Remote sensing land-cover change in Port Elizabeth during South Africa's democratic transition

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Urban population increase has caused significant urban landscape transformation globally. Before 1994, South Africa's highly regulated urban growth was shaped by the restrictive Prevention of Illegal Squatters Act of 1951. After the abolishment of the act in the 1980s, the period of transition to democracy in the 1990s was characterised by an unprecedented urban population influx that caused a myriad of socio-economic and environmental challenges. These challenges have consequently compounded the need to monitor urban growth for the planning and optimisation of urban spaces. The limitations of traditional mapping methods, such as surveying and photogrammetry, in urban mapping are well documented. In the recent past, satellite remote sensing has emerged as one of the most viable urban mapping tools. Using post-classification comparisons, we sought to monitor major land use and land cover (LULC) changes in the city of Port Elizabeth during South Africa's democratic transition (1990–2000). Images for 1990, 1995 and 2000 were acquired, geo-rectified and atmospherically corrected. An iterative self-organising data analysis (ISODATA) was then used to generate existing LULCs. Classes generated using ISODATA were then amalgamated to the city's major LULCs and resultant classes were validated using aerial photographs and field visits. Results showed that 'Built-up' and 'Bare surface' LULC classes had the highest increase and decrease, respectively. There was no change in the 'Beach or dune' LULC, whereas 'Green vegetation' and 'Water' classes had minimal changes. This study illustrates the efficacy of remote sensing in monitoring urban change and the potential of remote sensing to aid decision-making in rapidly changing urban landscapes.

Introduction

Globally, there have recently been unprecedented increases in the concentration of the population in cities, which have led to rapid urban landscape transformations. These transformations are often characterised by diverse biophysical and socio-economic processes related to the conversion of nonurban to urban lands and the resultant landscape heterogeneity.[1,2,3] Recent studies have shown that over 50% of the global human population resides in urban areas.[4,5] According to Montgomery and Hewett[6], the highest rates of urbanisation and its related spatial landscape changes are expected in developing countries. In sub-Saharan Africa for instance, urban population grew from 15% in the 1950s to 32% in the 1990s. By 2030 it is projected that 54% – 60% of the sub-Saharan population will live in urban areas.[5]

South Africa's urbanisation and urban landscape changes are markedly different from other countries on the African continent.[7,8] Over time, most sub-Saharan urban areas have experienced a 'natural' expansion, with landscape shape and form often determined by physical infrastructure, topography and geological factors.[9] In Nairobi, and indeed in many other sub-Saharan cities, major urban land uses have followed a radial pattern around roads from the city centre and within flatter surfaces suitable for construction.[8] Whereas these factors may have been critical to South Africa's urban development, her urban spatial growth and patterns have been mainly determined by a series of movement restrictions and the pre-1994 laws that date back to 1913.[10,11] A notable example is the Prevention of Illegal Squatters Act of 1951 which highly regulated settlement in South Africa's urban areas.[12,13] Between 1960 and 1983, about 860 000 people were moved from urban areas under the Group Areas Act.[14] Consequently, such laws significantly limited 'natural' urban growth through 'influx control'.[13,15] The beginning of unrestricted rural–urban movement in 1986 and the formal end of the Group Areas Act in 1991 saw a dramatic increase in urban population numbers.[15,16] From 1991 to 1996, the population of Black South Africans in urban areas increased by about 27%[15] and South Africa's urban population grew by 4.3% to 56% between 1996 and 2001.[17]

Like other South African cities, the unprecedented growth and transformation of the city of Port Elizabeth during South Africa's democratic transition led to enormous spatial planning challenges that affected social service delivery, infrastructural development and environmental degradation that led to a general decline in quality of life.[9,18,19] Port Elizabeth's sudden growth and the consequent landscape changes during this period compounded the need to monitor spatio-temporal land use and land cover (LULC) patterns.[18]

Generating up-to-date LULC change in dynamic urban landscapes using ground mapping techniques is often time consuming, expensive and tedious.[20,21] Other techniques, like conventional aerial photography, have a long history in urban studies but have various shortcomings, including a high cost per unit area and, until recently, the data were seldom available in digital formats.[22,23,24] Repetitive coverage, consistency in image quality, cost effectiveness and the development of change detection algorithms, amongst others, have made remote sensing a viable option in urban LULC change mapping.[21,24,25,26] Such benefits are essential for understanding past, present and future drivers and patterns of urban landscape changes.[9,27]

Although a number of researchers have studied urban LULC change (Mundia and Aniya[9], Abbot and Doughlas[28], Deng et al.[29], Dewan and Yamaguchi[30], Kesgin and Nurlu[31] and others), Hope[32] has argued that relevant urban strategies and remedies require cognisance of local socio-economic and cultural characteristics, as well as a site's uniqueness. Like other major urban areas in South Africa, the city of Port Elizabeth and its greater metropolitan area has undergone a series of transformations. These transformations include restricted, and hence regulated, urban growth before the democratic transition, urban influx during the democratic transition and post-transition policy-driven urban physical development transformations. In contrast to 'naturally growing' urban areas studied by the aforementioned authors, these factors have combined to make the city of Port Elizabeth a globally characteristically unique setting for studying LULC change. Consequently, the purpose of this study was to analyse major LULC changes in the city of Port Elizabeth during South Africa's democratic transition (1990–2000).

The study area

The city of Port Elizabeth was established in 1820. It is located at 33°57′29″S and 25°36′00″E on the south-eastern seaboard of South Africa (Figure 1). Port Elizabeth is the second oldest city in South Africa and has since been incorporated into the greater Nelson Mandela Bay Metropolitan area that includes the towns of Dispatch and Uitenhage. With an area of approximately 335 km^2 and a population of approximately 1 million (Statistics South Africa 2007 Community Survey[33]), it is the fifth largest city in South Africa. Population density varies across the city; higher-income low-density suburbs and farms at the city's periphery have 10–30 people/km^2, while the inner city, high-rise suburbs, low-income areas and informal settlements have over 3000 people/km^2. Major land uses within the city are 'residential', 'industrial' and 'retail', whereas 'small-scale to medium-scale animal and crop farming' predominates at the city's periphery. The city is a major industrial hub and is home to one of the major seaports in South Africa. The post-1994 era and the growing industrial, retail and tourism sectors have been the major causes of unprecedented growth of the city.

Materials and methods

Land-use and land-cover change detection

Change detection is premised on multidate spatial representation resulting from environmental conditions and human activities on multiple imagery dates.[26,34] It is possible to detect surface cover changes as a result of distinguishable reflectance values of LULC, which are often distinguishable from changes caused by soil moisture, solar illumination and atmospheric conditions, amongst others, at the time of image acquisition.[25,35,36] According to Chen[37], several change detection techniques, including multidate composite image change detection,[38] image change algebra,[35] image regression,[39] on-screen digitising,[40] post-classification comparisons[41] and fuzzy sets and fuzzy logic[42] have been developed (see Mas[25] and Lu[35] for a detailed review of existing change detection techniques). Because the quality of change detection is often determined by thematic, spectral and spatio-temporal limitations, appropriate selection from an array of existing techniques is of paramount importance.[36] In keeping with the increasing popularity of the post-classification approach,[26,43,44,45] for this study we adopted a multitemporal comparison of delineated classes. In this approach, each of the image spectral classifications are performed independently and the resultant areas within the thematic maps are compared.[26,29,44] The main advantages of this method are the detailed information that can be gained from the change matrix produced and the limited multitemporal imagery impact arising from calibration, atmospheric and environmental differences.[29,35] However, the original land covers often need to be reclassified or reweighted, and the quality of the resultant classes is dependent on the choice of training data.[29,35]

According to Deng[29], sensor, radiometric and spatial resolution commonalities are critical factors in multitemporal

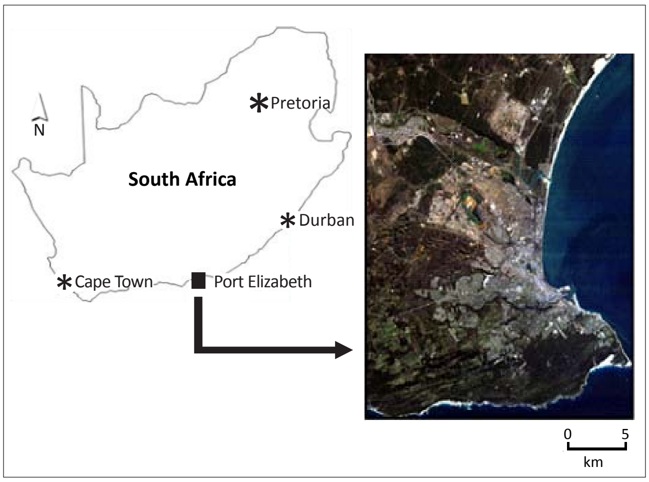

FIGURE 1: Location of the study area.

change detection. To eliminate multitemporal imagery inconsistencies arising from multiple seasons, the sun's inclination and phenological differences, it is paramount that the images used represent similar seasons or conditions.[29,46,47,48] To facilitate comparability and to determine multitemporal changes in major land-cover types in Port Elizabeth, similar dimensional extents around the city were extracted from three sets of Landsat 5 Thematic Mapper data (Table 1).

Precise registration of multitemporal image data sets is of critical importance to a change detection process.[49,50] To eliminate change detection errors arising from image misregistration, it is generally recommended that the accuracy of images registered be less than a pixel,[25] although, less than half a pixel is regarded as ideal.[29,51] In this study, the chosen images and respective aerial photos were rectified to the Universal Transverse Mercator projection and World Geodetic System 1984 datum. Fifty invariable points of features common to the 1:50 000 topographic maps and the images were selected for geo-registration. Additional evenly distributed GPS readings of ground control points common to the 1990 image and aerial photos were also collected and used for geo-rectification. With 1990 as a base image, the other images (Figure 2) were coregistered and resampled using nearest-neighbour interpolation. An accuracy of less than half a pixel was achieved in the three images.

Change detection processes require spatial resolution, phenology and radiometric characteristics to be comparable. In this study, these conditions were met as images were acquired at similar seasonal (winter) conditions (Table 1). However, other factors like sensor degradation, variations in solar illumination and effects of atmospheric scattering and absorption affect the quality of change detection outcomes.[25,52,53] To correct for these possible anomalies, relative dark and light pseudo-invariant features were identified and the imagery was normalised using the process described by Paolini et al.[47], Jensen[52] and Hartvich et al.[54] Geo-rectified aerial photographs were imported into the IDRISI Kilimanjaro raster-based software[55] and used to validate the resultant land-cover classes.

Land-use and land-cover classes

A hybrid classification technique comprising unsupervised and supervised classifications was used to classify the 1990, 1995 and 2000 images. Two algorithms – iterative self-organising data analysis technique (ISODATA) and K-means – were used for unsupervised classification.[43] Jensen[43] recommends the use of ISODATA as it involves further refinements for splitting and merging classes. Consequently, ISODATA was applied to the three image data sets. This process was performed for two reasons: firstly, to obtain a summary of the number of spectral differences in the image data sets and, secondly, to use this information as a basis for an amalgamated number of related LULCs through supervised classification. The ISODATA technique yielded 21 classes. The aerial photo mosaic corresponding to the imagery dates, a field survey and GPS readings of features considered invariant like roads, buildings and public spaces were used to distinguish and label the unsupervised classes and to identify training areas for a supervised classification. At least 120 pixels for each class were used to uniquely label new spectral signatures. Using the created signatures, the maximum likelihood algorithm was used to amalgamate LULC classes that were considered related. Consequently, the LULC classes were reduced from 21 using unsupervised classification to 5 using supervised classification: (1) beach or dune, (2) built-up area, (3) green vegetation, (4) bare surface and (5) water (Table 2).

From the three classified images, pixel-by-pixel comparisons were used to determine multidate LULC transitions followed by 'from–to' LULC comparisons to calculate the pixel number differences between the 1990 and 1995 images and between the 1995 and 2000 images. The areas of LULC surfaces were calculated by multiplying the imagery pixel spatial resolution (30 m x 30 m) and converting the surface areas of cover types into hectares.

Accuracy assessment is a critical process in LULC mapping. The error matrix technique is the most commonly used method of assessing the accuracy of LULC maps.[35,47] According to Congalton and Plourde[56], an error matrix is based on a set of ground truth data, a classification scheme, a sampling scheme, a spatial autocorrelation and sample size and units. With the aid of the aerial photo mosaic (1:25 000), invariant feature points and topographic sheets, the accuracy of the images was assessed using the error matrix technique described by Congalton and Plourde[56]. As recommended by Congalton[57] and Jensen[43], ground truth data for accuracy evaluation were identified through stratified random sampling. In total, 600 polygons were used to assess the classification accuracy of each of the temporal classifications (Table 3).

Results and discussion

The five amalgamated LULC classes were spectrally different. This difference allowed for spectral separation of the different

TABLE 1: Details of the images acquired in 1990, 1995 and 2000 for land-use and land-cover comparisons.

Image	Path/row	Acquisition		Resolution		Image centre		Sun	
		Date	Time	Spatial	Spectral	Latitude	Longitude	Azimuth	Elevation
1990	171/83	29/05/1990	7:30:40	30 m	7 bands	33°10′11.99′′S	25°09′99′′E	E41.88	22.36
1995	171/83	12/06/1995	7:16:48	30 m	7 bands	33°10′11.99′′S	25°10′12.00′′E	E43.94	18.9
2000	171/83	11/07/2000	7:47:34	30 m	7 bands	33°10′11.99′′S	24°57′00.00′′E	E39.91	23.12

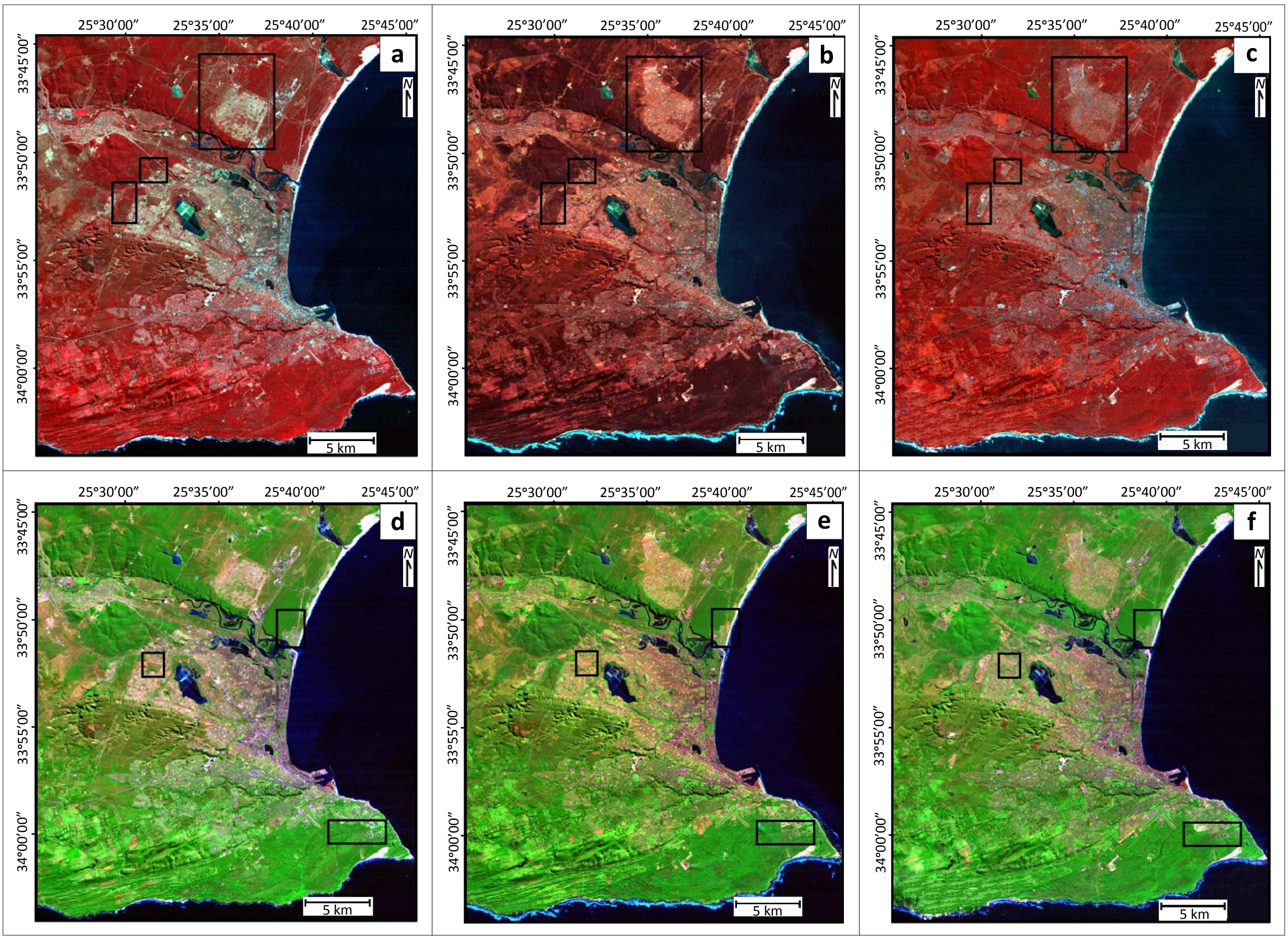

FIGURE 2: Images taken of Port Elizabeth in (a) 1990, (b) 1995 and (c) 2000 using thematic mapper TM432 false colour composite to accentuate changes in 'green vegetation' areas and in (d) 1990, (e) 1995 and (f) 2000 using TM742 false colour composite to accentuate the 'bare surface', 'water' and 'built-up area' classes.

LULC types using per-pixel delineation by the IDRISI remote-sensing software. The surface covered by 'beach or dune' had the lowest pixel count, area and percentage change during the study period (Table 4). Although the utmost care was taken during the classifications training process, there was some spectral confusion for the 'beach or dune' class. 'Bare rocky shoreline' for instance was confused for 'built-up area' and 'white shoreline waves' was confused for 'beach or dune' (Figures 3 and 4). The misclassification of 'rocky shoreline' as 'built-up area' was present in all three images analysed, whereas the misclassification of 'white shoreline waves' as 'beach or dune' occurred only for the 1995 and 2000 image data sets (Figures 3 and 4). The 'beach or dune' LULC class was not expected to change significantly over the study period. However, the inconsistent pixel percentage coverage of 2.3, 2.4 and 2.3 in 1990, 1995 and 2000, respectively, for the 'beach or dune' LULC class can be attributed to the presence of waves during image acquisition and the consequent spectral confusion for the 'beach or dune' cover class (Figure 3). The occurrence of spectral confusion is not unique to this study; according to Deng et al.[29] and Lo and Choi[58], a complex mosaic of urban land-cover types and the consequent mixed pixel problem is often a challenge in urban LULC classification.

TABLE 2: Original and re-coded land-cover classes.

Class	Original land-cover classes	Re-coded land-cover class
1	Open beach	Beach or dune
	Sand	
	Sand dune	
2	Residential	Built-up area
	Commercial	
	Industrial	
	Transport network	
	Drained salt pan	
3	Dense vegetation	Green vegetation
	Sparse vegetation	
	Farm	
	Grass	
4	Dry vegetation	Bare surface
	Open farm	
	Very sparse vegetation	
	Bare area	
5	River	Water
	Ocean	
	Salt pan with water	

There were noticeable changes in the 'built-up area', 'green vegetation' and 'bare surface' LULC classes in Port Elizabeth during the 10-year period (Figure 3). The 'built-up area' LULC

TABLE 3a: Classification accuracy assessment for the 1990 image.

Land-cover class	Beach or dune	Built-up area	Green vegetation	Bare surface	Water	Total	Accuracy (%)	
							Producer's	User's
Beach or dune	34*	7	0	5	4	50	85.00	68.00
Built-up area	2	142*	0	7	0	151	88.19	94.03
Green vegetation	0	0	133*	12	0	145	86.92	91.72
Bare surface	3	9	12	128*	9	161	81.01	79.50
Water	1	3	8	6	151*	169	92.07	89.34
Total	**40**	**161**	**153**	**158**	**164**	**676***	–	–

Values shown indicate pixels.
Overall accuracy = 86.98%; Kappa index = 0.8351.
*, Correctly classified pixels.

TABLE 3b: Classification accuracy assessment for the 1995 image.

Land-cover class	Beach or dune	Built-up area	Green vegetation	Bare surface	Water	Total	Accuracy (%)	
							Producer's	User's
Beach or dune	28*	4	1	4	2	39	75.67	71.79
Built-up area	3	161*	5	29	1	199	81.72	80.90
Green vegetation	1	2	182*	9	3	197	88.34	92.38
Bare surface	2	28	15	110*	9	164	71.42	67.07
Water	3	2	3	2	129*	139	89.58	92.80
Total	**37**	**197**	**206**	**154**	**144**	**738***	–	–

Values shown indicate pixels.
Overall accuracy = 82.65%; Kappa index = 0.7998.
*, Correctly classified pixels.

TABLE 3c: Classification accuracy assessment for the 2000 image.

Land-cover class	Beach or dune	Built-up area	Green vegetation	Bare surface	Water	Total	Accuracy (%)	
							Producer's	User's
Beach or dune	42*	2	0	7	1	52	71.18	80.76
Built-up area	5	189*	2	14	3	213	92.64	88.73
Green vegetation	1	1	197*	21	2	222	89.95	88.73
Bare surface	8	12	19	142*	4	185	75.93	76.75
Water	3	0	1	3	156*	163	93.97	95.70
Total	**59**	**204**	**219**	**187**	**166**	**835***	–	–

Values shown indicate pixels.
Overall accuracy = 86.94%; Kappa index = 0.8513.
*, Correctly classified pixels.

TABLE 4: Changes in land use and land cover during the study period.

Land-cover class	Area (ha)			Percentage change (%)		
	1990	1995	2000	1990–1995	1995–2000	1990–2000
Beach or dune	2410	2500	2419	0.1	-0.1	0.0
Built-up area	23581	29191	37369	4.4	8.9	13.3
Green vegetation	34545	31976	31286	-2.5	-0.7	-3.2
Bare surface	19612	16950	9236.8	-2.6	-7.4	-10.0
Water	23712	23242	23549	0.3	-0.4	-0.1

Area of land cover classes (ha) = number of pixels (each measuring 30 m x 30 m) divided by 10 000 m^2.

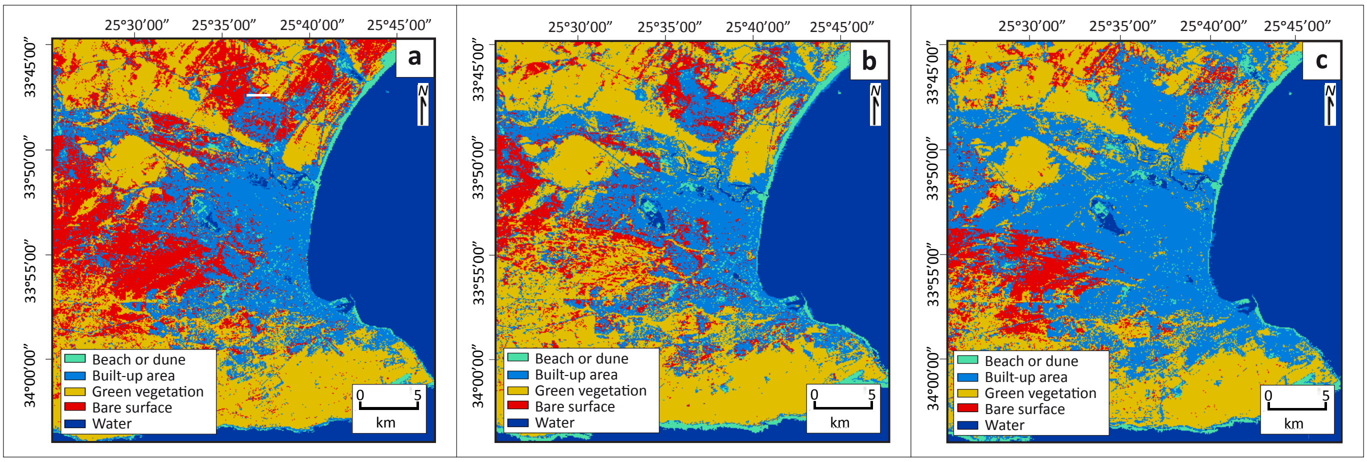

FIGURE 3: Land-use and land-cover types in Port Elizabeth in (a) 1990, (b) 1995 and (c) 2000.

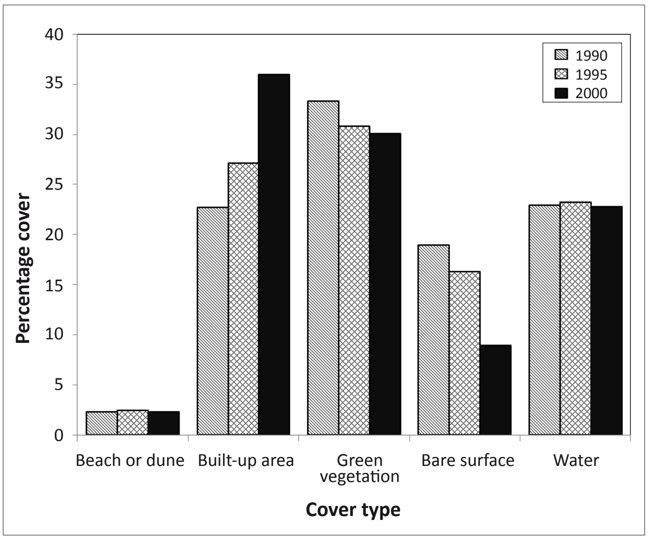

FIGURE 4: Area comparisons of multitemporal land-cover types in Port Elizabeth in 1990, 1995 and 2000.

class showed a general increase during the study period with a percentage change of 4.4% from 1990 to 1995 and 8.9% from 1995 to 2000 (Table 4). This increase constituted the greatest change of all the LULC types (Table 4). In contrast to the other LULC types with significant changes, the 'green vegetation' class showed a higher decline in area in the 1990–1995 period than in the 1995–2000 period (Table 4). The 'bare surface' land-cover class declined by a cumulative 10% in the 10-year period, with 7.4% of the decline occurring in the 1995–2000 period. This rapid loss in the 'bare surface' land-cover class can be attributed to two factors: firstly, vegetation in close proximity to urban informal settlements is used as fuelwood and, secondly, vegetation clearance is a requisite for construction and settlement.

The spatial increase in 'built-up area' at the expense of other land-cover types reflected in this study is consistent with urban demographic changes recorded in the literature. According to Kok and Collinson[17], South Africa's urban population grew by 4.3% to 56% between 1996 and 2001. Naude and Krugell[59] noted that in the recent past, South Africa has recorded one of the highest rates of urban growth with an expected further increase of up to 70% by 2030. This trend is directly attributed to urban influx during and after the democratic transition and the concentration of labour and income opportunities in urban areas.[7] Other reasons that spurred urbanisation and the consequent urban landscape transformation during the study period were the significant decline in rural agro-based employment in the 1990s,[60] tolerance to increasing urban informal settlement and a government-led policy for informal settlement upgrade through the Reconstruction and Development Programme.[12,28] Whereas there was a general increase in rural–urban movement depicted in the 2001 South African national population census, the largest proportion of the increase in movement was from secondary urban areas to major cities and peripheral towns.[16,18]

Changes in area covered by the 'water' land-cover class seem to have been influenced by the effects of weather on the sea (shown by white shoreline wave foams at the time of image acquisition) and the activities at the salt pans in the middle of the city (Figures 2 and 3). In the 1995 image classification, for instance, there was a significant spectral confusion between the 'white shoreline waves' on the southern coastline and the 'beach or dune' LULC class (Figure 3). The empty and water-filled salt pans are clearly visible in Figure 3a and 3b.

Conclusion

A rapid increase in urban settlement between 1990 and 2000 was the key driver of LULC change in Port Elizabeth. Like many other urban areas in South Africa, the dynamic urban landscape is directly attributed to pre-1994 laws and the new government's policies on the provision of social and physical infrastructure. Using remote sensing, this study has shown that built-up areas in the Nelson Mandela Bay Metropolitan increased by 13788.4 ha (representing a change of 13.3%). The gain in the 'built-up area' class was mainly attributed to a decline in the amalgamated classes, that is, open farms, dry vegetation, very sparse vegetation and bare areas that declined by 10375 ha (representing a 10% decrease) and the 'green vegetation' class that declined by 3.2%. The changes in the 'built-up area' and 'bare surface' LULC classes were more significant during the 1995 to 2000 period, whilst the change in the area covered by 'green vegetation' was more significant during the 1990 to 1995 period.

This study has shown that remote-sensing techniques offer a viable option for creating land-use inventory and monitoring systems in fast growing urban settings. These systems can be used to make optimal urban land use decisions. Whereas census-based literature has reported a general increase in South Africa's urban population during this period, this study has attempted to fill the gap in the literature on physical urban spatial trends.

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Competing interests

We declare that we have no financial or personal relationships which may have inappropriately influenced us in writing this article.

Authors' contributions

J.O. was the lead researcher, performed most of the experiments and wrote the manuscript. P.M. performed the experiments and wrote the manuscript. V.K. gave technical input into the field research and the writing of the manuscript.

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