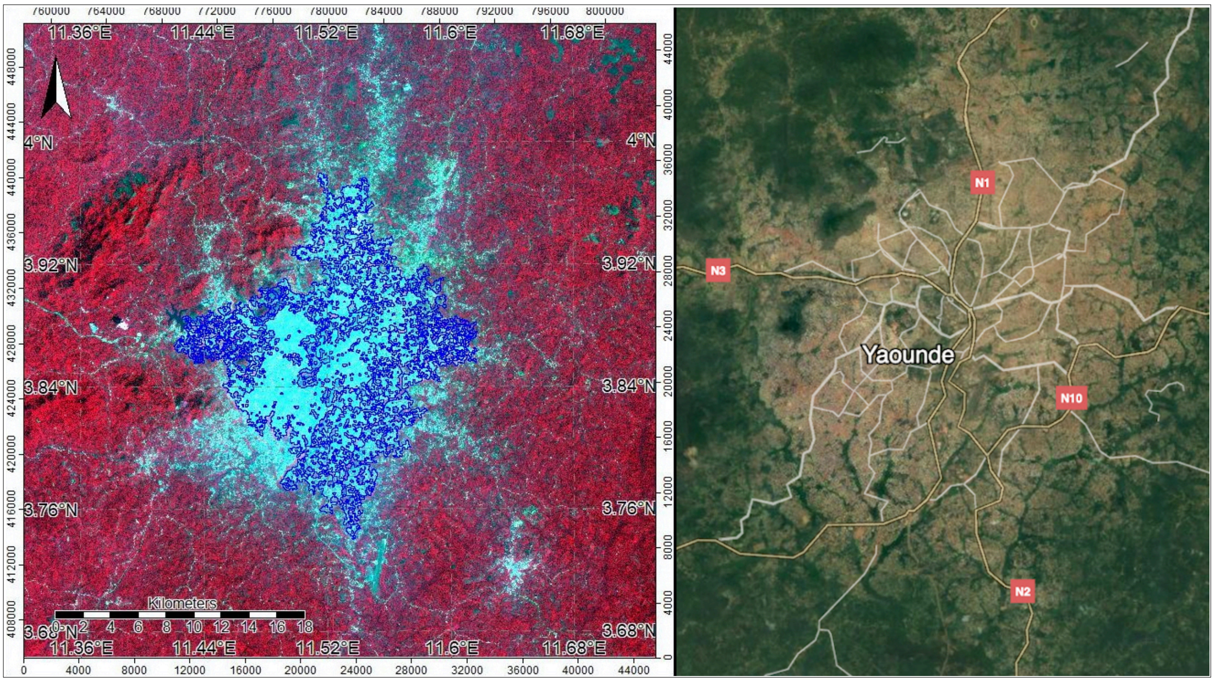
The challenging aspects of the machine-learning perspective in cartographic data processing persuaded the approaches in this study to adopt OBIS algorithm for image segmentation in order to better facilitate analysis of the urban growth in the selected study area. This paper dwells into the depth of image segmentation techniques using OBIS algorithm of SAGA GIS to know which technique of neighborhood, the Moore or the von Neumann, can perform better. The Sentinel-2A image was used to extract the region of interest, the city of Yaoundé. The results demonstrated that Neumann technique performs better compared to the Moore approach because the segmentation is being produced in a more generalized approach and the contours of the city quarters are selected more corrected. More precisely, the Neumann algorithm (Figure 3, b), the area of the Yaoundé city has clearer clusters in the segmented image, whereas applying the Moore method (Figure 3, a) has a higher threshold level and the contours are therefore more detailed, which in this regards is noisier.

Besides the visual assessment of the output results, the determination of the quality, the appropriate of the method and its suitability was performed using comparative analysis of the areas detected by the two different methods, in terms of location and extend, with a reference area. For this purpose, a Google Earth map with the boundaries of the urban area of Yaoundé city has been used showing the extent of the urban space on an aerial image. The accuracy assessment was based on the segmentation results (Figure 4 and 5) showing a final output of the Sentinel-2A classified image against the Google Earth aerial image covering the study area after SAGA GIS processing. The Google Earth map shows the overall contours of the city where the city spaces are clearly visible by the spectral reflectance on the image. The cloud computing platform of the Google Earth Engine enables to run the machine learning algorithms of both image classification and validation by generating the Error Matrix (Accuracy Assessment), classification of the imagery and results assessment (https://developers.google.com/earth-engine/guides/classification). Here the algorithms consisted in three steps: 1) making a Random Forest classifier for training pixels; 2) classifying the input imagery by GEE; 3) getting a confusion matrix representing re-substitution accuracy.



(a) **(b)**

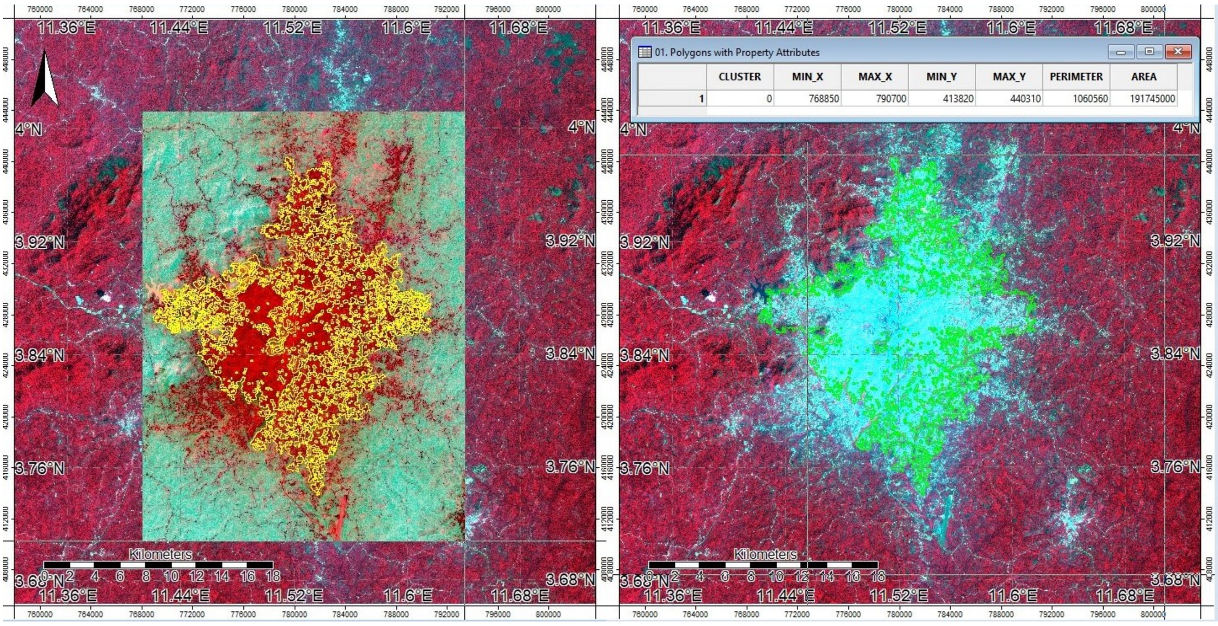
Figure 3. Results of the OBIS, Moore approach **(a)**; Results of the OBIS, Neumann approach **(b)**
Source: author



(a) **(b)**

Figure 4. Selected contours of city and suburbs: lines highlighted blue against the suburb areas as cyan **(a)**; Google Earth Engine cloud based platform aerial image used for verification of the results **(b)**
Source: author

The selected contours of city and suburbs are shown in Figure 4, a: contours highlighted red against other areas as black. To better visualize the remaining area the intermediate stage included selecting the contours of the city and suburbs, colored as blue vectors, while other areas were deleted (Figure 4, b). The selected segments of the city and suburban polygons now have a new attribute in the polygon table of the area in square meters. The properties of the attributes tool of this table were checked up (Figure 5, a) and the area and perimeter received in m^2 and m, respectively. These included the calculated area of the Yaoundé city with suburb, which is 191,745,000 km^2, and the perimeter which is 1,060,560 km (Figure 5, b).



(a) **(b)**

Figure 5. Merged area of the city (yellow lines) and suburbs (red lines) **(a)**; Computed area of the city (light green lines) and suburbs (bright green lines) **(b)**
Source: author

The final results (Figure 4) present the image of the Yaoundé city exemplified with detailed images of the Google Earth at a higher zoom level for a better presentation of the output results. At the next step, once the OBIA image classification results were received, the accuracy assessment was performed using independent validation data by the Google Earth aerial imagery using the Google Earth Engine processing environment (https://earthengine.google.com/). The result indicate the accuracy of the segmentation for both Neumann (74.63%) and Moore (71.47%) both attained over 70% accuracy in both categories (user's and producer's). This study included a comparative analysis of the effect of two methods, the Neumann and the Moore, on OBIS image segmentation in SAGA GIS. The used Sentinel-2A image high-resolution data with selected three bands 8-4-3 from a variety of different combination of the multi-spectral data with 13 bands in the visible, near infrared, and short wave infrared (SWIR) part of the spectrum finally produced a map for a separated urban area of Yaoundé in Cameroon.

This study implemented the experiment on the use of OBIS verified by a Google Earth image. The results of the segmentation were selected for the Moore and Neumann neighborhood approaches, respectively, and analyzed against the Google Earth for validation.

The results demonstrated that all the two methods resulted in moderately to highly accurate urban segmentation maps, with an overall accuracy of 74.63%. Among the two methods, the segmentation based on the Neumann method produced the highest accuracy (74.63%), followed by the Moore approach of the same input Sentinel-2A image (71.47%). The presented results from the classified Sentinel-2A results by OBIS in SAGA GIS and Google Earth. The Neumann and Moore approaches show the correct and misinterpreted results in the respective category of the segmented class.

The SAGA GIS based OBIS module demonstrated to be a useful technique for analysis and interpretation of Sentinel-2A images and can be used on similar imagery. Some flaws include two notes. First, data processing has rather a lower speed, which strongly depends on the size of the image. For instance, segmentation of the whole Sentinel-2A image was also tested but could not be completed due to the too long time needed by the computer memory for the whole image of 100 km^2. Second, the manual selection of the segments in the process of merging contours into one segment 'city' could not be replaced by the machine. That is, this part of the process is rather semi-automatic and may be subjective to a certain extent. However, despite these drawbacks, OBIS results in general present object based segmentation of the image and is a step further compared to the pixel-based image classification [72–74]. The algorithm includes the two repeatable approaches that can be chosen: a von Neumann and a Moore neighborhood pixel classification. Comparing the two approaches, the demonstrated method of Neumann works well with Sentinel-2A image having negligible noise in contour generation, while the Moore approach performed noisier.

5. DISCUSSION

This study adopted an OBIS image segmentation methodology. Image segmentation is an effective approach in remote sensing data processing. It is a specific machine-based computer vision methodology that facilitates the study of the land use types without human-based classification and prior knowledge using the applied theoretical algorithm of image processing. The OBIS is a methodology, in which the cartographer attempts to analyze city contours without the need for the supervised classification.

This study presented a comparison of the two methods in OBIS approach produced by SAGA GIS and remote sensing data such as Sentinel-2A and Google Earth. The OBIS method presented better results in merge of the city districts on the Sentinel-2A image, as their contours have been generalized to a city shape. Whereas both methods were applied and compared, the OBIS technique better performs using local threshold of the Neumann approach. The presented map (Figure 5, a) shows the differences between the areas of the city Yaoundé (yellow contour) read from the Sentinel-2A scene and that of the other land cover types. Figure 5, b, shows the selected and highlighted contours of the city with its suburbs with computed geometry (perimeter and area).

The SAGA GIS image segmentation seeks to characterize contours of urban areas and detect agricultural fields and other objects in a geographical space in a manner in which the pixels would be grouped into clusters based on their properties. The size of the detected objects is related to the spatial resolution of the satellite image and not to the image segmentation algorithm, which is useful for multi-scale segmentation. The research emphasizes that processing of the Sentinel-2A image was only partially adjusted by hand, while the major workflow consists of a machine learning algorithm for automatically detected urban areas based on the geometry and brightness of the image pixels using embedded algorithm in SAGA GIS. Categorizing pixels into clusters, or segments, on an image based on their spectral intensities, enables to yield a ‘smart’ image showing contours of objects, not the isolated pixels. This methodology of the segmentation is reviewed in the available literature both in theoretical and in practical aspects [75–77].

The comparison of the two approaches, the Moore and Neumann although demonstrated certain differences in the algorithm, but shown no major differences in the layout of the resulting images of the Yaounde city. In general, both methods are acceptable for image segmentation in SAGA GIS. The automatically detected contours of the urban core area of the Yaoundé city extends beyond the whole area including the city and its suburbs and on the margins of surrounding districts, because the geometry of their contours was also detected automatically and not mapped by hand.

The machine learning and programming techniques are progressively used in Earth sciences. Emerging literature also highlights the value of the machine learning in geographic studies where there is either a great deal of automatic data processing or, where the methods of the statistical data analysis are applied [78–82]. In brief, automatization in cartographic studies reduces the computational time of data processing due to the faster machine-based analysis and increases the precision of the final output by reducing misclassification in image segmentation. The OBIS method of SAGA GIS for image segmentation is a promising and faster way to cluster the satellite scene and receive an object-based machine-generated image against the pixel-based clustering. Machine learning methods in cartography, presented in this study, presented the analysis of the two approaches of image segmentation using Neumann and Moore neighborhood on a Sentinel-2A satellite image performed using a SAGA GIS indicated that Object Based Image Analysis is a promising cartographic method of spatial analysis of urban areas.

6. CONCLUSIONS AND RECOMMENDATIONS

Several broad conclusions can be drawn based on the results of the presented machine learning method in cartography. Image segmentation of urban areas against forest is related to the three factors: i) image resolution, ii) scale of the map, iii) research goal and object. Given these details, the theoretical approach of the OBIA algorithm may be adjusted to the final aim of the research and data quality and may vary [83–85]. It is essential that machine learning algorithms and computer vision of high-resolution data are used as important techniques for mapping. Therefore, the 2-m detailed VHR Pléiades image would be an asset for further studies. Testing of the OBIA/OBIA image segmentation models in other software (such as GRASS GIS, eCognition), besides the SAGA GIS are recommended in future studies for improving cartographic technologies and accuracy of the automatization and machine learning techniques.

Embedded OBIA algorithms available in various GIS software may result in segmentation of the images using GRASS GIS or eCognition vary from those using SAGA GIS. However, the OBIS algorithm of SAGA GIS does the machine learning based segmentation in cartographic output as a map based on the Neumann and Moore approaches and Sentinel-2A remote sensing data. The spatial coherence among the segmentation results by Neumann and Moore approaches was acceptable together with general high accuracy, showing that SAGA GIS is a suitable software for image segmentation.

The results communicate OBIS as an effective approach for image segmentation and, in conjunction with SAGA GIS, describe image analysis as promising approaches in environmental and urban studies that should be applied in cartographic workflow. The selection of the input data used in the OBIS is a crucial step, as they control the output segmentation results, particularly with mixed land cover types, and areas with intensive urban growth. Therefore, a recommendation for future studies would be to use a Very-High-Resolution (VHR) imagery for more detailed studies on building level. This would allow detecting building using spectral reflectance of roofs which differs from vegetation. The provided figures visualizing segmented original Sentinel-2A image present the algorithm of the OBIS in SAGA GIS for the remote sensing data processing. The accuracy of segmentation of the urban areas is specified with an initial resolution of the satellite scene (10 m for the Sentinel-2A). As the next recommendation for further studies, a combination of various datasets using vector layers and raster data can be applied.

This study answers the questions aimed to describe and characterize spatial discrimination between the urban and non-urban areas on a satellite Sentinel-2A image using SAGA GIS, and to perform segmentation in the geometry of the quarters within the city using selected bands of the multispectral image using advanced methods of OBIS. The image processing was performed in a straightforward and automatic manner to avoid errors. To automatically distinguish the urban areas from all other land cover types (savannah, forest, mountain, etc.) and to depict the contours of the city and distinguish it from the sub-urban areas using their geometric properties and spectral settings on an image, a comparative analysis of the two approaches of image segmentation, implemented in SAGA GIS, the Moore and Neumann was applied.

The study shows that: 1) urban areas are distinguishable from the neighbor land cover types on a Sentinel-2A multi-spectral satellite image, because its resolution (10 m) enables to discriminate them using a computer based approach; 2) The Neumann segmentation method provided better results for image clustering comparing to Moore method; 3) The OBIS automatization method of image segmentation significantly improves the environmental mapping increasing both the speed and the precision of the remote sensing data processing.

This conclusion justifies a rule concerning the use of multi-source geographic datasets and a comparison of various data. Data selection is crucial for quality research, and selection of the best image resolution and quality (e.g. no cloudiness) relating to the study area is a strong predictor of the final research results. An optimal scene coverage overlaid with detailed topographic vector map would assist in image interpretation and generalization. As a final recommendation, the application of various methods would increase the applicability of GIS analysis. For instance, besides the OBIS applied for remote sensing data, other methods include a statistical analysis and spatial metrics for environmental studies [86–87]. Therefore it is advisable that selected software and algorithms of image processing also target research aims and goals applied to the study area in future research.

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