Reconstructing the History of Urban Development in the Mining Town of Virginia, Free State between 1940 and 2015.

By

PAUL AJAYI O.

1482914

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In partial fulfilment for the degree Master of Science (Geographical Information Systems & Remote Sensing)

Supervisor: Dr. Stefania Merlo

Co. Supervisor: Ingrid Watson - Centre for Sustainability in Mining and Industry (C.S.M.I)

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DECLARATION

I, Paul Oluwanifemi Ajayi, declare that this research report is my own unaided work. It is being submitted as partial fulfilment for the degree Master of Science in Geographical Information Systems and Remote Sensing to the University of the Witwatersrand, Johannesburg. I also affirm that this research report has never been submitted for any degree or examination at any other university.

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Signature of Candidate

This ……………………day of ……………………….. 2017

ABSTRACT

The nature of urban development experienced by mining towns across the world has been a subject of concern among urban planners because of its transitory nature. Most times mining towns develop gloriously into booming urban centres that create employment, generate wealth and satisfaction. All these fades into oblivion as soon as the mines get depleted. Mining towns often go through a number of urban processes which have been considered an expression of 'infrastructural violence' especially in the earlier stage of urban growth, and continually persists throughout the town's life span.

This research sought to reconstruct the history of urban development in the mining town of Virginia, Free State, and to quantify the manifestations of infrastructural violence throughout its timeline using GIS and remote sensing. Hence, land use and land cover maps were produced from aerial photographs, topographical maps and Landsat images through manual on-screen digitizing and classification using supervised support vector machine algorithms. Land use change detection analysis was conducted on the produced images using the cross classification and tabulation tool of QGIS 2.18.4 and the post classification tool of ENVI 5.3. Landscape metrics were employed to calculate the dimensions of growth and change experienced by all the land use classes during the timeline under study.

Results obtained from this study confirmed the thoughts and findings of several theories vis a vis the nature of mining towns. Results reveal a rapid growth in the urban formal land use class up until 1995 with urban expansion and sprawl happening in the years between 1986 and 1995 with metrics of CA, NP and ED multiplying to twice their initial values ten years earlier. The urban informal land use class also experienced its subtle growth throughout the timeline of the study with its own urban expansion also happening between 1986 and 1995 with double increase in CA, NP and ED metric values. However, unlike the formal class that experienced decline after this period of urban expansion, the informal class continued to experience growth up until the end of the study period. Infrastructural violence was measured using the fractal dimension index (AWMPFD) of the landscape metrics for the formal and informal LU class. The results reveal continuous fragmentation throughout the period of study but with higher values in the years in which urban development started.

THIS RESEARCH REPORT IS DEDICATED TO EVERY YOUNG RESEARCHER IN THE PURSUIT OF KNOWLEDGE, PURPOSE AND FULFILMENT; MAY YOU NEVER GIVE UP. AMEN!

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ABBREVIATIONS AND ACRONYMS

AWMPFD	Area Weighted Mean Patch fractal Dimension
C.A	Class Area Metric
E.D	Edge Density
ETM	Enhanced Thematic Mapper
LULC	Land Use Land Cover
MPS	Mean Patch size
MNN	Mean Nearest Neighbour distance
NDVI	Normalized Difference Vegetation index
N.P	Number of Patches
TM	Thematic Mapper
USGS	United States Geological Survey

1. Introduction

1.1. Background of study

This study combines the technological approach of GIS and remote sensing and the sociological concept of infrastructural violence to study urban growth and development in the mining town of Virginia, Free State Province, South Africa, from the inception of mining activities in the 1940s until today.

Over the years, the mining industry of the South African Republic has been the major contributor to the nation's economy. The discovery of gold in Johannesburg in 1886 revolutionized the country's economy from an agrarian-based economy to one dependent on mining, energy and industry (Fedderke and Pirouz, 2000; Binns and Nel 2001). Since then, the mining sector has been the dominant source of tax revenue, the major employer of labour, and the major force driving the country's economic development (Fedderke and Pirouz, 2000). Also, it played a lead role in the growth of the manufacturing industries, which ultimately led to the materialization of financial services that drives the economic sector in Johannesburg today (Harrison and Zack, 2012). As mining activities prospered, economic activities increased which led to the creation of jobs. Also, there were changes in land use as more mining towns were built, and previous rural regions upgraded into prominent urban areas. The urban growth experienced by these mining towns was guided by stringent government policies (Harrison and Zack, 2012; Marais and Cloete, 2013). These policies supported spatial racial segregation in mining areas and unbalanced urban growth with an emphasis on mining towns to the detriment of the local townships (Bryceson and MacKinnon, 2012), leading to a phenomenon which Rodgers and O'Neill, (2012) have termed 'infrastructural violence'.

Infrastructural violence becomes engrafted into a society when its urban development evolves in ways that affects or subjugates the daily life of the city's population in a highly toxic manner (Rodgers 2012). It manifests in forms of infrastructural deprivation (Ferguson 2012), creation of enclaves and different forms of exclusion (Appel 2012) in its earlier stages, and advances into cases of environmental degradation, increase in crime rates (Rodgers and O'Neil 2012) and other depravities in the later stages of the city's development (Auyero and de Lara, 2012). It was recorded that South Africa had the largest known reserves of gold and the highest gold production in the world (Binns and Nel 2001). However, there has been a sharp decline in the value contribution of the mining sector to the nation's economy since 1970 (Fedderke and Pirouz, 2000). This decline was caused by the exhaustible supply of the resource being mined, reduction in gold reserves and the price of gold, the necessity to mine deeper and a changing labour structure (Crankshaw 2002). The decline has slowed down the process of urbanization, and caused a shrink of the resident population of mining towns, an increased poverty rate and the eventual death of mining towns (Bryceson and Mwaipopo, 2009; Marais and Cloete, 2013).

GIS and remote sensing have been effective in studying urban growth changes over the years, and a number of scholars such as Muller and Middleton (1994), Latifovic et al., (2005), Shalaby and Tateishi (2007), Antwi et al., (2008); Townsend et al.,(2009); Larondelle and Haase, 2012, have examined land use changes in mining regions using GIS and remote sensing techniques. These studies have individually revealed the impact that mining activities could have on land cover over a long period of time. Likewise, the use of spatial metrics to analyse urban environmental change has been a recent trend in urban change studies because of their ability to numerically quantify the spatial patterns and changes of land cover classes (Herold et al., 2002; Ji et al., 2006). When combined with remote sensing, spatial metrics has proven to be a valuable method of deriving accurate information about urban change (Pham and Yamaguchi, 2009). Spatial metrics can also be used to deduce underlying political, social and economic processes that drive observed urban forms (Seto and Fragkias 2005) because of their ability to recreate missing historical time periods in the evolution of urban towns (Xu et al, 2007).

This project primarily employed historical data such as aerial photographs, topographical maps and remote sensing data to study the urban growth of the mining town of Virginia and analyse proxies of infrastructural violence. Outcomes from this research should enable us to better understand the dynamic urban process that goes on in a mining town, ultimately assisting urban and regional planners to make informed decisions about planning sustainable mining towns in the future.

1.2. Statement of research problem

Studies that combine mining dynamics with urban growth and settlement patterns are very rare (Bryceson and Mackinnon, 2012), although attempts to understand the dynamics of the transitory nature of mining towns has been made for many years (Mitchell and O'Neill, 2016). These dynamics have specific outcomes that could be considered to show that little or no attention has been paid to the process, drivers and the cause for the decline of urban growth in mining settlements (Bradbury and St-Martin, 1983). Virginia falls under the Matjabeng municipality, which has been characterized by population decline, increase in unemployment and a decreasing population growth rate since 1996. Population numbers have drastically reduced from 472, 281 in 1996 to 406,461 by 2011, and total employment figures recorded 27,494 in 2011 as compared to the previous 97, 914 in 1996 (Marias et al., 2015). The environmental and economic impacts of these developments have been severe. Virginia has become desolate and different efforts to resuscitate the gold fields ever since has totally failed (Marias and Nel 2016). The mines around the town are depleted and have been shut down by Harmony gold, , the municipality is failing and the once vibrant gold town is now commensurate to a ghost town. Various attempts to resuscitate Virginia by diversifying the economy have failed blatantly (Stephens and John, 2015). Ethnographers have linked the end results of these urban processes in mining towns to infrastructural violence (Rodgers & O'Neil 2012). . As the knowledge of these urban processes enhances sustainable urban planning for mining towns (Pressman and Lander 1978). it then becomes important for urban planners to have an understanding of the historical developments and the unique problems of suchtowns

1.3. Research questions

1. How did the mining town of Virginia evolve spatially through time?
2. How did infrastructural violence manifest in Virginia's spatio-temporal urban growth over time?

1.4. Aim of the study

The aim of this study is to critically assess urban growth and development of the mining town of Virginia between 1940 and 2015 with a view to understanding its growth dynamics and the impacts of mining activities on its spatio-temporal variability, using remote sensing and GIS techniques. The study will also attempt to test the measurability of infrastructural violence through formal GIS analysis.

1.5. Objectives of the study

The objectives to pursue the aim of this study are to:

1. Create a time line of land use and land cover changes in Virginia between 1945 and 2015 (the years during and after the mining period) using remote sensing and GIS.
2. Analyse land use/land cover changes that occurred in Virginia between 1945 and 2015 using remote sensing and spatial metrics alongside published historic information.
3. Spatially quantify the manifestations of infrastructural violence in Virginia during the period under study using GIS analysis.

1.6. Outline of the report

This research report is articulated in six distinct chapters. Chapter one contains the introduction and background of study while chapter two covers the review of relevant literature. Chapter three outlines and explains the methodology and provides detail on the data used in answering the research questions and pursuing the objectives while chapter four contains the results. The fifth chapter of this report presents the discussion of the results presented in chapter four, while chapter six includes the conclusion of the research report which summarizes the major findings and the research limitations.

2. Review of relevant literature

This chapter comprises the review of relevant literature that explains the background of study. Each section of this chapter discusses topics that helps answer the research questions. Section 2.1 of this chapter discusses the timelines of ideal resource towns, and 2.2 describe mining activities and the need for mining towns. Section 2.3 discusses the urbanization and the urban growth of mining towns while 2.4 explains infrastructural violence and the role urbanization plays in its causes. Section 2.5 explains spatial metrics and their usefulness in urban growth analysis while section 2.6 contains the summary of the whole chapter.

2.1. Timeline of ideal resource towns

From purely agrarian rural communities to booming urban centres dictating the prosperity of geographic regions to shrinking dying cities, the life cycle of resource dependent cities unfolds (Bezerra et al., 1996). Lucas (1971) laid the foundation in his study on the social structure of resource towns. Bradbury and St-Martin’s (1983) critically examined their economic characteristics and Mitchell and O’Neill (2016) coined the resource dependency model to provide an explanation on economic transitions in resource towns. As illustrated in figure 1, Lucas (1971) classified the developmental stages of the ideal resource town into construction, recruitment of citizens, transition and maturity stage with the early stages characterized by land use change. Mitchell and O’Neill (2016) categorised the development of their resource dependency model into four stages that are quite similar to Lucas’ theory named pre-dependence, dependence, post-dependence and independence. Riffel (1975) established a baseline prior to the development of resource towns by introducing a pre discovery and preconstruction stage to compliment Lucas’ model.

Urban growth patterns of resource towns are highly influenced by government policies (Bradbury and St-Martin, 1983). In Africa, the colonial government patterned and structured the growth of mining urban centres with the intention of keeping Africans in their rural home area by using foreign planning practices (Pressman and Lander, 1978). This was accomplished using tools of racially segregated housing (Bryceson and MacKinnon, 2012), constructing infrastructures based on class, race, aesthetics of security, neo-liberalism and planning power, using the legislature to deprive vulnerable people in the society (Appel 2012). Winding down and closure are the final stages in this process and they are characterised by polluted and degraded environments, ruined agricultural resources, and the growth of informal settlements (Lucas 1971; Bradbury 1984).

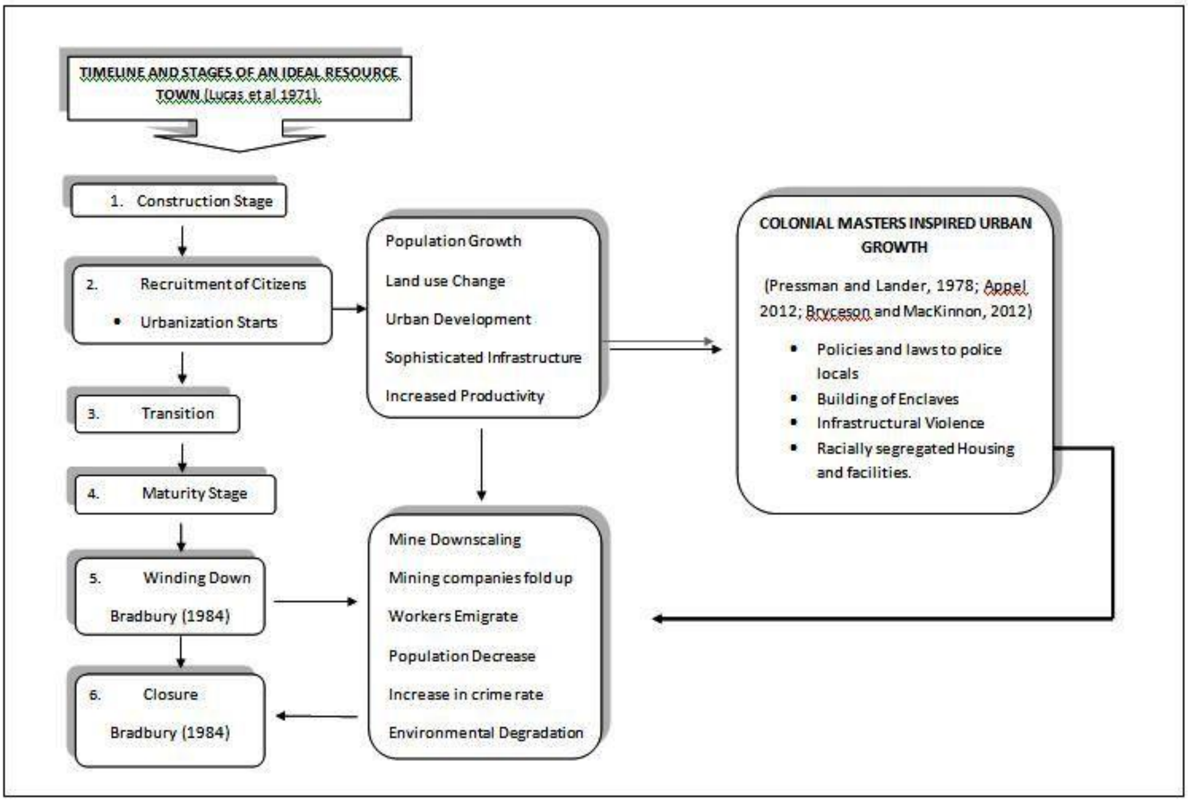

Figure 1. Timeline of resource towns as culled from Lucas et al (1971), Pressman and Lander (1978), Bradbury (1984), Bryceson and Mackinnon (2012) and Appel (2012).

2.2. Mining activities and the need for mining towns

Mineral explorations have the potentials of creating new settlements or upgrading existing ones (Bryceson and MacKinnon, 2012), just as Harrison and Zack (2012) noted that the South African mining industry was the driving force behind the urban development of modern South Africa. The need to have settlements that will take care of the rapidly increasing population brought about mining towns, which are characterized by high rates of turnover, mixed ethnic groups, high proportions of young people and young families, unbalanced sex ratios with large numbers of males relative to the number of females, an abundance of young children and the absence of older people with an alarming high birth rate (Lucas 1971). Although mining towns possess all the characteristics of single industry towns, their heavy reliance on non-renewable resources and their transitory nature makes them different from other types of single industry towns (Dale 2002). Martinez-Fernandez et al., (2012) further characterised them by their dependency on non–renewable resources, the proximity of their location to urban areas, economic instability, and the eventual inheritance of a wide range of environmental degradation and negative health impacts.

2.3. Urbanization and urban growth of mining towns

Bryceson and MacKinnon, (2012) defined mineralized urbanisation as "the influence of mineral production cycles and commodity chains on urban growth and settlement patterns at local, regional and national levels which occurs as a result of migration" (pg. 514). Urban growth is mostly driven by population and economic prosperity and it includes a number of dynamic processes that have long term consequences on natural features of the landscape (Rivas et al., 2006). Urban growth phases in mining towns are characterised by provision, investment and expansion of facilities (Bradbury and St-Martin, 1983) and fluctuating populations in mining towns is a normal occurrence that has been the resultant effect of the boom and bust nature of the global mining industry over the years (Martinez-Fernandez et al., 2012). The consequences associated with mineralised urbanisation are concentrated excavation, intensive transport, deposition of materials, creation of new landforms and environments, intensive erosion and flooding. (Rivas et al., 2006).

Bryceson and MacKinnon (2012) purported that the life span of an ideal mining town is dependent on the quantity of mineral deposits after which mine downscaling and closure is evident. Lucas (1971), Bradbury and St-Martin, (1983) and Bruce et al (2004) predicted the shrinkage and eventual death of these settlements. Mitchell and O'Neill (2016) were of the opinion that mining towns won't have to die if there is a shift away from the dependence on the primary resource of mining to alternative economic activity, but Martinez-Fernandez et al., (2012) contradicted that idea on the basis that several revitalisation tactics targeted towards resuscitating resource towns by attracting high order services and technology do not produce the sustainable change in these towns as the depleting resource do not have the ability to retain or attract new settlements.

2.4. Infrastructural violence

The term 'infrastructural violence' was coined by Appel (2012) to indicate social suffering, spatial injustice and the deprivation of infrastructure experienced by an inferior group of people within the society. Rodgers and O'Neill, (2012; 402) defined infrastructure "as a key factor shaping people's direct relationships both with each other and with their environment in cities. It demarcates both literally and figuratively which points in urban contexts can and should be connected, and which should not, the kinds of people and goods that can and should circulate easily, and which should stay put, and who can and should be integrated within the city, and who should be left outside of it". Appel (2012) categorised infrastructures as communal services such as road structures, water supply, sewers, energy, telecommunications, waste management and other soft infrastructures such as public education, health care and libraries. He further emphasized that the absence of these basic infrastructures where there is no justification for it is a form of violence which is being manifested in forms of exclusion, unequal distribution of infrastructure, disentanglement and disconnection through creation of enclaves. Paul Farmer (2004:307) defined infrastructural violence as 'violence exerted systemically – that is, indirectly – by everyone who belongs to a certain social order'. Infrastructural violence seeps into the society when a city's urban development evolves in ways that affects or subjugates the daily life of the city's population in a highly deleterious manner (Rodgers 2012) through infrastructural deprivation (Ferguson 2012).

The aim of creating new resource towns and convenient neighbourhoods in Africa was to create a 'western' environment and make life convenient for the expatriates and not necessarily to create 'ideal' mining towns (Appel 2012). Bryceson and MacKinnon, (2012) observed that in Africa's mining cities, the colonial governments structured urban policies under the excuse of ensuring European public health by first placing a limitation on urban growth with the plans of restricting Africans to their rural areas. The societal inequality that dominated the society resulted from spatial segregation and eventually led to infrastructural violence; it was made visible through the selective provision of sophisticated infrastructure such as walls, pipes, wires and roads that shaped the urban environment (Ferguson 2012). In South Africa, apartheid became the tool that was deployed to enhance spatial segregation (Mubiwa and Annegarn 2015). The Native Urban Areas Act of 1923 gave room for the establishment of racially segregated housing; (Fair et al., 1956). Veiga et al., (2001) and Marais and Cloete (2013) noted that in South African mining towns, the local mine workers and migrants from neighbouring African countries were housed in congested mine hostels while the highly skilled expatriates were lodged in exclusively designed mine-owned houses and the deprived local township remained dependent on the mining towns for employment, economic, social, and environmental or other benefits.

Even after the removal of enclaves and entanglements put in place by political power, infrastructural violence that has been created during the initial stage of urban growth never ends (Auyero and de Lara, 2012), as Mubiwa and Annegarn (2015) said concerning Gauteng City Region of South Africa that segregation regulations and the continuous establishment of racially segregated settlements left a strong spatial footprint in the region and it still evident till date.

2.5. Spatial metrics for urban growth analysis

There has been a growing interest in combining classified spatial images and spatial metrics to describe urban areas and land use change patterns. This could be due to the fact that, information obtained from urban change maps alone does not adequately explain the driving forces of urbanization, and spatial metrics supply the additional information which is needed to link the spatial structure of a city with its urban change processes (Pham and Yamaguchi 2009; Pham et al 2010).

Herold et al (2002) examined the use of landscape metrics derived from classified remote sensing data to describe structural changes in urban land use in six different counties of California between 1978 and 1998. The results showed a separation and increasing characterization of commercial, high density residential and low density residential urban land use types. Xu et al (2007) conducted a comprehensive spatial analysis to study the dynamics of rapid urban growth in the Nanjing metropolitan region of China between 1979 and 2003. This they did by combining multi temporal remote sensing data with landscape metrics. Their results revealed that urban growth in the area of study significantly increased, with the infilling, edge-expansion and spontaneous growth types present but the spontaneous growth type accounted for the highest proportion.

To understand the dynamics of land use change in four rapidly developing coastal cities in China, Seto and Fragkias (2005) conducted the first comparative analysis to study their growth over an eleven year period using landscape metrics and gradient analysis. Results of their study show correlation between the various landscape metrics indices, and they concluded that landscape metrics gives an exposure towards the unpredictable nature of urban forms over short periods of time. Sudhira et al (2003) also combined Shannon's entropy and landscape metrics to understand built up dynamics in Mangalore, and their results revealed that by the end of 2050, the percentage change in built up area would be equal to the percentage change in urban sprawl. Ji et al (2006), Pham and Yamaguchi (2009), and Jaeger et al (2010), among many others have also been successful in making scholars better understand the dynamic growth processes that goes on in urban centres through the combination of remotely sensed images and spatial metrics.

2.6. Literature Gap

The study of LULC change is not new in remote sensing applications. Several studies have been channelled towards the general study of LULC as reviewed by Singh (1989); Hoalst-Pullen and Patterson, (2011) and Patino and Duque (2013). However, studies that focus on LULC in mining regions are limited. In 2008, Ololade et al examined LULC changes in the mining region of Rustenburg in South Africa between 1972 and 2002 using conventional change detection techniques. They discovered that the influx of job seekers led to an increase in the formal and informal sections of built up areas and that the landscape has become highly disturbed due to increased mining. Prakash and Gupta (2010) further examined land use mapping and change detection in a coal mining area – case study in the Jharia coalfield of India between 1975 and 1994. The use of remote sensing and GIS techniques in change detection analysis, revealed that extensive mining, communication networks, settlement growth and vegetation decrease have remodelled the face of the terrain within the 19 year period. However, Chang-hua & Xiao-xiao (2011) took a diversion from the popular change detection technique and applied a qualitative and qualitative approach towards analysing the driving forces of LULC change in Lu'an mining area between 2000 and 2007. Using principal component analysis, their results reveal that the social and economic development in mining area from 2000 to 2007 demonstrates continuous accelerate trends, and the impacts of its overall driving force to land use change are increased gradually. In assessing the processes of land use change in mining region Sonter et al (2013) studied the Quadrangle mining region in Brazil between 1990 and 2010 and they compared their results with those of surrounding landscapes. Their findings revealed that the processes of LULC change within mining regions are distinct from those found elsewhere. In the study of LULC change in the mining areas of Wa East district of Ghana between 1991 and 2014, Basommi et al (2015) discovered that mining activities have the potentials of affecting vegetation negatively as revealed by the decrease of NDVI values. Wohlfart et al (2016) also conducted a LULC change analysis in the yellow river basin of China between 2000 and 2015 by analysing changes in mining, agriculture, forest and urban areas. By employing the random forest classifier to analyse Landsat time-series data, they were able to identify afforestation and urbanization as the prominent drivers of LULC change dynamics. Redondo-Vega et al (2016) conducted a 50 year study to examine the changes due to mining in the north western mountains of Spain. While relying on the use of colour orthophotos and area photographs, they were able to discover that the new post-mining topography represents a drastic change in the landscape and LULC in these areas, and that previous agricultural LULC has been taken over by mining LULC. These previous studies generally focused on LULC change in mining regions using similar methods of LULC classification and change detection. All but one of these studies highlighted above restricted their span of analysis to periods when satellite imagery is available. Since these previous LULC studies rarely incorporated old maps, no change detection methods has been developed for differently sourced datasets. Moreover, these studies do not attempt to articulate the causes of LULC change in mining regions through the application of spatial metrics. Also, none of these studies focused on the study of urban LULC growth neither do they consider LULC change of mining towns in the light of the transitory nature of mining towns as hypothesized by Lucas et al (1971), Pressman & Lander (1978) and Bradbury (1984). Hence the present study aims to develop a methodology that combines data from old topographical maps and Landsat images. It also aims to bridge the gap between hypothesized theoretical statements about mining towns and the tracing, through empirical remote sensing and GIS studies of the development of mining towns.

2.7. Conclusion

This chapter described the occurrences that are associated with the growth of urban centres in mining regions across the world. The timeline in mining towns across the world often follows a similar trend: as soon as mining activities start, the mining town develops and gradually transforms into an urban centre. This urban growth is associated with population growth, land cover changes and changes in the traditional informal settlements and can be measured by spatial metrics. Infrastructural violence occurs quietly during the beginning of the urban growth phase and manifests through fragmentation of the landscape and gradually graduates into spatial segregation. Urban growth often declines when mining production stops. However, infrastructural violence that manifested in the earlier phases of urban growth doesn't stop and continues to manifest till the mining settlement declines.

3. Methodology

This chapter outlines the methodology and methods that were followed in pursuing the research goals and objectives. This chapter also contains description on the physiographic layout of the study area, the historic timelines of the Free State province, the data used, and the processing of the data for analysis. This research used a combination of both quantitative and qualitative approaches in answering the research questions. As regards qualitative analysis, this research relied on previous research published on Virginia and the Free State province, while the quantitative analysis relied on the interpretation of processed satellite imagery to make conclusions.

3.1. Study area

3.1.1. Physiographic description

Virginia is a gold mining town, which is located within the Lejweleputswa district of the Matjabeng municipality in the Free State province of South Africa. Its geographic coordinates are 26^{o}52’30.63”E, 28^{o}6’13.88”S, the town lies at an average height of 1,325 m. above sea levels (figure 2). The town is located at about 143km away from the capital city of Bloemfontein in the north-western direction. The topography of Virginia is fairly level and the monotony of its landscape is broken up by the Sand River which flows through the middle of the town. The Sand River is an important tributary of the Vaal River as it flows roughly towards the east of Virginia and empties into the Vaal River (Viljoen 1994).

The climatic conditions of Virginia are widely influenced by the climatic conditions of the Orange Free State province which experiences a continental climate and is characterised by warm to hot summer and cool to cold winters. Its average yearly temperature for the summer months (November to March) is 22^{o}C with daily minimum and maximum temperatures that range between 16.6 ^{o}C and 37.7^{o}C. The mean temperature during winter is 1^{o}C with June being the peak of the coldest months (Viljoen 1994).

The most prominent grass species in the Virginian landscape are the riet-erasmus dorin and the palm spring sprout which surrounds the Sand River, while the most common plants are the thorn bushes from the banks of the Sand River (Viljoen 1994).

3.1.2. Historic timeline

Marais and Nel (2016) characterised the history of the Free State goldfields in three phases. The first phase was between 1947 and 1969 after the discovery of gold in St. Helena Farms in April 1939. Welkom was the first mining town in the province and was built in response to deliberate principles laid down by the Natural Resource Development Council in 1947 to guide and enforce the proper development of towns. Virginia and Allanridge settlements were established later after the first elections held under the apartheid legislations to service the mining activities in the Province (Marais and Nel 2016). Virginia is located under the Matjhabeng local municipality of the Lejweleputswa District (McCarthy et al., 2005), as illustrated in figure 2, and its associated township is Meloding (Crush and James 1995). Virginia has six political wards, two of which contained the mining town itself, and another two consists of Meloding, the local township.

Active drilling started in Virginia in 1946 and the town was created in response to one of the objectives of the steering committee set up by the Orange Free State provincial administration to investigate the future of Free State goldfields in 1951 (Muller, 1956; Marais & Nel 2016). The Virginian mines and Meloding are located around the Virginia railway station in Free State. The area became a prospective mining site when it was concluded that the gold deposits in Welkom extended eastwards over a large portion of the Virginia area (Muller, 1956). European mine workers in Virginia were housed in distinctly built, furnished and conveniently placed mine towns with essential infrastructures (Muller, 1956), while the local mine workers were housed in mine hostels (Crush and James, 1995).

1970 marked the beginning of the second phase and it lasted till 1989, it was majorly characterized by expansion, population growth, an increase in production figures (Marais and Nel 2016) and the beginning of the decline in the value of its contribution to the nation's economy (Fedderke and Pirouz, 2000). The drop in the price of gold combined with falling gold reserves in 1989 marked the beginning of the third phase of the Free State goldfields, during this period, the province lost its position as the major contribution to the country's economy, employment in the mining industry dropped below 30,000 in 2011 as opposed to 180,000 in 1988 which led to an increase in the poverty levels of the community and a massive redundancy of the mining workshop (Marais and Nel 2016).

The mining production figure in the Free State province has declined from a figure of 181.59 in 1984 to 34.41 in 2014 (StatsSA. 2012) while the population growth rate in the Mathjabeng municipality alone was -2.8 in 2001 and -0.4 by 2011 (Marais et al., 2015). At the first official census in 1996, Mathjabeng had a total of 472,800 people which gradually reduced to 408,171 in 2001 and 406,461 in the 2011 census (StatsSA.,2012). The environmental and economic impacts of these developments have been severe. Mining towns have become desolate and different efforts to resuscitate the gold fields ever since has totally failed (Marais and Nel 2016). Presently, Virginia has become a shadow of itself. The mines around the town are depleted and have been shut down by Harmony gold, crime rates are on a gradual increase, population has drastically reduced, the streets have become quiet, the municipality is failing and the once vibrant gold town is now commensurate to a ghost town. Various attempts to resuscitate Virginia by attempting to diversify the economy have failed blatantly (Stephens and John, 2015).

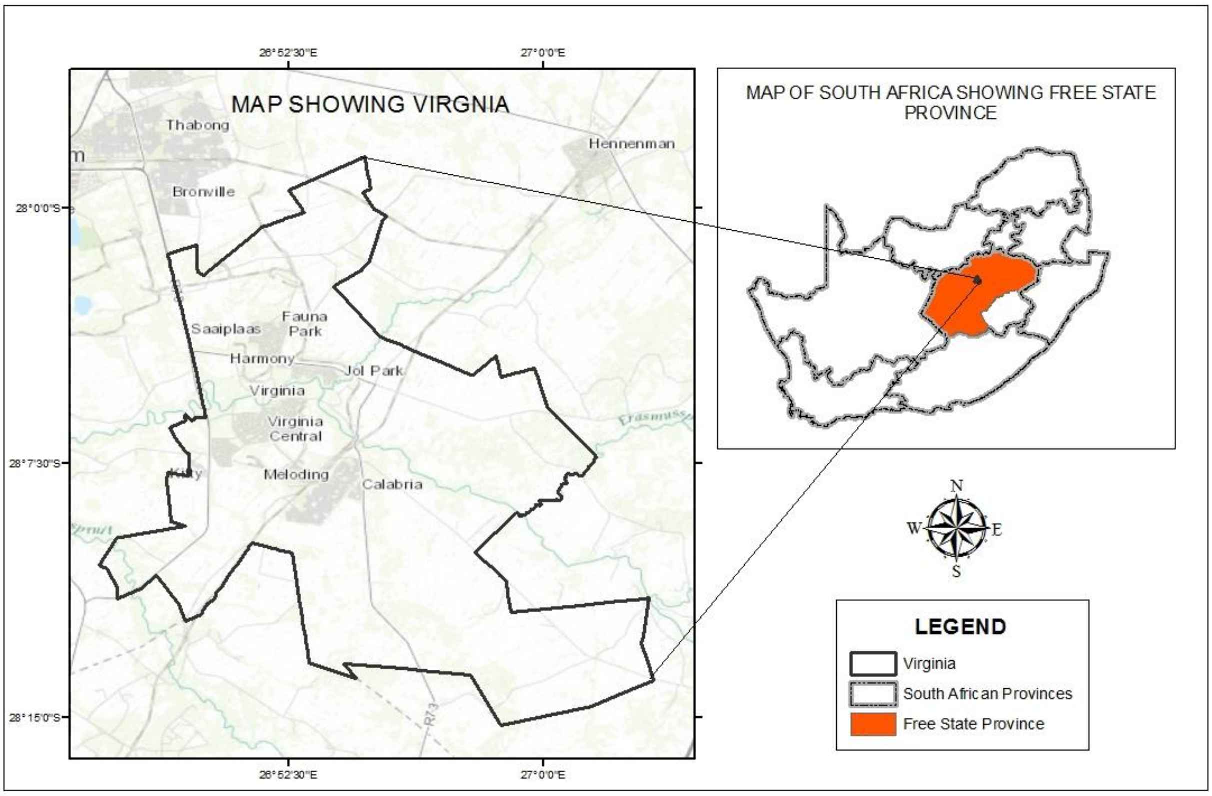

Figure 2. Map of South Africa showing Free State province and Virginia

3.2 Data

Due to the historic nature of this research, choice of image data was constrained by time. A part of this research relied on topographic maps and aerial photographs to produce the land use and land cover maps since satellite imagery was not available for early timelines in the study. The years that were studied for this project followed the timeline described in section 3.1.2 and are 1945 and 1954 for the first phase, 1975 and 1986, for the second phase and 1995, 2005 and 2015 for the third phase. The choice of timeline was based on data availability, in particular for the periods that precede the introduction of Landsat in 1986. Yildiz & Doekr (2016) maintained that in order to increase the accuracy of the classification while determining spatial change, the image must be acquired in the summer periods when the low cloudiness rate is obtained. Hence Landsat data for this study was acquired for the November and December period because these are the peak of the summer months in South Africa. These images also minimize spectral similarity due to excessive surface wetness during the summer period when everything appears green (Ololade et al 2008). Therefore the summer Landsat images would be useful to calculate the vegetation health using the NDVI indices.

The data used in the research are listed in table 1 below:

Table 1. Table showing data types and properties

TIMELINE	YEAR UNDERSTUDY	INPUT DATA	SPECTRAL AND SPATIAL CHARACTERISTICS OF THE DATA	SOURCE
1947 - 1969	1945	**Aerial photographs** 1944	Scale of photography: 1:20,000. Camera: F8; Focal length of camera: 7'; Resolution: 300dpi	NGI
		Topographical maps 1945	Resolution: 300dpi; Scale 1:50,000; Coordinate system: WGS 1984.	NGI
	1954	**Aerial photographs** 1952	Scale of photography: 1; 50,000. Camera: 69; height 19,500cm; Date of acquisition: 29th July 1952; Resolution: 300dpi.	NGI
		Topographical maps 1954	Resolution: 300dpi; Scale 1:50,000; Coordinate system: WGS 1984.	NGI
1970 - 1989	1975	**Topographical Maps** 1975	Resolution: 300dpi; Scale 1:50,000; Coordinate system: WGS 1984.	NGI
	1986	**Landsat 5 (TM) 1986** *Path 171, Row 79* *Acquired: 12-12-1986*	Band 1: PANCHROMATIC; 0.45 – 0.52 µm; 30m resolution; Band 2: BLUE; 0.52 – 0.60 µm; 30m resolution; Band 3: GREEN; 0.63 – 0.96 µm; 30m resolution; Band 4: RED; 0.76 – 0.90 µm; 30m resolution; Band 5: NEAR INFRARED; 1.55 – 1.75 µm; 30m resolution; Band 6: THERMAL INFRARED; 10.4 – 12.50 µm; 120m resolution; Band 7: SWIR; 2.08 – 2.35 µm; 30m resolution.	USGS
		Aerial photographs 1986	Scale of photography: 1:50,000. Camera: 5, Focal length of camera: 4.0. Date of acquisition: 22nd May 1986. Resolution: 300dpi	NGI
1990 - 2015	1995	**Landsat 5 (TM) 1995**	Band 1: PANCHROMATIC; 0.45 – 0.52 µm; 30m resolution; Band 2: BLUE; 0.52 – 0.60 µm; 30m resolution; Band 3: GREEN; 0.63 – 0.96 µm; 30m	USGS

		Path 171, Row 79 *Acquired: 21-12-1995*	resolution; Band 4: RED; 0.76 – 0.90 µm; 30m resolution; Band 5: NEAR INFRARED; 1.55 – 1.75 µm; 30m resolution; Band 6: THERMAL INFRARED; 10.4 – 12.50 µm; 120m resolution; Band 7: SWIR; 2.08 – 2.35 µm; 30m resolution.	
		Topographical maps 1997	Resolution: 300dpi; Scale 1:50,000; Coordinate system: WGS 1984	NGI
	2005	**Landsat 5 (TM) 2005** *Path 171, Row 79* *Acquired: 14-11-2005*	Band 1: PANCHROMATIC; 0.45 – 0.52 µm; 30m resolution; Band 2: BLUE; 0.52 – 0.60 µm; 30m resolution; Band 3: GREEN; 0.63 – 0.96 µm; 30m resolution; Band 4: RED; 0.76 – 0.90 µm; 30m resolution; Band 5: NEAR INFRARED; 1.55 – 1.75 µm; 30m resolution; Band 6: THERMAL INFRARED; 10.4 – 12.50 µm; 120m resolution; Band 7: SWIR; 2.08 – 2.35 µm; 30m resolution	USGS
		Aerial Photograph 2004	Scale of photography: 1:20,000; focal length: 4.0; Date of acquisition: 12^{th} July 2004	NGI
	2015	**Landsat 8 (ETM+) 2015** *Path 171, Row 79* *Acquired: 26-11-2015*	Band 1: COASTAL AEROSOL; 0.43 – 0.45 µm: 30m resolution; Band 2:BLUE; 0.45 – 0.51 µm; 30m resolution; Band 3:GREEN; 0.53 – 0.59 µm; 30m resolution; Band 4:RED; 0.64 – 0.67 µm; 30m resolution; Band 5: NEAR INFRA RED; 0.85 – 0.88 µm; 30m resolution; Band 6: SWIR 1; 1.57 – 1.65 µm; 30m resolution; Band 7: SWIR 2; 2.11 – 2.29 µm; 30m resolution; Band 8: PANCHROMATIC; 0.50 – 0.68 µm; 30m resolution; Band 9: CIRRUS; 1.36 – 1.38 µm; 30m resolution; Band 10: THERMAL INFRARED (TIRS) 1; 10.6 – 11.19 µm; 30m resolution; Band 11: THERMAL INFRARED (TIRS) 11; 1.50 – 12.51 µm; 30m resolution	USGS

3.3. Methods

This section presents the methods used to achieve each objective in the research separately, for clarity.

Objective 1

Create a time line of land use and land cover activities in Virginia during the mining period and beyond using Remote Sensing and GIS.

3.3.1. Pre-processing

The data pre-processing operations that were used to prepare the data for analysis are listed below:

1. Acquisition and pre-processing of Landsat images;
2. Acquisition and pre-processing of topographical maps and aerial photographs;
3. Vectorization and database creation.

These are explained in detail below:

Acquisition and pre-processing of Landsat images

Image pre-processing is the first required step in the process of utilizing a remotely sensed image. Meaningful information that aids better image interpretation are extracted from the data through this process, and its major processes include geometric correction or image registration, atmospheric corrections, and radiometric calibration. Image enhancement, noise removal, and topographic corrections are other steps applied only when necessary (Şatır and Berberoğlu 2012; Iqbal and Khan 2014). The Landsat imageries were acquired from the website of the United States Geological Survey library and were downloaded freely from www.earthexplorer.usgs.gov. As contained in table 1 above, five Landsat images that comprise of 1 Landsat MSS image, 3 Landsat 5TM images and 1 Landsat 8 (ETM+) were acquired for the years between 1975 and 2015. These images were acquired during the summer period i.e. the period between mid-October and mid-February. Although the Landsat images that were used for this study has been geometrically corrected from source, but radiometric calibrations and atmospheric corrections was conducted on the 1975, 1986, 1995, 2005 and 2015 imageries using the Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) of the ENVI 5.3 software.

Acquisition and pre-processing of topographical maps and aerial photographs

It is essential that satellite imagery and scanned maps are geo-referenced before they used for the production and updating of maps. Maps are usually geo-referenced by using ground control points (Javorovic et al., 2002). Hence the first step in pre-processing the aerial photographs is geo-referencing. Topographical maps and aerial photographs were acquired from the NGI; while the topographical maps have been geo-referenced the aerial photographs were manually geo-referenced by selecting control points from the base map provided on the ArcGIS 10.3 software using the 1st order polynomial transformation algorithm. The room mean square error of the geo-referencing module of ArcMap 10.3 was used to assess the accuracy of the geo-referenced map which did not exceed 2.52 metres.

Vectorization and database creation

Vectorization involves classifying features in a map into object classes based on themes systematically saved as points, lines or polygons depending on individual characteristics and further organised into spatial layers and can be used to produce land use land cover maps (Javorovic et al., 2002). Topographic symbols are attached to various objects so that they can be identified on a map and objects are ascribed attributes describing names and unique characteristics of each of them (San et al., 2005; Dewan and Yamaguchi, 2009). Historic databases allow mapping and analysing of historic events, it also provides the possibility of analysing long term spatial change using spatio-temporal data, one popular method is to use visual and descriptive methods to explore spatial patterns and how they have evolved over time (Mojica et al., 2013). The vectorization of features in this study was done through on-screen digitizing using topographical maps and aerial photographs as a guide with the ArcGIS 10.3 software and the vector files will be stored in the file geo-database of the software.

3.3.2 LULC classification

Classification is a process which involves the identification of the overall pattern related with similar pixels in a remotely sensed image as regards characteristics and objects that correspond to the earth's surface (Sunar 1998). The classification process in a remote sensing project is a complex one, and it involves the consideration of a wide variety of factors (Lu and Weng 2007). Its major steps include determining suitable classification system, training sample selection, image pre-processing, feature extraction, selecting classification algorithm, post-classification processing and accuracy assessment. The classification process can be done through the supervised or unsupervised method of classification (Lu and Weng 2007). The patterns of landuse and land cover are subject to changes over time, these changes occur in response to forces of social, economic and environmental factors. Understanding the nature and casual factors of these changes are essential in facilitating effective management, proper planning and regulation of land resources (Sunar 1998). Although the most common supervised classification technique presented in literature is the maximum likelihood classifier (Erbek et al, 2004), Hedge et al. (2014) and Mushore et al (2016) have recently proven that evolving machine learning algorithms such as the support vector machine are more accurate for classifying urban environments. Even though using remote sensing to classify urban environments can be quite difficult because of spectrally and spatially complex urban features, the SVM exhibits a higher degree of accuracy above others (Hedge et al 2014). Its major advantage lies in its ability to accurately classify features with relatively low amounts of training data compared to other classifiers (Mushore et al 2016). The support vector machine (SVM) classification was performed on the 1975, 1986, 1995, 2005 and 2015 Landsat images by using 8 land use classes illustrated in table 2.

Reference points for the classification were derived by selecting ground control points for each year of study. The ground control points for 1975 were derived with the aid of 1975 topographical maps while that of 1986 was derived from 1986 aerial photos. The 1997 topographical map was used to derive information about the probable state of the 1995 Landsat image because no topographical map or aerial photos were available for the year 1995. Furthermore the ground control points for 2005 and 2015 were derived from google earth images and the South African land cover map of 2015. 373 reference points were selected in all and randomly divided into 70:30 for training and testing purposes as suggested by Rogan et al 2008 and Millard & Richardson (2015).

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3.3.3. Support Vector Machines for LULC classification

SVM is a non-parametric statistical machine learning algorithm, which was originally aimed at binary classification by defining optimal hyperplane providing maximum margin for separating two classes. SVM which operate based on statistical learning theory; have been successfully applied to classify remotely sensed images (He. et al., 2014; Ustuner et al., 2015). The basic idea of the SVM is to map multidimensional data into a higher-dimensional space, in which there is a hyperplane that can be used to linearly separate the original data, thereby maximizing the margin between different classes (He. et al., 2014). The SVM classifier works by identifying the optimal hyperplane and correctly dividing the data points into two classes. There will be an infinite number of hyperplanes and SVM will select the hyperplane with maximum margin. The margin indicates the distance between the classifier and the training points (support vector) (Bahari et al., 2014; Delmai 2014). Support vector machines (SVM) have been shown to attain high accuracies in LUC mapping and outperform other algorithms. SVM have two significant advantages for LUC mapping (Paneque-Gálvez et al 2013; He. et al., 2014). First, since SVM classifiers seek to separate LUC classes by finding a plane in the multidimensional feature space that maximizes their separation, rather than by characterizing such classes with statistics, they do not need a large training set but just the training samples that are support vectors (Paneque-Gálvez et al 2013; He. et al., 2014). Second, SVM algorithms are independent of data dimensionality which is a key feature when using many spectral bands such in hyperspectral imagery or when ancillary data are included in the classification process; conversely, for classifiers that depend on dimensionality (e.g., artificial neural networks), training sets must exponentially increase in size to maintain classifier performance (Paneque-Gálvez et al 2013).

In order to derive high SVM classification accuracy, certain parameters have to be optimized correctly. These parameters are i) error penalty or cost (C) for the all kernels, ii) gamma (γ) for all kernel types except linear, iii) bias term (r) for polynomial and sigmoid kernel, and iv) polynomial degree (d) for polynomial kernel (Ustuner et al., 2015). This study used Ustuner et al., (2015) SVM"s parameter which produced the highest classification in the comparative study between different classification procedures. The polynomial method of SVM classification was used with a degree of 6, a bias term of 5, gamma value of 0.2 and an error penalty of 500.

Land use classification of Landsat images

The 2014 South African land cover classification scheme, which is also an abstraction from Thompson (1996), was used for this study. Seven of these classes are present in the area of study and contained in table 2 below. These are bare, cultivated, grassland, mines, formal (urban), dense bush and water. However, in order to study a number of infrastructural violence parameters, an attempt was made to distinguish between formal and informal urban/built areas during the classification, which proved successful.

Table 2. Land use and land cover classes.

CLASS	DESCRIPTION	TRAINING DATASET	TESTING DATASET
BARE	This comprises of all exposed and non-vegetated areas dominated by loose soil, rock, sand, or paved artificial surfaces. It can be man-made or natural.	37	11
CULTIVATED	Cultivated farmlands, pastures, dense forests, includes all forms of natural, semi-natural and planted vegetation.	32	14
GRASSLAND	This consists of the areas dominated by low shrubs. Its mainly natural or semi-natural in rural and urban environments.	39	16
MINES	All historic and present mining sites and dumps.	27	16
FORMAL	This includes residential areas of all densities, urban, built up areas, infrastructures, transportation and recreation facilities.	40	17
INFORMAL	This includes informal settlements, huts and farmsteads.	28	13
DENSE BUSH	These are the areas dominated by tall trees, bushes, with high canopy heights and compact densities. It could be natural or man-made in urban and rural environments.	32	17
WATER BODIES	Rivers, lakes, streams and all forms of exposed water either natural or manmade.	26	8

Land use and land cover classification of vector data

LULC maps were produced from the topographical maps and aerial photographs available for the study area for 1945, 1954 and 1975. The first approach was to aggregate the components of the topographical map into the proposed LULC classes of formal and informal residential, mines, water, grass, cultivated, bare and bushes. Hence, as contained in table 3 below, the developed settlements, roads and railways were aggregated into formal LULC while native huts were aggregated into the informal LULC. Rivers, non-perennial waters, pans, lakes, furrows, dams and canals were also aggregated into the water LULC. The grass LULC consisted of marshes, eroded areas and dry pans while the cultivated LULC was aggregated from the areas that represent plantations, orchards and cultivated lands on the topographical maps. Sandy areas and plain surfaces in the map represented the bare LULC type while the bush LULC was aggregated from bushveld, forests, windbreaks and avenue elements.

Table 3. LULC classes aggregated from topographical map features

SATELLITE IMAGE LULC CLASSES	TOPOGRAPHICAL MAP CORRESPONDING AGGREGATES
Formal	Developed neighbourhoods, Roads, Railway
Informal	Native huts
Mine	Excavations
Water	Rivers, non- perennial, Pans, Lakes, weirs, pipelines and Furrows, Dams, Canal
Grass	Marshes, Eroded Areas
Cultivated	Plantations, Orchards, Cultivated lands
Bare	Sand and plain surfaces on map
Dense Bushes	Bushveld, Forests, Windbreaks and avenues

The bush, bare, cultivated, grass and LULC types were vectorised manually as polygons into individual feature map layers from the topographic maps using the aerial photographs as a guide. The native huts were vectorised as points and converted into a 30 × 30m raster grid using the features to raster tool of ArcMap 10.3 so as to correspond eventually with the 30m resolution of Landsat images used in the later years. The 30 × 30m grid of informal settlements was then converted into rectangular polygons of 30 × 30m using the raster to polygon tool of ArcMap 10.3 to form the informal LULC.

The roads and railways that represented part of the formal LULC were vectorised as lines and converted into raster grid of 30 × 30m using the polygon to raster tool of ArcMap 10.3. The rasterized roads and railways were further converted into a feature class of 30 × 30m polygons. The built up areas were vectorised as polygons and later merged with the grided roads and railway into a single feature class using the merge feature tool of the data management tool of ArcMap 10.3.

The water class was aggregated from 8 other components as described in table 3 above. The major river that ran across Virginia was vectorised as a polygon. It could not be vectorised as lines because the topographical maps revealed that its width varies across space. However, the streams were vectorised as lines and converted into rasterized grids of 30 × 30m. These rasterized grids were then converted into polygons which retained the 30 × 30m properties and merged with the vectorised river polygon to derive the water LULC class using the merge feature tool of the data management tool of ArcMap 10.3.

The developed eight different classes in polygon data types were further merged to form a single feature class with LULC attributes using the merge feature tool of ArcMap 10.2. This single feature class in form polygon data type were then finally rasterized into a LULC map of 30 × 30m grid with the polygon to raster tool of the Arc Toolbox. The maximum combined area of the cell assignment type was used in the conversion process. Using the maximum combined area, if more than one LULC feature occurs in a 30×30m grid, the largest LULC class within the 30×30m cell determines the value that will be assigned to the entire cell.

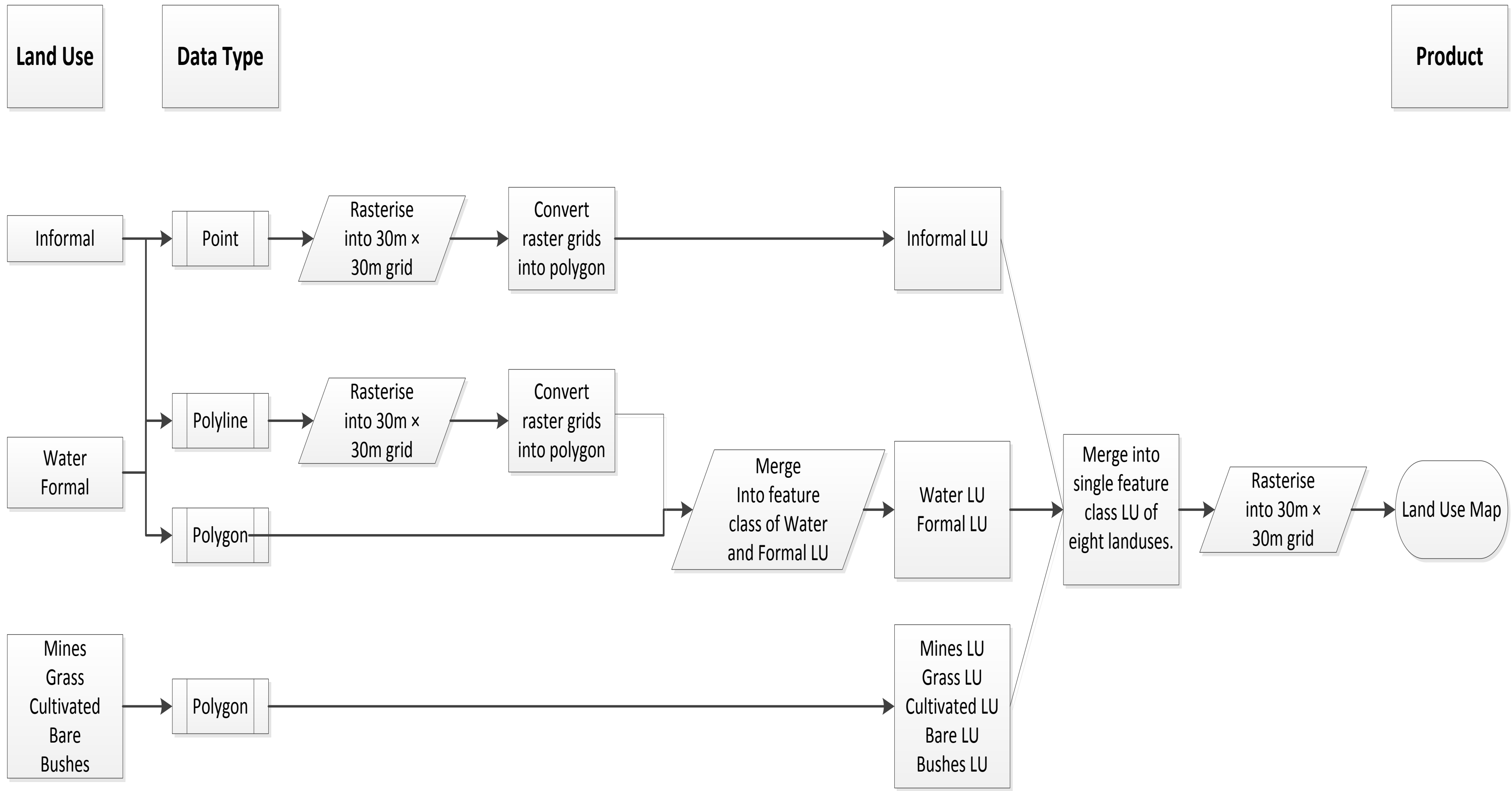


Figure 3. Steps followed in converting topographical maps to LULC

Lack of spatial data remains a major problem in historic analysis and this research data, the study area in this research was no exception. The available aerial photographs and topographical maps did not cover the full extent of the area of study hence they had to be combined in different proportions to develop LULC maps for 1945 and 1954. As displayed in the figure 4 below , the available aerial photographs for the years 1944 and 1952 both covered about 50% of the area under study which is just a fraction of the total area understudy. Hence, the topo maps of 1945 and 1946 was combined with 1944 aerial photos to produce the LULC maps for 1945. While the topographical maps for 1954 and 1951 were combined with the 1952 aerial photographs to produce the LULC map for 1954. However, the 1975 topographical map covered the entire extent of the study area hence did need any combination to make it complete. The topographical maps which were at a scale of 1:50,000 further introduced issues of scale dependency when combined with Landsat images which was at a higher resolution. Also, the LULC maps for years 1945, 1954 and 1975 that were developed from topographical maps may slightly differ from the aerial photographs that accurately depict the exact situation of things. This is because the topographical map is a cartographic exercise that may omit some information.

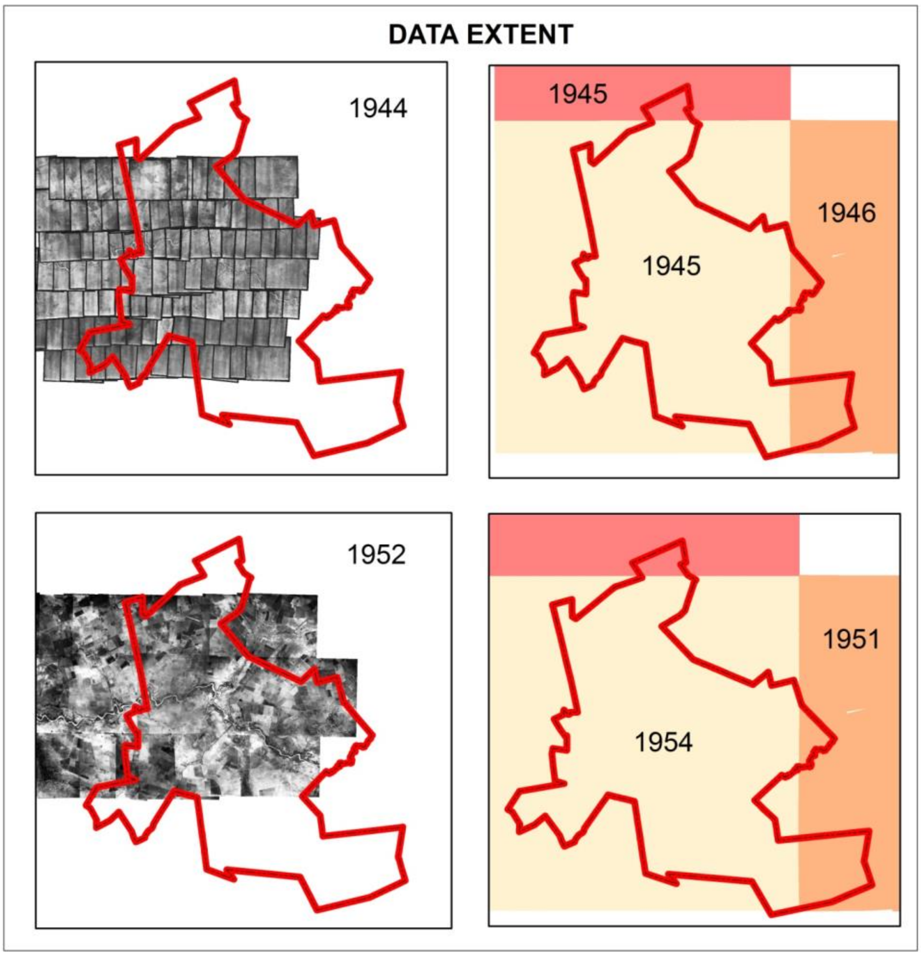


Figure 4. Data extent of the aerial photographs (left) and topographical maps (right) of the study area.

3.3.3 Accuracy assessment

Classification is incomplete until the degree of its accuracy is assessed; hence accuracy assessment is an important aspect of the classification process (Foody 2004). Classification accuracy is defined as the extent of resemblance between a remotely sensed imagery and its reference information (Iqbal and Khan, 2014). Standard methods for assessing the accuracy of classified images which are overall accuracy, error matrix, producer's accuracy and kappa index was applied.

A confusion matrix was created to calculate the overall, user and producers accuracies and the kappa statistics. The overall accuracy is usually represented as a percentage, and it's a representation of the probability that a randomly selected point on the map is correctly classified (Adam *et al.,* 2014). The overall accuracy assessment is determined by the formula below:

$$\text{Overall accuracy} = \frac{\Sigma\ (\textit{classes correctly classified along diagonal})}{\Sigma(\textit{Row total or Column total})}$$

The Kappa coefficient indicates the difference between the actual agreement of the reference data and the classifier; while the producer's accuracy shows the probability that the classifier in an image pixel was correctly labelled (Adam *et al.,* 2014). The kappa coefficient ranges from 0 to 1, while a kappa coefficient value of 1 indicates a perfect agreement between the classified images and the reference data, a value close to 0 indicates no agreement (Dorn.et al., 2015). The kappa coefficient is obtained by the formula below:

$$\textbf{\textit{Kappa}} = \frac{\text{observed accuracy} - \text{chance agreement}}{\text{1- Chance agreement}}$$

The producer's accuracy shows the probability by which the classifier has been rightly categorised in an image pixel (Adam, 2014). Often times it's also referred to as commission of errors, and its expressed in forms of percentages gotten by the differentiation of the users accuracy which is expressed as a percentage % from 100 (Petropoulos.et al., 2010)

Reference data that were collected from group of pixels from areas of known and defined land covers were selected for testing purposes with the aid of aerial photographs and topographical maps, which were later used as reference data to check classification accuracy. In this study, 112 ground control points which is 30% of the total reference points were used to assess the accuracy of the classified images.

3.4. Objective 2

Analyse LULC changes that occurred in Virginia over the timelines using change detection techniques and spatial metrics.

3.4.1. Change detection

Change detection is defined as the process of identifying changes in LULC over time (Antwi et al., 2008). It is also the process of observing changes in the appearance of a phenomenon by remotely monitoring it at different time intervals. It entails analyzing two registered images from the same geographical area which was obtained from two different times (Belal and Moghanm 2011).

One major application of data derived from remotely sensed images is change detection. It encompasses the use of remotely sensed images from multi-dates to differentiate areas affected by land cover changes between imaging dates (Sunar 1998). Data derived from Landsat images offers the abilities for detecting changes that occurs in land covers, land uses or cover conditions because of its short and regular 16 day and yearly coverage. With its constant acquisition of imagery, the Landsat data makes it possible to quantify the extent and types of LULC changes that occurs in an environment (Sunar 1998).

The post classification method of change detection was used to analyse the extent of LULC change in this study. The post classification change detection method analyses, describes and quantify the different changes that occur between images of the same landscape at different time intervals (Hegazy and Kaloop 2015). Often referred to as cross tabulation, it entails determining the quantities of the land cover that was converted to other categories at later dates (Hegazy and Kaloop 2015). The post classification comparison exceeds the simple change detection and attempts to numerically quantify the types of changes that have occurred in each category of LULC class although the success of the post classification depends on the accuracy of the maps derived from image classification (Belal and Moghanm 2011). Although the other type of change detection methods includes traditional post classification cross tabulation, cross correlation analysis, neural networks, object oriented classification, knowledge based expert systems and image segmentation (Rawat and Kumar 2014). The major advantages of the post classification is its ability to yield LULC transition matrices results (Rawat and Kumar 2014), bypass problems caused by inaccurate registration of multidate images (Singh 1989) and its ability to minimize normalization problems in atmospheric and sensor differences between different time limits (Belal and Moghanm 2011).

In this study, change detection was carried out on the LULC map produced for 1945, 1954 and 1975 with the cross classification and tabulation tool of QGIS 2.18.4 software while the post classification tool of ENVI 5.3 was used to analyse change for the classified Landsat images.

3.4.2. Spatial metrics

Spatial metrics is the information gotten from thematic maps through detailed analysis to show spatial heterogeneity. This analysis can be used to track historic changes in land cover patterns as it provides detailed information about spatial composition of land cover (Pham et al 2010). Often referred to as spatial metrics (Ji et al, 2006; Pham and Yamaguchi 2009; Pham et al 2010), or landscape metrics (Herold et al 2002; Sudhira et al, 2003; Seto and Fragkias, 2005; Xu et al 2007) by different scholars, these are quantitative indices that help urban planners to describe the structure and patterns of a landscape (Herold et al., 2002).

Spatio-temporal landscape metric analysis is important for understanding comprehensive shapes and processes of urban growth as it shows detailed information over only urban growth rates. It also gives an understanding behind variation in landscape patterns within and across cities to explain the relationships that urban forms share with policies (Seto and Fragkias, 2005). Metrics are derived based on information theory measures and fractal geometry, and they can be applied to study changes in landscape patterns, habitat fragmentation and biodiversity (Herold et al., 2002), and are obtained from the digital analysis of thematic maps that portray spatial uniqueness at different spatial scales and resolutions (Pham and Yamaguchi 2009). The combined use of remote sensing and spatial metrics is very useful for local city planners because it exposes them to valuable information that will enable them better understand the impact of planning policies in urban areas (Pham et al, 2010). Since the spatial metrics which will be used to analyse the pattern and trend of landuse change works with raster, the LULC maps produced from the topographical maps will be converted into raster like the classified Landsat images to produce the metrics and landuse change maps. Indices of spatial metrics used in this study are those that have been ascertained to yield information about LULC changes and fragmentation as stated by Herold et al., (2002) Ji et al., (2006) Pham and Yamaguchi (2009), Pham et al., (2010).

The chosen indices of spatial metrics that are used for calculating urban growth indices in this study are listed in table 3 and they are fully described as follows:

- Class Area Metric (CA): describes the growth of urban areas and measures the composition of landscape (Pham and Yamaguchi 2009; Pham et al, 2010).
- Number of Patches (N.P): it measures the extent of subdivisions of urban areas, its value is usually high when urban expansion is proportional to an increase in subdivided areas (Pham and Yamaguchi 2009; Pham et al, 2010).
- Edge Density (E.D): is defined as the measure of the total length of urban patch edges (Pham and Yamaguchi 2009; Pham et al, 2010).
- Largest patch index (LPI): this represents the portion of total land covered by urban area, it increases when the urban area becomes more amassed and integrated with urban cores (Pham and Yamaguchi 2009; Pham et al, 2010).
- Mean nearest neighbour distance (MNN): is the amount of open space between separate urban patches. Its value reduces when the distance between urban patches increases (Pham and Yamaguchi 2009; Pham et al, 2010).

- Area Weighted Mean Patch fractal Dimension (AWMPFD): This measures the complexity of the patch shape. If the patches become more complex and divided, the parameter increases to a higher fractal dimension (Pham and Yamaguchi 2009; Pham et al, 2010).

The landscape metrics were calculated from the land cover maps produced for the years under study in objective 1. These indices of spatial metrics were calculated using the patch analyst extension of FRAGSTATS 4.2 software program on the ArcGIS 10.3 interface. The FRAGSTATS 4.2 software was developed by Mcgrigal and Ene (2013) and its description are displayed in table 4 below. This program gives users the privilege to calculate diversity of landscape metrics.

Table 4. Table showing spatial metrics description by Mcgarigal & Ene (2013)

Metric	**Description**	**Units**	**Range**
CA – Class area	CA equals the sum of the areas (m2) of all urban patches, divided by 10,000 (to convert to hectares); that is, total urban area in the landscape.	Hectares	CA>0, no limit
NP—Number of patches	NP equals the number of urban patches in the landscape.	None	NP ≥1, no limit
ED—Edge density	ED equals the sum of the lengths (m) of all edge segments involving the urban patch type, divided by the total landscape area (m2), multiplied by 10,000 (to convert to hectares).	Meters per hectare	ED ≥ 0, no limit
MPS – Mean patch size	The area occupied by a particular type divided by the number of patches of that type.	Hectares	MPS>0, no limit
MNN—Euclidian mean nearest neighbour distance	MNN equals the distance (m) mean value over all urban patches to the nearest neighbouring urban patch, based on shortest edge-to-edge distance from cell center to cell center.	Meters	MNN>0, no limit
AWMPFD—Area weighted mean patch fractal dimension	Area weighted mean value of the fractal dimension values of all urban patches, the fractal dimension of a patch equals two times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m2); the perimeter is adjusted to correct for the raster bias in perimeter.	None	1 ≤ AWMPFD ≤ 2

3.5. Objective 3

Spatially quantify the manifestations of infrastructural violence in Virginia during the period under study Using GIS.

3.5.1 Land degradation as a dimension of infrastructural violence.

Rodgers and O'Neil (2012) established the fact that environmental or landscape degradation is one of the results of infrastructural violence in resource towns. One of the ways to assess land degradation is to quantify the degree of fragmentation of land cover classes in a given landscape. This could be caused by direct removal, decrease in patch sizes and increasing distance between remaining land cover patches (Mansour., et al 2016). Landscape metrics indices are noted for their ability to highlight land covers that are affected by degradation processes and their combined analysis with land cover change maps allows the identification of patches which could be more vulnerable to the degradation phenomena (Simoniello 2016). The landscape metrics indices that are suitable for quantifying landscape degradation as Mansour et al (2016) suggested are the percentage of land (%LAND), landscape level number of patches (NP), total area (TA), patch density (PD) and largest patch index (LPI). The trend of these indices between 1975 and 2015 will be monitored by comparing their increase or decrease in their rate of fragmentation over time.

Landscape degradation can also be exhibited in forms of decrease in biological activity which is reflected net primary production (NPP); this could be measured by the discontinuous monitoring of vegetation in a landscape through an index of vegetation mapping known as the Normalized Difference Vegetation Index (NDVI) (Waswa 2012). The NDVI was used to analyse the density and health of the vegetation, as a decrease in NDVI values signifies relative reduction in land cover, soil humidity and land degradation (Tagil 2007).

Exploratory NDVI statistics was performed for years 1975, 1986, 1995, 2005 and 2015. The comparative changes in NVDI over time will be assessed by using the image differencing method on these images to calculate the relative increase or decrease in the NDVI values (Tagil 2007). Although climate information (precipitation and temperature) will not be incorporated, the Landsat imageries that will be used for this study has been captured during summer which is the raining season. The NDVI will be calculated from the Landsat images using:

$$NDVI = (NIR – RED)/ (NIR + RED)$$

Where RED refers to the reflectance in the red channel and NIR refers to the near infra-red channel of the Landsat imagery (Lei and Bian 2010).

3.5.2 Social exclusion as a consequence of infrastructural violence

Infrastructural violence manifests itself in various forms of social exclusion; division of social class gets incorporated into architecture and urban planning by the introduction of city streets, fences and wall (Rodgers and O'Neill 2012), policies are made to support the violence by enacting rules and laws to segregate informal and the socially excluded population (Anand 2012).

Measures of lacunarity, fractal dimension and attributes of landscape patch derived from the analysis of satellite imageries have proven to be able to evaluate the proportion of wealth or poverty in an environment and help to have a better conception of the quality of life of the residents of such environments (Owen, 2011). Greenspace is a major contributor of life, hence economically deprived and informal settlements have extremely low patch sizes of vegetation. Research on quality of life has also shown that vegetation coverage would be less for informal areas; patch compactness would be greater with informal neighbourhoods having more circular shapes as against the more affluent settlements that possess elongated shapes which could have been as a result of deliberate ornamental planting (Owen, 2011).

Fractal dimension is also known to yield information about the economically viable areas of an environment, published results from the analysis of landscape metrics have shown that fractal dimension is inversely proportional to building size i.e the values of fractal dimension decreases as building size increases (Owen, 2011). The Area Weighted Mean Patch fractal Dimension (AWMPFD), which is one of the indices of urban metrics that yield information about fractal dimension was analysed and interpreted to show the areas of Virginia which has abysmally low building sizes that reveals fragmented informal settlements.

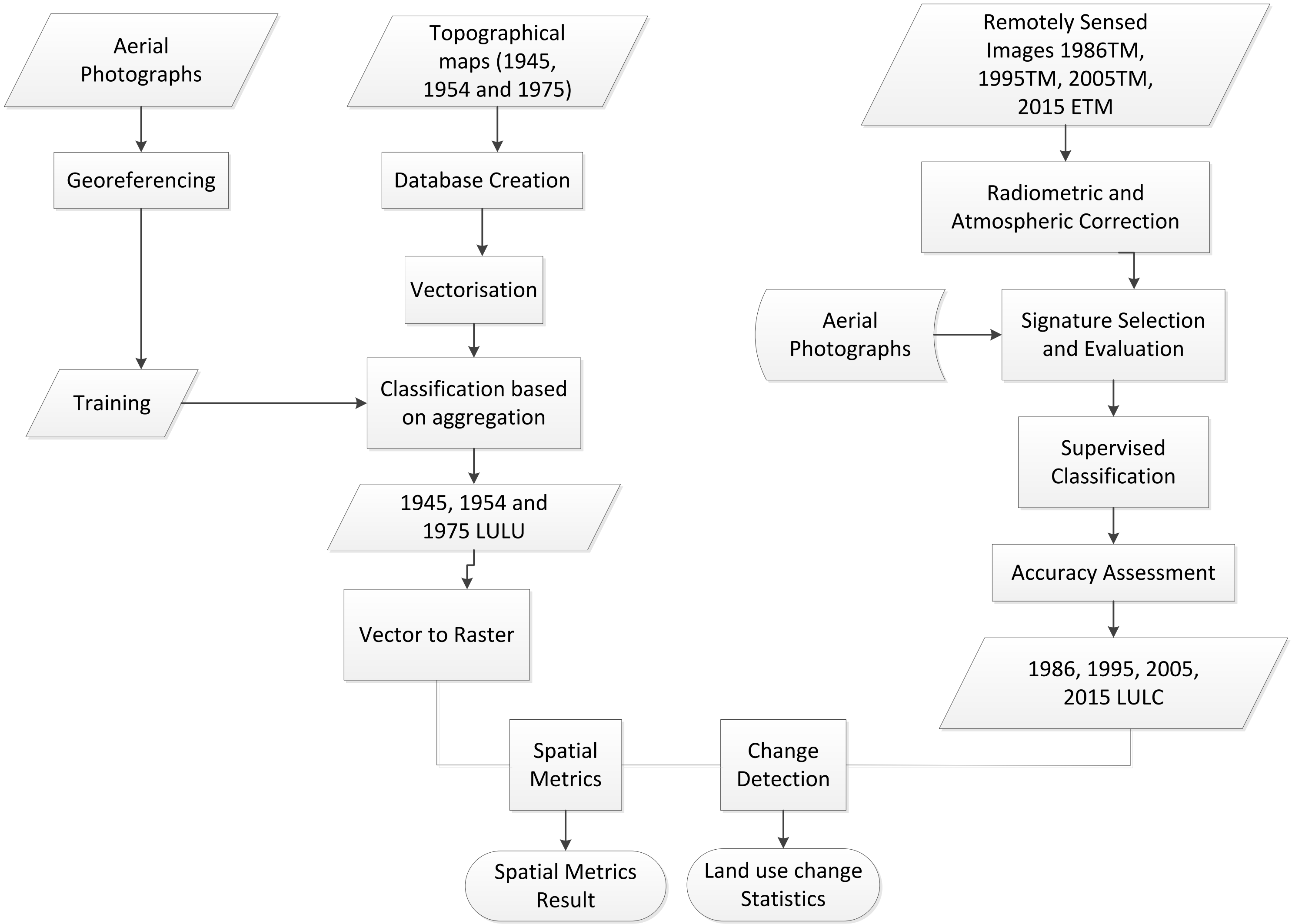


Figure 5. Research procedure workflow.

4. Results

This chapter contains the results of the analysis carried out in this research. These are presented in eight sections. Section 4.1 and 4.2 contain the results of reference data and accuracy assessment of classified images while sections 4.3 and 4.4 present the results of the LULC analysis and change detection. The results of landscape metrics analysis for both the formal LULC and informal LULC are presented in sections 4.5 and 4.6 while sections 4.7 and 4.8 contains land degradation and NDVI results respectively.

4.1. Reference data

The classified Landsat imagery was assessed for accuracy by using a confusion matrix table which can be created in the ENVI 5.3 software. The testing data set which is 30% of the entire dataset for each class was used as control points in assessing these accuracies. The validation of the classified images was done using a total number of 112 ground control points. All the classified Landsat images had accuracies that ranged from 86.35% to 90.56%. In order to better differentiate the various classes within the landscape, an exploratory NDVI analysis was conducted for each of the years under study and used to informally validate the class results.

4.2. Accuracy assessment

As shown in table 5 below, the users and producers accuracy of the mines yielded the highest accuracies through all the years with accuracies ranging from 82.2% to as much as 97.01%. This high accuracy could be due to the fact that the pixels representing the mine excavation had high reflectance as opposed to other classes hence making it difficult for it to be misclassified.

The accuracy assessment for the 1985 LULC analysis yielded an overall accuracy of 90.56% with a corresponding kappa coefficient of 0.94%. The bare LULC yielded the highest accuracy with a 92.9% and 97.3% producers and users accuracy respectively. The water LULC also yielded a producer accuracy of 92.9% and a user accuracy of 97.3%. Other LULC also had high accuracies that ranged from 80.6% to 94.7% in both categories of accuracy; however, the urban class yielded the least accurate of all the classes with 78.2% producer's accuracy and 88% user's accuracy.

The 1995 classified images yielded an overall accuracy of 89.7 with a kappa coefficient of 0.84. The agricultural LULC accounted for the highest accuracy with 94.4% producer's accuracy and 88.6% user's accuracy. Other LULC also had high accuracies ranging from 80.6% to 94.7% in both categories of accuracy. The urban LULC had the lowest accuracies with 80.6 and 80.2% producer and user accuracies respectively.

The 2005 classification result yielded an overall accuracy of 90.14% and a Kappa coefficient of 0.85. The class results produced relatively high accuracies that ranged from 80% to 97.1%. As usual, the mines exhibited the highest accuracies with 93.53% and 97.01% producers and user's accuracy respectively. Likewise also, the confusion matrix results for the LULC results for 2015 revealed an overall accuracy of 88.6% and a kappa coefficient of 0.83. The urban class was the most poorly classified with 75.5% producers and 86% users accuracy, the slightly low accuracy is due to the similar spectral characteristics between some buildings in the urban areas and the reflectance of the mine excavation surfaces. However, other LULC had satisfactory accuracies that ranged between 79.1 to 95.4 in both producers and user's accuracy. This classification results can be relied on for further analysis because the results surpass the 85% benchmark that is suggested by Anderson et al., (1976).

Table 5. Accuracy assessment results

Year	Overall Accuracy	Kappa	Accuracy type	Informal	Mines	Urban	Water	Bush	Culti-vated	Bare	Grass
1986	90.56	0.94	Producers	88.8	95.8	78.2	82.5	90.6	94.4	92.9	87.8
			Users	89.4	94.4	88	97.9	79.1	88.6	97.3	83.5
1995	89.7	0.84	Producers	85.5	90.9	80.6	82.5	80.6	89.4	94.9	91.2
			Users	85.5	88.9	80.2	95.9	86.2	93.1	94.7	84
2005	90.14	0.85	Producers	88.19	93.53	87.5	80	88.02	92.5	91.9	86.86
			Users	88.81	97.01	82.8	88.89	86.81	92.5	95.97	80
2015	88.62	0.83	Producers	91.5	93.9	75.5	82.5	86.2	93.5	90.4	85.2
			Users	85.5	95.4	86	85.45	79.1	88.6	97.3	76.7

4.3. Land use land cover analysis

The results of LULC analysis of Virginia as obtained from the LULC maps are summarised in table 6 and outlined in the following sub-sections:

Table 6. Summary of LULC analysis across the timelines

LULC	1945 (%)	1954 (%)	1975 (%)	1986 (%)	1995 (%)	2005 (%)	2015 (%)

Formal	1.84	4.21	6.42	6.74	16.83	12.11	9.46
Informal	0.05	0.05	0.23	0.68	1.93	2.89	5.62
Mines	0.01	0.91	2.58	4.21	5.18	4.63	4.68
Water	2.05	2.44	2.84	0.45	1.34	0.28	0.66
Grass	1.27	3.32	2.03	34.18	39.1	26.1	31.21
Cultivated	34.93	45.91	46.77	30.12	22.4	25.7	30.64
Bare	55.3	35.92	37.64	15.56	10.06	25.56	15.32
Dense bush	4.54	7.94	1.18	8.36	3.15	2.73	2.39

4.3.1. Results from LULC analysis

The results of the LULC analysis reveal that the LULC experienced vast changes during the seventy year period of this study. This section of the research contains a descriptive summary of the LULC classification results.

As highlighted in table 6 and the bar chart in figure 6, the formal LULC class which comprises of road transportation and rail transportation and built area covered 1.84% of the total study area in 1945. This increased steadily to 4.21% in 1954 and 6.42% in 1975. The formal LULC reached the peak of its growth in 1995 when it covered 16.83% of the total study area. After 1995, the formal (built) LULC class decreased with values of 12.11% in 2005 and 9.46% in 2015.

On the other hand, the informal (built) LULC class, which initially comprised of informal settlements in the form of randomly located farmsteads and huts that accommodated the local indigenous farmers living in this landscape, accounted for 0.05% in 1945 and 1954. This LULC steadily increased throughout the seventy year study period and, at the same time, it changed in nature. In fact by 1975 the nature of informal settlements had evolved into shacks and small buildings covered with corrugated roofs in the vicinity of the mines, whereas farmstead and huts almost disappeared. The informal (built) LULC class amounted to 0.23% in 1975. The percentage increased to 0.68% in 1986, 1.93% in 1995 and 2.89% in 2005. The Meloding Township which was located on the other side of the mines and separated from Virginia by the railway line contributed immensely to the informal LULC by 1975. The informal LULC recorded the highest in 2015 with coverage of 5.62% of the total study area.

Furthermore, the mining LULC, which includes the footprints of the open pit mines and excavations from underground mines, which were located strategically around the mining town of Virginia, contributed to just 0.01% of the entire study area in 1945. This steadily increased and recorded 0.91% in 1954, 2.58% in 1975 and 4.21% in 1986. The mining LULC recorded its highest values in 1995 with coverage of 5.18%. However, the mining LULC experienced reductions in its values and recorded 4.63% and 4.68% in 2005 and 2015 respectively.

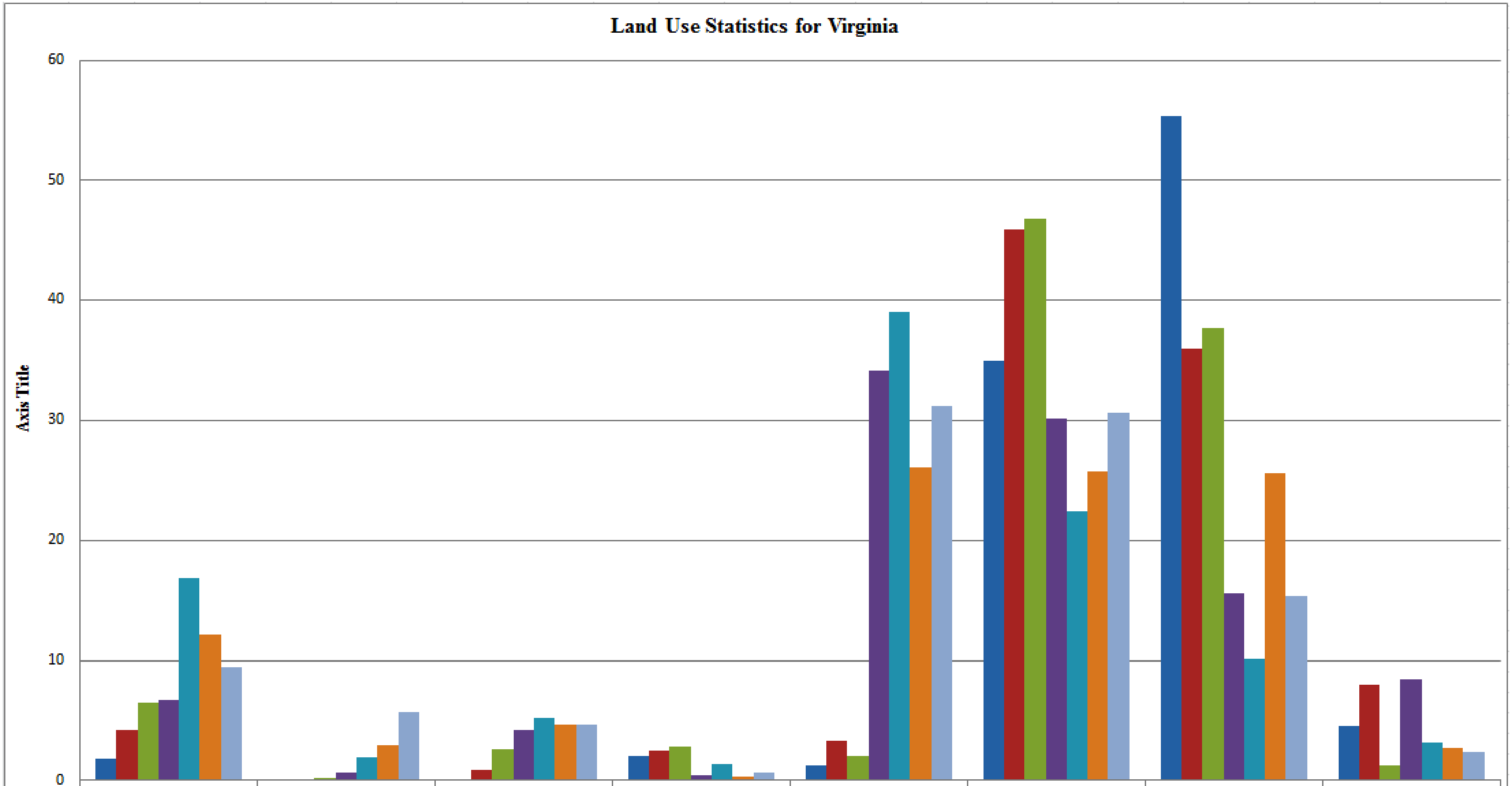
LULC analysis also revealed that the water class was not left out of this trend. As the LULC which primarily comprises of the Sand River that runs across Virginia, streams, and slime dams accounted for 2.05% in 1945. This class maintained consistencies in its coverage till 1975 with values of 2.44% and 2.84% in 1954 and 1975 respectively. However, this LULC experienced reduction in its values from 1986 with a reduction to 0.45% in 1986 as the width of the Sand River reduced and is now covered by the bush LULC. It further experienced unstable fluctuations in the remaining years with 1.34% recorded for 1995, 0.28% in 2005 and 0.66% in 2015.

In the grass category, the class recorded 1.27% in 1945, 3.32% in 1954 and an eventual 2.03% by 1975. However this LULC experienced vast increment to 34.18% by 1986 (see limitations section 6.2). The grass LULC class then went on to record 39.1% in 1995, 26.1% in 2005 and an eventual 31.21% in 2015.

At the beginning of the mining activities in 1945, the cultivated LULC, which comprises of farmlands, orchards and plantations, accounted for 34.93%. This increased to 45.91% in 1954 and recorded its highest value in 1975 with 46.77% recorded. However, the cultivated LULC experienced reduction in its previous values with 30.24% recorded for 1986, 25.7% in 2005 and 30.64% in 2015.

Also, the bare LULC constituted 55.3% of the entire study area at the beginning of mining activities in 1945. This reduced to 35.92% in 1954 and an eventual 37.64% in 1975. However, this LULC experienced reduction in its values to 15.56% in 1986 (See limitations on page 57) and fluctuated till 2015 with recorded values of 10.06% in 1995, 25.56% in 2005 and an eventual 15.32% by the end of 2015.

Lastly, in the bush LULC category, its LULC analysis recorded 4.54% at the inception of mining activities in 1945. This increased to 7.97% in1954 and decreased drastically to 1.18% in 1975. However, the bush LULC had its highest values in 1986 with more of its class occurring around the banks of the Sand River and coverage of 8.36%. However, this class decreased in the remaining years of study with 3.15% recorded in 1995, 2.73% in 2005 and an eventual 2.39% in 2015.



	Formal	Informal	Mines	Water	Grass	Cultivated	Bare	Dense bush
1945	1.84	0.05	0.01	2.05	1.27	34.93	55.3	4.54
1954	4.21	0.05	0.91	2.44	3.32	45.91	35.92	7.94
1975	6.42	0.23	2.58	2.84	2.03	46.77	37.64	1.18
1986	6.74	0.68	4.21	0.45	34.18	30.12	15.56	8.36
1995	16.83	1.93	5.18	1.34	39.1	22.4	10.06	3.15
2005	12.11	2.89	4.63	0.28	26.1	25.7	25.56	2.73
2015	9.46	5.62	4.68	0.66	31.21	30.64	15.32	2.39

Figure 6. Bar chart and figures showing LULC statistics in Virginia across the timelines considered

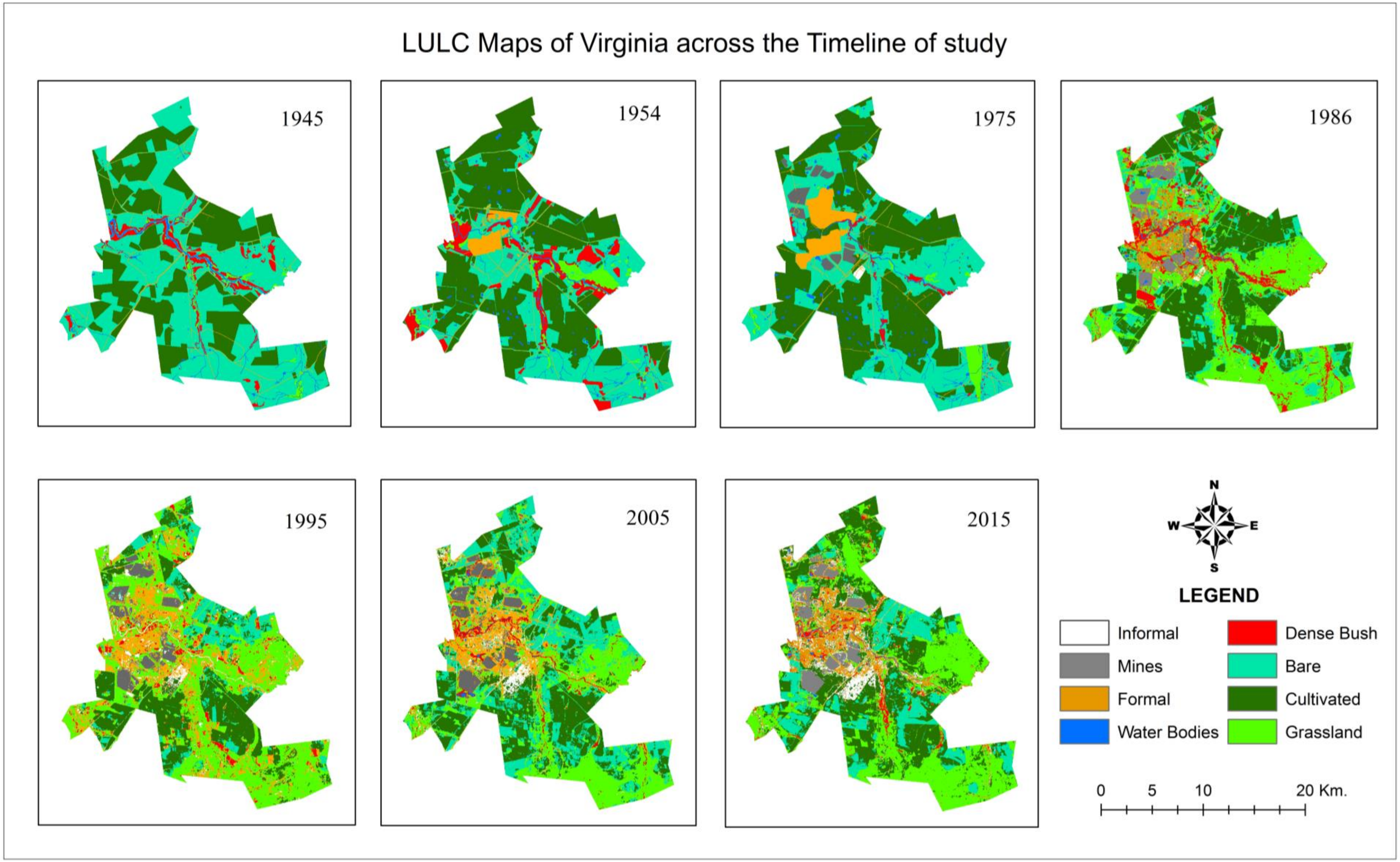


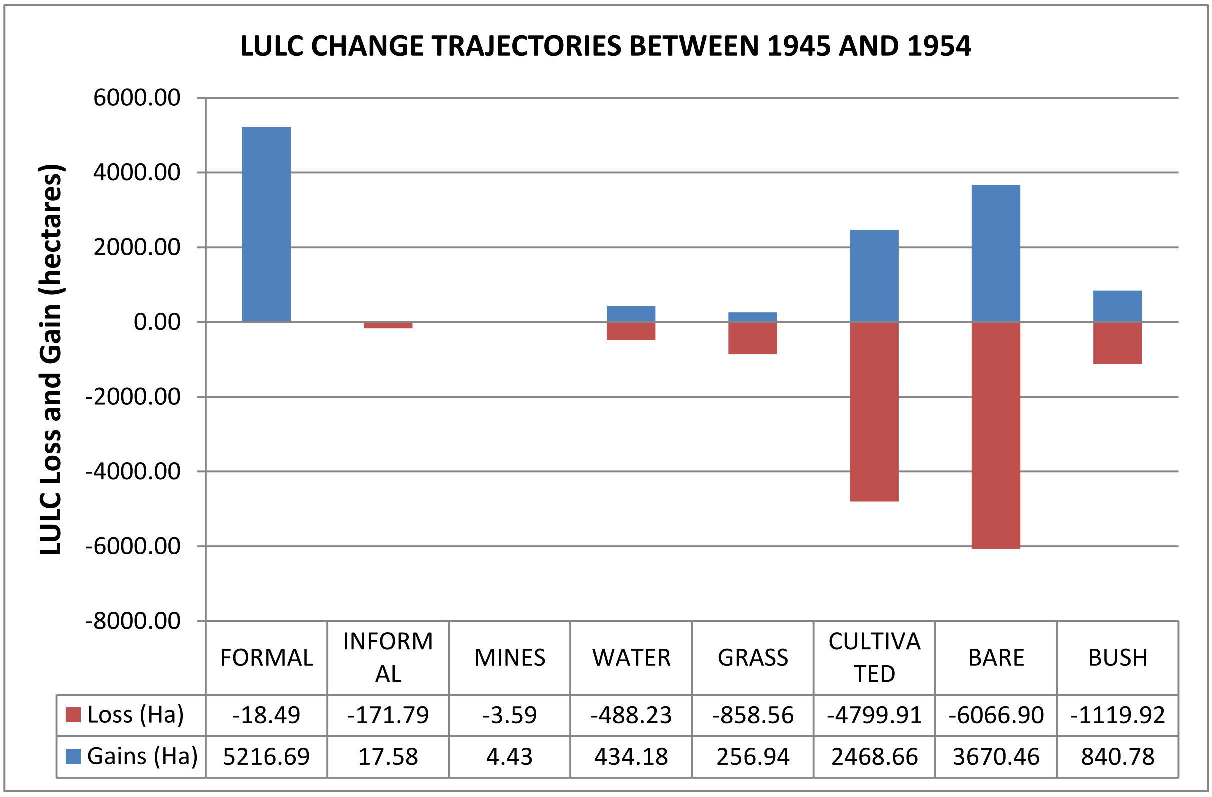
Figure 7. LULC maps of Virginia across the timeline of study

4.4 LULC change detection analysis

The post classification change detection algorithm of ENVI 5.3 and QGIS 2.18.4 software was used to compute the change detection statistics across the timeline of study in a bid to understand how the landscape changed over time. The LULC map developed from satellite images and topographical maps and the classified remotely sensed images were used to assess the changes that occurred between 1945-1954, 1954-1975, 1975-1986, 1986-1995, 1995-2005 and 2005-2015. A table containing a change matrix for each of the years was created. This change matrix contains the total changes experienced in each of the LULC throughout the time frame being considered in rows and columns. The class total row represents the sum of the initial stage of the LULC expressed in percentages. Within the seventy year study period, the eight different LULC types in Virginia have gone through a variety of changes. Results from the change detection of consecutive decade's timeframe are reported in this section.

4.4.1. Change trajectories between 1945 and 1954

- As shown in figure 8 below, the Virginia landscape experienced a wide variety of changes between 1945 and 1954. The key findings that were observed in the formal, informal, mines and other important LULC during this period are listed below:
- The formal LULC had increased tremendously with an addition of 5216.69 Ha which was converted from other land uses.
- The informal LULC however experienced some reduction with a loss of 171.79 Ha in it's initial coverage and an addition of 17.58 Ha.
- The mines experienced an addition of 4.43 Ha after the 9 year period.
- The cultivated and bare LULC experienced losses of 4766. 91 Ha and 6066.90 Ha respectively.



	FORMAL	INFORMAL	MINES	WATER	GRASS	CULTIVATED	BARE	BUSH
Loss (Ha)	-18.49	-171.79	-3.59	-488.23	-858.56	-4799.91	-6066.90	-1119.92
Gains (Ha)	5216.69	17.58	4.43	434.18	256.94	2468.66	3670.46	840.78

Figure 8. Change trajectories between 1945 and 1954

4.4.2. Change trajectories between 1954 and 1975

As summarised in figure 9 below, the Virginia landscape experienced wide variety of changes between 1954 and 1975. Table 8 below contains the change matrix of changes within this period. The key findings that were observed in the formal, informal, mines and other important LULC during this period are listed below:

- The formal LULC experienced further growth with an increase of 635 Ha to its initial land area by the end of the 21 year study period.
- The informal LULC experienced an increase of 202.03 Ha to its area. Meloding, the township associated with Virginia, which was characterized by informal settlements comprising of shacks, unplanned squatting, backyard shacks and traditional dwellings, had started growing at this stage and accounted for this increase in the informal LULC.
- Mining activities continued experiencing growth with an addition of 319.81 Ha to its initial coverage in 1975 and a loss of 20.96 ha
- The bare and cultivated both experienced significant reduction in their area with a loss of 5458.25 Ha and 3782.28 Ha respectively.

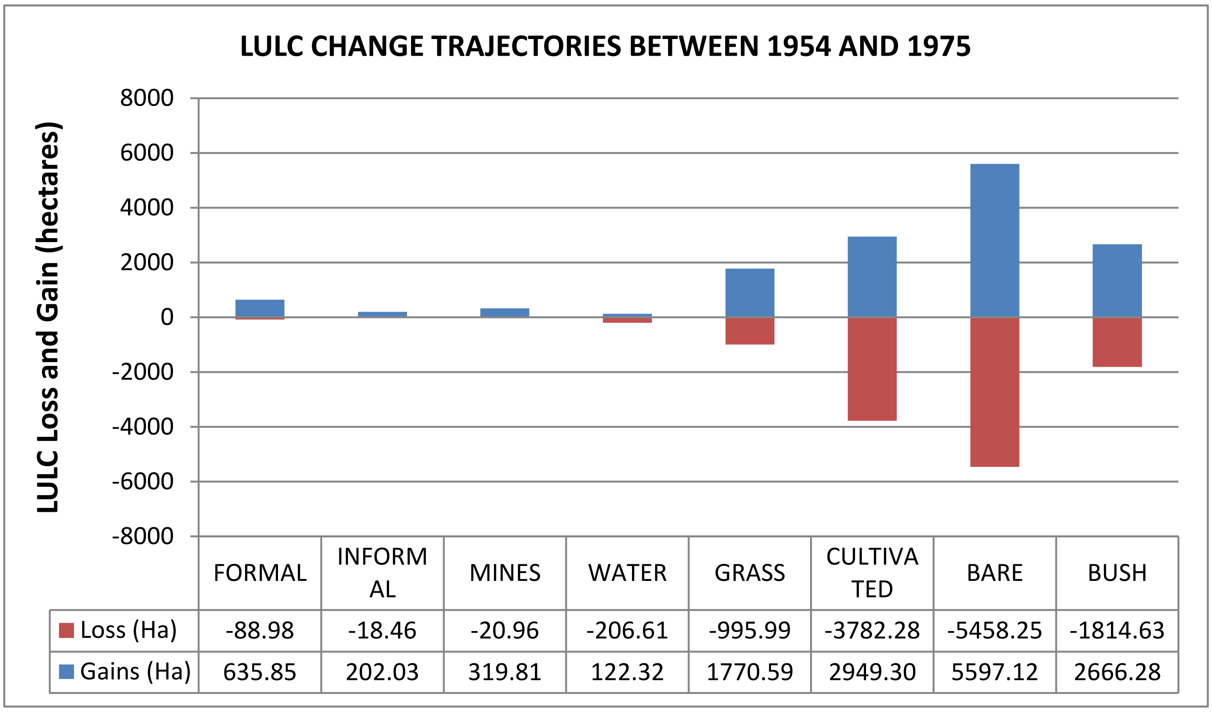


Figure 9. Change trajectories between 1954 and 1975

4.4.3. Change trajectories between 1975 and 1986

As reported in figure 10 below, the changes experienced by the Virginian landscape between 1975 and 1986 are diverse. Table 9 contains the change matrix of changes within this period; however the key findings that were observed in the formal, informal, Mines and other important LULC during this period are listed below:

- The landscape of Virginia experienced further increase in it's urban growth at this period as the formal LULC gained 1631.00 Ha between the 11 year period.
- The informal LULC also experienced it's own growth with an addition of 276.24 Ha to its area by 1986.
- Mining activities increased with the LULC gaining an additional 460.11 Ha.
- Agricultural activities during this period was pronounced as the cultivated LULC experienced an increase of 9064.70 Ha within the 11 year period.

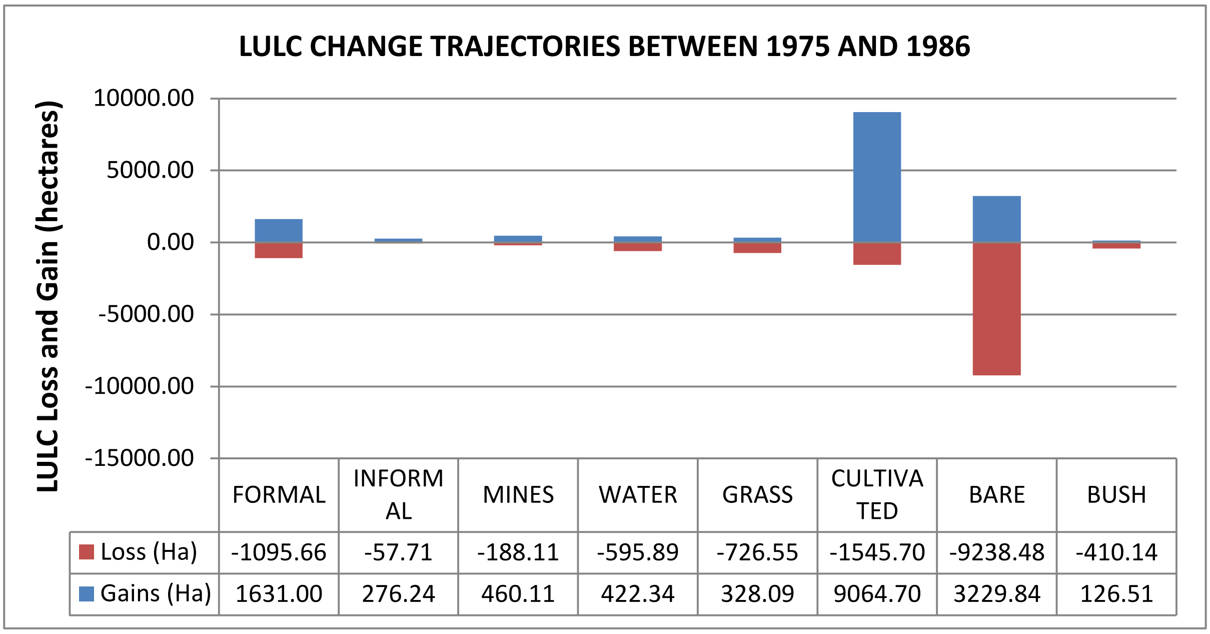


Figure 10. Change trajectories between 1975 and 1986

4.4.4. Change trajectories between 1986 and 1995

As contained in figure 11 below, the changes experienced by the Virginian landscape between 1986 and 1995 are various. Table 10 contains the change matrix of changes within this period; although the key findings that were observed in the formal, informal, Mines and other important LULC during this period are listed below:

- Urban expansion was more pronounced during this period as the formal LULC experienced tremendous growth during this period with an increase of 4665.69 Ha.
- The informal LULC experienced more growth as compared to the previous years with an increase of 651.69 Ha in its total land area.
- The cultivated and bare LULC experienced significant losses of 5242.84 Ha and 5306.14 respectively.

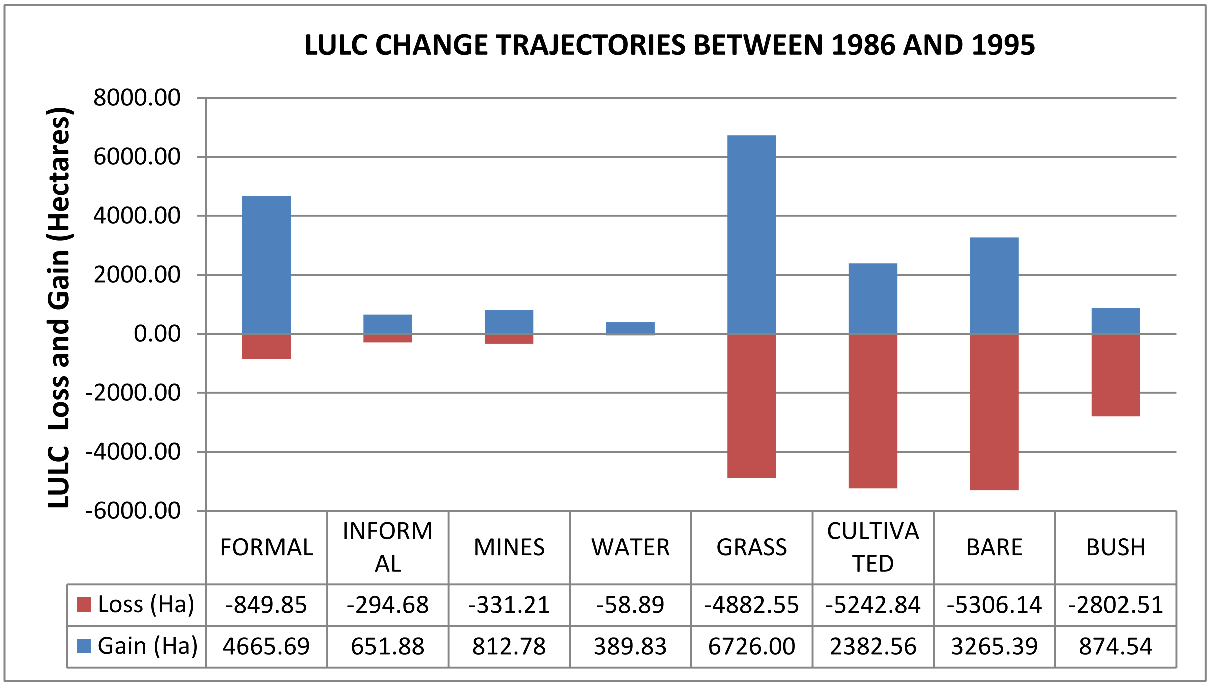
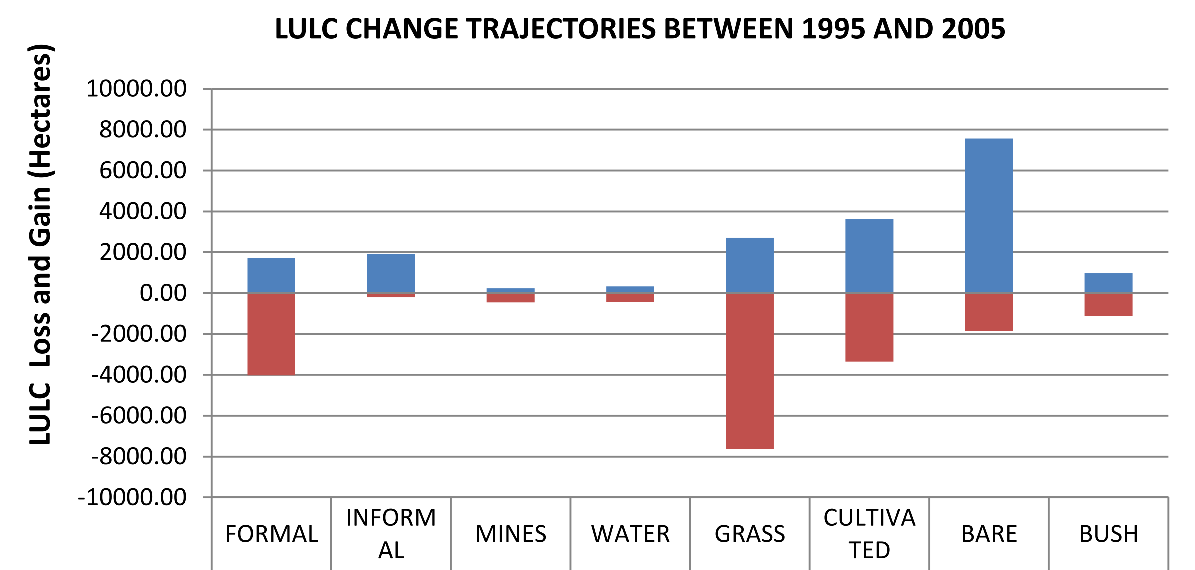


Figure 11. Change trajectories between 1986 and 1995

4.4.5. Change trajectories between 1995 and 2005

As contained in figure 12 below, the changes experienced by the Virginian landscape between 1995 and 2005 are diverse. Table 11 contains the change matrix of changes within this period; although the key findings that were observed in the formal, informal, Mines and other important LULC during this period are listed below:

- The formal LULC started experiencing a decline in its area with a loss of 4030.79 Ha.
- The informal LULC experienced the highest growth compared to the previous years with a gain of 1910.86 Ha and a minimal loss of 197.17 Ha from it's initial coverage.
- The grass LULC experienced a remarkable loss of 7625.34 Ha within the 10 year study period.
- The bare LULC also experienced an increase of 7562.62 Ha by the end of the study period.



	FORMAL	INFORMAL	MINES	WATER	GRASS	CULTIVATED	BARE	BUSH
Losses	-4030.79	-197.17	-447.70	-416.76	-7625.34	-3356.33	-1867.64	-1129.30
Gains	1710.57	1910.86	235.06	330.43	2707.81	3640.45	7562.62	973.23

Figure 12. Change trajectories between 1995 and 2005

4.4.6. Change trajectories between 2005 and 2015

As shown in figure 13 below, the changes experienced by the Virginia landscape between 2005 and 2015 are diverse. The key changes that were observed in the formal, informal, Mines and other important LULC during this period are listed below:

- The formal LULC experienced further reduction in its classes with a recorded loss of 2355.62 Ha and an increment of 845.84 Ha.
- The informal LULC experienced more growth during this period with a gain of 1845.88 Ha.
- The mines LULC also experienced continued depletion in its area coverage with a loss of 303.36 Ha.
- The bare LULC also experienced an increase of 6252.58 Ha over the 10 year study period
- The cultivated LULC experienced corresponding increase and losses within this time period with a gain of 3170 Ha and a loss of 7033.776 within the 10 year study frame.

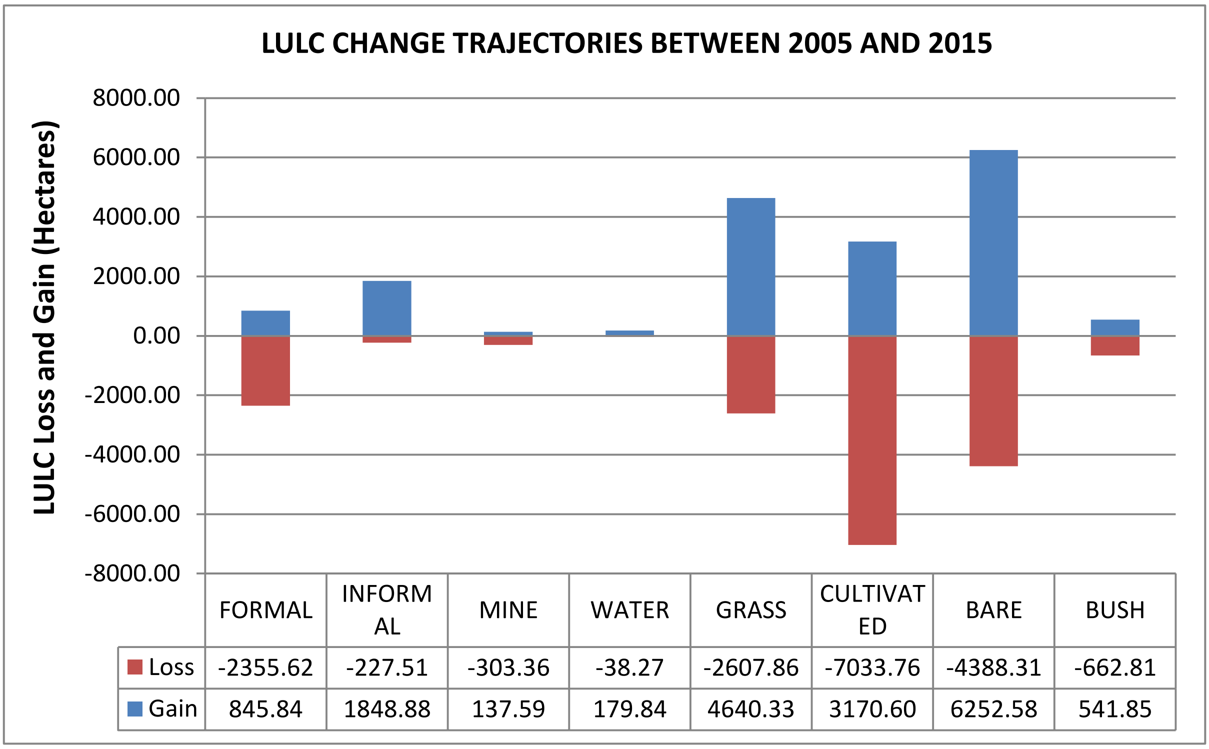


Figure 13. Change trajectories between 2005 and 2015

4.5. Spatio-Temporal transition of formal LULC change between 1945 and 2015 using spatial metrics

The dimensions of urban growth experienced by the formal LULC were assessed with six indices of spatial metrics which are CA, NP, ED, MNN, AWMPFD and MPS. The results are presented in table 13 and figure 8 and discussed as follows:

CLASS AREA (CA)

In 1945 the year in which mining activities started, the CA of the formal class was 682.36 Ha however it increased to 1572.77Ha by 1954. By 1975, the CA of the formal class had increased to 2048.94. As documented in table 13 and in the graph in figure 14 below, the formal LULC continued to experience further growth till 1995 as the value of CA increased from 2389.14 in 1986 to an eventual 6256.80 in the year 1995. However, there was a sharp reduction in the value of CA as it reduced to 4503.69 in 2005 and a further 3517.64 by the end of 2015.

NUMBER OF PATCHES (NP)

In the year in which mining activities began, the NP of formal patches recorded in the landscape was 346. The number of urban patches reduced to 193 in 1954 and then experienced an increase from

1734 in 1975 to 2010 in 1986; by the end of 1995 the number of patches had increased to 4449. However as shown in the graph in figure 14, between 1995 and 2005, there was a reduction in the number of patches from 1995 till 2015 as the number of patches reduced to 3053 in 2005 and 1791 by the end of 2015.

EDGE DENSITY (ED)

In 1945, the ED recorded a value of 11.86 and increased 12.12 by 1954. The graph in figure 14 shows that by 1975, the ED had further increased to 24.56 in 1975, 31.44 in 1986 and an eventual 76.25 in 1995. However, there was a reduction in edge density between 1995 and 2015 as its value plummeted from 76.25 in 1995 to 54.04 in 2005 and finally to 38.57 in 2015.

MEAN NEAREST NEIGHBOUR (MNN)

As shown in figure 14, the MNN recorded a value of 51.71 in 1945 and increased to 55.24 in 1954 and an eventual 67.8 in 1975. The increase in these values signifies an increasing connection between the urban patches between 1945 and 1975. However, there was a decreasing connection between the individual patches of the urban area between 1975 and 1995 as the value of the MNN of the urban class experienced a decrease from 67.8 to 49.91 within those twenty years understudy. Nonetheless, the value of the MNN increased further growth from 49.91 in 1995 to 57.43 in 2005 and eventually 68.01 in 2015.

AREA WEIGHTED MEAN FRACTAL DIMENSION (AWMPFD)

The AWMPFD recorded an index of 1.52 in 1945; this index of 1.52 indicates a high fragmentation rate of the formal class however this reduced to 1.48 in 1954. As the graph in figure 14 reveals, the formal LULC further experienced reduced fragmentation between 1954 and 1975 and now records a value of 1.04 in 1975. The fractal dimension for the informal patch increased in the years between 1975 and 2015, from 1.04 in 1975 to 1.25 in 1986, to a further 1.26 in 1995 and 1.31 in 2005 and an eventual 1.33 in 2015.

MEAN PATCH SIZE (MPS)

In 1945, the MPS recorded an index of 4.55 and experienced continuous reduction to 3.54 in 1954 and an eventual 1.04 in 1975. However, in the remaining timeline of study MPS experienced continuous increase, with an index of 1.19 in 1986, 1.41 in 1995, 1.48 on 2005 and an eventual 1.96 in 2015.

The summary of the key findings of the landscape metrics analysis for the formal LULC change are outlined as follows:

- Increase in CA, NP, ED values till 1995 indicates a growth in the formal LULC class up until 1995 as confirmed by the LULC analysis. In addition to that, there was a reduction in their corresponding values between 1995 and 2015 which indicates reduction or shrinkage in the formal LULC.

- NP: massive increment in NP signifies rapid urbanization dense formal growth/sprawl or massive urbanization between 1954 and 1995 as number of formal LULC patches seriously increased.
- ED: There was an increase in the total length of the edge of formal LULC patches as revealed by ED due to LULC fragmentation 1945 and 1995.
- The formal LULC was highly fragmented and complex in the initial years of urban development due to the construction and developmental projects as the AWMPFD recorded an index of 1.52 and 1.48 out of 2 in 1945 and 1954.

  After the drop of AWMPFD values to 1.04 in 1975, the formal LULC became increasingly fragmented and more complex and unordered as the AWMPFD gradually increased to 1.33 by the end of 2015

Table 7. Landscape metrics statistics for the formal LULC

YEAR	CA	NP	ED	MNN	AWMPFD	MPS
1945	682.36	346	11.86	51.71	1.52	4.55
1954	1572.77	193	12.12	55.24	1.48	3.54
1975	2048.94	1734	24.56	67.8	1.04	1.04
1986	2389.14	2010	31.44	63.65	1.25	1.19
1995	6256.8	4449	76.25	49.91	1.26	1.41
2005	4503.69	3053	54.04	57.43	1.31	1.48
2015	3517.64	1791	38.57	68.01	1.33	1.96

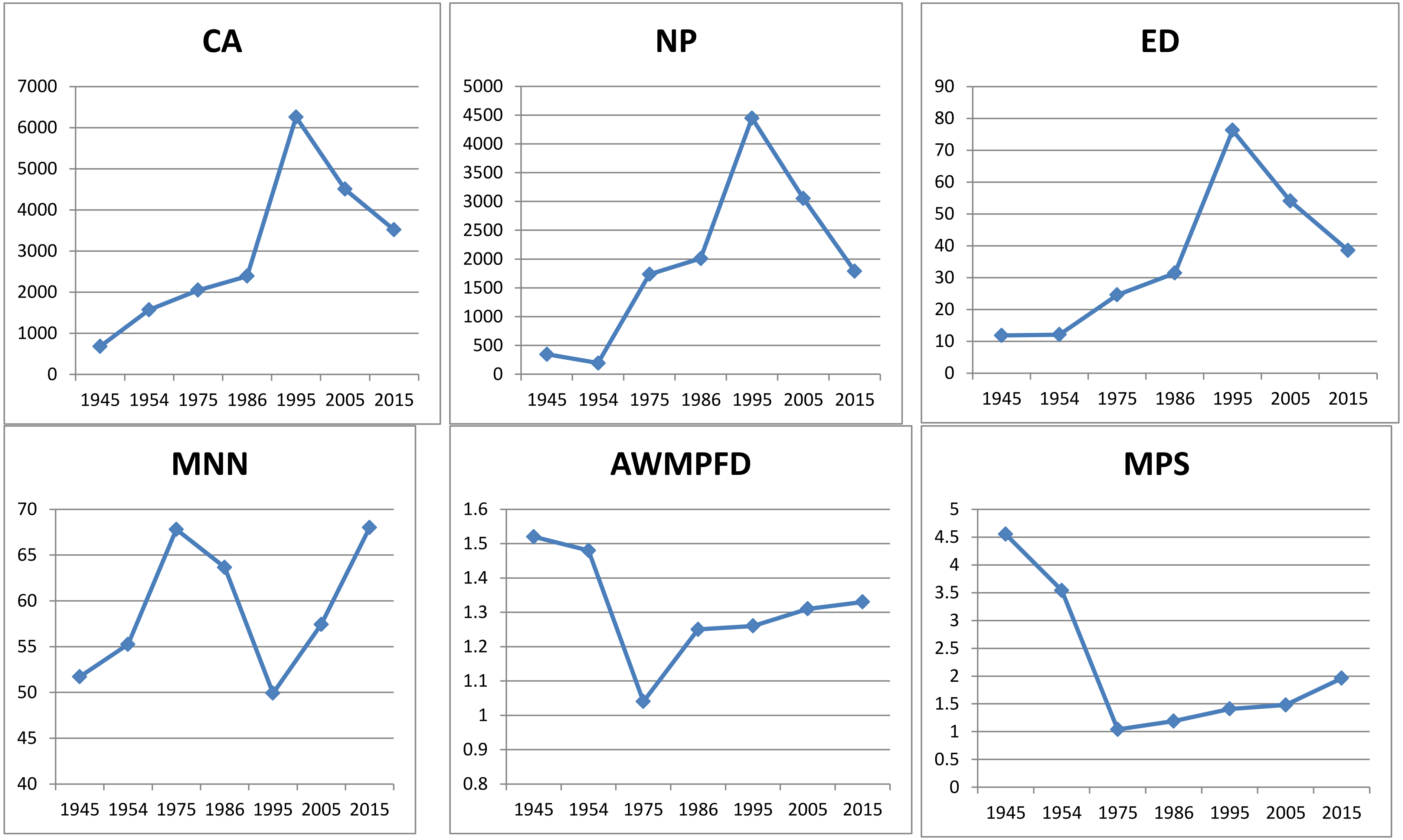


Figure 14. Landscape metrics graphs for the formal LULC

4.6. Spatio Temporal transition of informal LULC change between 1945 and 2015 using spatial metrics

The dimensions of urban growth experienced by the informal LULC were assessed with six indices of spatial metrics which are CA, NP, ED, MNN, AWMPFD and MPS. The results are presented as follows:

CLASS AREA (CA)

In 1945, the CA of the informal LULC recorded a value of 19.44 and experienced a reduction to 11.61 in 1954. As outlined in table 15 and the graphs in figure 9 below; its value increased continuously throughout the period under study. Its index recorded a value of 149.09 in 1975, 252 in 1986, 717.57 in 1995, 1074.06 in 2005 and 2091 in 2015.

NUMBER OF PATCHES (NP)

Informal class patches in Virginia recorded a value of 211 in 1945, this later reduced to 188 in 1954. This signifies a reduction of the informal LULC within the first nine years after mining activities started. However as shown by the graph in figure 15, its value increased to 202 in 1975, 741 in 1985 and 2202 in 1995. Its value later plummeted to 1952 in 2005 and an eventual value of 3138 by the end of 2015.

EDGE DENSITY (ED)

The edge density index of the informal class had a value of 0.69 in 1945, which later reduced to 0.57 in 1954. However it experienced continuous increase for the rest of the study with values of 3.82 in 1975, 5.24 in 1986, 14.92 in 1995, 18.21 in 2005 and 34.82 in 2015.

MEAN NEAREST NEIGHBOUR (MNN)

As shown by the graph in figure 15, in the years between 1945 and 1975, the MNN reduced from 136.2 in 1945 to 120.9 in 1954. This reduction between 1945 and 1954 signifies that the distance between existing informal patches reduced between those years however it started increasing from 1954 as it values plummeted to 159.02 in 1975. However, the MNN between the patches of the informal settlements experienced a reduction from 1975 to 2015. The MNN graph in the revealed that the MNN value recorded 159.02 in 1975, 139.44 in 1986, 99.33 in 1995, 76.44 in 2005 and 63.77 in 2015.

AREA WEIGHTED MEAN PATCH FRACTAL DIMENSION (AWMFD)

The AWMPFD of the informal class was 1.41 in 1945 and increased to 1.47 in 1954. However, the AWMPFD experienced a reduction to 1.01 in 1975. Nonetheless, as shown by the graph in figure 15, the AWMPFD gradually increased from 1.01 in 1975 to 1.11 in 1986, it further increased to 1.14 in 1995, 1.19 in 2005 and eventually 1.2 in 2015.

MEAN PATCH SIZE (MPS)

The values of the MPS fluctuated during the period understudy. The graph in figure 15 shows that it recorded a value of 0.09 in 1945 reduced to 0.06 in 1954. It further experienced an increase to 0.45 in 1975. Its values reduced slightly over the next 20 years as it recorded values of 0.34 and 0.33 in 1986 and 1995 respectively. However the MPS increased to 0.55 in 2005 and eventually 0.67 in 2015.

The summary of the key findings of the landscape metrics analysis for the informal LULC change are outlined below:

- Increase in CA, MP and ED values throughout the timeline of study within the informal LULC class signifies constant increase and growth within the informal LULC throughout the timeline.
- A slight decrease in the CA, MP and ED values between 1945 and 1954 signifies an attempt to get rid of the informal LULC completely.
- The informal LULC experienced its own massive growth between 1986 and 1995 as CA and NP became thrice its initial value.
- ED: There was an increase in the total length of the edge of informal LULC patches as revealed by ED due to LULC fragmentation throughout the timeline of study.
- The informal LULC experienced high fragmentation and complexity in the developmental years of Virginia due to the developmental with 1.41 and 1.47 values in 1945 and 1954.
- The fragmentation and complexity of the informal LULC gradually increased as the AWMPFD values gradually steadily increased from 1.01 in 1975 to 1.2 in 2015.

Table 8. Landscape metrics statistics for the informal LULC.

YEAR	CA	NP	ED	MNN	AWMPFD	MPS
1945	19.44	211	0.69	136.2	1.41	0.09
1954	11.61	188	0.54	120.9	1.47	0.06
1975	149	202	3.82	159.02	1.01	0.45
1986	252	741	5.24	139.44	1.11	0.34
1995	717.57	2202	14.92	99.33	1.14	0.33
2005	1074.06	1952	18.21	76.44	1.19	0.55
2015	2091.56	3138	34.82	63.77	1.2	0.67

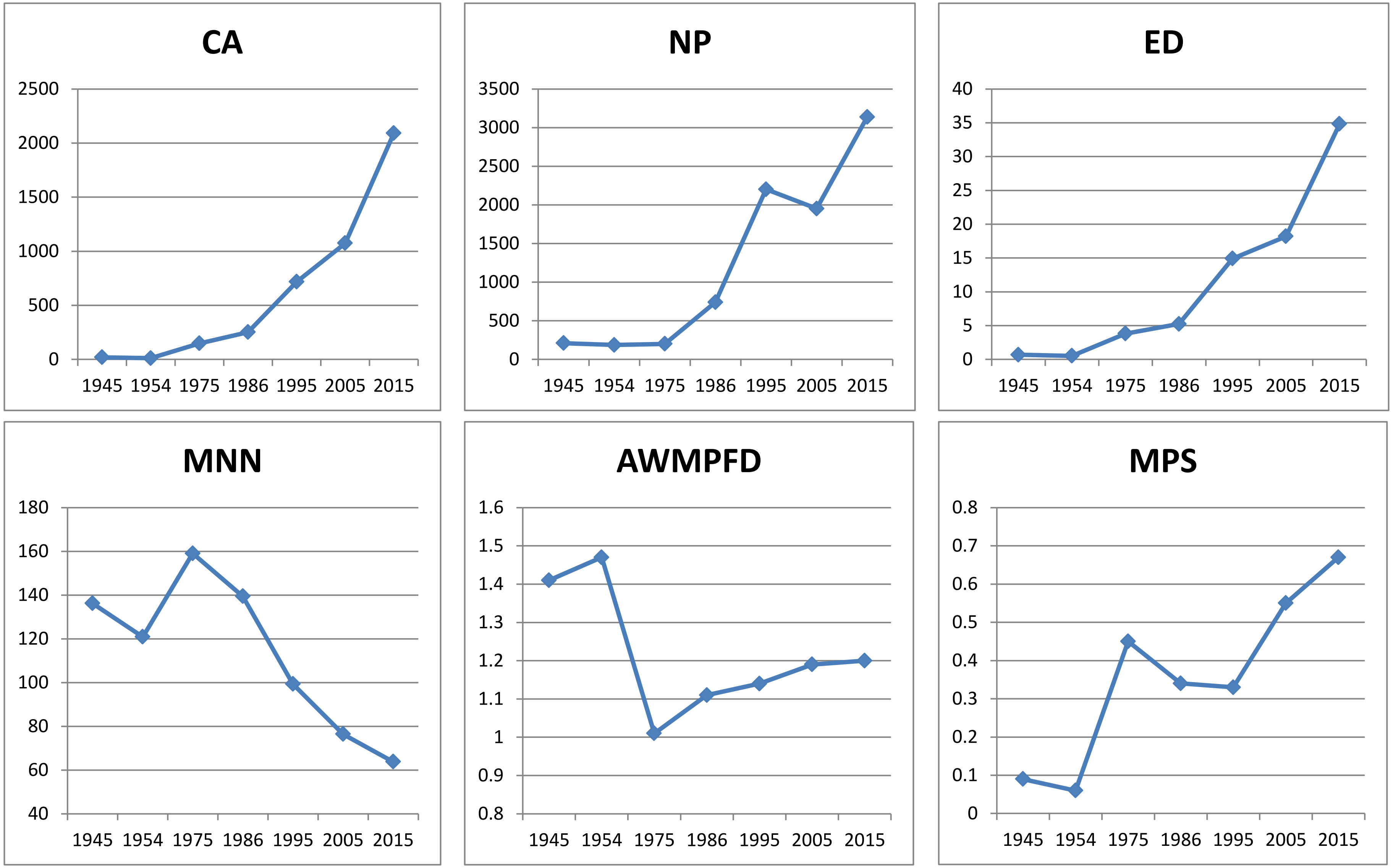


Figure 15. Landscape metrics graph for the informal class

4.7. Landscape degradation indices

Analysis at the landscape level revealed that there was an increase in NP between 1975 and 1995. In figure 10 below, the NP graphs revealed that it recorded values of 10,471 in 1975, 11,347 in 1986 and 13,439 in 1995. This increase in the number of patches indicates the further fragmentation of existing LULC classes into smaller ones hence increasing the local heterogeneity of such patches. This increase in patch sizes was also confirmed by the MPS results, as its values reduces gradually from 3.57 Ha in 1975 to 3.28 Ha in 1986 and an eventual 2.77Ha in 1995. Additionally, the fractal dimension results between 1975 and 1995 reveals an increase in landscape fragmentation and degradation between 1975 and 1995 with values of 1.21, 1.23 and 1.24.

Although the landscape experienced slight signs of degradation between 1975 and 1995, there seems to be a positive change in the landscape as NP reduced to 12703 in 2005 and an eventual 12299 in 2015 this reduction signifies an amalgamation between the existing landscape patches. Also, the increase in MPS confirms the landscape resuscitation as its values increase steadily to 2.93 in 2005 and 3.02 in 2015 although the landscapes are not compacted as the MPS value is less than 5Ha. The reduction in the fractal dimensions of the patches within the landscape also confirms the results of the NP and MPS as the fractal values remained in 1.24 in 2005 and decreased to 1.23 by the end of 2015.

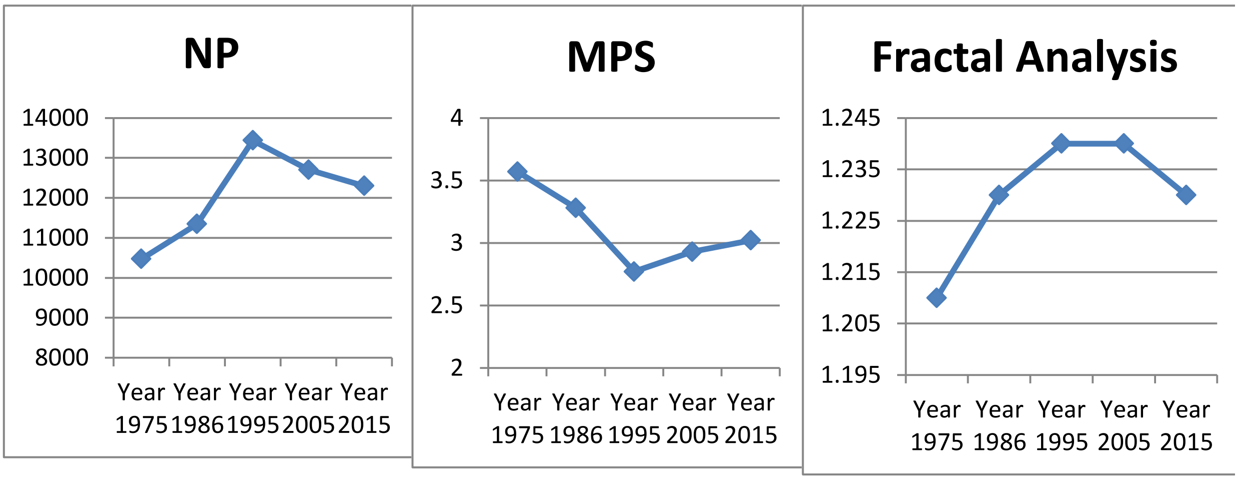


Figure 16. Graph showing land degradation indices of NP (number of patches), MPS (mean patch size) and fractal analysis for Virginia across the timelines.

4.8. Normalized Difference Vegetation Index

The general trend, as observed from the results obtained from the NDVI analysis revealed that in 1986, the NDVI index recorded minimum and maximum values of -0.72 and 0.49 and mean values of 0.23. The extremely low values are recorded along the river channel which is closer to the urban centre and mines. In the year 1995, the NDVI had minimum and maximum values -0.97 and 1.0. However, its mean value is -0.01 which suggests a much lower average as compared to 1986. The NDVI maps in figure 11 reveals that the lowest NDVI values in 1995 were recorded around the river course, and the urban centres and the mines. By 2005, the NDVI values range had improved a little and yielded an improved mean value of 0.33. Although its minimum and maximum values are 0.65 and 0.54, the NDVI maps in figure 17 reveal that there seem to be improved NDVI across the landscape as there are higher values along river channels and mining areas which had recorded low values previously in 1995. Rainfall data obtained for Virginia reveals that the landscape experienced adequate rainfall amounts of 120.5mm, 164.1mm, and 69.1mm in 1986, 1995 and 2005 respectively. As shown in table 16, these rainfall values obtained for the specific months of the NDVI shows that the recorded rainfall amounts exceeded the corresponding monthly average of each year. By 2015, the landscape seems to have become much better as its NDVI values now ranged between -1 and 0.92. The highest values are recorded along the river banks and the urban area of Virginia while the lowest NDVI values were recorded around the mines.

Table 9. NDVI results of the Virginia landscape between 1986 and 2015

Year	Minimum	Maximum	Mean	Standard Deviation
1986	-0.72	0.49	0.23	0.13
1995	-0.97	1.0	-0.01	-0.15
2005	-0.65	0.54	0.33	0.08
2015	-1	0.92	0.24	0.086

Table 10. Rainfall data of Virginia in 1986, 1995 and 2005

Year	NDVI Month	Rainfall Value (mm)	Monthly Average (mm)
1986	November	120.5	92.7
1995	December	164.1	62.5
2005	November	69.1	36.79

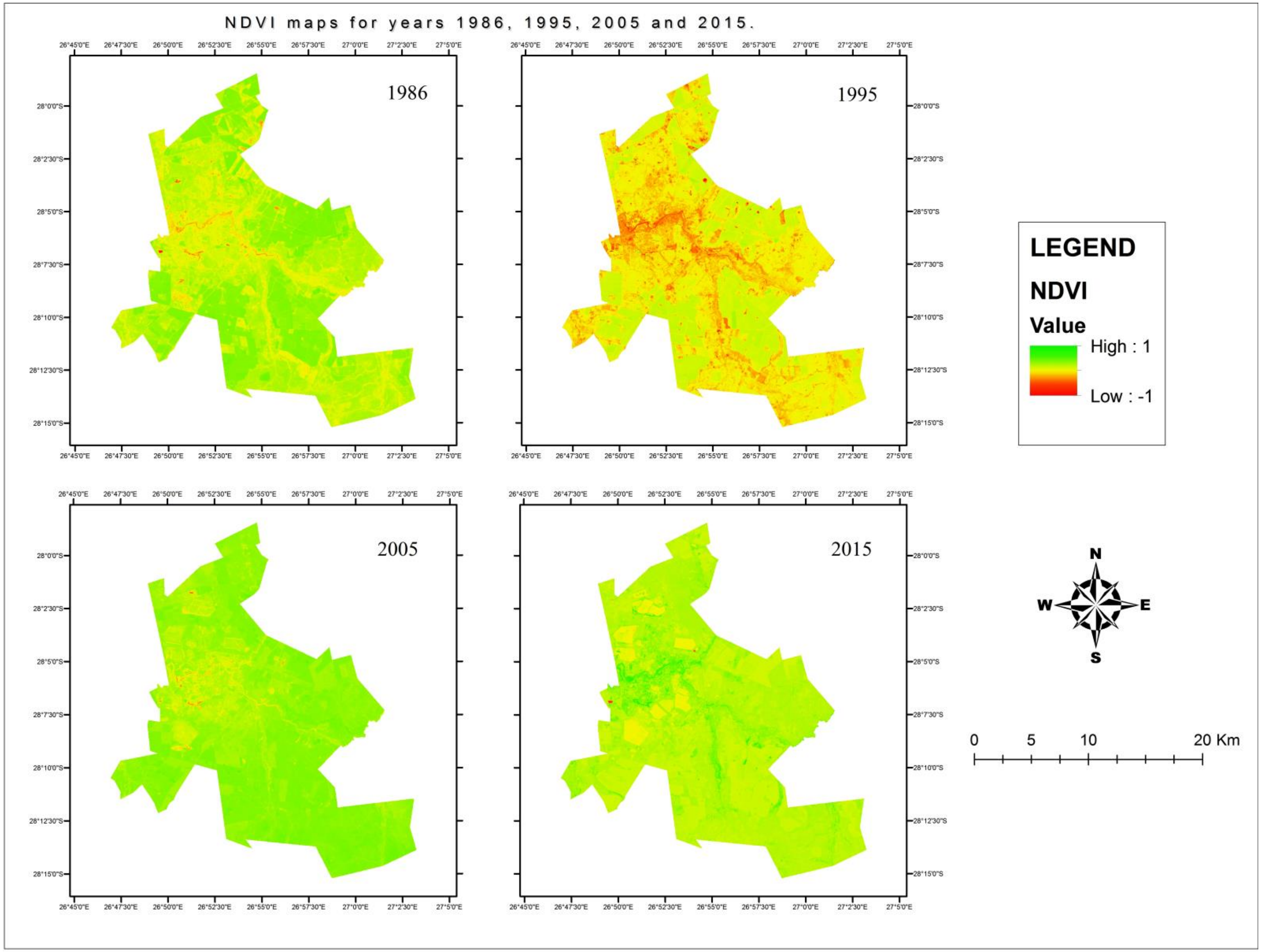


Figure 17. NDVI maps for years 1986, 1995, 2005 and 2015

5. Discussion

This chapter contains the discussion of the results presented in chapter four of this research paper and is subdivided into two sections. Section 5.1 contains the discussion about the phases of urban growth in the mining town of Virginia in relation to the phases of growth presented in resource town model in figure 1. While section 5.2 contains discussion about the manifestations of infrastructural violence in Virginia within the period understudy.

5.1. Urban growth trend in Virginia

Bezerra et al (1996) postulated that mining areas often evolve from purely agrarian communities into booming urban centres**.** The Virginia case study confirms this trend as the landscape was initially dominated by cultivated and bare LULCs at the start of mining activities in 1945. At this stage, mining activities had just started with a small portion of the landscape attributed to mining, Lucas (1971) referred to this stage as the construction stage in which the mining community starts developing and taking shape. As mineral explorations have the capabilities to create new settlements and upgrade existing ones just as Bryceson & Mckinnon (2012) claimed, formal settlements gradually increased as mining activities increased. Mineral explorations also continued to prosper as the mines LULC got more conversions from other LULC's by the end of 1954.

However, in 1947, the Orange Free State goldfields were proclaimed by the government to be a controlled area that would be subject to strict planning restrictions and was supervised by the Natural Development Council. One of the objectives of the council was not to permit haphazard development, particularly with regard to European native housing (Muller 1956). This was responsible for the reduction in the informal LULC and its conversion into mostly bare LULC by the end of 1954 as also evidenced by a reduction of the CA, NP, ED and MPS indices in 1954. This could also be ascribed to the Natural Resources Act No. 51 which was enacted in 1947. This Act gave room for the establishment of medium sized towns instead of large towns or small settlements located around mine shafts. The Act further allowed the conversion of traditional agricultural lands to accommodate the proposed new towns. The rationale behind the creation of these settlements was to avoid the unordered development that happened in the Witwatersrand (Marias and Nel 2016). Likewise, the Group Areas Act of 1950 (41 of 1950; 36 of 1956, 77 of 1957) which prevented illegal squatting and mandated population registration for inhabitants (Marias et al., 2015) of certain geographical areas caused the removal of several smaller scattered settlements and was probably responsible for the decline in the number of informal settlements hence by 1975, none of the huts and farmstead was left. Furthermore, the construction of aesthetically pleasing flats of various sizes which was available for purchase and rental could have warranted the conversion of the informal LULC that existed in the sites where these new flats were built (Muller 1956).

In the Free State Goldfields, mining compounds were used to accommodate the mine workers whilst urban areas consisted of white owned settlements, with low dense housing that possessed sophisticated levels of infrastructure. Informal settlements, which were huts and farmsteads, were black dominated. The urban areas were created to be permanent settlements while the settlements that held the mine workers were created through apartheid legislation to last temporarily (Marias and Nel 2016). Therefore by 1975, very few of the initial informal LULC (that comprises of huts and farmsteads) was left but the township of Meloding, which was majorly dominated by informal LULC types, had taken shape. Between the 1945 and 1975 time frame, the landscape of Virginia exhibited the nature of urban growth which is synonymous to the first and second phases of the resource towns model as postulated by Lucas (1971). These two stages are termed the construction stage and the recruitment of citizen's stage and they are characterised by gradual urbanisation, population growth, LULC changes and development of sophisticated urban infrastructures.

In addition to the dimensions of urban growth that Virginia experienced, its mining activities experienced its highest growth in 1986 with the value of its LULC coverage almost doubling the value recorded in 1975. This increase in mining activities happened simultaneously with a significant increment in the bush, formal and informal LULC. Significant increase in the formal and informal LULC from 1986 signifies urban growth and is an indication of the apex of mining activities in the Matjhabeng municipality with approximately 180,000 mine workers in the Free State province at that time (Marias et al., 2015). While this increase in formal and informal LULC can be partly attributed to prosperous mining activity in Virginia, the removal of the influx control could also be a reason. The apartheid government enacted the law of influx control to keep the blacks in their homeland and restrict their movements but by mid-1980's, the law was abolished so an end came to the restriction of movement and migration within the borders of South African towns hence there was an increase in migration in the mining regions (Marais 2013). Hence urban growth and sprawl in Virginia continued and it reached its highest potentials in 1995 as evidenced from the formal metrics of CA, NP and ED reaching their highest values. This peak of Virginia's urban growth in 1995 coincided with the apex of its mining activities.

The dimensions of growth that continued in the landscape of Virginia between 1975 and 1995 could be compared to the third and fourth phases of the resource town model. Most importantly because the formal and mining LULC of the landscape reached their highest potentials in 1995. Lucas (1971) termed these phases the transition stage and the maturity stage, and they are characterised by increased productivity, continuous population growth and urban sprawl.

However, as purported in literature by Bradbury and St. Martin (1963) and Bruce et al (2004), the shrinkage and death of urban growth in a mining town is evident after the quantifiable mineral resource has been exhausted. The decline in the mining industry in the 1990's resulted in the depopulation of the mining town, a massive reduction in the living standards of mine workers, community instability, and continuous health problems mine workers in such communities (Ntema., et al 2017). Unfortunately, this became the case for Virginia too as its formal LULC dipped and experienced shrinkage after 1995 till 2015 as evidenced by its CA, NP, and ED index. Conversely, as the formal LULC experienced its decline, the informal LULC continued to experience its own growth. This was evident in the LULC area as well as in the CA, NP and ED indices as their values increased till 2015. Ntema et al (2017) affirmed that the initial decline of mining activities within the Free State gold fields in early 1990's lead to an increment in the number of informal settlements, as mine workers who lost their jobs were forced to evacuate the mining hostels, majority of the mine workers moved into the surrounding informal settlements close to the mining areas and existing settlements. However, despite the decline of mining activities, there was an increase in the population of the FSG which resulted in more establishments of large scale informal settlements between 1991 and 1996. This however, could be attributed to the post-apartheid housing policy in 1994 whose aim was to create over three million low cost housing for poor households earning less than R3,500 a month (Ntema. J., et al 2017). Also, In 1994, the mine workers started getting paid living-out allowance which encouraged them to move out of the mining hostels in a bid to improve their living conditions and get rid of the compound system that was previously associated with mining in south Africa. However, this did not seem to achieve its aim as the living-out allowances contributed to the development of informal settlements and transferred the responsibility of infrastructural provision unto the local government (Marias et al., 2015).

This trend of results derived from the LULC analysis between 1995 and 2015 is synonymous with the fifth and sixth stage of the resource town models, which are termed as the winding down and closure stage as coined by Bradbury (1984). Bradbury (1984) alleged that this stage is characterised by mine downscaling and folding up, population decrease, workers emigration, and environmental degradation. Interpretation of LULC results analysis further affirms that Virginia currently passes through these last two phases of resource towns as revealed by the decrease in mining and formal LULC and an increase in informal LULC.

5.2. Infrastructural Violence

Appel (2012) and Bryceson and Mackinnon (2012) revealed that the conspicuous signs of infrastructural violence in African resource towns are social suffering and spatial injustice as evidenced by spatial segregation, which leads to the deprivation of infrastructures experienced by a group of people within the society. This is usually established firmly by policies and laws put in place by the government to police vulnerable people within the society (Ferguson 2012).

The results from LULC analysis revealed that the growth of the informal LULC of Meloding was guided by the strict provisions of the Native Urban Areas Act of 1923 which gave room for the establishment of racially segregated housing (Fair et al., 1956). Manual interpretation of the LULC maps produced from the topographical maps reveals that Meloding was dominated by informal settlements and majorly occupied by the locals and mine workers. Creation of enclaves, maginalisation of a group of people, which is often achieved by racial segregated housing are the major physical indications of infrastructural violence (Rodgers & O'Neil). The LULC maps revealed that Meloding developed a few kilometres away from the mining town of Virginia with most of its population housing the locals and some mine workers (Fair et al., 1956). The settlement comprises of predominantly informal LULC and was spatially segregated from Virginia with the mine dumps and the railway line acting as enclaves that separates both settlements. This confirms the view of Ferguson (2012) on infrastructural violence that the inequality that dominated the society resulted from spatial segregation and eventually led to infrastructural violence. This was made visible through the selective provision of sophisticated infrastructure such as walls, pipes, wires and roads that shaped the urban environment (Ferguson 2012). Auyero and de Lara (2012) opined that even after the removal of enclaves and entanglements created during the initial stage of urban growth, infrastructural violence doesn't stop. In the case of Virginia, infrastructural violence continued to manifest itself through continuous spatial segregation of the mining town and Meloding Township to date. The AWMPFD (area weighted mean patch fractal dimension) index of the urban metrics was also used as an index to measure infrastructural violence. The AWMPFD index of the formal and informal LULC was assessed and it was discovered that LULC fragmentation was equally pronounced in both LULCs. However, the formal LULC experienced more fragmentation than the informal LULC when Virginia started growing. The formal LULC obviously experienced more fragmentation because development was more pronounced in this LULC during the earlier stages of Virginia. However, the fragmentation rate gradually continued within the formal class throughout the timeline of Virginia as its values consistently reduced from 1975 till 2015. Conversely, the informal LULC class experienced its gradual growth till the end of 2015 but at a reduced pace than the formal LULC.

Results from the landscape metrics and NDVI analysis of the Virginia reveals that the landscape experienced the highest environmental degradation in December 1995 which was the year in which the mining and formal LULC reached their highest potentials. This is quite interesting because climate data for the Welkom municipality which was retrieved from the South African weather service shows that Virginia recorded a rainfall value of 164 mm in December 1995 which is far above the monthly average of 62.13 mm in 1995. In November 1986, the landscape experienced a rainfall of 120.5 mm against a monthly average of 92.7 mm in 1986, and it also had a 69.1mm of rainfall in November 2005 as against a monthly average of 36.79mm in 2005. Despite this varying amounts of rainfall experienced by the landscape in 1986 and 2005, the NDVI analysis for those years revealed that the landscape experienced minimal amount of degradation in those years.

This degradation of the landscape in 1995 was also confirmed by the NP, MPS and AWMPFD indices in 1995 as shown in figure 10. The landscape of Virginia experienced this amount of degradation in 1995 because urban expansion and mining activities reached their highest potentials in that same year as evidenced from the LULC analysis results.

Even with the improvement in the landscape after 1995 as revealed by the NDVI analysis and NP, MPS and AWMPFD indices; the LULC maps of 2005 and 2015 is still not a reflection of improvement as the landscape has not gone back to other environmental viable uses such as agriculture. The decline in the mining activities led to a reduction in the economic potential of Virginia and a permanent reduction in Virginia's population size (Marais et al., 2015). Stephens and John (2015) observed that various attempts to resuscitate Virginia by attempting to diversify the economy since the decline have failed completely. Although it is expected that the government should explore this improvement in environmental conditions of Virginia to divert into other economically viable activities like agriculture, international based practices and South African legislation dictates that mine land is restored to its pre-mining condition or rehabilitated to a sustainable post mining land use. However, previous research has shown that this is not feasible given the destructive and polluting nature of mining (Limpitlaw et al., 2005).

5.3. Implications of the methodology used in this study.

The aim of this study was to assess the urban growth dynamics of the mining town of Virginia between 1940 and 2015. The post classification change detection method was used to achieve this aim. This method analyses, describes and quantifies the different changes that occur between images of the same landscape at different time intervals (Hegazy and Kaloop 2015). The post-classification change detection method is also referred to as cross tabulation analysis. This is because it entails determining the quantities of LULC type that was converted to other LULC categories at later dates (Hegazy and Kaloop 2015).

LULC studies that examine pre-Landsat years through the incorporation of topographical maps with Landsat images are rare. Additionally, no method has been developed to combine topographical maps and Landsat images in a change detection analysis. The developed methodology entailed converting topographical maps into a raster format that is equivalent to that of Landsat images and performing post-classification change detection on them. More detail about the developed methodology are available in section 3.3.3 of this research report. The possibility of combining topographical maps with Landsat images in this new methodology implies that a wider time frame can now be considered in a LULC study. It also implies that differently sourced datasets with unique spatial attributes can be processed and standardized into a common format that makes the change detection analysis possible.

Additionally, previous LULC studies in mining areas have been done through conventional change detection technique. This limits those studies to the quantification of changes experienced in the LULCs alone. However, this study further employed spatial metrics to study the nature and form of growth of the informal and formal LULC. The results of such analyses were used to explore manifestations of infrastructural violence.. This study also confirmed that the resource town model which was proposed by Lucas et al (1971) is valid and traceable through the application of GIS and remote sensing techniques. This is because the LULC analysis across the studied timelines yielded results which correspond with the hypothesized stages in the resource town model. Some of the spatial metrics parameters and their quantification may be used as proxies for infrastructural violence (i.e. fragmentation).

Although the methodology which was applied in this study of LULC change in Virginia was in part new and successful, it has some limitations. One of its limitations in this study is the inconsistent temporal resolution of available topographical maps. Inconsistent temporal resolution of the topographical maps during the pre-Landsat period meant that there are large time intervals between consecutive study years. Small time intervals between consecutive study years would have produced more detailed results about the nature of urban growth in Virginia during the study period.

The second limitation of the methodology is the absence of complete aerial photographs. Aerial photographs would have been better suited for the pre-Landsat years but incomplete aerial photographs in those years necessitated the use of topographical maps. However, topographical maps have their limitations because they are official and very structured documents derived from aerial photographs. Therefore certain important information such as the degree of informal LULC could have been left out deliberately. This limitation implies that certain LULC classes which were derived from the topographical maps may not be the accurate representation of LULC at that time. The topographical maps which were used in this study are at scale 1:50,000. This introduces issues of scale dependency and is in contrast with the much higher resolution of Landsat.

In conclusion, the developed methodology proved reliable and can be adopted for future LULC change detection studies despite the observed limitations.

6. Conclusion

This study aimed at reconstructing the history of urban growth in the mining town of Virginia, Free State from the inception of mining activities in 1945 till 2015 through the use of remote sensing and GIS techniques, supported by a knowledge of the history of the town. This was made possible through the combination and analysis of historic aerial photographs, topographical maps, remotely sensed satellite images and other historic information. While change detection was used to analyse the LULC change matrices, indices of landscape metrics were employed in analysing the dimension of growth experienced in the formal and informal and other use classes and also analyse the proxies of infrastructural violence .

This research has been able to answer its questions and fulfil all its objectives. The research questions are:

1. How did the mining town of Virginia evolve through time?
2. How did infrastructural violence manifest in Virginia's spatio-temporal urban growth over time?

Results from the analysis as discussed in chapter 5 has been able to answer these questions by employing the use of the objectives stated below:

1. Create a time line of land use and land cover changes in Virginia during the mining period and beyond using remote sensing and GIS.

2. Analyse land use/land cover changes that occurred in Virginia over the timelines using remote sensing and spatial metrics alongside published historic information.

3. Spatially quantify the manifestations of infrastructural violence in Virginia during the period under study using GIS analysis.

The major findings are listed in the sub theme below:

6.1. Major Findings

1. Urban growth in Virginia started since inception of mining activities in 1945 and continued until 1995 with coverage of 16.83% in the formal LU class. However urban growth started experiencing decline and shrinkage from 1995 and started experiencing a reduction in the formal class as revealed by the CA, NP and ED indices and an eventual coverage of 9.46%. Hence corresponding to the period the mines downscaled and suspension of mining activities in Virginia in the mid 1990's.

2. The informal settlements experienced gradual growth from 0.05% coverage at the inception of mining activities in 1945 and it continued till 2015 with 5.2% coverage.
3. The informal LULC experienced more increase after 1995 as against the formal LULC, this was supported by the increment in the CA, NP, ED indices.
4. Infrastructural violence was more pronounced in the earlier stages of Virginia's growth, the urban areas experienced fragmentation all through the period under study from the 1975 till 2015.
5. The informal settlements experienced less fragmentation when compared to the urban settlements.
6. In assessing the infrastructural violence of the entire landscape, the NP and AWMPFD both experienced an increase in their values till 1995. This indicates that the entire landscape was more fragmented and contained more patches of homogenous LULC types during the time of active urban growth. However fragmentation reduced after the decline of urban growth in 1995.

7. The landscape experienced the greatest vegetation stress in the 1995; the year in which the urban and mining LULC recorded the highest values. This was revealed in the NDVI analysis with extremely low NDVI values being recorded along the river banks, mines and some parts of the urban settlements despite the fact that the rainfall in the Welkom area that year recorded 536.4mm which is above the average rainfall of 489.17mm.

8. This research confirms the hypothesis of previous researchers (such as Lucas et al (1971); Pressman and Lander (1978); Bradbury (1984); Bryceson and Mackinnon (2012) and Appel (2012)) as evidenced in Virginia about the transitory nature of resource towns, that urban mining settlements are not sustainable but shrink and decline as soon as the mines downscale.

6.2. Research Limitations

Although this research yielded interesting results that would define the future of urban growth studies, a number of limitations were encountered in the course of this study which altered the anticipated results. These limitations are:

1. Data contraints: This historic nature of this research necessitated the use of topographical maps and aerial photographs in developing the LULC map of this area in the pre-landsat years. However, aerial photographs and topographical maps were the only sources of spatial information that could be relied on between 1945 and 1975. Landsat images were used for the years that were studied between 1986 till 2015. However, the available aerial photos and topographic maps didn't cover the actual extent of the study area and had to be combined in different ways to produce respective LULC

maps. As displayed in the figure 12 below , the available aerial photographs for the years 1944 and 1952 both covered about 50% of the area under study which is just a fraction of the total area understudy. Hence, the topo maps of 1945 and 1946 was combined with 1944 aerial photos to produce the LULC maps for 1945. While the topomaps for 1954 and 1951 was combined with the 1952 aerial photographs to produce the LULC map for 1954. Hence, the LULC produced for 1945 and 1954 was an aggregation of the different combinations of topographical maps and aerial photographs and not the exact representation of the LULC maps at those years.

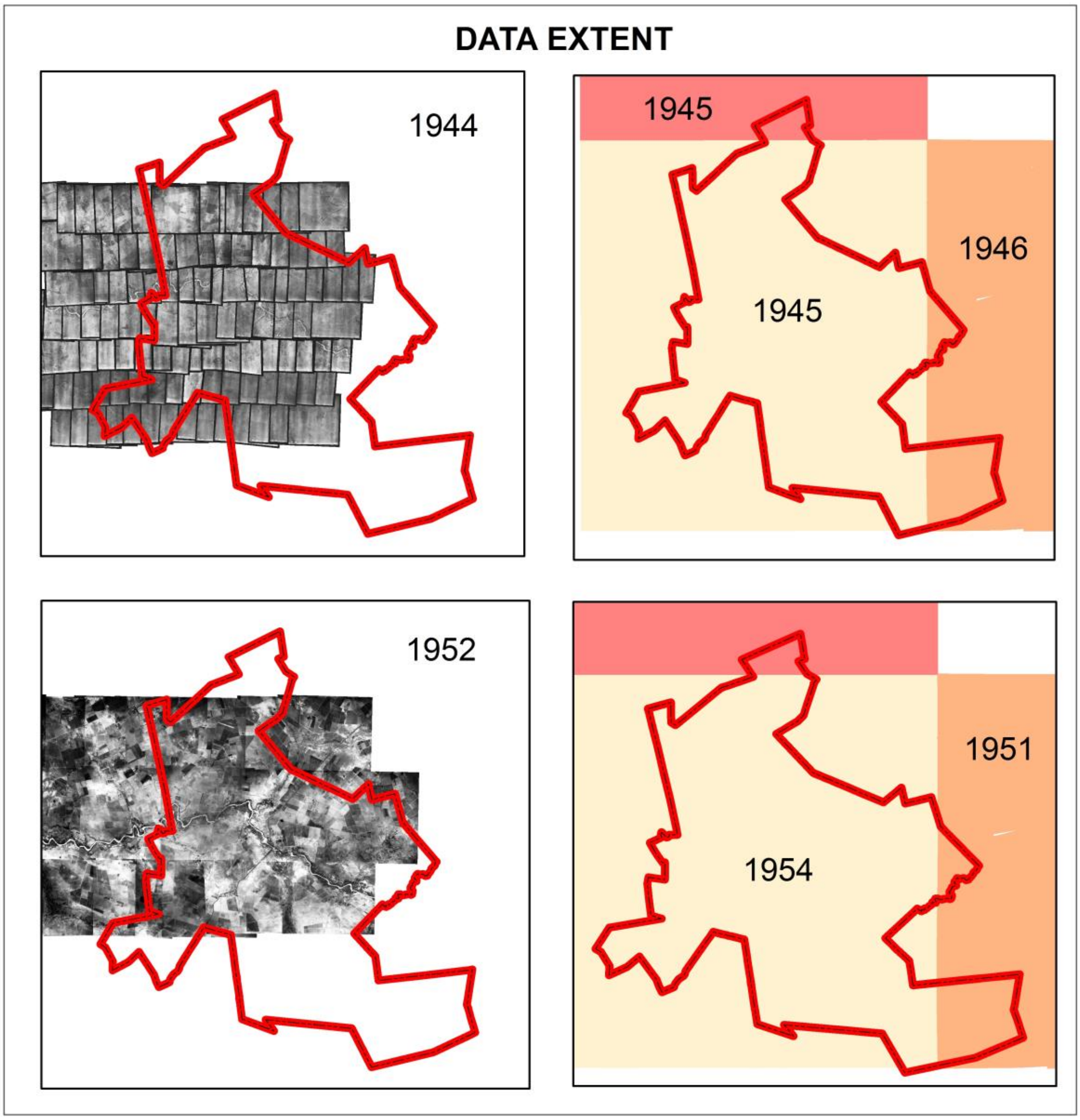


Figure 18. Extent of data coverage for study area.

2. Absence of consistent satellite imagery that has the Infrared and Near Infrared band in the earlier years understudy restricted the analysis of NDVI in the years between 1975 and 2015 alone.

3. When exchanging data formats between topographical maps and Landsat images, the topographical maps in 1945, 1954 and 1975 seems to represent part of the grass LULC as bare LULC so the grass LULC appeared less in the topographical maps. Therefore, the values recoded for the bare LULC and grass LULC in the topographical maps may not be too accurate.
4. This study has been able to visually investigate and interprete the claims of infrastrutural violence, however more GIS analysis techniques such as proximity analysis or spatial regression techniques could be employed to verify this claim in future studies.

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Appendix I : LULC Chage trajectories between 1945 and 2015

Land Use Change trajectories between 1945 and 1954

As contained in the table below, by the end of the nine year period, the land uses that contain the mining excavations experienced the most changes with only 3.28% of its initial area remaining after the first nine years. 47.51% of it has been converted into bare land uses while 49.08% was converted into cultivated lands. It further experienced a 0.13% conversion into bush land uses. As contained in table 7 below, the informal land use class also experienced massive conversion as just 5.43% of its initial area remained unconverted in 1954. 76.09% of the informal land uses became covered with bare lands, while 7.61% became bushes and 9.78% became cultivated. 0.54% became converted into formal landuses and another 0.54% became converted into water.

33.67% of the bush land use also remained unchanged by 1954 but 54.73% of it changed into bare land use, 2.83% into cultivated lands, 1.09% into formal land use, 3.28% into grasses, 0.07% into informal and 4.32% into water. The cultivated land use was not left out of the transformation even though 63.06% of it remained unchanged by 1954 but experienced the most changes into formal land uses at 20.84% and bare land use at 15.68%. However it experienced minor changes to other land use types, with 0.33% converted into bushes, 0.01% into informal and 0.09% into water.

35.96% of the water land use remained unchanged by 1945, but 41.95% got changed into water, 2.06% into bushes, 15.23% into cultivated lands, 0.55% into formal, 4.22% into grass, 0.01% into informal and 0.02% into mines. Grasses also experienced transformations with 18.20% remaining unchanged by 1954, but 64.87% of it changed into bare, 10.51% into bushes, 0.01% into cultivated, 0.11% into formal, 0.01% into informal and 6.28% into water.

The bare land use experienced minimal transformations with 71.22% of its initial area in 1945 unchanged by 1954, however it experienced changes into other land uses. 3.47% and 12.09% of it got transformed into bushes and formal land uses respectively, 10.75% of it also got transformed into cultivated land use. It also experienced very minimal changes to grasses, informal, mines and waters at 0.82%, 0.82%, 0.02% and 1.53%. The formal land use experienced the least transformations with 73.47% of its coverage being retained by 1954 but 9.85% got converted into bare, 2.56% into bushes, 13.19% changed into cultivated lands, 0.11% into grasses, 0.08% into informal and 0.75% into water land use.

FINAL STAGE 1954	INITIAL STAGE 1945							
	FORMAL	INFORMAL	MINES	WATER	GRASS	CULTIVATED	BARE	BUSH
FORMAL	**73.47**	0.54	0	0.55	0.11	20.84	12.09	1.09
INFORMAL	0.08	**5.43**	0	0.01	0.01	0.01	0.82	0.07
MINES	0	0	**3.28**	0.02	0	0	0.02	0.01
WATER	0.75	0.54	0	**35.96**	6.28	0.09	1.53	4.32
GRASS	0.11	0	0	4.22	**18.2**	0	0.82	3.28
CULTIVATED	13.19	9.78	49.08	15.23	0.01	**63.06**	10.75	2.83
BARE	9.85	76.09	47.51	41.95	64.87	15.68	**71.22**	54.73
BUSH	2.56	7.61	0.13	2.06	10.51	0.33	3.47	**33.67**
TOTAL	100	100	100	100	100	100	100	100

Land Use Change trajectories between 1954 and 1975

Changes continued to occur in the landscape and in the years between 1954 and 1975, the Virginian landscape further experienced significant changes. As revealed in table 8 below while 58.87% of the bare LULC remained unchanged throughout 21 year difference, 17.42% of the bare LULC got changed into cultivated, 16.46% changed into bushes, 6.35% changed into grasses, 0.13% into mines, 0.08% into informal, 0.28% into formal and 0.43% into water. In the cultivated LULC category, 77.69% of it remained unchanged at the end of the 21 year period but 19.70% of it changed into bare, 1.95% changed into bushes, 0.38% changed into grasses, 0.01% of it changed into mines, 0.03% into informal, 0.15% into formal and 0.09% into water. The bush LULC experienced its own transformations except 38.10% of its initial coverage, however 31.10% changed into bushes, 29.25% changed into grasses, 0.12% changed into formal and 1.42% changed into water. 18.78% of the grass LULC remained unchanged by 1975 but 67.83% changed into bare LULC, 4.45 changed into cultivated, 7.08% changed into bushes, 1.58 changed into 1.58% and 0.30% changed into water. 4.84% of the mining LULC remained unchanged by 1975 but 49.80% of it got transformed into bare LULC, 42.00 into cultivated, 2.39% into bushes, 0.47% of it changed into grasses, 0.02% of it changed into informal, 0.43% changed into formal and 0.06% changed into water LULC.

The informal LULC experienced the most changes during this 21 year period because 99.25% of its previous area got transformed into bare LULC while 0.75% got changed into formal LULC. However, 59.10% of the initial formal LULC remained unchanged by 1975 but, 14.51% of it changed into bare, 23.77% of it got transformed into cultivated, 2.12% into bushes, 0.07% into grasses, 0.13% into Mines, 0.01% into informal and 0.29% into water. In the water category, 77.06% of the its LULC remained unchanged by the end of 1975 but 11.39% of it changed into bare, 8.15% changed into cultivated, 2.73% changed into bushes, 0.40% changed into grasses while 0.03 changed into informal and 0.23% changed into formal LULC.

FINAL STAGE 1975	INITIAL STAGE 1954							
	FORMAL	INFORMAL	MINES	WATER	GRASS	CULTIVATED	BARE	BUSH
FORMAL	**59.1**	0.75	0.43	0.23	1.58	0.15	0.28	0.12
INFORMAL	0.01	**0**	0.02	0.03	0	0.03	0.08	0
MINES	0.13	0	**4.84**	0	0	0.01	0.13	0
WATER	0.29	0	0.06	**77.06**	0.3	0.09	0.43	1.42
GRASS	0.07	0	0.47	0.4	**18.78**	0.38	6.35	29.25
CULTIVATED	23.77	0	42	8.15	4.45	**77.69**	17.42	0
BARE	14.51	99.25	49.8	11.39	67.83	19.7	**58.87**	31.1
BUSH	2.12	0	2.39	2.73	7.08	1.95	16.46	**38.1**
TOTAL	100	100	100	100	100	100	100	100

Land Use Change trajectories between 1975 and 1986

The change detection statistics between 1975 and 1986 as contained in table 8 below revealed major changes across some classes of the landscape. In this years, 34.21% of the bare LULC remained unchanged while 1.55% of it transformed into water, 4.63% into formal, 0.19% into grasses, 57.14% into cultivated and 0.38% into bushes. In the water class, 43.75% of it remained unchanged while 21.61% changed into bare, 2.53% changed into formal, 9.11% changed into mines, 0.16% changed into grasses, 21.82% changed into cultivated and 1.02% changed into bushes. In the formal class, 31.06% transformed into bare LULC, 1.53% changed into water, 3.52% changed into mines, 1.02% changed into informal, 1.85% changed into grasses, 17.25% into cultivated and 2.05% changed into bushes however, 41.71% of the formal class remained unchanged by the end of 1986. So also, 52.19% of the mines remained unchanged by the end of 1986 however, 22.95% of it got transformed into bare, 1.17% changed into water, 9.08% changed into formal, 0.03% changed into informal, 0.05% changed into grasses, 14.47% changed into cultivated while 0.06% changed into bushes. In the informal LULC, 45.01% of it changed into bare, while 0.89% changed into water 19.32% changed into formal, 3.65% changed into mines, 3.36% changed into informal, 15.96% changed into cultivated and 0.39% of it changed into bushes however, 11.41% of the informal LULC remained unchanged.

Within the grass LULC, just 4.04% of its initial area remained unchanged by the end of 1986 however, 66.30% of it changed into bare LULC and 19.34% of it changed into cultivated while, 3.39% of it changed into water, 5.46% changed into formal, 0.17% changed into mines, 0.12% changed into informal and 1.17% of it changed into grasses. The cultivated LULC experienced the least transformation under this 11 year period as 91.14% of it remained unchanged during this period. However, 7.34% of it changed into bare, 0.46% changed into water, 1.00% of it changed into formal, 0.01% changed into mines, 0.03% changed into informal, and 0.02% of it changed into bushes.

Irrefutably, the bush LULC experienced the most transformations after the grass LULC with just 6.82% of its initial area remaining unchanged at the end of the period while 48.86% of it changed into bare, 11.39% changed into water, 7.81% changed into formal, 0.31% changed into mines, 0.04% changed into informal, 2.40% grass and 22.37% changed into cultivated LULC.

FINAL STAGE 1986	INITIAL STAGE 1975							
	FORMAL	INFORMAL	MINES	WATER	GRASS	CULTIVATED	BARE	BUSH
FORMAL	**41.71**	19.32	9.08	2.53	5.46	1	4.63	7.81
INFORMAL	1.02	**11.41**	0.03	0	0.12	0.03	0.19	0.04
MINES	3.52	3.65	**52.19**	9.11	0.17	0.01	0	0.31
WATER	1.53	0.89	1.17	**43.75**	3.39	0.46	1.55	11.39
GRASS	1.85	3.36	0.05	0.16	**4.04**	0	1.91	2.4
CULTIVATED	17.25	15.96	14.47	21.82	19.34	**91.14**	57.14	22.37
BARE	31.06	45.01	22.95	21.61	66.3	7.34	**34.21**	48.86
BUSH	2.05	0.39	0.06	1.02	1.17	0.02	0.38	**6.82**
TOTAL	100	100	100	100	100	100	100	100

Land Use Change trajectories between 1986 and 1995

In the years between 1986 and 1995, the Virginia landscape experienced noticeable changes across board. 64.7% of the water remained as water throughout the 9 year period while 26.09% now accounts for mines. This could be attributed to the increase in mining activities during the period of economic boom in the late 1980's. 1.56% and 3.45% of the initial water class was also transformed into informal and urban settlements respectively. As displayed in table 9 below; by 1995, water had also been converted into bare, bush, and grass at 0.43%, 0.38% and 3.39% respectively. Also, 78.7% of the mines remained unchanged by 1995, however, 9.98% of them have been converted into urban areas, 4.39% covered by water and 4.62% is now inhabited by grass. 0.49% was converted into informal, 1.29% into bare and just 0.02% became cultivated. As contained in table 10 below, the informal class however experienced transitions into other land use types during these 9 year phase as just about 27.07% of the areas covered by informal areas were retained. The informal LULC was transformed by 0.68% into water, 8.51% into mines, 2.18% into bare, 0.61% into bushes, and 10.98% into grassland. Transition from informal into urban appears the highest as 49.37% of informal LULC in 1986 was transformed into urban class by 1995.

The bare land use experienced the most change during the period understudy as just 8.03% of the initial 100% was left by the end of 1995. 47.02% of it has been converted into grassland, 17.84% was converted to cultivated lands, and 6.9% became bush. 16.83% of it transitioned into urban areas and 1.39% turned into informal settlements. The bush LULC also experienced noticeable changes after the 9 year period as just 9.58% of it remained unchanged. 6.32% of it got converted into water, 3.22% into mines, 0.23% into informal settlements, 11.26% into urban settlements, 2.65% into bare, 2.3% into cultivated lands and 64.44% into grass. By the end of 1995, the grass and cultivated land use experienced minimal changes. With 61.48% and 53.05% remaining unchanged in both categories respectively. However, grass land use experienced the highest transition into urban areas by 19.74% and 5% of cultivated lands was changed into urban areas by the end of the period. Grass LU lost 2.7% to informal settlements while bare land lost 0.94% to informal settlements.

FINAL STAGE 1995	INITIAL STAGE 1986							
	FORMAL	INFORMAL	MINES	WATER	GRASS	CULTIVATED	BARE	BUSH
FORMAL	**65.99**	49.37	9.98	3.45	19.74	5	16.83	11.26
INFORMAL	4.29	**27.07**	0.49	1.56	2.7	0.94	1.39	0.23
MINES	9.71	8.51	**78.79**	26.09	1.44	0.11	1.72	3.22
WATER	0.96	0.68	4.39	**64.7**	0.62	0.05	0.28	6.32
GRASS	14.44	10.98	4.62	3.39	**61.48**	13.88	47.02	64.44
CULTIVATED	1.03	0.61	0.02	0	9.9	**53.05**	17.84	2.3
BARE	0.95	2.18	1.29	0.43	2.58	25.13	**8.03**	2.65
BUSH	2.63	0.61	0.43	0.38	1.55	1.84	6.9	**9.58**
TOTAL	100	100	100	100	100	100	100	100

Land Use Change trajectories between 1995 and 2005

In the years between 1995 and 2005, the Virginian landscape experienced further changes across its land uses. At the end of the period as outlined in table 10 below, 76.76% of the mine excavation remained unchanged but 16.18% of the mine surfaces are now filled with water, 1.47% of it has been transformed into informal settlements, and 0.91% of it is now recognized as formal. Some of the mine surfaces in 1995 also became transformed into bush, grass, bare and cultivated land uses at 1.21%, 1.7%, 0.35% and 1.42% respectively. 16.37% of the water class remained unchanged by 2005. However 14.69% of it was transformed into formal, 11.26% into mines, 1.41% into informal, 31.33% into bushes, 21.38% into grasses, 2.6% into bare land and 0.96% into cultivated. By 2005, 72.53% of the informal settlements remained unchanged, yet 0.23% of it was transformed into mines, 0.04% into water, 0.03% into bush, 3.75% into grass, 3.56% into bare, 13.71% into cultivated and just 6.15% of it was changed into formal. However, the formal class witnessed serious reduction during the period understudy as just 35.6% of it remained unchanged. 21% of it was transformed into informal, 22.13% into grass, 16.9% into bare land uses, 1.43% into cultivated, 0.01% into water and 2.03% into mines. The bush LULC experienced serious loss to other land use types as just 3.6% of it remained unchanged by 2005. 17.6% of it transformed into informal settlements, 1.05% into formal, 30.6% of it into grass, 36.09% into bare land uses and 11.06% into bare land. However, none of bush class was transformed into mines and water. Furthermore, 0.24% of the initial grass land use became transformed into mines, 0.24% into water, 1.64% into informal settlements, 10.1% into formal land use, 5.02% into bushes, 22.53% into bare land, 12.79% into cultivated but just 47.56% remained as grass over the 10 year period. Also, 59.71% of cultivated land use remained unchanged by 2005 while 1.25% of it was transformed into informal settlements, 0.54% into formal, 0.02% into bushes, 5.34% into grass and 33.14% into bare land uses. 50.08% of the bare land use remained unchanged by 2005 while 0.41% changed into mines, 0.01% into water, 0.33% into informal, 1.33% into formal, 0.15% into bush, 9.44% into grass and 38.25% into cultivated land. By 2005, bush and water class experienced the most changes by 96.4% and 83.63% respectively. While urban land use experienced deterioration with a 64.41% change in its category.

FINAL STAGE 2005	**INITIAL STAGE 1995**							
	FORMAL	INFORMAL	MINES	WATER	GRASS	CULTIVATED	BARE	BUSH
FORMAL	**35.6**	6.15	0.91	14.69	10.1	0.54	1.33	1.05
INFORMAL	21	**72.53**	1.47	1.41	1.64	1.25	0.33	17.6
MINES	2.03	0.23	**76.76**	11.26	0.24	0	0.41	0
WATER	0.01	0.04	16.18	**16.37**	0.12	0	0.01	0
GRASS	22.13	3.75	1.7	21.38	**47.56**	5.34	9.44	30.6
CULTIVATED	1.43	13.71	1.42	0.96	12.79	**59.71**	38.25	11.06
BARE	16.9	3.56	0.35	2.6	22.53	33.14	**50.08**	36.09
BUSH	0.9	0.03	1.21	31.33	5.02	0.02	0.15	**3.6**
TOTAL	100	100	100	100	100	100	100	100

Land Use Change trajectories between 2005 and 2015

In the last 10 years understudy, 82.38% of the mining landscape remained unchanged but 11.13% of it has been changed into 11.13%, 0.09% into bush, 1.55% into water, 2.07% into formal, 0.93% into grass, 0.06% into cultivated and 1.79% into bare land. As further displayed in table 12 below, 78.83% of informal settlements remained unchanged by 2015 while 8.99% of it had been changed into grass, and 7.05% into bare. 2.91% has been transformed into mines 0.38% into Bush, 0.28 into water, 0.44% into formal and just 1.12% into cultivated. The bush LULC experienced a 65.29% change into other land uses by the end of 2015 with 0.35% changed unto mine, 1.36% into informal dwellings, 9.04% into water, 13.6% into formal, 26.99% into grass, 1.98% into cultivated and 11.97% into bare land. 63.24% of the water land use remained unchanged while 3.11% of the initial area is now covered by water, 1.29% now changed into informal settlements, 4.33% into formal, 14.77% into grass, 4.14% into cultivated and 1.81% into bare. 47.69% of the formal areas remained unchanged while 21.34% of it changed into informal settlements. 0.62% of it changed into mines, 4.63% into bush, 0.78% into water, 10.06% into grass, 1.09% into cultivated and 13.79% into bare. 73.13% of the portion of land covered by grass remained unchanged by the end of 2015, however 12.94% of it changed into bare land, 5.62% into urban, 3.76% into informal settlements, 1.94 into bush and 0.15% into mines. The agricultural

LULC experienced a loss of 73.6% of its area into other land uses. It experienced 43.88% transformation into bare land, 26.62 into grass, 1.05% into urban, 0.02% into water, 1.26% into Bush, 1.23% into informal settlements and 0.04% into mines.

The bare LULC experienced a 46.17% transformation into other classes, 0.56% of the bare LULC became mines while 2.09% transformed into informal settlements. 0.12% changed into bush and 0.01% changed into water. 0.18% of the bare land use became transformed into formal areas, 13.06% transformed into grasses and 30.15% was left unchanged.

FINAL STAGE 2015	**INITIAL STAGE 2005**							
	FORMAL	INFORMAL	MINES	WATER	GRASS	CULTIVATED	BARE	BUSH
FORMAL	**47.69**	0.44	2.07	4.33	5.62	1.05	0.18	13.6
INFORMAL	21.34	**78.83**	11.13	1.29	3.76	1.23	2.09	1.36
MINE	0.62	2.91	**82.38**	3.11	0.15	0.04	0.56	0.35
WATER	0.78	0.28	1.55	**63.24**	0.21	0.02	0.01	9.04
GRASS	10.06	8.99	0.93	14.77	**73.13**	26.62	13.06	26.99
CULTIVATED	1.09	1.12	0.06	4.14	2.25	**26.4**	30.15	1.98
BARE	13.79	7.05	1.79	1.81	12.94	43.38	**53.83**	11.97
BUSH	4.63	0.38	0.09	7.31	1.94	1.26	0.12	**34.71**
TOTAL	100	100	100	100	100	100	100	100