THE INFLUENCE OF SAMPLE SIZE ON URBAN PARCEL-BASED FEATURE EXTRACTION

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Abstract
Sample size plays a pivotal role on the accuracy of results obtained in remote sensing image classification. The aim of this research is to assess the influence of sample size on urban parcel-based information extraction using Sentinel-2 satellite image. The selection of training sample sizes of 30, and 60 for each land cover class were analyzed on Support Vector Machine(SVM) Classifiers for user and producer accuracy for each category as well as overall accuracy. Based on the sample sizes selected, six classes of features were extracted. The results showed 86% and 74% accuracy for 30 and 60 samples respectively at a parameter scale of 50. However, when the scale parameter was adjusted to 30, the overall accuracy improved to 95% at 30 sample sizes and 96% at 60 sample sites. The results were compared to reveal the most suitable sample size for image classification. The study has made a significant contribution with respect to training sample size for optimal classification of medium resolution satellite imagery.

Keywords: Sample size, urban feature extraction, support vector machine, sentinel-2

1 INTRODUCTION

Remote sensing and Geographic information system (GIS), are considered as an essential tool and technology in socio-economic studies and urban related environment due to their capacity to provide spatial and temporal information on urban land cover(Jin, Stehman, & Mountrakis, 2014).One of the critical and important processes in remote sensing application for information extraction is image classification(Kalsom *et al*., 2014). The pixels of an image having different spectral values with similar spectral characteristic are assigned to one class of thematic mapping; this is called Image Classification (Jensen, 2005).Classification approaches used to determine the land cover are pixel-based and parcel-based (object-based). The Pixel-based approaches work on each individual pixel as unit of analysis and also extract information from remotely sensed data, based on spectral information only.

On the other hand, Parcel-Based information extraction approach interprets an image not only by single pixel but also as meaningful image objects know as segments or parcels and their mutual relationships (Jensen, 2005). Foody *et al.*, (2006) indicated that the accuracy of a supervised image classification is a function of the training data used. As reviewed from past literatures, no prior study has been conducted on optimal number of training samples, for testing the sensitivity of an algorithm to the size of training samples.

It is essential to maintain large enough sample size so that any analysis performed is statistically accurate (Congalton, 1991). Van Niel*et al.*, (2005) suggested that a training sample size for each class should not be fewer than 10-30 times the number of bands. However, a lot of studies have been carried out to examine and evaluate the performance of different classifiers (Duro*et al*. 2012; Wieland and Pittore, 2014;Li *etal* 2014). Few of these studies have also look at effect of repeated sampling on classification accuracy, which can lead to variation in classification results. Furthermore, most of the studies have been centered on urban areas and utilized high resolution imagery. Conversely, this study focused on assessment of influence of sample size on Support Vector Machine (SVM) algorithm, which is often used with parcel-based approach. In addition, the classification results accuracy was

compared with varying training sample size by using medium resolution multispectral imagery from sentine-2 sensor. Specifically, the study explored various land cover types in the study area. Influence of varying sample size, on classifiers and it effect on image accuracy was also assessed. Ultimately, based on the outcome of the study, recommendations were made with respect to choice of training sample size for image classification of medium resolution satellite dataset.

2 STUDY AREA

This study was carried out in Abuja, the Federal Capital Territory, Nigeria, which lies within longitude 7° 23′ E to 7° 30′ E and latitude 8° 57′ N to 9° 7′ N (Figure 1).

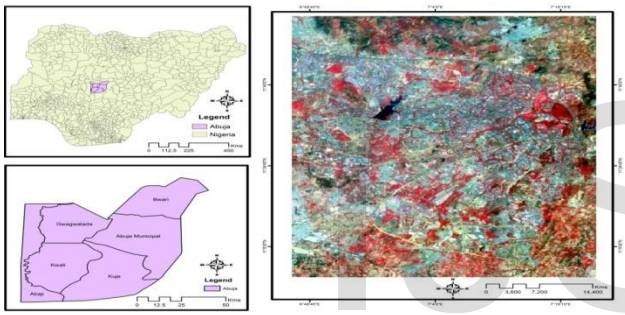


Figure 1: Study Area Map

3 DATA AND METHODOLOGY

The satellite data used was sentinel-2 that has 13 bands, captured in February 2019. The metadata of the dataset used is shown in Table 1.Visual interpretation of the Santine-2 data, aided by a land cover map, was carried out and six (6) main classes were identified as follows; water, vegetation, shadow, rock, built up and bare surface.

Table 1: Characteristics data used

Data	Data Acquisition	Resolution	Path/ Row	Spectral Band	Sources
Sentinel-2	01/02/2019	10m	191/055	2,3 and 8 bands	Sentinel.ESA
GPS points					Field work
Land cover map					NASRDA

The method utilized in the study is parcel-based or segment-based approach implemented in eCognition Developer 9.0 software developed by DEFINIENS. eCognition supports various supervised classification techniques as well as variety methods to train and build up a knowledge base for the classification of image objects (Yoon, Cho, Jeong, & Park, n.d.). The satellite image was classified using the object-based approach. Delineating of homogenous groups of pixels into meaningful objects, based on texture, size, shape and other information, have led to object-oriented classification method (Djenaliev & Hellwich, 2014). The object-oriented classification process can generally be divided into the two main workflow steps: segmentation and classification of the resulting image objects.

Segmentation refers to grouping of neighboring pixels into regions or segments, based on similarity such as scale, color and form. Segmentation is the most important step in object- oriented image analysis. As a result, the homogeneous pixels are grouped into separate image object. The degree of homogeneity of objects is controlled by the following parameters: scale, color, shape, compactness and smoothness (Mashee & Malthus, n.d).The scale parameter determines the highest heterogeneity for the resulting image objects. Assigning a larger scale value creates larger image objects. The color criterion is the most important for creating meaningful objects. The value of the

shape criterion modifies the relationship between shape and color criterion, where it helps to improve the quality of extracting objects. The compactness criterion optimizes the resulting image objects, with regard to the overall compactness, within the shape criterion. The smoothness optimizes the resulting image objects, with regard to smooth borders, within the shape criterion (eCognition Developer 9.0, 2014). An image analyst can control these parameters and change them to obtain the best segmentation results. However, human interpretation is the best way to evaluate the segmentation results (Mashee&Malthus, n.d). eCognition software package provides several algorithms for image segmentation. The choice of the algorithm depends on the application and the goal of the segmentation process. In this rule set, Chessboard Segmentation, Multi resolution Segmentation and Spectral Difference Segmentation algorithms are mostly used (Murcko, 2017).

In this study, the methodology implemented was depicted in Figure (2).The first step was creation of project. Then multi-resolution segmentation algorithm was selected. Multi-resolution segmentation algorithm is a bottom-up region-growing technique, starting at the pixel level and merging pixels into image objects. In subsequent steps, small image objects with similar spectral values are merged into larger objects as observed by Benz et al (2004).

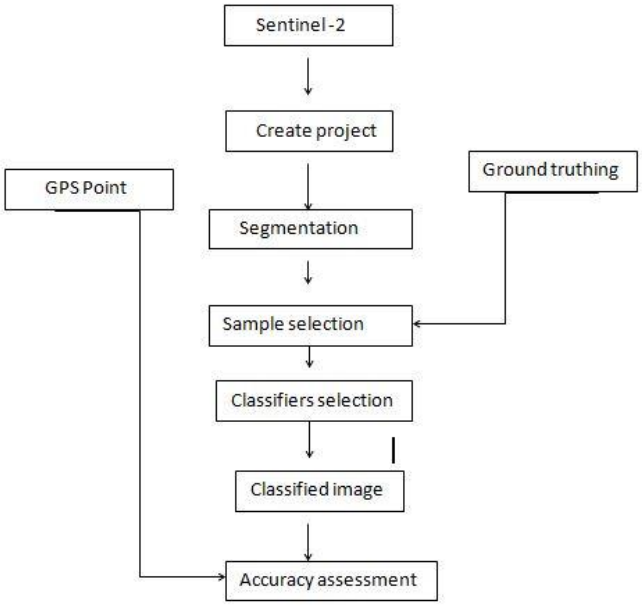


Figure 2: Methodology Flowchart

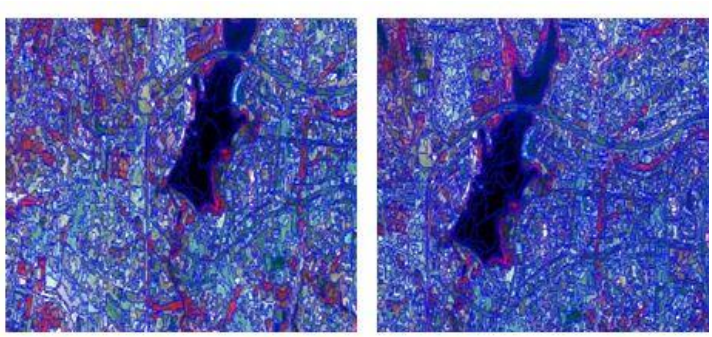
The image segmentation algorithm grouped pixels to form segments, as homogeneous parts in close proximity, according to the spectral and spatial extent. For selection of optimal parameters, segmentation operations were performed by testing different shapes, compactness and scale parameters, using 2, 3 and 8 bands combinations on the sentinel-2 satellite image. In the process, each layer weight is 1, while the shape and compactness are set to 0.3 and 0.8 respectively. The scale parameter is set at 30 and 50 at different stage. The results of segmentation achieve good effects. After segmentation, the image objects of interest and the land cover polygon were produced. These objects have the similar attribute information. The image segmentation parameters' setting is based on the basic rules and can debug again and again. After segmentation, each class was assigned different color and samples to determine which class an object belongs. Samples were selected for each class and training areas were created. By this, classification repository was set up. The resulting segments, act as image objects, which were classified in next step.

Then classification method was selected. Based on the samples created, SVM classifier generated classification automatically.SVM is a supervised classification method with fuzzy rules. It classifies image objects with an assigned image feature and samples for the concerned classes. Consequently, the classified image objects are displayed as the classification results. Where a satisfactory classification result is not attained, the samples and the classification procedure can be re-edited severally, until the best classification result is achieved.

The next step, involved accuracy assessment of classified earth surface features using Confusion matrix in eCognition software. Accuracy assessment involves the comparison of a classified thematic map with the classification of randomly selected samples of referenced data (Stehman, 1997). All the six (6) classes of land covers were generated. Total 30 and 60 samples of all the 6 classes were taken to perform this assessment. In order to examine the influence of sample size and algorithm on the classification, the producers and users' accuracies were assessed for each of the land cover category, based on randomly selected sampled sizes. The overall accuracies were also evaluated.

4 Results and Discussion

The results of multi-resolution segmentation executed is depicted in Figure 3(a) and (b).



a) At 50 scale parameter b) At 30 scale parame

Figure 3: Segmented Image

From the figure, it was observed that the resulting polygons or segments sizes, was large at 50 scale parameter and produced 57,422 objects. Meanwhile, at 30 scale parameter, the segment size is small and 127,587 objects or segments were obtained. This implies that the decrease in scale parameter causes increase in number of objects or segments. The more, images objects or segments the higher the homogeneity of resulting segmentation. The more homogeneous the image objects are the better classification result.

Figure 4(a, b, c &d) shows the classified image of sentinel-2 of study area, with the six (6) identified classes, i.e. water body, bare surface, built up, rock, shadow and vegetation. The accuracies are also displayed.

Overall Accuracy = 86%

Classes	Producer Accuracy (%)	Users Accuracy (%
Water	100	100
Vegetation	100	100
Built up	60	60
Bare surface	100	100
Shadow	100	100
Rock	60	60

Overall Accuracy = 95%

Classes	Producer Accuracy (%)	Users Accuracy (%)
Water	100	100
Vegetation	100	100
Built up	86	86
Bare surface	100	100
Shadow	90	100
Rock	83	83

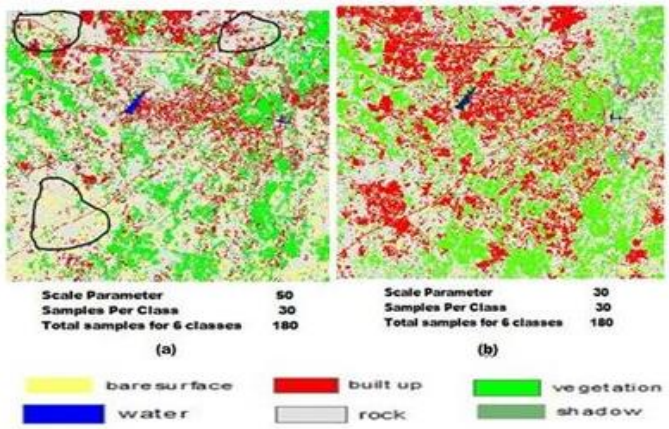


Figure 4: Classified image

At 30 sample size per land cover class and 50 scale parameter, it was discovered that there was miss classification among the built up, shadow and rock, indicated by areas circled in figure 4a. However, it was properly categorised to it class, when the scale parameter

was adjusted to 30 (Figure 4b) and produced 86% and 95% overall accuracy respectively.

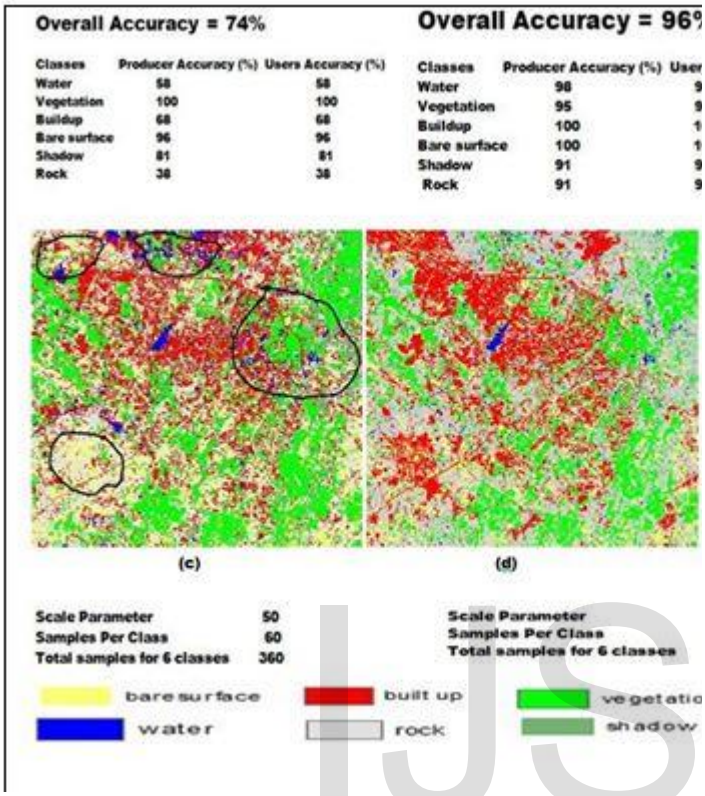


Figure 4: Classified image

Furthermore, at 60 sample size and 50 scale parameter, it was observed that built up, rock and shadow land covers were miss classified as water body. This was later categorized to it appropriate class after adjusting the scale parameter to 30 (Figures 4 c & d),which produced 74% and 96% overall accuracy respectively.

It was discovered when comparing Figures 4a & c,that at 50 scale parameter(size of parcel) with dissimilar sample sizes of 30 and 60 per category, the result was said to be 180 and 360 total samples for all the 6 classes. This made the overall accuracies to decrease from 86% to 74%. However, with 30 scale parameter, the overall accuracies increase from 95% to 96% respectively.

Figure 4(a) showed that built up and rock classes; have not given better producer and user accuracies. This was due to the fact that the parcel size created through segmentation is less homogeneous in both categories.Meanwhile, the homogeneity improved in built up and rock classes as seen in Figure 4(b). This was as a result of adjustment in parcel size by scale parameter.Therefore, producers and users' accuracies of built up and rock classes haveimproved.Correspondingly, it was observed that built up, rock and water body classeshavenot yielded satisfactory producers and users' accuracies, even though the sample size is large enough as showedin Figure 4(c). This is because the segment size was large, resulting in less homogeneity in rock, built up and water classes, which causes miss classification in the three categories.

4 conclusions

Satellite image plays a pivotal role in map production. The accuracy and quality of a map produced from satellite image is of considerable significance and importance to its applications in scientific research, investigations and policy decisions. Understanding the factors that influence classification accuracies, may guide the decision of selecting sampling design for training the classification algorithm. This study provides insight into the potential impact of training sample size on the performance of classifications.

With respect to the classification of medium-resolution imagery of an urban fringe area, the aim of this study was to investigate the influence of sample size on the classification results. It was also aimed at evaluating the performance of SVM classifier at varying samples sizes. The specific objectives were to study the behavior of the classification accuracy with changes in the size of the training dataset and the scale parameter variables, using parcel-based approach. The parcel-based (object-oriented)

information extraction with eCognition provides a new opportunity and tool for automated image analysis. This study has revealed that parameters and context information can be used to classify earth features. The multi-scale segmentation is an important and essential base for classifying earth features. The choice of scale parameter depends on the category or class type to be extracted. Different features require diverse segmentation scale parameters.

In this study, only accuracy assessment for the classification information was synthetically carried out and it results compared. There are still some inquiry and questions in parcel-base information extraction. Further studies are required to establish the relationship of image and segmentation scales parameters. Structure groups for classification need to be developed, established and organized. There is also the need to integrate the extracted information with GIS.

REFERENCES

[1] Benz, U. C., Hofmann, P., Willhauck, G., Lingenfelder, I., & Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready in- formation. *ISPRS Journal of Photogrammetry and Remote Sensing*, 58(3–4), 239–258

[2] Congalton, R.G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, 37, 35–46.

[3] Djenaliev, A., & Hellwich, O. (2014). Extraction of built-up areas from Landsat imagery using the object-oriented classification method.

[4] Duro D.J, Franklin S.E. and Dube M.G., 2012. A comparison of pixel-based and object-based image analysis with selected machine learning algorithms for the classification of agricultural landscapes using SPOT-5 HRG imagery. Remote Sensing of Environment 118, 259–272.

[5] eCognition Reference Book, 2014. Trimble eCognition® Reference Book (Munich, Germany: Trimble Germany GmbH).

[6] H. Mashee, T. Malthus, "Object-oriented image analysis for monitoring urban expansion in the city of Riyadh, Saudi Arabia".

[7] Jensen, J.R., 2005. "Introductory Digital Image Processing, A Remote Sensing Perspective", Third edition, Upper Saddle River, Pearson Education, Inc., 526 p.

[8] Jin, H., Stehman, S. V., & Mountrakis, G. (2014). Assessing the impact of training sample selection on accuracy of an urban classification: A case study in Denver, Colorado. International Journal of Remote Sensing, 35(6), 2067–2081. https://doi.org/10.1080/01431161.2014.885152.

[9] Jiang, N. et al. (2008) 'Semi-automatic building extraction from high resolution imagery based on segmentation', in 2008 International Workshop on Earth Observation and Remote Sensing Applications, pp. 1–5. doi: 10.1109/EORSA.2008.4620311.

[10] Jumlesha, S. K. et al. (2012) 'Automatic Urban Feature Extraction Using', International Journal of Engineering Research and Applications (IJERA), 2(3), pp. 221–225.

[11] Kalsom, U., Hashim, M., Ahmad, A., Technology, C., Teknikal, U., & Jaya, H. T. (2014). The Effects Of Training Set Size On The Accuracy Of Maximum Likelihood , Neural Network And Support Vector Machine Classification. 2014(October), 1477–1481.

[12] Khatriker, S., & Kumar, M. (2018). BUILDING FOOTPRINT EXTRACTION FROM HIGH RESOLUTION SATELLITE. XLII (November), 20–23.

[13] Kalsom, U., Hashim, M., Ahmad, A., Technology, C., Teknikal, U., & Jaya, H. T. (2014). THE EFFECTS OF TRAINING SET SIZE ON THE ACCURACY OF MAXIMUM LIKELIHOOD , NEURAL NETWORK AND SUPPORT VECTOR MACHINE CLASSIFICATION.

[14] Li, X.; Liu, X.; Yu, L.(2014) Aggregative model-based classifier ensemble for improving land-use/cover classification of Landsat TM Images. Int. J. Remote Sens., 35, 1481–1495.

[15] Mondal, A., Kundu, S., Chandniha, S. K., Shukla, R., & Mishra, P. K. (2012). Comparison of Support Vector Machine and Maximum. (January).

[16] Murcko, J. (2017). Master Thesis.

[17] Stehman, S. V. (1997) Selecting and interpreting measures of thematic classification accuracy, Remote Sensing of Environment, 62, 77-89.

[18] User Guide. Trimble Documentation: eCognition Developer 9.0, 2014.

[19] van Niel, T. G., T. R. McVicar, and B. Datt. 2005. "On the Relationship between Training Sample Size and Data Dimensionality: Monte Carlo Analysis of Broadband Multi-Temporal Classification." Remote Sensing ofEnvironment 98: 468–480.

[20] Wieland, M., & Pittore, M. (2014). Performance Evaluation of Machine Learning Algorithms for Urban Pattern Recognition from Multi-spectral Satellite Images. 2912–2939. https://doi.org/10.3390/rs6042912.

[21] Yoon, G., Cho, S. I., Jeong, S., & Park, J. (n.d.). Object oriented classification using Landsat images. 1–3.