Assessing the Accuracy of Different Supervised Classification Methods of Satellite Image

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Research Note

Abstract  
Assessing the accuracy of the classification map is an essential area in remote sensing digital image process. This is because a poorly classified map will result in inestimable errors of spatial analysis and modeling arising from the use of such data. This study was designed to evaluate different supervised classification algorithms in terms of accuracy assessment with a view of recommending an appropriate algorithm for image processing. The analysis was carried out using Andoni L.G.A. Rivers State, Nigeria as the study area. Supervised classification of ETM+ 2014 Landsat image of the study area was carried out using ENVI 5.0 software. Seven land use/land cover categories were identified on the image data and appropriate information classes were also assigned using region of interest. The classifiers adopted for the study include SAM, SVM, and MDC and each classifier was set using appropriate thresholds and parameters. The output error matrix of the classified map produced overall accuracy and kappa coefficient for MDC as 94.00% and 0.91, SAM as 64.45% and 0.53, and SVM as 98.92% and 0.98 respectively. The overall accuracy obtained from SVM indicates that a perfect classification map will be produced from the algorithm. The advanced supervised classification should be utilized for classification of land use/land cover for both high and medium resolution images for improved classification accuracy.

Keywords: Classification Accuracy, ENVI, Landsat Image, Image Classification, Mahalanobis Distance Classifier, Support Vector Machine, Spectral Angle Mapper

1. Introduction  
Image classification of remotely sensed data is an important element in remote sensing. Classification also serves as a tool for the examination of the digital image. It’s involved the process of interpretation and identification of information on remotely sensed image data (Momani et al 2011). (Richards and Xiuping 2006) defined image classification as the categorization or labeling the pixels as belonging to particular spectral and thus information classes using the available spectral data. The spectral class corresponds to specific ground
cover types that are identified and labeled. The spectral class is used for the extraction of information from satellite images. The classification process can also include features that are not derived from the satellite image such as land surface elevation and the soil type (Anji 2008). According to (Eastman 2003) classification of remotely sensed image data can be grouped as supervised versus unsupervised, hard versus soft, spectral response patterns versus signatures, and multispectral versus hyperspectral classifier. In contract, image classification can be grouped as supervised and unsupervised, or parametric and non-parametric, or hard and soft (fuzzy) classification, or per-pixel, subpixel, and per-field (Lu and Weng 2007, Shivakumar Pallavi 2013). But (Michie et al 1997) viewed classification according to different professional and academic groups in three perspectives such as statistical, machine learning, and neural network. In addition, other researchers viewed Image classification under two headings such as supervised and unsupervised classification methods (Hasmadi et al 2009). However, the combination of supervised and unsupervised classification resulted in a special type of classification called hybrid classification (Abburu and Golla 2015). The unsupervised classification is a type of classification process that does not require the selection of a training site (Pandya et al 2013). In this case, a pixel in the image data is assigned to spectral classes without the user or image analyst having knowledge of the existence of those classes. In addition, unsupervised classification is often performed using the clustering method (Richards and Xiuping 2006) as seen in IDRISI TAIGA software. ENVI 5.0 tutorial identified two unsupervised classification methods which are IsoData and K-Mean. In supervised classification procedure, the image analyst identified and trained land cover type to represent the feature class. Of note, the most important factor in the performance of supervised classification is the accurate selection of training sites (Abburu and Golla 2015). The selection of training sites can either be polygon, seed, or pixel (Lu and Weng 2007). According to (Anji 2008) supervised classification is carried out in three stages namely: the training stage, the classification stage, and the output stage. The classification output is the thematic map of the study area showing different land cover categories. Thematic map of classification results can be used for many application areas in remote sensing, such as spatial distribution and pattern of land cover, the estimate of the areal extent of cover classes, data for environmental modeling, and as a basis of policy analysis (Liu et al 2006). However, (Lu and Weng 2007) listed some of the challenges confronting image classification which include; the complexity of the study area landscape, selected remotely sensed data, and image processing and classification methods. In addition, the classification output map assists in validating the obtained classification accuracy of image data.

Supervised image classification (SIC) may be performed using different algorithms and software packages. (Richards and Xiuping 2006) grouped supervised image classification into statistical, non-statistical, and geometric methods. Some of the examples of statistical classification approach are maximum likelihood classification, minimum distance classification, parallelepiped classification, Mahalanobis classifier, the nearest neighbor classifier (kNN), context classification, Gaussian mixture models, etc. The first three of the statistical method (maximum, minimum, and parallelepiped) are called hard classifiers (Eastman 2003). The geometric (non-parametric) classifiers include; support vector machine (SVM), neural network (NN), spectral angle mapping (SAM) (Richards and Xiuping 2006), decision tree classifier (DTC), expert system (ES), evidential reasoning (ER) (Lu and Weng 2007) which are found in different software applications. The non-parametric classifiers are used to estimate the probability density function (Kumar and Sahoo 2012). Of note, there is no single software package that may include all the classifiers and the strength and weaknesses of different GIS software differ in their classification performance.

Comparative assessment of different classifiers has been carried out at different areas using selected software and sensors data. Some researchers adopted traditional classifiers while
others employed advanced classifiers technique in their studies. (Fauzi et al 2001) compared maximum likelihood and neural network classifiers using Landsat -7 ETM, JER-1 SAR, ERS-2 SAR, and Radarsat-1 SAR sensors. (Perumal and Bhaskaran 2010) compared hard classifiers (parallelepiped, minimum distance, maximum likelihood, and Mahalanobis) with some advanced classifiers like an artificial neural network, and spectral angle mapper and concluded that Mahalanobis classifier performed optimally. Similarly, (Pradhan et al 2010) classified land use/land cover using Bayesian and Hybrid classifiers and observed 91.57% using hybrid and 90.53% using the Bayesian classifier. It was clear that none of these classifiers of remotely sensed data has been applied in any part or the whole of Andoni L.G.A. Rivers State. Neither the traditional classifiers nor the advanced classification has been utilized for any study in the area. Hence, the study was structured to compare two non-parametric classifiers which are support vector machine and spectral angle mapper, and one statistical supervised classification like Mahalanobis distance classifier. These classifiers were chosen because of their availability in ENVI 5.0 software.

1.1 Support vector machine (SVM)
The support vector machine is machine learning for two groups of classification problems (Vladimir and Cortes 1995). SVM has been applied in real-world problems such as image classification and tone recognition (Srivastava and Bhambhu 2009). It has been widely applied to machine vision fields such as character, handwriting digit, and text recognition and recently introduced in remote sensing image classification (Shinde et al 2014). SVM uses an optional linear separating hyperplane to separate two sets of data in feature space (Vanitha and Venmathi 2011). SVM created a hyperplane in-between datasets to indicate which class it belongs to. SVM is found to be easier than an artificial neural network (Hsu et al 2016) and produced a high degree of accuracy by generalizing well as compared to traditional classifiers (Priti et al 2012).

1.2 Spectral angle mapper (SAM)
Spectral angle mapper classifier is useful in the classification of hyperspectral satellite images (Shrestha et al 2002). The classifier algorithm determines the spectral similarity between two spectra by calculating the angle between them and treating spectra as vectors in a space (Shafri et al 2007, Moughal 2013). The spectral class may be taken from field observations, directly from the image, and obtained from the laboratory. In SAM classifiers, image pixels with similar shape patterns are classified into the same information class (Sohn and Rebello 2002).

1.3 Mahalanobis distance classifier
Mahalanobis distance measure was introduced by P. C. Mahalanobis in 1936 (Li and Fox 2011). Mahalanobis distance classifier (MDC) is an example of a hand classifier of the supervised classification. It is a classification algorithm that uses the distance from the training site and the unknown to categorize the unknown pixel (Aziz et al 2016). MDC is similar to minimum distance to mean classifier except for the application of covariance in the equation (Murtaza and Romshoo 2014, Wang et al 2011). The MDC is given by the algorithm according to (Xiang et al 2008) as
\[ d_A(X_1 - X_2) = (X_1 - X_2)^T A(X_1 - X_2), \]
where \( X_1 \) and \( X_2 \) are two data points.

2. Study Area
The study area is Andoni Local Government Area, Rivers State, Nigeria. It is located between latitude 04° 26' 40"N - 04° 35' 00"N and longitude 07°16'30"E - 07°33'00"E. It has a total landmass of 342 square kilometers with a population of 211,009 peoples (National Bureau of Statistics 2006). The study area is bounded by Gokana and Khana LGAs in the north, Opobo/ Nkoro LGA in the
east, Bonny LGA in the west, and South Atlantic Ocean occupied the whole southern part of the area. The area is situated in the mangrove forest of the Niger Delta region with annual precipitation of 3540mm and temperature ranges from 22°C to 31°C (Okujagu and Beka 2016). Being a coastal tribe of the Niger Delta region the people are predominantly fishermen. The landmass is made-up of tributaries of Rivers, Creeks, and Lagoons of the main ocean which serves as a fishing ground for the people to earn a living. The study area was chosen because of the distinctive land cover categories such as built-up, water bodies, vegetation, and Nypa palm along shorelines that can be accurately trained during classification processes. Besides, the vast knowledge of the area also influenced the choice of this area for the study.

Figure 1. Study area location map

3. Methodology
3.1. Dataset and software
In comparing the various classification methods ETM+ Landsat satellite image data of 2014 was sought for and used in achieving the expected results. The image was downloaded from its website (http://glovis.usgs.gov/) using internet explorer with java 8 installed. The image has a path and row as p188r57 and spatial resolution of 28.5m x 28.5m, and the image was acquired on January 6th, 2014. The image was utilized for the purpose of extracting land use/land cover such as water body, built up vegetation, and Nypa palm identified in the study area. Landsat 2014 was chosen because it is capable of providing recent development in land use/land cover for this period of the study. Similarly, the Nigeria L.G.As shapefile obtained from the Office of the Surveyor-General of the Federation (OSGOF) was used to extract Andoni L.G.A. boundary and this was used in the clipping of the Landsat image. Adoni L.G.A. was selected for the study because of the general knowledge of landmass which offers a great advantage in image classification.

The software used for the study is ESRI ArcGIS 10.1 and ENVI 5.0. But (Souza et al 2013) used ENVI 4.7 to performed supervised image classification. The choice of ArcGIS was based on its ability
for vector operations. The ArcGIS 10.1 software was utilized to performed map compilations and clippings of image data to study area extent. While ENVI software was utilized for the classification and extraction of land use/land cover types in the area.

3.2. Data processing

For every remote sensing data analysis processing preceded all the activities. The ETM+ 2014 Landsat image as downloaded contained periodic lines dropout that must be corrected before performing any classification on the image data. The periodic line dropout resulted in gaps in the image data and was corrected using PANCROMA™ (John 2012). The software can be downloaded from the website www.PANCROMA.com for both trial and license applications. Landsat satellite image developed gaps (missing data) due to the failure of the Scan-Line Collector (SLC) on May 31, 2003 (Pat et al 2004, Landsat Technical Guide 2004). The gaps filling was performed using Landsat image 2013 ETM+ as the adjust image to fill the 2014 image being the target image in the application software. Other researchers like (Jonh and Nobukazu 2011) performed gap filling on the 2009 image using Frame and _ Fill_Win32 program from NASA. Landsat Gap filling operations replaces missing data created by gaps in the target image (image with gaps) to produce a fill image without gaps that can be used for further analysis and modeling.

The 2014 image was clipped to the study area extent in ArcGIS 10.1 using the Local Government Area shapefile (Richard and Chima 2016, Brand 2012). The image was saved in Tag Image File Format (TIFF) in ArcGIS in the individual band so that they are compatible with ENVI. The image bands used for the supervised classification are band 432 which are required to form a color composite. This color composite is simply referred to as a false-color composite (Minakshi 2003). These bands (432) were chosen because band 4 (near-infrared) is preferable in the delineating interface between land and water (Centre for Biodiversity and Conservation 2004), and band 3 (red band) may be used in the mapping of urban areas and identification of plant species. The color composite was performed in ENVI 5.0 by loading near-infrared (band 4), red (band 3), and blue (band 2) into band combination dialogue box.

The land use/land cover (lu/lc) classification processes were based on the level 1 classification scheme as suggested by (Anderson et al 1976, Anji 2008). The supervised classification was performed in ENVI software (El_Rahman 2016, Singh and Mishra 2011). ENVI was chosen base on the fact the application contains most of the classifiers as compared to other raster software. The cover types identified on the image include water body, vegetation, Nypa palm, wetlands, built-up, and sand dune that is along the coast of the Atlantic Ocean.

3.3. Image classification

Supervised classification was performed on the composite image in ENVI 5.0 software. The classification was implemented by selecting suitable classifiers which are Mahalanobis, spectral angle mapper, and support vector machine. Training sites for all the cover types were selected by adhering to the minimum class size. However, sufficient training class for each land cover was taken for quality classification. The Mahalanobis distance classifier was performed using region of interest (ROI) representing training classes. For spectral angle mapper, the classification was based on endmember collector spectra. Endmember spectra are used for all supervised classification and advanced spectral techniques image classification (Kruse et al 1993). The spectral angle was set to 0.5 radians in the set maximum angle and this was chosen to ensure a closer match with the reference spectrum.
Table 1. Total number of pixel per land use/land cover category

| Lulc       | MDC (ha) | SAM (ha) | SVM (ha) |
|------------|----------|----------|----------|
| Waterbody  | 8128.53  | 8492.04  | 10765.71 |
| Built-up   | 1137.96  | 1573.29  | 887.85   |
| Sand dune  | 381.60   | 930.60   | 277.11   |
| Vegetation | 5045.67  | 5300.19  | 4951.08  |
| Nypa Palm  | 9072.45  | 8796.78  | 9892.17  |
| Cloud Cover| 215.37   | 1370.16  | 214.11   |
| Wetlands   | 4527.99  | 3348.54  | 2823.57  |
| Total      | 29811.60 | 29811.60 | 29811.60 |

Similarly, the support vector machine was performed using the ROI representing the classes. The SVM option selected was radial basis function, the kernel function 0.333, and the threshold of 0.00 was used in the algorithm. The output classification maps were used to validate classification accuracy.

3.4. Classification Accuracy

Assessing classification accuracy is an essential process in digital image classification. Digital image classification is a complex process and as such, there is a need to assess the reliability of the results. Classification accuracy assessment of remotely sensed images is crucial because of the infiltration of errors from various sources. (Lu and Weng 2007) listed such errors as those from classification, interpretation errors, poor quality of training sites, and positional errors. Accuracy assessment can be represented using an error matrix (Congalton 1991). In some literature, the error matrix is also called the confusion matrix. The matrix columns represent the reference data while the rows indicate the classification map categories. To measure the classification accuracy of the thematic map is to calculate the user’s accuracy, producer’s accuracy, and the overall accuracy of the classifier from the error matrix (Shao and Wu 2008). Also, the error matrix provides errors of exclusion (omission errors) and errors of inclusion (commission errors) for the classified map (Congalton 2005). Error matrix also produced the kappa coefficient which is based on the difference between the actual agreement in the error matrix and the chance agreement (Lentilucci 2006, Lu and Weng 2007). It is through these results that an analyst can ascertain the accuracy of a thematic map produced from a remotely sensed image. There is no standard to quantify the accuracy of image classification, but the analyst results depend on the available software, skills, and selected image data. In this study, thematic map accuracy will be evaluated based on overall accuracy and kappa statistics.

4. Results and discussions

The results of the classification map as shown in table 1 above represents total pixels per class of each classifier. The total area per class was represented in hectares (ha). For spectral angle mapper (SAM) the total pixels for the waterbody were 8492.04ha and that obtained from the support vector machine classifier was 10765.71ha. The difference in areas of water body between the two classifiers was 2273.67ha, this shows that SVM was able to account and classified spectral patterns in waterbody in the study area than SAM as indicated in the thematic map. Similarly, for the Built-up areas the total area with SAM was 1573.29ha, and with SVM classifier was 887.85ha. SAM classifier classified more map area as built-up with a difference of 685.44ha in excess of SAM classifier. For vegetation, the total area for the SAM classifier is 5300.19ha and 4951.08ha for the SVM classifier. The SAM classifier allocates more class as vegetation. Similar variations in areas were identified for sand dune, Nypa palm, cloud cover, and wetlands land use/cover categories. The total pixels in the study area were 29811.60ha, and this was the same for both SAM and SVM classifiers.
The results of the classification accuracy for each classifier were shown in Table 2 below. The classification accuracy assessment was based on producer's and user's accuracy, overall accuracy, and kappa coefficient of agreement. The producer's and user's accuracy for waterbody were 97.88% and 100.00% with the application of the SAM classifier algorithm. By applying the SVM classifier, the producer's and user's accuracies were 100.00% and 100.00% for the same water body. Also for built-up, the producer's and user's accuracies were 91.04% and 59.22% with SAM algorithm and 100.00% and 100.00% for the SVM algorithm. There is a higher producer's and user's accuracy with the application of the SVM algorithm than SAM classifier except for the producer's accuracy for sand dune that is 27.59% for SAM against 17.24% for SVM classifier. The higher user's accuracy for SVM is a representation of the reliability of the thematic map to the user (Murty and Tiwan 2015).

The difference was even more pronounced with the obtained overall accuracy of 98.92% for SVM and 64.45% for SAM classifiers. The classification of this remotely sensed data of the study area shows that there was a perfect classification with the utilization of SVM. The obtained classification accuracy using SVM was better than the minimum level standard of the United State Geological Survey (USGS) which is 85.5% for interpretation of accuracy of image data (Anderson et al 1997). But this accuracy standard is very rare to achieve in actual image classification (Shoa and Wu 2008) due to a number of factors. A different supervised classification algorithm will produce different overall accuracy and kappa coefficient.

| Lulc          | Mahalanobis Classifier | Spectral Angle Mapper | Support Vector Machine |
|---------------|------------------------|-----------------------|------------------------|
|               | Producer’s Acc. (%)    | User’s Acc. (%)       | Producer’s Acc. (%)    | User’s Acc. (%)       | Producer’s Acc. (%) | User’s Acc. (%)       |
| Waterbody     | 90.30                  | 100.00                | 97.88                  | 100.00                | 100.00              | 100.00                |
| Built-up      | 91.04                  | 91.04                 | 91.04                  | 59.22                 | 100.00              | 100.00                |
| Sand dune     | 27.59                  | 57.14                 | 27.59                  | 53.33                 | 17.24               | 83.33                 |
| Vegetation    | 99.32                  | 99.66                 | 99.32                  | 94.19                 | 100.00              | 100.00                |
| Nypa palm     | 89.86                  | 98.52                 | 82.43                  | 95.31                 | 99.32               | 98.00                 |
| Cloud cover   | 96.39                  | 79.21                 | 96.39                  | 76.92                 | 98.80               | 77.36                 |
| Wetlands      | 97.80                  | 81.65                 | 94.51                  | 91.49                 | 96.70               | 98.88                 |
| Overall Acc.  | =94.00%                | Overall Acc. =64.45%  | Overall Acc. =98.92%   |
| Kappa Stat.   | =0.91                  | Kappa Stat. =0.53     | Kappa Stat. =0.98      |
Accordingly, the kappa coefficient of 0.98 was obtained with SVM classifier which indicates strong agreement and good accuracy between reference data and classification map. But for the SAM algorithm, the kappa statistics were 0.53 indicating moderate agreement between reference data and the thematic map. The kappa statistics greater than 0.80 represents a strong agreement, from 0.40 – 0.80 indicates moderate agreement, and less than 0.40 indicates poor agreement. The kappa statistics for SAM were 0.53 representing moderate or middle agreement. The kappa coefficient for SVM is 0.45 more than the SAM classifier.

Comparing one statistical and two non-parametric supervised classifications, it was discovered that the overall accuracy for Mahalanobis distance classifier (MDC) was 94.00% representing the perfect classification of image data. This overall accuracy is higher than the overall accuracy for spectral angle mapper (SAM) of 64.45% but lower than SVM of 98.92% in the same study area. The kappa coefficient for MDC was 0.91 indicating strong agreement between reference data and classification map.

5. Conclusion
Remotely sensed image classification involves the utilization of different software, algorithms, and methods to derived thematic maps. A thematic map is the output data for any digital image processing and is used in almost all GIS analysis and modeling. To evaluate the performance in terms of accuracy assessment, three classifiers including one hard (MDC) and two non-parametric (SAM, SVM) classifiers were considered in the study. A number of information classes were selected to represent the land cover category as identified in the area. It was observed that the overall accuracy for MDC, SAM, and SVM are 94.00%, 64.45%, and 98.92% respectively. In conclusion, the higher overall accuracy of SVM classifier signified a perfect classification map and better algorithms for image classification accuracy assessment. For further study, the classification of remotely sensed image data should be carried out using different image processing software on the same dataset and compare their results in terms of classification accuracy. Secondly, reasonable numbers of training sites should be selected per class for improved producer's and user's accuracy and the final overall accuracy of the process map.

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