UNDERSTANDING THE BUILT-UP EVOLUTION AND COMPLEXITY OF FAST-GROWING BUILT-UP AGGLOMERATION USING THE CENTROID SHIFT MODEL AND FRACTAL DIMENSION

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ABSTRACT

Understanding Built-up evolution and complexity over time is attained to exercise sustainable development and smart implementations in the future. The Spatiotemporal evolution of built-up analysis is carried out using the centroid shift model considering the geometry of the built-up from 1975 to 2019 (1975, 1990, 1999, 2009, and 2019). The centroid shift indicates the trajectory of the growth pattern and the future direction of growth. The study area experienced a unidirectional growth pattern till 2009, considering 1975 as the base year, and by 2019 the growth direction shifted by 3.52 degrees, and the overall centroid shift magnitude was 2.42 km^2. The non-Euclidean geometric nature of the physical world puts forward fractal geometry to understand the complexity of built-up. The mean fractal dimension index shows the growth type in the study area; a directional approach towards the mean fractal dimension provides a critical understanding of the complexity around the built-up Centroid. Among all the eight directions considered, NW_W showed maximum built-up growth with infilling growth type, and the E_SE direction showed a significant jump in an area with external expansion by 2019. This direction indicates the future growth direction. The study concludes that complexity analysis critically enhances the spatiotemporal dynamics of built-up evolution.

1. INTRODUCTION

1.1 Background

Since the Anthropocene Era, Earth's Land Cover has transformed into Land Use unprecedentedly. Currently, 20% of the terrestrial land surface is built-up, and this occupancy is not uniform; it varies from biome to biome. Cold landscapes have experienced fewer human interventions compared to tropical and temperate landscapes. This drastic transformation has led to devasting anthropogenic climate changes, natural resource depletion, and ecosystem imbalance. The factors influencing the transition from Natural Landscape to the built-up landscape are the availability of Natural resources, transportation and communication, industrialization and commercialization, educational and recreational, and economic pull. To curb the actions of humans above biological processes, understanding and quantifying the present built-up landscape is needed, which mitigates the climate crisis and supports biodiversity if managed effectively. A quantitative understanding of the existing built-up and its evolution is complex as the stated factors' influence on built-up growth varies from place to place and over time. But to attain qualitative measures for sustainable planning and scope for future development, understanding the level of complexity and existing development constraints is required.

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1.2 Literature Studies

Mid-19th Century built-up studies gained importance in the research field (Longley, 2005). Built-up is a terrestrial landscape where human beings interact. As per the United States Geological Survey, Level one scheme of land classification, Urban, Rural, Industrial, commercial, transportation, and other impervious surfaces are categorized as built-ups (Anderson et al., 1976). Sometimes these built-ups are called Urban (National Remote Sensing Centre, India backs this definition). R.LeGates (2001) noted the core twelve domains of Built-up studies. Namely, the evolution of cities; urban culture; urban society; urban politics and governance; urban economics, public finance, and regional science; urban and metropolitan space and form; megacities and global city systems; technology and cities; urban planning, urban design, landscape architecture, and architecture; race, ethnicity, and gender in cities; urban issues and policy; and urban futurism. The domains' evolution of built-up and urban and metropolitan space and form is the scope of our study.

In built-up studies, the topo sheets and past cadastral maps serve as the study documents. These records are updated timely through the survey. But, in inaccessible or remote areas, information update is time-consuming and tedious, hence limiting the studies on the evolution of built-up growth temporally in a particular landscape (Roy et al., 2015). It would have been challenging, if not impossible, to examine the Land Cover (LC) patterns at a regional and global scale without the readily available and free satellite imageries. Remote Sensing has been a useful aid in studying the patterns of LC with a decreased cost and less effort. Various global LC data have been produced over the years, such as GLC2000, MCD12, and GLCNMO, GlobCover, IGBP DISCover, MODIS Collection 5 global land cover, Global Land Surface Satellite Global Land Cover (GLASS-GLC), Global Human Settlement Layer, GLC30, GLC10, ESA CCI Land Cover time-series, ESRI 10 m, etc. (Aman et al., 2021).

The foundation of LC is image classification, wherein we give LC classes to a multiband raster image. Pixel-wise classification, sub-pixel-wise classification, and object-based image classification are the three main categories of image classification in remote Sensing. According to the spectral signature and its derivatives, such as vegetation indices, pixel-wise classification categorizes each pixel as pure and assigns it to a specific land use-LC type. This classification is further separated into unsupervised and supervised classification (Li et al., 2014). Numerous research studies have employed unsupervised categorization based on building clusters and assigning classes.

On the other hand, supervised classification uses samples as training data and classifies using them. Land Use Land Cover classification algorithms like Maximum likelihood, Isodata, Artificial Neural Networks, Support Vector Machines, and most advanced algorithms like Convolution Neural Networks, deep learning algorithms, Decision Trees, etc., are used in the preparation of Land Use Land Cover data sets for various spectral and spatial resolution data. Mainly, freely available Landsat data of 30m resolution is widely used to prepare the LULC maps for understanding the built-up growth and dynamics. LULC data products provide information on regions' past and present built-up landscapes. Tracking the movement of the center of change of a particular LC through time is just as important as analysing the current situation of that LC. The varieties of regional land use have seen substantial changes recently due to expanding urbanization. Because of this, they understand the area's development, and providing references for resource management and territorial planning can be accomplished by the study of the central displacement of LC. A change in the Center of Gravity (CoG) of the specific LC class has been researched for this purpose. The geometric center of the LC class is the CoG in terms of space. The CoG model, called the Centroid shift model, helps explain regional shifts along the development axes. (Shi et al., 2015) and (Xiong et al. 2019) studied the built-up growth using the spatial centroid shift method. They also assessed the environmental impact because of built-up evolution over time.

The elemental quantification of Spatio-temporal dynamics is carried out by estimating the landscape growth area. The landscape analysis is categorized into structural, functional, and change characteristics. Landscape structure deals with the spatial relationships among the distinctive ecosystems or elements; Landscape function is the interaction among the spatial features. Landscape change focuses on altering the structure and function of ecological mosaics over time. The landscape structure and complexity measures are carried out using various landscape matrices. These matrices are area/density/edge matrices, shape matrices, core area matrices, isolation/proximity matrices, connectivity matrices, evenness metrics, dominance matrices, and diversity matrices. Among these matrices, the shape matrices deal with the landscape's geometry (Gkyer, 2013). One majorly used shape index is the fractal dimension indices, derived from fractal geometry. Fractal geometry is put forward as the Physical world structures are complex polygons that do not represent any geometric shape of Euclidean (Circle, triangle, etc.); these polygons are measured using fractals. Fractals are complex, hierarchically ordered structures revealing self-similarity across scales (Batty & Longley, 1994). FRAGSTATS interface (MacGarigal, 1995) has a mean fractal dimension index ranging from 1 to 2 in a two-dimensional plane. These values define the complexity of the built-up areas. (1994) presented that fractals depend on the scale and vary from one scale to another. (Ramachandra et al., 2012) (Chen, 2020) studied the fractal dimensions of an urban morphology to understand its structure and ecological functioning.

From past studies, the understanding of evolution is drawn majorly through quantifying the area and its change over time. The studies on the Centroid shift model and the knowledge of geometric complexity are limited. Hence, the study investigates the built-up evolution of a fast-growing city agglomeration using the Euclidean Centroid shift model and the fractal geometry's complexity analysis. The study attempts to understand the built-up's directional complexity, considering the geometric Centroid as the origin over time.

2. STUDY AREA AND DATA

2.1 Study Area

Districts are subdivided into Tehsils as per the Government of India. This study adopted Vasai Tehsil (433 Km^2), located at 19.3919° N, 72.8397° E of Thane District (Thane District is one of the three major units of the Mumbai Metropolitan Region) to analyse the evolution and Complexity of Built-up from 1975 to 2019. The study area is in the Northwest of the Mumbai Metropolitan Region (Figure 3.1), surrounded by Vaitarna in the North, Vasai Creek in the South, Bhiwandi tehsil in the East, and the Arabian Sea in the West. Vasai has a terrain range of up to 663m. This highly elevated area is the Tungareshwar National Forest; this green belt lies in the East of Vasai. Vasai Tehsil remained under the green zone, with small strips of built-up along the coast. With increased urbanization and population explosion in the Mumbai region, the population started growing in Vasai Region; hence in 1983 Maharashtra government converted 8,500 hectares of the green zone into urbanisable land (Sharma et al., 1991). This allocation attracted the human population for settlements resulting in built-up evolution. The availability of good public transport and its connectivity to the neighbouring cities resulted in increased human occupancy in the Vasai region. Vasai road railway station bypasses Mumbai connecting Vadodara to Konkan Railways and Pune Junction towards Bengaluru and Hyderabad. Vasai road railway station bypasses Mumbai connecting Vadodara to Konkan Railways and Pune Junction towards Bengaluru and Hyderabad.

The Municipal Corporation buses connect all the major routes within the town, and State Transport buses provide long-distance travel to and from Vasai. Besides, auto rickshaws are the primary source of transport in the region for shorter trips. The introduction of Local Train Service to MMR in 1867 by Indian Railways enhanced the growth by increasing mobility at a lesser cost; further, the 4 minutes frequency of the local train between Virar and Churchgate made the local train a reliable, time-saving, and cost-effective mode of travel. Noting the transportation and Infrastructure development in Vasai Tehsil, quantifying the complexity of growth concerning the built-up evolution over time is done.

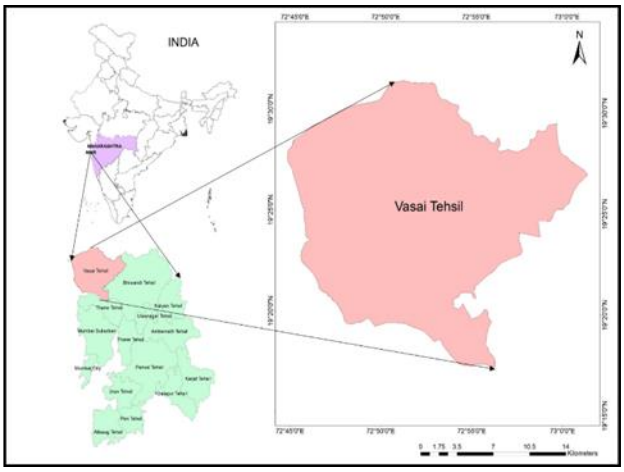

Figure 1. Study Area Vasai Tehsil

2.2 Data

This research required Built-up feature data sets from 1975 to 2019. Cloud-free Landsat Thematic Mapper of 30m spatial resolution for 1999 and 2009, Operational Land Imager + Thermal Infrared Sensor combined Landsat imagery for 2019 of 30m spatial resolution and Acquisition of Global Human Settlement Layer (GHSL) for 1975 and 1990 of 30m spatial resolution. GHSL data set is a Joint Research Centre (JRC) European Commission initiative for providing global time-series geospatial data sets in the public domain. The GHSL data were released in 2016 as an open and free data package (GHS P2016) (Corbane et al., 2018). The GHS P2016 is generated from temporal Landsat imageries, using different Landsat series sensors, namely Multispectral Scanner for 1975 and Thematic Mapper from Landsat 4 & 5 for 1990. The applicability of these data sets has been emphasized and analyzed for Indian conditions proving suitable for estimating Landscape matrices and understanding built-up growth dynamics (Nautiyal & Maithani, 2020). The administrative boundary information of Vasai Tehsil is extracted from the district shapefile of the Mumbai Metropolitan Region obtained from MMRDA (Mumbai Metropolitan Region Development Authority) Development Plan 2016.

3. METHODOLOGY

This research adopts a methodology consisting of three main steps. Step 1 involved the extraction of Built-up features. Step 2 involved computation of the Built-up Centroid and understanding the temporal shift in the Centroid. Step 3 deals with the understanding of complexity in the Built-up geometry directionally.

3.1 Built-up feature extraction

A supervised classification schema is applied to generate land cover maps from satellite images. The main classification features used in this study were the TM and ETM+ multispectral bands. Band composite and mosaic operations are performed to create a False Colour composite considering Red, Green, and NIR bands. The maximum Likelihood algorithm m is adopted for Land Use Land Cover classification, obtaining an overall accuracy and Kappa coefficient of 90.13% and 0.87 for 1999, 91.97% and 0.90 for 2009, and 89.73% and 0.87 for 2019, respectively. The overall accuracy of the land cover maps is >85% for all the years, which was sufficient for extracting the built-up region. Later, the built-up class for 1999, 2009, and 2019 is retrieved from the Land Use Land Cover map. For the years 1975 and 1990, the Built-up class is extracted from the Global Human Settlement Layer. GHSL are prepared based on the symbolic machine learning approach from Landsat images (Pesaresi et al., 2016). It is a time series data for four epochs, 1975, 1990, 2000, and 2014. The built-up area product used for the built-up extraction is 30m spatial resolution data. The data has a 0-6 index, where index six of 1975 and index five of 1990 are considered for the study.

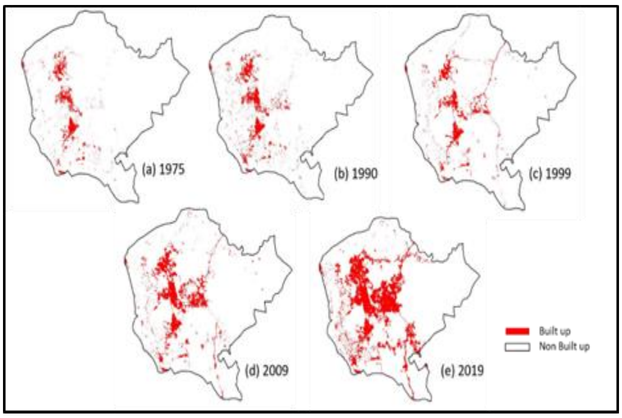

Figure 2. Built-up Areas

3.2 Built-up evolution analysis

A built-up centroid is defined as the geometric center of the centroids of input polygons. For the past four and half decades, analysis of the built-up evolution has been drawn by summation of area-weighted spatial built-up Centroid and tracing the trajectory of changes in the built-up Centroid over time. A quantitative and intuitive description of the spatial change characteristics of built-up is drawn from Euclidean Centroid Shift Model. The model quantifies centroid changes concerning magnitude and direction. Equation 1& 2 spatially locates the built-up Centroid (Xiong et al., 2019) and (Tu et al., 2016). Where X_t and Y_t Indicate the area-weighted abscissa and ordinate of all the built-up land patches in the t^{th} year, respectively; C_{ti} is the area of built-up land patch i in the t^{th} year, n is the total number of patches of built-up land, and X_i and Y_i are the abscissa and ordinate of built-up land patch *i*, respectively.

$$X_t = \sum_{i=1}^{n}(C_{ti} \times X_i)/\sum_{i=1}^{n} C_{ti} \quad (1)$$

$$Y_t = \sum_{i=1}^{n}(C_{ti} \times Y_i)/\sum_{i=1}^{n} C_{ti} \quad (2)$$

Equation 3 calculates the magnitude with which the built-up centroid movement has occurred over the period of time (1975-1990, 1990-1999, 1999-2009, and 2009-2019). Finally, the overall shift in the Centroid for the past four and half decades is estimated. Equation 4 is the measure of directionality in the centroid movement over a period of time. It is calculated by finding the slope of the line linking the two centroids. Equations 3 and 4 are as follows (Tu et al., 2016):

$$D = \sqrt{(X_{t_2} - X_{t_1})^2 + (Y_{t_2} - Y_{t_1})^2} \quad (3)$$

$$\alpha = \begin{cases} \tan^{-1}\left(\frac{Y_{t_2}-Y_{t_1}}{X_{t_2}-X_{t_1}}\right), X_{t_2} \geq X_{t_1}, \\ \pi - \tan^{-1}\left(\frac{Y_{t_2}-Y_{t_1}}{X_{t_2}-X_{t_1}}\right), X_{t_2} < X_{t_1} \end{cases} \quad (4)$$

Where 'D' is the distance of the centroid shift; 'α' is the centroid shift angle and X_{t_1} ,X_{t_2}, and Y_{t_1}, Y_{t_2} is the area-weighted abscissa and ordinate of all the built-up patches in the years of t_1 and t_2, respectively, t_1 is the beginning of the monitoring period, and t_2 is the end of the monitoring period.

3.3 Geometric Complexity of Built-up

Among the various structural landscape matrices, the Fractal dimension is considered to understand the geometric complexity of built-up with time. Fractal dimension matrices define the spatial and structural complexity the study area is experiencing with evolution. The fractal dimension 'D' value is calculated to the whole study area extent, and overall complexity is understood. Later on, the analysis is carried out in eight directions (N, NE, E, SE, S, SW, W, and NW), considering the built-up Centroid for a particular time interval. The study area is divided into eight sectors, and the built-up form lying in each sector is calculated with fractal dimension 'D' value. The equation used for calculation is (MacGarigal, 1995):

$$D = \frac{2 \ln p_{ij}}{\ln a_{ij}} \quad (5)$$

Where p_{ij} is the perimeter and a_{ij} is the area of the built-up patch. The value ranges from 1 to 2. If the value is > 1 for a two-dimensional patch, then it is a departure from Euclidean geometry, and values closer to 2 indicate that the built-up form is highly complex (MacGarigal, 1995). The temporal analysis of built-up complexity also explains the period where the growth was higher and the type of growth. A fundamental characteristic of fractal objects is that their measured metric properties, such as length or area, are a function of the measurement scale. This study adopts a 30 m scale for understanding the complexity.

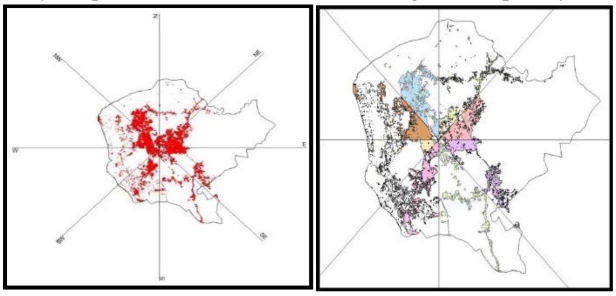

Figure 3. Directional Division of Built-up considering built-up Centroid as the center (2019).

4. RESULTS AND DISCUSSION

4.1 Built-up feature

The built-up area extracted from the GHSL data set for Vasai for 1975 and 1990 is 15.11 km^2 and 19.3 km^2. Similarly, the built-up area extracted from Landsat LULC imagery for 1999, 2009, and 2019 is 22.14 Km^2, 32.42 Km^2, and 65.91 Km^2, respectively. A pictorial representation of the built-up for each year is shown in Figure 2. The quantified area values show that from 1975 to 2019, there was an increasing trend of built-up growth with a varied percentage growth interval. From 1975 to 1990, the growth rate was 27.73%, whereas from 1990 to 1999, the growth percentage was 14.71. From 1999 to 2009, the growth is rapid, with an amount of 45.61%, and from 2009 to 2019, it experienced an increased growth of 104.43%. Vasai's overall built-up class coverage in 1975 was 3.49%, reaching 15.23% by 2019.

4.2 Spatial Centroid Shift

The resulting area trends show that the policy and population explosion in the neighbouring city majorly influenced the spatial pattern of Vasai Tehsil over the past 44 years. Vasai has experienced unprecedented urban growth over the past four decades, with an increased rate of 336% from 1975 to 2019. This amount of growth calls for a deeper understanding of the evolution and complexity of the study area. The city's geometric Centroid is one parameter for quantifying the spatial evolution of built-up. With growth, the built-up geometric Centroid varies spatially, shifting towards the areas where the built-up is more concentrated and has evolved. The geometric centroids of each year is tabulated in table 1.

Year	Longitude (decimal degrees)	Latitude(decimal degrees)
1975	72.818	19.407
1990	72.820	19.408
1999	72.829	19.411
2009	72.833	19.4137
2019	72.840	19.4133

Table 1. Temporal Geometric Built-up Centroid

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From 1975 to 2019, the spatial Centroid shifted at a very irregular rate and distance in Vasai. From 1975-1990 the shift distance was 265 meters, whereas, from 1990-1999, the shift was 1 km, indicating a shift rate of 281%. Post-1999, the urban centroid shift from 1999-2009 is 489 meters which are approximately 51% lesser than the 1990-1999 shift rate. From 2009-2019 the Centroid shifted 728 meters, showing a shift rate of 48.7%. The overall shift from 1975 to 2019 is for a distance of 2.42 Km.

Time Interval	Shift Distance(D) in m	Shift Angle(α) in degrees
1975-1990	265	30.3
1990-1999	1011	17.58
1999-2009	489	28.86
2009-2019	728	-3.52
1975-2019	2420	15.73

Table 2. Centroid Shift Distance and Angle

Apart from displacement, directional understanding of centroid shift plays a vital role in understanding the future evolution direction and possibilities. Vasai's overall shift direction between 1975 to 2019 is NE with an amount of 15.73 degrees. Its evolution has been unidirectional till 2009, i.e., in North East Direction. The angular shift between 2009-2019 shows a change in direction from NE to SE with a minimum of 3.5 degrees. The angular shift between 1975-1990, 1990-1999, and 1999 – 2009 is listed in table 2. Figure 4(I) gives the spatial representation of the built-up centroids, and 4(II) shows the shift trajectory.

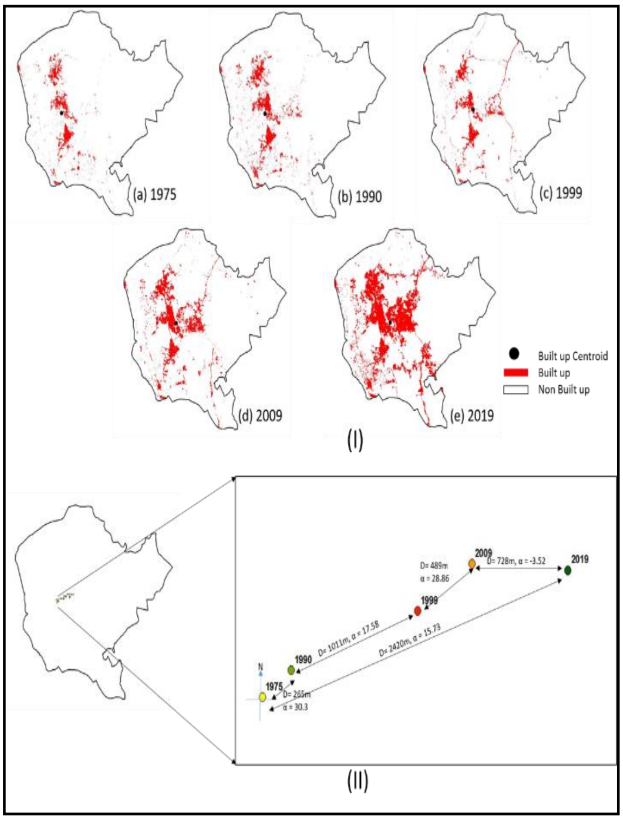

Figure 4 (I) Built-up Area Centroids (II) Centroid Shift Trajectory

4.3 Geometric Complexity of Built-up

Visualizing the spatial pattern of built-up shows that the landscape evolution doesn't follow any Euclidean shapes. Growth is not channelized to one particular geometric shape in the physical world. Vasai Tehsil clearly shows that the built-up evolution is complex. Hence fractal analysis is carried out, where the geometric shapes or boundaries are defined as fractals to understand the complexity involved with the growth. The Mean Fractal Dimension from 1975- 2019 is listed in table 3.

Year	Mean Fractal Dimension (D)	Remarks
1975	1.44	A value higher than 1 indicates an increase in shape complexity.
1990	1.43	Internal Filling
1999	1.42	Internal Filling
2009	1.43	External expansion
2019	1.43	Internal Filling

Table 3. Mean Fractal Dimension of Vasai Tehsil

The Results show that Vasai Tehsil built-up has a complex geometry (Not defining Euclidean Geometry) with an average value of 1.43. The overall mean calculation doesn't critically explain the complexity within the built-up region. Hence the built-up areas are divided into eight directions (Figure 3), considering the built-up Centroid as the reference point. Figure 5 is the wind rose diagram representing the mean fractal values defining the complexity over a time interval in eight different directions. Calculating the directional fractal dimension shows that the Geometric complexity is not the same in every direction. Considering 1975 as the base year for understanding directional geometric complexity, it has been infilling till 2019. In 1975 W_NW had a high Fractal Dimension Value. S_SW has a low Fractal dimension value. In 1990 S_SW experienced an edge filling/external filling indicating a high fractal dimension compared to 1975 S_SW. In all other directions, it is infilling. 1999 shows that in all directions, it has infilling growth.2009 shows an infilling in all directions except the E_SE direction, as the Fractal dimensions indicate that this direction has undergone external growth since 1990. 2019 Fractal dimensions indicate that in N_NE, NE_E, E_SE and SW_W has experienced outward growth from 1990. In the SE_S direction, the geometric complexity was higher than in 1999 and 2009, indicating edge filling. Results also indicate that complexity is not truly increasing with an increasing area over time. It is highly dependent on the type of growth happening in that direction. In 1975 the built-up area in NW_N and SE_S direction was higher, and the mean fractal value in NW_N and NE_E was higher, indicating that SE_S growth was compact in nature, whereas NE_E has a scattered growth increasing the complexity though being a less area coverage. In 1990, NW_N and SE_S has high built-up area coverage but the mean fractal is high in SE_S direction indicating a scattered growth or external filling. In 1999 the trend has a shift showing that N_NE, NE_E has a higher mean fractal value though the built-up area is high in S_SW, W_NW and NW_N showing an infilling growth in these directions. From 1999 to 2009 a drastic jump in the built-up growth in all directions is seen, where E_SE, S_SW, SW_S and NW_N exhibited higher complexity proving external filling. Further from 2009 to 2019 there is an unprecedented growth in built-up in all the directions on an average of 127.88% from all directions, but directions E_SE and SW_W direction showed some minor external fillings and rest others showed compact and infilling.

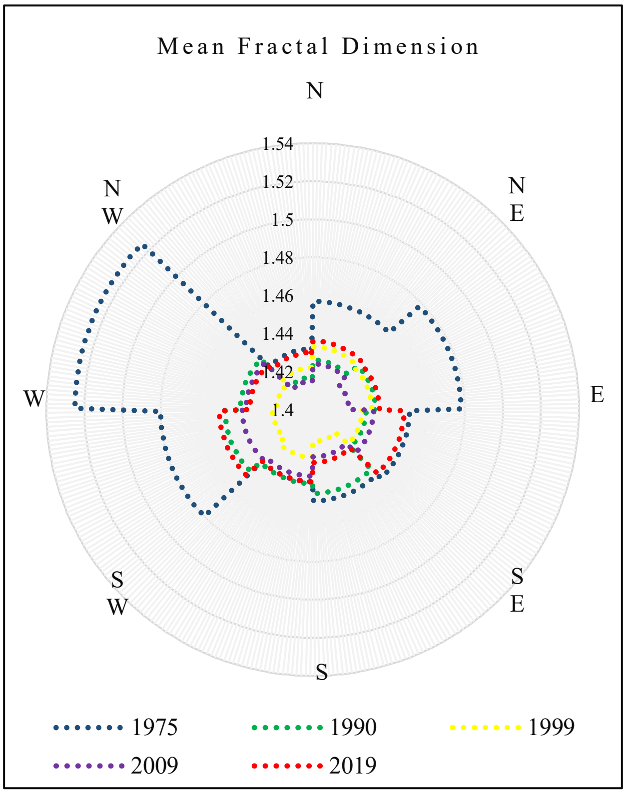

Figure 5. Directional Mean Fractal Dimension

5. CONCLUSION

The Unprecedented built-up growth has put natural Land Cover into Land Use over time, resulting in the need for practicing Sustainable development and smart implementation. Sustainable implementations are needed to curb global warming and rapid climatic changes. Hence, understanding the built-up evolution and its geometrical complexity is studied in the present work for a fast-growing built-up agglomeration. Evolution of built-up for forty-four years from 1975 base year to 2019 is carried out. The Centroid shift model finds the area-weighted geometric Centroid of the built-up temporally and calculates the shift in the Centroid with time. The shift is quantified both in magnitude and direction. The present study area experiences an overall shift of 2.42 $Km^{2,}$ and the evolution pattern changed from unidirectional (E_NE) to another path (E_SE) by an amplitude of 3.52 degrees. The Centroid shift model yielded the overall growth trajectory of the built-up, and the complexity in the geometry of the built-up was analyzed by fractal dimension Index. Fractal geometry is applied because the built-up in the physical world does not follow. Euclidean geometry of simple shapes. The Mean fractal dimension value for the entire study area remained almost equal to 1.4 showing significant complexity in geometry.

year	NW_N D	NW_N Area (Km^2)	W_NW D	W_NW Area (Km^2	SW_W D	SW_W Area (Km^2)	S_SW D	S_SW Area (Km^2)	SE_S D	SE_S Area (Km^2)	E_SE D	E_SE Area (Km^2)	NE_E D	NE_E Area (Km^2)	N_NE D	N_NE Area (Km^2)
1975	1.432	5.21	1.525	0.84	1.48	0.16	1.438	1.59	1.448	4.39	1.451	0.94	1.478	0.58	1.457	1.36
1990	1.417	6.04	1.438	1.42	1.446	0.29	1.439	2.68	1.444	4.32	1.428	1.69	1.433	1.33	1.426	2.1
1999	1.422	5.9	1.419	3.3	1.421	0.95	1.425	3.93	1.417	2.78	1.426	2.34	1.431	1.96	1.433	0.98
2009	1.415	7.69	1.435	4.56	1.437	1.52	1.435	5.77	1.425	3.26	1.432	3.79	1.419	3.95	1.424	1.7
2019	1.43	11.77	1.433	10.11	1.449	3.98	1.438	9.96	1.428	6.21	1.448	8.81	1.435	8.82	1.436	6.25

Table 4. Directional Mean Fractal Dimension (D) and Area of Vasai Tehsil

To draw an in-depth understanding of complexity, the study area's directional division into eight directions considering the built-up Centroid showed that the complexity varies in all directions and is highly dependent on the type of growth than the amount of development happening in the study area. Among all the eight directions considered, NW_W showed maximum built-up growth with infilling growth type, and the E_SE direction showed a major jump in the area with external expansion by 2019. This direction indicates the future growth direction. Hence, the study inferred that complexity analysis critically enhances the spatiotemporal dynamics of built-up evolution.

Fractal Dimension analysis using the Mean fractal index showed that the complexity in geometry is related to the type of growth a city is experiencing. For a comprehensive understanding of geometric complexity, other spatial matrices like the Number of built-up Patches, mean shape index, and built-up patch size also need to be calculated, and statistical correlation with these indices and area needs to be established. The factors like demographic, topographic, socio-economic, transportation, etc., influence the evolution of built-up and play a major role in geometric complexity as well. The results also indicate that the complexity of the urban form needs to be understood on a larger scale. Along with directional complexity analysis using a higher scale, complexity at the proximity of the built-up Centroid need to be assessed to know the variation in complexity within the built-up core.

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