Comparison of Object-Based Classifiers and Traditional Pixel-Based Classification Techniques using Landsat Imagery*

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Abstract

Object-Based Image Analysis (OBIA) is becoming dominant in remote sensing image classification. Many supervised classification approaches have been applied to objects rather than pixels, and studies have been conducted to evaluate the performance of such supervised classification techniques in OBIA. This study compares both the pixel-based and object-based techniques in classifying Landsat imagery. Pixel-based image classifiers such as the Maximum Likelihood Classifier and object-based image classifiers such as; Support Vector Machine (SVM), Random Forest (RF) and Decision Tree (DT) were compared using Landsat 8 imagery. The findings indicate that the SVM and RF methods obtained 94.86% overall accuracy with 0.9323 kappa, and 93.60 % overall accuracy with 0.9150 kappa, respectively as opposed to 92.73 % overall accuracy with 0.9077 kappa, for the pixel-based approach. From the results of this study, it was observed that the pixel-based image classification was constrained because the image pixels are not true geographical objects and the pixel topology is limited. It was also observed that the pixel-based classification largely neglects the spatial and photo-interpretive elements such as texture, context, and shape, which leads to the classifier resulting in lower classification accuracies. In contrast, the object-based method, OBIA works on (homogenous) image segmentation objects and can use more elements in the classification. This study therefore recommends that when classifying Landsat imagery for projects with higher accuracy requirements, the OBIA methods should be considered.

Keywords: Object-Based Image Analysis, Pixel-Based Classification, Support Vector Machine

1 Introduction

Object-based classification has shown a successful development in the past two decades with several data-intensive technical and scientific fields, such as search engines, speech recognition and robotics (Ma *et al*., 2017). Several object-based algorithms have been introduced to the remote sensing community for decades, ranging from simple to advanced classification and regression algorithms such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and Artificial Neural Networks (ANN) (Nitze *et al*., 2012). Image classification has become one of the main applications for demonstrating object-based capabilities. With recent advances in remote sensing earth observation techniques, several remote sensing specialists are collecting data with distinctive properties. The data obtained from the remote sensing sources are so large and complex, as a result, several methods have been developed to analyse and process remotely sensed imagery and derive as much information as possible. The preference for specific technique or algorithm depends on the goal of the study. The two main approaches used to analyse remotely sensed images are the traditional pixel-based and object-based approaches. The object-based approach could also be termed as Object-Based Image Analysis (OBIA). OBIA has been the most commonly applied methodology in the last decade since it classifies images based on their spectral and contextual details. In recent times, the pixel-based and the OBIA techniques have been used in many remote sensing operations. For example; performance of Support Vector Machine (SVM) and Random Forest (RF) for object-based vegetation mapping have been explored (Zhang and Xie, 2013). A pixel-based classification approach has also been used to demarcate more realistic homogeneous areas with much detail (Jenssen and Middelkoop, 1992; Hutchinson, 1982). Whiles some studies have been made on both pixel-based and object-based classification techniques, limited literature is available in remote sensing technical papers on the use of both techniques in satellite image analysis to extract meaningful information from it, especially in developing countries such as Ghana. There has been an argument recently as to what algorithm is best for analysing satellite imagery (Jenssen and Middelkoop, 1992; Hutchinson, 1982; Zhang and Xie, 2013). The goal of this study was to compare different object-based and pixel-based classification methods for interpretation of Landsat imagery in Ghana.

1.1 Image Pre-Processing

Remotely sensed image is used for classification, analysis and description. The first stage is pre-processing, which include radiometric and geometric corrections. Radiometric correction is the procedure used to remove unwanted device noise and ambient interference with the light value of the image (Story and Congalton, 1986; Lillesand and

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Kiefer, 1994; Congalton, 1991). The three classes of radiometric corrections are; cosmetic rectification to account for data errors; relative atmospheric correction based on ground reflectance properties and actual atmospheric correction based on information from atmospheric processes (Bakker *et al.*, 2004). The architectural dimension deals with different sensors and device systems, geometric characteristics and how they influence the configuration of the resulting image object. Geometric irregularities are naturally present in remotely sensed images and the correction compensates for the following factors: device movement and height, altitude and velocity, screening machine orientation, camera optics, landscape, relief and curvature and earth rotation (Anon., 2014). Precise modelling of the movements of the sensor and frame as well as their spatial interaction with the planet could be used to resolve the variability of nature (Anon., 2014).

1.2 Image Segmentation

Image segmentation is a critical and important step in OBIA, as the image artefacts arising from this method form the basis for the object-based image classification. The objective of image segmentation is thus to partition an image into specific properties such as texture, colour, shape, size and grey level (Hossain and Chen, 2019). The final feature extraction and classification in OBIA are highly dependent on the quality of image segmentation (Ming *et al*., 2012; Duro *et al*., 2011). Segmentation has been used in remote sensing image processing since the advent of the Landsat-1 satellite mostly for pixel labelling. The paradigm of pixel labelling has however changed to object-based analysis (Hossain and Chen, 2019; Li *et al*., 2016). As a result, the purpose of segmentation has been changed from pixel labelling to object identification. There is, however, no common optimum scale (Hay *et al*., 2003; Hay and Castilla, 2006), and researchers are attempting to identify scales unique to the dominant image artefacts within a setting. Multi-resolution segmentation (MRS) has been widely used among all the segmentation algorithms. The main challenge in MRS is to select suitable parameters as geographic objects vary in size, shape and texture (Ma *et al*., 2015). Scale plays a vital role in MRS among the parameters. The choice of object-based scale in segmentation is vital in OBIA because an inaccurate scale could result in either over-or under-segmentation (Ming *et al*., 2012). An iterative trial-and-error approach is widely used in remote sensing to assess an appropriate scale (Eisank *et al*., 2014). However, the trial-and-error approach is time-consuming and inefficient for many implementations (Ma *et al*., 2015). Classification algorithms use shapes of items derived from the segmentation to determine object patterns. The classification algorithms are also used to measure the spectral characteristics of each object. Apart from the shape, the position of artefacts is also important for geospatial study. Traditional pixel-based precision assessment methods are also capable of calculating the shape and location of objects (Clinton *et al.,* 2010).

1.1 Object-Based Classification

Remote sensing has developed into a multidisciplinary area in which object-based and signal processing algorithms already play an important role to effectively process acquired data and provide reliable information (Camps-Valls and Bruzzone, 2005; Camps-Valls *et al*., 2008). Recently, object-based classification has seen a rapid increase as a classifier of remotely sensed images due to improved classification accuracy over traditional techniques, fast processing time, ability to handle high data dimensionality and the availability of a variable value metric that allows collection of useful predictions. Object-based algorithms are often categorised as supervised, unsupervised, semi-supervised and reinforced learning. A supervised algorithm is the one that uses coded samples to predict future incidents and adapt what has been learned in the past to new data. Upon sufficient training, the system can provide expectations for any new input (Ma *et al*., 2017). In comparison, unsupervised algorithms for object-based are used when the knowledge used to train is neither marked nor numbered. Unsupervised learning explores how a machine can infer a feature from unlabeled data to define a secret framework. Semi-supervised learning falls in between supervised and unsupervised learning. Mostly, the cost to label is quite high, as skilled experts are required. So, in the absence of labels, semi-supervised algorithms are the best approach for classification (Fumo, 2017). Reinforced learning aims at using observations gathered from the interaction with the environment to take actions. Reinforcement learning algorithm continuously learns from the environment in an iterative manner. In the process, the algorithm learns from its experiences of the environment until it explores the full range of possible scenarios (Fumo, 2017).

2 Resources and Method Used

2.1 Resources

The resources used for this study include: Landsat 8 satellite imagery with acquisition date of 24th December, 2019; the path and row for the imagery is 194 and 055 respectively; stratified random sampling points from the Landsat 8 image composite from each landcover; ArcGIS software for generating maps; eCognition developer software for image segmentation and supervised classification to obtain the sample data for the object-based classification. Statistical analysis was also performed on the classification results.

2.2 Methods Used

The methods employed for this study include: the pixel-based image classifier and the object-based classification techniques.

2.2.1 The Pixel-Based Image Classifier

The pixel-based classification procedure include: visual interpretation of the Landsat imagery; supervised image classification and accuracy assessment. The process of supervised image classification involves five main steps (Bakker *et al*., 2004). The steps include: selection and preparation of the image data; defining the training and signature file; selection of classification algorithm; running the actual classification and validation of the results. Figure 1 shows the procedures in performing both supervised and unsupervised classification. Object processing plays a specific role in translating image data to thematic data (Lillesand and Kiefer, 1994). The thematic features such as ground cover, land use, or soil type are of importance and can be used for study than their reflectance values (Lillesand and Kiefer, 1994). The correct image data is selected based on the knowledge groups of interest and their Spatio-temporal characteristics (Bakker *et al*., 2004). ArcMap's Image Classification toolbar was used for generating comparisons of training and signature files used in the supervised classification. The primary system of classification is the Maximum Likelihood Classification (MLC) function (Lillesand and Kiefer, 1994). A signature file defining the groups and their detail was a required input to this method. The signature file was generated through the Image Classification toolbar, utilising training samples for supervised classification. In this step, the pixels were picked to reflect patterns that are known or could be recognised using other references to support. Before choosing the training samples, awareness of the results, the classes needed and the algorithm to be used was necessary (Anon., 2014). The algorithm was trained to recognise trends and patterns in the image pixels with similar characteristics. In supervised sorting, the algorithm decides how to distribute certain pixels. Specific algorithms include the minimum distance, the maximum likelihood, and the Mahalanobis distance (Lillesand and Kiefer, 1994). When the training samples or algorithms are decided, the samples are indicative of the target groups and can be separated from each other (Lillesand and Kiefer, 1994). The Maximum Likelihood Classification method was used to classify the image in this study. This approach is based on the theory of maximum likelihood estimation (Nitze *et al*., 2012). This assigns each pixel to one of the different classes, depending on the individual signatures (stored in a signature file) Once all spectral classes have been identified and the classifier algorithm is chosen, the actual classification is performed. Based on the values of the digital numbers, each pixel in the image is allocated to one of the predefined groups that result in the final classification results (Bortolot, 1996).

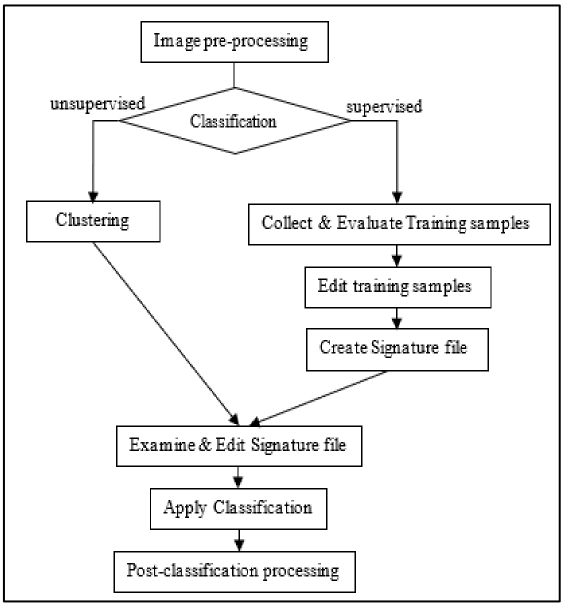

Fig. 1 Procedures in Performing Pixel-Based Image Classification

2.2.2 Object Based Classification Techniques

***Image Segmentation*:** The Landsat 8 image was segmented at 3 levels; each segmentation process had unique results. Different object layers were used for the classification of structures of different scale. Image objects at the smallest possible scale were produced which in turn produced unique image regions. To get ideal results, a different colour and shape criteria were tried as much as possible to produce image objects of the best border smoothness and compactness. The reason for this rule was that the spectral information is ultimately the primary information contained in image data (Dehvari and Heck, 2007). In this study, the segmentation of the image was conducted using the multi-resolution segmentation (MRS) algorithm contained in the 64-bit edition of eCognition Developer 9.0 (Anon., 2010a). A multi-resolution segmentation algorithm is a bottom-up technique that transforms pixels or individual images into larger ones based on relative homogeneity parameters (Qian *et al*., 2014). Parameters of scale, shape and compactness can be modified to determine the size and shape of segmented objects. The scale parameter determines the overall standard deviation of the homogeneity criterion for the weighted image layers. In general, the higher the scale value, the greater the object size, and the higher the variance (Qian *et al*., 2014). The scale parameters were chosen using the iterative "trial and error" method often employed when conducting object-based image analysis (Duro *et al*., 2011; Everingham *et al*., 2010). Three reference rates were generated with the scale values set at 10, 20 and 30 also referred to as Level 1, Level 2, and Level 3. To establish homogeneous blocks, the relatively small value of 10 was set to prevent the effect of mixed land cover. The value of 30 was also set to produce broader segments representing a larger land cover of interest. The two parameters for compactness and smoothness were set as well. Compactness parameters were set at 0.2 for level 1 and 0.3 for levels 2 and 3 respectively and then the smoothness was selected to be 0.5 for each of the levels. Equal weights were defined for each of the 7 original image layers for segmentation.

Support Vector Machine (SVM): The objective of SVM is to find a hyperplane that can separate the input dataset into a discrete predefined number of classes consistent with the training samples (Qian *et al*., 2014; Zhang and Xie, 2013). The radial basis function (RBF) kernel was used for the classifications based on the SVM algorithm. The parameters used by the SVM algorithm have been shown to affect the overall accuracy of classification. The RBF kernel has two important tuning parameters. The tuning parameters are "size" (C) and "sigma" (μ) for SVM models using the RBF kernel in "kernlab" package (Duro *et al*., 2011). Raising the former leads to detecting errors that could produce an overfit layout (Alpaydin, 2014), whereas increasing the latter parameter affects the configuration of the dividing hyperplane (Duro *et al*., 2011), and could, therefore, affect overall classification accuracy. In the kernlab package, an analytical method was adopted utilising the "most appropriate" feature (Duro *et al*., 2011) to measure μ directly from the training results (Kuhn, 2011).

Decision Tree: Decision Tree (DT) learning is an approach to modelling in statistics, data mining, and object-based modelling. The DT is used to move from observations on the item to conclusions on the target value of the item. System models where the focus variable will take a discrete range of values are called classification trees; in such systems, the leaves reflect the labels of the class, and the roots reflect the conjunctures of the features that correspond to the labels of the class. DTs in which the goal variable take on continuous values are referred to as regression trees (Nitze *et al*., 2012). The "full depth" tuning feature, which specifies the maximum depth of every particular node in the tree, was checked for multiple values for classifications based on the DT (Duro *et al*., 2011).

The initial DT model was used with the "caret" bundle on all training data to achieve maximum depth of any node and was then used to establish the upper bound on the cross-validation values for the subsequent model construction (Kuhn, 2011; Duro *et al*., 2011). The "rpart function" kit uses 10-fold cross-validation of the training data by design to achieve internal classification error rates (Breiman *et al*., 1984). By choosing the tree with the minimum cross-validation error within 1 standard error (Duro *et al*., 2011), the tree was then sliced by the "harm complexity" (cp) value that is the tree size defined by the "1 standard error code".' The "rpart" package maintained the cp value (0.01) by default and was adjusted for DT-dependent categorisation only with the parameter for maximum depth.

Random Forest: The distinction between the Random Forest (RF) algorithm and the DT algorithm is that the root node and the function nodes in Random Forest processes are uniformly separated (Rodriguez-Galiano *et al*., 2012). In the field of remote sensing image processing, it has been continuously developed since the RF classification was introduced (Breiman and Cutler, 2007) and is a reliable classifier (Li *et al*., 2016). To construct a prediction model, the classifier needs only the specification of two parameters: the number of classification trees (k) and the number of prediction variables (n) in each tree node used to render it. When the tuning parameter to be used with the RF classification is taken into consideration (Li *et al*., 2016) it has shown that a large number of trees (k) and a limited number of split variables (n) is preferred for minimising the error of generalisation and the association between trees. The default number of 500 trees were specified for RF based on literature to prevent overfitting (Duro *et al*., 2011; Breiman and Cutler, 2007). The general procedure for the object-based classification is shown in Fig. 2.

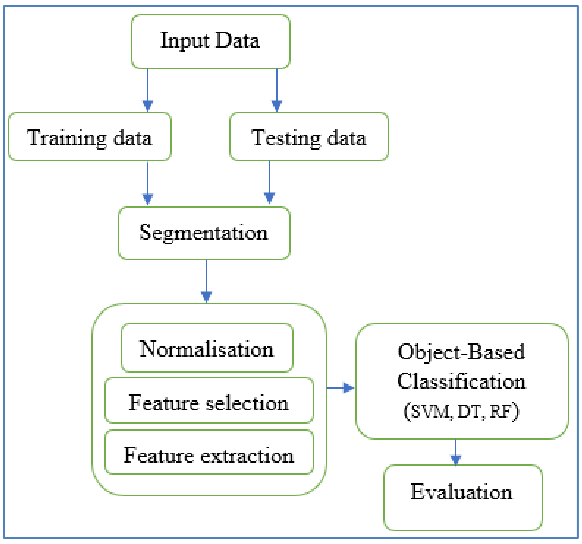

Fig. 2 General Procedure for Object-Based Image Classification

3 Results and Discussion

3.1 Results

3.1.1 Pixel-Based Classification Results

Five land cover classes were differentiated using the Maximum Likelihood pixel-based approach. The classes were settlement, forest, vegetation, water bodies and bare lands. The classified image is shown in Fig. 3. The forest was denser on the east side of the map and small spots were on the north and the lower southeast side.
Almost every part of the south is occupied by foliage, with the exception of few north-west regions. In the eastern side of the map and the southern section, the water source is marked in a blue hue, with a smooth and a blended form.

3.1.2 Pixel-Based Accuracy Assessment

One of the most important challenges in remote sensing is to adequately assess the accuracy of land cover maps. The procedures for interpretation and calculation of reference data are the final component for the accuracy evaluation. The core analytical and estimating procedures for accuracy evaluation in pixel image analysis have so far been the error matrix or sometimes called the confusion matrix or contingency table (Hehman, 1997; Stehman and Czaplewski, 1998). Table 1 displays each class, the base reality of the class chosen, the incorrect points and the overall percentage of each class. Tables 2 and 3 show the details of the producer's accuracy and the user's accuracy respectively. The Maximum Likelihood Classification method computed using Equation 1, yielded an overall accuracy of 92.73%, which is an acceptable pixel-based classification accuracy as described by Anderson, (1971) and Anderson *et al*., (1976). A closer examination of the error matrix reveals that major confusion occurs in the following pairs of land-cover types: Settlement verses forest verses vegetation and water bodies, forest verses vegetation and water bodies, vegetation verses forest verses settlements and water bodies. Water bodies and bare lands were classified correctly with no confusion.

The kappa coefficient, which is 0.9077, is quite high indicating the MLC method is still satisfactory for one to classify remotely sensed images.

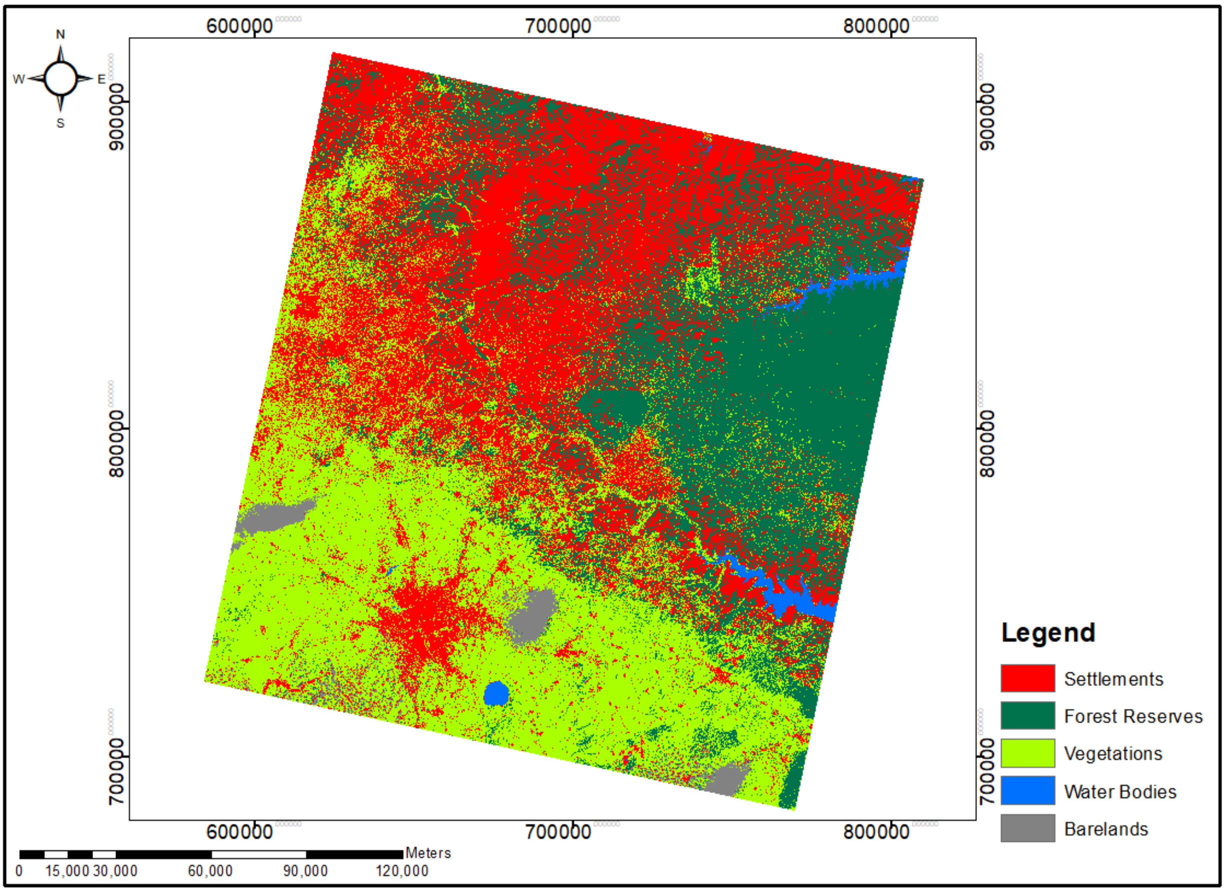

Fig. 3 Final Classified Land Cover Map

Table 1 Confusion Matrix with the Accuracy from Pixel-Based Approach

Class Names	Land cover ID	Settlements	Forest Reserves	Vegetations	Water Bodies	Bareland	Ground truth Totals	Percentage (%)
Settlements	1	225	22	3	9	0	259	86.87
Forest Reserves	2	0	152	5	8	0	165	92.12
Vegetations	3	1	22	212	1	0	236	89.83
Water Bodies	4	0	0	0	213	0	213	100.00
Bare lands	5	0	0	0	0	104	104	100.00
	Totals	226	196	220	231	104	977	

Table 2 Producer's Accuracy from Pixel-Based Approach

Producer's Accuracy				
Class names	Landcover ID	Correctly classified	Total samples	Percentage (%)
Settlements	1	225	226	99.56
Forest Reserves	2	152	196	77.55
Vegetations	3	212	220	96.36
Water Bodies	4	213	231	92.21
Bare lands	5	104	104	100.00

Table 3 User's Accuracy from Pixel Based Approach

Class names	Landcover ID	Correctly classified	Total truth Samples	Percentage (%)
Settlements	1	225	259	86.87
Forest Reserves	2	152	165	92.12
Vegetations	3	212	236	89.83
Water Bodies	4	213	213	100.00
Bare lands	5	104	104	100.00

The overall accuracy is computed using Equation (1).

$$\text{Total (overall) accuracy} = \frac{\text{Number of corrected points}}{\text{total number of points}} \times 100 \qquad (1)$$

Kappa can be used as a measure of agreement between model predictions and reality (Tilahun and Teferie, 2015) or to determine if the values contained in an error matrix represent result significantly better than random. Kappa was computed using Equation (2).

$$K = \frac{\sum_{i=1}^{r} xii - \sum_{i=1}^{r}(xi+xx+i)}{N^2 - \sum_{i=1}^{r}(xi+xx+i)} \qquad (2)$$

4.1.3 Object-Based Classification Results

Three reference rates were generated with the scale values set at 10, 20, and 30 (also referred to as Level 1, Level 2 and Level 3). To establish homogeneous blocks, the relatively small value of 10 was set to prevent the effect of mixed land cover. The value of 30 was set to produce broader segments representing a larger land cover of interest. Also, the two parameters for compactness and smoothness were set. Shape parameters were set at 0.2 for level 1 and 0.3 for level 2 and 3 respectively and then the smoothness was selected to be 0.5 for each of the levels. Equal weights were defined for each of the 7 original image layers for segmentation. In this study, Level 1 segmentation was chosen in analysing the dataset since each class was well segmented. Similar segmented classes were merged to form a single class segment so that the sample selection to be used for analysis would be small and simple. Three different algorithms were implemented in this study. They include; Support vector machine (SVM), Random Forest (RF) and Decision tree (DT). The dataset used was partitioned with the same training and testing data as inputs for the algorithms to avoid any biased estimates. A total of 6 877 samples were used and partitioned with 70% training set and 30% testing set. The total number of support vectors were 3 541 with 20-fold cross-validation on the training dataset (Fig. 4). The SVM model was fitted using the training data and yielded an overall accuracy of 93.68% on the training data (Fig. 4). The accepted optimum trained SVM model was further processed to make predictions using the testing set. Confusion matrix was generated from the testing set based on the predictions and the overall statistics were given as shown in Fig. 5. The SVM approach gave an overall accuracy of 94.86% with its corresponding kappa coefficient of 0.9323. Figure 6 shows the details of the results obtained from the random forest classifier with 2 064 samples from the testing data, 2 predictors, and 10-folds cross-validation on the testing set. The "mtry" value for the predictor was chosen between a range of 0 and 1 to select the optimal model using the largest value. The final value used for the model was "mtry" = 1 which gave an accuracy of 93.60% with a kappa coefficient of 0.9150. From all the three algorithms, decision tree produced the lowest accuracy and kappa statistics of 87.75% and 0.8243 respectively (Figs. 7 and 8). Classes 1, 2, 3, 4 and 5 represents settlement, forest, vegetation, water body and bare land respectively. The accuracy and kappa coefficient for each of the algorithms used are shown in Table 4.

```
Call:
svm(formula = GRIDCODE ~ ., data = training_set,
    gamma = 5^7, cost = 2^4, cross = 20, trcl =


Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  radial
       cost:  16

Number of Support Vectors:  3541

 ( 400 1203 588 699 651 )


Number of Classes:  5

Levels:
 1 2 3 4 5

20-fold cross-validation on training data:

Total Accuracy: 93.68377
```

Fig. 4 Results of SVM model on Training Data

```
Confusion Matrix and Statistics


pred_2   1   2   3   4   5
     1 293   0   0   0   0
     2  30 726  40  13  23
     3   0   0 208   0   0
     4   0   0   0 370   0
     5   0   0   0   0 361

Overall Statistics

               Accuracy : 0.9486
                 95% CI : (0.9382, 0.9578)
    No Information Rate : 0.3517
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.9323

 Mcnemar's Test P-Value : NA

Statistics by Class:

                     Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
Sensitivity            0.9071   1.0000   0.8387   0.9661   0.9401
Specificity            1.0000   0.9208   1.0000   1.0000   1.0000
Pos Pred Value         1.0000   0.8726   1.0000   1.0000   1.0000
Neg Pred Value         0.9831   1.0000   0.9784   0.9923   0.9865
Prevalence             0.1565   0.3517   0.1202   0.1856   0.1860
Detection Rate         0.1420   0.3517   0.1008   0.1793   0.1749
Detection Prevalence   0.1420   0.4031   0.1008   0.1793   0.1749
Balanced Accuracy      0.9536   0.9604   0.9194   0.9830   0.9701
>
```

Fig. 5 Results of SVM Model on Testing Data

```
Random Forest

2064 samples
  2 predictor
  5 classes: '1', '2', '3', '4', '5'

No pre-processing
Resampling: Cross-Validated (10 fold, repeated 1 times)
Summary of sample sizes: 1857, 1858, 1859, 1859, 1856, 1857, ...
Resampling results across tuning parameters:

  mtry  Accuracy   Kappa
  0     0.9355596  0.9143863
  1     0.9360427  0.9150390

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was mtry = 1.
>
```

Fig. 6 Results of RF Model on the Testing Data

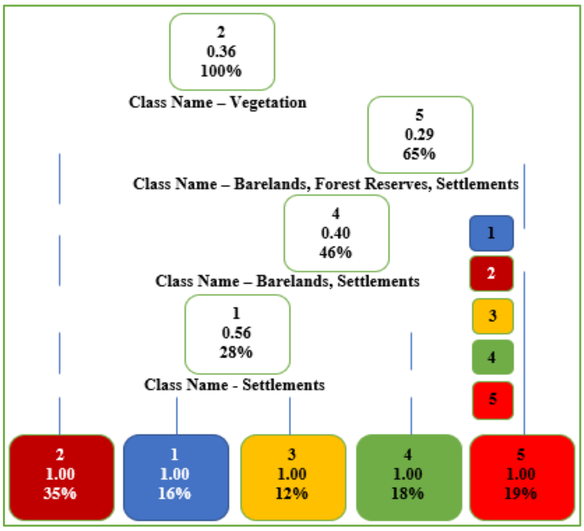

Fig. 7 Tree Generated from the DT Algorithm

```
  predict_unseen
      1    2    3    4    5
  1 758    0    0    0    0
  2   0 1690    0    0    0
  3   0    0  590    0    0
  4   0    0    0  882    0
  5   0    0    0    0  896
> accuracy_tune <- function(fit) {
+   predict_unseen <- predict(fit, training, type = 'class')
+   table_mat <- table(training$GRIDCODE, predict_unseen)
+   accuracy_Train <- sum(diag(table_mat)) / sum(table_mat)
+   accuracy_Train
+ }
> print(paste('Accuracy for train =', accuracy_Train*100))
[1] "Accuracy for train = 100"
> control <- rpart.control(minsplit = 4,
+                          minbucket = round(5 / 3),
+                          maxdepth = 3,
+                          cp = 0)
> tune_fit <- rpart(GRIDCODE~., data = testing, method = 'class', control = control)
> accuracy_tune(tune_fit)
[1] 0.8774917
```

Fig. 8 Accuracy Report from the DT Algorithm

Table 4 Resulting Accuracies and Kappa for Each Algorithm

Algorithms	Accuracies	Kappa Statistics
Maximum Likelihood Classifier	92.73%	0.9077
Support Vector Machine	94.86%	0.9323
Random Forest	93.60%	0.9150
Decision Tree	87.75%	0.8243

3.2 Discussion

The overall classification accuracy of pixel-based algorithm in this study was 92.73% with kappa coefficient equals to 0.9077 as shown in the error matrix in Tables 2 and 3, which includes the producers' and user's accuracy for each class. The users and producers' accuracy are commonly used to measure the accuracy of each class alone in pixel-based classification, and therefore generates an overall accuracy report. The SVM algorithm results, yielded overall classification accuracy of 94.86% and kappa coefficient of 0.9323. The RF algorithm produced overall accuracy of the classification of 93.60% and kappa coefficient 0.9150. The DT algorithm also produced overall classification accuracy of 87.75% and kappa coefficient of 0.8243. From the above findings, it can be observed that the object-based algorithms produced higher accuracies than the pixel-based classification. This result shows that object-based classification has great potential for extracting land cover information from Landsat imagery. The limitation of pixel-based classification where information from surrounding pixels are not used in accurately classifying LULC could be solved by the object-based classifiers.

4 Conclusions and Recommendation

This paper successfully compared object-based classifiers such as SVM, RF and DT as well as the pixel-based MLC. From the results of this paper, it was observed that RF and SVM algorithms produced better classification accuracies compared to DT-based algorithms in object-based classification. Also, RF and SVM performed better than the pixel-based MLC method. This study thus concludes that SVM was the most effective and robust classification algorithm for performing classification on Landsat imagery in the study area, when compared with the pixel-based classification method and other object-based algorithms such as the RF and DT. It is recommended that when performing classification on Landsat imagery in the study area, object-based approach specifically SVM should be considered over RF and DT and pixel-based classification methods.

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