GEOGRAPHICAL ANALYSIS

ORIGINAL ARTICLE

OPEN ACCESS

Received: 08.12.2024

Accepted: 10.08.2025

Published: 01.12.2025

Citation: Kumar SM, Thirumalai P, Krishnan RT, Prakash K, Masilamani P, Killivalavan J. (2025). Evaluation of Urban Expansion and Landuse Land Cover Changes using Index-Based Built-up Index and Geospatial Techniques in Kumbakonam Taluk, Tamil Nadu, India. Geographical Analysis. 14(2): 5-13. https://doi.org/10.53989/bu.ga.v14i2.24.262

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Funding: None

Competing Interests: None

Published By Bangalore University, Bengaluru, Karnataka

ISSN

Print: 2319-5371

Electronic: XXXX-XXXX

Evaluation of Urban Expansion and Landuse Land Cover Changes using Index-Based Built-up Index and Geospatial Techniques in Kumbakonam Taluk, Tamil Nadu, India

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Abstract

Over time to time, the urban areas have been expanding at a rate with exponential growth of the population. This rapid invasion of population leads to a change in the landuse land cover pattern of the areas. Therefore, making cities sustainably suitable for living can be achieved by monitoring the spatiotemporal dynamics of land use and land cover changes, as well as the urban expansion pattern. This study primarily focuses on urban expansion and land-use/land-cover changes in Kumbakonam Taluk, Thanjavur District, from 1994 to 2024. The present study investigated spatiotemporal land-use patterns, SAVI, NDWI, NDBI, and IBI for Kumbakonam Taluk for 1994, 2004, 2014, and 2024 using Landsat 5 and Landsat 8 datasets. The landuse and land cover changes of Kumbakonam Taluk were generated using the supervised classification method with the Support Vector Machine algorithm. The result of the LULC shows that the built-up classes have rapidly expanded from 1994 to 2024, from 21 sq. km to 82.3 sq. km, respectively. The city's periphery has a high expansion of built-up areas resulting from the conversion of agricultural land from 2014 to 2024. Over the study period, agricultural land, vegetation, and water body were reduced to 22 sq. km, 17.3 sq. km and 9 sq. km, respectively. The result from IBI shows the higher expansion of urban areas on the peripheries of the city towards its western side from 1994 to 2024. The present study provides a framework for analyzing land use and land cover changes over three decades, as well as the direction and pattern of urban expansion. The results of the study will help not only urban planners but also policymakers to develop new sustainable strategies for urban development, assess environmental impacts such as *the loss of green cover, and aid in formulating effective spatial policies and governance strategies.*

Keywords: IBI; LULC; SAVI; NDBI; MNDWI

1 Introduction

Urbanisation is a day-to-day process which is evolving in nature and reflected in spatial growth patterns. The growth of urban areas has been increasing drastically all around the globe in recent decades as economic opportunities in urban areas attract growing populations to cities[(1)]. According to the United Nations, around 55% of the population in the world lives in urban it will rise to 70% by the year 2050[(2)]. India is one of the fastest-growing urbanised nations and is experiencing rapid urban population growth. By 2030, about 40% of the population will live in urban centres and by 2050 urban population in India will be around 416 million[(3–5)]. Key impacts of urbanisation involve wetland fragmentation, decreased drainage capacity, alterations to landscapes for agriculture, and a decline in water quality[(6)]. Mapping built-up areas is vital for tracking urban growth and is a key factor in assessing related environmental challenges[(7)]. On the other hand, Landuse and land cover (LULC) are also an impactful factor in examining urban growth and dynamics. LULC is changing drastically in recent times, which can affect the environment directly or indirectly and quantifying the temporal changes is inevitable in attaining a sustainable future. Nowadays, the advancement of remote sensing makes a way to add valuable insights into understanding the complex LULC dynamics of an area[(8)]. Over the past decade, advanced classification algorithms, including neural networks, contextual, object-oriented, and knowledge-based methods, have been developed to enhance the accuracy and efficiency of the classification process[(9)].

There have been numerous studies conducted to study LULC dynamics in many urban areas in our country, such as Chennai[(10)], Mumbai[(11)], Kolkata[(12)], Delhi[(13)], Pune[(14)], Tiruppur[(15)], Ahmedabad[(16)] and Coimbatore[(17)], etc. Remote sensing and GIS play a significant role in urban extraction mapping-oriented research. Often, there is an advancement in the indices to improve the accuracy of the results. As enhanced vegetation index (EVI) is the updated version of the normalized vegetation difference index (NDVI) to identify green vegetation. Likewise, the modified normalized water difference index (MNDWI) is the enhanced version of the normalized vegetation difference index (NDVI) to map the water bodies. Selecting a proper threshold point is essential to extract exact features from the satellite image it may differ for each image. Especially for extracting built-up using a satellite image normalized difference built-up index (NDBI), it distinguishes between built-up land and vegetation[(18)]. However, the Index-based Built-up Index (IBI) can more accurately extract built-up than NDBI[(19)]. Ansari et al. (2023)[(20)] studied the effect of urban expansion on the land surface temperature along with NDBI and NDVI. Choudhury et al. (2023)[(21)] correlated the built-up expansion and the land surface temperature by employing NDBI and NDVI and forecasted the LULC and UHI using a Cellular Automata–Artificial Neural Network (CA–ANN) model. The urban land expansion was evaluated by Ghosh et al. (2018)[(22)] using five remote sensing indices to extract built-up areas such as NDBI, EBBI, IBI, UI, and NDBaI.

In the current study, Kumbakonam Taluk of Thanjavur District, Tamil Nadu, has been selected as the study area. Kumbakonam is one of the ancient cities in Tamil Nadu, well known for its rich cultural heritage and significant contributions to history. The prime economic activity in the taluk is agriculture. The urban growth is also rapid in Kumbakonam due to its religious importance.

So, it may affect agriculture and other activities. Only very few studies have been conducted regarding the Urban dynamics in Kumbakonam. Kandasamy and Kesavaperumal (2020)[23] have studied the urban heritage management of Kumbakonam; Kiruthiga and Thirumaran 2018[24] have examined the effect of urbanisation in Kumbakonam. No eminent study has been conducted to examine the temporal urban dynamics that led the way to implement this study in Kumbakonam Taluk. Earlier studies may not have fully comprehended the integration of remote sensing, GIS-based change detection, and index-based classification, which this study holistically integrated the LULC change and IBI. The objectives of the study are to assess the urban dynamics using various indices such as MNDWI, SAVI, NDBI and IBI from 1994 to 2024 and to examine the changes in the LULC of the study area for three decades. The current study would be helpful for policymakers to build Kumbakonam as a sustainable city.

2 Study area

Kumbakonam Taluk is spread between 10º 5' 47" N to 11º 3' 55" N latitude and 76º 06' 46" E to 79º 31' 12" E longitude in the Thanjavur District of Tamil Nadu, India (Figure 1). Kumbakonam has a geographical area of 281 sq. km and is often referred to as the "Temple Town", due to its numerous ancient temples scattered across the region. Kollidam and Kudamurutti rivers are the major drainages flowing through Kumbakonam Taluk. Kumbakonam is famous for its traditional arts, architecture, and festivals, particularly the Mahamaham festival, which draws pilgrims from all over the country. As per the 2011 Census, Kumbakonam Taluk has a total population of 4,04,123, out of which 2,00,194 are male population and 2,03,929 are female population. Kumbakonam Taluk is well-connected by a network of state and national highways, facilitating easy transportation to other parts of Tamil Nadu. NH-36 runs through Thanjavur to Nagapattinam and passes through Kumbakonam and the state highway SH-8 (Vickravandi - Kumbakonam - Thanjavur Road), SH-22 (Kallanai Grandanaicut - Cauveripattinam road), SH-64 (Kumbakonam - Sirkali road), SH-65 (Thiruvarur - Kudavasal - Kumbakonam road) SH-66 (Kumbakonam - Mannargudy - Adirampattinam road), SH-67 (Kumbakonam - Sirkali road) and SH-147 (Kumbakonam - Karaikal Road) are the prominent road networks.

3 Materials and methods

To execute the current study, satellite images (Landsat 5 (TM) for the years 1994 and 2004 and Landsat 8 (OLI) for the years 2014 & 2024) were obtained from the United States Geological Survey Earth Explorer site (https://earthexplorer.usgs.gov). The landuse land changes have been generated using the Support Vector Machine algorithm in

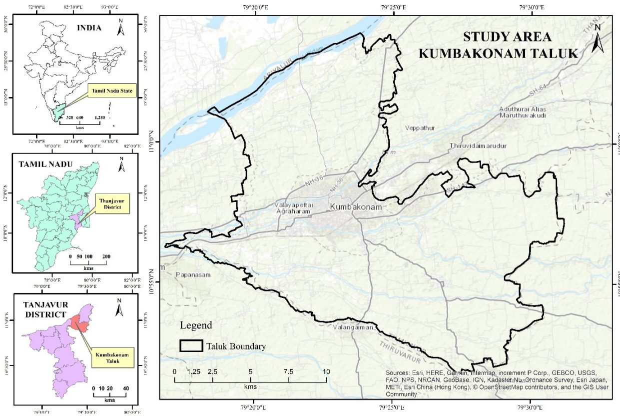

Fig. 1. Location of the study area

ENVI software. The IBI was produced using three indices such as SAVI, NDWI, and NDBI. To examine the temporal changes in urban growth in Kumbakonam Taluk, all the indices and the landuse land cover change were analysed (Figure 2).

3.1 Modified Normalized Difference Water Index

MNDWI is a modified version of NDWI, which has less noise than NDWI and can give proper output to identify the water content on the surface. The formula to derivate MNDWI follows below (Equation (1)).

$$MNDWI = \frac{GREEN - MIR}{GREEN + MIR} \tag{1}$$

3.2 Soil-Adjusted Vegetation Index

SAVI was first utilized by A.R Huete in the year 1988. Initially, the NDVI was used by most of the researchers to examine the condition of the vegetation over an area using satellite images, SAVI is a kind of modified version of NDVI which accounts for soil brightness in areas where vegetation cover is low or sparse. It helps minimize the influence of soil reflectance on vegetation monitoring.

The SAVI formula introduces a correction factor (L) to reduce soil noise, which is especially useful in arid or semi-arid regions. The formula to calculate SAVI is given below (Equation (2)).

$$SAVI = \frac{(NIR - RED)(1 + L)}{NIR + RED + L} \tag{2}$$

Where, L is the representation of the correlation factor ranging from 0 to 1, "0" is given to very high plant densities and "1" to very low plant densities. To detect the low-density vegetation in an urban area, SAVI will be more suitable than NDVI because SAVI can effectively work in an area with a vegetation cover of less than 15% (Xu 2008). However, NDVI will be only suitable for an area with a vegetation cover of more than 40%. In this study area, the L factor is taken as 0.3.

3.3 Normalized Difference Built-up Index

The NDBI efficiently emphasizes the built-up areas in remote sensing data sets. When combined with appropriate threshold selection, it can be utilized to identify impervious surfaces in urban environments. The NDBI values range between -1 to +1. The positive values in the NDBI represent the built-up area. Equation (3) was used to examine the NDBI.

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \tag{3}$$

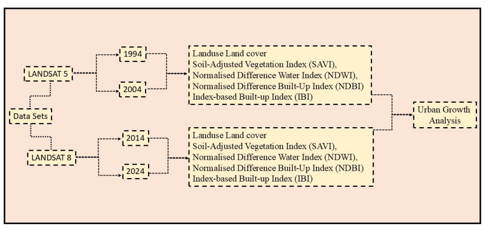

Fig. 2. Methodological flow chart of the study

3.4 Index-based Built-up Index

IBI is used to extract the built-up more precisely using satellite images. It ranges between -1 to 1 in which zero to negative values represent the noise and other features in an area and the positive values represent the built-up. Equation (4) used to examine the IBI

$$IBI = \frac{[NDBI - \frac{SAVI + MNDWI}{2}]}{[NDBI + \frac{SAVI + MNDWI}{2}]} \tag{4}$$

3.5 Support vector machine (SVM) classification to map landuse and land cover

In the present study, the SVM classification algorithm has been used to execute the LULC map of the study area in the ENVI platform. Landsat images have been utilized to map the LULC for 1994, 2004, 2014 and 2024. The satellite images were classified based on the training samples specified by the Region of Interest (ROI). The SVM calculated an optimal hyperplane for class separation based on training data, with the gamma parameter set to 0.01 to improve both efficiency and classification accuracy. ENVI software facilitated the classification, using a penalty parameter of 100 to minimize misclassification. A classification threshold of zero was set to ensure precise pixel assignments. The ROI was used to establish spectral signatures for five LULC categories: built-up, bare land, vegetation, forest, and water. The process included selecting training areas, generating ROIs, and classifying the images, with around 200 ground control points used for validation.

3.6 Change Detection

LULC changes were analyzed for the periods 1994—2004, 2004—2014, and 2014—2024 using post-classification comparison methods. A change detection matrix was used to track how each LULC class transitioned into others, with categories listed in rows and columns. Changes were quantified in both hectares and percentages, with percentage changes calculated using a specific formula (Equation (5)).

$$LULC\ Change\ (\%) = \frac{(a_{2} - a_1)}{a_1} \times 100 \tag{5}$$

In this a_2 refers to the area of the specified class in the current year; a_1 represents the area of the same class in the previous year.

4 Result & Discussion

4.1 Modified Normalized Difference Water Index

MNDWI plays a crucial role in extracting water bodies in the study area and has been analyzed for the years 1994, 2004, 2014 and 2024 (Figure 3). The higher value MNDWI represents the areas that have water body, and vegetation. while the low values represent the built-up and bare soil areas. In 1994, approximately 54% of the area was classified as High to Very High in MNDWI, with only 5% falling under the Very Low category. By 2004, the Low to Moderate MNDWI class dominated the region, covering 59% of the area. In 2014, the Very Low to Low classes expanded significantly, occupying 59% of the study area. However, by 2024, the Very Low to Low classes decreased to 26%, indicating a positive trend in waterbody coverage. Spatially, the Very High MNDWI values were consistently observed in the southeastern and northern parts of the study area throughout all the years, though the extent of coverage varied. Conversely, lower MNDWI values were predominantly found in built-up areas, reflecting the impact of urbanization on waterbody distribution.

4.2 Soil Adjusted Vegetation Index

The extraction of vegetation can be enhanced by using SAVI instead of NDVI, particularly in areas with high soil influence (Figure 4). The lower SAVI values indicate bare soil, and rocky terrain & the higher value indicates urban with impervious surface domination. SAVI results indicate a decline in vegetation coverage over time. In 1994, the very high vegetation class was found in 86 sq. km (30%) of the study area and was distributed across the region. By 2004, this coverage decreased to 19% (56 sq. km.). The reduction continued, with the very high category covering only 27 sq. km (9%) by 2014, mainly along rivers and streams. However, in 2024, SAVI values showed a slight growth, with the very high class increasing to 14%. This improvement is likely due to increased soil moisture, particularly in the southern and central parts of the study area. The gradual reduction in vegetation coverage highlights the need to closely monitor land use and soil conditions to understand environmental changes.

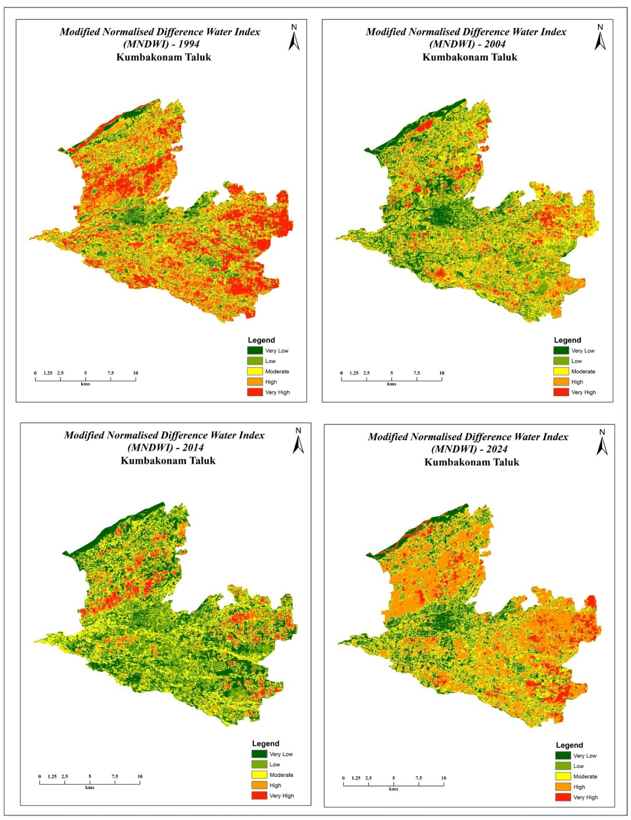

Fig. 3. Spatial Distribution of Modified Normalized Difference Water Index

4.3 Normalized Difference Built-up Index

The NDBI is used to extract built-up and concrete surfaces from satellite images. In the NDBI, built-up will show high value and vegetation, waterbodies and bare soil will show lower value (Figure 5). Analysis of NDBI values over the years reveals a gradual increase in the very high class of built-up

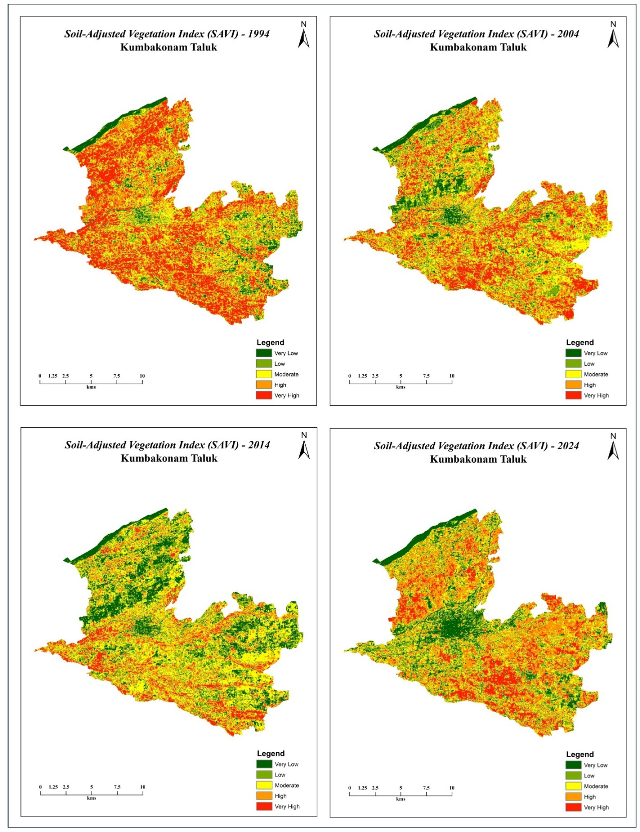

Fig. 4. Spatial Distribution of Soil Adjusted Vegetation Index

areas. In 1994, approximately 14 sq. km (5%) of the taluk, mainly concentrated in Kumbakonam city and bare land near the river, exhibited very high NDBI values. By 2004, this area expanded to 22 sq. km (7%). In 2014, the very high NDBI class increased significantly to 45 sq. km (16%), primarily covering the central and southern parts of Kumbakonam Taluk. However, by 2024, the very high class decreased to 30 sq. km (10%), with its spatial distribution more concentrated in the central part, where Kumbakonam city is located.

4.4 Index-based Built-up Index

The IBI is recognised for its effectiveness in extracting built-up areas and is considered more accurate than the NDBI. In this study, IBI values have shown a significant increase over recent decades (Figure 6). The very high IBI class covered 6 sq. km in 1994, expanded to 12 sq. km in 2004, increased further to 34 sq. km in 2014, and reached 51 sq. km in 2024. Compared to NDBI, IBI provided more precise results in identifying built-up areas. However, IBI does not perform well in clearly differentiating between bare land near rivers and built-up zones. Despite this limitation, the spatial analysis revealed a steady expansion of built-up areas over time, especially in the urban fringes of Kumbakonam. This

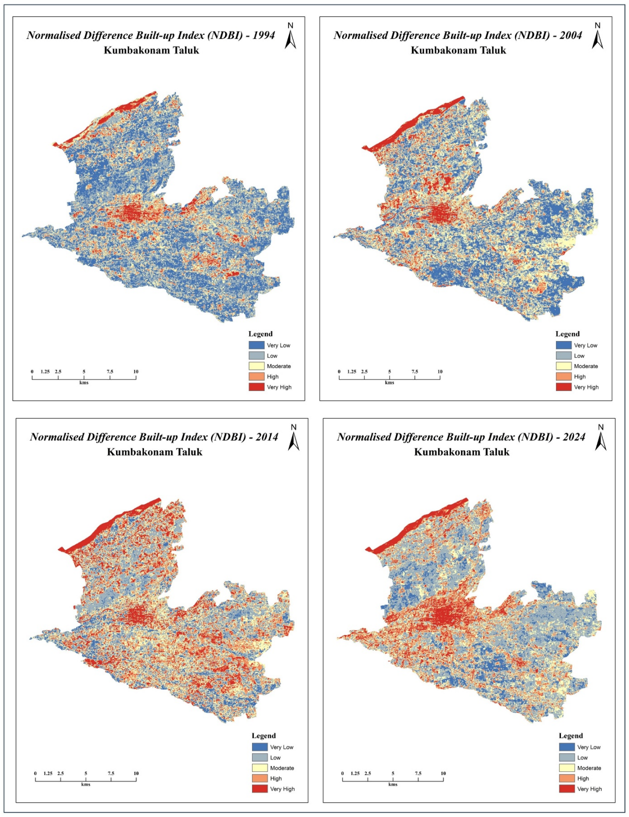

Fig. 5. Spatial Distribution of Normalized Difference Built-up Index

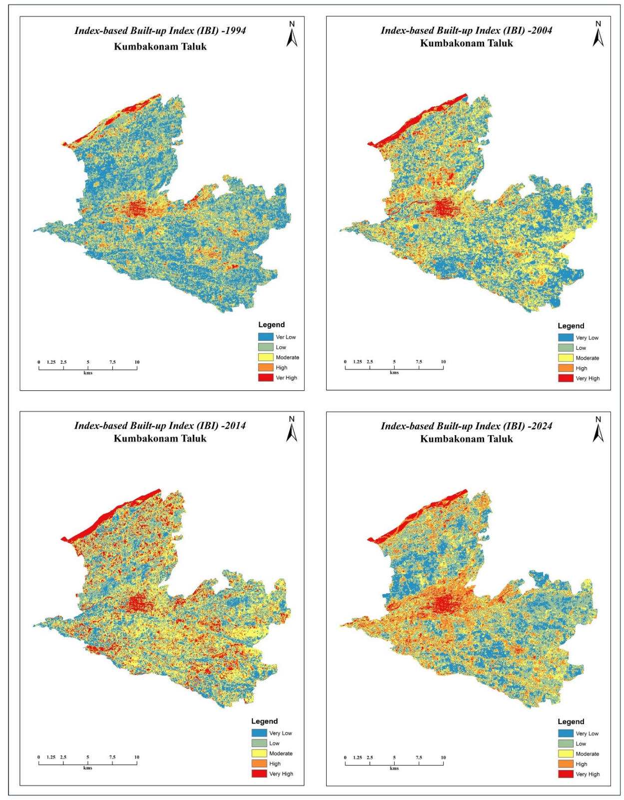

Fig. 6. Spatial Distribution of Index-based Built-up Index

trend highlights the ongoing urbanisation in the region, with growth concentrating around the city's periphery, indicating the importance of monitoring urban sprawl for future planning and land use management. The correlation shows the relation between the two variables, such as IBI and SAVI, with the help of a scatterplot (Figure 7) for 1994, 2004, 2014 and 2024. The result shows a negative correlation between IBI & SAVI. As the built-up increases, the vegetation decreases.

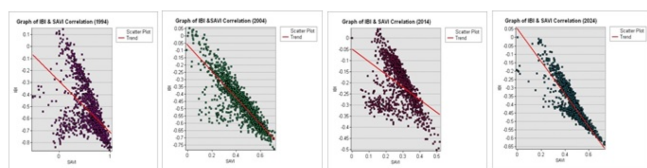

Fig. 7. Scatter plot for the correlation between IBI & SAVI from 1994 to 2004

4.5 Landuse and Land Cover Changes

The temporal change of LULC of Kumbakonam was classified as per the NRSC level 1 classification, and the classes are built-up, agricultural land, vegetation, barren land and waterbody (Figure 8). In 1994, agricultural land was spread over 212 sq. km of the study area, and only 16 sq. km of land was barren, while waterbody was 14 sq. km and 18 sq. km of vegetation (Table 1). The build-up was spread in the centre and scattered in the southern part of the area, about 21 sq. km (Figure 9).

In 2004, the agricultural land decreased to 208 sq. km, while waterbody decreased to 10 sq. km and the vegetation drastically changed to 2 sq. km. Barren land was increased to 32 sq. km and build-up increased to 29 sq. km because some parts of the agricultural land changed into barren land & build-up. In 2014, the build-up was spread over about 38 sq. km and the barren land was extended by about 34 sq. km. Although agricultural land was reduced to 200 sq. km, vegetation was reduced to 1 sq. km and waterbody were reduced to 7 sq. km. In 2024, there was a rapid increase in the build-up to 83 sq. km and barren land was reduced to 3 sq. km. Whereas, the agricultural land, waterbody and vegetation were also reduced to 190 sq. km, 5 sq. km and 0.7 sq. km, respectively. In a LULC classification, accuracy assessment is a crucial aspect for analyzing the reliability of the generated image. In this study, a confusion matrix using ground truth ROIs was utilized to evaluate the accuracy. The overall classification accuracies for the years 1994, 2004, 2014 and 2024 were 83.64%, 84.27%, 91.17% and 94.62%, respectively, with Kappa Coefficients of 0.73, 0.74, 0.86 and 0.90.

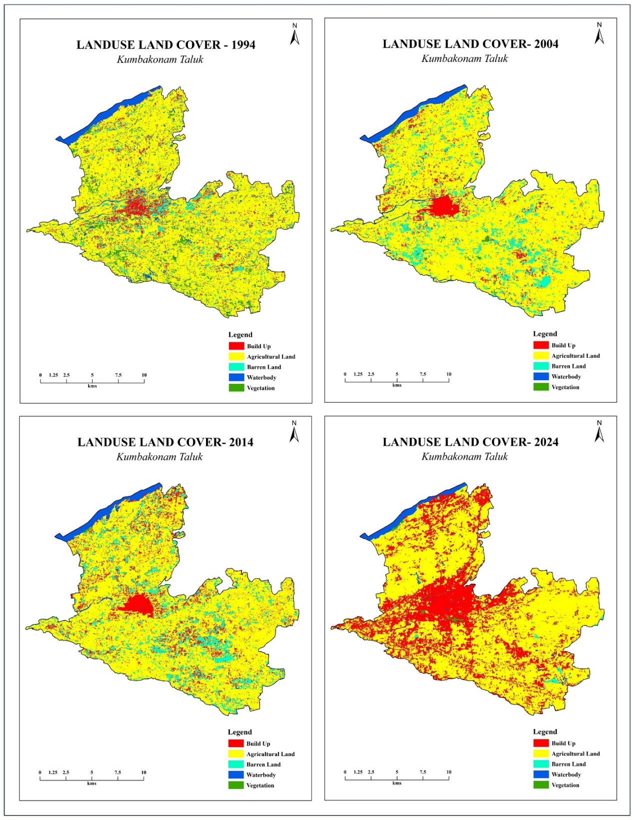

Fig. 8. Spatial Distribution LULC

Table 1. Area under each LULC class over 1994-2024

LULC Classes	1994 (sq. km)	2004 (sq. km)	2014 (sq. km)	2024 (sq. km)
Built-up	21	29	38	83
Agriculture Land	212	208	200	190
Barren Land	16	32	34	3
Waterbody	14	10	7	5
Vegetation	18	2	1	0.72

From 1994 to 2024, there was a drastic increase in the build-up from 37.6% to 117.6 %, agricultural land, vegetation and waterbody decreased by -1.9 % to -5.2 %, -87.4% to -28.4 % and -26.5% to 32.8 % (Table 2). Whereas barren land was increased by 100% in 2004, but it was reduced in 2024 as-91.2%. Most of the agricultural land, vegetation and waterbody were changed into built-up areas from 1994 to 2024. The rapid increase in the build-up was mostly increased as a result of the population expansion and in 2021, the Kumbakonam town was upgraded to a municipal corporation.

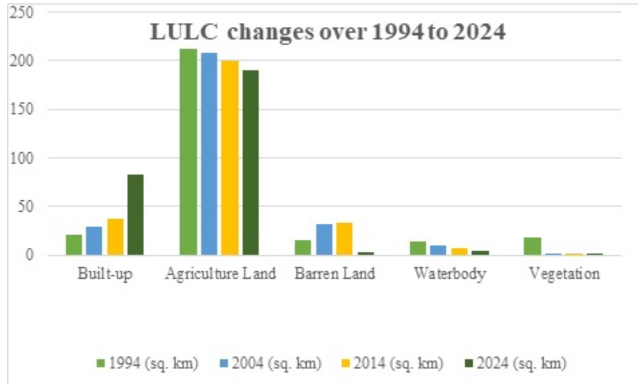

Fig. 9. Graphical representation of LULC changes from 1994 to 2004

5 Discussion

The current study analysed the dynamics of urban expansion and LULC change in Kumbakonam Taluk over three decades using geospatial technology and remote sensing data. The density of urban and built-up areas was extracted using the NDBI. Higher NDBI values indicate a greater concentration of built-up areas and correspond to lower SAVI values. Urban expansion is predominantly concentrated in the central region of the study area. The correlation between SAVI and the IBI reveals a strong negative relationship, indicating that increasing built-up areas reduce vegetation cover. From 1994 to 2024, there has been a drastic increase in built-up area, largely at the expense of agricultural land, water bodies and vegetation. In 2021, Kumbakonam Municipality was upgraded to a Municipal Corporation, which enhanced urban services such as roads, water supply, sanitation and the sewer system. This improvement in infrastructure boosted overall accessibility and facilitated urban expansion. As a major pilgrimage destination, Kumbakonam also experiences sustained tourist-driven demand for accommodation and services. These factors collectively influenced urban growth from the center of Kumbakonam toward the surrounding regions, particularly to the west and north. The expansion patterns and trends derived from the indices proved useful in identifying regions experiencing higher rates of urban growth.

6 Conclusion

This study evaluates the expansion of urban areas for four decades, 1994, 2004, 2014, 2024 in Kumbakonam Taluk. The urban expansion was identified by examining the landuse land cover changes, SAVI, MNDWI, NDBI and IBI. From the

Table 2. Percentage of LULC changes from 1994 to 2024

Year / Classes	Build up	Agricultural Land	Vegetation	Waterbody	Barren land
1994-2004	37.6	-1.9	-87.4	-26.5	100
2004-2014	31	-3.7	-55.9	-25.6	6.25
2014-2024	117.6	-5.2	-28.4	-32.8	-91.2

result of landuse and land cover, the build-up has expanded exponentially from 1994 to 2024 by converting agricultural land, vegetation and waterbody. The spatial distribution map of SAVI, NDBI, MNDWI and IBI supported this. Thus, urban expansion is occurring from the periphery region to the outskirts, mainly towards the western area, because of the location of the district headquarters in the western part. Kumbakonam is known as a temple town, so there could be a resettling of the population happening and recently Kumbakonam town has upgraded to a municipal corporation. These might be a cause of the increasing build-up of classes. The study discovers some critical understanding of the urban expansion of Kumbakonam taluk to improve the quality of life of the population of the region.

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