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Temporal Characterization of Land Use Change and Landscape Processes in Informal Settlements in the City of Cape Town, South Africa

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Abstract

This study conducted a Land Use Change (LUC) analysis on informal settlements in Cape Town, South Africa, using bi-temporal steps, S1 (2010) and S2 (2016), to characterize land use (LU) conversions and landscape processes for informed policymaking. Utilizing the 2011 national land cover dataset and post-classification methods, two LU datasets and maps, D1 for S1 and D2 for S2, were derived. These classifications achieved an overall accuracy exceeding 95%, with Kappa coefficients above 0.9. The analysis employed change trajectories and conversion labels to evaluate LU changes and landscape dynamics, providing a thematic representation of LUC within informal settlements. Landscape reclamation processes, including abandonment, urban development, and RDP (Reconstruction and Development Programme) development, constituted approximately five percent of the total LU conversions, while degradation processes like persistence and intensification dominated, affecting approximately 93% of the area. Partial reclamation, notably through interspersed RDP (RDPi), accounted for about two percent of conversions. These findings highlight the importance of accurate and timely LUC data reporting in informal settlements to address socioeconomic challenges effectively and support policy decisions to enhance these communities' physical and socioeconomic infrastructure.

Keywords: *Informal Settlements; Post-classification Methods; Land Use Change; Land Use Conversions; Landscape Processes; Reconstruction Development Programme (RDP) Policy*

1. Introduction

Informal areas or settlements characterized by poorly built houses and shacks[1] have emerged in South Africa due to inadequate urban planning, affordable housing shortages, and various socioeconomic factors (Pojani, 2019). These settlements lead to a range of complex

[1]Shacks are makeshift structures often constructed from various materials including corrugated iron, wood, plastic, and cardboard. These structures are typically small and rudimentary, lacking insulation and rarely, if ever, equipped with amenities like running water or electricity. Usually built without legal approval, shacks are situated in areas with scarce access to basic services and are predominantly occupied by low-income earners.

environmental, social, and economic challenges, including limited access to basic services, high poverty levels, and scarce employment opportunities (Brown-Luthango et al., 2017; Williams et al., 2019). The sporadic formation and periodic changes in informal settlements further complicate national database records (HDA, 2013), a situation that is exacerbated by the rapid pace of urbanization and rural-urban migration (Niva et al., 2019), which drives land use change. Accurately assessing landscape activities in these areas is crucial for understanding land use change and landscape processes over time. As Hersperger et al. (2018) highlight, quantifying land use changes in informal regions is essential for evaluating the effectiveness of public policies aimed at urban planning and poverty reduction (DME 1998).

In the framework of this study, the distinction between land use (LU) and land cover (LC) becomes particularly significant when analyzing informal areas. (Simwanda and Murayama, 2018). While LU focuses on human land applications, such as agriculture and urban development, LC encompasses the physical and biological attributes of the earth's surface, including both naturally occurring features and human-made modifications (Ahearn and Alig, 2017). The transformations between natural or semi-natural LC and human-modified LU - often observed in informal settlements - highlight the dynamic nature of land utilization and its implications for sustainable urban planning (Smith et al., 2016; Vadrevu et al., 2019). Analyzing Land Use Change (LUC) is essential for promoting sustainable urban planning and development ((Hersperger et al., 2020) and for quantifying anthropogenic impacts in informal areas (Roy et al., 2022). Accurate observations of LUC (Msofe et al., 2019) support the development of models that link landscape changes to underlying processes and environmental impacts (Reed et al., 2016). Such analyses distinguish between different classes or categories in LU maps over time (Kastner et al., 2022), providing insights into LU conversions and change trajectories. However, the challenge lies in the insufficient empirical geospatial data available to accurately depict the drivers of these changes, complicating the analysis of landscape change mechanisms (Münch et al., 2017).

Comparative post-classification analysis, a method widely recognized for comparing and evaluating the accuracy of LU classification over different periods (LIU et al., 2020; Okoye, 2016), is pivotal in domains such as environmental monitoring, agricultural investigations, bathymetry studies, disaster assessments, military strategies, and urban planning - the focal point - amongst others - of this study (Du Toit et al., 2022; Henrico et al., 2021; Meinen and Robinson, 2020; Nguyen et al., 2021; Zheng et al., 2021). This technique leverages satellite-based Earth observation and Geographical Information System (GIS) resources, which are invaluable for LU classification and LUC monitoring (Johnson et al., 2017; Shah et al., 2023), providing extensive coverage that facilitates the generation of LU maps for LUC analysis (Munthali et al., 2019; Shah et al., 2023).

Image analysis utilizes various techniques to extract valuable information from images using spectral and spatial properties, texture, shape, and statistical parameters (Taubenböck and Kraff, 2014; Zhang et al., 2018), including advanced methods like deep learning (Li et al., 2019). An example of such an application is the overlay technique used for merging and extracting features from multiple LU datasets, creating a new layer that combines features from the input layers (Wang et al., 2015; Zhao et al., 2019).

Furthermore, computer-based change modeling and post-classification techniques enhance the precision of LU maps by identifying shared and unique features across multiple data (Okoye, 2016) and by reducing discrepancies between LU classes and improving the accuracy of classification results (Hassan et al., 2016; Wang et al., 2018). These adjustments include reclassification (Okoye, 2021), visual interpretation (Mundia and Aniya, 2005), and rigorous accuracy assessment (Liu and Zhou, 2004), which evaluates the precision of classification results by comparing classified data with reference or ground-truth data, identifying classification errors that could affect LUC results (Foody, 2010).

Accuracy assessments produce an error matrix that compares the classified data samples with reference data (Morisette and Khorram, 2000), offering insights into the overall accuracy of the data and the accuracy of individual classes. This matrix helps determine the producer's and user's accuracy, reflecting the proportion of correctly classified pixels relative to the total number of pixels in the reference and classified data, respectively (Congalton and Green, 2019).

Finally, an indicator-based detection approach identifies LUC over time by selecting indicators that best describe LU conversions and landscape processes, further informing effective policy and decision-making (Münch et al., 2017).

Research indicates that informal areas experience rapid transformation (Simwanda and Murayama, 2018) due to accelerating urbanization rates (Weimann and Oni, 2019) and environmental degradation (Ngarava et al., 2021) and other contributing factors, such as population growth, economic development, and land-use policies (DME, 1998; Yin et al., 2022). These challenges underscore the need for strategies that meet these communities' immediate needs and promote sustainable urban development in South Africa (SEA, 2014). Post-data classification and geospatial resources have been recognized as reliable methods (DHS and SANSA 2011) for capturing the LUC dynamics in these communities (Okoye, 2021). As interest in analyzing urban landscapes and their change dynamics increases (Magidi and Ahmed, 2019; Samper et al., 2020), there is a pressing need for effective investigation of these processes, specifically within informal setting.

This paper aims to comprehensively analyze land use change (LUC) and landscape processes in informal areas of the City of Cape Town over time, utilizing spatial techniques and tools previously discussed. The objectives are threefold: 1) to perform the post-classification editing of existing national land cover data to generate an initial land use (LU) data, followed by a second LU data, and to assess the accuracy of both maps; 2) to conduct detailed LUC analysis; 3) to analyze LU conversions and the change trajectories that underpin landscape processes. The insights gained from this study are intended to inform policy and enhance sustainable urban planning, development, and management practices.

2. Materials and methods

2.1. The City of Cape Town Description

The City of Cape Town, a prominent urban center in South Africa's Western Cape province, spans approximately 2,446 km² (Wilkinson, 2000) (Figure 1). This diverse city features a blend of urban, suburban, and rural areas with varying levels of infrastructural development. It comprises 43 suburbs, many of which are well-equipped with essential utilities like on-site water and electricity. However, akin to many sub-Saharan African cities, Cape Town includes numerous informal settlements sprawling throughout its suburbs. Commonly referred to as shacks, these settlements are predominantly situated on the outskirts, in areas not designated for formal housing or commercial activities (Mbatha, 2001). Lacking in basic amenities, these settlements vary greatly in size - from very small to quite large -with moderately sized settlements being the most common throughout the suburbs. The smallest settlements are concentrated particularly in areas like Khayelitsha, Gugulethu, and Nyanga.

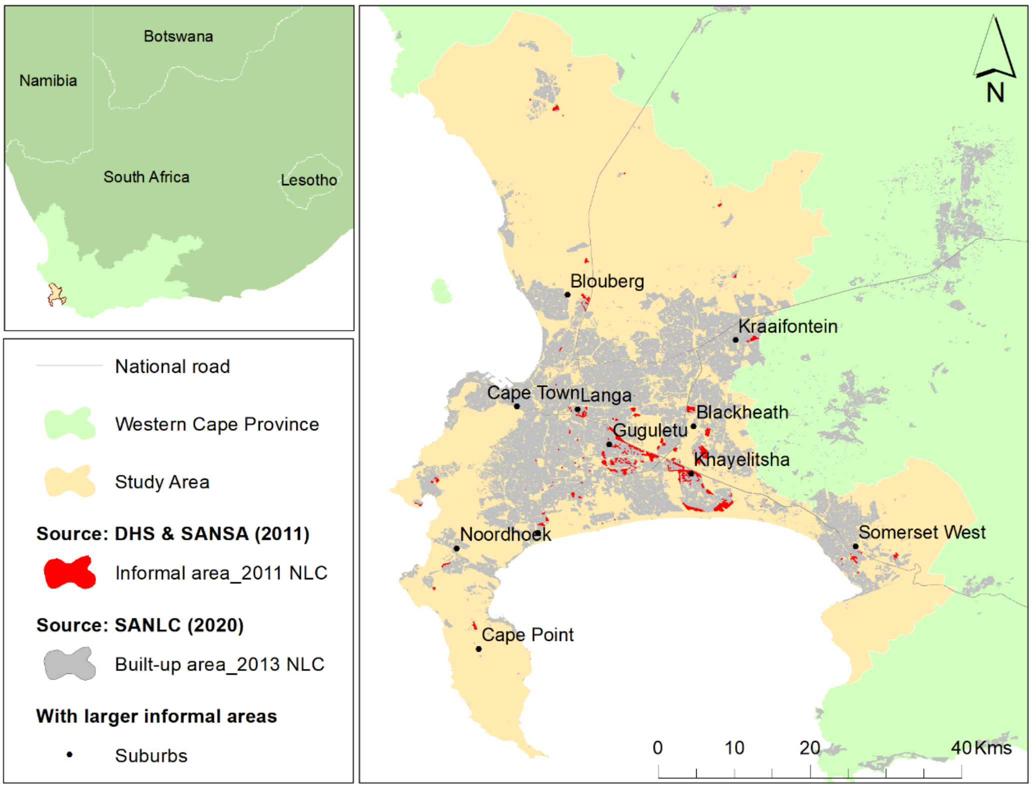

Figure 1: Map showing Informal (2011) and Built-up (2013) Areas in the Study Area

2.2. Data Selection

Table 1 outlines the geospatial datasets employed for LU classification and LUC analysis of informal areas in the City of Cape Town, considering Bi-temporal steps (S1 and S2). The initial step (S1) corresponds to the LU in 2010, aligning closely with the National Land Cover (NLC) reference data (R1) depicted in Figure 1. The NLC data, derived from SPOT 5 (Satellite Pour l'Observation de la Terre) imagery with a 2.5-meter spatial resolution, was processed using supervised classification techniques (DHS and SANSA, 2011). An additional reference dataset (R2), consisting of aerial photographs from 2010 for S1 and 2016 for S2), was also utilized. Ancillary data, such as road networks and cadastral information, assisted in identifying informal areas near essential utilities and social services.

Table 1: Secondary Data used in LU Classification and LUC Analysis of Informal Areas and other Generated Datasets in the Study Area

Secondary Data	Purpose	Data Source
2011 National Land Cover (NLC) - Informal areas	Reference data (R1) for LU classification and LUC analysis	Department of Human Settlements (DHS and SANSA, 2011)
Aerial Photographs (2010 and 2016)	Reference data (R2) to supplement LU classification, LUC analysis, and accuracy assessment	National Geospatial Information (NGI)
Derived LU Maps (2010 and 2016)	Derived data (D1 for S1; D2 for S2) on LU features in the study area	City of Cape Town
Ancillary Data: 2013 NLC-built-up Boundary Roads, Cadastral	Provide additional context and information for the study area.	SANLC, 2020 City of Cape Town
Google Earth Map Street View	Provides high-resolution imagery for validation purposes	Google
2013 National Land Cover (NLC) – Built-up areas	Acts as a constraining feature in accuracy assessment	SANLC, 2020

2.3. Comparative post-classification and accuracy assessment

The flowchart in Figure A1 (see Appendix A) details the procedures and steps utilized for the LU and LUC analyses performed in ArcGIS 10.3 (ESRI, 2009). Manual classification was applied, incorporating all informal settlements, including shacks located in the backyards of formal houses. The initial LU data, labeled D1, was created for the S1 step using R1 and R2-2010 data, supported by visual inspection via Google Street View (Table 1). This dataset, D1, subsequently served as the basis for generating the second LU dataset, D2, for the S2 step, following similar procedures but incorporating R2-2016 data as the new base input. This approach enabled precise delineation and digitization of existing and new informal area polygons in both D1 and D2 datasets.

Post-classification editing was performed on the D1 and D2 datasets to enhance the classification results and ensure data integrity, utilizing the 'Repair Geometry' and 'Smooth Polygon' tools (Ledoux et al., 2014). The 'Repair Geometry' tool corrected polygon errors, including self-intersections, gaps, and overlaps. Concurrently, the 'Smooth Polygon' tool was applied to refine the geometries, thereby improving the accuracy of area calculations.

An accuracy assessment was carried out to evaluate the classification accuracy of the R1 dataset against the D1 and D2 datasets (Lü et al., 2020). This assessment aggregated built-up area boundaries encompassing formal, informal, and commercial areas from the 2013 NLC (SANLC, 2020) into a single class. This class was used to exclude vast open spaces in natural or semi-natural states and agricultural landscapes, particularly in the northeast of the study area, before ground truthing. A total of 800 reference points - 400 each for R1, D1, and D2 - were randomly generated and classified into informal or built-up areas by visually inspecting aerial photographs for the S1 and S2 steps. The 'Spatial Join' tool was used to overlay and align the LU datasets (S1 for R1 and D1; S2 for D2) with the reference data. This alignment facilitated the calculation of the frequency of similarities and disparities for each class (informal and built-up areas), resulting in an error matrix. The accuracy of each class was determined by cross-tabulating the predicted and observed values. Key accuracy measures, such as overall accuracy (OA), producer's accuracy (PA), and user's accuracy (UA), were also calculated.

2.4. LU change detection and conversions

Using the 'Intersect' and 'Symmetrical Difference' tools, computer-based change modeling was employed to identify patterns and variations between the D1 and D2 datasets (Morisette and Khorram, 2000). The 'Intersect' tool detects overlapping features (informal areas) between the two data layers by merging them based on their geometries (Okoye, 2016). Conversely, the 'Symmetrical Difference' tool identifies features unique to each dataset, highlighting areas where land use change (LUC) has occurred. The resulting LUC data is labeled DD3.

Indicator-based detection was used to identify LU conversions and landscape processes by analyzing spatial and temporal characteristic changes within the DD3 data (Münch et al., 2017). Table 2 categorizes the six LU conversion labels under the two landscape processes. Table 3 illustrates a conceptual schema that maps the intersection of LU conversions and change trajectories within the study area. Landscape reclamation processes, including Abandonment, Urban Development, and RDP[2] Development, describe LU conversions where informal areas are

[2] The Reconstruction and Development Programme (RDP) policy was launched in South Africa in 1994 with the goal of revitalizing the economy, bridging social disparities, and ensuring equal resource distribution among all citizens. A principal aim of the RDP policy is to provide thermally efficient, low-cost housing, which supports energy access, usage efficiency,

replaced with bare soil (Ab) and built-up structures (UD, RD). Due to the complexity of finely delineating RDP houses interspersed within informal areas (RDi), the category labeled RDP Development (interspersed) was introduced as a partial reclamation process. Conversely, landscape degradation processes, including Persistence and Intensification, illustrate areas where informal settlements have persisted (Pe) and intensified (In).

Table 2: Conversion Labels and Landscape Processes of Informal Areas in the City of Cape Town (Adapted from Münch et al., 2017)

Landscape processes	Labels	Descriptions
Degradation	In - Intensification	Areas where shacks have invaded empty lands
	Pe – Persistence	Areas where shacks persisted in area size
Reclamation	Ab – Abandonment	Areas where shacks have been converted to bare soil
	UD - Urban Development	Areas converted to formal houses and built-up structures
	RD - RDP Development	Areas where shacks have been replaced with RDP houses
Partial reclamation	RDi - RDP Development (Interspersed)	Informal areas interspersed with RDP houses

Table 3: Conversion Labels Describing the Change Trajectories of LU Conversions for the Bitemporal Steps. (Adapted From Münch et al., 2017)

		S2					
S1	**Class labels**	**Bare Soil**	**Expanded Informal Area**	**Informal Area**	**RDP Houses**	**RDP houses & Shacks**	**Houses & Built-up area**
	Informal Area	Ab					
			In				
				Pe			
					RD		
						RDi	
							UD

The LU conversion labels and landscape processes outlined in Table 2, along with the conceptual schema in Table 3, were employed to analyze LU conversions, change trajectories, and statistics in DD3 (Münch et al., 2017). Area calculations for the D1, D2, and DD3 datasets were performed, and the resulting attribute tables were exported to Excel for detailed cross-tabulation using the pivot system (Excel, 2013). Additionally, statistics reflecting gains and losses, as well as the percentage of area and the rate of area change within DD3, were comprehensively computed.

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and conservation for impoverished households. Through this policy, the government offers free and subsidized formal housing to economically disadvantaged citizens. Additionally, the RDP policy has influenced the development of energy policies and regulatory frameworks concerning electricity pricing, tariffs, and subsidies, and has fostered improvements in the structures governing electricity supply and demand.

3. Results

3.1. LU classification, change, and accuracy analysis

The LU datasets, D1 and D2, display larger area sizes than the R1 data (Table 4). This expansion is due to the redefinition of existing informal area boundaries and the inclusion of new polygons in the D1 and D2 datasets, highlighting the enhanced precision in mapping informal areas. The analysis of DD3 indicates a significant 28% area change between the bi-temporal steps (S1 and S2), demonstrating notable land use change (LUC) within the six-year interval from 2010 to 2016.

Table 4: Calculated Areas of Informal areas in LU and LUC Data and Percentage Change in LUC Data

	Informal areas LU	
Datasets	Area (ha)	% Change
2011 NLC reference (R1)	1319.00	-
2010 Derived (D1)	1448.16	-
2016 Derived (D2)	1356.49	-
	Informal areas LUC	
2010 D1 vs 2016 D2 (DD3)	379.05	27.94

Building on the enhanced precision in mapping informal areas highlighted earlier, Table 5 details the accuracy assessment results for R1 and D1 datasets at the S1 and D2 at the S2 steps. The table delineates the actual classes (reference counts), while the columns represent the predicted classes (LU and LC data), where values outside the diagonal indicate misclassifications or model errors. These results illustrate the proportion of correctly classified pixels for specific classes and take into account the expected agreement by chance (Congalton and Green, 2019). The accuracy of the D1 and D2 datasets was compared with that of the R1 since it served as the primary baseline for generating the two LU datasets. Notably, while the D1 and D2 datasets demonstrate an overall accuracy (OA) of almost 100%, showcasing a substantial improvement in classification precision over the R1 dataset's OA of approximately 96%, they also reveal near-perfect concordance between actual and predicted values across the datasets, as evidenced by a Kappa value close to one. Moreover, the D1 and D2 datasets exhibited user’s accuracy (UA) and producer’s accuracy (PA) values near 100%, contrasting the lower UA values in the baseline dataset. This improvement in OA of almost four percent over the uncorrected baseline dataset underscores the significant advancements in accuracy achieved by the D1 and D2 datasets.

Table 5: Accuracy Assessments for NLC 2011 (R1) and LU Datasets (D1 and D2) in 2010 (S1) and 2016 (S2)

LULC Data	Class	Built-up	Informal area	Total	% PA	UA	OA	Kappa
R1_NLC_2011	Built-up	281	0	281	100	94.93	96.25	0.91
	Informal area	15	104	119	87.39	100.00		
	Total	296	104	400				
D1 _S1	Built-up	294	0	294	100.00	99.66	99.75	0.99
	Informal area	1	105	106	99.06	100.00		
	Total	295	105	400				
D2_S2	Built-up	295	1	296	99.66	99.66	99.50	0.99
	Informal area	1	103	104	99.04	99.04		
	Total	296	104	400				

3.2. LU conversions of Informal Areas across S1 and S2

Table 6 displays the percentage of area change in DD3 for LU conversion labels between the bitemporal steps (S1 and S2). The results indicate that landscape degradation processes significantly influenced the LU conversions in informal areas. Notably, the Persistence (Pe) label, which means no change in the extent of informal regions, represented over 89% of the total conversions. This high rate highlights the entrenched nature of informal settlements despite ongoing policy efforts to improve housing and infrastructure in these communities.

Intensification (In) refers to a landscape degradation process where previously bare soil or vacant land transitions into developed informal areas, constituting approximately four percent of the total LU conversions (Table 6). The encroachment upon surrounding undeveloped land that leads to intensification has significant implications for urban planning and land use management. Moreover, informal areas often intensify without geographical expansion, leading to denser settlements. This pattern of densification poses challenges analogous to those seen in the Intensification (In) and Persistence (Pe) processes. Figure 2 illustrates a typical scenario where Persistence (Pe) and dense Intensification (In) occur concurrently within an informal area, highlighting the complex dynamics at play in the management and evolution of such spaces.

Reclamation processes occur when the size of informal areas in the S2 step decreases relative to their size in the S1 step (Table 6). These processes account for approximately five percent of the total area change observed. Abandonment (Ab) refers explicitly to instances where informal areas are deserted or cleared, leaving behind bare soil, or where portions of informal areas are removed for future development (DHS and SANSA 2011). This process constituted less than one percent of the total conversions, indicating its relative rarity. Figure 3 depicts a typical scenario where an informal area is abandoned and transformed into bare soil due to urbanization or shifting population patterns.

Table 6: Area Calculations of Land Use Conversions in Landscape Processes Across Bitemporal Steps in DD3

Landscape processes	Conversion labels	DD3 (D1-S1 vs D2-S2)	
		Area (ha)	**% of total**
Degradation	In – Intensification	141.00	4.43
	Pe – Persistence	2824.14	88.71
Reclamation	Ab – Abandonment	43.68	1.37
	RD - RDP Development	103.80	3.26
	UD - Urban Development	7.60	0.24
Partly reclaimed	RDi - RDP Development (Interspersed)	63.49	1.99
Total		**3183.69**	**100.00**

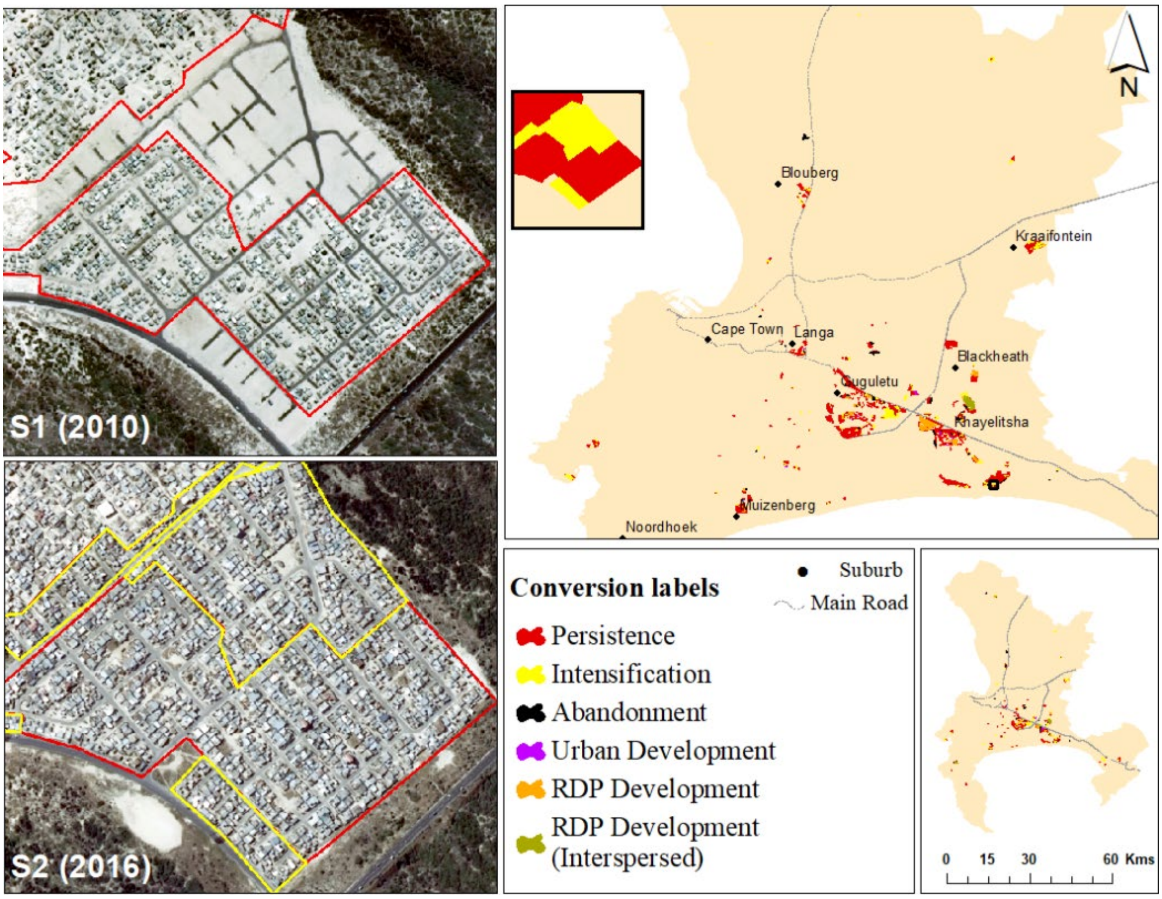

Figure 2: LU conversions in DD3 (Map) and R2 data (aerial photographs), highlighting Persistence (Pe) and Dense Intensification (In) across bitemporal steps S1 to S2 in the study area.

Urban Development (UD) represents another reclamation process that transforms informal areas into urban built-up areas (Table 6). This conversion typically involves upgrading informal settlements by installing essential infrastructure such as roads, water supply systems, sanitation facilities, and electricity networks. These upgrades often formalize informal settlements into recognized urban areas, fostering sustainable urbanization. However, Urban Development (UD) accounted for less than one percent of the LU conversions. This modest impact may stem from inadequate urban planning and design or a lack of political commitment to resolve issues within informal settlements. Figure 4 illustrates a typical scenario where urban development efforts transform an informal area into an urban built-up area.

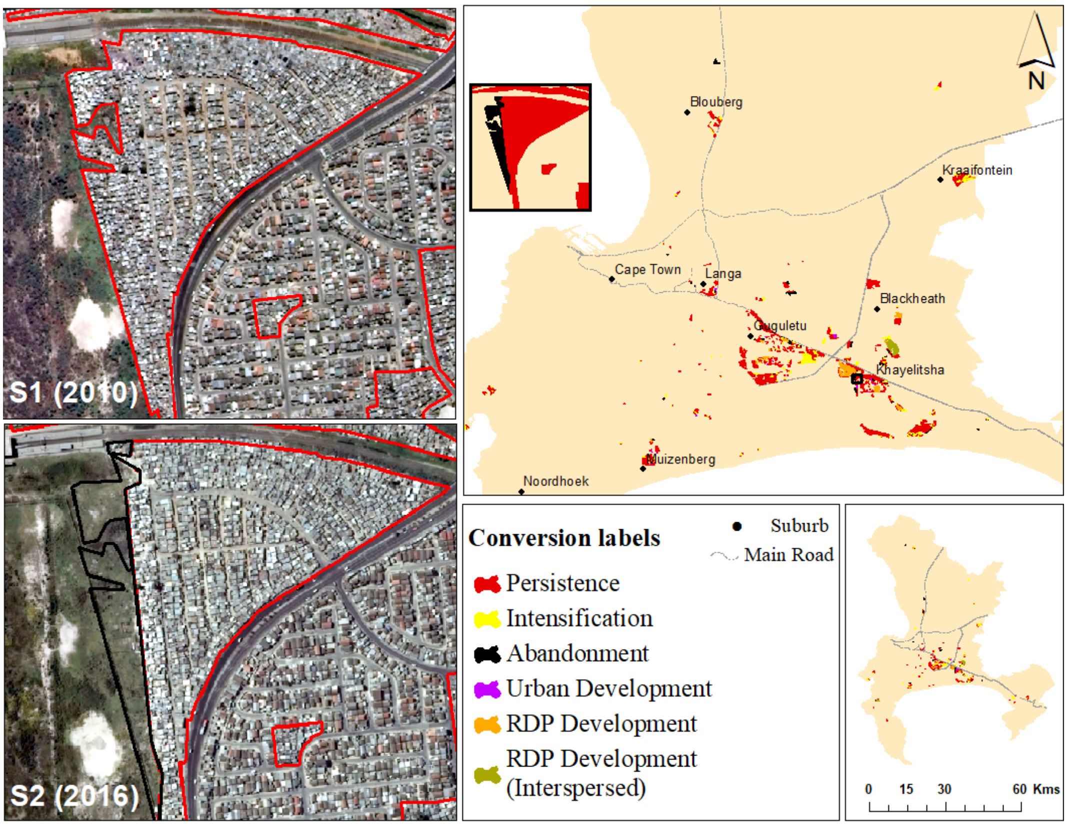

Figure 3: LU conversions in DD3 (map) and R2 data (aerial photographs), highlighting Abandonment (Ab) across bitemporal steps S1 to S2 in the study area.

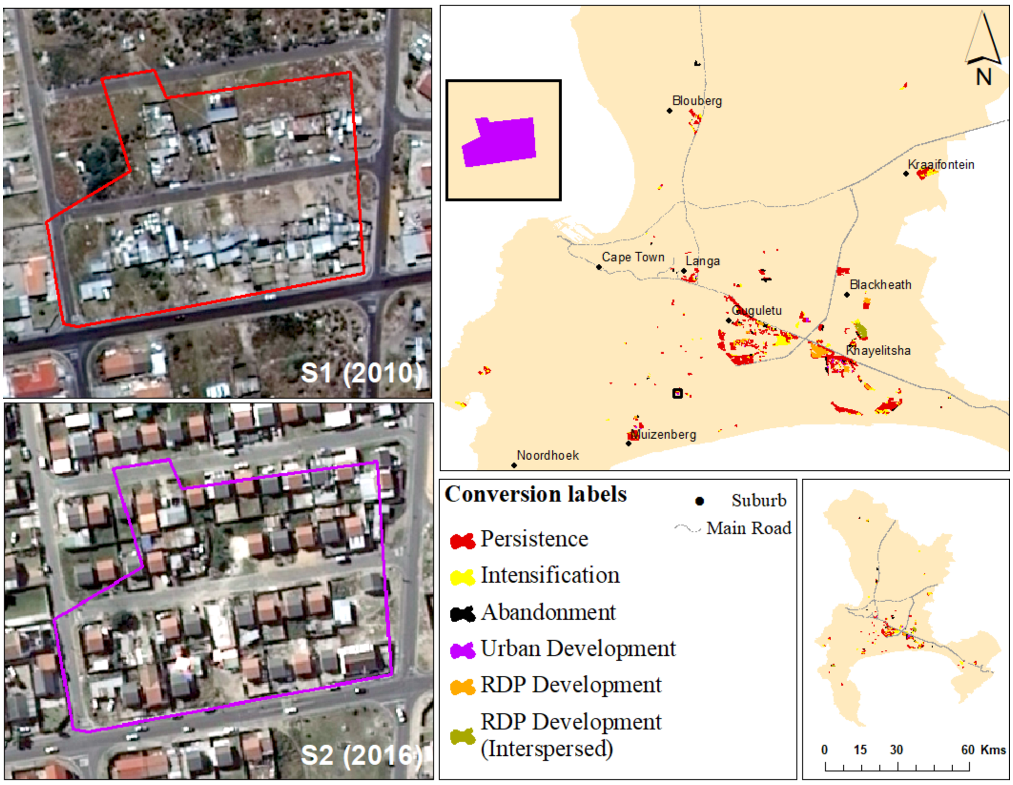

Figure 4: LU conversions in DD3 (map) and R2 data (aerial photographs) highlighting Urban Development (UD) across bitemporal steps S1 to S2 in the study area.

The RDP Development (interspersed) (RDi) is a partial reclamation process where segments of informal areas are replaced with RDP houses (Table 6). This process, characterized by piecemeal development, often lacks comprehensive planning or integration into the broader landscape, which precludes it from being considered a complete reclamation effort. RDP Development (interspersed) contributes only about two percent of the total LU conversions. Figure 6 illustrates a typical example within the study area, where RDP houses have replaced parts of the informal areas, highlighting the segmented nature of this development.

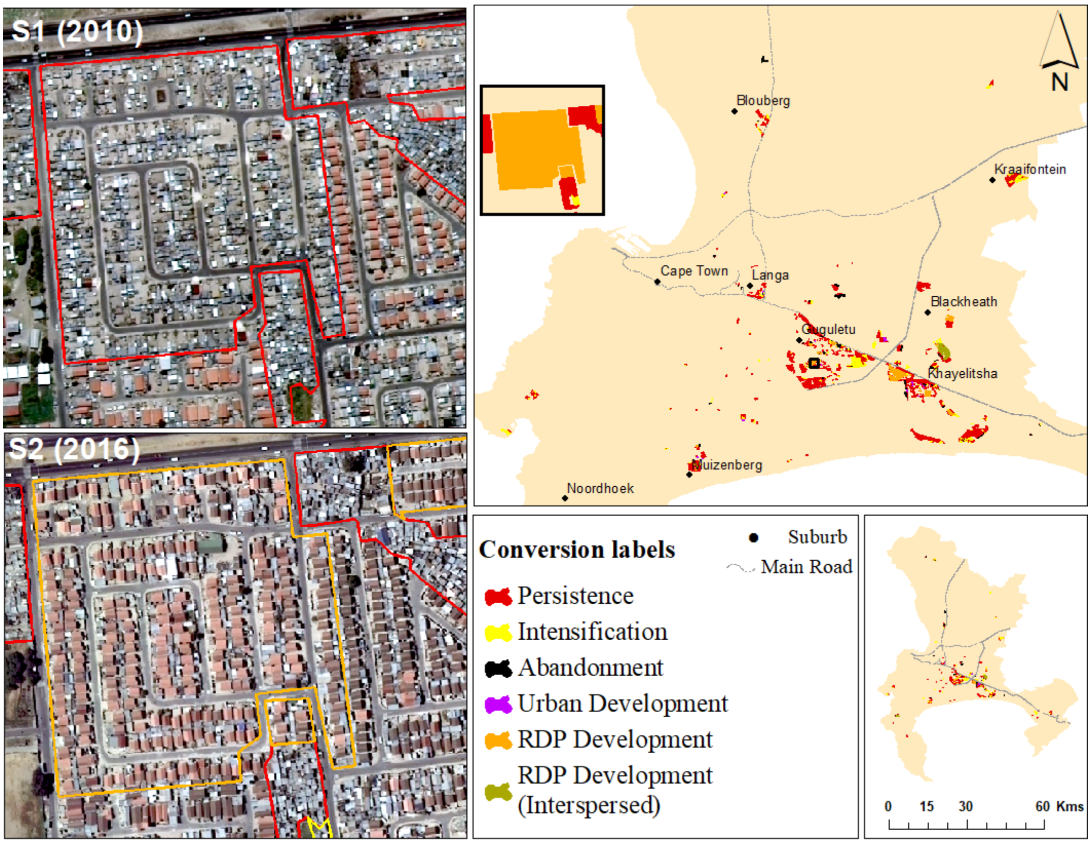

Figure 5: LU conversions in DD3 (map) and R2 data (aerial photographs) highlighting RDP Development (RD) across bitemporal steps S1 and S2 in the study area

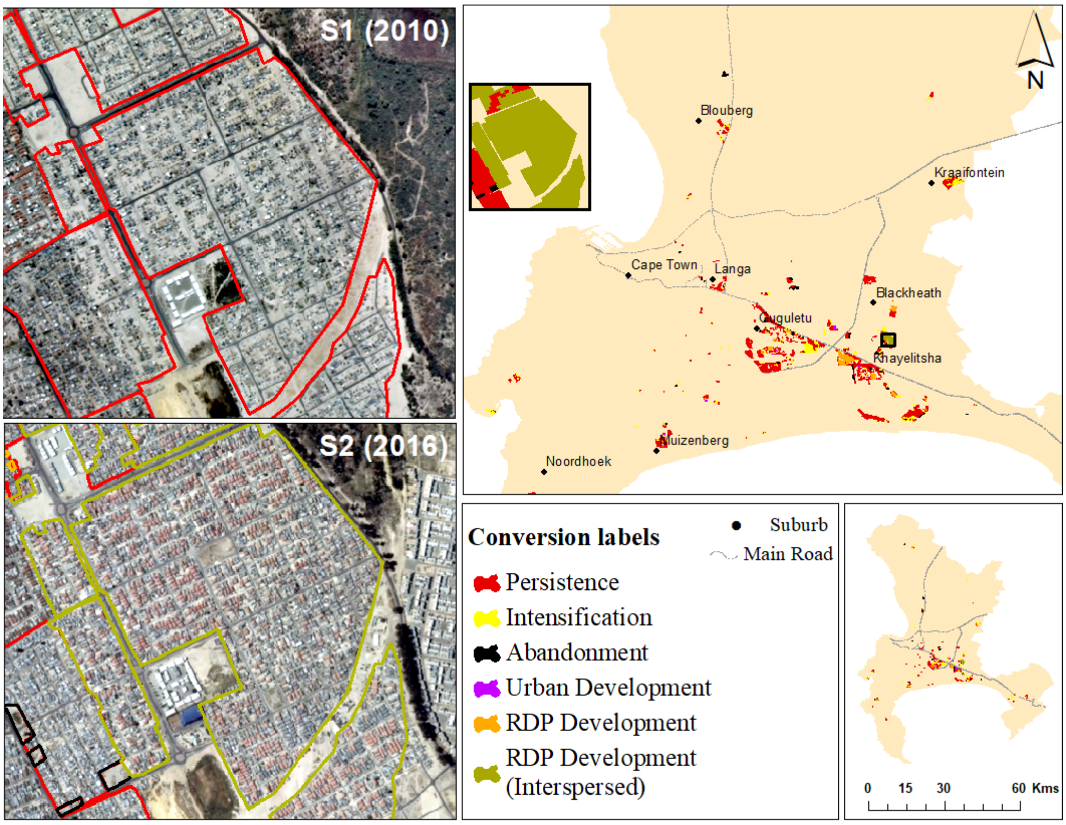

Figure 6: LU conversions in DD3 (map) and R2 data (aerial photographs) highlighting RDP Development (interspersed) (RDi) across bitemporal steps S1 to S2 in the study area

4. Discussions

This paper systematically outlines and describes the steps undertaken for LU classification and change analysis of informal areas in the City of Cape Town, focusing on LU conversions and landscape processes between two temporal steps (S1-2010 and S2-2016), as represented by the LUC dataset (DD3) derived from the intersection of the two LU datasets (D1 and D2), developed through post-classification methods. The manual approach produced robust LU classification results, particularly for the highly fragmented informal area landscapes, enabling more precise delineation of backyard and non-backyard informal areas. The increase in land-mass suggests that the D1 and D2 data capture the extent of informal settlements more accurately than the R1 baseline dataset, thereby providing a more precise representation of on-ground realities. The post-classification editing enhances the accuracy of the D1 and D2 datasets by aligning them more closely with the actual spatial distribution of informal settlements. This adjustment not only improved the datasets' accuracy but also their completeness. The overall accuracy (OA) of these datasets, determined to be above 90%, is considered highly acceptable in light of existing literature (Novack and Kux, 2010). The DD3 provides bitemporal insights into the magnitude and direction of LUC from steps S1 to S2. The application of a schema for change analysis, as outlined in Table 3, further summarises the drivers of LUC and landscape processes in the study area.

Analysis of DD3 reveals that Persistence (Pe), accounting for over 80%, and Intensification (In), about 4%, were the predominant processes affecting informal areas (Table 6). These LU conversions are mainly indicative of landscape degradation in these zones. The primary drivers behind these trajectories can be attributed to poor households intentionally occupying vacant land, transforming it into densely packed shack areas. Additionally, dense intensification often arises when financial constraints force rural-urban migrants to settle in informal areas (DHS and SANSA, 2011). These dynamics further compound the challenges facing informal settlements, undermining the effectiveness of the Reconstruction and Development Programme (RDP) policy due to its inherent limitations (DME, 1998).

The LU conversion analysis indicates landscape degradation processes and some minor instances of anthropogenic rehabilitation or landscape reclamation within informal areas. Despite their limited extent, these processes are promising for urban and RDP development to harness civilization benefits. Urban Development (UD), though a gradual process, has proved to be a valuable policy tool, accounting for less than one percent of the change in LU conversion areas. Nonetheless, it holds the potential to help transform informal settlements into formal urban areas. Meanwhile, RDP Development (RD) has achieved the most substantial reclamation in the study area, underscoring its success in providing decent housing to the impoverished (DME, 1998). The complete transformation of informal areas into formal RDP houses could significantly alter the study area's physical, social, and economic landscapes. RDP Development (interspersed) (RDi), representing partial reclamation, likely arose from the ongoing RDP housing projects during the period covered by the S1 and S2 steps. It accounted for approximately two percent of the total LU conversions. Despite its modest contribution to the overall LUC, it serves - and continues to serve - as a reclamation process that addresses the housing shortage and enhances the living conditions of informal households.

This study generally reveals the complex interplay between reclamation and degradation processes within informal areas, which are often overlooked in urban planning and initiatives. Despite the potential benefits of reclamation, these processes accounted for less than three percent of the land use changes during this study's bi-temporal interval (S1 to S2). This discrepancy between landscape degradation and reclamation rates presents significant challenges for policymaking and its efficacy. It highlights that efforts to improve informal areas are not keeping pace with the ongoing landscape degradation, thereby limiting the long-term value of current policies. Consequently, there is an urgent need in the City of Cape Town for more comprehensive policy measures and frameworks to address the causes and effects of land use changes to foster sustainable urban planning and development. The study can inform the City's future policies and decision-making related to land use and sustainability by analyzing LU conversions and landscape processes in the study area.

Furthermore, identifying the dominant change trajectories in land use is essential for policymakers to tailor interventions effectively in informal areas. The Persistence (Pe) and Intensification (In) trajectories often exacerbate landscape degradation, while signals of reclamation such as Abandonment (Ab), RDP Development (RD), and Urban Development (UD) can indicate policy success and urban sustainability (Münch et al., 2017). Understanding these landscape dynamics is crucial for shaping policies that address the unique challenges of informal settlements in South Africa. As it stands, persistent and expanding informal settlements require focused policy interventions, whereas informal areas experiencing reclamation through abandonment or redevelopment should continue to benefit from current policy support.

5. Conclusions and limitations

This paper has demonstrated the utility of autonomous land use (LU) maps for analyzing land use change (LUC) in informal areas of Cape Town, South Africa. Through advanced post-classification techniques and the national land cover (LC) dataset, the research achieved high accuracy levels (99.7% for S1 and 99.5% for S2), underscoring the methods' precision. The findings highlight persistent landscape degradation linked to socioeconomic challenges, such as poverty and policy inefficiencies, while also pointing to the potential of reclamation efforts like Abandonment (Ab), RDP Development (RD), and Urban Development (UD) as mechanisms to counteract these negative impacts. However, the reclamation pace lags behind the degradation rate, indicating a critical area for policy focus. The volatility of informal settlements further emphasizes the need for accurate and timely data to support effective urban planning and policymaking. Ultimately, this study not only enriches our understanding of LUC dynamics but also serves as a crucial reference for future research and strategic development to enhance urban environment sustainability.

It is crucial to acknowledge the potential limitations encountered in this study to safeguard the validity and utility of the data. For instance, higher temporal resolution data would be beneficial to more accurately determine the recent reclamation activities under the RDP Development (interspersed) (RDi) label. Integrating the degradation gradient associated with this label could enhance landscape development through more informed planning and design. Although the LU maps demonstrated high accuracy, it is possible that the boundaries of informal areas were not captured with complete precision, especially in delineating shacks in backyards or RDP houses amidst shacks. This could introduce some uncertainty in the classification results due to potential errors in user interpretation. Despite these challenges, the study has provided highly accurate data on the distribution and extent of informal areas in the City of Cape Town, useful for updating national database records (HDA, 2013) and informing relevant policy decisions.

Data Availability Statement: Data supporting this study are archived and publicly accessible via a Google Drive folder, which includes links to the datasets analyzed and generated during this research. Access to the folder is available upon request.

6. References

Ahearn, M.C., Alig, R.J., 2017. A discussion of recent land-use trends. Econ. Rural Land-Use Chang. 11–26.

Brown-Luthango, M., Reyes, E., Gubevu, M., 2017. Informal settlement upgrading and safety: experiences from Cape Town, South Africa. J. Hous. Built Environ. 32, 471–493.

Congalton, R., Green, K., 2019. Assessing the accuracy of remotely sensed data: principles and practices.

DHS, (Department of Human Settlements), SANSA, (South African National Space Agency), 2011. Informal Settlements Change Assessment 2006-2011.

DME, (Department of Minerals and Energy), 1998. White Paper on the Energy Policy of the Republic of South Africa. Gov. Gaz. 402, 1–110.

Du Toit, L., Henrico, I., Bezuidenhout, J., Mtshawu, B., 2022. Analysing the changes in the bathymetry of Saldanha Bay between the years 1977 and 2021. South African J. Geomatics 11, 325–339.

ESRI, (Environmental Systems Resource Institute), 2009. ArcMap 10 ESRI [WWW Document]. Calif. Redlands.

Foody, G., 2010. Assessing the Accuracy of Remotely Sensed Data: Principles and Practices, The Photogrammetric Record. CRC press.

Hassan, Z., Shabbir, R., Ahmad, S.S., Malik, A.H., Aziz, N., Butt, A., Erum, S., 2016. Dynamics of land use and land cover change (LULCC) using geospatial techniques: a case study of Islamabad Pakistan. Springerplus 5.

HDA, (Housing Development Agency), 2013. Research Report Gauteng: Informal settlements Status (2013) [WWW Document]. URL http://www.thehda.co.za/uploads/files/HDA_South_Africa_Report_lr.pdf (accessed 12.26.18).

Henrico, I., Vukea, M., Smit, H., 2021. Examining the impact of military training exercises on vegetation: case of the South African Army Combat Training Centre Lohatla. Spat. Inf. Res. 29, 557–568.

Hersperger, A.M., Bürgi, M., Wende, W., Bacău, S., Grădinaru, S.R., 2020. Does landscape play a role in strategic spatial planning of European urban regions? Landsc. Urban Plan. 194, 103702.

Hersperger, A.M., Oliveira, E., Pagliarin, S., Palka, G., Verburg, P., Bolliger, J., Grădinaru, S., 2018. Urban land-use change: The role of strategic spatial planning. Glob. Environ. Chang. 51, 32–42.

Johnson, B.A., Iizuka, K., Bragais, M.A., Endo, I., Magcale-Macandog, D.B., 2017. Employing crowdsourced geographic data and multi-temporal/multi-sensor satellite imagery to monitor land cover change: A case study in an urbanizing region of the Philippines. Comput. Environ. Urban Syst. 64, 184–193.

Kastner, T., Matej, S., Forrest, M., Gingrich, S., Haberl, H., Hickler, T., Krausmann, F., Lasslop, G., Niedertscheider, M., Plutzar, C., Schwarzmüller, F., Steinkamp, J., Erb, K.H., 2022. Land use intensification increasingly drives the spatiotemporal patterns of the global human appropriation of net primary production in the last century. Glob. Chang. Biol. 28, 307–322.

Ledoux, H., Arroyo Ohori, K., Meijers, M., 2014. A triangulation-based approach to automatically repair GIS polygons. Comput. Geosci. 66, 121–131.

Li, S., Song, W., Fang, L., Chen, Y., Ghamisi, P., Benediktsson, J.A., 2019. Deep learning for hyperspectral image classification: An overview. IEEE Trans. Geosci. Remote Sens. 57, 6690–6709.

Liu, H., Zhou, Q., 2004. Accuracy analysis of remote sensing change detection by rule-based rationality evaluation with post-classification comparison. Int. J. Remote Sens. 25, 1037–1050.

LIU, J., BI, H., Wang, M., 2020. Using multi-source data to assess livability in Hong Kong at the community-based level: A combined subjective-objective approach. Geogr. Sustain. 1, 284–294.

Lü, D., Gao, G., Lü, Y., Ren, Y., Fu, B., 2020. An effective accuracy assessment indicator for credible land use change modelling: Insights from hypothetical and real landscape analyses. Ecol. Indic. 117, 106552.

Magidi, J., Ahmed, F., 2019. Assessing urban sprawl using remote sensing and landscape metrics: A case study of City of Tshwane, South Africa (1984–2015). Egypt. J. Remote Sens. Sp. Sci. 22, 335–346.

Mbatha, L.S., 2001. Determining the Changes in the Sustainable Livelihoods of Informal Settlements in the City of Cape Town Metropolitan From.

Meinen, B.U., Robinson, D.T., 2020. Mapping erosion and deposition in an agricultural landscape: Optimization of UAV image acquisition schemes for SfM-MVS. Remote Sens. Environ. 239.

Morisette, J.T., Khorram, S., 2000. Accuracy assessment curves for satellite-based change detection. Photogramm. Eng. Remote Sensing 66, 875–880.

Msofe, N.K., Sheng, L., Lyimo, J., 2019. Land use change trends and their driving forces in the Kilombero Valley Floodplain, Southeastern Tanzania. Sustain. 11, 505.

Münch, Z., Okoye, P.I., Gibson, L., Mantel, S., Palmer, A., 2017. Characterizing degradation gradients through land cover change analysis in rural eastern cape, South Africa. Geosci. 7, 1–22.

Mundia, C.N., Aniya, M., 2005. Analysis of land use/cover changes and urban expansion of Nairobi city using remote sensing and GIS. Int. J. Remote Sens. 26, 2831–2849.

Munthali, M., Botai, O.J., Munthali, M.G., Botai, J.O., Davis, N., Adeola, A.M., 2019. Multi-temporal Analysis of Land Use and Land Cover Change Detection for Dedza District of Malawi using Geospatial Techniques Remotely Sensing Invasive Alien Plants View project Crop yields estimations: Applications of satellite indices View project Multi-. Artic. Int. J. Appl. Eng. Res. 14, 1151–1162.

Ngarava, S., Zhou, L., Mushunje, A., Chaminuka, P., 2021. Vulnerability of Settlements to Floods in South Africa: A Focus on Port St Johns 203–219.

Nguyen, H.A.T., Sophea, T., Gheewala, S.H., Rattanakom, R., Areerob, T., Prueksakorn, K., 2021. Integrating remote sensing and machine learning into environmental monitoring and assessment of land use change. Sustain. Prod. Consum. 27, 1239–1254.

Niva, V., Taka, M., Varis, O., 2019. Rural-Urban Migration and the Growth of Informal Settlements: A Socio-Ecological System Conceptualization with Insights Through a "Water Lens." Sustainability 11, 3487.

Novack, T., Kux, H.J.H., 2010. Urban land cover and land use classification of an informal settlement area using the open-source knowledge-based system InterIMAGE. J. Spat. Sci. 55, 23–41.

Okoye, P.I., 2016. Grassland rehabilitation after alien invasive tree eradication: landscape degradation and sustainability in rural Eastern Cape. Master's thesis.

Okoye, P.I., 2021. A novel systems approach to energy poverty in sub-Saharan Africa: A South African informal settlement case study.

Pojani, D., 2019. The self-built city: theorizing urban design of informal settlements. Archnet-IJAR 13, 294–313.

Reed, J., Van Vianen, J., Deakin, E.L., Barlow, J., Sunderland, T., 2016. Integrated landscape approaches to managing social and environmental issues in the tropics: learning from the past to guide the future. Glob. Chang. Biol. 22, 2540–2554.

Roy, P.S., Ramachandran, R.M., Paul, O., Thakur, P.K., Ravan, S., Behera, M.D., Sarangi, C., Kanawade, V.P., 2022. Anthropogenic Land Use and Land Cover Changes—A Review on Its Environmental Consequences and Climate Change. J. Indian Soc. Remote Sens. 50, 1615–1640.

Samper, J., Shelby, J.A., Behary, D., 2020. The paradox of informal settlements revealed in an ATLAS of informality: Findings from mapping growth in the most common yet unmapped forms of urbanization. Sustain. 12, 1–25.

SANLC, 2020. GIS Data Downloads | EGIS [WWW Document]. Dep. For. Fish. Environ. Repub. South Africa. URL https://egis.environment.gov.za/data_egis/data_download/current (accessed 2.27.23).

SEA, 2014. Tackling Urban Energy Poverty in South Africa. Sustain. Energy Africa 9, 1–20.

Shah, A., Kantamaneni, K., Ravan, S., Campos, L.C., 2023. A Systematic Review Investigating the Use of Earth Observation for the Assistance of Water, Sanitation and Hygiene in Disaster Response and Recovery. Sustain. 15, 3290.

Simwanda, M., Murayama, Y., 2018. Spatiotemporal patterns of urban land use change in the rapidly growing city of Lusaka, Zambia: Implications for sustainable urban development. Sustain. Cities Soc. 39, 262–274.

Smith, P., House, J.I., Bustamante, M., Sobocká, J., Harper, R., Pan, G., West, P.C., Clark, J.M., Adhya, T., Rumpel, C., Paustian, K., Kuikman, P., Cotrufo, M.F., Elliott, J.A., Mcdowell, R., Griffiths, R.I., Asakawa, S., Bondeau, A., Jain, A.K., Meersmans, J., Pugh, T.A.M., 2016. Global change pressures on soils from land use and management. Glob. Chang. Biol. 22, 1008–1028.

Taubenböck, H., Kraff, N.J., 2014. The physical face of slums: A structural comparison of slums in Mumbai, India, based on remotely sensed data. J. Hous. Built Environ. 29, 15–38.

Vadrevu, K., Heinimann, A., Gutman, G., Justice, C., 2019. Remote sensing of land use/cover changes in South and Southeast Asian Countries. Int. J. Digit. Earth 12, 1099–1102.

Wang, W., Li, W., Zhang, C., Zhang, W., 2018. Improving Object-Based Land Use/Cover Classification from Medium Resolution Imagery by Markov Chain Geostatistical Post-Classification. L. 2018, Vol. 7, Page 31 7, 31.

Wang, Y., Liu, Z., Liao, H., Li, C., 2015. Improving the performance of GIS polygon overlay computation with MapReduce for spatial big data processing. Cluster Comput. 18, 507–516.

Weimann, A., Oni, T., 2019. A systematised review of the health impact of urban informal settlements and implications for upgrading interventions in South Africa, a rapidly urbanising middle-income country. Int. J. Environ. Res. Public Health 16.

Wilkinson, P., 2000. City profile: Cape Town. Cities 17, 195–205.

Williams, D.S., Máñez Costa, M., Sutherland, C., Celliers, L., Scheffran, J., 2019. Vulnerability of informal settlements in the context of rapid urbanization and climate change. Environ. Urban. 31, 157–176.

Yin, J., Fu, P., Cheshmehzangi, A., Li, Z., Dong, J., 2022. Investigating the Changes in Urban Green-Space Patterns with Urban Land-Use Changes: A Case Study in Hangzhou, China. Remote Sens. 14, 5410.

Zhang, L., Zhang, Q., Du, B., Huang, X., Tang, Y.Y., Tao, D., 2018. Simultaneous spectral-spatial feature selection and extraction for hyperspectral images. IEEE Trans. Cybern. 48, 16–28.

Zhao, K., Jin, B., Fan, H., Song, W., Zhou, S., Jiang, Y., 2019. High-performance overlay analysis of massive geographic polygons that considers shape complexity in a cloud environment. ISPRS Int. J. Geo-Information 8.

Zheng, Z., Zhong, Y., Wang, J., Ma, A., Zhang, L., 2021. Building damage assessment for rapid disaster response with a deep object-based semantic change detection framework: From natural disasters to man-made disasters. Remote Sens. Environ. 265.

Appendix

Figure A1: A flowchart for LU classification and LUC analysis of informal areas in the City of Cape Town