Geosfera Indonesia
p-ISSN 2598-9723, e-ISSN 2614-8528
available online at : https://jurnal.unej.ac.id/index.php/GEOSI
Vol. 9 No. 2, August 2024, 157-175

https://doi.org/10.19184/geosi.v9i2.44499 **Research Article**

Analysis of Urban Form Dynamics in The Suburbs of Surakarta City 2013-2023

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ARTICLE INFO

Received :
1 December 2023

Revised :
20 June 2024

Accepted :
9 July 2024

Published :
24 July 2024

ABSTRACT
Urban Form has become necessary for city planning management to see the sustainability of a city. A better understanding of different urban forms is imperative to facilitate the evolution of cities towards a more sustainable urban development trajectory in the future. The study aims to analyze the dynamics of urban form and the changes in land cover within the peri-urban area of Surakarta City, which is directly influenced by the development of Surakarta City. The analysis was conducted from a landscape ecology perspective, employing a spatial metrics approach at the landscape level to assess the dynamics of urban form using quantitative descriptive, including a spatial approach. A similar approach was adopted at the class level in order to examine the dynamics of land cover changes. The results of the image analysis were validated using the Kappa index, yielding an image accuracy level of 0.86 (86%). The results of this study show that the urban form in the peri-urban area of Surakarta City tends to move towards a compact urban form. Meanwhile, each land cover, vegetation, and water body become increasingly fragmented, with areas becoming narrower as time passes. Built-up and agricultural land are becoming more compact and concentrated along with development. In conclusion, the dynamics of urban form in the peri-urban area of Surakarta City tends to lead to compact urban form.

Keywords: Land Cover Change; Landscape Ecology; Urban Form; Spatial Metrics

INTRODUCTION

The role of cities is becoming increasingly essential, which in turn makes sustainability an important issue (Estrada et al., 2022). Urban areas, as complex and dynamic structures of growth and development in their regions, are influenced by various factors, both internal and external (Jatayu et al., 2020; Cengiz et al., 2022). The predominant and unavoidable trend of urbanization in modernization can lead to unsustainable growth in regions and promote unregulated regional development, exemplified by phenomena like urban sprawl and the transformation of rural land into suburban areas (Cattivelli, 2021; Lu et al., 2022). The development of urban regions can have an impact on suburban areas (Permatasari & Pradoto, 2019). Urban growth significantly influences the increase in land requirements (Buchori et al., 2020). A rise in the demand for land that surpasses the availability of permanent land resources results in the unregulated expansion of urban areas extending beyond the city's administrative boundaries (Permatasari & Pradoto, 2019). Fragmented land cover patterns could be more efficient, sustainable, and challenging to manage (Jatayu et al., 2020).

Optimizing land cover can serve as a pathway to establishing a sustainable urban structure, contributing to developing a sustainable urban form (Handayanto et al., 2017). Land fragmentation as an essential output of urban sprawl needs to be monitored and studied to base it on sustainable development (Dupras et al., 2016). A sustainable city can be achieved by not only focusing development on the core urban area but also in other areas around it (peripheral areas) (Jatayu et al., 2022). Peri-urban areas have great potential to realize sustainable cities at the global level as a challenge due to urban sprawl that various cities in the world must face (Wandl & Magoni, 2017).

In suburban development, sustainability is a key objective that strives to foster the creation of cities and settlements that are characterised by inclusivity, safety, resilience, and overall sustainability. This aligns with the SDGs' 11th goal to build sustainable cities and communities (Jatayu et al., 2022). It would be beneficial for urban planning management to have detailed information about urban form and land cover characteristics in order to assess the sustainability of a city (Hosea et al., 2019). Enhancing comprehension of diverse urban forms is essential to facilitate the future development of cities, and its crucial to studying the formation and development of a city's physical environment over time (Hermand & Quesada, 2019). The principles of urban form should consider landscape, metropolitan, and urban design perspectives to ensure a comprehensive approach to city planning and development is effectively incorporated into public policy (Clifton et al., 2008). An effective urban form seamlessly integrates the principles of sustainability and resilience, enabling support for urban functions and the sustainable utilization of resources. By adopting this approach, cities can establish a solid economic foundation and guarantee their residents a high quality of life (Jatayu et al., 2022). Jabareen (2006) stated that the compact city is the most sustainable city model among the four urban form models considered sustainable city forms, namely compact city, eco-city, neo-traditional development, and urban containment.

The influence of land cover change on the progression of urban development, in consideration of the multitude of anthropogenic activities that are currently taking place across our global landscape (Abdo & Prakash, 2020). Land use activities pose a significant issue and challenge in urban planning, which is crucial in building a sustainable city. They play a pivotal role in preserving and managing environmental quality (Bhat et al., 2017; Maimaiti et al., 2017; Sidiq et al., 2022). The dynamics of land cover conversion occur when land can no longer meet space needs due to an increase in population (Krishnan & Ramasamy, 2022; Rahmi et al., 2022). Peri-urban areas refer to regions that undergo substantial changes in land cover primarily because of the development of adjacent cities (Kurnianingsih et al., 2021; Tavares et al., 2012). It may also be helpful to analyse the dynamics of land cover changes in these areas.

The urban development of Surakarta City has had a significant impact on the surrounding areas. It is hoped that the research results will prove useful as a reference in development planning in Surakarta City and the surrounding suburbs. There have been several studies on city form (Handayanto et al., 2017; Ray & Shaw, 2018; Hermand & Quesada, 2019; Hosea et al., 2019; Jatayu et al., 2020; Kang et al., 2021; Jatayu et al., 2022; and Al-Safar & Sen, 2022). However, a few researchers have focused on the Shimpson's Diversity Index (SIDI) matrix in analysing diversity indicators in sustainable urban forms at the landscape level and landscape ecology approaches. Furthermore, this study can explain the dynamics of urban forms specifically from the land cover aspect, which may help to fill the gaps in urban form analysis. Therefore, this study aims to analyse the dynamics of city form and alterations in land cover in the periphery of Surakarta City.

METHODS

Study Area

The study was conducted in the peri-urban zone adjacent to Surakarta City. The total area of the peri-urban of Surakarta City is 26,039.49 Ha which includes the areas of Karanganyar Regency, Sukoharjo Regency, and Boyolali Regency which are spread across eight sub-districts, namely Jaten District, Gondangrejo District, Ngemplak District, Colomadu District, Kartasura District, Baki District, Grogol District, and Mojolaban District. The research area is presented in Figure 1.

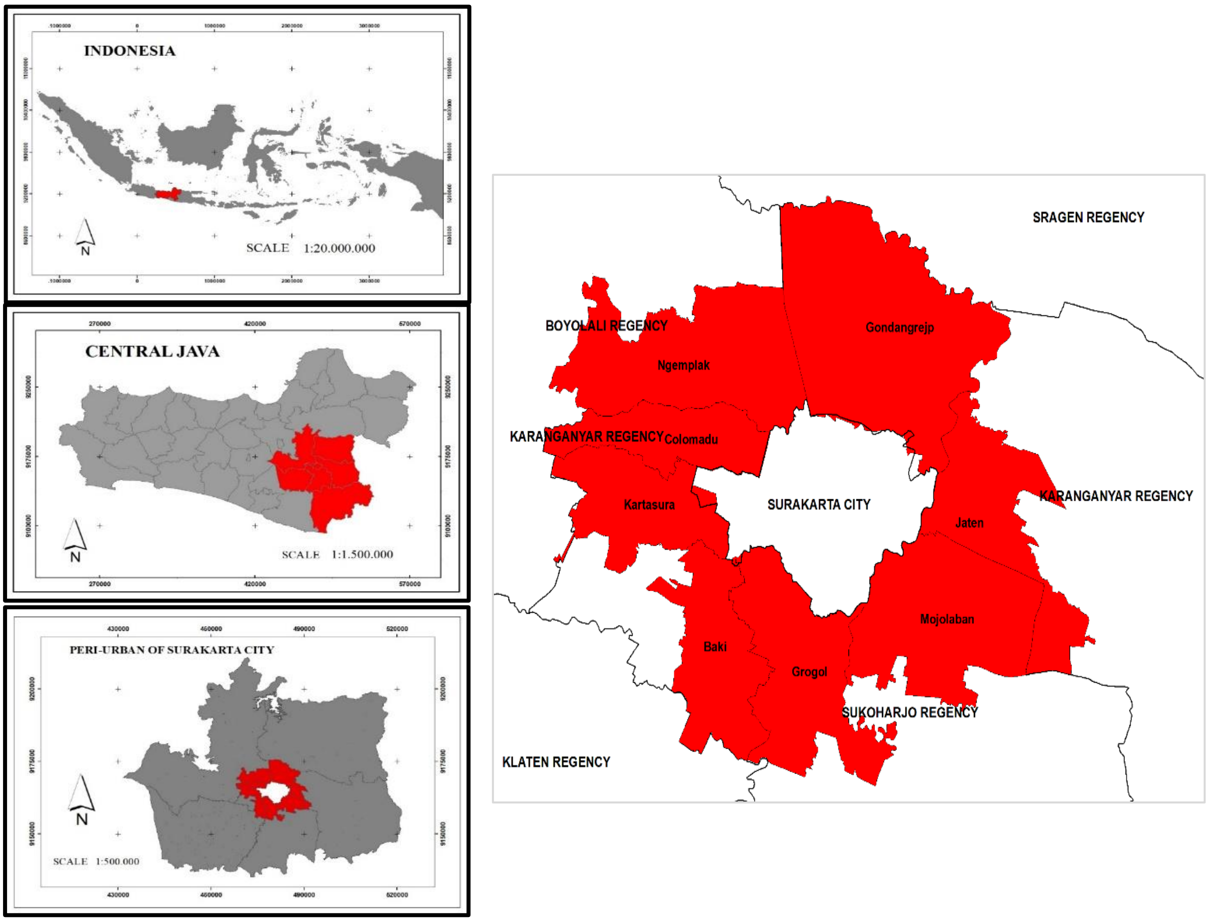

Figure 1. Study Area

The study used time series data to observe the evolving dynamics of urban form in the peri-urban of Surakarta City spanning from 2013 to 2023. The selection of the year was based on a shift in the direction of the development of Surakarta City, which was initially directed to the North, now tends to go South, and spread to the East and West sides after the development of the Solo Baru Residential Area and Dr. Oen Hospital in the period 1998 to 2006 (Fitriana et al, 2017). Development occurred after the construction of several large shopping centers in the Grogol District, namely The Park Mall, Hartono Lifestyle Mall, and Hartono Trade Center, which was completed in 2012 and supported by the development of high industrial areas and higher accessibility in the South side of Surakarta City (Fitriana et al., 2017; Permatasari & Pradoto, 2019). Therefore, the year 2013-2023 was chosen because of the massive land use change and the direction of development that affects the dynamics of urban form.

Data Sources

Land cover data was obtained from the interpretation of Landsat 8 imagery with 11 bands with spatial resolution to provide spatial resolution data of 15, 30, and 100 meters and temporal resolution of 16 days (Fawzi & Husna, 2021). Landsat imagery has a medium resolution that allows the identification of land cover with different spectral reflectances, resulting in classifications with overall accuracy values exceeding 86% (Anua & Wong, 2022; Boonpook et al., 2023; Bungsu & Arif, 2023). Google Earth Engine processing uses guided classification with the Classification and Regression Trees (CART) algorithm, an image classification technique with good predictive capabilities (Basheer et al., 2022; Oo et al., 2022; Li et al., 2023). The land cover classification in this study involves categorizing it into four main classes: vegetation, agricultural land, water bodies, and built-up land; the outcomes of the land cover classification were validated through Google Earth and on-site field verification. The verification results are then measured by the level of image accuracy using the confusion metric to see the level of accuracy of the producer, user, and the overall level of accuracy as well as measuring the quality of the Kappa coefficient image accuracy (Rwanga & Ndambuki, 2017). The validation sample area is determined using the Slovin formula :

$$n_i = \frac{N}{1+Ne^2} \qquad (1)$$

Where (N) is the total population, namely the total grid of each region, and (e) is the tolerance limit used. The use of the Slovin formula considers the large population numbers. The probability-based Slovin formula can provide a solid basis for making representative sample estimates, especially for large samples (Imron, 2017). Sample determination with the Slovin formula provides freedom in determining the estimation error limit according to the needs of researchers (Setiawan, 2007). The tolerance error limit used in this study is 15%, which is based on the minimum value of Kappa coefficient accuracy value that is feasible to use, which is 0.80-0.85 (80%-85%) (Wulansari, 2017). The results of the sample calculations, conducted with a tolerance limit of 15%, indicated that the number of land cover samples required to validate the level of image accuracy was 44 pixels in each sub-district. Consequently, the total number of samples obtained from the land cover verification process is 352, distributed in an even manner.

Data Analysis

In order to ensure comprehensive understanding of the changes in land cover over the specified period, analyzing the dynamics of urban form and changes in land cover involves applying urban form calculations through a spatial or landscape metrics approach. This analysis is conducted using FRAGSTAT software, which processes land cover raster data in the peri-urban of Surakarta City. Spatial metrics stand out as one of the foremost techniques in landscape quantification and have served as the foundation for the evolution of various other methods in this field (Hosea et al., 2019; Jatayu et al., 2022). Apart from measuring spatial patterns and shapes, the Spatial Metrics approach can also be used to measure changes in land cover, identify regional shapes and regional expansion phenomena, and to be able to measure and explain spatial structure in various ways at the patch, class of patch, and landscape levels, including analyze a region's shape in a time series to identify development trends in an area (Hosea et al., 2019; Jatayu et al., 2022). The selection of the spatial matrix is based on four indicators of sustainable city form, namely compactness (PD and SHAPE) (Rao et al., 2021), continguity (CONTIG and COHESION) (Lemoine-Rodriguez et al., 2024), connected (SPLIT and MESH) (Jaeger, 2000) and diversity (SIDI) (Momeni & Antipova, 2022) and the PLAND metric to determine the percentage of each land cover (Sertel et al., 2018).

RESULTS AND DISCUSSION

Urban form analysis is an important design tool for studying the formation and development of a city's physical environment over time (Hermand & Quesada, 2019). Urban form develops constantly and is generally divided into 2 (two) main types, namely compact and sprawl, which can be understood using the concept of urban pattern and structure (Jatayu et al., 2022). The land cover classification of the peri-urban of Surakarta City for 2013-2023 is presented in Figure 2.

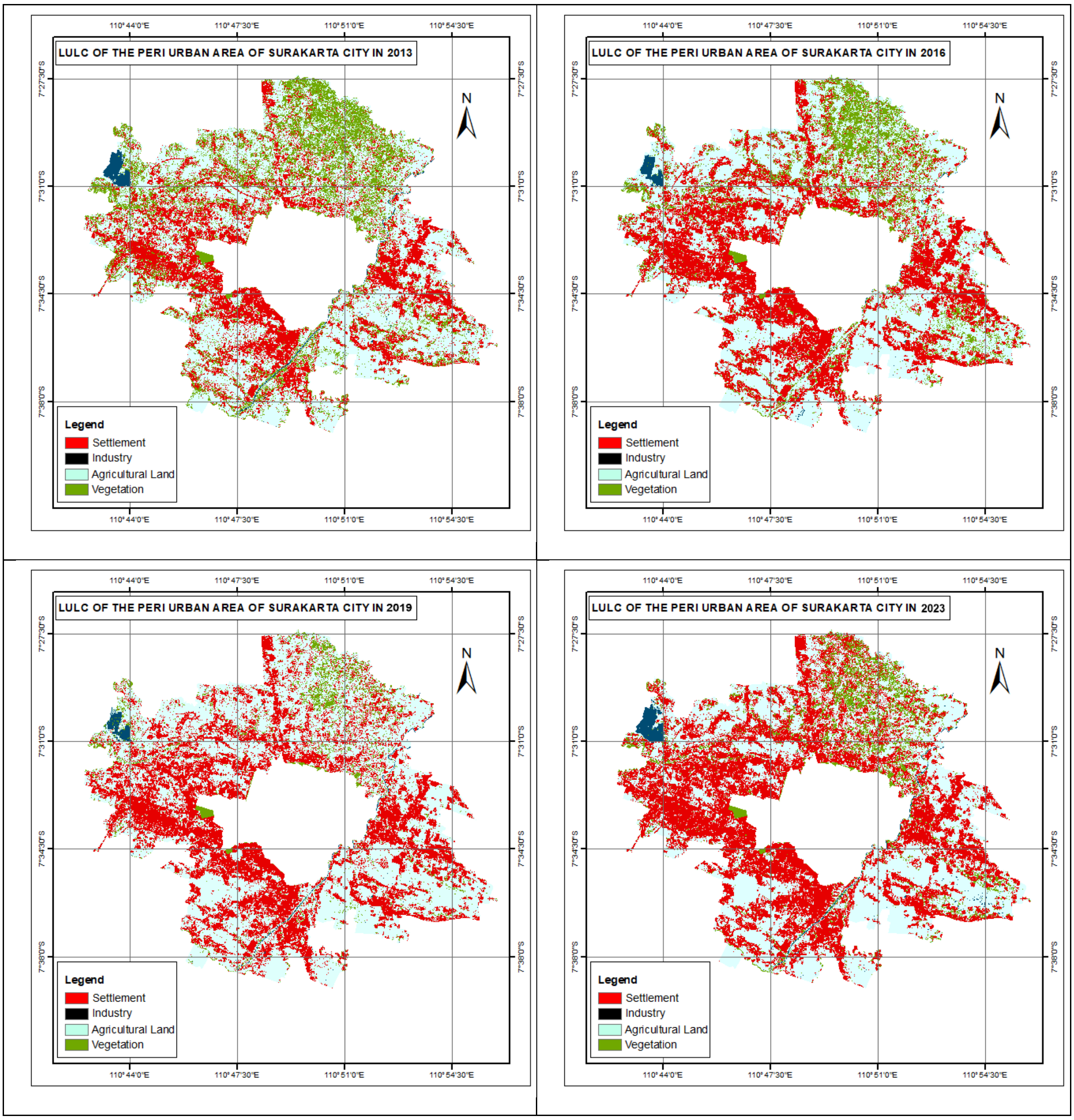

Figure 2. Land Cover Classification 2013-2023

Urban Form Analysis Using Landscape Metric

The landscape-level matrix analysis results indicate that the urban form in the peri-urban of Surakarta City is generally trending towards greater compactness. While a decline was observed from 2019 to 2023, it was insignificant. More fully, the dynamics of urban forms in the peri-urban area of Surakarta City at the landscape level based on the dynamics of matrix values are as follows:

Compactness

Indicators of sustainable city form compactness are represented by matrix shape index (SHAPE) and Patch Density (PD) values. SHAPE helps assess how irregular or intricate the boundaries of patches are, providing insights into the overall shape complexity of landscape elements. A higher SHAPE value indicates more significant irregularity or complexity in patch shapes (McGarigal et al., 1995). It shows whether a city is at a managed size and density by its area to support regional functions. Cities with managed density can optimize space use. A SHAPE value approaching 1 signifies a trend toward increasingly compact shapes, and when the SHAPE value reaches precisely 1, it indicates a perfectly compact form. In essence, SHAPE serves as a valuable metric for assessing the level of compactness or regularity in the shapes of landscape patches, with higher values indicating greater compactness, PD indicates patch density within a 100-hectare area, and The higher patch density value suggests the area is more compact and concentrated (Hosea et al., 2019; Jatayu et al., 2020).

Table 1. Compactness of the peri-urban of Surakarta City 2013-2023

Compactness	2013	2016	2019	2023
SHAPE	1.11	1.1	1.13	1.13
PD	56.7	94.91	40.31	50.89

The peri-urban of Surakarta City from 2013-2023 based on the compactness indicator shows a trend in urban form that is becoming more compact from 2013-2016 and growing more fragmented from 2016-2019 and relatively stable from 2019-2023, as can be seen from the matrix value SHAPE and PD as presented in Table 1.

When examined individually, Figure 3 illustrates the dynamics of the urban form in the peri-urban of Surakarta City using SHAPE values. The trend observed from 2013 to 2016 indicates that the development is becoming more compact and is expanding within a size and density range effectively governed by its regional boundaries. Specifically, there is a decrease in the SHAPE value from 1.11 to 1.10 during this period. This decrease suggests that the shapes of urban areas are approaching a perfect score (value 1), indicating a closer alignment with idealized compact forms. Meanwhile, there was a fragmentation trend from 2016 to 2019, where the SHAPE value increased from 1.10 to 1.13, which means that developing areas are becoming more irregular because they are moving away from the value of 1. From 2019 to 2023, the urban form based on the SHAPE matrix will move steadily at a value of 1.13.

Based on the patch density (PD) value graph, as shown in Figure 3, indicates that there is a trend in urban form becoming more compact in 2016, where the patch density value increases from 56.70 to 94.91, which shows that land cover is developing more compactly and is concentrate between land covers. A downward trend also occurred in 2019, where the PD value fell from 94.91 to 40.31 and increased again to 50.89 in 2023.

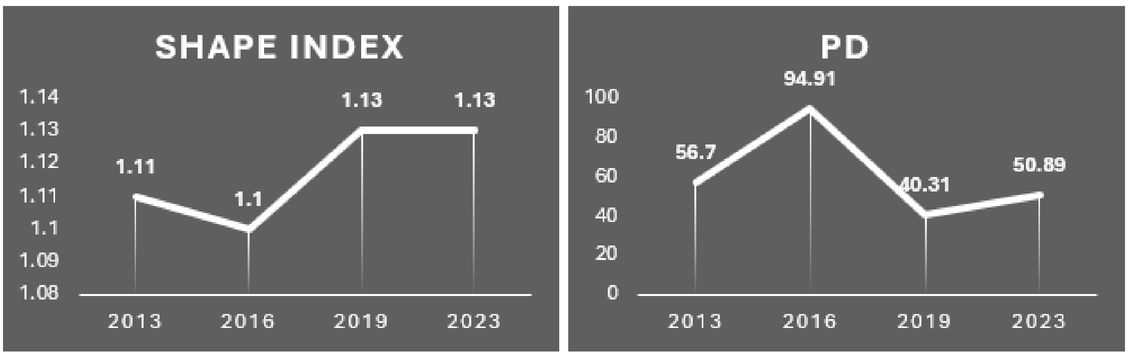

Figure 3. SHAPE and PD Values 2013-2023

Continguous

Continguous sustainable urban form indicators are measured using the continguity index (CONTIG) and cohesion (COHESION) matrices. CONTIG assesses the spatial connectivity or closeness between grids in each land cover patch (Hosea et al., 2019). The higher the CONTIG value indicates, the higher the closeness between the grids (Jatayu et al., 2020). The CONTIG value will increase closer to the maximum limit of 1 as the closeness and connectedness between patches increase. COHESION shows the relationship between patches in the same land cover class (Hosea et al., 2019). A higher COHESION value indicates that patches within one type of land cover class are more physically connected and less fragmented (Hosea et al., 2019; Jatayu et al., 2020).

Table 2. Contiguity of the peri-urban of Surakarta City 2013-2023

Contiguity	2013	2016	2019	2023
CONTIG	0.35	0.31	0.29	0.29
COHESION	98.56	98.53	99.43	99.02

According to the CONTIG and COHESION matrix values presented in Table 2, it is evident that land cover is experiencing a trend of increasing fragmentation. Although the decrease in proximity between patches is not highly significant, the rise in connectivity levels is noteworthy. Consequently, as indicated by the contiguity indicator, the urban form in the peri-urban of Surakarta City demonstrates a tendency towards becoming more compact. Suggests a complex interplay between fragmentation and connectivity dynamics within the landscape.

Separately, based on the CONTIG matrix value, the urban form of the peri-urban of Surakarta City tends to experience a trend towards a more fragmented city (sprawl) seen from the decline in the CONTIG value from 0.35 to 0.29 from 2013-2019 and tends to stabilize at 0.29 in 2023. This finding is in line with previous studies by McGarigal et al. (1995) and Hosea et al. (2019) which found that the closer the value is to 0, the more patches between land cover classes are not close to each other. In more detail, the proximity dynamics between patches are present in the CONTIG graph in Figure 4**.**

According to the COHESION matrix values, the urban form in the peri-urban of Surakarta City exhibits an ascending trend towards compactness. This trend is visually represented in the COHESION graph depicted in Figure 4. The increasing values in the COHESION matrix and graph signify a strengthening cohesion among patches, indicating a more compact and connected urban landscape in the specified peri-urban region. The COHESION value shows that the level of connectivity between patches in each land cover is increasing so that the land cover patches are increasingly physically connected. This finding is in line with previous study by Hosea et al. (2019) which found that the higher COHESION value, indicating the more connected the patches in each land cover class are and not spread to each other. The increasing value of connectedness complements the low value of closeness between patches of each land cover class so that connections between patches far from each other are maintained.

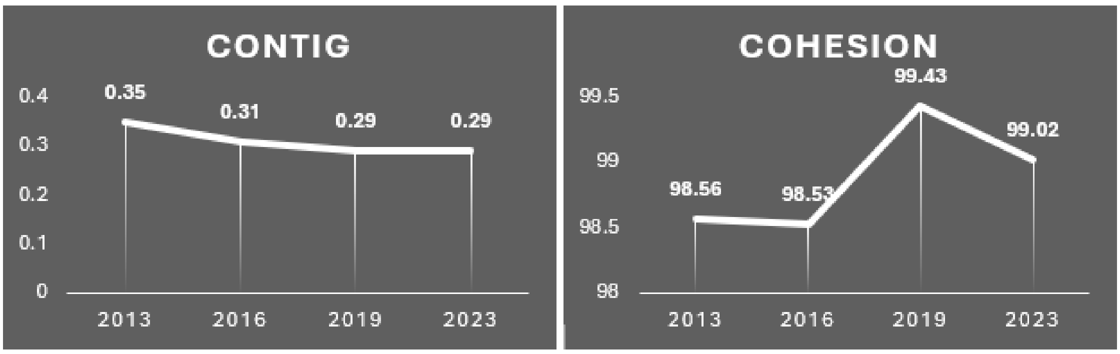

Figure 4. CONTIG and COHESION Values 2013-2023

Connectivity

Connectivity shows that urban areas are only fragments connected through integrated infrastructure. This study's Connectivity indicators are assessed using two matrices: the Splitting Index (SPLIT) and the Effective Mesh Index (MESH). These matrices provide a quantitative measure of connectivity within the landscape (Spanowicz & Jaeger, 2019). Conversely, the Effective Mesh Index gauges the number of practical meshes in the landscape, with lower values pointing toward higher fragmentation (Schmiedel & Culmsee, 2016). Together, these matrices offer insights into the spatial connectivity and fragmentation patterns within the peri-urban of Surakarta City. The SPLIT and MESH matrices show the fragmentation and grouping of land cover classes (Jatayu et al., 2020). SPLIT rises when the landscape experiences more division into smaller components, signifying a growing level of fragmentation in the areas (McGarigal et al., 1995; Spanowicz & Jaeger, 2019). MESH has properties opposite SPLIT, where the higher the MESH value, the less shared the landscape in an area is (McGarigal et al., 1995).

Table 3. Connectivity of the peri-urban of Surakarta City 2013-2023

Connectivity	2013	2016	2019	2023
SPLIT	25.7	25.15	8.95	13.57
MESH	1013.99	1036	2906.14	1917.18

Based on urban form connectivity indicators in the peri-urban of Surakarta City (Table 3), there is a trend towards a more compact city form, as seen from the MESH matrix value (Figure 5), which is higher than the SPLIT matrix from 2013-2023. However, suppose you look at the SPLIT matrix value. In that case, it shows a variation trend, where from 2013 to 2016, it shows a decreasing trend in the SPLIT matrix value from 25.70 to 25.15 in 2016 and 8.95 in 2019, which means that the level of landscape separation is decreasing, so that the urban form in the peri-region urban areas is increasingly moving towards more compact urban forms. Meanwhile, from 2019-2023, the level of landscape fragmentation has increased again, and the urban form is moving towards a sprawl of more fragmented urban form 2019-2023.

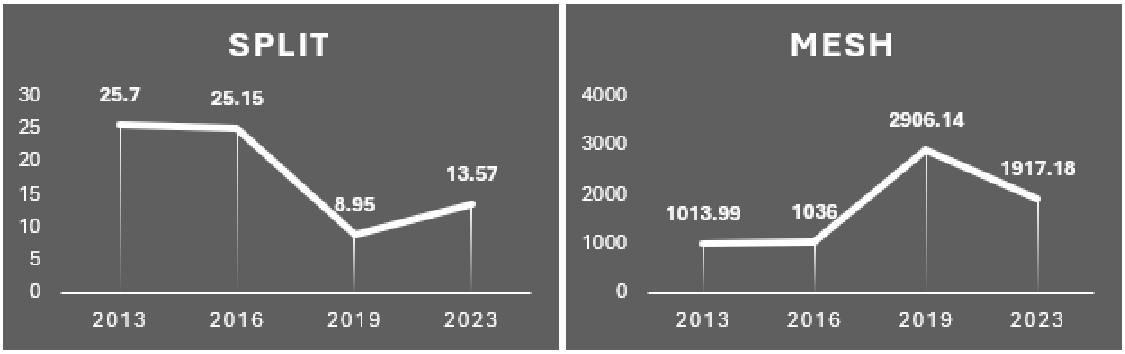

Figure 5. SPLIT and MESH Values 2013-2023

Diversity

An area's diversity level indicates a sustainable city form (Jatayu et al., 2020). Diversity shows the level of land cover diversity. A high level of diversity suggests that the region has a low level of fragmentation, Momeni & Antipova (2022) reported that the increasing number of patches causes the level of diversity to decrease and indicates regional fragmentation. Diversity indicators use the Simpson's Diversity Index (SIDI) matrix.

Table 4. SIDI Values in the peri-urban of Surakarta City 2013-2023

Diversity	2013	2016	2019	2023
SIDI	0.6	0.59	0.52	0.58

Based on the SIDI matrix values as shown in Table 4, in general, the level of land cover diversity in the peri-urban of Surakarta City shows a downward trend, which means that the urban form in the peri-urban of Surakarta City shows a trend towards a more fragmented urban form. The decline in the matrix value occurred significantly in 2019 from 6.0 to 0.59 in 2019 and fell drastically to 0.52 in 2019. On the other hand, by 2023, the urban form is anticipated to transition towards a more compact city, evident in the elevated SIDI value reaching 0.58 to better understand the dynamics of diversity levels. The diversity graph in Figure 6 provides a visual representation.

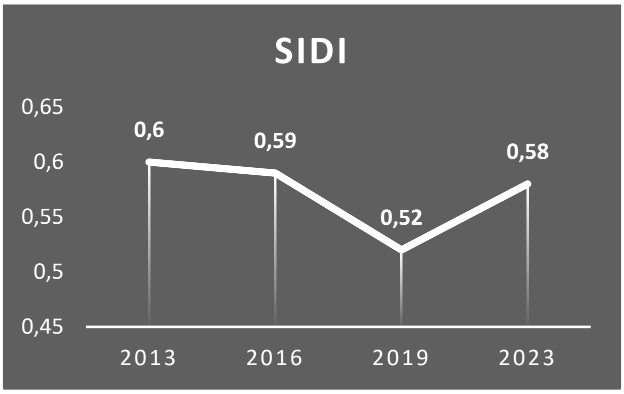

Figure 6. SIDI Values 2013-2023

Dynamic of Land Cover Change

The changes in land cover dynamics can be observed through the alterations in land cover from 2013 to 2023 and by employing spatial metric measurements on the land cover raster data during the same period.

Table 5. Changes in Land Cover in the peri-urban of Surakarta City 2013-2023

Land Cover	Hectars/Years			
	2013	2016	2019	2023
Water Body	294.92	189.76	204.69	208.26
Agricultural Land	14199.00	13576.75	14874.80	13072.64
Built Area	7075.67	9087.03	9388.97	11537.95
Vegetation	4480.06	3195.52	1581.43	1231.12
Total	**26049.64**	**26049.06**	**26049.90**	**26049.97**

Based on Table 5, built-up land from 2013 to 2023 shows an increasing trend of up to 4,462.29 hectares, from 7,075.67 hectares to 11,537.95 hectares. The increase in built-up land occurs every year due to the rise in population, which will, of course, influence the increase in land requirements (Hosea et al., 2019; Kurnianingsih et al., 2021). The increase in built-up land occurred quite significantly between 2013-2016 and 2019-2023. This significant increase occurred partly due to the construction of large shopping centers in the Grogol District, such as The Park Mall, Hartono Lifestyle Mall, and Hartono Trade Center, so the expansion of built-up land is primarily directed towards the southern part of Surakarta City (Aulia, 2018) as illustrated in Figure 2. The enhanced accessibility of the southern part of Surakarta City influences the expansion of built-up land towards the south. This trend is further facilitated by the availability of land suitable for large settlements and the robust development of industrial areas in the peri-urban region of Surakarta City on the southern side (Fitriana et al., 2017). The built-up land expansion aligns with a concurrent decrease in the vegetation area by 3,248.94 hectares. Specifically, the vegetation area was reduced from 4,480.06 hectares to 1,231.12 hectares.

Meanwhile, the proportion of land cover comprising water bodies and agricultural land exhibits fluctuations. This reduction may be associated with the conversion of agricultural land into developed areas. Conversely, a significant proportion of the vegetative cover has been transformed into agricultural land, as illustrated in Figure 2. The reduction in the area of water bodies could be influenced by variations in water volume, either increasing or decreasing annually. Look at the percentage of landscape (PLAND) matrix measurement results. It is evident that agricultural land will continue to represent the predominant land cover in the peri-urban areas of Surakarta City until 2023, as illustrated in Table 6.

Table 6. Percentage of Land Cover in Surakarta City Peri-Urban Area 2013-2023

Land Cover	**Land Cover (%)**			
	2013	**2016**	**2019**	**2023**
Vegetation	17.34	12.65	8.8	7.26
Agricultural Land	54.34	51.9	59.26	47.26
Water Body	1.13	0.76	0.80	1.27
Built Area	27.18	34.69	36.14	44.22

Based on Table 6, it can be seen that Agricultural land, as the dominant land cover, 2023 will be followed by built area, where agricultural land takes up 47.26% of the area and built area has reached 44.22% of the area. Significant developments have occurred in the built area, and the percentage continues to increase yearly. Since 2013-2023, the rate of built-up land has risen by 17.04% or an area of 4,462.29 hectares. A decline also occurred in vegetation where the percentage of vegetation in peri-urban areas continues to decline, and in 2023, the percentage of vegetation will only be 7.26% of the area. Along with the development of the peri-urban of Surakarta City, there is the potential for the built-up area to emerge as the predominant land cover and a significant component of Surakarta City's peri-urban landscape in the future. As in Surakarta, this development requires spatial control to prevent uncontrolled regional development (Hosea et al., 2019). In more detail, land cover change dynamics are also measured using spatial metric analysis through compactness, continuous, and connectivity indicators.

Compactness

Similarly to the analysis at the landscape level, compactness indicators are analyzed through Patch Density (PD) and Shape Index (SHAPE) matrix measurements. Based on the results of the PD and SHAPE matrices, as shown in Table 8, it is known that vegetation is the most compact land cover seen from the high density between patches, namely in the range 13.17 – 38.73, which is then supported by the SHAPE value which is closest to number 1, namely from 1.07 – 1.10, which means that vegetation develops in boundaries that are still well managed. From the PD value, agricultural land and built areas show increasingly compact development, as seen from the patch density figures, which are pretty high compared to water bodies. This finding is in line with previous study by Istanabi et al. (2023) which found that the developed area in the peri-urban area of Surakarta City tends to be more cohesive and compact but refute the statement that agricultural areas in the peri-urban area of Surakarta City are increasingly fragmented. However, in the SHAPE matrix, agricultural land and built areas are moving increasingly towards irregular shapes because the values are moving away from the number 1 (Hosea et al., 2019;

Jatayu et al., 2022). Water bodies show fluctuating development, both in terms of patch density and shape development. The compactness dynamics are presented in the PD and SHAPE value graphs in Figure 7.

Table 7. PD and SHAPE Values of LULC 2013-2023

Land Cover	Patch Density (PD)				Shape Index (SHAPE)			
	2013	**2016**	**2019**	**2023**	**2013**	**2016**	**2019**	**2023**
Vegetation	23.96	38.73	13.17	16.36	1.10	1.07	1.07	1.10
Agricultural Land	16.45	31.64	10.98	19.54	1.15	1.11	1.16	1.38
Water Body	0.63	2.09	1.41	0.89	1.19	1.02	1.1	1.19
Built Area	15.65	22.45	14.75	14.10	1.11	1.13	1.16	1.14

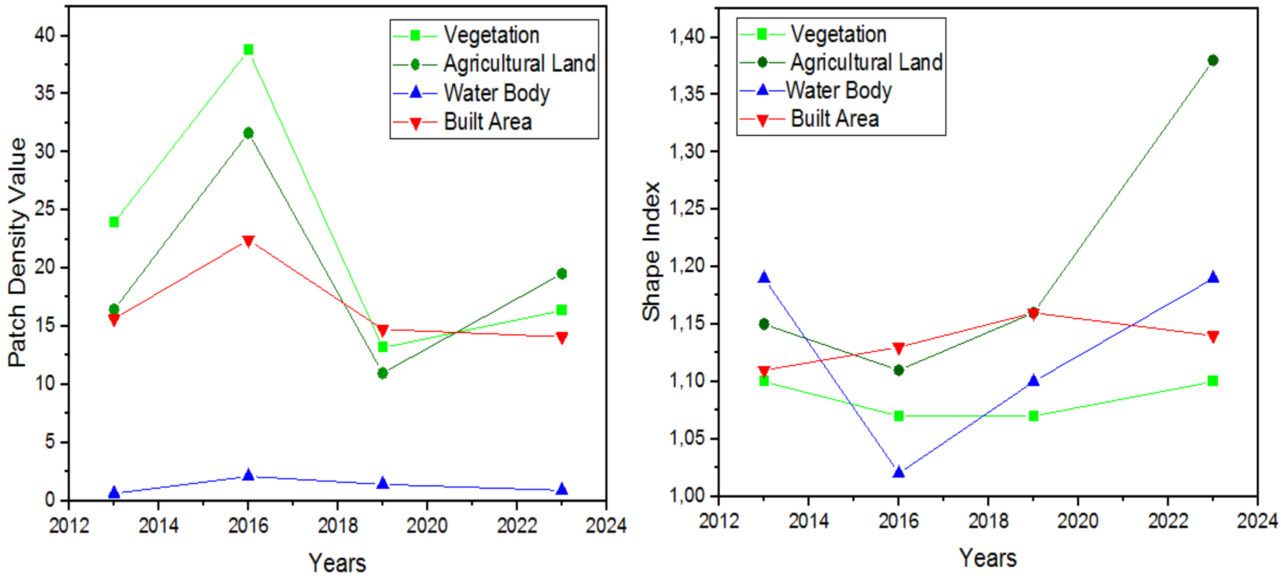

Figure 7. PD and SHAPE 2013-2023

Continguous

Continguous indicators are analyzed using the Contingity Index (CONTIG) and Cohesion Index (COHESION) matrices as in the analysis at the landscape level. The analysis of the CONTIG and COHESION matrix values, as shown in Table 8, shows that vegetation tends to grow increasingly fragmented, as seen from the decrease in CONTIG and COHESION values. A decrease in the CONTIG matrix shows a lower proximity value between vegetation patches (Petsas et al., 2021). This condition is supported by the decreasing level of spatial connectivity between vegetation patches as indicated by the decreasing COHESION value. The increasingly fragmented vegetation implies interventions occurring in both agricultural and built-up lands. Concurrently, agricultural land, water bodies, and built-up land exhibit fluctuating developmental dynamics, albeit generally trending towards increased compactness. This dynamic will continue with the development of the peri-urban of Surakarta City. The increasingly fragmented vegetation is correlated with various environmental problems (Abdo & Prakash, 2020). Therefore, allocating adequate attention and implementing effective management strategies is imperative. This is crucial to ensure that alterations in land cover within peri-urban areas are carefully handled, supporting the sustainability of urban spaces and the well-being of their residents. The contiguous dynamics are presented in the PD and SHAPE value graphs in Figure 8.

Table 8. CONTIG and COHESION Values for Land Cover in the peri-urban of Surakarta City 2013-2023

Land Cover	Contingity Index (CONTIG)				Cohesion (COHESION)			
	2013	2016	2019	2023	2013	2016	2019	2023
Vegetation	0.34	0.31	0.29	0.29	96.05	88.92	87.64	86.32
Agricultural Land	0.37	0.32	0.32	0.29	99.14	98.93	99.67	98.66
Water Body	0.33	0.24	0.23	0.31	94.84	89.01	91.37	94.26
Built Area	0.37	0.32	0.30	0.30	98.23	98.85	99.01	99.45

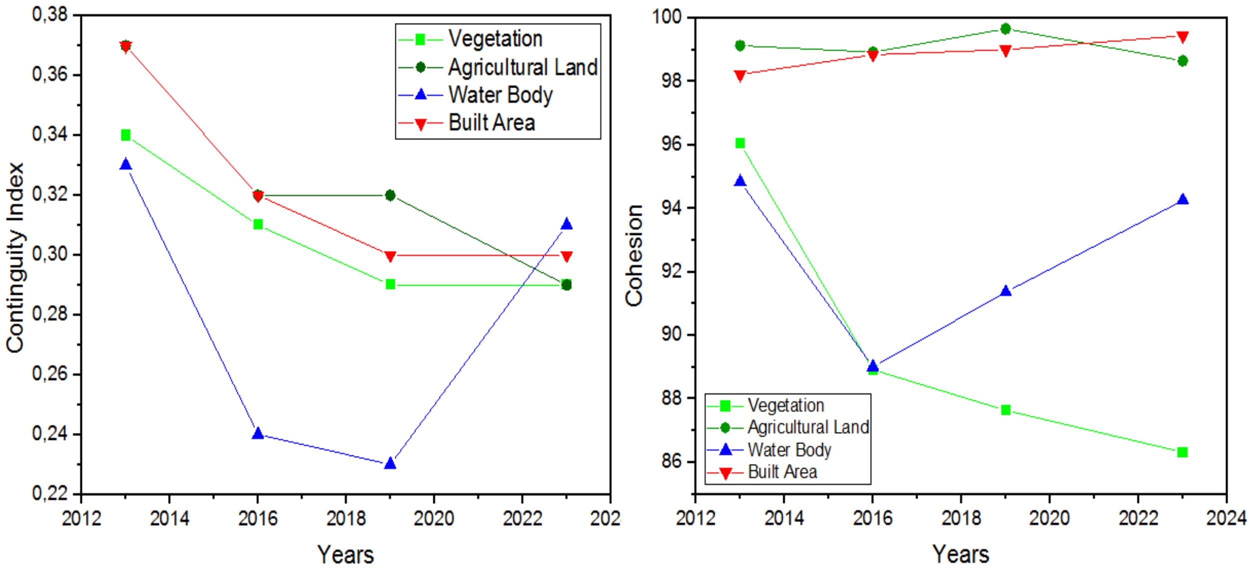

Figure 8. CONTIG and COHESION 2013-2023

Connectivity

Connectivity measures the level of connectedness between patches in each land cover, which is analyzed using MESH and SPLIT matrix measurements. As shown in Tables 9 and 10, the MESH and SPLIT matrix values show that vegetation and water bodies are increasingly fragmented, as seen from the SPLIT value, which is greater than the MESH value (Jatayu et al., 2020). The observed fragmentation may arise from converting vegetation into agricultural or built-up land. Meanwhile, fragmentation in water bodies can be caused by the location of land cover patches that are far apart because the water bodies are classified as reservoirs or dams, which are only found in a few areas. In contrast to vegetation and water bodies, agricultural land, and built-up land are undergoing a trend of more compact development. Built-up land shows development towards compactness, with movement continuing to increase every year. The increase in population drives the development of increasingly compact built-up land (Deng et al., 2021; Schiavina et al., 2022), so built-up land, especially settlements that were previously fragmented, is filling in so that what was initially fragmented is now beginning to develop more compactly—the continuity dynamics in the PD and SHAPE value graphs in Figure 9.

Table 9. MESH Values for the peri-urban of Surakarta City 2013-2023

Land Cover	MESH			
	2013	2016	2019	2023
Vegetation	54.89	4.03	0.28	0.87
Agricultural Land	751.28	593.59	2378.38	409.19
Water Body	1.58	0.64	0.6	2.09
Built Area	206.3	437.75	526.89	1505.13

Table 10. SPLIT Value for the Peri-Urban Region of Surakarta City 2013-2023

Land Cover	SPLIT			
	2013	2016	2019	2023
Vegetation	474.73	6468.6	93466.47	33609.18
Agricultural Land	34.69	43.9	10.94	63.59
Water Body	16478.16	40747.37	43689.2	12567.29
Built Area	126.31	59.52	49.39	17.29

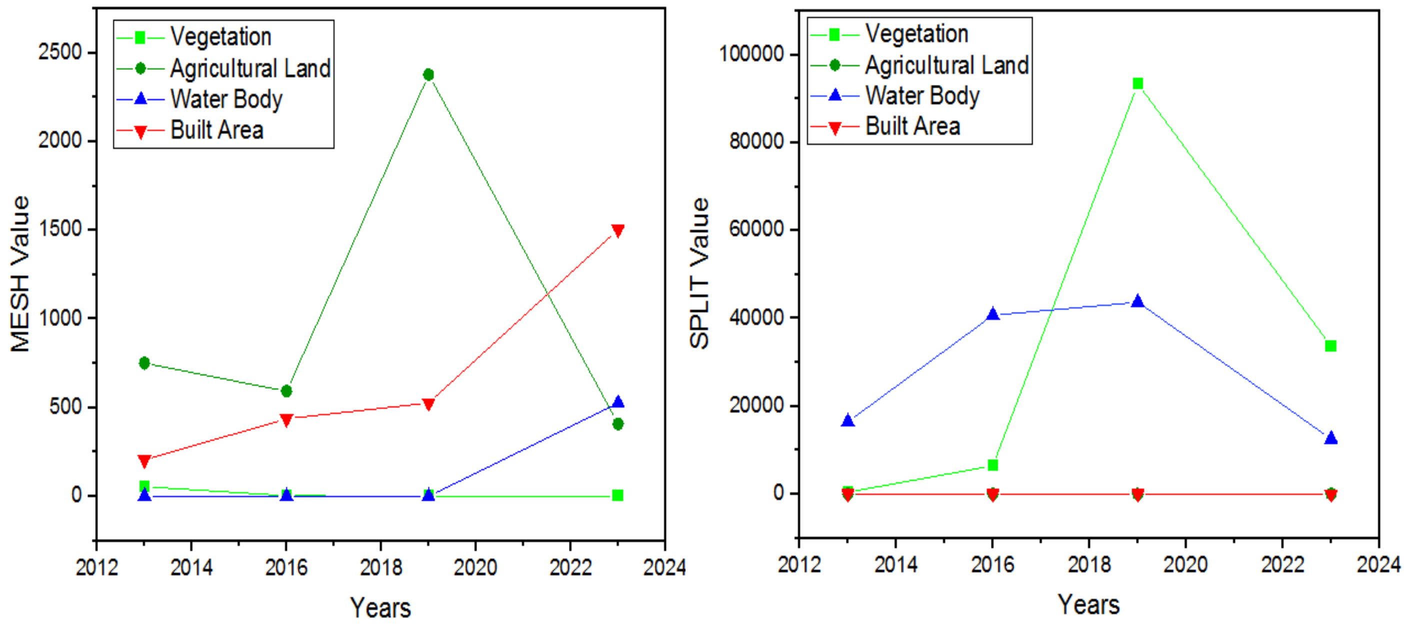

Figure 9. MESH and SPLIT 2013-2023

Image Accuracy Rate

The level of image accuracy is analyzed with a confusion matrix to see the level of accuracy of makers, users, and overall accuracy levels, as well as measuring the quality of image accuracy using the Kappa coefficient (Rwanga & Ndambuki, 2017). The results of the accuracy test are presented in Table 11.

Table 11. Confusion Matrix

		LULC Field Survey Results (User)				**Total**	**User Accuracy (%)**	**Error Commission (%)**
		Built Area	Vegetation	Agricultural Land	Water Body			
LULC Analysis Results Google Earth Engine CRAT algorithm (Producer)	Built Area	86	2	0	0	88	97.73 %	2.27%
	Vegetation	5	76	7	0	88	86.36 %	13.64%
	Agricultural Land	2	11	75	0	88	85.23 %	14.77%
	Water Body	0	3	6	79	88	89.77 %	10.23%
	Total	93	92	88	79	**352**		
						316		
	Producer's Accuracy (%)	92.47%	82.61%	85.23%	100.00%	**Overall Accuracy (%)**	**89.77%**	
	Error Omission (%)	5.38%	17.39%	14.77%	0.00 %			

Based on the results of the analysis, the accuracy level of the producer, user, and overall accuracy level is obtained. The overall accuracy rate is 89.77% with a Kappa coefficient of 0.86 (86%), so the quality of accuracy at the level is outstanding according to the classification of the quality level of accuracy of the Kappa coefficient. This finding is in line with previous study by Naikoo et al., (2020) which reported that for accurate interpretation and identification, the minimum accuracy value should not be <80%.

The calculation results show that the LULC classification using the CART algorithm has a high quality of interpretation, reaching 89.7%. Meanwhile, Li et al., (2023) and Zhao et al., (2024) reported that CART is one of the classification algorithms with guided classification on the Google Earth Engine (GEE), which has high results. This finding is in line with previous study conducted by Indraja et al., (2024), which reported that LULC classification with the CART algorithm in the supervised classification method can produce accuracy values between 80% to 94%.

CONCLUSION

Urban form can be measured quantitatively through a spatial matrix approach using FRAGSTAT software. The research findings indicate that the City of Surakarta's growth has positively impacted the evolution of urban form in its peri-urban area. The predominant trend in this development leans towards a compact urban form, aligning with the perception that such a form is deemed more sustainable. In class-level measurements for each land cover, vegetation and bodies show increasingly fragmented development. Meanwhile, built-up land and agricultural land tend to develop more compactly. The dynamics of urban form and land cover changes demand careful attention from local governments. Regional development needs to be steered towards creating a sustainable city. This involves urban form, land cover, and various other factors. A holistic approach to city development is crucial to ensure that it consistently enhances the quality of life for all residents within its boundaries.

ACKNOWLEDGMENTS

We gratefully acknowledge Aditya Eka Saputra, Aida Nur Azqiya, Evrina Rakhmanita, Fitri Hakiki, and Kaltsum Hana Arini who have helped in the data collection process.

DECLARATIONS

Conflict of Interest

We declare no conflict of interest, financial or otherwise.

Ethical Approval

On behalf of all authors, the corresponding author states that the paper satisfies Ethical Standards conditions, no human participants, or animals are involved in the research.

Informed Consent

On behalf of all authors, the corresponding author states that no human participants are involved in the research and, therefore, informed consent is not required by them.

DATA AVAILABILITY

Data used to support the findings of this study are available from the corresponding author upon request.

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