Comparison of Support Vector Machine and Maximum Likelihood Classification in and around Granite Quarries

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Abstract

Monitoring land cover changes is of prime importance for the effective planning and management of natural and man-made resources. Historically, mapping and monitoring of land cover changes was achieved through field surveys which was time-consuming and costly. Remote Sensing provides an alternative method of land cover monitoring which is less costly and more practical. Capabilities of covering large spatial areas–coupled with the ease of availability of historic and high spatial, spectral and temporal resolution data–remote sensing technology has been widely applied in mapping and monitoring land use land cover changes. This study compared the Maximum Likelihood Classifier (MLC) and Support Vector Machines (SVM) classification algorithms for land cover classification in granite quarries. The two classification algorithms were used to investigate the capability of differentiating granite quarries from other land cover types with similar spectral properties such as platinum and chrome mining areas, built-up land, bare land and the rock formations where quarrying takes place. A Landsat surface reflectance image acquired in November 2016 was used in the study. The image was classified using MLC and SVM and accuracy of classification was evaluated using 532 random points on Google Earth™. The results of the study revealed that SVM was more accurate (overall accuracy: 78% and kappa: 76%) than the MLC (overall accuracy: 73% and kappa: 68%).

1. Introduction

Land cover is an important variable that links and impacts on many parts of the human and physical environment (Foody, 2002). Changes in land cover can be indicative of major degradation of the environment including at the global scale (Cheruto *et al*, 2016). Such changes can be a result of human-induced or natural activities. An example of human-induced changes result from the extraction of mineral resources from the earth's crust. This activity results in notable impacts on the environment, natural landscapes and biological communities (Bell *et al.*, 2001; Singh *et al.*, 2010). Mining activities that may result in land cover changes include the building of infrastructure such as roads and waste facilities.

Over 70% of granite production in South Africa is from the North West province (Naidoo, 2006). The grey-black granites (gabbros and gabbro-norites) are dominant in the Rustenburg and Belfast areas of the North West and Mpumalanga provinces (Naidoo, 2006; Ashmole and Motloung, 2008). Stone quarrying (granite, marble, sandstone etc.) has potential to affect the environment through destruction and loss of vegetation, destruction of animal habitat, soil erosion and water pollution to nearby rivers through siltation (Ashmole and Motloung, 2008; Darwish *et al.*, 2011). The history of granite quarrying in South Africa dates back to the late 1930s (Ashmole and Motloung, 2008). It is therefore important to identify mining sites in order to monitor potential impacts that may arise from these activities.

Monitoring mining activities and associated potential impacts contributes to improved decision-making for policy makers; the information allows them to implement appropriate land management measures and control environmental degradation (Qian, Zhou and Hou, 2007; Schmid *et al.*, 2013). Traditional methods used to monitor variables associated with mining activities have largely utilized field mapping and surveys. These have the disadvantages of being costly, time-consuming and labour-intensive. Furthermore they provide inadequate quality of data when implemented over large spatial areas (Zhang *et al.*, 2012). The evolution of remote sensing techniques in the past four decades has provided a cost-effective method for mapping land cover and land use; it can also be applied to monitoring and managing land resources. Remote sensing provides accurate and reliable data across various ranges of spatial, spectral and temporal resolutions. Its use in the field of geology and application to the mining sector has been well documented.

From a geological point of view, remote sensing has been used *inter alia* for lithology and structural mapping (Mwaniki, Matthias and Schellmann, 2015), volcanic deposit and volcano monitoring (Mia, Fujimitsu and Nishijima, 2017), natural oil seep detection, landslide mapping (Van Westen, Castellanos and Kuriakose, 2008) and for mineral exploration (Manuel *et al.*, 2017). In the mining industry, remote sensing has been applied to aspects including: mapping and monitoring of surface mine expansion (Latifovic *et al.*, 2005); mine waste management (Yucel, Yucel and Ileri, 2017); mine reclamation processes (Padmanaban, Bhowmik and Cabral, 2017); effects of mining on vegetation (Yang *et al.*, 2018); and impacts of mining on water resources (Rudorff *et al.*, 2018). Even though remote sensing is being widely used for land cover mapping and monitoring, a limitation has been the accuracy of classification especially in areas where there are spectral similarities in the land cover types (Thakkar *et al.*, 2017). Apart from the heterogeneity of land cover, other factors that may affect the accuracy of classification is the type of remote sensing data used to evaluate land cover, image processing and classification techniques (Lu and Weng, 2007). Two major types of classification techniques are recognized, namely parametric and non-parametric classifiers (Srivastava *et al.*, 2012). Parametric classifiers assume that the sample data follows a specific distribution such as Gaussian distribution and that the statistical parameters generated from the samples are representative (Gibbons and Chakraborti, 2010; Qi, Yeh and Li, 2015). The most commonly used parametric classifier is Maximum Likelihood Classifier (MLC) which quantitatively evaluates the variance and covariance of the category spectral response patterns when classifying an unknown pixel (Lillesand, Kiefer and Chipman, 2014). In non-parametric classifiers, there is no assumption of a particular probability density distribution of the input data, and no statistical parameters are needed to separate images (Gibbons and Chakraborti, 2010; Qi, Yeh and Li, 2015).

Such classifiers include Artificial Neural Networks (ANN), Support Vector Machines (SVM) and decision trees among others (Seto and Kaufmann, 2005; Srivastava *et al*., 2012).

Koruyan *et al*. (2012) assessed the expansion of marble quarries and the affected vegetation using Landsat and ASTER. Red-Green-Blue (RGB) clustering was performed on the images; these were then recoded and pixel classes were grouped so as to separate marble quarries from non-vegetated and agricultural areas. Schmid *et al*. (2013) used remotely-sensed data for monitoring a mercury mining site before, during and after the mine closure. In the study, the SVM algorithm was applied to classify satellite images acquired from Advanced Land Imager (ALI), Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+). The results of the study indicated remote sensing was effective in identifying mining sites and in quantifying distribution of areas affected by mining activity. Similarly, Karan *et al*. (2016) utilized MLC and SVM techniques on Landsat data for change detection analysis in coal mining. The results showed that SVM performed better in detecting coal mines and classification of land cover features compared to MLC. Recently, Zhao *et al*. (2018) applied Random Forest (RF) classification to monitor the expansion of aggregate quarries using Landsat data. The study separated land cover into two classes, namely quarry class and non-quarry class. Classification accuracy of the two classes in the study was found to be very high, indicating that the RF classifier was effective in separating between the classes.

These previous studies have proved the effectiveness of remote sensing in mapping and monitoring quarries. However, there is limited research on granite quarries. In addition, the difficulty in separating land cover features has been identified in these studies due to similarities within spectral properties. In this study, we evaluate the use of remote sensing in identifying granite quarries. The second objective is to compare the application of MLC and SVM classification for land use and land cover classification within and around granite quarries.

2. Study Area

The study area is located between Rustenburg and Madibeng Local Municipalities in the North West Province, South Africa (Figure 1). Granite quarries in this area occur in the Main Zone of the Rustenburg Layered Suite (RLS) in the Bushveld Igneous Complex (BIC). The RLS is made up of five zones: Marginal; Lower; Critical; Main; and Upper Zones. The Critical Zone contains platinum group metals and chrome deposits, while the Upper Zone contains magnetite deposits from which palladium is mined. The Main Zone is characterized by gabbro and norite, commercially referred to as black granite (Naidoo, 2006). Mineralogical composition of the black granites under study is comprised of plagioclase, orthopyroxene and clinopyroxene with minor amounts of quartz, magnetite, apatite, hornblende and mica. In terms of vegetation, the study area comprises low, semi-open to closed woodland, consisting of dense deciduous shrubs and trees accompanied by large areas devoid of vegetation (Mucina *et al.*, 2006). The landscape is characterized by plains and undulating plains with scattered occurrence of hills and lowlands, and parallel hills. The most prominent of these hills are the Magaliesberg and Pilansberg ranges, as well as the norite koppies. Granite quarrying activity occurs on the norite koppies which causes massive damage to the vegetation, some of which only occurs on these koppies (Lamprecht *et al.*, 2011).

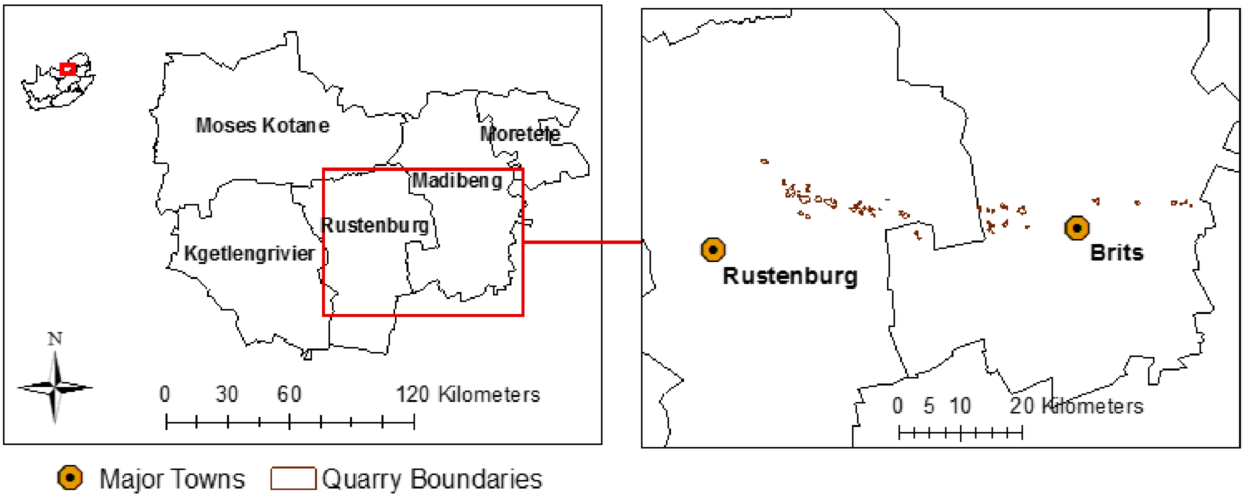

Figure 1: Location of the study area

3. Data and Methods

3.1 Remote Sensing Data

Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) satellite image was downloaded from the United State Geological Survey (https://earthexplorer.usgs.gov/). The acquired image was a level 1T surface reflectance that has already been corrected for geometric, radiometric and topographic errors and was acquired on the 28th November 2016. Landsat 8 comprises 11 bands, and this study made use of bands 2–7 (Blue–Short-wave Infrared (SWIR)) with the spatial resolution of 30 m. Bands 2–4 fall within the wavelength range of 0.452–0.673 µm, band 5 (Near-infrared) 0.851–0.879 µm, while bands 6 and 7 (SWIR 1 and 2) fall within the 1.566–2.294 µm wavelength. Band 5 is useful for ecology because healthy plants reflect it while bands 6 and 7 are used for geology (Loyd, 2013). Landsat data was chosen for the study because it provides data with a distinctive combination of spatial, spectral and temporal resolutions; these cover a large area, resulting in information that can support land cover management and monitoring (Wulder *et al.*, 2012). In addition, Landsat offers freely accessible data (Wulder *et al.*, 2012). Also of great relevance is that several studies have shown the effectiveness of Landsat imagery in land cover mapping and monitoring of mining areas (Mwaniki, Moeller and Schellmann, 2015; Sari and Rosalina, 2016; Qian *et al.*, 2017; Garai and Narayana, 2018).

3.2 Data Processing

The major steps involved during image classification may include determination of a suitable classification system, selection of training samples, image pre-processing, feature extraction, selection of suitable classification approaches, post-classification processing and accuracy assessment (Lu and Weng, 2007). The classification workflow of data using MLC and SVM included creating training samples, training the MLC and SVM using the same training samples and classifying the image. Various image classification techniques exist, and MLC and SVM have been widely used in classifying surface mining areas (Demirel, Emil and Duzgun, 2011; Ustuner, Sanli and Dixon, 2015; Karan, Samadder and Maiti, 2016; DeWitt *et al.*, 2017). In addition, SVM has been reported to increase classification accuracy (Pal and Mather, 2005; Demirel, Emil and Duzgun, 2011).

Maximum Likelihood Classification (MLC) is a commonly used supervised classification method applied in classification of remotely sensed data (Richards, 2012). The training data in MCL is used to create a class signature based on the variance and covariance. The algorithm assumes a normal distribution of each class sample in the multidimensional space, where the number of dimensions equals the number of bands in the image (Richards, 2012). Support Vector Machine (SVM) is a supervised non-parametric statistical learning technique that does not make assumptions about the underlying data distribution (Vapnik, 1999). SVM classification aims to fit an optimal separating hyperplane between classes by focusing on the training samples that lie at the edge of the class distributions, namely the support vectors (Cortes and Vapnik, 1995; Mathur and Foody, 2008). The South African Land Cover Classification System (SANS 1877) was adopted in classifying land cover types in the study area. Training samples ranging from 5–50 were collected from each land cover class (Table 1) to train the MLC and SVM classifiers. These samples were collected by digitizing homogenous pixels onto up-to-date medium spatial resolution acquired Landsat OLI/TIRS. The digitized polygons consisted of pixels ranging from a minimum of 4 to a maximum of 30 pixels. In training SVM classifier, an important parameter to control is the maximum number of samples to use for defining each class. A default value of 500 on ArcGIS was used for training of the classifier.

Table 1: Number of training and validation points per class for MLC and SVM classification and accuracy assessment

Land cover classes	**Training data**	**Validation points**
Water bodies	5	76
Granite quarries	12	75
Exposed rock formation	5	25
Built-up land	15	55
Bare land	14	95
Vegetation	50	121
Other mines	13	85

‘Exposed rock formation’ in this study refers to the gabbro and norite koppies where quarrying takes place. The ‘Granite quarries’ are characterized by fresh rocks appearing white-greyish in colour on Google Earth™ whilst the koppies appear brown in colour due to weathering. ‘Other Mines’ refers to chrome and platinum mines, including mine tailings. These mines are found in the Merensky Reef and chromitite layers of the RLS. The Merensky Reef is comprised of igneous rocks such as leuconorite, anorthosite, chromitite and melanorite (Wilson, Lee and Brown, 1999). Mine tailing dumps with low chrome content appear white in colour (similar to granite quarries) while those with chrome content display greyish colour on Google Earth (Jubileus, 2008). ‘Granite quarries’ were differentiated in this study from ‘Other mines’ by presence of terraces and large benches within the quarries. However, it was not clear if remote sensing would be able to distinguish these classes. Similarly, ‘Built-up land’ is known to display spectral confusion with other land cover classes such as barren land and asphalt concrete due to similar spectral characteristics (Chen *et al.*, 2017). In this study, ‘Built-up land’ referred to areas where there are buildings and other man-made structures while ‘Bare land’ referred to non-vegetated areas, or areas of very little vegetation cover where substrate soil exposure is clearly apparent (excluding agricultural fields with no crop cover, open cast mines and quarries). The ‘Vegetation’ class in this study referred to areas covered by vegetation including agricultural land.

3.3 Accuracy Assessment

Error matrix analysis was used to measure accuracy of classification. Accuracy assessment was evaluated using reference data obtained from Google Earth™. Google Earth images provided by Google Inc., is a virtual globe programme that maps the earth by superimposition of high-resolution satellite image (Jaafari and Nazarisamani, 2013). Since its launch in 2005, Google Earth has been providing high-resolution data (<2.5m) to view the world (Potere, 2008). Several studies have utilized Google Earth data for accuracy assessment of land cover classification (Pulighe, Baiocchi and Lupia, 2016; Rwanga and Ndambuki, 2017). A set of 532 stratified random points (Table 1) were plotted on Google Earth™ and classification results were compared with the reference data. Google Earth™ was set to a date corresponding with Landsat data for accuracy assessment. The points were used for assessing accuracy of both MLC and SVM classification. Error matrix was generated from which overall accuracy, producer’s accuracy, user’s accuracy and kappa coefficient were computed.

The overall accuracy quantifies the total accuracy of classified image. This measure is computed by dividing the number of correctly classified pixels (sum of diagonals) by the total number of reference pixels (Lillesand, Kiefer and Chipman, 2014). Producer’s accuracy measures errors of omission and is computed by dividing the number of correctly classified pixels in each category by the number of training pixels used for that category. User’s accuracy (commission errors) is computed by dividing the number of correctly classified pixels in each category by the total number of pixels classified in that category (Congalton and Green, 2008; Lillesand, Kiefer and Chipman, 2014). Kappa analysis is a popular multi-variate technique used for accuracy assessment. The estimate of kappa is called KHAT statistics and is used to measure agreement or accuracy (Fleiss and Cohen, 1973; Smits, Dellepiane and Schowenerdt, 1999). The result of kappa ranges from -1 to +1 where positive one indicates perfect agreement, zero indicates chance agreement while a negative value indicates less than chance agreement (Fleiss and Cohen, 1973).

4 Results

4.1 Image classification

Using both MLC and SVM, Landsat data was classified into seven land cover types: 'Water bodies'; 'Granite quarries'; 'Exposed rock formation'; 'Built-up land'; 'Bare land'; 'Vegetation'; and 'Other mines' (platinum, chrome mines and their tailing dumps). Figure 2 shows Granite quarries in the reference data (top) and Granite quarries in classified images. Comparison between reference data and classification results show that SVM was better in identifying Granite quarries compared to MLC.

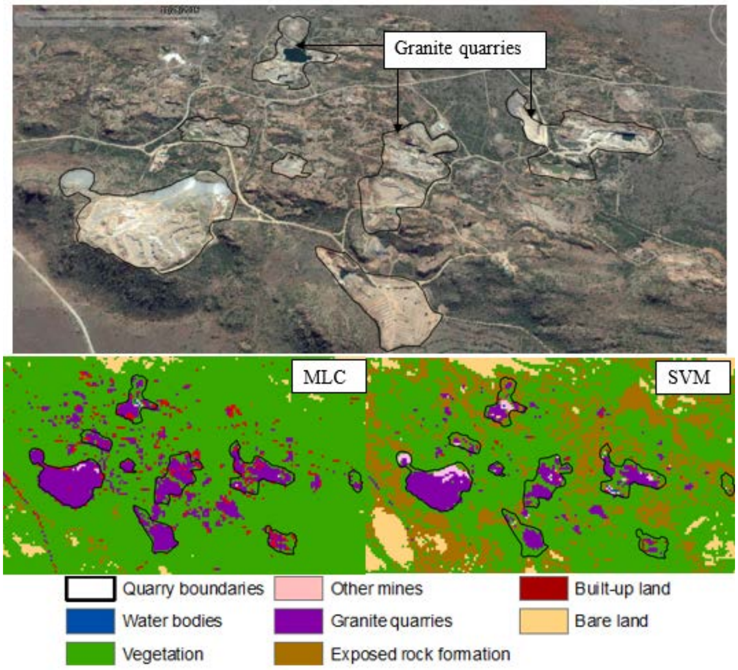

Figure 2: Comparison of classification using MLC and SVM within Granite quarries

Figure 3 shows a comparison of MLC and SVM classification around platinum and chrome mines and mine dumps classified here as 'Other mines'. The top image in Figure 3 shows the portion of the study area in Google Earth^{TM}. In MLC classification, Other mines are classified as Granite quarries and Built-up land. Conversely, SVM classification shows better classification in distinguishing Other mines from Granite quarries and Built-up land. Figure 4 shows detection and classification of water body inside a Granite quarry. In the MLC classification, the Water body was not detected. The Water body was detected using SVM classification showing that SVM is more effective compared to MLC in detecting small Water bodies inside the quarries.

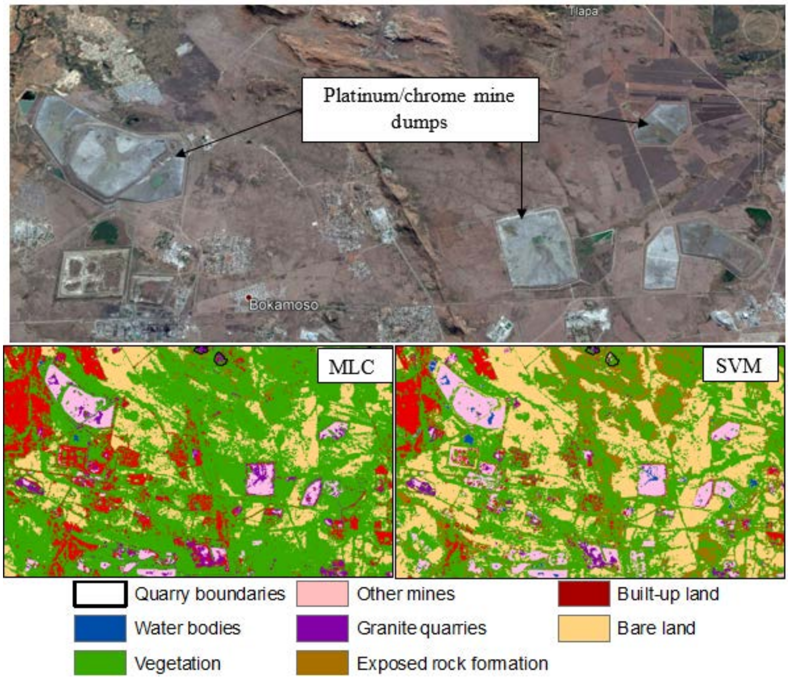

Figure 3: Comparison of classification results of MLC and SVM around Other mines

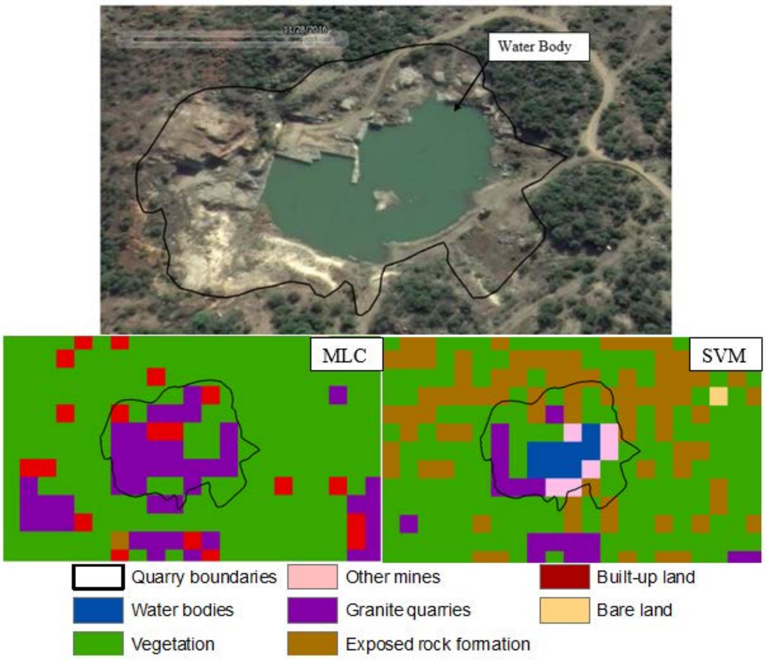

Figure 4: Detection of Water bodies inside Granite quarries using MLC and SVM.

4.2 Accuracy Assessment Results

Classification accuracy results for MLC and SVM classification are presented in Table 2. The overall accuracy of MLC was 73% with kappa of 0.68 slightly lower than that obtained from SVM classification (78%; 0.73). Classification of Water bodies in MLC was confused with Granite quarries and Vegetation while SMV was better in separating water bodies from other classes. In SVM water bodies were confused with Other mines. Classification of Granite quarries was confused with Built-up land indicating that MLC was not effective in separating between the two land cover classes attributed to their similar spectral properties. SVM proved to be more effective in distinguishing Granite quarries from other land cover types. Using MLC, Exposed rock formation was misclassified with Built-up land and Vegetation while in SVM the Exposed rock formation was confused only with Built-up land. Both MLC and SVM classification performed poor in separating Built-up land from other classes. MLC classification confused Built-up land with Vegetation while SVM resulted in confusion with Granite quarries and to a lesser extent with Vegetation. Bare land was highly confused with Built-up land, Exposed rock formation and Vegetation in MLC classification while in SVM, it was highly misclassified as Exposed rock formation, Built-up land and Other mines. Both MLC and SVM performed poorly in separating Bare land from Exposed rock formation and Built-up land. In both SMV and MLC, Vegetation was largely confused with Exposed rock formation, Built-up land and Bare land and to a lesser extent with Granite quarries in SVM. In SVM, Other mines were confused with Granite quarries while in MLC it was confused with Water bodies, Granite quarries, Built-up land and Vegetation.

Table 2: Error matrix derived from MLC and SVM classification

			Reference Data								
		Method	**Wb**	**Gq**	**Erf**	**Bul**	**Bl**	**V**	**Om**	**Tot.**	**User's Accuracy (%)**
Classified Data	Water bodies (Wb)	MLC	63	4	0	1	0	5	3	76	82.9
		SVM	71	1	0	0	0	0	4	76	93.4
	Granite Quarries (Gq)	MLC	0	54	0	20	0	1	0	75	72.0
		SVM	0	74	0	0	0	0	1	75	98.7
	Exposed rock formation (Erf)	MLC	0	0	16	3	0	6	0	25	64.0
		SVM	0	0	24	1	0	0	0	25	96.0
	Built-up land (Bul)	MLC	0	1	0	45	0	9	0	55	81.8
		SVM	0	6	0	46	0	1	0	55	83.6
	Bare land (Bl)	MLC	0	0	12	11	59	13	0	95	62.1
		SVM	0	0	19	9	67	0	2	95	70.5
	Vegetation (V)	MLC	0	0	18	10	3	90	0	121	74.4
		SVM	0	3	28	15	4	70	1	121	57.5
	Other mines (OM)	MLC	4	7	0	9	0	6	59	85	69.4
		SVM	0	22	0	0	0	0	63	85	74.1
	Total (Tot)	MLC	67	66	46	99	62	130	62	386	
		SVM	71	106	71	71	71	70	71	415	
	Producer's Accuracy (%)	MLC	94.0	81.8	34.8	45.5	95.2	69.2	95.2		
		SVM	100	69.8	33.8	64.8	94.4	98.6	88.7		

MLC : Overall Accuracy =73%, Kappa =0.68
SVM : Accuracy Assessment 78%, Kappa = 0.73

5. Discussion

This study compared the utility of MLC and SVM in classification of granite quarries. The aim was to determine the technique with capabilities to separate quarries from other land cover types with similar spectral properties. The study area is populated by land cover types that are difficult to distinguish from each other due to spectral similarities. Results of classification showed that SVM was better at separating land cover types with similar reflectance. Granite quarries were well separated from other classes in SVM classification while in MLC, the quarries were confused with Built-up land. Similarly, SVM was effective in classifying Exposed rock formation and Built-up land compared to MLC. Bare land was confused with Exposed rock formation and Built-up land in both classifications. In the same way, Vegetation was confused with Exposed rock formation, Built-up land and Bare land in both classifications. Both SVM and MLC were not effective in separation of 'Other mines' from other land cover classes. The results of accuracy assessment derived from ML classification was slightly lower than that obtained from SVM classification. Overall accuracy for MLC was 73% with kappa coefficient of 0.68 while that of SVM was 78% with kappa of 0.73. Misclassification of small land cover types (i.e.: Water bodies, Built-up and Vegetation) was caused by pixel mixing due to medium spatial resolution (30 m) of Landsat data. Misclassification of classes such as Built-up land, Granite quarries, Other mines and Bare land was due to spectral similarities. Platinum and chrome mine tailings with high silica content reflected similar spectral properties with that of Granite quarries and hence resulted in misclassification. Misallocation of Water bodies as Vegetation was a result of algae in water while confusion between Granite quarries and Other mines was due to accumulation of silt and sand material (especially in water bodies) found inside mining areas and quarries. According to Lu and Weng (2007) and Phiri and Morgenroth (2017), MLC is associated with two major drawbacks in land cover classification; 1) data for highly heterogeneous land cover usually does not have a normal distribution; and 2) there is a lot of uncertainty associated with distribution of land cover surfaces which cannot be described based on data distribution. The SVM have been reported useful and effective in separating land cover types in heterogeneous landscape. This is because it does not base classification on a normality assumption or statistical parameters. The effectiveness of SVM in separating land cover features with similar spectral properties has been reported by other researchers. Mondal *et al*. (2012), compared the use of MLC and SVM in land use classification to evaluate classification accuracy between the two methods. The results of the study showed that SVM method provided better results than MLC. Karan *et al*. (2016), assessed accuracy of land use change detection using SVM and MLC techniques in open-cast coal mining areas. The results of their study similarly indicated that SVM provided greater overall classification accuracies compared to MLC. The technique also exceeded MLC in handling the challenge of classifying features with near similar spectral signatures.

6. Conclusion

The aim of this study was to compare MLC and SVM classification method for land cover classification in granite quarries. The results of classification and accuracy assessment evaluation indicated that SVM is better at classifying land cover types within the study area. Overall accuracy of SVM was 78% with a kappa of 76% slightly; this was higher than that of MLC with overall accuracy of 73% and kappa of 68%. Neither MLC nor SVM could overcome the problem of misclassification. Nevertheless, SVM proved better than MLC at distinguishing between land cover features with similar spectral properties in the study area Granite quarries, Built-up land, Other mines and Bare land. In addition, SVM classification was moderately better than MLC at detecting smaller Water bodies inside granite quarries.

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