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Assessing Industrial Development Influence on Land use/Cover Drivers and Change Detection for West Bank East London, South Africa

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Abstract

South Africa's nationwide socio-economic industrial development zone drive focuses on alleviating of the apartheid social ills legacy. To ensure sustainable industrial ecological development, land-cover monitoring is needed though limited attention has been accorded. This study, aimed at assessing the influence of East London Industrial Development Zone (ELIDZ) on land-use/land-cover (LULC) drivers and detecting LULC changes for 15 years over the West Bank East London. An integration of remote sensing with qualitative approaches was adopted to provide robust temporal and spatial LULC change analysis. Object-based classification was performed on the satellite images for 1998, 2007 and 2013. Normalised Difference Vegetation Index (NDVI) and Normalised Difference Built-up Index (NDBI) complemented and validated observed land cover changes. The study reveals that industrial development has been a key driver for land-use changes in West Bank. The classification indicated that vegetation (5.97%) and bare land (-9.06%) classes had the highest percentage increase and decrease respectively. Water (0.02%) and bare land (-0.6%) classes had the lowest annual rate of change. Built-up and bare land classes varied considerably. An overall land-cover classification mean accuracy assessment of 97.24% and a mean Kappa coefficient of 0.95 were attained for the entire study period. This study offers the value of integrated methods in monitoring land-cover change to enhance informed decision-making especially in rapidly changing landscapes for conservation purposes.

Keywords: LULC, NDVI, NDBI, change detection, multi-technique, West Bank East London South Africa

INTRODUCTION

Industrialisation has been central in directly or indirectly influencing other land uses to alter the natural environment for subsistence purposes and of recent for commercial gains. The degree of freedom to change the land use pattern or to intensify land use is now governed by legal and administrative regulations, land ownership rights, socio-cultural conditions and natural restrictions arising from climate or edaphic conditions (Irwin and Geoghegan, 2001; Krausmann et al., 2003). These catalysed industrial-induced shifts in land use are responsible for the current land cover change. Globally, land use changes have led to a great decline in vegetative cover over the years (Goldewijk and Battjes, 2001). For example, China lost an estimated 1 million ha of cropland to infrastructure expansion between 1988 and 1995 (Seto et al., 2000).

Consequently, industrialisation's contribution to the pace, magnitude and spatial human alterations of the Earth's surface are unprecedented (Lambin et al., 2001). Industrialised land use change affects the global carbon cycle (Zaehle et al., 2007), contributes to local and regional climate change and global climate warming (Chase et al., 1999; Houghton et al., 1999), it impact directly on biotic diversity worldwide (Sala *et al*, 2000), as well as soil degradation (Tolba et al., 1992). The resultant impact of industrialisation is the alteration of ecosystem services that support human needs (Vitousek, 1994; Lambin et al., 2001; Ray and Foley, 2013). Such changes also influence the vulnerability of places and people to climatic, economic or socio-political perturbations (Kasperson et al., 1995; Lambin et al., 2001) and eventually it impoverish communities. In general, industrial LULC change is an important variable of global environmental change affecting both physical and chemical environmental aspects. Therefore, monitoring of industrialisation LULC changes is essential for sustainable industrial ecological development.

Over the past two decades, several parametric and non-parametric approaches for LULC change detection using satellite imagery have been formulated, adopted and verified in different studies (Mas, 1999; Lu et al., 2004; Lu and Weng, 2007; Otukei and Blaschke, 2010; Malahlela et al., 2014). The use of remote sensing and GIS has improved LULC mapping and change detection, providing advantages of frequent revisit, global coverage, and low cost (Zhang et al., 2003; He et al., 2011; Ishola et al., 2016; Orimoloye et al., 2018) as opposed to the traditional approaches (Adam et al., 2014; Malahlela et al., 2014). Monitoring and mapping of LULC has been done using SPOT (Huang and Siegert, 2006; Otunga et al., 2014), Landsat (Ramankutty et al., 2008; Otukei and Blaschke, 2010; Odindi et al., 2012), ASTER (French *et al*, 2008), MODIS (Stefanov and Netzband, 2005), RapidEye (Adam et al., 2014), and WorldView-2 (Malahlela et al., 2014). Interestingly, the Landsat heritage mission offers the possibility of mapping

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changes in LULC at the spatial scale that was otherwise not realised using MODIS data.

It is upon this premise that this study attempted to assess land cover configuration using Landsat multi-temporal data. The study sought to assess the use of multi-temporal remote sensing technology for understanding changes in South African spatial landscape which are notably different from other countries on the African continent (Odindi et al., 2012). For example, the South African urban landscape has developed on 'artificial' rather than 'natural' dimensions as predetermined by physical infrastructure, topography and geological factors (Mundia and Aniya, 2005) in order to deconstruct apartheid inequality legacies. Information regarding the potential drivers of such changes is lacking, particularly considering the geo-political stance of the pre-democratic South African era. Yet, the magnitude of change continues to be large (Lambin et al., 2011), poorly enumerated (IPCC, 2000), and characterised by land cover data shortages (Foody, 2002) which limits our knowledge of the LULC drivers and cover changes. Therefore, can impact of industrial development influence other land cover change drivers? In addition, can remote sensing reveal the spatial extent of post-1994 industrial development initiatives in redressing the South African apartheid legacies? Finally, are the different stakeholders aware of the impact of industrial development on West Bank?

Consequently, the study aimed at assessing the influence of East London Industrial Development Zone (ELIDZ) on LULC change drivers and detect the land cover changes over the West Bank East London area for 15 years. The study has the following objectives:

a. To assess the influence of industrialisation (ELIDZ) on other LULC change drivers, and people's recognition of these changes;
b. To map the spatial distribution of changed land cover type trajectories while detecting class changes, and
c. Finally, assess the accuracy for the change detection method.

To this end, the study adopted a mixed method in the analysis: documentary analysis, key informants' views and visual interpretation with remote sensing in the study analysis. This was because, Lu et al. (2004) called for timely and accurate change detection of the earth's surface features to provide the basis for a better understanding of the inter-relationships between human and natural phenomena in order to better manage and use the resources. Therefore, the analysis of the influence of industrial development on the environment and provided timely information about land cover changes in the phytoecological zone to enhance sustainable industrial development.

MATERIALS AND METHODS

Study Area

The West Bank area of East London is located in the Buffalo City Metropolitan Municipality (BCMM) of the Eastern Cape Province in SA (Figure 1). This is an area that forms part of a rich ecosystem adjacent to the Indian Ocean, with rivers such as the Igoda River and the Buffalo River. The area's biodiversity contributes tremendously to South Africa's rare, endemic and indigenous vegetation species. This is because of the area being one of the few phyto-ecological zones of the world. The Potter's Pass and Umtiza nature reserves are found in the area and these form part of the country's protected zones. On the other hand, the climate is characterised by mean annual surface temperature ranging from 17 °C to 20 °C, while the annual rainfall varies from 400 mm to 700 mm (BCMM, 2004). However, Kalumba *et al* (2013) has observed statistically significant increasing trends of maximum and minimum mean annual temperatures at 95% level for the 1975 - 2011 periods.

The West Bank is characterised by a mixed land use pattern with industrialisation and associated predominant activities affecting landscape dynamics. The ELIDZ was the first operational industrial development zone in South Africa (Marawu, 2012) under the country's industrial development programme. The industrial development zoning is intended to promote economic and social transformation to redresses apartheid legacies of unemployment, poverty and inequality. In West Bank, ELIDZ designation proposals started in 1998 and finally designated in 2002 (BCMM, 2004). Amidst all this, the area has about 40 buildings of historical and heritage significance (Tshani et al., 2005). Land in West Bank is owned by the BCMM, government entities like the Department of Public Works, Portnet, and Spoornet, as well as private individuals (BCMM, 2004). Currently, a section of the land is under restitution (Tshani et al., 2005; Walker, 2008) which is typical of apartheid legacies. In general, West Bank offered a regional, characteristically matchless setting for studying LULC change at both macro and micro scale in SA. This warranted exploration to extend the existing body of knowledge on LULC change. Moreover, despite a wealth of literature about LULC change drivers, information about the industrial influence on other drivers for land cover is still scanty.

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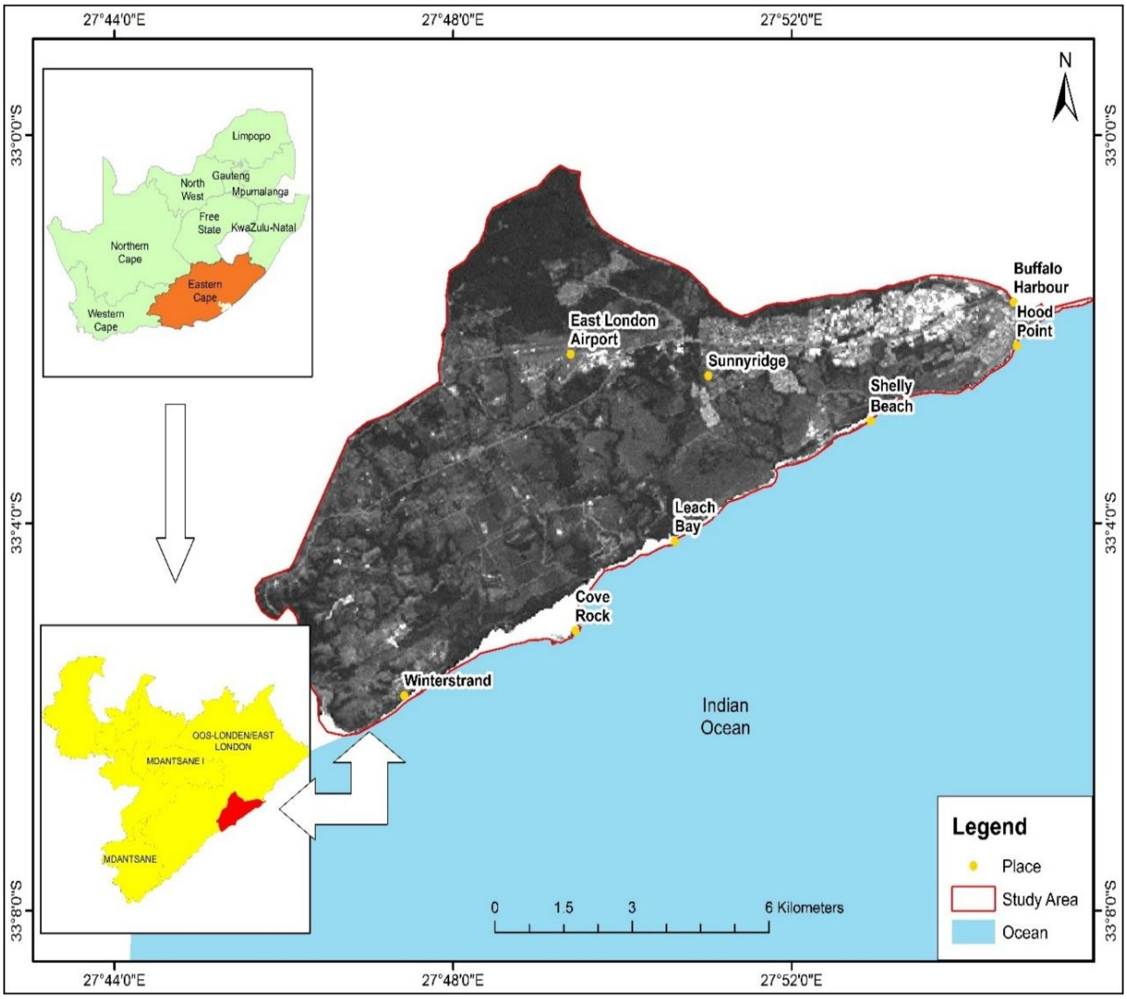

Figure 1: West Bank East London in the Buffalo City Metropolitan Municipality, Eastern Cape Province, South Africa

Data sets and Software

Multi-temporal Landsat imageries (1998, 2007 and 2013) were acquired from Global Land Cover Facility (http://glcfapp.glcf.umd.edu:8080/esdi/) and http://www.glovis.usgs.gov (Table 1) at the beginning and end of winter. These winter images were cloud free with no stripes and freely available for use. The South African National Land Cover map of 2000, 1998 aerial from the South African National Geospatial Information centre (NGI) and Google earth images (for 2007 and 2013) were also used in guiding the analysis.

ArcGIS 10.2 and ENVI 5.0 software were used in image processing and analysis. In addition, field observations and content analysis of the Integrated Development Plans, Environmental Impact Assessment reports and other BCMM documents were further sources of information. To counter the difficulties of interpreting historic image classification (Lu et al., 2004; Munyati and Kabanda, 2009) cognisance was paid to avoid satellite imagery deficits (Mas, 1999). As such images with similar climate seasonal attributes (Table 1) were selected for this study.

Table 1: Details of images used in the study analysis

(*TM means Thematic Mapper (Landsat 5); ETM+ means Enhanced Thematic Mapper Plus (Landsat 7) and OLI & TRIS mean Operational Land Imager and Thermal Infrared Sensor (Landsat 8) respectively*)

Image	Path/row	Acquisition date	Resolution	Sensor	Source
1	169/083	1998/08/09	30 x 30 m	TM	USGS
2	169/083	2007/08/18	30 x 30 m	ETM+	USGS
3	169/083	2013/05/30	30 x 30 m	OLI & TIRS	USGS

Analysis of Industrial Influence on LULC Drivers

To establish the influence of industrialisation on other LULC drivers, a dual-approach was adopted such as secondary data documentary analysis and in-situ data collection. To this end, Government documents and other published literature about BCMM and West Bank East London area in particular were explored to determine the influence of ELIDZ in the area. Furthermore, field observations were conducted in two phases: during August and September of 2013 and May of 2015. During fieldwork, photos were taken and 150 respondents asked to identify the applicable land use and vegetation changes attributed to ELIDZ in the West Bank area. The respondents constituted West Bank community residents, government officials, ELIDZ and industrialists outside the zoned area as key stakeholders.

Image Pre-Processing for Change Detection

The images were geometrically registered using the image to image registration technique (UTM projection, Zone 36S, WGS 84) for pixel harmonisation and land cover classification accuracy. In addition, layer stacking of all the bands before analysis was performed in ENVI 5.0, and subsequently all the image bands were assigned wavelength band centres. A quick atmospheric correction (QUAC) was performed in ENVI to enhance the appearance of features in the. Thereafter, the study area was clipped out in ArcGIS 10.2 for all the three images. The study images were selected based on these factors which are influenced by the climatic season.

Image Processing

Image processing was done to determine land use in the study area, which is, invariably, one of the primary land cover change determinants. Land cover change is defined as the transition of subsequence of a pixel's time series from one cluster to another cluster, after which it remains assigned to the second cluster for the remainder of the time series (Salmon et al., 2011). Change detection was premised on multidate spatial representation resulting from environmental conditions and human activities on multiple imagery dates (Odindi et al., 2012). The differences in reflectance values of land cover for change detection are influenced by changes in soil moisture, solar illumination and atmospheric conditions, as well as the time of image acquisition which affect change detection analysis (Singh, 1989; Mas, 1999). The study images were selected based on these factors which are influenced by the climatic season.

Accordingly, a false colour composite using 4, 3 and 2 image band combination for the 1998 and 2007 images, and 5, 4 and 3 for the 2013 image were performed to enhance image features (Figure 2). The displayed features were key descriptors for developing a land cover classification scheme as proposed by Alphan et al. (2009). The South African National Land Cover map legend (Table 2) was used in the four study classes' amalgamation and re-classification of vegetation, bare land, built-up area and water. In addition, 1998 aerial photography and Google earth images (for 2007 and 2013) were also used for visual inspection of land cover type classification accuracy. The general pattern of features on the images was used as a major basis for comparison between the higher resolution (aerial and Google earth) and the medium resolution Landsat images.

Table 2: Land cover class amalgamations and re-classification

SA NLC 2000 classes (*Fairbanks, et al., 2000, legend class definitions*)	**Re-classified land cover**
30 - 49	Built-up
15 - 17	Bare land
1 – 12 & 18 - 29	Vegetation
13 - 14	Water

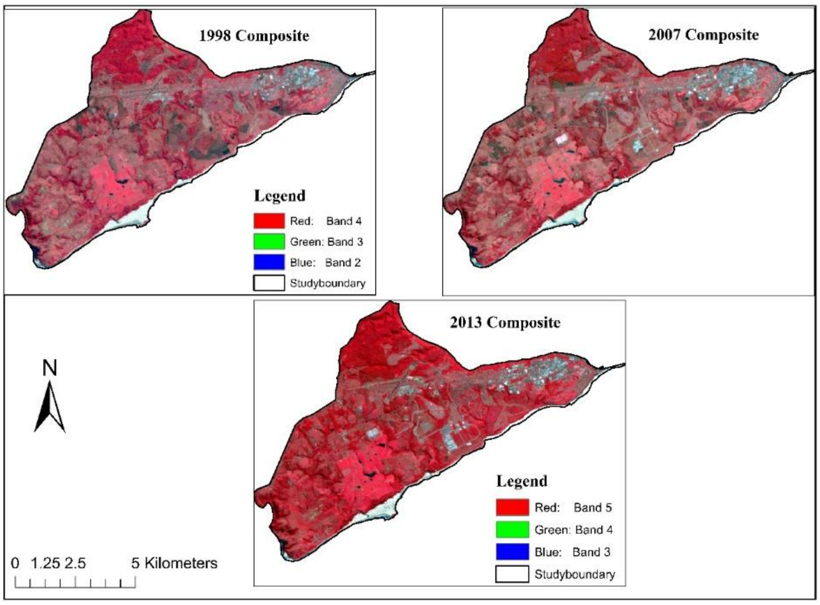

Figure 2: West Bank East London area composite images for 1998, 2007 and 2013

Object-based Classification (OBC), NDVI and NDBI

In order to make sense of the analysis, the OBC was tested. Object-based classification was employed due to its ability to remove salt-and-pepper effect common in pixel based classification (Campagnolo and Cerdeira, 2007; Blaschke, 2010). Object-based classification also reduces the computational time usually required for subsequent analysis, since the base processing targets are aggregated pixels and not individual pixels (Malahlela et al., 2014). Goa and Mas (2008) established that OBC produces thematic maps with higher accuracies than the traditional pixel based methods across the imagery resolution. To this end, OBC segments, regionalises and delineates homogeneous objects across the image. In general, a considerable number of empirical studies in peer-reviewed journals have provided sufficient proof for the object-based improvements over per-pixel analysis (Blaschke, 2010). For our study area the dominant land features are industrial structures, with defined shape and length. The use of OBC was designed to take into account of the various spatial structures, and is adequate for our study.

Therefore, false colour composite images were uploaded into ENVI to perform an OBC. An ENVI feature extraction module was used in image classification processing. Image segmentation was done using the edge and full lambda schedule algorithms, the segment settings were at a scale level of 25 and merge level of 90 respectively. This scale parameter was used in our study due to the size of the study area, and the morphology of individual objects. Texture kernel size was left at a default value of 3 x 3, and the composite image brightness and contrast was set at 50 and 30 respectively.

The class statistics were computed for the three images to determine the coverage area and percentages of the LULC. The extracted class regions of interest (ROI's) from the individual images were overlaid on an aerial photograph of 1998 for visual inspection. Also for the corresponding 2007 and 2013 image ROIs were visually compared with 2007 and 2013 Google earth images. The ROI layers were saved, exported as vector layers and later imported into ArcGIS to create LULC classification maps.

In addition, NDVI and NDBI indices for the three satellite images were computed to validate the observed changes in the OBC outputs. These indices are most widely applied for vegetation and built-up (buildings and bare surfaces) land cover analyses (Liu and Zhang, 2011) respectively. The choice of these indices was based on the need to demonstrate the differences in the spectral feature. Accordingly, negative NDVI values indicate water/tarred roads, while positive values near zero indicate bare soil and higher positive values of NDVI (0.1 to 0.5) indicates sparse to dense green vegetation (0.6 to 1). On the other hand, positive NDBI values indicate built-up and bare land. The equations (Liu and Zhang, 2011) below were used to compute these indices.

$$NDVI = \left[NIR - RED\right] / \left[NIR + RED\right] \quad (1)$$

Where: NIR = Near-Infrared (Band 4 for TM and band 5 for OLI & TIRS); RED = Red band (Band 3 for TM and band 4 for LCDM)

$$NDBI = \frac{[MIR - NIR]}{[MIR + NIR]} \quad (2)$$

Where:

MIR = medium Infra-Red (Band 5 for TM and band 6 for OLI & TIRS)

NIR = Near Infra-Red (Band 4 for TM and band 5 for OLI & TIRS)

(*Source: Liu and Zhang, 2011*)

Post-classification and Determination of LULC Change Trends

In several studies, post-classification is gaining increasing popularity (Odindi et al., 2012) in change detection analysis. In this case, post-classification method was also adopted to detect the LULC changes over West Bank by comparing multi-temporal images. Consequently, aspects such as the need to establish if change had occurred, and identifying and measuring the nature of class change to provide the spatial pattern of the detected LULC changes required consideration of change detection assessment. Therefore, the key pre-requisites for successful post-classification change detections are accurate image registration and classification (Munyati and Kabanda, 2009) as images were already radiometrically corrected (LT1). An ENVI change detection statistics module was used to compute the percentage land cover class statistics. A cross tabulation analysis was generated to determine the quantity of transformation from a particular LULC class to another. The percentage area change, the rate of change between 1998 and 2013, and the annual rate of change were computed to infer on the influence of industrial development on West Bank, East London area.

Accuracy assessment

Accuracy assessment is a standard process in LULC mapping (Foody, 2002; Congalton and Green, 2008; Odindi et al., 2012) and a criterion for a correct classification determination. Confusion error matrix technique is the most commonly used method for assessing the accuracy and reliability of classification results (LULC maps) (Lu et al., 2011), and was therefore adopted in this study. Food (2002) argues that a simple cross-tabulation of mapped class label against the sampled case observed reference data at specific points provides a foundation for accuracy assessment. In keeping with this, classification accuracy was performed using independent regions of interest (ROIs) randomly selected from the false colour composite images. In addition, selected ROIs for the different LULC class types were visually compared with the high resolution 1998 aerial photograph (1: 50000) and Google earth images using the historical function for the 2007 and 2013 years. This same approach was also used by Lidzhegu and Palamuleni (2012). The confusion matrix provided the basis for describing classification accuracy and to characterise the errors, and the most popular percentage of cases correctly allocated (overall accuracy) (Foody, 2002) was adopted.

Therefore, confusion matrix modular was used by inputting the ground truth ROIs into ENVI to perform accuracy assessment statistics. As recommended by Foody (2002), Kappa coefficient as a standard measure of agreement was adopted in this study.

RESULTS

Industrial (ELIDZ) Influence on LULC Drivers

The results of our study showed that the industrial development in the study area influenced other drivers of LULC changes. These included the following: policy adherence, population growth, land invasions and economic and infrastructural developments which were particular to the West Bank case. These drivers are manifested by changes in the spatial configuration of landscape from 1998 to 2013 characterised with paving, vegetation conservation and removal during construction among others (See Plate 1).

The East London Industrial Development Zone revitalised industrialisation in the area and thus influenced numerous land use policies. For instance, the spatial planning and land use management is currently implementation and enforced under clause 26 (e) of the Municipal Systems Act (32) of 2000 to ensure proper development planning in West Bank. In addition, industrial development was subjected to an environmental impact assessment as per the National Environmental Management Act (107 of 1998, and as amended in 2013) and Integrated Coastal Zone Management Plan (ICZMP) (BCMM ICZMP, 2005) to reduce the possible development and operation impact onto the West Bank environment.

In keeping with ELIDZ establishment, the BCMM was motivated to implement other spatial development initiatives (SDIs) and local economic development (LED) projects to provide services to the industrial zone and for the growing population in the area. These included improved service delivery (roads, water and electricity) and socio-economic development which redefined West Bank's landscape and land cover changes. For instance, in 2006/2007 financial year, out of the R2.1bn development budget, R150m was allocated to housing to clear the backlog housing provision (Mabindla, 2006a). In addition, East London airport was upgraded with R60m over two years (2007/2008) (Mabindla, 2006b) and East London harbour upgraded (Mabindla, 2006 a, c). The establishment of ELIDZ also created anticipation of economic prospect as some residential houses were converted into lodges.

Plate 1: Typical example of ELIDZ influence on LULC changes in the area (Courtesy of ELIDZ, 2013)

In addition, the establishment of ELIDZ influenced people to migrate into West Bank and BCMM area in search of employment and service delivery. Stats SA census data (2011) revealed that BCMM population grew by 0.6% for the 1996 – 2001 period and by 0.7% for the 2001 – 2011 period. Interlinked with ELIDZ, is the land invasion which continues to manifest itself in West Bank. For example, 'upper class' houses continue to be built on Bongweni farm Department of Public Work's land (Daily Dispatch newspaper, 2013) while the Orange Grove informal settlement continues to encroach onto the East London airport land. Other registered resultant effects of industrial development were observed during fieldwork as depicted in Plates 2 and 3 respectively.

Plate 2: Typical effects of ELIDZ in form of bush burning from the shanty shelters erected opposite the Potter's Pass Nature Reserve by the homeless people

Plate 3: Typical ELIDZ influence on the area dynamics in form of rubbish dumping and road closure in a section of the Potter's Pass Nature Reserve

Furthermore, due to ELIDZ establishment, the West Bank area was transformed into a global export-oriented zone of SA. More industries (26 companies) have relocated and now operate in the zone (ELIDZ 2013/2014 annual review) (ELIDZ, 2014) while other industries are opening up in West Bank. Due to this, numerous benefits in terms of coastal node tourism resort growth especially around the Cove Rock area and land selling have been registered (Plate 4).

Plate 4: Typical ELIDZ influence on area rezoning and Cove Rock plot selling

Finally, the responses from the 150 informants revealed that the influence of ELIDZ on land use changes in West Bank are predominated by industrial (130) and settlement (95) activities. These had impact on vegetation in terms of vegetation loss (99), species composition (68) and leaf pigment (67) as observed vegetation changes in the area (Figure 3). Added to this, field observations revealed that ELIDZ has managed and even eradicated invasive vegetation species in West Bank. This was done at both zone level and the entire West Bank (Plate 5). In addition, vegetation corridors for conservation and preservation of rare and indigenous plant species were observed during fieldwork in the ELIDZ area as shown already in Plate 1. Outside the zone, the Potters Pass and Umtiza nature reserves are being closely monitored by increased patrols to ensure vegetation protection.

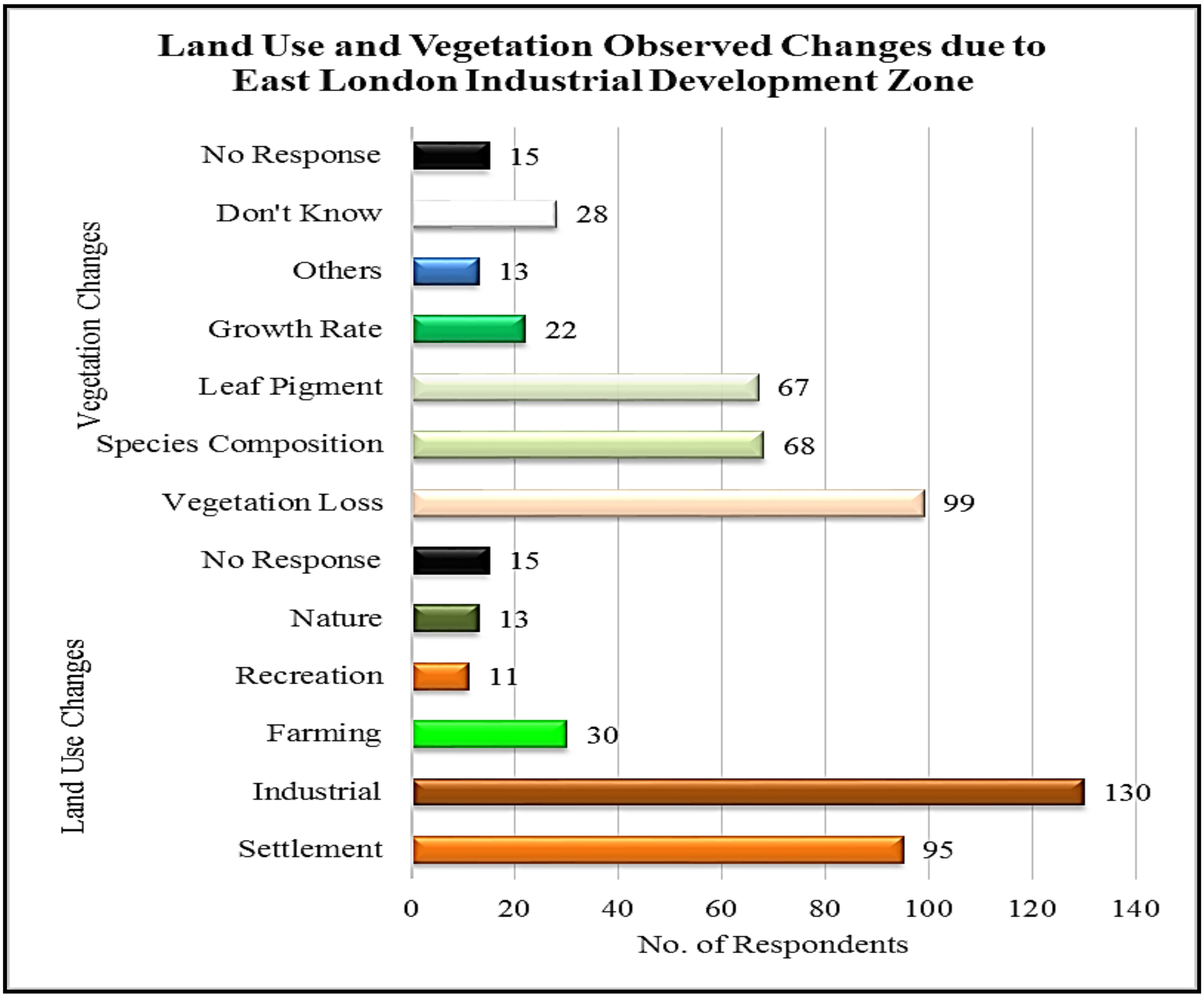

Figure 3: Respondents observations of ELIDZ's influence on Land use and Vegetation Changes

Plate 5: Typical of invasive plant species eradication management control by ELIDZ and BCMM

Classification (object-based)

Industrial development has influenced the West Bank mixed land use mixed pattern leading to land cover changes. From the classification results, vegetation and built-up areas have increased over the years (1998 to 2013) (Figure 4). Cross tabulation temporal land-over class conversion statistics results are presented in Tables 3 and 4. Accordingly, the 1998 – 2013 period revealed that the vegetation class witnessed an increase of 5.97% at an annual rate of change of 0.4%, built-up and water classes also increased (2.76% and 0.33%) at an annual rate of change (0.18 and 0.02%) respectively. In 2007, 75% of the class decline was recorded (vegetation, water and bare land), while 50% of class increase for vegetation and water was registered for 2013.

Table 3: Percentage (%) land cover class pixel statistics for the 1998 – 2013 period

LULC	1998	2007	2013
Vegetation (Veg)	59.78%	58.17%	65.75%
Built-Up (Bu)	27.3%	35.98%	30.06%
Water (Wa)	1.94%	1.92%	2.27%
Bare land (Bl)	10.98%	3.93%	1.92%

Further analysis of class change detection involved a tabular comparison of different classification image pixels percentages (%) from 1998 – 2007 and 2007 – 2013 as presented in Table 4. The percentage pixels along the major diagonal of the matrices shows a specific class per the exact class change dynamics for the compared year (Nori et al., 2008). Considering 1998 as the base year for 2007, the study reveals that: 22.4% of the vegetation was converted into built-up, 32.7% of water areas were colonised by vegetation, and close to half (42.12% and 41.6%) of the bare land and built-up changed to vegetation respectively. For the period, 2007 – 2013, less than a quarter (10.1%) of the vegetation was transformed into built-up, while more than one-third (33.6%) of the built-up, 14.3% of water and more than half the bare land were converted into vegetation (Table 4). The rest of the changes were very minimal and varied across classes.

Table 4: Comparison of classification change detection relative to the number of percent pixels for 1998 – 2007, and 2007 – 2013 (basis: all image pixels)

		Classification 1998				
		Veg	Bu	Wa	Bl	∑
Classification 2007	Veg	**74.3**	30.8	32.7	42.12	100
	Bu	22.4	**66.6**	1.8	41.6	100
	Wa	0.8	0.4	**63.5**	0.4	100
	Bl	2.5	2.1	1.9	**15.8**	100
	∑	100	100	100	100	
		Classification 2007				
		Veg	Bu	Wa	Bl	∑
Classification 2013	Veg	**88.1**	33.6	14.3	50.5	100
	Bu	10.1	**65.8**	4.3	7.8	100
	Wa	1.2	0.2	**73.9**	1.3	100
	Bl	0.4	0.4	2.7	**38.3**	100
	∑	100	100	100	100	

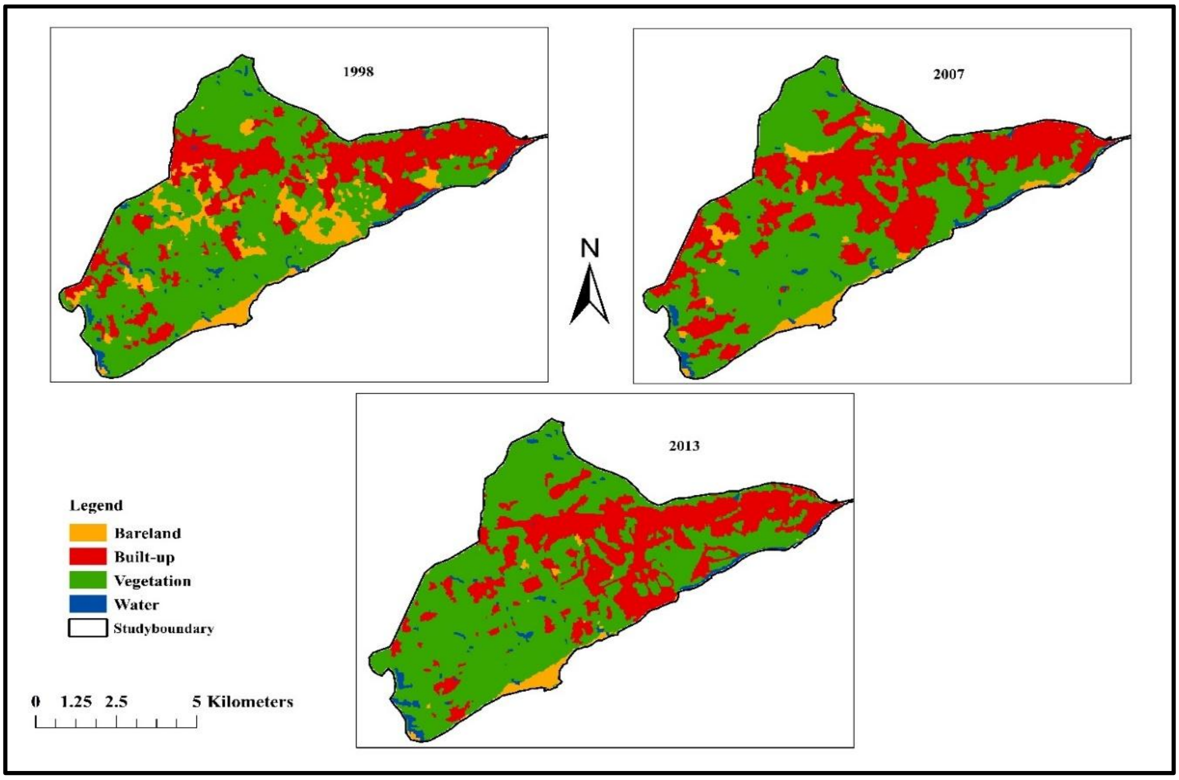

Figure 4: Spatial distributions of changed trajectories for land cover types

Image differencing (NDVI, NDBI)

Both NDVI and NDBI (Figure 4) for the study area also depict a varying trend in maximum, minimum and mean values. Overall, 2013 depicts the lowest NDVI with maximum (0.543), minimum (-0.199) and a mean (0.246). This situation is also depicted in the 2013 NDBI with maximum (0.194), minimum (-0.414) and mean (-0.135). This could imply that the vegetation experienced a lot of stress.

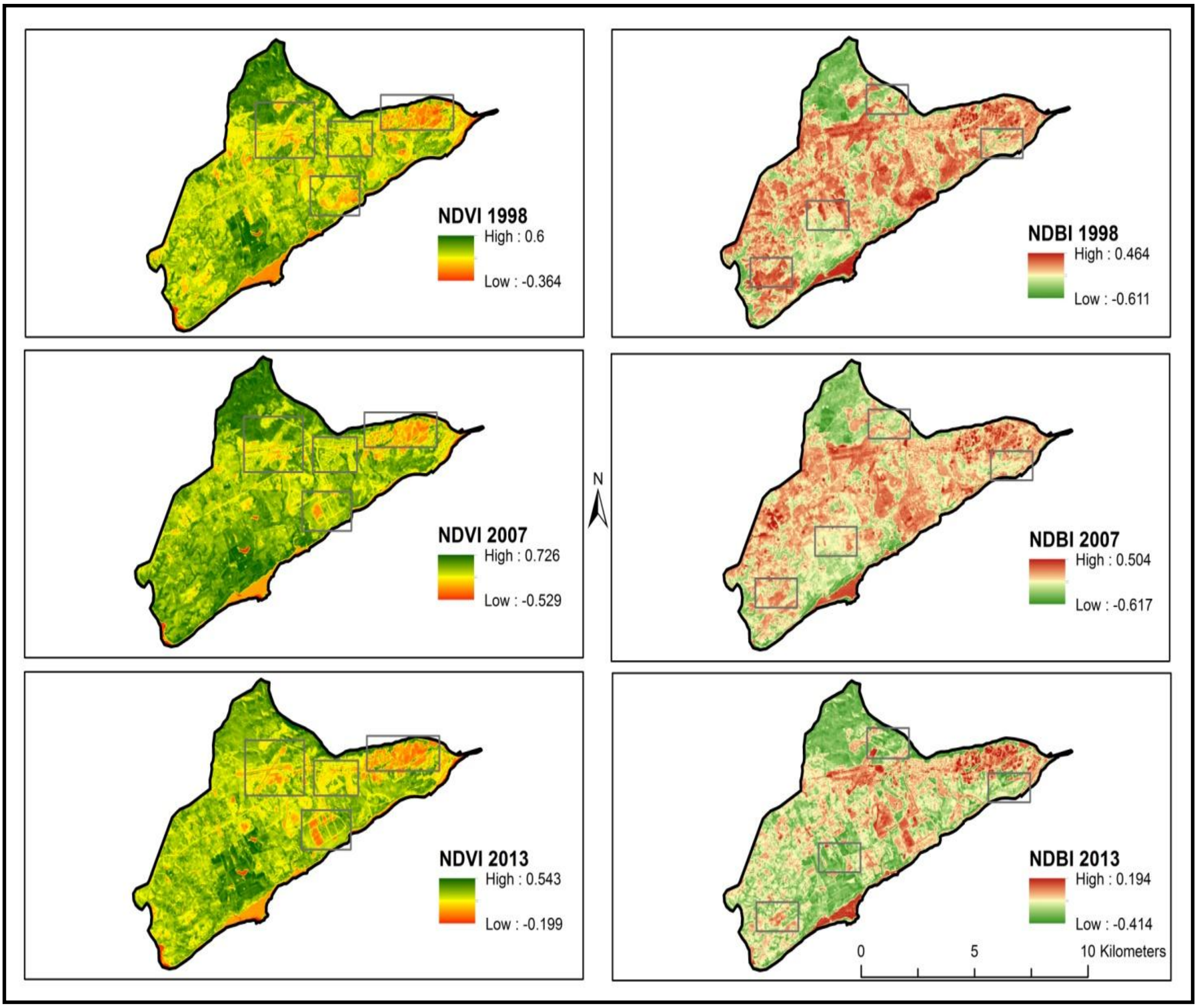

Figure 5: Depicting observed changes based on NDVI and NDBI for 1998 to 2013 period

Accuracy assessment

The overall accuracy and Kappa coefficient for the OBC classified imagery provides the accuracy and the reliability of the results. Table 5 provides 1998, 2007 and 2013 land cover classification class accuracies. For the 1998 classification results, the overall accuracy of 97.94% and Kappa Coefficient = 0.97, implies that the spectral contrast of the polygons made it easy in image class selection. The accuracy assessment for the 2007 classification image yielded an overall accuracy of 94.71%, with a Kappa Coefficient = 0.91. Accordingly, both the users' and producers' accuracies range between 93.29 to 100%, except for the producers of the bare land whose accuracy that was very low at 65.02%. In 2013, overall accuracy assessment was 99.07% with a Kappa Coefficient = 0.98. In addition, in 2013, users' accuracies (UA) were the same on average, ranging between 98.45% (vegetation) to 99.4% (built-up), while producer's accuracies (PA) were between 93.67% (water) and 99.82% (vegetation). Overall, the 2013 class image registered the highest user's mean accuracy (98.78%) and the lowest being in 2007 (97.21%) (Table 5). However, the highest producer's mean accuracy was recorded in 1998 (97.96%) and the lowest being witnessed in 2007 (90.46%) (Table 5).

Table 5: Accuracy Assessment for 1998, 2007 and 2013 Image Classification

Classified data 1998	Vegetation	Built-up	Water	Bare land	Total	UA (%)
Vegetation	400	2	1	0	403	99.26
Built-up	15	180	0	0	195	92.31
Water	0	0	28	0	28	100.00
Bare land	0	0	0	249	249	100.00
Total	415	182	29	249	875	
PA (%)	96.39	98.90	96.55	100.00		
Overall Accuracy = 97.94%, Kappa Coefficient = 0.97						
Classified data 2007	**Vegetation**	**Built-up**	**Water**	**Bare land**	**Total**	**UA (%)**
Vegetation	1015	2	0	71	1088	93.29
Built-up	30	642	0	0	672	95.54
Water	0	0	56	0	56	100.00
Bare land	0	0	0	132	132	100.00
Total	1045	644	56	203	1948	
PA (%)	97.13	99.69	100.00	65.02		
Overall Accuracy = 94.71%, Kappa Coefficient = 0.91						
Classified data 2013	**Vegetation**	**Built-up**	**Water**	**Bare land**	**Total**	**UA (%)**
Vegetation	2224	22	10	3	2259	98.45
Built-up	4	4391	0	20	4415	99.46
Water	0	2	148	0	150	98.67
Bare land	0	6	0	407	413	98.55
Total	2228	4421	158	403	7237	
PA (%)	99.82	99.32	93.67	94.65		
Overall Accuracy = 99.07% , Kappa Coefficient = 0.98						

DISCUSSIONS

LULC Drivers

This study provides insights into the influence of industrial development zones on specific LULC change drivers underpinned by the post-apartheid policy and socio-economic dynamics. From the content analysis, fieldwork and remote sensing data, it was evident that the East London Industrial Development Zone (ELIDZ) in South Africa had considerable influence on vegetation dynamics and conservation, the development of new settlements and expansion of Orange Grove informal settlement over the years. This is attributed to the influx of people anticipating to find a job in the zone. This implies that industrial development has a huge multiplier effect on both proximate and non-proximate drivers of LULC changes. To this end, industrialisation practically affects every region and sector of the entire environment.

Therefore, increasing population in the region is explained by migration from the hinterland in search of jobs and better services. A notable case of this effect, was the housing project (*Amagelelo ambovu*) at Leaches Bay developed by the BCMM, in partnership with the ELIDZ, and a planned mixed-development for Tsholomnqa (Getnews, 2013). The improved service delivery boosted socio-economic development in the area (Mabindla, 2006a). In this way, the Leaches Bay housing project resonates with the observation by Pillay and Sebake (2008) that post-1994 government has focused on formalising informal settlements across South Africa. This is an initiative for redressing apartheid legacies. In this case, ELIDZ played a central role in the formalisation of the Leaches Bay settlement.

On the other hand, the increasing unemployment in the Eastern Cape Province and the entrenched effects of apartheid on West Bank's hinterland will motivate more people to migrate into this area in search for jobs and better services. This would imply increasing demand for houses, services, firewood, poles and land invasions which poses serious threats to the conserved vegetation and the environment in general. Therefore, this could affect the entire area ecosystem functioning. Accordingly, Lidzhegu and Palamuleni (2012) established that population increase in Makotopong village increased demand for food, shelter, energy and construction materials which led to a decrease in woody areas. Invariably, this could be a resultant factor in West Bank if the situation is not abated. Therefore, the attraction of the foreign direct investments (FDIs) in the form of industrial land use change has influenced landscape dynamics, urban growth aspirations and rural-urban population dynamics (Lambin and Geist, 2007) for West Bank and its hinterland since 1998 to date. These industrial developments are created in a bid to fulfil and meet government's ambitions of economic growth and regional balanced development to redress apartheid legacies.

Image Classification, Differencing and Accuracy

ELIDZ has caused an increase in permanent structures (industrial units, houses and road networks) and a shift in land use thus resulting in land cover change. For instance, the decrease in bare-land class cover over the years at -9.06% and with a -0.6% annual rate of change, implies that a large portion of previously bare-land is now covered by other classes especially vegetation, while industrial development and the expansion of the Orange Grove informal settlement could account for the increase in built-up area of 2.76% in West Bank. Similar findings were revealed by, Liu et al. (2010) who observed that in China built-up areas expanded due to national macro-land use strategy, rapid socio-economic development and urbanisation. Therefore, our study results highlight parallel trends with Liu et al. (2000) with a tangent on industrial development zoning (IDZ) in South African government development strategy. Also, the 8.68% increase in the built-up area, and decrease in bare land (7.05%) between 1998 and 2007, was due to the massive construction of industrial units and associated temporary structures used for the storing construction equipment. This study finding is in line with Odindi et al. (2012) and Ludzhegu and Palamuleni (2012) Port Elizabeth and Makotopong village, South African cases' registered findings. Also a similar trend of expansion has been observed elsewhere in the world e.g. Kagera basin (Wasige et al., 2003) and South-East Transylvania in Romania (Vorovencii, 2013) although at different scales.

In addition, the decline in vegetation (1.61%) for the same period was due to the area vegetation clearance which exposed remnants of old buildings and erection of informal structures. On the other hand, Madindla (2006b and c) observed that West Bank East London airport and harbour were upgraded to boost economic growth with construction work extending to 2007. The variation witnessed across the years among the built-up and bare land classes is a clear manifestation of industrial influence on West Bank's land cover changes. For instance, the decline in built-up class between 2007 and 2013 could indicate that temporary construction structures erected between 2004 and 2007 were demolished. In addition, field observations revealed that a temporary tar road above the race track next to the Potter's Pass nature reserve was closed. Furthermore, buildings in the same area along the coastline were vandalised and slowly disintegrating. There were also some abandoned farm units for sale especially, to industrialists or expansion of the ELIDZ. Furthermore, curtailing of activities and patrol of the nature reserve areas (Potter's Pass and Umtiza nature reserve) bolstered area vegetation conservation. In addition, the efforts to eradicate invasive species from both the ELIDZ and BCMM could also explain the increase in the vegetation class which contradicts with the existing literature. All these could have created more room for vegetation area colonisation which could account for the observed increase in the vegetation class.

Object based feature extraction capabilities were robust in merging pixels with the spectral features representing a particular class. This was portrayed in both high user and producers accuracies above 90%. The classes with 90% and above of either user or producers indicates that the sample data appeared very well and could easily be separated from other classes for the entire study period as per the different years. Therefore, these results were above the recommended target accuracy of 85% (Foody, 2000). In general, the lowest registered users' and producers' accuracies were in built-up (92.31%) and vegetation (96.36%) respectively. This could be attributed to the pixel classification mixing and the nature of the relief which made it difficult to select the spectral features for this class across the study area.

LIMITATIONS OF THE STUDY

The observed spectral confusion in the classification of land cover types is not only limited to this study, as several other authors such as Nori et al. (2008), Ludzhegu and Palamuleni (2012) and Odindi et al. (2012) among others have encountered a similar mixed pixel challenges in their LULC change classification. To this end, high resolution imageries could have addressed the above challenge but there were no resources to secure them. Despite these limitations of the study, the results are paramount in offering an understanding about the industrial development zone's influence on the micro LULC changes and the entire environmental ecosystem.

CONCLUSION

This study offered insights of IDZs influence on accelerating other drivers of LULC changes on the physical environment. For instance, ELIDZ influenced land cover changes especially through revitalising manufacturing operations in West Bank and redressing of apartheid legacies. In addition, this study showed the importance of integrating of GIS and remote sensing, with documentary analysis and field work in monitoring post-apartheid LULC changes. An overall mean accuracy assessment of 97.24% and a mean Kappa coefficient of 0.95 for the entire study period was proof for the object-based classification robustness. An increase in the vegetation class could be explained by invasive species area colonisation, although the NDVI results indicated that vegetation experienced environmental stress. The vegetation increase results contrast with the South African LULC literature thus highlighting the importance of continued land cover change monitoring. Therefore, this study is useful in helping to develop early warning systems or remedial solutions to address invasive vegetation species colonisation as a form of environmental degradation.

However, there is a need to curb land invasions, the expansion of the Orange Grove informal settlement, and illegal settlements (few shanty structures) observed during fieldwork to prevent vegetation degradation and the associated environmental carbon footprints as the ecological effects of land cover conversion could lead to changes in soil and water quality, soil erosion, biodiversity loss and habitat availability

(Wasige et al., 2013). Consequently, these could have multiple negative socio-economic and health effects on human beings.

Therefore, future studies should consider establishing the influence of the industrial development on the chemical composition of soil, vegetation and species composition to establish the environmental quality of the West Bank area.

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COMPETING INTERESTS

The authors declare that they have no competing interests.

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