Quantifying Land Cover Changes Caused by Granite Quarries from 1973-2015 using Landsat Data

Refilwe Moeletsi[1,2,*] and Solomon Tesfamichael[1]
[1]*Department of Geography, Environmental Management and Energy Studies, University of Johannesburg, Auckland Park, 2006, Johannesburg, South Africa*
[2]*Mintek, 200 Malibongwe Drive, Randburg, 212, South Africa*

Keywords: Remote Sensing, Land Cover Changes, Granite Quarries, Landsat, Supervised Classification.

Abstract: Environmental monitoring is an important aspect in sustainable development. The use of remote sensing in the mining industry has evolved significantly and allows for improved mapping and monitoring environmental impacts related to mining activities. The aim of this study was to measure land cover changes caused by granite quarrying activities located between Rustenburg and Brits towns, North West Province, South Africa using Landsat time series data. Landsat data used in the study were acquired in the years 1973, 1986, 1998 and 2015. Each image was classified using supervised classification and change detection was subsequently applied to measure land cover changes. Furthermore, the normalized difference vegetation index (NDVI) was used to highlight the dynamics in vegetation in the quarries. Accuracy assessment of the classification resulted in an overall accuracy and Kappa coefficient of 75% and 0.71, respectively. The results of post –classification change detection revealed a significant increase of 907.4 ha in granite quarries between 1973 and 2015. The expansion in granite quarries resulted in development of water bodies (2.07 ha) within the quarries. Correspondingly, there were significant losses in vegetation (782.1 ha) and bare land (119 ha). NDVI results showed variability in mean NDVI values within the digitized quarries. The overall mean NDVI values trends showed that most granite quarries had the highest vegetation in 1998, while the least vegetation cover was observed 1986.

1 INTRODUCTION

Land cover monitoring and management is an important concept in sustainable development (Demirel *et al.*, 2011). Increases in human-induced land use and land cover changes have called for the need to monitor and quantify environmental changes of such activities (Pierre and Sophie, 2016).

Mining activity is amongst anthropogenic factors that lead to environmental degradation. This activity has resulted in many organizations implementing systems aimed at monitoring and managing environmental impacts of surface mining operations (Latifovic, 2005; Demirel *et al.*, 2011). Monitoring activities that lead to environmental degradation requires continuous observations using automated techniques such as remote sensing (Günther *et al.*, 1995; Lein, 2014). In recent years, remotely sensed data have been applied in environmental management of mining operations and areas affected by mining (Paull *et al.*, 2006). Latifovic *et al.* (2005), used Landsat data to investigate land cover changes resulting from oil sands mining development. Duncan and Kuma (2009), assessed land use changes in an open pit gold mining. Similarly, Charou *et al.* (2010), used data acquired from Landsat, SPOT and ASTER satellites sensors to monitor impacts of mining on water resources and land use in Greece. Musa and Jiya (2011) investigated the impacts of tin mining on vegetation cover using Landsat data. Mouflis *et al.* (2008), conducted a study to investigate the impacts of marble quarry expansion using Landsat remotely sensed data. In the same way, Koruyan *et al.* (2012) employed ASTER and Landsat data to investigate impact of marble quarries expansion on vegetation.

Granite quarrying activity in South Africa started in Bon-Accord area, near Pretoria in the late 1930s. Since then, the quarrying industry increased drastically owing its expansion to improved mining technologies. Quarrying activity however, results in severe environmental impacts (Abu and Abdelall, 2014). Damage to biodiversity is the most common

Moeletsi, R. and Tesfamichael, S.
Quantifying Land Cover Changes Caused by Granite Quarries from 1973-2015 using Landsat Data.
DOI: 10.5220/0006675901960204
In *Proceedings of the 4th International Conference on Geographical Information Systems Theory, Applications and Management (GISTAM 2018)*, pages 196-204
ISBN: 978-989-758-294-3

environmental impact associated with quarrying activities (Lameed and Ayodele, 2011). Removal of vegetation, destruction of natural habitat and wetlands are some of the direct biological impacts caused by quarrying (Koppe, 1997). Quarrying activities can also have severe impacts on landscape patterns (Mouflis *et al.*, 2008), hydrological systems through sediments erosion (Gonzalez *et al.*, 2006), noise and air pollution through blasting and drilling (Jain, 2015). In the present study, we evaluated the effectiveness of remote sensing techniques in monitoring land cover changes within granite quarries between Brits and Rustenburg towns in the North West Province, South Africa. The objective of the study involves utilizing Landsat time series data over the period of 42 years (1973-2015) to assess land cover changes. Assessing and monitoring impacts of quarrying and mining on the environment is critical in achieving the goals of sustainable development.

2 STUDY AREA

The study area is located between two towns namely Rustenburg and Brits which are found in the North West Province, South African (Figure 1). The area was selected based on the geology and the known location of the granite quarries. The geology of the area is dominated by the rock of the Bushveld Igneous Complex (BIC) which constitutes the most voluminous mafic layered intrusion in the world (Cawthorn *et al.*, 2006). Granite deposits of interest to the study are found in the Main Zone of the Rustenburg Layered Suite of the BIC. The Main Zone comprises of a thick succession of norite and gabbro-norite, with minor anothorsite and pyroxenite layers (Nex *et al.*, 1998; Cawthorn *et al.*, 2006).

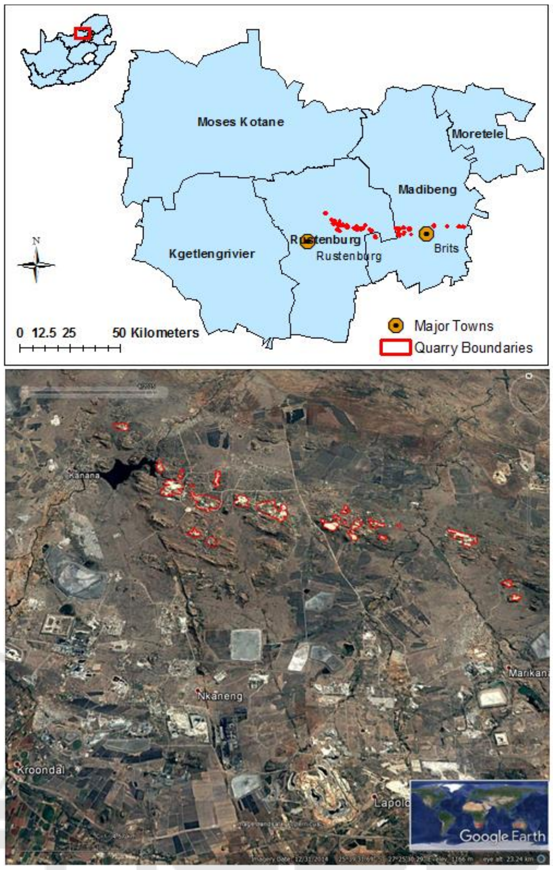

Figure 1: Location of study area and Google EarthTM image showing granite quarries and surrounding landscape.

3 METHODOLOGY

3.1 Sampling Design and Reference Data

Quarries were sampled based on their spatial coverage and the distance between them. A minimum distance of 200 m between the quarries and spatial coverage of 1 hectare were set out as a limit for quarries analysed in this study. This was to avoid overlap of samples and to enhance comparison with the spatial resolution of remotely sensed data. Consequently, forty quarries were selected for the study. The use of accurate reference data is essential to calibrate and evaluate land cover classification in remote sensing (Lillesand *et al.*, 2014). As a result, Google Earth^{TM} was used as a source of reference data for the study. The high spatial resolution offered by Google Earth^{TM} allows for easy discrimination of major natural land cover features as well as built environments, including houses, industrial facilities and roads. Granite quarries were located by using geographical coordinates of known granite quarries. The coordinates were overlain on Google Earth that aided digitizing process and were subsequently converted to shapefiles in ArcGIS® (ESRI 2016, ArcMap 10.4, Redlands, California, USA). Google Earth^{TM} images used for digitizing granite quarries were acquired in April 2015 corresponding with remotely sensed data used in the study. Google Earth was launched in 2005 (Potere, 2008) and therefore, digitization could not be done for dates earlier than that.

3.2 Data Acquisition

A series of Landsat data acquired from the United

States Geological Survey (https://earthexplorer.usgs.gov/) was used for this study. Landsat was preferred for this study due to the availability of historic dataset. In addition, several studies have shown the effectiveness of Landsat imagery in land cover mapping and monitoring of mining environments as discussed in the previous section. The list of Landsat data used in the study is given in Table 1.

Table 1: Landsat data used in the study.

Image dates	Sensor
10 March 1973	Landsat 1 Multispectral Scanner
18 May 1986	Landsat 5 Multispectral Scanner
16 March 1998	Landsat 5 Thematic Mapper
16 April 2015	Landsat 8 Operational Land Imager/Thematic Infrared Sensor

3.3 Processing and Analysis

3.3.1 Radiometric Calibration

The Landsat images were radiometrically calibrated using absolute calibration method. This method enables comparison of images acquired at different times from different sensors (Chander *et al.*, 2009). Data was calibrated by firstly converting the Digital Numbers (DNs) to at-sensor spectral radiance. The second step involved converting at-sensor spectral radiance to exoatmospheric Top of Atmosphere (TOA) reflectance using equations adopted from (Chander *et al.*, 2009).

3.3.2 Image Classification

Classification of multispectral images was achieved using supervised classification method. Supervised classification depends on the user to identify areas on the image that are known to belong to each land cover category. The most common algorithm used for supervised classification is the maximum likehood classifier (MLC) algorithm (Sun *et al.*, 2013) which was also used for this study.

3.3.3 Accuracy Assessment

Accuracy assessment is necessary to measure the degree of correctness in image classification (Foody, 2002). It is considered to be the most important step in land cover change detection studies (Congalton and Green, 2008). Error matrix was used to evaluate the classification accuracy. Error matrix is a square of array numbers set out in rows and columns which express the number of samples allocated to each land cover feature relative to reference data. Accuracy assessment in this study was evaluated using reference data obtained from Google Earth^{TM}. A random set of 189 points were overlaid on Google Earth^{TM}, the name of each class was then recorded using visual interpretation of features on Google Earth. The recorded class names in the reference data were then compared to classes generated from Landsat using supervised classification. An error matrix was then generated and subsequently, overall, producer's and user's accuracies were computed.

Kappa coefficient is a common technique used in accuracy assessment to measure the difference between the actual agreement and chance agreement in the error matrix (Congalton and Green, 2008). The results of kappa ranges from -1 to +1 where positive one indicates perfect agreement, zero indicates change agreement while a negative value indicates less than chance agreement (Fleiss and Cohen, 1973; Viera and Garrett, 2005).

3.3.4 Change Detection

In land use and land cover (LULC) investigations, the purpose of change detection is to detect and define location of changed areas when comparing images from different times and to measure the amount of change (Singh, 1989). There are various methods of change detection such as image differencing, image regression, vegetation index differencing, post classification comparison, image rationing etc. (Mas, 1999; Lu *et al.*, 2004). This study used post classification and normalized difference vegetation index change detection methods to evaluate land cover changes within granite quarries.

Post-classification

Post-classification technique involves classification of each of the images independently, followed by a comparison of the corresponding pixel labels to identify areas where change has occurred (Singh, 1989; Deer, 1995). Post-classification method was applied on the multispectral images to quantify land cover changes within the 40 digitized granite quarries.

Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index is a widely known index for measuring vegetation vigour from spectral data (Gandhi *et al.*, 2015). NDVI is defined as the ratio of the difference between the near-infrared band (NIR) and the red band, and the sum of these two bands (Tucker, 1979). NDVI is aimed at separating healthy green vegetation from all other features (such as soil moisture, man-made features and water) and therefore any feature with prominent vegetation would yield high NDVI value. Very low NDVI values (0.1 and below) correspond to barren areas, sand or snow. Moderate values represent land cover types such as shrubs and sparse grassland (0.2 to 0.3) (Lam et al. 2008; Pettorelli 2013; Gandhi et al. 2015) while high values indicate dense vegetation (0.6 to 0.8) (Jackson and Huete, 1991). Bare soil is represented with NDVI values close to 0 and water bodies are presented with negative NDVI values (Gandhi *et al.*, 2015).

4 RESULTS

4.1 Accuracy Assessment

Error matrix presented in Table 2 was completed only on imagery acquired in 2015 due to availability of reference data during the same time. The overall accuracy was 75% with a kappa coefficient of 0.71, while Water bodies had perfect producer's and user's accuracies. Bare land and Vegetation had good producer's accuracy (≥80%). Other mining showed relatively good producer's accuracy while Granite quarries had moderate producer's accuracy. Low producer's accuracy was obtained for Exposed rock formation and Built-up land due to misclassification with more classes. The result of low producer's accuracy in Exposed rock formation was due to being confused with Bare land and Built-up land while the results of low producer's accuracy in Built-up land was caused by confusion with Bare land. Granite quarries had very high user's accuracy and were confused with Other mining areas. User's accuracies obtained for Exposed rock formation, Vegetation and Other mining areas were relatively high (>80% in all cases). Built-up land had fairly good user's accuracy, however, this class was confused with Granite quarries, Exposed rock formation and Other mining areas. Bare land on the other hand resulted in the lowest user's accuracy due to confusions with Granite quarries, Exposed rock formation, Built-up land, Vegetation and Other mining areas.

4.2 Post Classification Change Detection

The results of classification of multi-temporal Landsat data are shown in Figure 2. In 1973, most areas were covered by Vegetation and Bare land, while relatively few areas were covered by Granite quarries in the south west part of the study area. Water bodies in the same year are observable by the dam located in the western part of the study area. Increases in Granite quarries and Bare land were observed in 1986. There was a corresponding decrease in Vegetation cover; however, the area indicated by the quarry boundaries in 1973 and 1986 were predominantly covered by Vegetation. The dam close to Granite quarries also decreased in size as compared to the year 1973. Exposed rock formations and Other mining areas started to appear in the south western part of the study area.

The year 1998 experienced a significant increase in Granite quarries, Other mining areas, Built-up land and Water bodies. On the other hand, there was a decrease in Bare land as compared to the year 1986; this land cover type is more dominant in the south western part in 1998 whereas it occurred mostly in the north and the eastern part of the study area in 1986.

The year 2015 saw an increase in Granite quarries with quarry lakes also developing in few Granite quarries. A decrease in Vegetation class is observed compared to 1998 especially in the southern part of the study area where it was mostly covered by Bare land. An increase in Built-up land is observed in the south western part of the study area. Water bodies saw an increase with an occurrence of water stream on the south eastern part of the study area.

4.2.1 Quantitative Measures of Land Cover

Area based comparison based on the forty digitized quarries was applied to Landsat data in order to measure land cover changes over the time period supported by acquired data (Table 3). The pattern in land cover types from 1973, 1986, 1998 to 2015 shows increases in Water bodies and Granite quarries, and decreases in Bare land as well as Vegetation. No Water bodies or quarry lakes were observed in 1973 and 1986 inside the quarries. Even though Water bodies were not clearly visible inside Granite quarries in the classified images due to map scale (Figure 2),

Table 2: Error matrix of classification derived from Landsat imagery taken in 2015.

		Reference Data								
		WB	GQ	ER	BUL	BL	V	OMA	Tot.	UA (%)
Classified Data	WB	10	0	0	0	0	0	0	10	100
	GQ	0	20	0	0	0	0	1	21	95
	ER	0	3	19	0	0	0	0	22	86
	BUL	0	2	2	19	0	0	3	26	73
	BL	0	1	9	11	24	3	4	52	46
	V	0	0	0	0	6	27	0	33	82
	OMA	0	3	0	0	0	0	22	25	88
	Tot.	10	29	30	30	30	30	30	141	
	PA (%)	100	69	63	63	80	90	73		
	Overall accuracy = 75%, Kappa = 0.71									

Key: WB=Water Bodies, GQ= Granite Quarries, ER= Exposed Rock Formations, BUL=Built-Up Land, BL=Bara Land, V=Vegetation, OM= Other Mining Areas, Tot. =Total, PA=Producer's Accuracy, UA= User's Accuracy.

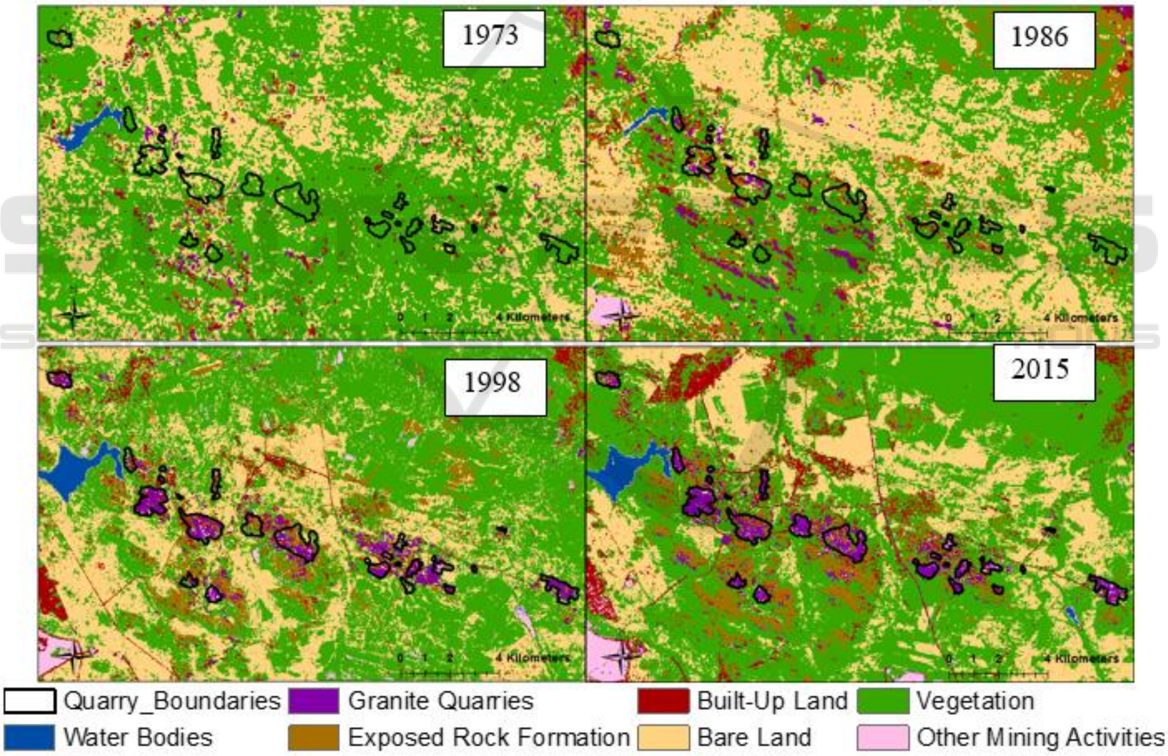

Figure 2: Land cover distributions created using supervised classification of Landsat images acquired in 1973, 1986, 1998 and 2015.

Table 3 shows that there was an increase in Water bodies within Granite quarries from 1973 to 2015. The increase in Granite quarries from 1973 and 2015 (3 ha to 910.4 ha) is significant. Bare land increased from 1973 to 1986, but decreased in 1998 and 2015. Vegetation cover inside granite quarry boundaries gradually decreased from the year 1973 to 2015. There was no change in Water bodies from 1973 to 1986, while the year 1998 and 2015 shows development and increase in Water bodies within Granite quarry boundaries. An increase in Granite quarries is observed from 1973 to 2015. The year

Table 3: Land cover change summary within granite quarries.

Classes	Area of classes (ha)				Difference (ha)		
	1973	*1986*	*1998*	*2015*	*1986-1973*	*1998-1986*	*2015-1998*
Water Bodies	0.0	0.0	0.2	2.07	0.0	0.2	1.9
Granite Quarries	3.0	70.2	433.5	910.4	67.2	363.3	476.9
Bare Land	121.7	130.0	19.2	2.7	8.2	-110.8	-16.5
Vegetation	1095.2	981.7	793.7	313.1	-113.5	-188.0	-480.6

1973 showed little quarrying activities, which increased in 1986, 1998 and 2015. The increases in quarrying activities resulted in decreases in bare land and vegetation over the same period.

4.3 Normalized Difference Vegetation Index

Normalized Difference Vegetation Index (NDVI) was computed to distinguish between amounts of vegetation in the study area. NDVI is aimed at separating healthy green vegetation from all other features (such as soil moisture, man-made features and water) and therefore any feature with prominent vegetation would yield high NDVI value. Figure 3 shows comparisons of mean NDVI values within digitized Granite quarry boundaries for the year 1973, 1986, 1998 and 2015 using Landsat data. High mean NDVI values are observed in the year 1998 indicating the presence of green vegetation. This was followed by the year 1973 and 2015 while the year 1986 displayed low mean NDVI values. Quarry No. 1 was sampled for closer statistical observation of changes in NDVI values over acquired time series data. Distribution of NDVI values in the quarry was categorised using the Natural Breaks (Jenks) classification approach. The statistical comparison of NDVI values was based on 322 pixels and was explored using frequency distribution graph (Figure 4). Data acquired in 1973 and 1986 was resampled to 30 m spatial resolution for consistent comparison. The graph shows that 95% and 79% of the pixels in the years 1973 and 1998, respectively, have NDVI values above 0.29 while the majority of pixels in the year 1986 and 2015 are distributed within NDVI values below 0.29.

5 DISCUSSION

The results of classification obtained from Landsat data revealed a substantial strength of agreement of classification with kappa of 0.71 and an overall classification accuracy of 75%. Producer’s accuracy showed that Water bodies were classified correctly. The error matrix however, showed a certain degree of confusion between classifications of some classes. Granite quarries, which is the main class of interest in this study, yielded moderate producer’s accuracy, and was mainly confused with Exposed rock formation, Built-up land, Bare land and Other mining areas due to similar spectral properties. User’s accuracy for Granite quarries showed that only one reference point was misclassified as other mining areas.

Distribution patterns of land cover within Granite quarries and surrounding areas using Landsat imagery revealed major changes in the land cover between 1973 and 2015. Land cover within digitized Granite quarries boundaries in the year 1973, before intense quarrying activity started, was predominantly covered by Vegetatation, Bare land, Exposed rock formation with minor occurrences in Granite quarries. Increase in granite quarrying activity in the years 1986, 1998 and 2015 revelead significant change in land cover within Granite quarries. The year 2015 revealed significant increase in water bodies within granite quarries which form as a result of expansion in quarries. There was also a significant loss of vegetation and bare land due to substantial increase in granite quarrying activity.

Comparison of mean NDVI values used to assess the presence or absence of vegetation cover within granite quarries revealed variability across all granite quarries over Landsat time series. The overall mean NDVI values trends showed that most granite quarries had the highest Vegetation in 1998, followed by 1973, 2015 and the year with least Vegetation

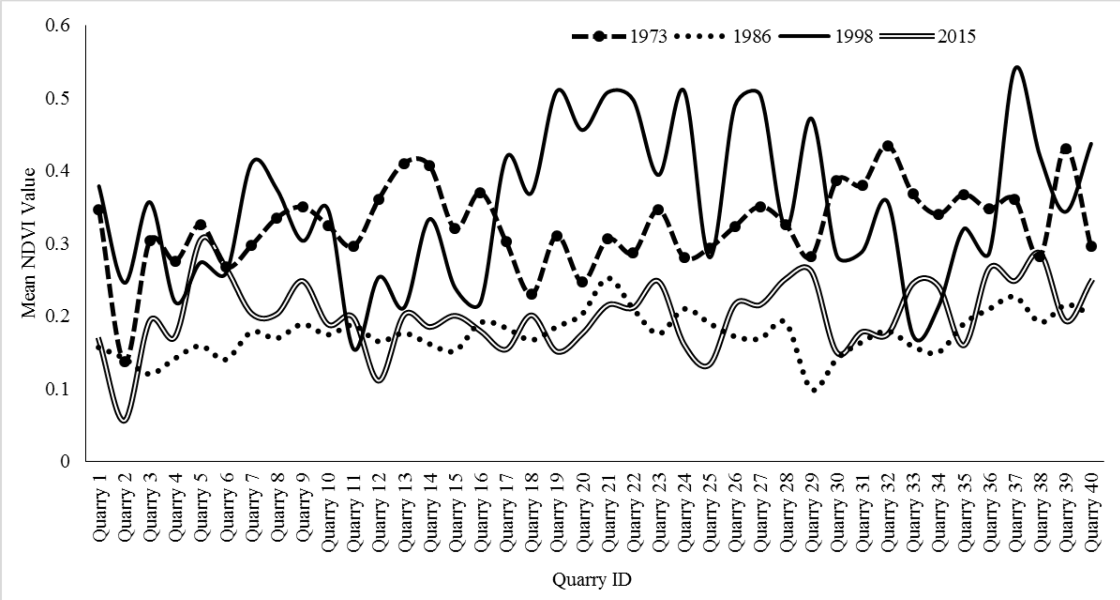

Figure 3: Comparison of mean NDVI values within digitized quarries.

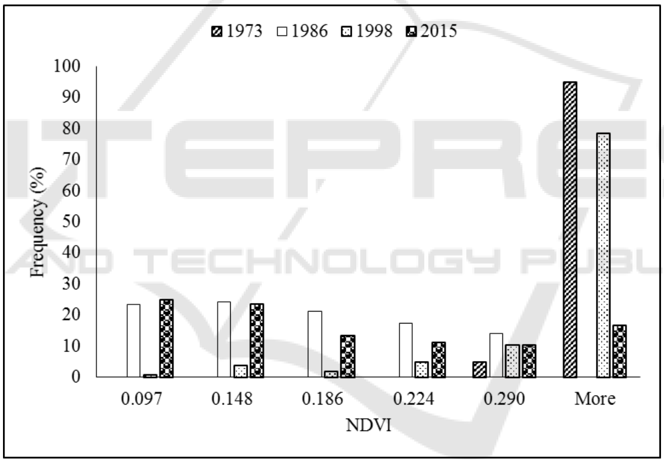

Figure 4: NDVI frequency distribution for the year 1973, 1986, 1998 and 2015 at 30 m spatial resolution.

cover was 1986. Analysis of NDVI pattern based on individual pixels within Quarry No. 1 over acquired time series data revealed that more pixels had high positive NDVI values in the year 1973 and 1998 indicating dominance of green Vegetation cover while the year 1986 and 2015 had more pixels with low NDVI values.

The results of this study showed the significance and the potential of Landsat data in mapping and monitoring land cover changes within granite quarries. The results of this study support other studies that have demonstrated the abilities of Landsat in monitoring quarry activities (Mouflis et al., 2008; Koruyan et al., 2012; Thakkar et al., 2017).

6 CONCLUSIONS

The aim of this study was to quantify land cover changes caused by Granite quarries located between Rustenburg and Brits, North West Province, South Africa. The use of Landsat data was chosen for this study due mainly to availability of archival data at no cost. The overall classification accuracy was 75% (kappa coefficient of 0.71). The study revealed a significant increase in Granite quarries from the year 1973 to 2015. Increase and expansion in Granite quarries resulted in an increase in accumulation of Water bodies within Granite quarries. There was also a substantial decrease in Vegetation and Bare land cover due to the quarrying activity. Although Landsat was able to measure land cover changes in the study area, there were misclassifications due to spectral similarities. Another limitation encountered during the study was inability of Landsat to detect small Water bodies within Granite quarries. Recommendations that can address these limitations in the future is the use of high spectral resolution data such as hyperspectral remote sensing which is able to distinguish between features with similar spectral properties. Another recommendation is the use of high spatial multispectral resolution data that is able to detect small features such as water bodies within granite quarries.

ACKNOWLEDGEMENTS

This study was sponsored by the University of Johannesburg and Mintek.

REFERENCES

Abu, A. and Abdelall, S. (2014) ‘Sustainable development of stone and marble sector in Palestine’, *Journal of Cleaner Production*, 84, pp. 581–588.

Cawthorn, G. ., Eales, H. ., Walraven, F., Uken, R. and Watkeys, M. . (2006) ‘The Bushveld Complex’, in Johnson, M. ., Anhaeusser, C. ., and Thomas, R. . (eds) *The Geology of South Africa*. Johannesburg: Geological Society of South Africa, pp. 261–281.

Chander, G., Markham, B. L. and Helder, D. L. (2009) ‘Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors’, *Remote Sensing of Environment*. Elsevier Inc., 113(5), pp. 893–903.

Charou, E., Stefouli, M., Dimitrakopoulos, D., Vasiliou, E. and Mavrantza, O. D. (2010) ‘Using remote sensing to assess impact of mining activities on land and water resources’, *Mine Water and the Environment*, 29(1), pp. 45–52.

Congalton, R. G. and Green, K. (2008) *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Second Edi. Boca Raton: CRC Press.

Deer, P. (1995) ‘Digital change detection techniques in remote sensing.’, p. 53.

Demirel, N., Emil, M. K. and Duzgun, H. S. (2011) ‘Surface coal mine area monitoring using multi-temporal high-resolution satellite imagery’, *International Journal of Coal Geology*. Elsevier B.V., 86(1), pp. 3–11.

Duncan, E. E. and Kuma, J. S. (2009) ‘Open pit mining and land use changes: An example from Bogosu-Prestea, South West Ghana’, *The Electronic Journal of Information Systems in Developing Countries*, 36(3), pp. 1–10.

Fleiss, J. F. and Cohen, J. (1973) ‘The equivalence of weighted kappa and the intraclass correlation coefficient as measure of reliability’, *Educational and Psychological Measurement*, 33, pp. 613–619.

Foody, G. M. (2002) ‘Status of land cover classification accuracy assessment’, *Remote Sensing of Environment*, 80(1), pp. 185–201.

Gandhi, G. M., Parthiban, S., Thummalu, N. and Christy, A. (2015) ‘Ndvi: Vegetation Change Detection Using Remote Sensing and Gis - A Case Study of Vellore District’, *Procedia Computer Science*. Elsevier Masson SAS, 57, pp. 1199–1210.

Gonzalez, E. P., Lopez, J. S., Martin, J. D., Burgos, A. J. and Agudo, J. P. (2006) ‘Analysis of the mobilization of solid loads and heavy metals in runoff waters from granite quarries’, *Environmental Geology*, 50(6), pp. 823–834.

Günther, O., Radermacher, F. J. and Riekert, W.-F. (1995) ‘Environmental Monitoring : Models , Methods , and Systems’, in *Environmental Informatics*. Netherlands: Springer, pp. 13–38.

Jackson, R. D. and Huete, A. R. (1991) ‘Interpreting vegetation indices’, *Preventive Veterinary Medicine*, 11, pp. 185–200.

Jain, P. K. (2015) ‘Environmental Degradation Due to Open Cast Mining Activities in Bundelkhand and Gwalior Region of M. P., India’, 4(3), pp. 725–731.

Koppe, J. C. (1997) ‘impacts and mining reclamation of ornamental stone quarries’, in Marinos, P. G., Koukis, G. C., Tsiambaos, G. C., and Stournaras, G. C. (eds) *Engineering Geology and the Environment*. Netherlands: CRC Press, pp. 2441–2446.

Koruyan, K., Deliormanli, a. H., Karaca, Z., Momayez, M., Lu, H. and Yalçin, E. (2012) ‘Remote sensing in management of mining land and proximate habitat’, *Journal of the Southern African Institute of Mining and Metallurgy*, 112(7), pp. 667–672.

Lam, N., Zhou, G. and Ju, W. (2008) ‘Relating Visual Changes in Images with Spatial Metrics’, in Yuan, M. and Hornsby, K. S. (eds) *Understanding Dynamics of Geographic Domains*. Boca Raton, London: CRC Press, pp. 115–132.

Lameed, G. and Ayodele, E. (2011) ‘Effect of quarrying activity on biodiversity: Case study of Ogbere site, Ogun State Nigeria’, *African Journal of Environmental Science and Technology*, 4(11), pp. 740–750.

Latifovic, R. (2005) *Satellite RemoteSensing in Assessing the Environmental Impactsof Large-Scale Surface Mining*. PhD Thesis, Department De Genie Des Mines, De La Metallurgie Et Des, Univerite Laval Quebec.

Latifovic, R., Fytas, K., Chen, J. and Paraszczak, J. (2005) ‘Assessing land cover change resulting from large surface mining development’, *International Journal of Applied Earth Observation and Geoinformation*, 7(1), pp. 29–48.

Lein, J. K. (2014) ‘Toward a remote sensing solution for regional sustainability assessment and monitoring’, *Sustainability (Switzerland)*, 6(4), pp. 2067–2086.

Lillesand, T., Kiefer, R. W. and Chipman, J. (2014) *Remote Sensing and Image Interpretation*. 7th edn. New York: John Wiley & Sons.

Lu, D., Mausel, P., Brondizio, E. and Moran, E. F. (2004) 'Change detection techniques', *International Journal of Remote Sensing*, 25(February), pp. 2365–2407.

Mas, J.-F. (1999) 'Monitoring land-cover changes: A comparison of change detection techniques', *International Journal of Remote Sensing*, 20(1), pp. 139–152.

Mouflis, G. D., Gitas, I. Z., Iliadou, S. and Mitri, G. H. (2008) 'Assessment of the visual impact of marble quarry expansion (1984-2000) on the landscape of Thasos island, NE Greece', *Landscape and Urban Planning*, 86(1), pp. 92–102.

Musa, H. D. and Jiya, S. N. (2011) 'An Assessment of Mining Activities Impact on Vegetation in Bukuru Jos Plateau State Nigeria Using Normalized Differential Vegetation Index (NDVI)', *Journal of Sustainable Development*, 4(6), pp. 150–159.

Nex, P. A., Kinnaird, J. A., Ingle, L. J., Van Der vyver, B. A. and Cawthorn, R. G. (1998) 'A new stratigraphy for the main zone of the Bushveld Complex, in the Rustenburg area', *South African Journal of Geology*, 101(3), pp. 215–223.

Paull, D., Banks, G., Ballard, C. and Gillieson, D. (2006) 'Monitoring the Environmental Impact of Mining in Remote Locations through Remotely Sensed Data', *Geocarto International*, 21(1), pp. 33–42.

Pettorelli, N. (2013) *The Normalized Difference Vegetation Index*. New York, USA: OUP Oxford.

Pierre, D. and Sophie, B. (2016) 'Revisiting Land-Cover Mapping Concepts', in Giri, C. P. (ed.) *Remote Sensing of Land Use and Land Cover: Principles and Applications*. Boca Raton: CRC Press, pp. 49–64.

Potere, D. (2008) 'Horizontal positional accuracy of google earth's high-resolution imagery archive', *Sensors*, 8(12), pp. 7973–7981.

Singh, A. (1989) 'Review Article Digital change detection techniques using remotely-sensed data', *International Journal of Remote Sensing*, 10(6), pp. 989–1003.

Sun, J., Yang, J., Zhang, C., Yun, W. and Qu, J. (2013) 'Automatic remotely sensed image classification in a grid environment based on the maximum likelihood method', *Mathematical and Computer Modelling*. Elsevier Ltd, 58(3–4), pp. 573–581.

Thakkar, A. K., Desai, V. R., Patel, A. and Potdar, M. B. (2017) 'Post-classification corrections in improving the classification of Land Use/Land Cover of arid region using RS and GIS: The case of Arjuni watershed, Gujarat, India', *Egyptian Journal of Remote Sensing and Space Science*. National Authority for Remote Sensing and Space Sciences, 20(1), pp. 79–89.

Tucker, C. J. (1979) 'Red and photographic infrared linear combinations for monitoring vegetation', *Remote Sensing of Environment*, 8(2), pp. 127–150.

Viera, A. J. and Garrett, J. M. (2005) 'Understanding Interobserver Agreement: The Kappa Statistic', *Family Medicine*, 37(5), pp. 360–363.