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► **To cite this version:**

Shelton Mthunzi Sithole, Walter Musakwa, James Magidi, Alain Kibangou. Characterising landcover changes and urban sprawl using geospatial techniques and landscape metrics in Bulawayo, Zimbabwe (1984–2022). *Heliyon*, 2024, 10 (6), pp.e27275. <10.1016/j.heliyon.2024.e27275>. <hal-04664059>

HAL Id: hal-04664059

<https://hal.science/hal-04664059v1>

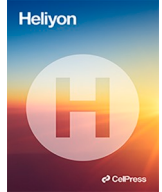
Submitted on 29 Jul 2024

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Review article

Characterising landcover changes and urban sprawl using geospatial techniques and landscape metrics in Bulawayo, Zimbabwe (1984–2022)

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ARTICLE INFO

Keywords:

Urban sprawl
Land cover changes
Geospatial technology
Support vector machine
Landscape metrics
Bulawayo

ABSTRACT

Urbanisation is a global trend that significantly impacts sustainable urban development and the quality of urban life. Assessing urban sprawl is critical for sustainable urban planning and aligns with the key objectives of the United Nations sustainable development goals. This study employed geospatial technology and landscape metrics to comprehensively assess, map, and quantify the extent of urban sprawl in Bulawayo from 1984 to 2022. The study leveraged the Support Vector Machine (SVM) supervised machine learning algorithm coupled with landscape metrics to achieve this objective. The combined approach allowed for the classification, detection of land cover changes, analysis of urban dynamics, and quantification of the degree of urban sprawl. The results revealed a 228% increase in built-up areas between 1984 and 2022, while non-built-up areas (agricultural land, vegetation, bare land) decreased by 29.28%. The landscape metrics and change analysis indicated an encroachment of urban-like conditions into urban areas. Land use change assessment revealed that Bulawayo exhibits four district types of urban sprawl: leapfrog, strip/ribbon, low density, and infill. Urban expansion is attributed to urbanisation and evolving land use policy. Urban sprawl has numerous urban planning implications on transport management, habitat loss and deforestation, reduction and contamination of freshwater sources, and many others. This study is strategic to planners, researchers, and decision-makers/policy makers as it provides relevant, up-to-date, and accurate information for sustainable urban planning.

1. Introduction and background

Urbanisation is a global phenomenon that significantly affects sustainable urban development and the quality of urban life [1]. A particular consequence of urban population growth is urban sprawl, an outward expansion of urban-like conditions into adjoining non-urban environments [2]. Urban sprawl can cause multiple problems, including escalated traffic congestion, heightened inequality,

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<https://doi.org/10.1016/j.heliyon.2024.e27275>

Received 25 August 2023; Received in revised form 7 February 2024; Accepted 27 February 2024

Available online 10 March 2024

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poverty, pollution (air, land, water, and noise), reduction in agricultural land, and habitat loss [3]. Also, it is widely regarded as the primary driver of significant land use changes in cities and rural hinterlands globally [3]. More than 55% of the world’s population are urban dwellers, and according to the United Nations’ most recent forecasts, the world population is projected to reach 8.5 billion in 2030, 9.7 billion in 2050, and 10.4 billion in 2100 [4,5]. Sub-Saharan African countries are projected to experience the highest population growth rates, accounting for more than half of the worldwide population increase by 2050 [6,7]. Despite the rapid occurrence of urban sprawl in Sub-Saharan Africa, there remain a limited number of studies that focus on the assessment and monitoring of urban sprawl using geospatial techniques in the region [8,9], thereby negatively affecting sustainable urban planning. Like other developing countries, Zimbabwe’s urban areas are also affected by urban sprawl [10]. Urban sprawl in Zimbabwe is primarily driven by the relaxation of colonial post-independence policies, accelerating urbanisation. There are also various government initiatives, such as the Economic Structural Adjustment Programmes (ESAP) and the Fast Track Land Reform Programme (FTLRP), which also had a bearing on urban sprawl [11]. In 2005, Zimbabwe embarked on Operation Murambatsvina (*‘clear the dirt’*) to clear informal settlements and backyard houses within urban areas [12]. This was followed by Operation Hlalani Kuhle/Garikai (Better Life), a housing scheme that further expanded urban regions [13]. According to Matamanda [14], Zimbabwe is beginning to witness the emergence of informal settlements, a non-existent trend. These developments significantly transform land use and land cover patterns in Zimbabwe’s urban environments.

Land use and land cover changes (LCC) can be classified using a variety of algorithms, such as maximum likelihood [15], fuzzy method [16], support vector machine [17], artificial neural network deep transfer [18], random forest [19], to mention just a few. Support Vector Machine (SVM) is a non-parametric machine learning algorithm that can theoretically identify crucial spectral signatures using a limited number of training samples (support vectors). These support vectors derive a hyperplane in a multidimensional space, which helps achieve reliable, accurate land cover classification. Several studies have found SVM to be the best classification algorithm for multispectral remotely sensed data [17,20,21]. SVM is found to be the best-suited algorithm for classifying areas with high variability in spectral signatures, like urban areas. Jombo, Adam [22], Maronedze and Schütt [23] applied SVM in Zimbabwe, while Kamosoko and Aniya [24] and Kamosoko, Gamba [25] applied SVM coupled with landscape metrics to analyse land cover changes. However, none of the studies have applied this algorithm to assess the changes in land use and land cover (LULCC) in the City of Bulawayo. Against such background, only a few studies have applied geospatial technology to monitor, quantify, and characterise land use and land cover changes in Zimbabwe. A few studies were done in Harare and Gweru [22,23,26] and none on Bulawayo, even

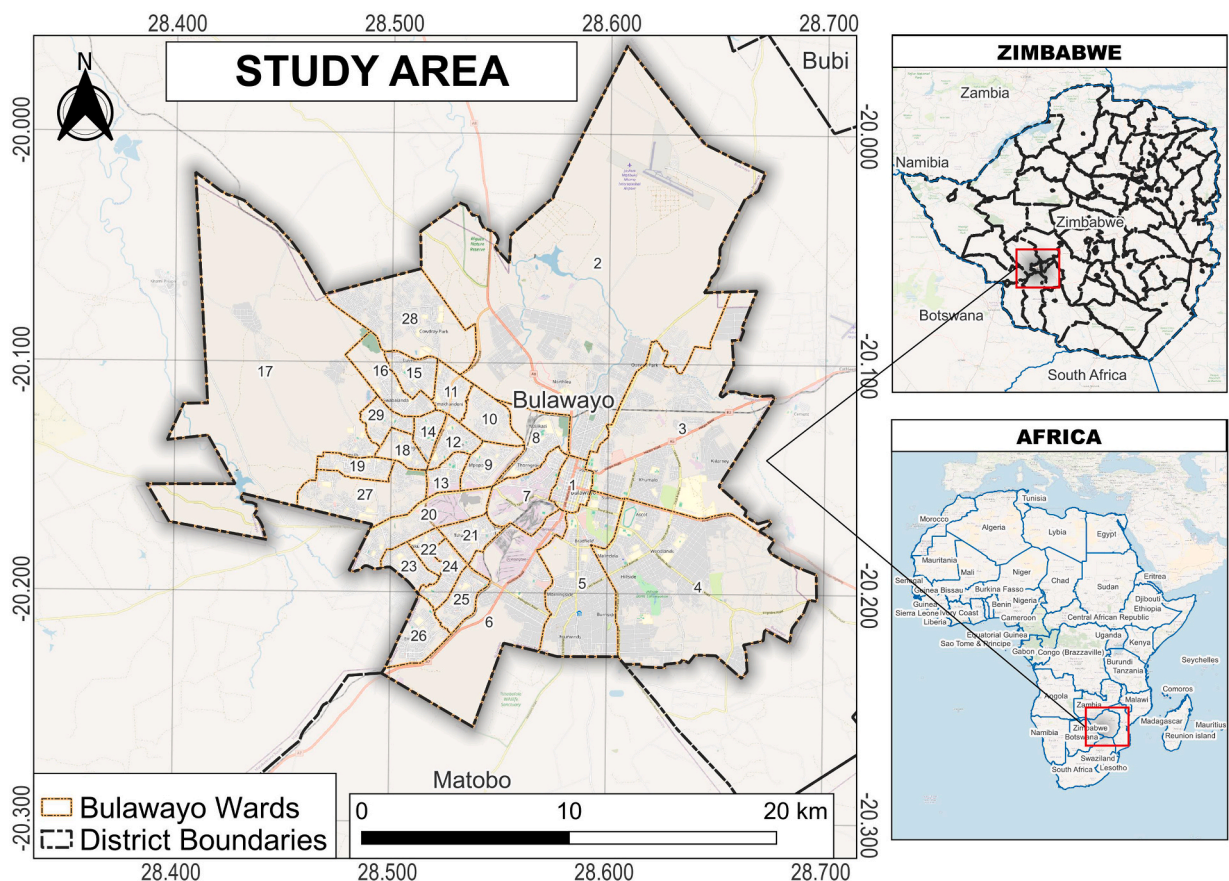


Fig. 1. Study area map for the city of Bulawayo.

though it's Zimbabwe's second-largest city.

The objective of this study is to assess, detect, map, monitor, and quantify landcover changes in the city of Bulawayo from 1984 to 2022. Landscape metrics characterise the composition, configuration, and connectivity of land-use patches. This approach addresses two key research questions: How has land cover changed over time? What are the drivers of the land cover changes? The application of landscape metrics to analyse configuration, connectivity, and composition provides insights into the dynamics, extent, degree, and type of urban sprawl in the CoB.

This analysis holds critical importance for several reasons: First, it enriches the body of knowledge on urban sprawl and its environmental implications in the Global South. Second, this study holds particular significance in considering the "Decade of Action" for the attainment of Sustainable Development Goals (SDGs) by 2030 [27]. Data-driven Insights from this study provide a baseline for sustainable urban planning and enable various stakeholders to make informed decisions and policies on environmental strategies, land use zoning, densification strategies and transport networks. It allows planners and decision-makers to understand the nexus between land uses and ecological processes. It can inspire them to design climate change-resilient cities, promote sustainable land management practices and formulate sustainable policies and decisions [28]. Furthermore, the study provides a deeper understanding of spatio-temporal urban dynamics in Bulawayo.

This study's novelty is assessing and monitoring land cover changes and analysing the degree and dynamics of urban sprawl in a new study area, i.e., the City of Bulawayo, which has not been explored before. The novelty also lies in the application of new methodologies (i.e., machine learning algorithms) in classifying landcover coupled with applying new techniques (landscape metrics) in analysing landcover for Bulawayo.

One of the study's limitations is that it did not cover the period before 1984, including 1980 when Zimbabwe gained its independence [29,30]. Cloud-free Landsat remotely sensed data for this study area is only available after 1984; hence the remote sensed data was collected from 1984 onwards. Analysing land cover changes and sprawl levels before independence would have provided planners and policymakers with valuable insights for developing sustainable and equitable development strategies in the new Zimbabwe.

2. Study area

Bulawayo, the second largest city in Zimbabwe, is located on the southeastern side of the country and has an estimated population of 665 940 [31]. The city was initially called koBulawayo, interpreted as "the place of slaughter or killing". It was the original home of one of the last Matabele kings-King Lobengula. It is the heart of three of Zimbabwe's provinces, i.e., Matabeleland South, North, and

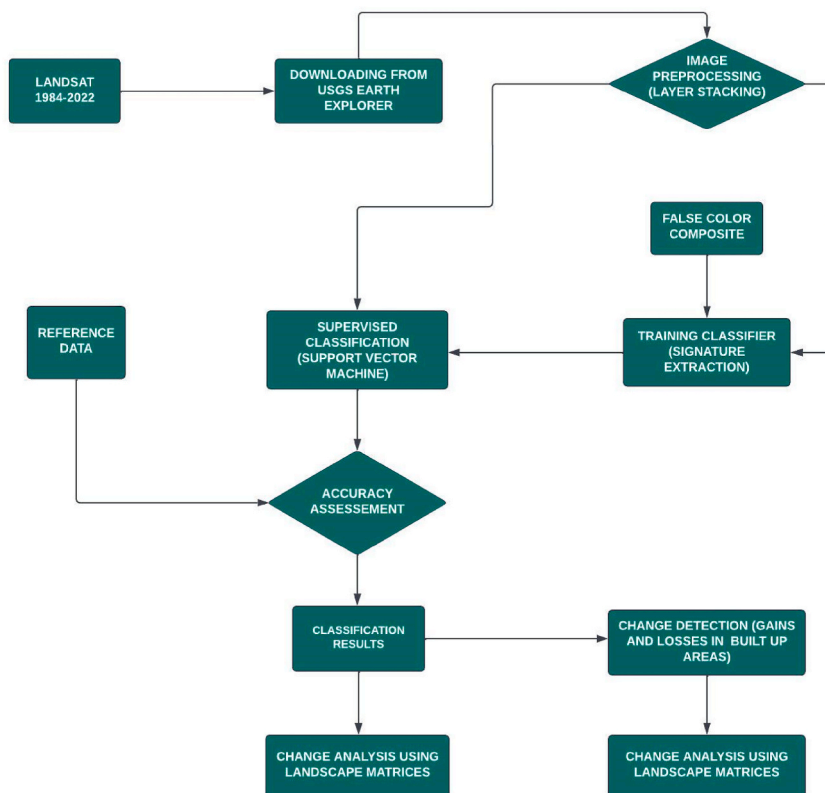


Fig. 2. Methodology Flow Chart applied in this research.

Bulawayo. The city lies between latitude 19° 57' 57.07" S to 20° 18' 10.27" S and longitude 28° 22' 02.99" E to 28° 46' 16.83" E (see Fig. 1), with an altitude of 341 m above sea level. It is in a semi-arid region with erratic rainfall averaging about 600 mm annually. The city lies close to the Kalahari desert, making it prone to droughts [32]. The city has an estimated housing stock of about 140000 units with a housing backlog of over 100000. The city attained its town status in 1894, and by 1943, it was elevated to a city owing to its rapid growth. Bulawayo has a dual role of being Southern Zimbabwe's capital and the link to the interior of Southern Africa. The arrival of the railway in 1897 and its proximity to South Africa, Botswana, and Zimbabwe made it ideal to be the country's industrial, mining, and ranching centre. The City of Bulawayo has a robust governance system and was named the best-run city in Zimbabwe in 2018. Bulawayo was the first to have an operative Master Plan in an independent Zimbabwe. To date, it has had three operative Master Plans and is currently engaged in reviewing the 2000–2015 Master Plan. The city has about twenty local development plans to ensure that every square inch of land is planned according to various land uses. The city of Bulawayo prides itself as the citadel of city planning, management, and development and is currently the only city in Zimbabwe with a standalone town planning department. Other cities in Zimbabwe still have town planning units falling under engineering or works departments. Bulawayo experienced rapid urbanisation in the late 20th century due to its status as the country's industrial hub, the *Gukurahundi* genocide – as it became the place of refuge to its neighbouring provinces [33] and the relaxation of colonial restrictions on black people settling in urban areas after independence in 1980 [34].

Currently, the City of Bulawayo (CoB) struggles to cope with service delivery, with housing demand now estimated to be over 110 000 [35]. Bulawayo's sprawling was also driven by various agencies' drive to build homes for people, for example, the World Bank and other Building Societies in the 1990s and HomeLink housing finance programmes for those in the diaspora [35].

3. Data and methods

The methodology applied in this study is a multi-step process that involves downloading, pre-processing, training, classification, accuracy assessment, change detection and change analysis using landscape metrics, as outlined in Fig. 2.

3.1. Pre-processing

Data was downloaded freely from the United States Geological Survey (USGS) Earth Explorer geoportal and were geo-referenced, cropped and projected in the Universal Transverse Mercator (UTM) Zone 35 south coordinate system. The final step was to stack all the bands for each year into a single image. Quantum GIS 3.16 was used to pre-process the satellite images. The pre-processing of the Landsat TM and OLI satellite images for 1984, 1990, 2001, 2011 and 2022 was conducted to ensure that the images were high quality and suitable for analysis. The idea was to conduct a decadal period; however, data limitations forced the study to dwell on the abovementioned dates. The detailed characteristics are outlined in Table 1.

3.2. Classification process

Several training sites were digitised on the false colour composite of the Landsat imagery, and attributes were added based on knowledge of spectral response curves. ArcMap 10.12 was used to run the SVM classification algorithm for classification. The Support Vector Machine (SVM) algorithm was employed to classify the images into four main classes: built-up areas, water, vegetation, and agriculture. The algorithm was chosen due to its multifarious benefits, which include providing a high level of accuracy, excellent prediction, efficient ability to handle large datasets and the fact that it is a multi-tasker in performing both classification and regression tasks [36]. Scholars note that, whereas the accuracy of other classification algorithms declines with the training data size, SVM's classification accuracy increases almost continuously as a function of the features [37]. The SVM is a versatile and powerful machine-learning algorithm chosen due to its robustness to outliers [38,39]. It does this because it focuses on data points nearer to the decision boundary and is less influenced by outliers from the boundary. SVM was also chosen due to its efficient training ability, even for large data sets. It has this advantage because of its convex training algorithm, which guarantees finding even the minimum. ArcGIS 10.12.

3.3. Accuracy assessment

Google Earth was used as input in assessing the land cover classification accuracy. The assessment was carried out using random ground control points generated using ArcMap. The generated datasets were split into two, i.e. training and testing sets. The training

Table 1

Characteristics of the sensor, number of bands, path, rows and date of acquisition.

Sensor	Number of Bands	Path/Row	Date of Acquisition
Landsat 4–5 TM	7 Bands	171/074	1984/10/19
Landsat 4–5 TM	7 Bands	171/074	1990/09/18
Landsat 4–5 TM	7 Bands	171/074	2001/08/15
Land sat 4–5 TM	7 Bands	171/074	2011/10/04
Landsat 8–9 OLI	11 Bands	171/074	2022/10/14

sets were used to train the SVM classifier, and the testing set was employed to evaluate the classifier's performance. The kappa coefficient was employed to assess the accuracy of the SVM algorithm. Each classified data was compared with the reference data. The classified images were further reclassified into two main classes, i.e., built-up and non-built-up, as described in Table 2.

3.4. Landscape metrics quantification

The study used twelve (12) landscape metrics from the FRAGSTATS 4.2 to calculate the size of urban areas in their relative, absolute, complex, and isolated states. Gökyer [40] defines landscape metrics as algorithms that measure the spatial organisation of patterns, more specifically, land cover, within a given geographic area. Landscape metrics are significant for understanding landscape structure and changes [40]. Two indices were applied to measure the absolute size of Bulawayo's features, including the Class level and the landscape level. A detailed list and description of these indices are depicted in Table 3. These twelve landscape metrics were chosen because they are vital in measuring units of the landscape and, in many cases, act as surrogates for change (Lambin et al., 2001). They were also applied due to their ability to act as surrogates for change and for their inherent ability to allow for the elucidation and quantification of spatial patterns and ecological processes over space and time [41]. Landscape metrics have been applied globally to quantify the extent of land use and land cover changes. Some of the commonly used metrics include Euclidean nearest neighbour distance mean (ENND_M), patchy density (PD), number of patches (NP), patch cohesion Index, landscape shape Index (LSI), mean patch area, Shannon's diversity Index (SHDI), and Simpson's diversity Index (SDI), edge density, class area and mean shape index metrics [42–44].

4. Results and discussion

4.1. Accuracy assessment

The accuracy assessment of the classified images of the landcover changes was performed using the confusion matrix. The results indicate that the landcover maps created using the SVM algorithm have excellent overall classification accuracy. The recorded classification accuracy values for the years 1984, 1990, 2001, 2011 and 2022 were 92%, 94%, 87%, 93% and 93% respectively as shown in Table 4.

The kappa coefficient values of the classified land cover change maps of 1984, 1990, 2001, 2011 and 2022 were found to be 0.65, 0.85, 0.73, 0.84 and 0.85, respectively. Bindajam, Mallick [46] Cohen's kappa coefficient is a commonly used index to assess the agreement between two raters [47]. Several scholars agree that kappa statistics closer to 0.8 indicate an excellent classification performance that strongly agrees with the classified image and the reference image [48]. These results suggest that the SVM algorithm is a highly effective tool for land cover classification. SVM can be employed to produce reliable land cover maps. The results also provide valuable insights into the temporal dynamics of land cover change in Bulawayo.

4.2. Land use and land cover changes

Regarding land cover changes, the reclassified landcover maps of 1984, 1990, 2001, 2011 and 2022 demonstrate tremendous changes, with built-up expanding at the expense of non-built areas in the CoB. The expansion of the built-up has the potential to lead to the loss of green spaces, traffic congestion, and air and noise pollution, with urban sprawl exacerbating water challenges faced by Bulawayo.

Fig. 3 Built-up and non-built-up area in the CoB derived from supervised image classification using the SVM machine learning classifier for 1984, 1990, 2001, 2011 and 2022.

4.3. Built-up areas vs non-built-up computations

The City of Bulawayo was found to have 48650.13 ha (87.99%) being non-built up and 6642.81 ha (12.01%) occupied by built-up areas. Findings reveal that six years later (in 1990), there was a significant shift in the land use pattern, with the built-up classes expanding to cover a vast area of 13794.48 ha with non-built-up decreasing to 41498.46 ha (75.05%). In 2001, the LCC map showed that 40152.78 ha (72.62%) were non-urban areas while 15140.16 ha (27.38%) were built-up areas. The LCC of map 2011 indicated that the built-up areas occupied 39913.02 ha (72.18%). Finally, the LCC classified map of the year 2022 revealed that 33503.58 ha of the CoB were non-urban areas while 21789.36 ha (39.41%) were occupied by built-up areas, as shown in Table 5. This data suggests a gradual increase in the built-up areas over the past 38 years. This shift in land-use patterns highlights the need for effective urban planning and management to ensure sustainable growth and development of the city.

The research findings demonstrate that built-up areas in Bulawayo have been expanding at the expense of non-built areas. From

Table 2
Characteristics of the landcover classes applied in the study.

Land cover class	Description
Built-up area	Commercial areas, industrial areas, transport infrastructure and communication network systems, formal and informal residential areas
Non-built –area	Water reservoirs, bare land, vegetation, grassland, agriculture land, irrigated land, dams, swamps rivers, riverine, and urban green spaces.

Table 3
Delineation of landscape metrics applied in this study [45].

Metric	Description
Percentage of landscape (PLAND)	The proportion of the landscape that is made up of a specific patch type.
Patch Area Mean (AM)	Is the summary of each class as the mean of all patch areas belonging to a certain class (class i)
Landscape Shape Index (LSI)	A standardized metric of patch compactness that accounts for patch size
Shannon's Diversity Index (SHDI)	Equals 1 minus the sum, across all patch types, of the proportional abundance of each patch type squared.
Simpson's Diversity Index (SIDI)	Equals 1 minus the sum, across all patch types of the proportional abundance of each patch type multiplied by that proportion
Patch Cohesion Index	An aggregation Index which characterizes the connectedness of patches belonging to a particular class.
Patch Density (PD)	Number of patches of the same type (class) per unit area
Total Core Area	The total of each patch's core regions (m2)
Euclidean Nearest Neighbour Distance Area Weighted Mean (ENN_AM)	The shortest straight-line distance (m) between a focus patch and its nearest class neighbour.
Euclidean Nearest Neighbour Distance Area Weighted Mean (ENN_MN)	Summarizes each class as the mean of each patch belonging to class I and measures the distance to the nearest neighbouring patch of the same class
Number of Patches (NoP)	The number of patches of each patch type (class)
Largest Patch Index	The size (m2) of the greatest patch in the landscape divided by the overall area of the landscape (m2)

Table 4
Cohen's Kappa coefficient and accuracy assessment on the classified images.

Year	Kappa Index	Accuracy (%)
1984	0.68	92
1990	0.85	94
2001	0.73	87
2011	0.84 ^{gj}	93
2022	0.85	93

1984 to 2022, the built-up areas increased from 6642.81ha to 21789.36ha, representing a significant increase of 15 146 ha or 227%. This trend is consistent with other studies conducted in Zimbabwe, such as [10,23] that have reported a similar phenomenon. The results further demonstrate that the City of Bulawayo experienced the most significant growth rate between 1984 and 1990, with an increase of 7151ha (106%). The city gained 1345 68 ha (9.76%) from 1990 to 2001 and 239.76ha (1.58%) of built-up growth from 2001 to 2011. However, from 2011 to 2022, the city experienced a substantial built-up growth rate of 6409.44ha (41.67%). The study results reveal that the built-up area has exhibited variable growth rates. Specifically, the annual average growth rate of the built-up area was 1191.95ha (17.94%) between 1984 and 1990, significantly dropping to 122.33 ha (0.89%) per annum from 1990 to 2001. Between 2001 and 2011, the built-up area's annual growth rate decreased to 23.98% (0.16%) per year. However, from 2011 to 2022, the built-up growth rates increased significantly to 582.7 ha (3.379%) per annum, as denoted in Table 6. This translates to a growth rate of 136.36 ha(228.01%) growth rate of built-up areas in the CoB over the thirty-six (36) year study period with an average annual expansion rate of 420.76 ha (6.3) per year from 1984 to 2022. Interestingly, the study's findings are consistent with a previous study conducted in Surat, India, which reported an increase in built-up areas by 175.22 between 1993 and 2019 (Sridhar et al., 2020). The significance of the present study lies in its relevance to urban planners and policymakers who can use the information to support Zimbabwe's National Human Settlement Policy (ZNHSP) [49]. The policy emphasises the need for densification and well-planned, sustainable human settlements. The study provides insights into the extent of Bulawayo's urban sprawl over the years and offers urban planners a range of growth options and evidence-based decision-making strategies. Furthermore, this study can provide indicators for the SDGs.

4.4. Population dynamics

According to the world population data, Bulawayo had a population of 446542,570046,670201,655931 and 643427 in 1984,1990,2001,2011 and 2022, respectively. This translates to a population gain of 27.66% and 17.57% from 1984 to 1990 and 1990–2001, respectively. The same data reveals that Bulawayo's population decreased by 2.13% and 1.91% from 2001 to 2011 and 2011–2022, as shown in Table 7.

Table 5
Changes in built-up and non-built-up classes from 1984 to 2022.

Year	1984	1990	2001	2011	2022
Built-up Areas	6642.81	13794.48	15140.16	15379.92	21789.36
Non-built-up Areas	48650.13	41498.46	40152.78	39913.02	33503.58
Total Area	55292.94	55292.94	55292.94	55292.94	55292.94
Percentage % (Built-up)	12.01	24.94%	27.38	27.82	39.41
Percentage % Non-Built up	87.99	75.05	72.62	72.18	60.59

Table 6
Built-up land cover gains over the 36 years.

Period From To	1984 1990	1990 2001	2001 2011	2011 2022
Time lag	6	11	10	11
Gains	7151.67	1345.68	239.76	6409.44
Built-up Change %	107.66	9.76	1.58	41.67
Rate per Annum%	17.94	0.89	0.16	3.79

Interestingly, when the population increased by 27.66 from 1984 to 1990, Bulawayo's built-up increased by 107.66% in the same period. However, a 17.57% increase in the population from 1990 to 2001 was matched by an increase of about 9.76% built-up or urban change. Still, a 2.31% population decrease from 2001 to 2011 saw a slight change in the built-up by 1.58%. In 2011–2022, Bulawayo's population decreased by 1.91% whilst the built-up increased by 41.67%, as shown in Table 7. Despite experiencing a notable population decrease, Bulawayo exhibits persistent urban sprawl (see Table 8), presenting a unique and seemingly contradictory phenomenon. Several potential drivers could be contributing to this discrepancy: It could be that the accuracy of Bulawayo's official population figures warrants scrutiny. Another driver could be that the revitalization of Bulawayo's eastern and northern residential suburbs bordering the central business district (CBD) through commercial development displaces residents. This relocation pressure fuels sprawl as displaced populations seek accommodation further from the CBD. Moreover, Another driver could be an appetite for multiple property investment amongst both residents and the Bulawayo diaspora and this can contribute to sprawl even amidst population decline. Ineffective Planning Policies: Weak zoning regulations and a proclivity for single-use development within Bulawayo's planning framework create conditions conducive to sprawl. Without effective density controls and mixed-use development strategies, urban expansion is facilitated regardless of population trends.

4.5. Landscape metrics

During the study period, an increase in the number of urban patches was observed, indicating the urban sprawl phenomenon. Specifically, the NP The number of patches increased from 3920 to 7163 in 1984–2022, which suggests that contiguous areas were transformed into smaller, more fragmented patches to make room for new subdivisions and transport infrastructure development. This indicates that built-up areas increased discontinuously throughout the years. Such an increase in built-up areas was driven by urbanisation, necessitated by the country's independence in 1980. The relaxation of colonial laws and regulations, which limited the number of people who could work and live in the cities, also contributed to the built-up increase. During the same years, the city announced several suburbs, especially to the West, as evidenced in Fig. 3. In 2011–2022, there was a reduction in the number of patches, revealing the agglomeration driven by the city's adoption of compact policies, which saw it growing through infill development.

Class-level analysis was conducted to investigate each class's spatial arrangement of patches. The results revealed a significant increase in the values of class areas from 6642.81 in 1984–16275.64 in 2022, thus confirming an increase in built-up areas extracted from LULCC maps. This corresponds with the Saud Arabia results, which concluded that from 1990 to 2018, class area values increased from 6943 to 33970, respectively (Bindajam et al., 2021). The percentage landscape also increased from 12.01 to 29.38 from 1984 to 2022. The patch density of Bulawayo increased from 7.09 to 12,93 in 2022, signifying an increase in the number of patches per unit area. The Largest patch Index (LPI) increased from 8.53% to 22.74% during the study period indicating that the largest index in 1984 is less than the largest index in 2022 and vice versa. The inference made from this is that the shapes of the landscape of the built-up patches were irregular in each corresponding year. These results tally with those conducted in Mali for Bamako Districts, where it was noted that LPI increased from 13.70% to 55.40% from 1990 to 2018 [50]. Furthermore, the largest shape index (LSI) also increased to 98.41 in 2022 from 66.37 in 1984, indicating an increase in the complexity of the built-up areas see Table 9. The mean area also reveals that the built-up area was increasing as it has values above 1.

The data from the percentage of landscape index has revealed that there has been an increase in urban sprawl and built-up over time. The percentage of landscape moves towards 100 when the landscape shifts towards becoming a single patch type. This indicates a higher abundance of built-up, which in turn has led to urbanisation [45] and signifies a higher abundance of built-up area [46] (Bindajam et al., 2021). The Landscape shape index was also measured and analysed, and the results show that the CoB landscape shape index increased from 66.37 to 99.40 in 1984–2011, indicating that the city was becoming more irregular through urban sprawl. It, however, reduced from 99.40 to 98.41 between 2011 and 2022 as the city was becoming more regular through compact growth.

Table 7
City of Bulawayo's population changes from 1984 to 1990.

Period	From To	1984 1990	1990 2001	2001 2011	2011 2022
Time lag		6	11	10	11
Population Gain		123 504	100 155	−14 270	−12 504
Percentage Change		27.66	17.57	−2.13	−1.91
Growth/annum		4.61	1.6	−0.21	−0.17

Table 8
Population changes vs urban (built-up) changes for CoB from 1984 to 2022.

From	1984	1990	2001	2011
To	1990	2001	2011	2022
Urban change %	107.66	9.76	1.58	41.67
Population change %	27.66	17.57	-2.13	-1.91

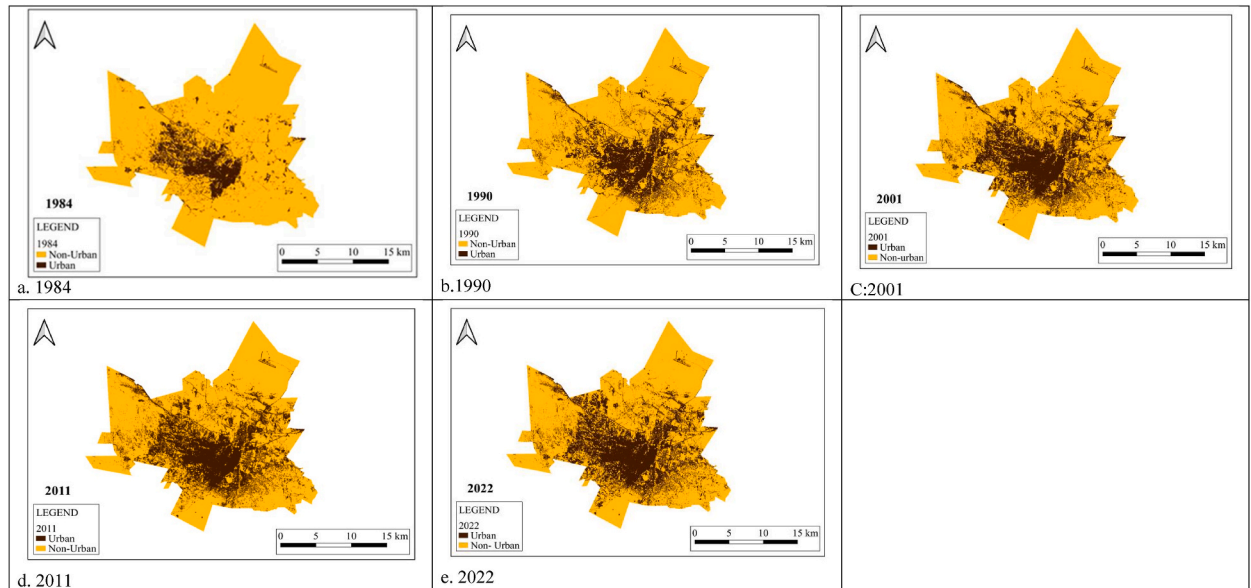


Fig. 3. Built-up and non built-up area in the CoB derived from supervised images classification using the SVM machine learning classifier for 1984,1990,2001,2011and2022.

Table 9
Landscape metrics values for 1984–2022 derived from built-up areas.

Index	CA	PLAND	NP	PD	LPI	LSI	Area MN	ENN MN	ENN AM	COH	DIV
Year											
1984	6642.81	12.01	3920	7.09	8.53	66.37	1.69	97.19	65.00	99.09	0.99
1990	11556.27	20.99	6822	12.39	14.73	95.30	1.69	84.16	62.41	99.36	0.9783
2001	15140.16	27.38	7206	13.03	20.72	95.39	2.10	81.46	62.01	99.55	0.957
2011	15204.24	27.50	7363	13.32	20.91	99.40	2.07	80.20	61.96	99.56	0.9563
2022	16275.64	29.38	7163	12.93	22.74	98.41	2.27	80.65	61.79	99.61	0.9483

Furthermore, the mean Euclidean Nearest neighbour distance (ENN_MN) was used to quantify the Euclidean distance of a particular patch from the nearest one in the neighbourhood. This measurement also helps to determine the centrality of the built-up areas [45]. The findings reveal that ENN_MN values kept decreasing over time, which indicates that urban sprawl is spreading away from the city centre. The ENN_AM values for the CoB showed a continuous decrease from 65.00 in 1984 to 61.79 in 2022. This signifies those built-up patches, over the years, have been becoming closer to each other over the years. However, from 2011 to 2022, the values increased as the type of growth was through infill growth of patches closer to the Central Business District. These findings are consistent with a similar study conducted in Lucknow City in India, where the values were very high but kept decreasing from 1985 to 2005 [51]. The Average Weighted Mean Euclidean Nearest Neighbour (ENN_AM) was also employed in this study to show the proximity of patches to one another. Overall, these measurements and analyses provide valuable insights into the urbanisation patterns and growth of the CoB. These findings can be used to inform future planning and development in Bulawayo.

The Landscape metrics analysis conducted for Bulawayo revealed that the built-up class in the city was highly contiguous, with increasing clustering towards 2022 as evidenced by higher cohesion values of 99.09, 99.55, 99.56 and 99.61 in 1984, 1990, 2001, 2011 and 2022, respectively. Furthermore, the Shannon’s Diversity Index (SHDI) and Simpson’s Diversity Index (SIDI) corroborated the evidence of sprawl in the City of Bulawayo over the past thirty-six years, as evidenced in Fig. 4. During this period, SHDI and SIDI increased from 0.37 to 0.60 and 0.33 to 0.41, respectively, from 1984 to 2022, suggesting that the built-up area in Bulawayo was becoming more prosperous and more even over the years. These results are consistent with a study conducted in Tennessee in Memphis

that analysed urban sprawl and blight using similar methods, which revealed that the values were increasing due to sprawl [52].

4.6. Type of sprawl and built-up gains in Bulawayo

The findings from the gains map and the landscape metrics analysis indicate that the CoB has undergone all four types of development: leapfrog, infill, strip/ribbon, and low-density development. The city's expansion has been a complex and dynamic process, with growth occurring in various directions but with the most significant intensity in the north-western, northeastern, southeastern, and southwestern areas see Fig. 5. Between 1984 and 1990, the city's eastward expansion was accelerated by low-density urbanisation, propelled by the relaxation of the colonial legislature and economic stability. During the same period, high-density development significantly expanded the city's western outskirts. From 1990 to 2001, the city experienced significant and robust expansion to the east, with the development of high-density suburbs such as Cowdray Park. From 2001 to 2011, the city's growth was less built-up and spread uniformly in both densities. The years 2011–2022 saw intensified growth within the already-developed suburbs, with Cowdray Park being the most pronounced example.

As argued above, the city underwent various forms of development between 1984 and 2022: infill, leapfrogging, strip/ribbon, and low density. From 1984 to 1990, the city witnessed an increase in low-density and single-dwelling development to the east, facilitated by the expansion of the black bourgeoisie. This development trend was characterised by the ownership of large plots measuring above 4000 sqm situated on the eastern side of Bulawayo. From 1984 to 2001, development leapfrogged to cheaper western areas of the city like Cowdray Park and Pumula, leaving substantial empty spaces in between. Throughout the years, strip/ribbon development was evident mainly along major transport networks like the Luveve Road, Harare Road, Johannesburg Road, Khami, and Hyde Park roads, forming linear patterns along these and other major regional and arterial roads in the city.

After 1990, the city experienced infill development, which became more intense after 2011. The city authorities encouraged the development of vacant spaces to increase density. Currently, the city is further densifying residential areas by allowing smaller minimum subdivisions and changing reservations in areas that were generous in terms of urban green spaces. Additionally, a gains map between scheduled intervals revealed that the CoB experienced infill development after 1990, which intensified in 2011.

4.7. Implications for urban planning

Urban sprawl has various implications for urban planning, including increased traffic congestion, decreased reliance on public transportation, increased infrastructure costs, loss of urban green spaces, farmland, and increased social segregation. As the city expands, people may be compelled to travel longer distances to destinations for business, employment, school, and religious purposes, leading to traffic congestion. According to a recent traffic survey report from the City of Bulawayo, the city is witnessing traffic congestion in selected roads connecting its suburbs to the Central Business District, particularly between 0645 and 0800 h. This traffic congestion has ripple effects, leading to decreased productivity, increased noise levels, and air pollution, which can cause further traffic congestion and decreased air quality in Bulawayo. Urban sprawl may lead to reduced use of public transport as more people will be motivated to drive when they reside in sprawling communities. This is true for Bulawayo, as evidenced by the increase in privately owned vehicles over the years, especially in suburbs further from the CBD. This phenomenon might also increase infrastructure costs like schools, hospitals, new roads, water, and sewer.

In Bulawayo, urban sprawl has resulted in the loss of urban green spaces and agricultural land as most of the agricultural, vegetation and bare land has been converted to built-up development. In the context of climate change, this could lead to increased flood risks through increased water runoff and loss of aquatic and terrestrial biodiversity.

An understanding of agricultural land depletion will improve the city's food security as policy will shift towards sustainably managing the growth of urban areas. Through these findings, urban planners and policymakers would be able to formulate strategies that will minimise the abovementioned consequences. Understanding land cover changes is important for sustainable development

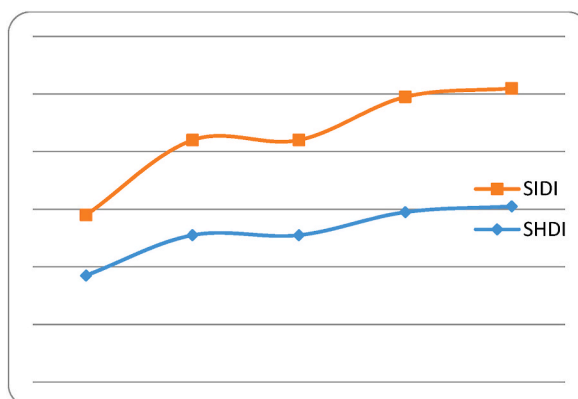


Fig. 4. SHDI and SIDI values for the CoB.

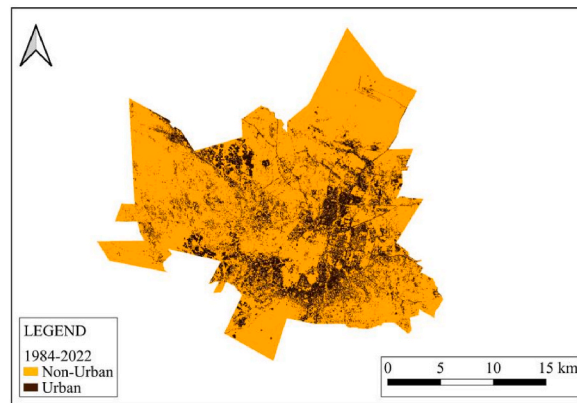


Fig. 5. location of gains in the CoB between 1984 and 2022.

[53,54]. The study will help urban planners in their forward plans (master and local plans) to ascertain how the city will grow, coupled with land allocation and regulation. Formulating a densification strategy will now be informed by evidence rather than pressure from the central government and guesswork. Currently, city planners from Bulawayo are planning without the LULC dynamics, implying that these plans are limited in terms of reality on the ground. This study formulates a baseline for other studies, such as unravelling LULCC's impact on climate change. Studies can now be conducted on the implications of these changes on land surface temperatures and urban green spaces. Modelling of future scenarios is now possible due to the findings of this study.

Numerous urban municipal authorities, including Bulawayo in Zimbabwe, often lack a complete grasp of their urban populations, the intricate spatial-temporal dynamics of the built environment, and the associated factors influencing its expansion or shrinkage, including the rate of change over time. This study responds to this challenge by conducting a spatial-temporal analysis of the built-up (urban sprawl) in Bulawayo from 1984 to 2022. This study has been integral in providing an urban dataset that can be comparable to other global cities for longitudinal analysis. This data will allow Bulawayo to be benchmarked with other cities in Sub-Saharan Africa regarding urbanisation. Monitoring and quantifying built-up areas is pivotal in urbanisation analysis, and understanding these trends will aid the city in exploring future directions [55].

This study will contribute to Sustainable Development Goals (SDGs) 11,13 and 15. SDG 11 calls for inclusivity, safety, resilience, and sustainability in cities [56]. This study will aid the city in formulating policies that will make it resilient and sustainable by minimising the negative impacts of urban sprawl. This can be achieved through rezoning for densified communities, mixed uses, and investing in protecting green spaces. Sustainable Development Goal 13 speaks to taking urgent action to combat climate change and its impacts [57]. The study will aid CoB in mitigating all the elements that might promote climate change by formulating policies that will reverse and/or halt land degradation, sustainably manage vegetation, and combat desertification in line with SDG 15 [58].

5. Conclusion

In conclusion, this study has attempted to conduct a spatio-temporal urban sprawl assessment of the City of Bulawayo using geospatial technologies and landscape metrics. Five thematic maps were developed to illustrate the changes between the built-up and the non-built areas from 1984 to 2022. The most compelling evidence suggests that the Support Vector Model as a classification algorithm is an excellent and accurate land use-land cover analysis tool. Twelve landscape metrics were applied to quantify urban sprawl in Bulawayo. Notably, landscape metrics results and landcover changes provide evidence of urban sprawl and landcover changes in the City of Bulawayo. These were largely driven by the relaxation of colonial laws after independence and the rural-urban migration coupled with the *Gukurahundi* genocide and the pursuit of a better life. The results broadly indicate that Bulawayo's built-up increased by 228.01% in the 38-year study period. The study also discovered through the landscape metrics that the pattern of urban sprawl in Bulawayo was characterised by all forms of urban sprawl, i.e. leapfrog, infill, strip/ribbon, and low-density development. Results from the landscape metrics indicated significant fragmentation of non-built-up areas because of the built-up development. These findings have profound implications for urban planning and management in Bulawayo. The negative impact of urban sprawl and land cover changes include biodiversity loss and increased risk of flooding. Given these challenges of intensive urban sprawl and landcover changes, Bulawayo's city planners are faced with the daunting task of formulating sustainable urban management strategies. Two strategies would be adopting and encouraging mixed-use development and densification as they prepare new and review old spatial plans. Mixed-use development and densification will reduce the environmental impact of urban sprawl by reducing the reliance on private vehicles, thereby promoting sustainable transportation options like walking and cycling. This study contributes to the growing corpus of research from the Global South by applying geospatial technologies as appropriate tools for quantifying and monitoring urban sprawl.

CRediT authorship contribution statement

Shelton Mthunzi Sithole: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Walter Musakwa:** Writing – review & editing, Validation, Formal analysis, Conceptualization. **James Magidi:** Writing – review & editing, Validation, Methodology, Data curation, Conceptualization. **Alain Y. Kibangou:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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