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Combining Remote Sensing Inputs and Census Data for Assessing Urban Growth Patterns in Puducherry District, India

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Abstract

Monitoring the spatiotemporal changes that affect the landscape and coast due to urbanization process is important because of its impacts on the environment and population. In relation to that, this research aims to explore the use of remote sensing imagery, census data and different spatial metrics to assess the urban growth patterns and processes that occurred in Puducherry district (India) between 2011 and 2020. Urban development forms, landscape patterns and urban sprawl measurements are, respectively, performed using three complementary software packages: Urban Landscape Analysis Tool (ULAT), FRAGSTAT program and Urban Sprawl Metrics (USM) Toolset. Four land cover maps of 2011, 2014, 2017 and 2020 are created by using image interpretation of very high-resolution remote sensing images. In parallel, urbanized areas and urban footprint maps are generated and new development patterns during the study time periods are analyzed. The results highlight a significant increase in built-up areas, which are unevenly distributed over space and time. In addition to that, the analysis of spatial metrics illustrates a continuous fragmentation process of built-up area. Besides, the quantitative analysis of urban growth process indicates that the urban development from 2011 to 2020 was dominated by the expansion and leapfrogging growth patterns. The Weighted Urban Proliferation (WUP) metric, which is computed based on 2011 census data, indicates that the spatial urban patterns presented a low level of urban sprawl during the last decade. This study can help the city decision-makers to manage urban expansion in a sustainable way by providing useful results and input data for further analysis including the evaluation of the effectiveness of past urban planning policies and the simulation of future urban development scenarios.

Keywords

Urban Growth, Sprawl, Spatial Metrics, Remote Sensing, Census Data

1. Introduction

The urbanization levels across different geographic regions and development contexts are considerably diverse. Still, urbanization is a worldwide phenomenon that has soared significantly in the last century (UN, 2019). Currently, more than one half of the world's population lives in urban areas with the proportion of urban dwellers rising from 30% in 1950 to 55% in 2018 (UN, 2019). Likewise, India has been undergoing rapid urbanization process with unprecedented growth rates over the last decades (Joshi et al., 2011; Sharma & Joshi, 2013; Ali et al., 2018). According to UN estimations, 41% of India's population is expected to reside in urban areas by 2030.

This global trend of urban population leads to irreversible land use transformations (Owen et al., 1998). It also increases demand and pressure on natural land resources for urban housing, commercial, industrial and recreational use. For instance, urbanization has a significant impact on the water demand. In fact, the excessive groundwater pumping, which is due to rapidly increasing population, causes groundwater-related problems in coastal areas (Kagabu et al., 2011). Furthermore, urbanization is considered as one of the most important factors of landscape change (Antrop, 2004). Its process results in mixed compact and dispersed spatial patterns of urban growth (Solon, 2009; Salvati et al., 2018). Actually, urban sprawl consists of a dispersed urban development that changes the landscape of human settlement and poses a major threat to sustainable land use. It is a serious worldwide concern for several and mostly irreversible environmental, economic and social consequences (EEA, 2016). For example, the shoreline progradation is mainly due to coastal engineering (Chu et al., 2013). Accordingly, monitoring, understanding and modeling spatial characteristics of urban landscape over time and how they interact with urban microclimate, ecological, economic, social and environmental processes are major issues in sustainable urban growth research, urban planning and land use management (Croci et al., 2008; Pellissier et al., 2008; Masson et al., 2014; Houet et al., 2016; Kohler et al., 2017; Hassan & Elhassan, 2020; John et al., 2020).

Urbanization phenomenon involves land use patterns (Thapa & Murayama, 2009) and spatial expansion processes (Xiao et al., 2006). Measuring and managing the spatial structure of a city are complex and challenging (Kotharkar et al., 2014). Spatial metrics calculated using remote sensing and GIS-based technology are extensively used in the study of urban landscape including the characterization of urban form (O'Neill et al., 1988; Herold et al., 2002; Herold et al., 2003; Sudhira et al., 2004; Herold et al., 2005; Aguilera et al., 2011; Estoque & Murayama, 2015; Al Mashagbah, 2016; Ali et al., 2018; Mandal et al., 2020). They are mainly used in studying the spatial characteristics of urban growth processes and patterns in a very effective manner by capturing and quantifying changes in the characteristics of urban patches, their size, shape and spatial configuration (McGarigal et al., 2002; Al Mashagbah, 2016). Besides, they are useful in evaluating urban planning scenarios (Aguilera et al., 2011) and validating the performance of urban growth simulation models by comparing the actual and the predicted urban growth patterns (Aguejdad et al., 2017; Aguejdad, 2021). Furthermore, dispersion, permeation and proliferation metrics are specifically developed to characterize the degree of urban sprawl by combining spatial and census data related to built-up areas within a landscape or reporting unit (Jaeger & Schwick, 2014; EEA, 2016; Nazarnia et al., 2016). Moreover, developed areas can be classified into distinct urban growth patterns (infill, leapfrog and expansion) based on built-up density level and proximity to development (Angel et al., 2007; Parent et al., 2009; Jason, 2009; Liu et al., 2010; Angel et al., 2012; Sharma & Joshi, 2013).

Most of the existing studies using spatial metrics focus on cities in the USA and Europe (Seto & Frakias, 2005; Aguilera et al., 2011). Indeed, the Urban Sprawl Metrics toolset (Jaeger & Schwick, 2014) is mostly applied to European cities. Accordingly, this work aims to contribute to existing knowledge by analyzing the captured spatial changes which reflect the urban transformations that Indian cities such as Puducherry district experienced from 2011 to 2020. This study, which is one of the first and rare studies on the city of Puducherry, will provide quantitative measurements and a qualitative characterization of spatial patterns and processes of urbanization in 2011, 2014, 2017 and 2020. The different urban growth tools and metrics mentioned above are rarely performed together. In relation to that, this study explores the most commonly used urban development metrics based on very high-resolution remote sensing inputs and census data. In addition to that, this is the first time that the WUP method has been carried out to measure the degree of urban sprawl in Puduchery district.

2. Materials and Methods

2.1. Study Area

Puducherry district, which is one of the four unconnected districts that make up the Union Territory of Puducherry, is located in the south-eastern part of India (**Figure 1**). The area of Puducherry district, which is nestled within the state of Tamil Nadu, covers an area of 294 km^2 spread out over four non-continuous sub-districts or "Taluks" (Bahour, Ozhukarai, Puducherry and Villianur). The non-continuous geographical area of Puducherry district is organized into seven administrative entities: two municipalities (Puducherry and Oulgaret) and five commune Panchayats (Villianur, Ariyankuppam, Bahour, Nettapakkam and Mannadipet). As per the government of India census of 2011 (Census of India, 2011), Puducherry district has a population of 945˚364 inhabitants. The city of Puducherry (11˚55′N and 79˚49′E) is considered as the 29th most populous and the third most densely populated of the States and Union Territories of India. Based on the Köppen-Geiger climate classification, the climate of Puducherry is tropical wet and dry with a temperature range from 23 to 41˚C.

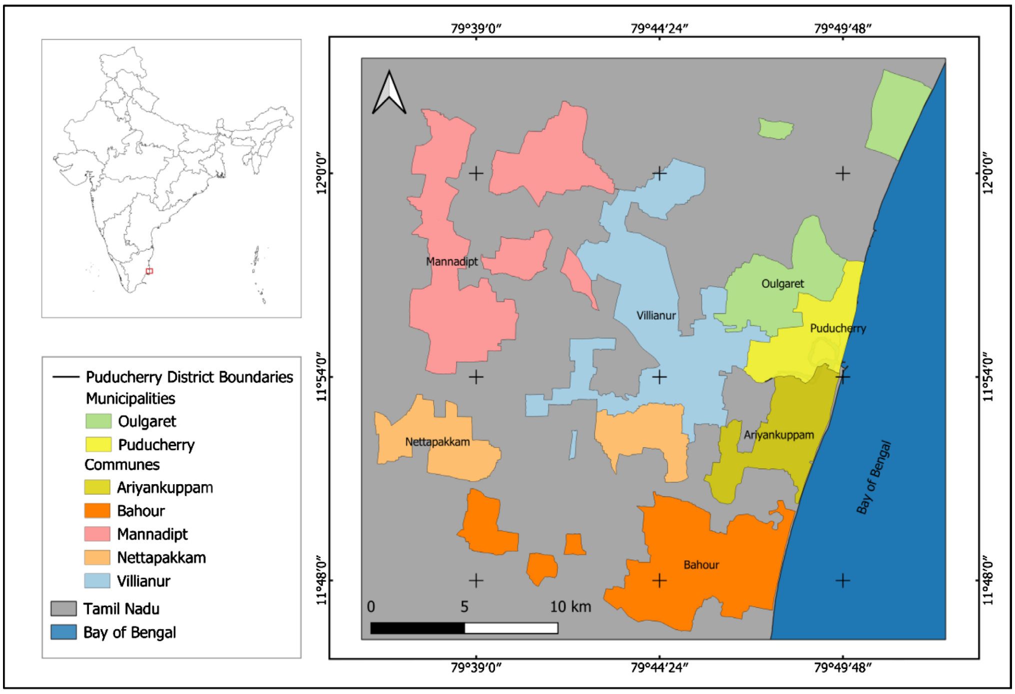

Figure 1. Location of Puducherry district area.

2.2. Data

Many land cover datasets and remote sensing images such as Landsat large-scale 30 m images are delivered with a certain spatial and temporal accuracy that is often unsuitable for an accurate spatial and temporal change analysis in urbanized landscapes. Consequently, the input land cover maps used in this study are performed using an image interpretation technique in order to reduce errors resulting from misclassification and then to meet a high level of spatial accuracy requirements. Accordingly, the manual delineation of the urban areas is carried out from the ESRI's World Imagery basemap in ArcGIS Online. World Imagery provides satellite and aerial imagery with a ground resolution of 1 m or less. For example, the satellite images used for mapping impervious surfaces in 2020 are provided with an accuracy of 8.5 m and a ground resolution that varies between 30 cm and 50 cm. In addition to that, increased built-up areas from 2011 to 2020 are mapped using visual interpretation of historical Google Earth's free and public high-resolution images whose resolution varies according to the source of data.

An urban area, which is composed mainly of residential areas and associated network of roads and parking lots, includes all types of buildings and urban structures. In addition to that, waterbodies, urban green spaces and vacant lands located between buildings are included in the settled areas. Some other relevant features such as the Puducherry airport and the industrial and facilities structures are also considered as urban areas.

2.3. Urban Patterns Analysis Tools

2.3.1. Urban Sprawl Metrics Toolset

The Weighted Urban Proliferation (WUP) method is developed to qualify the degree of urban sprawl in a given landscape or reporting unit that includes built-up areas (Jaeger et al., 2010; Jaeger & Schwick, 2014; Nazarnia et al., 2016) based on the definition of urban sprawl adopted by Jaeger and Schwick (2014). The authors combine the amount of built-up area, its spatial configuration in the landscape (dispersion) and the uptake of built-up area per inhabitant or job (utilization intensity). Accordingly, the WUP method helps to measure the degree of dispersion, the utilization intensity and the degree of permeation and proliferation of built-up areas in a given landscape (**Table 1**). Actually, when the amount and the dispersion of built-up area in the landscape go up and the utilization intensity of the same built-up area decreases, the degree of urban sprawl rises (Jaeger & Schwick, 2014). The WUP metric is measured in urban permeation units (UPU) per square meter of landscape (UPU/m^2). The European Environment Agency report on urban sprawl distinguishes six categories of sprawl level based on WUP (UPU/m^2) values at the territorial units level (EEA, 2016): not sprawled (WUP < 1), slightly sprawled (1 < WUP < 2), intermediate levels of sprawl (2 < WUP < 4), highly sprawled (4 < WUP < 6), very high levels of sprawl (6 < WUP < 9), and extremely high levels of sprawl (9 < WUP).

Table 1. Metrics used for measuring urban sprawl using USM tool (source: EEA, 2016).

Metric	Name	Unit	Formula
DIS	Dispersion of built-up area	UPU per m^2 of built-up area	Degree of urban dispersion
PBA	Percentage of built-up area	%	PBA = $A_{\text{built-up}}/A_{\text{reporting unit}}$ $A_{\text{built-up}}$: size of built-up area in the reporting unit $A_{\text{reporting unit}}$: area of the reporting unit
LUP	Land uptake per person (per inhabitant or job)	m^2 of built-up per inhabitant or job	LUP = $A_{\text{built-up}}/N_{\text{inh+jobs}}$ $N_{\text{inh+jobs}}$: number of inhabitants and jobs in the built-up area of the reporting unit
UD	Utilization density	Number of inhabitants and jobs per km^2 of built-up area	UD = 1/LUP
UP	Urban permeation	UPU per m^2 of landscape	UP = PBA * DIS
WUP	Weighted urban proliferation	UPU per m^2 of landscape	WUP = UP * w_1(DIS) * w_2(LUP) w_1 and w_2: weighting functions

The WUP metric and its components of urban sprawl DIS (Dispersion), PBA (Percentage of built-up area), and LUP (Land uptake per person) are calculated using the Urban Sprawl Metrics (USM) toolset. This script, which is developed using Python and C$^+$ languages, needs to be loaded into ArcToolbox. Two input data are formatted to meet the USM toolset requirements. The first one is the binary map of built-up areas in the ESRI raster format. The second one is the map of reporting units in the shape file format. Information on the number of inhabitants and jobs per unit has to be saved in the attribute table associated to the reporting units shape file. This study uses a horizon of perception (HP) of 2 km. The area of the reporting unit ($A_{reporting\ unit}$) corresponds to the study area which is Puducherry district. Concerning the number of inhabitants and jobs ($N_{inh+jobs}$) in the built-up area of the reporting unit, only jobs belonging to secondary and tertiary sectors are considered. Jobs in agricultural sector are excluded from the calculation of the Land uptake per person (LUP) metric.

2.3.2. Urban Landscape Analysis Tool

The dynamic of urban expansion from 2011 to 2020 is quantitatively split into three development forms as infill, leapfrog and expansion (Angel et al., 2007; Liu et al., 2010; Angel et al., 2012) using the Urban Landscape Analysis Tool (ULAT). The ULAT script, which is developed by Jason (2009) in Python 2.5 for ArcGIS 9.3, needs to be loaded into ArcToolbox (Jason, 2009; Parent et al., 2009). ULAT is implemented to classify developed areas of different built-up density levels as well as to identify rural open lands and undeveloped areas that are likely to be degraded based on their proximity to development.

For each time period [T_0 T_1], two input categorical maps including four classes (no data, other, water and urban) are required to run ULAT. Two urban footprint maps are generated based on urbaneness and edge disturbance zone. In addition to water and rural open land, each urban footprint map shows five urban density classes of the built-up area and undeveloped lands (urban built-up, suburban built-up, rural built-up, fringe open land and captured open land) that are likely to be degraded due to their close proximity to development. In addition to that, a cross tabulation is performed between the first urban footprint map (T_0) and the observed change in built-up area that occurs between two consecutive time points T_0 and T_1. The resulting map shows that new urban development lands are classified into infill, expansion and leapfrog development forms. Infill growth refers to newly developed pixels that are in the captured open land of the previous time point (T_0). Expansion growth area corresponds to non-infill new development built-up pixels in the fringe open land of the previous time period. Then, leapfrog development refers to newly developed pixels which are non-overlapping with existing urban area and are occurring within the rural open land of the previous time period (Angel et al., 2007).

2.3.3. Spatial Metrics Using the FRAGSTATS Program

A set of fifteen commonly used spatial metrics is calculated using the FRAGSTATS spatial pattern analysis program for categorical maps (McGarigal et al., 2002). The selected metrics are implemented to measure the spatial configuration of urban development patterns between 2011 and 2020. They are computed at the entire study area level using binary urban maps with cell size of 15 m and based on eight cells neighborhood rule. These metrics comprise the Number of Patches (NP), Patch Density (PD), Largest Patch (LP), Largest Patch Index (LPI), Landscape Shape Index (LSI), Mean Patch Area (MPA), Mean Euclidean Nearest Neighbor Distance (ENND-MN), Contiguity, Perimeter-Area Fractal Dimension (PAFRAC), Clumpy, Cohesion, Splitting Index (Split), Effective Mesh Size (Mesh), Aggregation Index (AI), and Dispersion (DI). The calculation of the dispersion index is performed after the normalization of the number of patches and the largest patch metrics (Taubenböck et al., 2018; Gerten et al., 2019).

3. Results

3.1. Urban Growth Dynamic between 2011 and 2020

The spatiotemporal dynamic of built-up areas is analyzed at the entire Puducherry district area based on LULC maps of 2011, 2014, 2017 and 2020 (**Figure 2**). Additionally, this study uses the average annual change in built-up areas, urban growth rate and urban expansion intensity index (Hu et al., 2007; Alam et al., 2023) to quantify the observed urban expansion dynamic. In this study, the urban growth rate is computed to quantify the average annual rate of developed areas between two time periods. The urban expansion intensity index measures the speed or intensity of urban land development in a certain period.

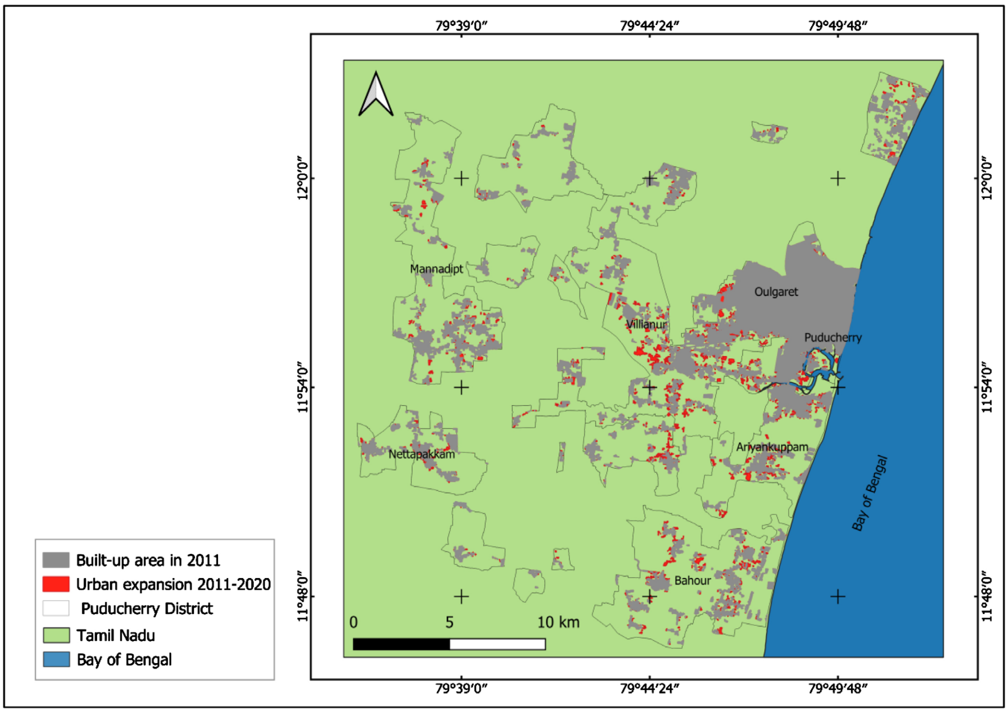

Figure 2. Urban development patterns between 2011 and 2020.

The first results indicate that Puducherry district experienced a continuous increase in built-up area in the last decade (**Table 2**). An increase of 641 ha is observed between 2011 and 2020 with an average annual growth of 71 ha/year. Actually, built-up areas increased by 194 ha from 2011 to 2014, 219 ha from 2014 to 2017 and 228 ha from 2017 to 2020. The results also indicate a slow urban expansion intensity with values between 0.22 and 0.26 (Ren et al., 2013; Alam et al., 2023). Besides, the urban growth dynamic remained slightly constant between 2014 and 2020 as illustrated by the average annual growth of built-up areas and their expansion rate. Furthermore, Puducherry district is highly urbanized and built-up areas in 2011 and 2020 reached 23% and 25% of the entire study area, respectively.

Table 2. Urban growth in Puducherry district from 2011 to 2020.

Date	Area (ha)	Percentage of landscape (%)	Period	Expansion area (ha)	Annual change (ha/year)	Growth rate (%)	Expansion Intensity
2011	6765.02	22.77	-	-	-	-	-
2014	6959.27	23.42	2011-2014	194.26	64.75	2.87	0.22
2017	7178.58	24.16	2014-2017	219.31	73.10	3.15	0.25
2020	7406.28	24.89	2017-2020	227.70	75.90	3.17	0.26

The observed urban development dynamic during the last decade is irregular over the territory (**Figure 2**). The east of Puducherry district is more urbanized than the west because of its attractiveness. However, built-up areas are highly spreading towards the south and west of Puducherry and Oulgaret (Uzhavarkarai) municipalities and along the principal roadways (NH-45, SH-203, NH-66 and SH-49) which connect Puducherry planning area to other cities and towns around (Villupuram, Cuddalore, Tindivanam and Chennai). With respect to that, **Figure 3** illustrates that the high increase in built-up areas from 2011 to 2020 occurred in the south of Villianur, Oulgaret, Ariyankuppam, the north of Bahour, the south of Mannadipet and the east of Nettapakkam. Actually, the urban development process has already resulted in a large conurbation area including Puducherry, Oulgaret, a part of Villianur, and a part of Ariyankuppam.

The analysis of urban growth dynamic between 2011 and 2020 at the level of municipalities and commune Panchayats shows that Villianur hit the record of the highest increase in built-up (206 ha) over the study period (**Table 3**). In fact, Villianur alone accounts for one third of the total increase in built-up at the entire Puducherry district area during the period 2011-2020. It is followed by Bahour (100 ha), Mannadipet (84 ha), Oulgaret (83 ha), Ariyankuppam (66), Nettapakkam (52 ha) and Puducherry (49 ha). Furthermore, the highest growth rate is reached in Bahour (18.4) and Villianur (17.9%) whereas the lowest growth rate is associated with Puducherry (4.1%) and Oulgaret (3.7%).

Table 4 indicates that in 2011, the proportion to the total area of each spatial unit covered by built-up structures, was the highest in Oulgaret (64%) and Puducherry (62%) municipalities compared to the five commune Panchayats (Ariyankuppam, Villianur, Nettapakkam, Manadiped and Bahour). These results witness that more residential development was occurring in Oulgaret and Puducherry municipalities. The results also show a high number of inhabitants and jobs that were associated with secondary and tertiary sectors. However, the lowest proportion of built-up area compared to the total commune area is observed in Bahour (10%) followed by Mannadipet (12%) and Nettapakkam (13%). In fact, agricultural land area is the largest in Mannadiped, Villianur and Bahour communes where the agricultural activities represent the main occupation of the majority of the population (CDP, 2019). Bahour commune Panchayats, which consists of rural villages and known by its fertile agricultural land, is considered as the rice bowl of Puducherry planning area. Hence, only regulated development is allowed in certain parts of this area which is preserved by declaring dedicated agriculture zone under the current development plan—2036 (CDP, 2019).

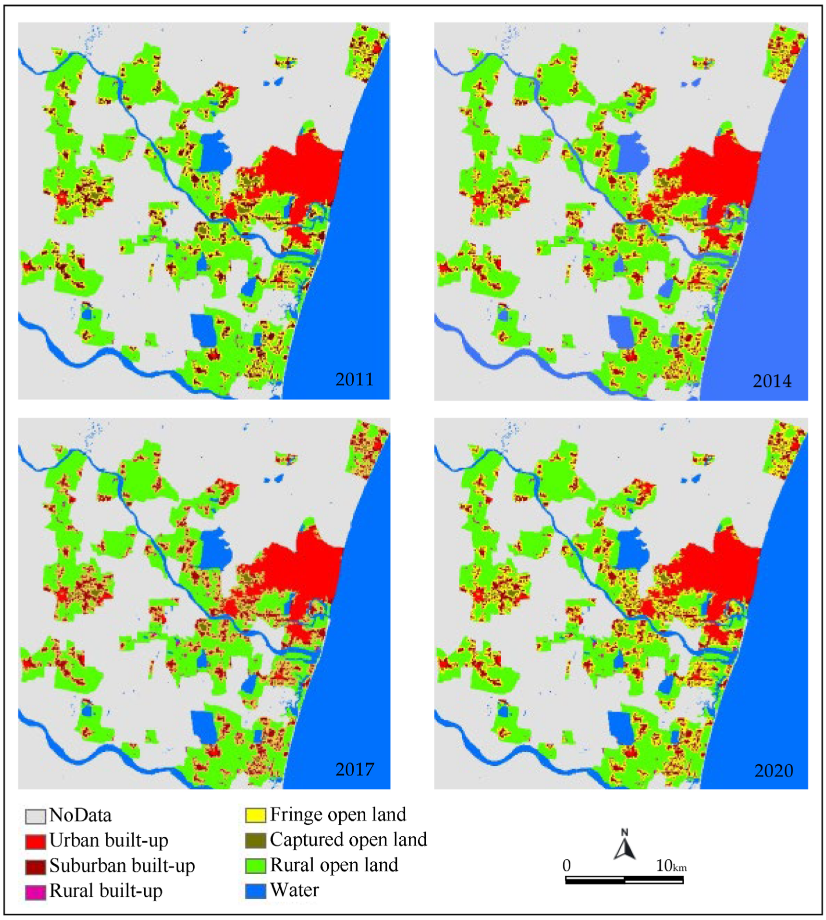

Figure 3. Built-up density levels and rural open land classes for 2011, 2014, 2017 and 2020.

Table 3. Urban growth in the seven spatial units from 2011 to 2020.

Spatial unit	Built-up in 2011 (ha)	Built-up in 2020 (ha)	Expansion 2011-2020 (ha)	Growth rate %
Ariyankuppam	475.96	542.07	66.11	13.89
Bahour	546.45	646.97	100.52	18.40
Mannadipet	777.50	861.96	84.46	10.86

Continued

Nettapakkam	390.41	442.79	52.39	13.42
Oulgaret	2217.08	2299.99	82.90	3.74
Puducherry	1205.24	1254.22	48.98	4.06
Villianur	1152.38	1358.27	205.90	17.87
Total	6765.02	7406.28	641.27	

Table 4. Urban areas and population statistics in 2011.

Spatial unit	Unit area (ha)	Urban area (ha)	Urban area (%)	Population (Nb)	Hab/urban area (Nb/ha)	Inhabitants and jobs (Nb)
Puducherry	1955.27	1205.24	61.64	244,377	202.64	330,829
Oulgaret	3456.73	2217.08	64.14	300,104	135.57	405,223
Villianur	6601.99	1152.38	17.46	126,778	110.06	162,759
Mannadipet	6688.18	777.50	11.62	81,575	105.03	97,713
Ariyankuppam	2439.19	475.96	19.51	72,055	151.42	93,645
Bahour	5510.51	546.45	9.92	68,757	125.77	80,709
Nettapakkam	3062.21	390.41	12.75	51,718	132.36	60,671

3.2. Urban Development Forms from 2011 to 2020

Figure 3 shows the urban footprint maps of 2011, 2014, 2017 and 2020 that are generated using ULAT program. Seven urbanized area categories are mapped: urban built-up, suburban built-up, rural built-up, fringe open land, captured open land, rural open land and waterbody. The analysis of different built-up density categories depicts a significant increase of both urban and suburban built-up areas over the study time period (Table 5). Actually, the urban built-up area ranged from 3647 ha in 2011 to 3912 ha in 2020. The highest increase (+99 ha) occurred between 2011 and 2014. Additionally, a constant increase of 82 ha is observed from 2014 to 2020. At the same time, the suburban built-up rate of increase is higher than the urban built-up growth rate. It, respectively, achieved 97 ha, 141 ha and 163 ha within the periods 2011-2014, 2014-2017 and 2017-2020. Conversely to that, rural built-up areas decreased from 2011 to 2020, and way more during 2017-2020. The highest decrease that occurred during this period accounts for −16 ha compared to −5 ha within 2014-2017 and −2 ha within 2011-2014. Furthermore, the fringe open land, where future expansion growth pixels can occur, also increased as built-up areas increased from 2011 to 2020. The fringe open land area varied from 5487 ha in 2011 to 6453 ha in 2020. However, the area of the captured open land category decreased by 42 ha during 2011-2017 while it significantly increased during 2017-2020. This increase attained 44 ha of available areas for hosting potential infill growth pixels.

Table 5. Areas of developed lands of distinct built-up density levels and rural open land classes.

Land cover classes	2011 (ha)	2014 (ha)	2017 (ha)	2020 (ha)
Urban built-up	3647.16	3746.56	3830.00	3912.21
Suburban built-up	2931.82	3028.79	3170.16	3333.10
Rural built-up	197.35	194.98	189.86	173.38
Fringe open land	5486.74	5710.90	6079.77	6452.96
Captured open land	220.23	190.10	178.02	221.96
Rural open land	15058.73	14670.76	14094.47	13449.96

The observed new development in different time periods from 2011 to 2020 is classified into three spatial forms of urban development: infill, expansion and Leapfrog (Table 6). The expansion form globally accounts for two thirds of the total observed new urban development whereas the leapfrog form accounts for, only, one third. In fact, the expansion development remains the dominant spatial form compared to the infill and leapfrog forms. Therefore, the majority of the captured new urban development built-up pixels is mainly in the fringe open land. Conversely, the share of the infill form in the total urban change remains minimal. Its maximum value, which is reached during the period 2011-2014, accounts for only 2.3% (4.4 ha) of the total observed urban growth (194.4 ha) during the same time period. In the last period 2017-2020, the share of the leapfrog form reached 37%. However, its value (around 25%) remained constant between 2011 and 2017.

Table 6. Spatial forms of new development in Puducherry district from 2011 to 2020.

Urban development form	2011-2014		2014-2017		2017-2020	
	Area (ha)	% of urban area	Area (ha)	% of urban area	Area (ha)	% of urban area
Infill	4.41	2.27	0.74	0.34	1.10	0.49
Expansion	140.36	72.38	164.77	75.06	142.45	62.64
Leapfrog	49.16	25.35	54.00	24.60	83.85	36.87

3.3. Urban Patterns between 2011 and 2020 Using Spatial Metrics

The analysis of the actual spatial growth patterns, which are measured at the entire study area scale using spatial metrics, shows a non-stationary dynamic. The physical expansion of built-up areas in the rural landscape resulted in significant changes in the spatial landscape patterns over the study period (Table 7). For example, Split, Aggregation, Contiguity, Clumpy, ENND-MN, and MPA metrics decreased from 2011 to 2020, while Mesh, Dispersion NP, PD, LP, LPI, and LSI increased. However, Contiguity, PAFRAC, Clumpy, Cohesion, and Aggregation metrics presented slightly small variations over the study period. Besides, the comparison between the three time periods reveals that the urban development process is not spatially homogeneous because significant differences in spatial patterns are observed over time. In fact, the amount of built-up area in 2017-2020 is higher compared to 2014-2017 and 2011-2014. The analysis of all metrics indicates that the highest significant changes in spatial patterns of built-up area occurred intensively during 2014-2017 followed by 2011-2014 then 2017-2020.

Table 7. Spatial metrics of built-up areas in Puducherry district for 2011, 2014, 2017 and 2020.

Metrics	Units	Range	2011	2014	2017	2020
Area (ha)	ha	Area > 0	7108.92	7311.19	7540.75	7777.99
Number of Patches (NP)	none	NP ≥ 1	713	805	1092	1149
Patch Density (PD)	Number per 100 ha	PD > 0	2.40	2.71	3.67	3.87
Largest Patch (LP)	ha	LP > 0	3692.36	3744.64	3834.69	3877.16
Largest Patch Index (LPI)	%	0 < LPI ≤ 100	12.43	12.61	12.91	13.05
Landscape shape Index (LSI)	none	LSI ≥ 1	31.89	33.42	36.32	38.65
Mean Patch Area (MPA)	ha	MPA > 0	9.5	8.66	6.58	6.46
Mean Nearest Neighbor Distance (ENND-MN)	m	ENND-MN > 0	68.16	64.71	55.70	53.95
Contiguity	none	0 ≤ CONTIG ≤ 1	0.58	0.56	0.49	0.50
Perimeter-Area Fractal Dimension (PAFRAC)	none	1 ≤ PAFRAC ≤ 2	1.31	1.31	1.31	1.32
Clumpy	%	−1 ≤ CLUMPY ≤ 1	0.93	0.92	0.92	0.91
Cohesion	none	0 < COHESION < 100	98.91	98.92	98.94	98.93
Splitting Index (Split)	none	1 ≤ SPLIT ≤ Number of cells in the landscape area squared	64.19	62.39	59.48	58.16
Effective Mesh Size (Mesh)	ha	Ratio of cell size to landscape area ≤ MESH ≤ Total landscape area	462.94	476.34	499.60	510.99
Aggregation (AI)	%	0 ≤ AI ≤100	94.36	94.16	93.74	93.43
Dispersion (DI)	none	0 ≤ DI ≤ 100	44.98	45.05	45.38	45.41

The number of urban patches has consistently increased between 2011 and 2020 leading to the increase in patch density and the decline in mean patch area. These results reveal a trend of continued fragmentation process of built-up area over time. Actually, the number of patches (NP) increased significantly from 713 in 2011 to 1149 in 2020. The highest increase in the number of patches (+287) took place during the period 2014-2017 followed by 2011-2014 (+92) whereas the lowest increase (+57) occurred between 2017 and 2020 (Figure 4, Table 7). Therefore, the patch density increased during the study period and exhibited the highest increase (+0.96) between 2014 and 2017. The area of the largest urban patch, which also increased between 2011 and 2020, presented a significant rise of more than 90 ha during 2014-2017, with 30 ha/year in average. Furthermore, the mean patch area (MPA) decreased from 9.5 ha in 2011 to 6.46 ha in 2020 due to the observed increase in built-up area as well as their number during the time period. In addition to that, there has been a slight *decline* in the mean distance (ENND-MN) which decreased from 68 m in 2011 to 54 m in 2020.

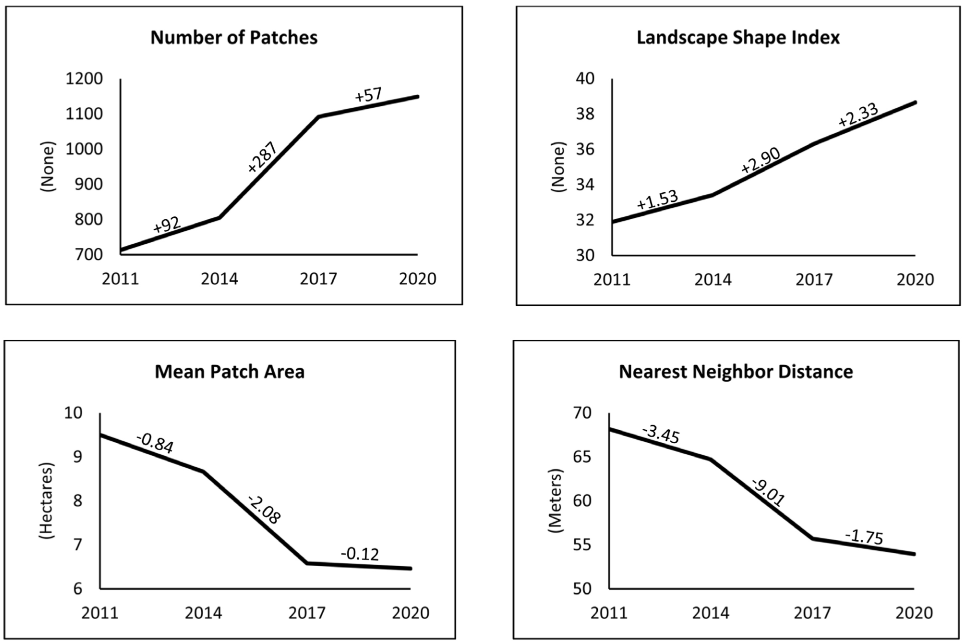

Figure 4. Temporal dynamic of spatial composition metrics for built-up areas from 2011 to 2020.

In terms of the shape complexity and the spatial configuration of built-up areas in the landscape, Dispersion and Mesh metrics increased, while Contiguity, Aggregation and Split decreased slightly over the last decade (Figure 5, Table 7). However, the values of PAFRAC are almost identical indicating that there has not been significant change in the shape of built-up area during the study time period. In fact, a value of 1.3 reveals an intermediary shape between shapes with very simple perimeters (PAFRAC = 1) and shapes with highly convoluted perimeters (PAFRAC = 2). Moreover, LSI increased slightly from 32 in 2011 to 39 in 2020. LSI, which equals 1 when the landscape consists of a single square patch, increases as landscape shape becomes more irregular. This index can also be interpreted as a measure of landscape disaggregation. In fact, the greater the value of LSI, the more dispersed is the patch type. Thus, the increase in the value of LSI between 2011 and 2020 indicates that built-up area in 2020 is more dispersed in comparison to 2011.

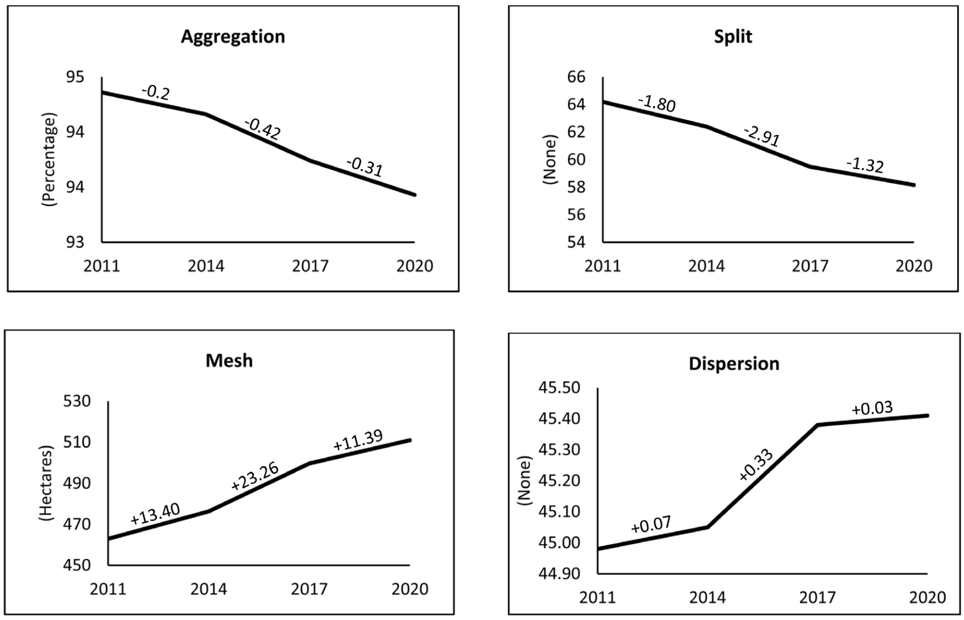

Figure 5. Temporal dynamic of spatial configuration metrics for built-up areas from 2011 to 2020.

3.4. Level of Urban Sprawl in 2011

Oulgaret and Puducherry presented the largest proportion of built-up area (PBA) in 2011 with a level exceeding 60% (**Table 8**). However, the proportion of built-up areas in the other reporting units varies from 10% to 20% of the total reporting unit area. For example, Bahour is still the least urbanized area in Puducherry district with a proportion of built-up area of 9.92%.

Table 8. WUP and its components calculated using USM toolset.

Spatial Unit	PBA (%)	DIS (UPU/m² of built-up)	UP (UPU/m² of landscape)	UD*	LUP**	WUP (UPU/m² of landscape)	WUP' (UPU/m² of landscape
Puducherry	61.64	48.15	29.71	27432.40	36.50	0.0001	0.0001
Oulgaret	64.14	47.76	30.59	18306.30	54.60	0.0327	0.0330
Villianur	17.46	45.55	7.95	14129.20	70.80	0.0968	0.1063
Mannadipet	11.62	43.91	5.10	12581.30	79.50	0.1408	0.1436
Ariyankuppam	19.51	45.24	8.83	19679.40	50.80	0.0035	0.0042
Bahour	9.92	44.14	4.38	14763.40	67.70	0.0329	0.0379
Nettapakkam	12.75	43.46	5.55	15527.40	64.40	0.0249	0.0257

* Number of inhabitants and jobs per km² of built-up area; ** m² of built-up per inhabitant or job; WUP': new WUP values after exclusion of areas unsuitable for development.

Figure 6 shows that the dispersion (DIS) values are broadly close to each other although the small differences that exist between the seven reporting units. For example, Puducherry has the largest dispersion of settled areas (48.15 UPU/m^2) followed by Oulgaret which accounts for 47.76 UPU/m^2. The spatial configuration of built-up areas in Nettapakkam (43.46 UPU/m^2), Mannadipet (43.91 UPU/m^2) and Bahour (44.14 UPU/m^2) is slightly more compact than in other areas that present high values of DIS. However, Bahour, which has less proportion of built-up area, exhibits more dispersion than Nettapakkam which is characterized by the lowest dispersion value.

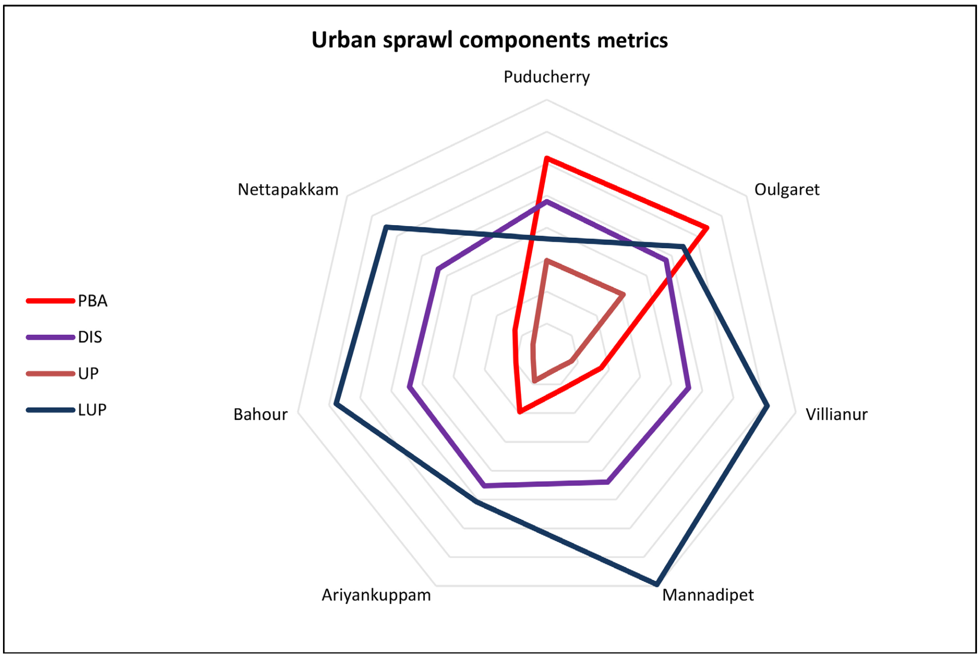

Figure 6. PBA, DIS, UP and LUP metrics in Puducherry district based on 2021 census data.

Urban permeation metric (UP), which is determined by both extent of urban area and its dispersion, is the highest (30 UPU/m^2) in Oulgaret and Puducherry municipalities compared to the other spatial entities of Puducherry district (Table 8). The UP values in Puducherry and Oulgaret are close to each other since the two municipalities present the same proportion of built-up area and same level of dispersion. Conversely, the lowest level of urban permeation in Puducherry district exists in Bahour (4.38 UPU/m^2), Mannadipet (5.10 UPU/m^2) and Nettapakkam (5.55 UPU/m^2) due to the low proportion of settlement area in these reporting units. For example, the UP in Oulgaret municipality is more than 7 times higher than in Bahour commune Panchayats.

The utilization density metric (UD) shows that built-up area in Puducherry municipality, which has more inhabitants and workplaces, is more intensively used than the other reporting units (Table 8). Density, which measures the number of people living or working in Puducherry municipality, accounts for 27,432 workplaces and inhabitants per km^2 of built-up area. Hence, Puducherry municipality has the lowest level of sprawl compared to the other communes and municipality that have a low utilization density. For example, Mannadipet has the lowest density of workplaces and inhabitants (12,581 per km^2 of built-up area).

The spatial distribution of land uptake per person (LUP) is illustrated in Figure 7. The visual analysis shows that land uptake per inhabitant or job varies considerably across the reporting units. In fact, three main groups can be identified. Oulgaret, Puducherry and Ariyankuppam have the lowest LUP followed by Bahour and Nettapakam, and then Vilianur and Mannadipet. The results indicate that the area of land used per inhabitant or workplace accounts for 36.50 m^2 in Puducherry which holds the lowest value. Conversely, high values of LUP reveal that more space is used per inhabitant or workplace, especially in Mannadipet, Villianur and Bahour. For instance, the amount of land uptake per person in Mannadipet commune (79.5%) is more than twice as in Puducherry municipality (36.5%).

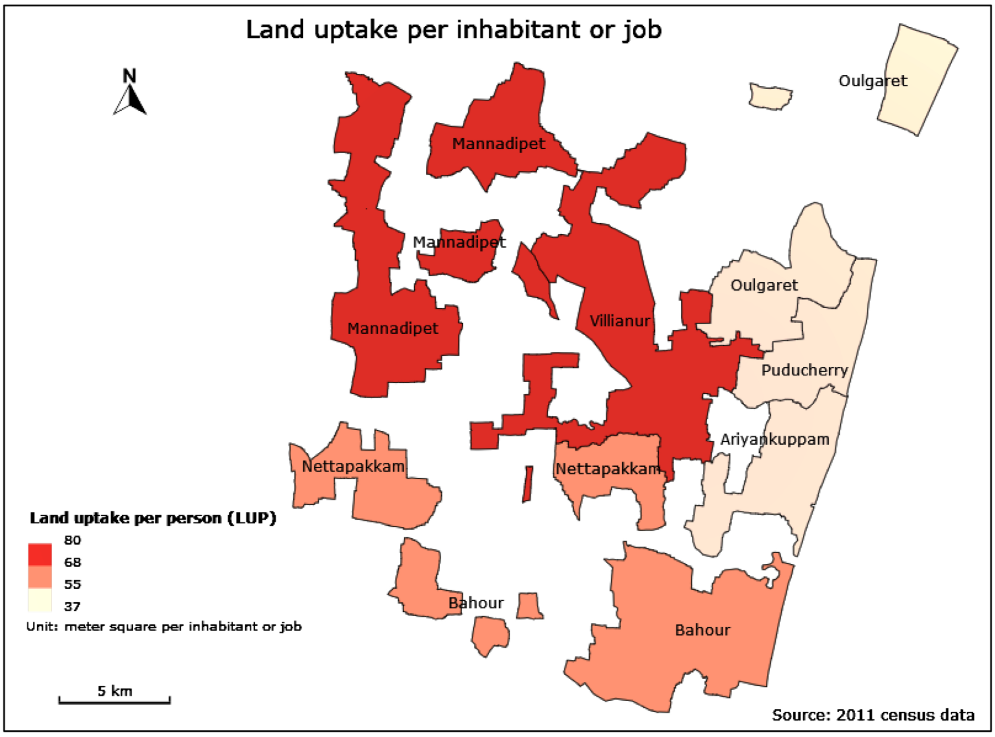

Figure 7. Spatial distribution of LUP metric in Puducherry district based on 2021 census data.

After excluding the area of waterbodies from the size of each reporting unit, the updated WUP values (WUP') are summarized in Table 8. Puducherry municipality yields the lowest value of urban sprawl (0.0001 UPU/m^2) followed by Ariyankuppam (0.0042 UPU/m^2) due to their high degree of utilization density (Table 6). Because of high workplaces and inhabitants, built-up area in Puducherry is more intensively used, hence less sprawled, than other areas with lower utilization density. For example, Oulgaret is more sprawled than Puducherry due to its relatively small number of population and labor force in its built-up area. However, the two municipalities present slightly the same level of PBA, DIS and UP. Conversely, the

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highest level of urban sprawl is observed in Mannadipet (0.1436 UPU/m^2) and Villianur (0.1063 UPU/m^2) because of their high land uptake per person compared to the other reporting units (Figure 8).

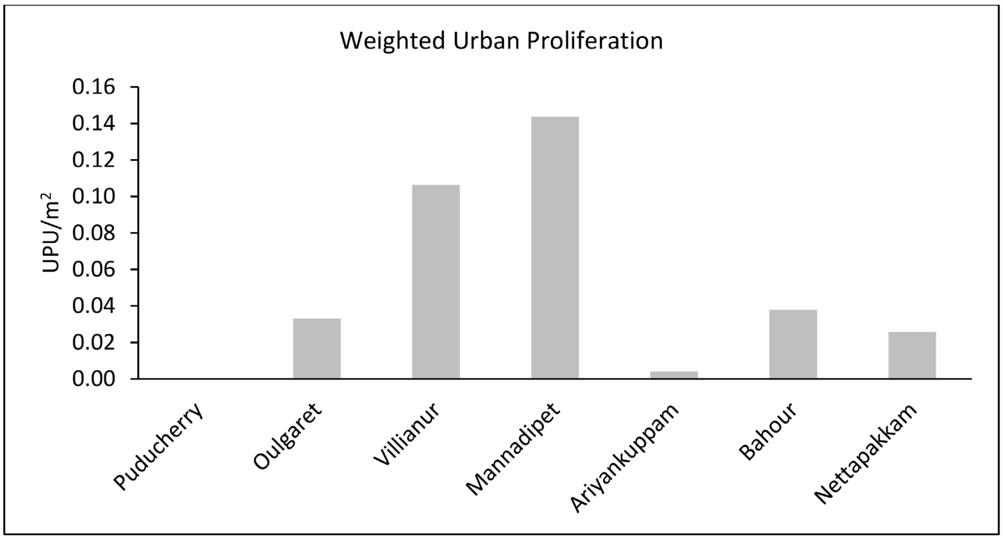

Figure 8. Degree of urban sprawl (WUP) in Puducherry district based on 2021 census data.

This early signs of sprawled development patterns can be referred to large industrial zones which are located in Villianur and Mannadipet. However, residential area is much high in Oulgaret and Puducherry which contains the highest share of commercial area. Moreover, the results highlight that Bahour and Oulgaret exhibit the same level of urban sprawl. In fact, their WUP values are close to each other even though PBA and UP are much higher and LUP slightly smaller in Oulgaret than in Bahour.

4. Discussion

4.1. Historic Development from 2011 to 2020

The maps of developed areas of 2011, 2014, 2017 and 2020 are accurately carried out using a manual digitization method of very high-resolution images available from the ESRI's World Imagery basemap in ArcGIS Online. Even though delineating urban built-up areas based on visual interpretation of historical Google Earth's images is a time-consuming process, it provides an alternative to deal with the problem of non-access to spatial information especially in data-poor contexts.

The results indicate that Puducherry district experienced a continuous increase in built-up during the last decade. Actually, built-up areas increased by 641 ha from 2011 to 2020, with an average annual growth of 71 ha/year. According to the urban expansion intensity index, Puducherry district experienced low speed urban growth with values ranging from 0.22 to 0.26. The urban growth rate accounted for 2.87, 3.15 and 3.17% during the periods 2011-2014, 2014-2017 and 2017-2020, respectively.

The results also show that Villianur reached the highest increase in built-up area between 2011 and 2020 (206 ha) followed by Bahour (100 ha), Mannadipet (84 ha) and Oulgaret (83 ha) whereas Puducherry had the least increase (49 ha) with an annual growth rate that accounts for somewhat more than 5 ha/year. Built-up area in 2011 covered 64% and 62% of the total area of Oulgaret and Puducherry municipalities, respectively. Furthermore, built-up area in 2020 covered 25% of the entire Puducherry district area which is still one of the highest urbanized territories in India. For instance, Puducherry district (297 km^2) is composed of 23% of built-up areas compared to Delhi (1483 km^2) where built-up areas occupied 44% in 2011 (Sharma & Joshi, 2013). According to the Indian census data in 2011 (Census of India, 2011), the National Capital Territory of Delhi was the most urbanized among all the states and union territories with 97.5% urban population followed by Chandigarh (97.25%), Daman (75.2%), Diu (75.2%) and Puducherry (68.3%).

Furthermore, the impervious surfaces are unevenly distributed over space. In fact, they are more concentrated on the east of the study area. Besides, the visual analysis shows that the urban development process has resulted in a large conurbation area including Puducherry and Oulgaret, a part of Villianur and a part of Ariyankuppam due to population growth, physical expansion of built-up areas and the influence of the two major transport corridors NH-45A and SH-203 towards Cuddalore and Villupuram. In fact, the development of the East Coast Road to Cuddalore via Ariyankuppam and the attractiveness of Cuddalore, which is considered as a major industrial town on the south of Puducherry region, have promoted the high urban growth rate in Ariyankuppam. Subsequently, they have reinforced the development of this urban conurbation zone towards the south-eastern side of Puducherry planning area.

The findings of the current study are in agreement with previous studies by showing the role and the capacity of spatial metrics in capturing urban growth patterns and processes (Thapa & Murayama, 2009; Aguilera et al., 2011; Aguejdad & Hubert-Moy, 2016; Taubenböck et al., 2018; Mandal et al., 2020). In fact, the results point out the opportunity of using a complementary approach. This perspective brings data together by combining remote sensing and census data collection. It also improves the analysis by using different urban growth tools and metrics. Actually, landscape structure of built-up area using spatial metrics (FRAGSTAT program), classification of urban development forms based on the degree of urbaneness and edge disturbance zone (ULAT), and urban sprawl measurement using the WUP method (USM toolset) are performed to better understand the spatial urban growth patterns and processes that have taken place in Puducherry district.

First, several commonly used spatial metrics are computed at the entire study area in order to capture the physical dimension of urban growth from 2011 to 2020. The analysis of all these metrics suggests that urban development, which follows a fragmentation process of built-up area, was increasing continuously even if significant differences are observed over time. The most significant changes in spatial urban pattern took place from 2014 to 2017. These spatial transformations increased the landscape fragmentation by creating new individual patches, increasing their total number, and decreasing their mean area.

Second, urban areas of density levels from 2011 to 2020 are classified based on urbaneness, edge disturbance zone, and proximity to development. The statistics show that the new development area, which occurred in Puducherry district from 2011 to 2020, consists of two main categories of urban development: expansion and leapfrog. The expansion and leapfrog patterns dominate the observed development process while the proportion of the infill pattern remains very low. In fact, the great part of the new development between 2011 and 2020 is attributed to the expansion pattern that accounted for 73% and 63% of the total development in the three study periods, respectively. Indeed, the highest increase (+165 ha) in built-up is due to the expansion pattern that accounts for 75% of the total new development that occurred from 2014 to 2017. Besides, the proportion of the leapfrog pattern increased from 49 ha during 2011-2014 to 84 ha during 2017-2020. From 2017 to 2020, the expansion pattern decreased to 63% while the leapfrog pattern increased to 37%. At last, the contribution from the infill pattern, which accounted for 2% of the new development between 2011 and 2014, declined to 0.3% and 0.5% in 2014-2017 and 2017-2020, respectively.

Third, the analysis of the spatial metrics indicates that Puducherry district particularly experienced an accelerated process of fragmentation of built-up area from 2014 to 2017. This result is summarized in **Table 7** and clearly illustrated in **Figure 4** and **Figure 5**. However, the analysis of new development forms using ULAT reveals that the expansion pattern, which corresponds to built-up pixels in the fringe open land of the previous time period, prevailed during the same period since it reached more than 75% of the total new development. The comparison between these two different findings suggests that such expansion form does not correspond to an edge-growth pattern since the number of urban patches during this period increased from 805 in 2014 to 1092 in 2017. The observed fragmentation process using FRAGSTAT is captured as an expansion pattern by ULAT. This can be explained by the criteria of proximity and density threshold that are used to generate urban density classes of built-up areas based on urbaneness and edge disturbance zone (Sharma & Joshi, 2013). Moreover, the observed process of fragmentation, which occurred in the vicinity of the existing built-up areas in 2014 without creating new urban areas close to them, could be followed by an aggregation process. Actually, the aggregation process clusters individual patches through forming patches of a larger size and reducing their total number in the landscape.

At last, the degree of urban sprawl is measured using the WUP method which has already been applied to Montreal, Quebec and Zurich cities (Nazarnia et al., 2016). Overall, the application of the WUP method to Puducherry district area indicates that the level of urban sprawl was very low in 2011. Nevertheless, these first findings show that early signs of sprawling process are observed in Mannadipet (0.14 UPU/m^2) and Villianur (0.11 UPU/m^2) compared to the other reporting units which yield lower values, especially in Puducherry municipality (0.0001

UPU/m^2) where the built-up area has been intensively used.

Accordingly, further studies should be performed in order to complement the current analysis. For example, it is recommended that the same urban sprawl analysis be carried out on the basis of the 2021 census data, which is not yet available due to the Covid-19 pandemic. In addition to that, it would be interesting to carry out the spatiotemporal urban growth dynamics prior to 2011 based on available Landsat time series images and census data. Such retrospective analysis allows determining the spatial dynamics of urban sprawl process over time. Moreover, more detailed studies are needed in order to better capture local and specific changes in the spatial configuration of built-up areas along specific urban-rural transects, in the fringe of main growth centers and in the vicinity of highways and other main transportation arteries (Luck & Wu, 2002; Aguilera et al., 2011). For example, further analysis of spatial patterns and directional changes at the local scale can be carried out by combining an urbanization gradient and concentric rings analysis with landscape metrics (Luck & Wu, 2002; Mandal et al., 2020). The forecast outcomes are expected to generate a better understanding of the relationship between urban growth dynamics, urban morphology, microclimate, and ecological and socioeconomic processes.

4.2. Limits and Advantages of WUP

Several limitations related to the application of the WUP method need to be considered. One of these limitations is that both WUP and UP depend on the size of the entire reporting unit which may include areas of land where it is impossible to build (Jaeger & Schwick, 2014). In this specific case, values of WUP and UP are correspondingly low since the study area contains a large quantity of excluded areas from urbanization (waterbodies, cliffs, steep slopes, protected areas…). After the adjustment, the new values of WUP and UP are obtained by dividing the current values by the real proportion of land that can be settled. The biggest modification concerns the WUP values associated with Villianur and Bahour communes. The observed difference is attributed to the presence of Bahour and Oussudu waterbodies that slightly affect the proportion of land that can be settled. These waterbodies, which are the largest lakes in Puducherry district, account for 13% and 9% of the total reporting unit area, respectively.

Another limitation of the WUP method refers to the change in the size of the study area over time. In contrast to WUP and UP, which are study area dependent metrics, DIS and UD do not change because they refer to the settlement area and not to the size of the entire study area. Therefore, monitoring and comparing temporal changes in urban sprawl dynamics are only possible when the size of the reporting units is unchangeable over time. Hence, such constraint can limit the application of the WUP metric to the reporting units that could change in their spatial size over time.

Besides, the current study highlights an important research question related to the interpretation of WUP values then consequently the corresponding categories of sprawl level that can be distinguished. This issue requires more clarification of the way to interpret the ranges and thresholds of WUP values while qualifying a given urban expansion as a sprawl pattern. For instance, different ranges and categories of sprawl level are already applied to the European context through distinguishing between the country and the Nomenclature of Territorial Units for Statistics (NUTS) levels (EEA, 2016). NUTS level corresponds to regions, provinces, states or prefectures. Therefore, further research needs to examine more closely the characterization of urban sprawl categories based on the interpretation of WUP values. For example, comparative studies in other contexts can be conducted to explore the impact of geographic context on the interpretation of WUP values. Otherwise, any misinterpretation of WUP values leads to inconsistent results especially in comparing findings from different case studies and contexts.

In spite of all these limits, WUP has several practical applications. Actually, it makes the study more objective by providing quantitative measurements of the degree of urban sprawl of a given built-up area. In addition to that, it can be fulfilled by few datasets (Nazarnia et al., 2016). In fact, computing the WUP metric and its components requires a binary map of built-up areas and a reporting units map which must include information related to inhabitants and jobs. Moreover, the WUP metric can be applied using any reporting unit at any spatial scale (Nazarnia et al., 2016). Among a variety of deployed approaches and interpretations of urban sprawl, WUP has also the advantage of combining three intuitive and complementary criteria related to the proportion of built-up area, its spatial configuration in the landscape, and the utilization intensity (Jaeger & Schwick, 2014). However, the application of the WUP method requires a temporal match between land cover maps and census data. As a result, the lack of data will lead to failure in regular spatiotemporal monitoring of urban sprawl dynamic using the WUP method.

The WUP method is a valuable instrument that can be used in conducting territorial diagnostics or future scenarios studies. The WUP tool determines the urban sprawl criteria that could be improved in order to control and mitigate urban sprawl. In fact, it evaluates the effectiveness of urban planning policies through the analysis of past urban development, the sustainability assessment of projected development scenarios, the definition of new regulations, and the identification of areas with high urban sprawl risk (Nazarnia et al., 2016). In addition to that, WUP can be used to understand how spatiotemporal changes in urban growth pattern interact with social and environmental processes. For example, the relationship between spatial characteristics of urban sprawl and its negative consequences related to urban heat island and pollution can be investigated using the WUP metric and its components.

5. Conclusion

The present work aims to discuss the importance of combining remote sensing inputs, census data and spatial metrics in capturing and understanding the physical dimension of spatial patterns and processes of urban growth and sprawl at the scale of Puducherry district from 2011 to 2020. Actually, four LULC maps of 2011, 2014, 2017 and 2020 are prepared using image interpretation of very high-resolution remote sensing images. From 2011 to 2020, built-up area increased continuously by 641 ha with an average annual growth of 71 ha/year. According to the urban expansion intensity index, Puducherry district experienced minimal urban growth intensity between 2011 and 2020. Besides, the results show that Puducherry district is highly urbanized. In fact, built-up area, which is mainly concentrated in the east, reached 25% of the total study area in 2020. Moreover, the observed development was taking place along the main roadways, almost in all directions that connect Puducherry planning area to Villupuram, Cuddalore, Tindivanam and Chennai. Consequently, the urban development process has resulted in a large conurbation area that includes Puducherry, Oulgaret, a part of Villianur, and a part of Ariyankuppam.

The patterns and processes of the observed new development that occurred from 2011 to 2020 are analyzed using the ULAT and FRGASTAT computer software programs based on four LULC maps. Spatial metrics are calculated for three time periods between 2011 and 2020. The results indicate that the captured new development was mainly due to the expansion and leapfrog patterns which account for an average of 70% and 29% of the total observed development, respectively. Conversely, the proportion of the infill development presented an average of only 1% of the total development from 2011 to 2020. On the one hand, the analysis of the urbanized areas and urban footprint maps shows a positive trend of urban built-up, suburban built-up, fringe open land. On the other hand, it shows a negative trend of rural built-up and rural open land. Furthermore, the analysis of the spatial metrics values illustrates a continuous fragmentation process of the built-up area over the study time span. Puducherry district experienced significant changes in the spatial structure of urban development due to an accelerated fragmentation process of built-up areas between 2014 and 2017.

The degree of urban sprawl at the level of the municipalities and commune Panchayats of Puducherry planning area is explored using the WUP method based on built-up area and census data inputs. The results reveal that the degree of urban sprawl in 2011 was very low, especially in Puducherry municipality (0.0001 UPU/m^2) where built-up areas were intensively used. They also provide an indication that can help identify potential areas most vulnerable to the risk of urban sprawl such as Mannadipet (0.14 UPU/m^2) and Villianur (0.11 UPU/m^2). In relation to that, additional studies using more historical data would be useful to assess the significance of the current WUP results. However, regular monitoring of urban sprawl using the WUP metric depends primarily on the availability of census data.

This study can help the city decision-makers to improve the urban expansion governance and meet the complex challenges facing the territories. Useful results and input data will serve as a base for future studies including the evaluation of the effectiveness of past urban planning policies and the simulation of future urban development scenarios. The findings of the present paper demonstrate that combining different spatial metrics and complementary urban expansion tools is useful in capturing and monitoring the spatial patterns and processes of urban growth. At the same time, this research raises many questions that require further investigations in order to complement the current results. Actually, a comprehensive analysis of urban land development dynamic should be conducted by considering more census data, land use and land cover, transportation, climate, socio-economic and environmental dimensions.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Aguejdad, R. (2021). The Influence of the Calibration Interval on Simulating Non-Stationary Urban Growth Dynamic Using Ca-Markov Model. *Remote Sensing, 13,* Article 468. https://doi.org/10.3390/rs13030468

Aguejdad, R., & Hubert-Moy, L. (2016). Suivi de l'artificialisation du territoire en milieu urbain par télédétection et à l'aide de métriques paysagères. Application à une agglomération de taille moyenne, Rennes Métropole. *Cybergeo*. https://doi.org/10.4000/cybergeo.27465

Aguejdad, R., Houet, T., & Hubert-Moy, L. (2017). Spatial Validation of Land Use Change Models Using Multiple Assessment Techniques: A Case Study of Transition Potential Models. *Environmental Modeling & Assessment, 22,* 591-606. https://doi.org/10.1007/s10666-017-9564-4

Aguilera, F., Valenzuela, L. M., & Botequilha-Leitão, A. (2011). Landscape Metrics in the Analysis of Urban Land Use Patterns: A Case Study in a Spanish Metropolitan Area. *Landscape and Urban Planning, 99,* 226-238. https://doi.org/10.1016/j.landurbplan.2010.10.004

Al Mashagbah, A. F. (2016). The Use of GIS, Remote Sensing and Shannon's Entropy Statistical Techniques to Analyze and Monitor the Spatial and Temporal Patterns of Urbanization and Sprawl in Zarqa City, Jordan. *Journal of Geographic Information System, 8,* 293-300. https://doi.org/10.4236/jgis.2016.82025

Alam, I., Nahar, K., & Morshed, M. M. (2023). Measuring Urban Expansion Pattern Using Spatial Matrices in Khulna City, Bangladesh. *Heliyon, 9,* e13193. https://doi.org/10.1016/j.heliyon.2023.e13193

Ali, A., Khalid, A., Butt, M. A., Mehmood, R., Mahmood, S. A., Sami, J. et al. (2018). Towards a Remote Sensing and GIS-Based Technique to Study Population and Urban Growth: A Case Study of Multan. *Advances in Remote Sensing, 7,* 245-258. https://doi.org/10.4236/ars.2018.73017

Angel, S., Parent, J., & Civco, D. (2007). *Urban Sprawl Metrics: An Analysis of Global Urban Expansion Using GIS*. https://www.asprs.org/wp-content/uploads/2011/01/0003.pdf

Angel, S., Parent, J., & Civco, D. L. (2012). The Fragmentation of Urban Landscapes: Global Evidence of a Key Attribute of the Spatial Structure of Cities, 1990-2000. *Environment and Urbanization, 24,* 249-283. https://doi.org/10.1177/0956247811433536

Antrop, M. (2004). Landscape Change and the Urbanization Process in Europe. *Landscape* *and Urban Planning, 67,* 9-26. https://doi.org/10.1016/s0169-2046(03)00026-4

CDP (2019). *Comprehensive Development Plan for Puducherry Planning Area—2036. Puducherry Planning Authority, Final Report.* https://ppa.py.gov.in/comprehensive-development-plan

Census of India (2011). https://censusindia.gov.in/census.website/

Chu, Z., Yang, X., Feng, X., Fan, D., Li, Y., Shen, X. et al. (2013). Temporal and Spatial Changes in Coastline Movement of the Yangtze Delta during 1974–2010. *Journal of Asian Earth Sciences, 66,* 166-174. https://doi.org/10.1016/j.jseaes.2013.01.002

Croci, S., Butet, A., Georges, A., Aguejdad, R., & Clergeau, P. (2008). Small Urban Woodlands as Biodiversity Conservation Hot-Spot: A Multi-Taxon Approach. *Landscape Ecology, 23,* 1171-1186. https://doi.org/10.1007/s10980-008-9257-0

EEA (2016). *Urban Sprawl in Europe. Brochure No 11/2016.* European Environment Agency.

Estoque, R. C., & Murayama, Y. (2015). Intensity and Spatial Pattern of Urban Land Changes in the Megacities of Southeast Asia. *Land Use Policy, 48,* 213-222. https://doi.org/10.1016/j.landusepol.2015.05.017

Gerten, C., Fina, S., & Rusche, K. (2019). The Sprawling Planet: Simplifying the Measurement of Global Urbanization Trends. *Frontiers in Environmental Science, 7,* Article 140. https://doi.org/10.3389/fenvs.2019.00140

Hassan, M. I., & Elhassan, S. M. M. (2020). Modelling of Urban Growth and Planning: A Critical Review. *Journal of Building Construction and Planning Research, 8,* 245-262. https://doi.org/10.4236/jbcpr.2020.84016

Herold, M., Couclelis, H., & Clarke, K. C. (2005). The Role of Spatial Metrics in the Analysis and Modeling of Urban Land Use Change. *Computers, Environment and Urban Systems, 29,* 369-399. https://doi.org/10.1016/j.compenvurbsys.2003.12.001

Herold, M., Goldstein, N. C., & Clarke, K. C. (2003). The Spatiotemporal Form of Urban Growth: Measurement, Analysis and Modeling. *Remote Sensing of Environment, 86,* 286-302. https://doi.org/10.1016/s0034-4257(03)00075-0

Herold, M., Scepan, J., & Clarke, K. C. (2002). The Use of Remote Sensing and Landscape Metrics to Describe Structures and Changes in Urban Land Uses. *Environment and Planning A: Economy and Space, 34,* 1443-1458. https://doi.org/10.1068/a3496

Houet, T., Marchadier, C., Bretagne, G., Moine, M. P., Aguejdad, R., Viguié, V. et al. (2016). Combining Narratives and Modelling Approaches to Simulate Fine Scale and Long-Term Urban Growth Scenarios for Climate Adaptation. *Environmental Modelling & Software, 86,* 1-13. https://doi.org/10.1016/j.envsoft.2016.09.010

Hu, Z. L., Du, P. J., & Guo, D. Z. (2007). Analysis of Urban Expansion and Driving Forces in Xuzhou City Based on Remote Sensing. *Journal of China University of Mining and Technology, 17,* 267-271.

Jaeger, J. A. G., & Schwick, C. (2014). Improving the Measurement of Urban Sprawl: Weighted Urban Proliferation (WUP) and Its Application to Switzerland. *Ecological Indicators, 38,* 294-308. https://doi.org/10.1016/j.ecolind.2013.11.022

Jaeger, J. A. G., Bertiller, R., Schwick, C., Cavens, D., & Kienast, F. (2010). Urban Permeation of Landscapes and Sprawl per Capita: New Measures of Urban Sprawl. *Ecological Indicators, 10,* 427-441. https://doi.org/10.1016/j.ecolind.2009.07.010

Jason, R. P. (2009). *Urban Landscape Analysis Tool. Center for Land Use Education & Research (CLEAR).* https://clear.uconn.edu/tools/ugat/index.htm

John, J., Bindu, G., Srimuruganandam, B., Wadhwa, A., & Rajan, P. (2020). Land Use/Land

Cover and Land Surface Temperature Analysis in Wayanad District, India, Using Satellite Imagery. *Annals of GIS, 26,* 343-360.
https://doi.org/10.1080/19475683.2020.1733662

Joshi, P. K., Bairawa, B. M., Sharma, R., & Sinha, V. S. P. (2011). Assessing Urbanization Patterns over India Using Temporal DMSP–OLS Night-Time Satellite Data. *Current Science, 100,* 1479-1482.

Kagabu, M., Shimada, J., Delinom, R., Tsujimura, M., & Taniguchi, M. (2011). Groundwater Flow System under a Rapidly Urbanizing Coastal City as Determined by Hydrogeochemistry. *Journal of Asian Earth Sciences, 40,* 226-239.
https://doi.org/10.1016/j.jseaes.2010.07.012

Kohler, M., Tannier, C., Blond, N., Aguejdad, R., & Clappier, A. (2017). Impacts of Several Urban-Sprawl Countermeasures on Building (Space Heating) Energy Demands and Urban Heat Island Intensities. A Case Study. *Urban Climate, 19,* 92-121.
https://doi.org/10.1016/j.uclim.2016.12.006

Kotharkar, R., Bahadure, P., & Sarda, N. (2014). Measuring Compact Urban Form: A Case of Nagpur City, India. *Sustainability, 6,* 4246-4272. https://doi.org/10.3390/su6074246

Liu, X., Li, X., Chen, Y., Tan, Z., Li, S., & Ai, B. (2010). A New Landscape Index for Quantifying Urban Expansion Using Multi-Temporal Remotely Sensed Data. *Landscape Ecology, 25,* 671-682. https://doi.org/10.1007/s10980-010-9454-5

Luck, M., & Wu, J. (2002). A Gradient Analysis of the Landscape Pattern of Urbanization in the Phoenix Metropolitan Area of USA. *Landscape Ecology, 17,* 327-339.
https://doi.org/10.1023/a:1020512723753

Mandal, S., Kundu, S., Haldar, S., Bhattacharya, S., & Paul, S. (2020). Monitoring and Measuring the Urban Forms Using Spatial Metrics of Howrah City, India. *Remote Sensing of Land, 4,* 19-39. https://doi.org/10.21523/gcj1.20040103

Masson, V., Marchadier, C., Adolphe, L., Aguejdad, R., Avner, P., Bonhomme, M. et al. (2014). Adapting Cities to Climate Change: A Systemic Modelling Approach. *Urban Climate, 10,* 407-429. https://doi.org/10.1016/j.uclim.2014.03.004

McGarigal, K., Cushman, S. A., Neel, M. C., & Ene, E. (2002). *FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps, Computer Software Program Produced by the Authors at the University of Massachusetts, Amherst.*

Nazarnia, N., Schwick, C., & Jaeger, J. A. G. (2016). Accelerated Urban Sprawl in Montreal, Quebec City, and Zurich: Investigating the Differences Using Time Series 1951-2011. *Ecological Indicators, 60,* 1229-1251. https://doi.org/10.1016/j.ecolind.2015.09.020

O'Neill, R. V., Krummel, J. R., Gardner, R. H., Sugihara, G., Jackson, B., DeAngelis, D. L. et al. (1988). Indices of Landscape Pattern. *Landscape Ecology, 1,* 153-162.
https://doi.org/10.1007/bf00162741

Owen, T. W., Carlson, T. N., & Gillies, R. R. (1998). An Assessment of Satellite Remotely-Sensed Land Cover Parameters in Quantitatively Describing the Climatic Effect of Urbanization. *International Journal of Remote Sensing, 19,* 1663-1681.
https://doi.org/10.1080/014311698215171

Parent, J., Civco, D., & Angel, S. (2009). *Measuring Spatial Patterns and Trends in Urban Development.* https://clear.uconn.edu/tools/ugat/index.htm

Pellissier, V., Rozé, F., Aguejdad, R., Quénol, H., & Clergeau, P. (2008). Relationships between Soil Seed Bank, Vegetation and Soil Fertility along an Urbanisation Gradient. *Applied Vegetation Science, 11,* 325-334. https://doi.org/10.3170/2008-7-18448

Ren, P., Gan, S., Yuan, X., Zong, H., & Xie, X. (2013). Spatial Expansion and Sprawl Quantitative Analysis of Mountain City Built-Up Area. In *Communications in Computer and*

Information Science (pp. 166-176). Springer. https://doi.org/10.1007/978-3-642-45025-9_19

Salvati, L., Zambon, I., Chelli, F. M., & Serra, P. (2018). Do Spatial Patterns of Urbanization and Land Consumption Reflect Different Socioeconomic Contexts in Europe? *Science of the Total Environment, 625,* 722-730. https://doi.org/10.1016/j.scitotenv.2017.12.341

Seto, K. C., & Fragkias, M. (2005). Quantifying Spatiotemporal Patterns of Urban Land-Use Change in Four Cities of China with Time Series Landscape Metrics. *Landscape Ecology, 20,* 871-888. https://doi.org/10.1007/s10980-005-5238-8

Sharma, R., & Joshi, P. K. (2013). Monitoring Urban Landscape Dynamics over Delhi (India) Using Remote Sensing (1998–2011) Inputs. *Journal of the Indian Society of Remote Sensing, 41,* 641-650. https://doi.org/10.1007/s12524-012-0248-x

Solon, J. (2009). Spatial Context of Urbanization: Landscape Pattern and Changes between 1950 and 1990 in the Warsaw Metropolitan Area, Poland. *Landscape and Urban Planning, 93,* 250-261. https://doi.org/10.1016/j.landurbplan.2009.07.012

Sudhira, H. S., Ramachandra, T. V., & Jagadish, K. S. (2004). Urban Sprawl: Metrics, Dynamics and Modelling Using GIS. *International Journal of Applied Earth Observation and Geoinformation, 5,* 29-39. https://doi.org/10.1016/j.jag.2003.08.002

Taubenböck, H., Wurm, M., Geiß, C., Dech, S., & Siedentop, S. (2018). Urbanization between Compactness and Dispersion: Designing a Spatial Model for Measuring 2D Binary Settlement Landscape Configurations. *International Journal of Digital Earth, 12,* 679-698. https://doi.org/10.1080/17538947.2018.1474957

Thapa, R. B., & Murayama, Y. (2009). Examining Spatiotemporal Urbanization Patterns in Kathmandu Valley, Nepal: Remote Sensing and Spatial Metrics Approaches. *Remote Sensing, 1,* 534-556. https://doi.org/10.3390/rs1030534

UN (2019). *World Urbanization Prospects. The 2018 Revision. Department of Economic and Social Affairs, Population Division*.

Xiao, J., Shen, Y., Ge, J., Tateishi, R., Tang, C., Liang, Y. et al. (2006). Evaluating Urban Expansion and Land Use Change in Shijiazhuang, China, by Using GIS and Remote Sensing. *Landscape and Urban Planning, 75,* 69-80. https://doi.org/10.1016/j.landurbplan.2004.12.005