

Application of Landscape Metrics to Quantify the Magnitude and Patterns of Urban Expansions: Central Fragile Area, Sri Lanka

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Abstract

Urban expansion is a complex spatial process that transforms non-constructed areas into constructed areas. Often, they occur in environmentally sensitive areas and may cause serious environmental issues. This study examines the urban expansions in the Central Fragile Area (CFA), of Sri Lanka in order to help manage the process.

For this purpose, the built-up areas considered as indicators of urban expansion are extracted from Landsat images for 1997, 2010, and 2020. A set of landscape metrics are used for the purpose of revealing the magnitude and patterns. The study is divided into six concentric zones with eight directions by applying the gradient analysis. Each metrics was analyzed through concentric zones and the relationship between them were analyzed by Pearson Correlation Analysis.

The results indicate that the urban expansion of CFA has continuously increased from 1997 and the patterns of density, distance, complexity and aggregation are highly significant with types of expansion (infilling, edge expansion and outlying expansion). This study offers information on the magnitude and patterns of the urban environment and directs towards sustainable urban developments.

Keywords: Urban Expansion, Landscape Metrics, Magnitude, Pattern, Central Fragile Area.

Introduction

According to the 2014 world urbanization prospects notes, majority of the world population lives in urban areas, which is expected to increase by 2.5 million by 2025. Rapid urban expansions convert the non-constructed land to constructed land to cater to the increasing populations (Zeng, et al., 2012). The transformation of earth's surface creates serious problems such as loss of natural recourses, climate change, flood hazard, and habitat fragmentation (Qian & Wu, 2019). Urban expansions are seen as a danger to sustainability (Sudhira, Ramachandra, & Subrahmanya, 2009). Therefore, it is important to understand the urban expansion phenomenon in developing countries especially from the spatial and statistical perspectives (Sudhira, et.al, 2009).

Xu, Zheng, and Zhang (2018) point out that “a quantitative analysis of urban expansion can offer better support for urban planning and management”; and landscape metrics are powerful tools to quantitatively describe the landscape pattern, quantity, intensity and especially the patterns that may sometimes not be visible to the naked eye. (Akinrinola, 2019; Cao, et al., 2017). Landscape metrics are frequently utilized in landscape ecology due to their capacity to quantitatively comprehend the spatial and temporal patterns of the landscape (Feng & Li, 2012). Thus, the application of landscape ecology theory for urban expansion related studies facilitates to understand the magnitude and patterns of urban expansions. This study will contribute to a better understanding of the magnitude and patterns of urban expansions, as well as provide vital information for formulating successful urban planning and management strategy orientations with minimal negative consequences for future urban developments.

As discussed before, the urbanizing process has received interest in the past few decades due to the direct or indirect effects of it on the function of the earth (Abebe, 2013). “Although urban expansion is an inescapable process, effect can be made to protect the natural resource and improve the livelihood through proper way of urban planning and management” (Soffianian, et.al, 2010). To do so, urban planners need further innovations and more efficient techniques to acquire knowledge about the magnitude and patterns of urban expansions (Abebe, 2013).

Several landscape ecology studies have justified that landscape metrics are strong tools to quantitatively measure the landscapes but those studies have specifically focused on the natural land use types such as water bodies, forest patches, farmlands, and wetland (Tamagnone, et.al, 2020; Sertel, et.al, 2018; Malinen, 2017). There are few studies in ecology which attempt to quantify the “from-to” transformations, considering built-up land as a main determinant: for example, how much of vegetation cover has been converted to built-up cover annually (Yi, et.al, 2016). However, none of the studies has specifically given attention to quantify the urban expansions by applying landscape metrics in the Sri Lankan context for the Central Fragile Area (CFA).

The International Union for the Conservation of Nature (IUCN) define the fragile area as “areas of land and/or sea, especially dedicated to the protection and maintenance of biological diversity and of natural and associated cultural resources, and managed through legal or other effective means” (IUCN, 1994). This study focused on the terrestrial fragile area. However, urban expansion studies done in the international contexts have used terms such as protective area, sensitive area, and mountain/hill zone area to address the fragile areas. They have focused on identifying the factors contributing to urban expansion, hazard risk level and simulations on future expansions (Rimal, et.al, 2018; Yuan, et.al, 2019), rather than understanding the ground reality of urban expansions in terms of quantity, intensity, and patterns. The ground reality elements such as quantity and intensity emphasizes the magnitude (seriousness) of urban expansions (Heidarinejad, 2017), while the patterns explain the characteristics of spatial change (Abebe, 2013). As planners, understanding the ground reality is more important than the prediction for better planning practices, because, “planning and management of urban spaces require a comprehensive knowledge of the development process and physical dimension of cities” (Klosterman, 1999).

There are some other quantitative measures/models’ planners have frequently used; GIS integrated cell-based modeling such as Land use transportation (LUT) model, Cellular automata model (CA), and Agent-based model for planning practice (Li & Gong, 2016). The CA models used geospatial metrics instead of landscape metrics. Hence, CA considers the parameters such as density (e.g. population density, road network density), centrality (e.g. distance to CBD, centrality index), accessibility (e.g. distance to park, distance to bus stand),

connectivity (e.g. internal connectivity, external connectivity), in its modeling approach. These metrics are very diverse and complex especially when measuring the built environment (Reis, et.al, 2015). They mainly focus on performing simulations based on socio-economic & physical factors and that is just an approximation to the reality (Yeh & Li, 2006).

As discussed above, this study attempts to fill two main gaps: (1) the application of landscape metrics to CFA. (2) Combination of technique in landscape metrics to understand the urban expansions in CFA. Several studies have justified that quantity, intensity, and patterns are good measures to understand space. However, each of these measures have been used separately according to the need. Herold, et.al (2005) point out that “combined method gives better results than using either of them separately”. Therefore, this research develops an integrated method along with landscape metrics to give a better understanding of urban expansions in terms of magnitude and patterns.

Objectives

The objectives of this research are as follows:

1. To quantify the magnitude of urban expansion in the central fragile area of Sri Lanka
2. To investigate the pattern of urban expansion in the central fragile area of Sri Lanka

The study area

The ‘Central Fragile Area’ (CFA) is the geographic body that comprises the accumulation of natural resources, lands with sensitive natural ecosystems, and is crucial in terms of water resources. These areas cover the upper catchments of all major rivers of the island and are highly vulnerable to landslide.

Accordingly, “central fragile area” has been declared as a soil conservation zone along with a 300m contour line with a few exceptions (Fig. 1). “The Fragile Area defined by the NPPD covers an extent of 11,100sq km which represents approximately 17% of the total land area of the country. It includes 2 Districts (Kandy and Nuwara Eliya) and parts of 8 Districts (Matale, Kegalle, Monaragala, Badulla, Kalutara, Ratnapura, Galle and Matara). A total of 79 Divisional Secretariat Divisions fall within the Fragile Area (NPPD – 2017)”

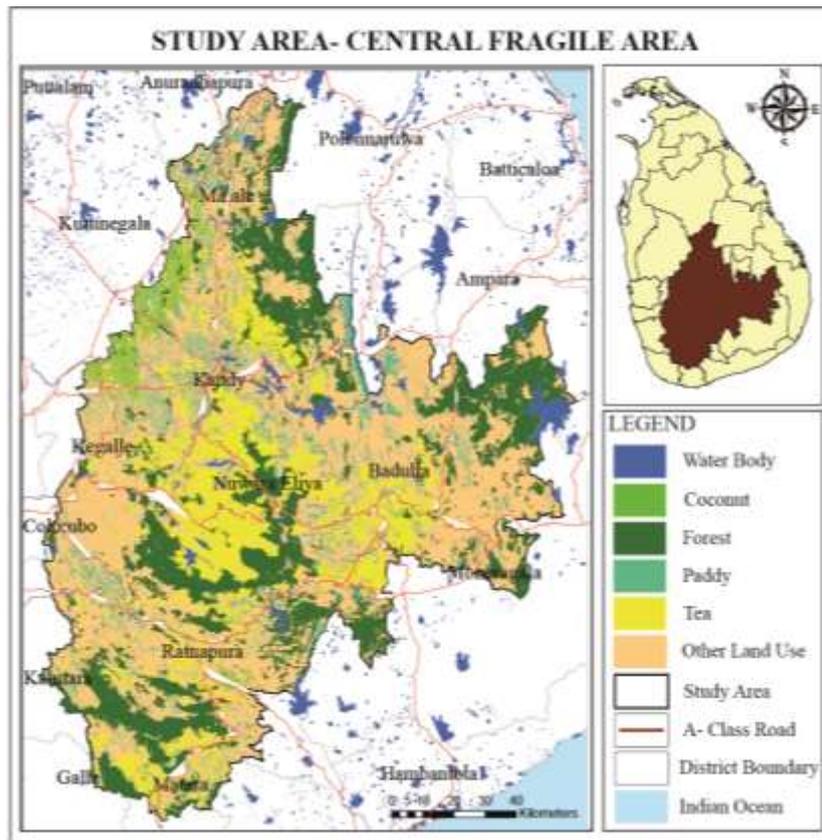


Fig 1: Boundary of Central fragile area
Source: Author

The research method

Temporal analysis needs minimum two different times to compare the urban expansions. Considering the data availability, cloud cover (less than 10%) and reasonable time gap satellite images of year 1997, 2010 and 2020 were considered. Another reason for the selection of Landsat images for this study is the availability of Near-Infrared (NIR) and Shortwave Infrared (SWIR) bands to calculate the Urban Index (UI). Therefore, relatively clear images with 30m spatial resolution can be obtained from Landsat 5 and 8. Table 2 provides detailed information about selected Landsat images.

Table 1: Required Data,
Source: Author

No	Input data	Source and link	Purpose
01	Satellite image (Landsat 5 – 1997)	USGS (https://earthexplorer.usgs.gov/)	To extract the build-up and non-build-up area False colors image used to clarification of ground truth points
02	Satellite image (Landsat 7 – 2010)	Detailed data- Table 3	
03	Satellite image (Landsat 8 – 2020)		
04	Ground truth points	Produced by the author through Google earth pro and false color image	To do the accuracy assessment
05	Land use map	Survey department of Sri Lanka	

Image classification and accuracy assessment

To quantify the urban expansion, the selected images have been classified as built-up area and non-built-up area. Several indices are used to map the built-up area such as NDBI, BUI, BAEI, NBI, VIBI, IBI, UI and BSI. Out of them, UI (urban index) is the most suitable index to evaluate the urbanization (Osgouei, et.al, 2018). Hence, UI index has been used to classify the satellite images into built-up and non-built-up areas. Built-up areas include the residential, commercial, industrial, road and railway networks and parking lots, construction site sports and leisure facilities. Non-built-up lands included agriculture lands, grasslands, forests, shrubs lands, green spaces, wetlands, bare soils and all types of water bodies.

The built-up land was extracted using Arc GIS 10.3.1 as per the following equations:

$$\text{Landsat 5 UI} = \frac{TM7 - TM4}{TM7 + TM4} \quad (1)$$

$$\text{Landsat 7 UI} = \frac{TM7 - TM4}{TM7 + TM4} \quad (2)$$

$$\text{Landsat 8 UI} = \frac{OLI7 - OLI5}{OLI7 + OLI5} \quad (3)$$

Accordingly, by applying the UI index, built-up and non-built-up areas have been extracted from the Landsat 5, 7, and 8 images for the years 1997, 2010 and 2020 respectively.

After the image classification, accuracy assessment was performed to assess the accuracy of the classified images. Classification accuracy is the most critical aspect for determining the reliability of the final output maps (Abebe, 2013). The ultimate focus of the evaluation is to ensure classification quality and user trust in the product (Foody, 2002). The accuracy of classification for the years 1997, 2010, and 2020 is evaluated in this study utilizing 300 randomly picked ground truth points obtained from Google Earth. Survey Department's land use maps have been used as referencing images.

Gradient model

“Gradient can be defined as the rate of change with distance in a particular direction” (Kohli, 2006). Gradient analysis connects spatial data to specific locations, allowing for comparisons of changes in certain metrics and those locations, improving the capacity to identify patterns and processes (Kong & Nakagoshi, 2006). Accordingly, the study area has been divided into 8 directions as North, East, South, West, North East, South East, South West and North West; and has been further divided into 6 concentric zones having a width of 20Km for the purpose of assessing the rate of changes of urban expansions in different directions.

Selection of metrics to detect the magnitude and patterns

There are more than 100 landscape metrics, within which the metrics selected for this study are based on the previous work and the level of understanding the landscape patches.

Accordingly, 8 landscape metrics have been selected for this study. The following table includes the metrics and the descriptions.

Table 2: Landscape metrics used in this study

Source: <http://www.umass.edu/>

Magnitude & Patterns (Parameters)		Definitions	Abbreviation of metrics and units	Metrics and Equation
Magnitude	Quantity	The amount of land expanded over a specific time period	CA/TA (Ha) PLAND (%)	Total or Class Area Percentage of Landscape $CA = \sum_{j=i}^n a_{ij} \left(\frac{1}{10,000} \right)$ (4)
		The rate of land expanded over a specific time period	PLAND (%)	Percentage of Landscape $\%PLAND = pi = \frac{\sum_{j=1}^n a_{ij}}{A} (100)$ (5)
	Intensity	It used to compare the growth rate of the built-up area in a unit, interval time to investigate the speed/pace of urban expansion (fast, moderate, and slow)	UEII (%)	Urban Expansion Intensity index $UEII = \frac{(ULAt_2 - ULAt_1)}{(TLA \times \Delta t)} \times 100\%$ (6)
Patterns	Diversity	Quantifies the largest patches to know whether the landscape is entirely covered by single land use or diverse	LPI (%)	Largest Patch Index $LPI = \frac{\max_{j=1}^n (a_{ij})}{A} (100)$ (7)
	Distance	Distance between two patches	ENN_MN (Meters)	Mean Euclidean Nearest-Neighbor Distance $ENN = h_{ij}$ (8)
	Complexity / regularity	Measures whether an urban settlement has a regular shape or a complex shape with a ragged edge	LSI (None)	Landscape Shape Index $LSI = \frac{e_i}{\min e_i}$ (9)
	Aggregation / Fragmentation	Measures how close (aggregated) or far apart (fragmented) are the urban settlements (or patches)	AI (%)	Aggregated index $AI = \left[\frac{g_{ij}}{\max \rightarrow g_{ij}} \right] (100)$ (10)
	Type	Infill, Edge expansion, and outlying	LEI (None)	Landscape expansion index $LEI = \frac{L_c}{p}$ (11)

Pearson Correlation

Pearson correlation analysis was conducted to understand the relationship between landscape metrics used to quantify the patterns of CFA.

The Pearson Correlation generates a coefficient of sample correlation, *r*, which measures the strength and direction of linear relations between pairs (Samuels & Gilchrist, 2014).

$$r_{xy} = \frac{cov(x,y)}{\sqrt{var(x)}\sqrt{var(y)}} \tag{12}$$

Where *cov*(*x*, *y*) is the sample covariance of *x* and *y*; *var*(*x*) is the sample variance of *x*; and *var*(*y*) is the sample variance of *y*.

Correlation can take on any value in the range of (-1 to +1). The sign of the correlation coefficient indicates the direction of the relationship, while the magnitude of the correlation indicates the strength of the relationship.

- -1: perfectly negative linear relationship
- 0: no relationship
- +1: perfectly positive linear relationship

Findings and analysis

Classification of Landsat images, accuracy assessment and application of gradient model

The Landsat 5, 7, and 8 satellite images were classified into built-up and non-built-up areas based on the UI index for the years 1997, 2010 and 2020 respectively. Table 5 shows the results of the accuracy assessment for the three classified images. Accordingly, for all the three images, producers and user’s accuracy is greater than 80% and the overall accuracy is greater than 85%. As per the USGS guidelines (Lea & Curtis, 2010) for classified images with accuracy levels greater than 80% is considered as a good classification.

Table 3: Results of accuracy level

Source: Prepared by author

Land cover class	1997		2010		2020	
	Producer's	User's	Producer's	User's	Producer's	User's
Non-Built-up	96	84.21	94	85.61	92	90.2
Built-up	82	95.35	84	91.34	90	91.84
Overall Accuracy	89%		89%		91%	

For the purpose of application of the gradient model, to assess the direction-wise and zone wise magnitude of urban expansions, the study area has been divided into several concentric zones. The built-up area extracted from the image classification were super imposed with these concentric zones for further analysis (Fig. 2 (a) - (c)).

Accordingly, until 1997, the built-up area has been spread over the CFA and in between 1997-2010, the growth has concentrated to main town centres such as Kandy, Nuwara-Eliya, Badulla, Gampola, Matale, and Bandarawela. In between 2010-2020, the expansion happened as connecting the main town centres, ex: example Kandy-Gampola.

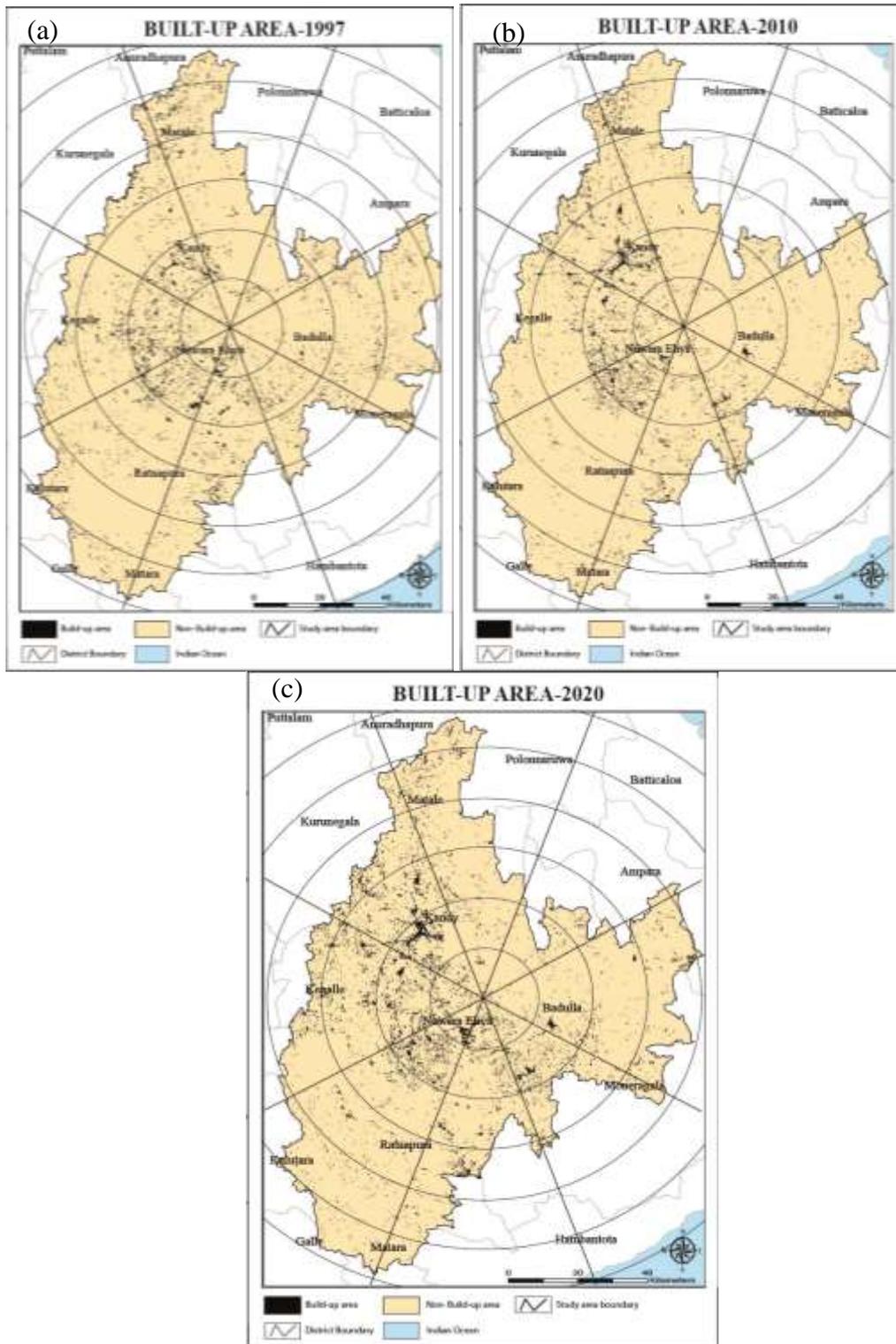


Fig 2: Built-up and Non-built-up area of (a) 1997, (b) 2010 and (c) 2020
Source: Author

Quantification of magnitude of urban expansion

The magnitude of urban expansions was measured in terms of quantity and intensity. The metrics used to quantify the urban growth and intensity are CA or TA, PLAND and UEII. CA used to quantify the total area, PLAND measure the percentage of built-up area and UEII quantify the intensity.

The table 4 illustrates the CFA urban expansion in 1997 which is 3194.91 Ha. In 2010 this is 6531.56 Ha, and in 2020 it had grown to 8882.55 Ha. It indicates that within 23 years, nearly 5687.64 Ha of built-up areas have been added to the CFA. Once compared to the overall CFA, the built-up area percentage in 1997 is 0.20%, in 2010 0.49 and in 2020 it is 0.57%.

Table 4: Built-up area analysis based on TA/CA and PLAND,

Source: Author

Year	Total/Class Area [TA/CA (Ha)]	Percentage of Built-up area [PLAND (%)]	Time span (years)	Expansion growth rate (%)
1997	3194.91	0.20		
2010	6531.65	0.49	13	8.03
2020	8882.55	0.57	10	3.59

Thus, it indicates that even though the urban expansions happen, the non-built-up area dominates within the CFA and that is a positive sign compared to the 1997-2010 growth rate. The 2010-2020 growth rate has been reduced to 3.59% from 8.03%. Along with the above growth understanding, the intensity will give more meaning of the magnitude of CFA, because it used to compare the growth rate of the built-up area in a unit, and interval time to investigate the speed/pace of urban expansions with combination of zone and directions. Urban Expansion Intensity Index (UEII) has been used to calculate the intensity of each zone and has been categorized into fast, moderate and slow expansion zones.

Fig. 3 shows that in 1997-2010 and 2010-2020, the first three zones have the fast expansions. Among the 38 sub zones, the majority of the study area is covered by moderate expansion zones. Even though the location of the fast expansion zone changed from 1997-2010 to 2010-2020, the counts remains and is concentrated in the main town centres such as Kandy, Matale, Nuwara-Eliya, Badulla and Bandarawela. The moderate expansion zone is reduced to 16 sub zones from 17 sub zones and slow expansion zones have increased from 15 sub zones to 16 sub zones.

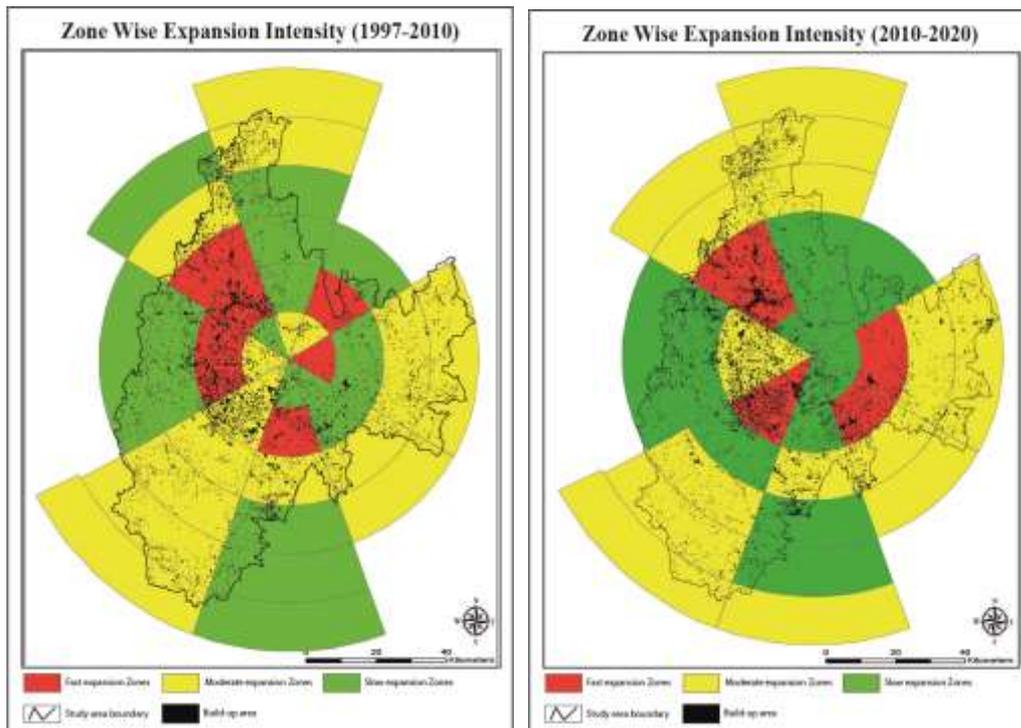


Fig 3: Zone wise expansion intensity (a) 1997-2010 and (b) (2010-2020)

Source: Author

Even though the NPPD was established in 2000, the first NPPD plan was prepared in 2007 and was enacted in 2011. The present NPPD plan was gazetted in June 2019. Thus, it clearly indicates that the intensity pattern of 2010-2020 was influenced through the NPPD plans guidelines.

It is also important to understand that even though the guidelines supported to reduce the growth rate and intensity of CFA, still the natural resources are located within the fast expansion zones.

As planners know, the magnitude is important to understand the seriousness of urban expansions (Heidarinejad, 2017). However, it is still not sufficient to drive the sustainability guidelines of the CFA. Therefore, understanding the pattern is also equally important to explain the characteristics of spatial changes (Abebe, 2013) and to drive guidelines.

Quantifying the patterns

Landscape expansion index (LEI), Largest patch index (LPI), Landscape shape index (LSI), Aggregated index (AI) and Euclidean Nearest-Neighbor Distance (ENN) are used to quantify the patterns of CFA.

Quantifying the type of expansion

LEI used to quantify the type of expansions such as infilling; edge expansions and outlying expansions. Fig. 4 shows that the CFA is dominated by outlying expansions with 58% and 51% in 1997-2010 and 2010-2020 respectively. Edge expansion does not have huge

differentiations, but it is still increased from 22% to 23%. Infilling expansions have increased from 20% to 26% in the years of 2010-2020.

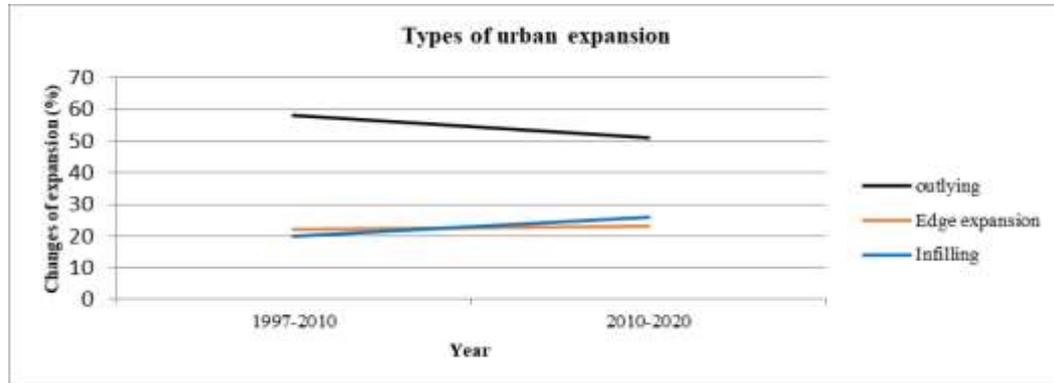


Fig 4: Types of expansion in between (1997-2010) and (2010-2020)

Source: Author

According to the analysis, each town centre has its own type of expansion though it remains unchanged during the periods of 1997-2010 & 2010-2020. For example, as shown in Fig. 17, Kandy and Nuwara-eliya towns have mixes of three types of expansions; Matale is dominated by edge expansions, Gampola has high infill expansions and Badulla is dominated by outlying expansions.

As edge expansion and infilling do not have huge differentiations between 1997-2010 and 2010-2020, spatially. It is not visible but still the outlying expansion is visible due to the dominance of the CFA. It is dominant specifically along the arteries connecting Kandy and Nuwara-Eliya towns.

Quantifying the diversity

The expansion or the merging of small patches into largest patches, is measured through the Largest Patches Index (LPI). “LPI approaches 0 when the largest patch in the landscape is increasingly small. LPI= 100 when the entire landscape consists of a single patch; that is, when the largest patch comprises 100% of the landscape” (Abebe, 2013).

Fig. 5 shows the highest value of LPI in CFA which is 18%. It indicates that the CFA is not covered by a single landuse patch; it is diversified. It also indicates that in between 1997-2010, LPI reduced and in 2010-2020, it increased. It means in 1997-2010, new urban patches have grown in this area and in the years of 2010-2020 nearby patches have merge together and have become large town centers.

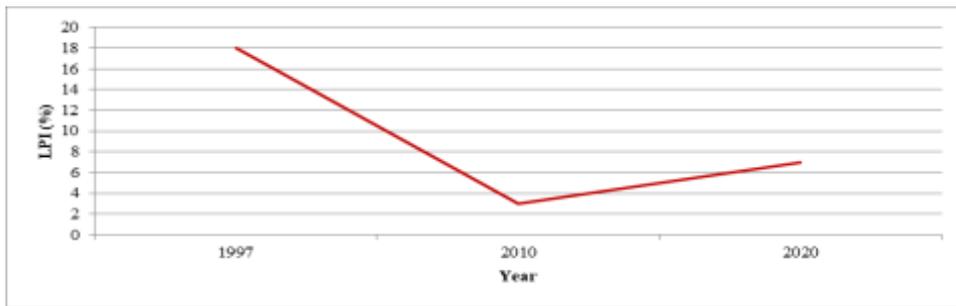


Fig 5: Year wise LPI analysis
Source: Author

According to Fig. 6, the largest patch is located in the 2nd zone, NW direction (Around Kandy) due to all three types of expansions and other large patches (>0.1) located within 1st and 2nd zones. The majority of the study area is covered by the 0.05-0.1 range, which means it has possibilities to large patches in future. If so, the current moderate and slow expansion zones will be converted as fast and moderate expansion zones. That will directly affect the natural resources.

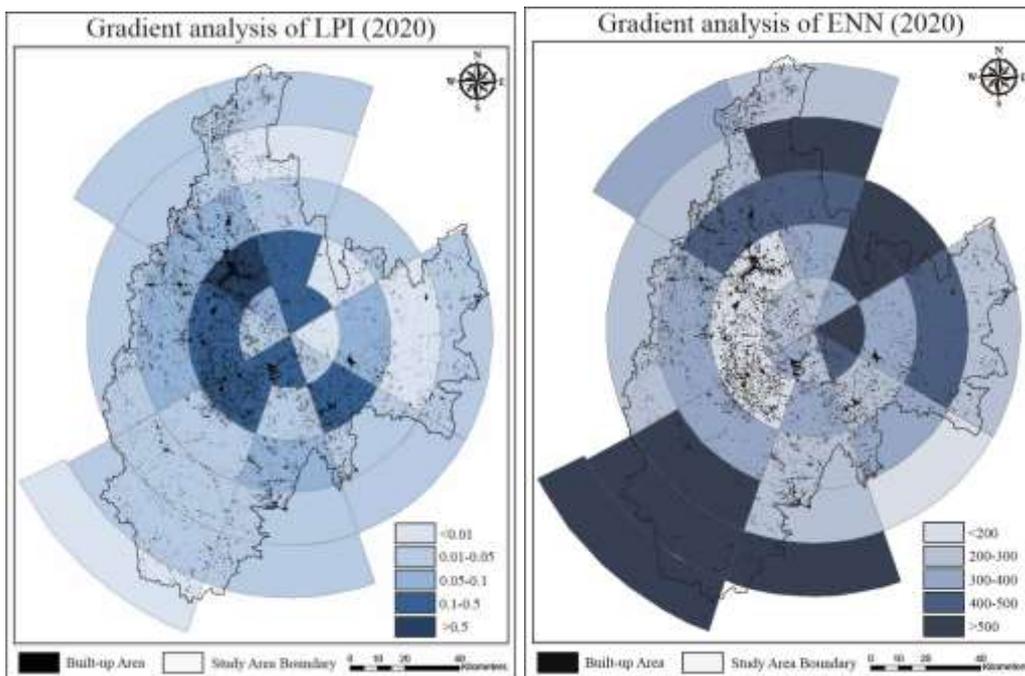


Fig 6: Direction wise LPI analysis

Fig 8: Direction wise ENN analysis
Source: Author

Quantifying the distance

The Euclidean Nearest-Neighbour Distance (ENN) measures the distance to the nearest neighbourhood patches. “ENN approaches zero as the distance to the nearest neighbour decreases” (Posada, 2012).

According to the Fig. 7, the overall ENN value is >250m in CFA. This means the distance between two urban patches are high and it gradually reduces from 1997 to 2020. It

indicates the merging patterns of nearby patches. Due to that, the distance between the two patches are reducing.

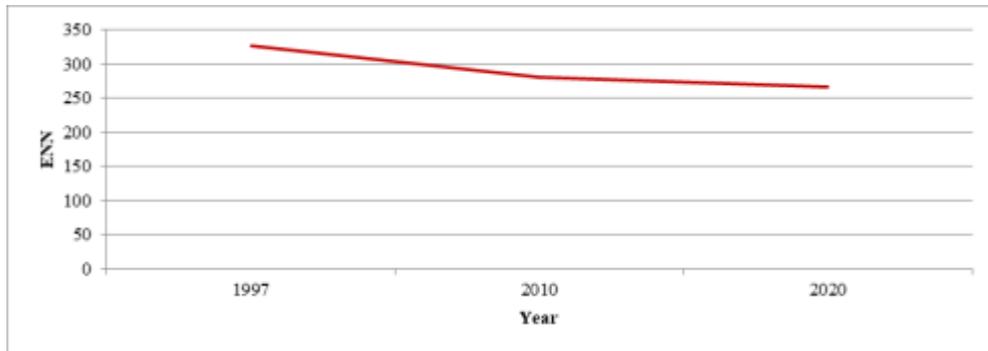


Fig 7: Year wise ENN analysis
Source: Author

Fig. 8 shows the >400m distance built-up patches that are located in 3rd, 4th, 5th and 6th zones. Unfortunately, the majority of the natural resources are located within these zones. To increase the accessibility and facilitate the public, the distance will be reduced through the increase of built-up areas. If it happens, the network of the non-built-up areas will be in risk.

Quantifying the complexity

The spatial complexity is measured through the Landscape Shape Index (LSI). If the value is near to “0”, the landscape has a more regular pattern and if it is $\leq 10,0$ then the landscape has a high complex pattern.

As indicated in Fig. 9, in all three years LSI is >100; this means that the CFA has high complex patterns. In 1997-2010, the spatial complexity has increased and then it has been slightly reduced to 117.50 in the years 2010-2020. It can be related with the LPI value. Both metrics has inverse relationships. If the LPI is reduced, the spatial complexity increases. It means, that if the new urban patches have grown seperately without merging with the old patches, it creates a complex landscape.

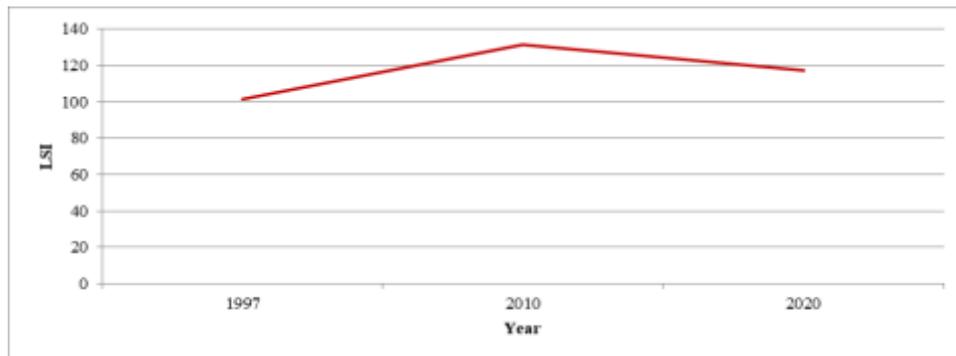


Fig 9: Year wise LSI analysis
Source: Author

According to the Fig. 10, less complexity is located in less built-up areas in the NE direction and the majority of the study area is >20 due to the dominance of the outlying expansions. High spatial complexity is located around Kandy and Nuwara-Eliya due to the road network connetions towards the main town center.

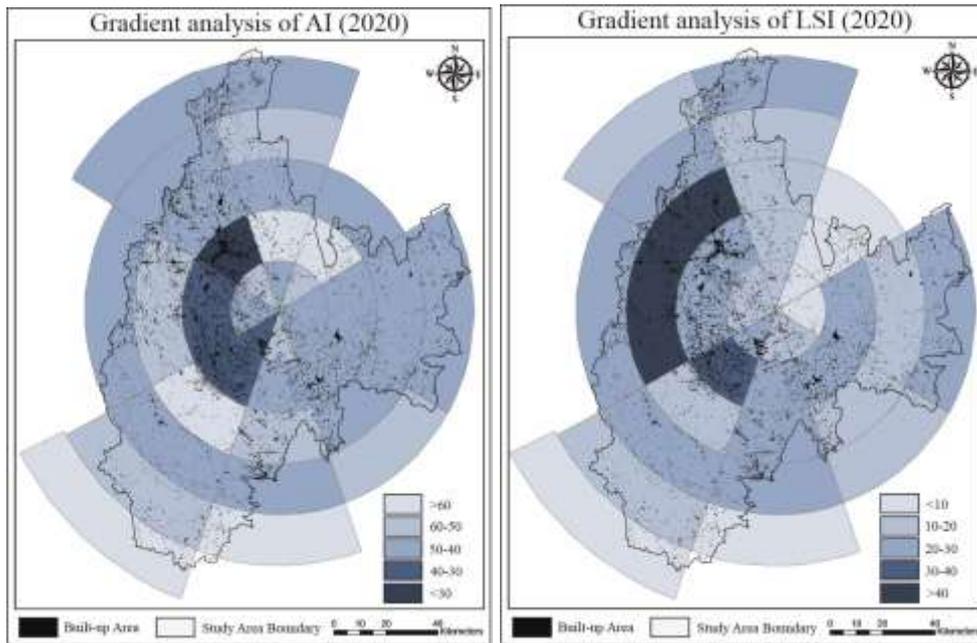


Fig 10: Direction wise LSI analysis **Fig 12:** Direction wise AI analysis
 Source: Author

Quantifying the aggregation

The Aggregated Index (AI) measures the level of aggregation and fragmentation. If the AI value is near “0”, it is highly aggregated and if it is ≥ 100 , the landscape is highly fragmented.

As the AI ranges between 40-70, CFA has moderate aggregation and the level of aggregation is continuously increasing from 1997 to 2020. It also indicates the combining or the merging of nearby urban patches. Due to that, the level of fragmentation is reduced and the aggregation is increased (Fig. 11).

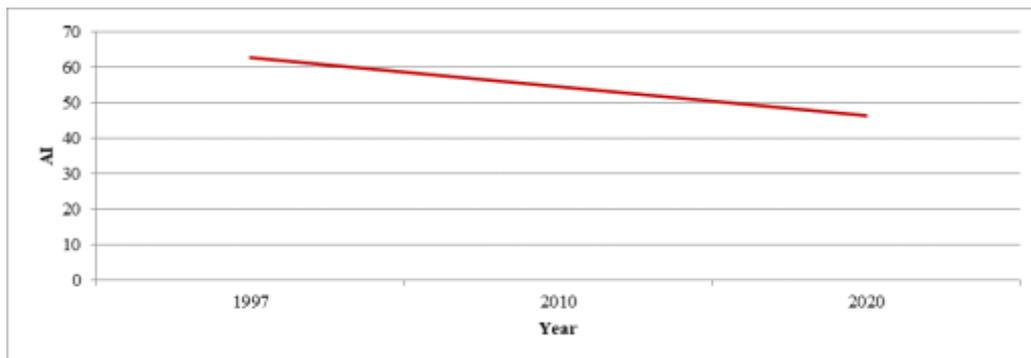


Fig 11: Year wise AI analysis
 Source: Author

According to the Fig. 12, most of the aggregation is located in the 2nd zone SW,W and NW direction. The majority of the study area is covered by >50 aggregated levels. Increasing level of aggregation of built-up areas creates fragmentation of the non-built-up areas.

Relationship between the landscape metrics used to quantify the patterns

The Pearson Correlation Analysis was conducted to understand the relationship between landscape metrics used to quantify the patterns of CFA. Accordingly, the values related to LEI have strong positive relationships with other metrics. The other metrics also have strong positive or negative relationships according to their own relationships.

Table 5: Pearson coorelationship analysis,
Source: Author

1997-2010						2010-2020					
Metrics	LPI	LSI	ENN	AI	LEI	Metrics	LPI	LSI	ENN	AI	LEI
LPI	1	-.991**	-.687	.937**	.715**	LPI	1	-.994**	-.765	.960**	.994**
LSI		1	.268	-.973**	.714**	LSI		1	.247	-.985**	.961**
ENN			1	-.630**	.481	ENN			1	-.692	.166
AI				1	.470**	AI				1	.781**
LEI					1	LEI					1

**Correlation significant at the 0.01 level (2-tailed)

As mentioned in the person correlation, each of these metrics are highly significant. Specially, LPI, LSI, ENN and AI are positively correlated to LEI with .994, .961, .166 and .781 respectively in 2010-2020.

Table 6: Comparision of the metrics
Source: Author

LEI	Other metrics
Edge expansion or infilling expansion increase	LPI increase
Outlying expansion increase	LSI (complexity) increase
Edge expansion increase or outlying expansion reduces	ENN (distance) reduces
Edge expansion/infilling increase or outlying expansion reduces	AI (aggregation) increases

LPI has a strong negative relationship with LSI (-.994) and ENN (-.765) because when largest patches increase, the spatial complexity and the distance between the patches will reduce. At the same time, the LPI has a strong positive relationship with the AI (.96) because the largest patch increase means the aggregation will also increase.

LSI has a moderate positive relationship with the ENN (.247) because spatial complexity increase means the distance also increases, at the same time and has a strong negative relationship with AI (-.985). If the complexity increases, the level of aggregation will reduce and make a fragmentation.

ENN has a strong negative relationship with the AI (-.692) because if the distance between patches increases the aggregation will reduce. Accordingly, it's clear that infilling, edge expansion and outlying expansions contribute to the spatial diversity, complexity, distance and aggregation.

Conclusions and recommendations

Urban expansion is a topic frequently discussed among urban planners due to its effect on sustainable planning. This research also attempted to develop a quantitative method of urban expansion in terms of magnitude and patterns by using eight different landscape metrics (CA,

PLAND, UEII, LEI, LPI, LSI, ENN and AI) collaborated with gradient analysis. Research is tested in the Central Fragile Area (CFA), Sri Lanka in the years 1997, 2010 and 2020. Accordingly, compared to 1997, nearly 5687.64 Ha of built-up area has been added in 2020. However, the growth rate has reduced to 3.59% in 2010-2020 from 8.03% in 1997-2010. The intensity is concentrated to the main town centres such as Kandy, Matale, Nuwara-Eliya, Badulla and Bandarawela in 2010-2020. Regarding the pattern, CFA is dominated by the outlying expansions, in which the new built-up areas have emerged isolated from the old built-up areas. However, during the period 2010-2020, the outlying expansion type has been reduced and the infilling expansion has been increased by 6%, which is the expansion pattern that fills the gaps between the old built-up areas by new built-up areas. According to the Pearson Correlation Analysis, it is clear that the expansion types have contributed to the spatial diversity, complexity, distance and aggregation with .994, .961, .166 and .781 significant level respectively in 2010-2020. Currently the CFA is in coalescence phase due to the infilling expansion. Therefore, the nearby urban patches merge and the non-built-up area are likely to receive great pressure from land transformations. According to the finding, it is clear that the natural resources such as water bodies and forest covers located in 2nd and 3rd zones of the South West, West, and North West direction will face greater pressures.

As per the findings, the landscape metrics and the gradient analysis can be used to define the levels of spatial understandings and exact locations. Accordingly, the guidelines can be applied specifically. Very few metrics could also be able to capture the complex spatio-temporal dynamics of urban expansions. Compared to this approach, the traditional geospatial metrics on quantifying the urban expansion consumes more time, as it involves the identification of different driving factors which cause different growth patterns between different parts of the same city, i.e. road network to define the expansion level from distance to the main arteries.

As planners, the detrimental impact of pressure of expansion to the natural resources should be mitigated for the sustainability of CFA. Rather than generalizing the guidelines for the entire CFA, the findings of this research could be supportive to find the exact location of high-pressure zones and drive guidelines specifically. This method could be on time process compared to traditional methods specifically in developing countries, where the data is limited and high speed of expansions occur.

Further, this method can be applied to understand urban expansions on different fragile areas i.e. Coastal fragile areas. Though this research stopped at this point, it opens a path for future research on identifying the drivers, incorporating expansion types in the spatial explicit models, such as CA models and developing simulation models from this understanding for the purpose of developing more meaningful, supportive and reliable guidelines. Since the gradient analysis is a more flexible approach, the concentric zones can be further subdivided to specify the exact location. Due to the time and data limitation, the study was limited to the CFA, but it can be applied for entire Sri Lanka at different scales for better planning practices.

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