GEOGRAPHICAL ANALYSIS

RESEARCH ARTICLE

Tracing and Analysis of Urban Footprint and its Future Implications in an Emerging Metropolis of Mysuru, India, Using Geoinformatics Techniques

C S Manjunatha[1]*, **K Dhanaraj**[2], **B Chandrashekara**[3]

1 *Assistant Professor, Dept. of Geography Karnataka State Open University, Mysuru*
2 *Assistant Professor – I, Amity Institute of Geoinformatics and Remote Sensing, Amity University, Noida, Sector 125, Noida, Uttar Pradesh, 201313, India*
3 *Professor, Department of Geography, University of Mysuru, Manasagangothri, Mysuru, Karnataka*

OPEN ACCESS

Received: 12.02.2023
Accepted: 15.05.2023
Published: 18.06.2023

Citation: Manjunatha CS, Dhanaraj K, Chandrashekara B. (2023). Tracing and Analysis of Urban Footprint and its Future Implications in an Emerging Metropolis of Mysuru, India, Using Geoinformatics Techniques. Geographical Analysis. 12(1): 1-12. https://doi.org/10.53989/bu.ga.v12i1.23.1

* **Corresponding author**.
geomanju.ksou@gmail.com

Funding: None

Competing Interests: None

Published By Bangalore University, Bengaluru, Karnataka

ISSN
Print: 2319-5371
Electronic: XXXX-XXXX

Abstract

Rapid urbanization is a global phenomenon that is exerting a substantial influence on the land use and land cover. In India, urbanization is occurring at an unparalleled rate, with the urban population expected to double by 2050. Small and mid-sized cities in the developing world are witnessing a substantial increase in urban expansion, indicating a significant upward trend. This rapid growth presents numerous challenges and opportunities, putting a strain on natural resources and leading to environmental degradation. Regrettably, small and mid-sized cities like Mysuru have been overlooked and excluded from policy negotiations in India, despite presenting a crucial opportunity for targeted action and intervention. In the current study, the dynamics of urban expansion in the mid-sized city of Mysuru, located in southern India. The research utilizes earth observation and geoinformatics techniques to assess land use and land cover changes in the rapidly urbanizing areas surrounding Mysuru for the years 1995, 2001, 2007, 2014, and 2022. The study area has witnessed dynamic changes in land use and land cover triggered by rapid urban growth accounting for 235 per cent during the last 27 years. The open/fallow and vegetation land was converted to meet the growing demand for built-up areas in Mysuru, challenging sustainable development. The study's findings offer valuable perspectives on the scope and characteristics of urbanization, along with the related alterations in land use and land cover, within Mysuru and its environs. The findings can inform decision-making processes for urban planning, resource management, and environmental conservation. The study contributes to filling the gap in research on emergent small and mid-sized cities, particularly in southern part of India, and emphasizes the importance of sustainable planning for the future development of these cities.

Keywords: LULC; Urban Growth; MidSized City; Remote Sensing; GIS

Introduction

In recent decades, swift urbanization has emerged as a notable worldwide occurrence, placing substantial stress on the dynamics of land use and land cover in numerous regions across the globe [1,2]. Urban growth in developing countries, such as India, is a complex phenomenon characterized by rapid rural-to-urban transition [3]. The urban population of India has been experiencing an unparalleled growth rate, driven by factors including the shift from rural to urban areas, natural population growth, and the expansion of economic prospects within urban centres. Small and mid-sized cities in India are experiencing unparallel urban growth as evidenced by the rise of innumerable Census Towns (CTs) since the early 2000s [4] . Urban expansion in small cities of the developing world is experiencing a significant upward trend. The rapid growth of these cities poses several challenges and opportunities at the same time [5]. On one hand, urban expansion can lead to increased economic opportunities, improved access to services, and enhanced living standards. However, it also brings forth a range of issues, including strain on infrastructure, environmental degradation, social inequalities, and inadequate provision of basic services [6–10]. Sustainable urban planning and effective governance are vital to address these challenges and ensure that urban expansion in small and mid-sized cities is carried out in a means that promotes equitable development, preserves the environment, and improves the quality of life for all inhabitants [11] .

According to the World Bank, India's urban population is projected to witness a staggering increase of 404 million urban dwellers by the year 2050, making it one of the fastest-urbanizing countries in the world (United Nations, 2018). What makes this growth even more significant is that it is expected to occur primarily in cities with populations of less than one million. This presents a critical opportunity for focused action and intervention in numerous small cities like Mysuru. Unfortunately, policy negotiations in India have largely neglected small cities, as they have been overlooked and excluded from the discussion [12]. However, it is essential to acknowledge that the true advantages of urbanization can only be fully realized if small and mid-sized cities are developed with a strong emphasis on sustainability [13]. This notion is reinforced by the understanding that a significant portion, ranging from 70 to 80 per cent, of India's urban structure slated for completion by 2030 remains to be constructed [14,15]. In India, this scenario offers a unique chance to intentionally develop sustainable infrastructure and strategically formulate land-use policies that will define the cities of tomorrow. Therefore, small and mid-sized cities like Mysuru hold the key to India's future sustainable development.

Mysuru, a city located in the southern part of India, has experienced significant urban growth and transformation in the past years. This growth has directed in drastic fluctuations in land use and land cover patterns, resulting in various socio-economic and environmental consequences. Comprehending and evaluating these dynamics is essential for proficient urban planning and the promotion of sustainable development in the area. There is a serious dearth of studies on emerging small and mid-sized cities, particularly among the southern Indian cities. The region is diverse within itself, displaying both urban primacy and dispersed, inclusive urbanisation at the same time [16]. The current study, therefore, attempts to fill the gap by examining the subtleties of urban expansion in the mid-sized city of Mysuru. The present study aims to assess the dynamics of land use and land cover changes in the fast-urbanizing areas surrounding Mysuru, using earth observation and Geographic Information System (GIS) techniques. Through analysing multi-temporal Landsat imageries and employing spatial analysis tools, the study attempt to track and measure changes in land use and land cover classes, such as agricultural, vegetation, water bodies, and urban areas for the years 1995, 2001, 2007, 2014 and 2022. Moreover, the study aims to explore the spatial patterns and trends of these changes, aiming to comprehend the fundamental drivers and their effects on the environment and society. The results of this study will offer valuable perspectives on the scope and character of urbanization, as well as the related modifications in land use and land cover, encompassing Mysuru and its environs up to a radius of 15 km from the Central Business District (CBD). These insights will contribute to informed decision-making for urban planning, resource management, and environmental conservation. By identifying areas of rapid change, policymakers and stakeholders can develop strategies to mitigate negative impacts, promote sustainable development, and ensure the well-being of both urban and rural communities in the region. This study will stand as a pioneering effort within the research domain, as it concentrates on unravelling the dynamics of urban expansion and underscores the urgency of sustainable planning.

Study area

Mysuru is a historical city and erstwhile capital and is situated in the southern part of Karnataka state. The district of Mysuru shares its borders with Tamil Nadu to the south-east, Kodagu district to the west, To the north, Mandya district is situated, while the northwest is bordered by Hassan district, and the northeast is adjacent to Bangalore district. The city's geographical coordinates span from 12° 14' 41" to 12° 22' 25" N latitudes and 76° 34' 20" to 76° 43' 23" E longitudes (Figure 1). The Cauvery River drains the northern region of the city, while the Kabini river drains the southern region. In addition, there are numerous tanks and lakes situated throughout Mysuru city and its outskirts. Additionally, Mysuru boasts numerous tanks and lakes, both within the city and its peripheries, further enhancing its ecological and hydrological significance. The distinctive spatial and environmental attributes of the Mysuru study area establish it as a perfect context for delving into the repercussions of swift urbanization on alterations in land use and land cover. It is a historically significant city known for its rich cultural heritage and is often referred to as the Cultural Capital of Karnataka. Mysuru is governed by a Municipal Corporation and plays a crucial role as an administrative, educational, and economic centre in the region. The city is located approximately 146 km southwest of the state capital, Bengaluru. Mysuru is renowned for its magnificent palaces, including the iconic Mysuru Palace, which attracts tourists from around the world. In recent years, Mysuru has experienced rapid urban expansion and development, leading to various land use and land cover changes [(17)]. The expansion of residential areas, commercial establishments, and infrastructure projects has transformed the city's landscape. These changes have consequences for the environment, socio-economical aspects, and general sustainability of the city. Considering the unique characteristics and ongoing urbanization dynamics, Mysuru provides an excellent case study for examining the impacts of urban expansion, land use changes, and the need for sustainable planning. The present study, an area encompassing 15 km from the CBD of Mysuru has been chosen for studying the LULC change dynamics for a period of 17 years.

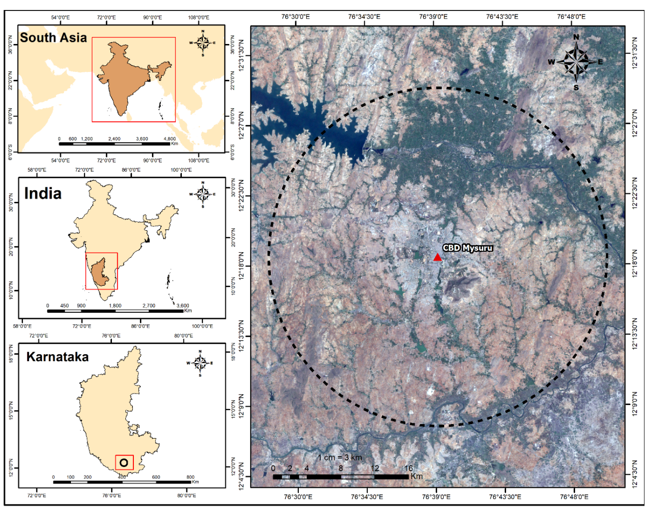

Fig. 1. Location of the study area (Mysuru)

Methodology

Materials

In this study, a blend of primary and secondary data was employed. The primary data was collected through on-site observations and surveys conducted in the study area. Secondary data, on the other hand, was obtained from various sources. Regarding satellite imagery, a collection of five distinct Landsat images, encompassing TM, ETM+, OLI, and TIRS imageries, was procured from the United States Geological Survey (USGS) (https://earthexplorer.usgs.gov/) to cover the years 1995, 2001, 2007, 2014, and 2022 (Table 1). The selection of these images was grounded in their accessibility, absence of cloud cover, and alignment with seasons that offered optimal visibility of the analysed features. In addition, the secondary data were acquired from various sources, including both physical offices and online platforms. High-resolution images were acquired from Google Earth, while toposheets, city maps, plans, and boundaries were procured from pertinent administrative offices. The demographic data, crucial for the analysis, were collected from the Census of India. Ground observations were undertaken in the study area to collect primary data. This entailed conducting on-site visits to gather GPS reference points, which were subsequently utilized for satellite image classification and precision evaluation. The processing and classification of satellite imagery, along with the examination of changes in land use and land cover and urban expansion, were executed using software including ERDAS Imagine, ArcGIS, and QGIS.

Satellite image pre-processing

These pre-processing techniques are essential to improve the quality and accuracy of the data obtained from satellite images [(18,19)]. By applying pre-processing methods, the inherent limitations and distortions in the images can be corrected, allowing for more reliable and meaningful analysis. Landsat collection-2 level-1 datasets are of the highest standard and are considered suitable for time series analysis (EROS, 2020). In this study, atmospheric correction of the Landsat images was conducted by employing the Semi-Automatic Classification Plugin (SCP) within the QGIS 2.6.1 software. The SCP tool facilitated the correction of atmospheric influences present in the satellite images, ensuring more accurate and reliable data for further analysis. To create a comprehensive analysis, the Landsat images were processed by combining their respective bands to generate composite images for each year under investigation (1995, 2001, 2007, 2014, and 2022). Afterward, a segment of the composite image was isolated by extracting the 15 km buffer zone surrounding Mysuru's CBD for each Landsat image, thereby concentrating the analysis on the designated study region.

Satellite image classification

Following the pre-processing stage, the pre-processed satellite data was put under a supervised classification procedure to classify the pixels into distinct LULC classes. Supervised classification involves an expert overseeing the process of pixel assemblage using training sites that provide spectral statistics for each feature type. These training sites are used to guide the computer algorithm in assigning labels to the spectral signatures, categorizing them according to their respective land cover classes [20]. The objective of this classification process was to categorize each pixel based on its spectral characteristics and assign it to the appropriate LULC class [20,21]. The supervised classification technique employed in this study involved the utilization of known reference samples for training the classification algorithm [22,23]. The reference samples were meticulously chosen relying on the ground truth data gathered through field observations. By associating the spectral signatures of the reference samples with their corresponding LULC classes, the maximum likelihood classifier algorithm used has identified similar spectral patterns in the satellite imagery. Following an initial visual interpretation of the images and taking into account the sensor's spatial resolution, a total of five Land Use and Land Cover (LULC) Level I classes, as outlined by Anderson, Hardy, Roach, & Witmer in 1976, were discerned. Then a signature file was created by selecting pixels that exhibited uniform surface types across the study area [24]. The signature file was then used to assign the pixels to five distinct land use and land cover classes, viz., agriculture land, vegetation, water bodies, built-up and open/fallow land.

Afterwards, the model was executed using ERDAS Imagine software to generate the LULC map consisting of five thematic classes. To enhance the thematic accuracy of the classified map, post-classification error correction techniques were employed [25,26]. These methodologies were employed to detect and rectify any misclassifications or inaccuracies that could have arisen during the initial classification procedure. To rectify any incorrectly classified pixels, manual corrections were carried out, aided by field data and supplementary information. The final land use and land cover maps, comprising five distinct classes, were generated by refining the initial generalized maps for the years 1995, 2001, 2007, 2014 and 2022.

Classification accuracy assessment

An accuracy assessment is a method employed to determine the level of accuracy of LULC classes showed in a thematic map concerning the real classes observed on the ground [23,27]. The error matrix serves as a valuable tool for quantifying and expressing the accuracy of the map. By comparing the assigned LULC classes in the map with the corresponding ground truth information, the error matrix provides a comprehensive and efficient means of evaluating the overall accuracy and consistency of the thematic map. To conduct the accuracy assessment, reference data were obtained through a combination of field visits and digital sources. For the 2022 image, ground truth data was obtained during field visits using a handheld GPS (Global Positioning System). To acquire reference images for the past imageries (1995, 2001, 2007 and 2014), high-resolution Google Earth images and toposheets belonging to the study area were utilized. In the accuracy assessment, a stratified random sampling method was used, ensuring the inclusion of a diverse range of sample points for each image [1,28]. With over 200 sample collection points allocated for each classified image, this sampling approach allowed for a robust evaluation of classification accuracy. The accuracy assessment includes four key measures: Users' accuracy, Producers' accuracy, overall accuracy and Kappa accuracy [27] (Table 2). Although the accuracy assessment of the classified image using the error matrix technique is a valuable tool, it is not without limitations [29]. Errors introduced during the assessment phase have the potential to influence the thematic accuracy of the map.

Change analysis

The technique of cross-tabulation and dynamic change was employed to detect and analyse the changes in LULC during two periods. This method facilitated the comparison and examination of the spatial dispersal and transition of various land use classes. The change matrix method involved overlaying the LULC maps of the two periods, enabling pixel-to-pixel comparison [30]. To create the Land Use and Land Cover (LULC) change, the overlay tool within ArcMap 10.3 and the pivot table function in Excel were employed. The objective was to analyse changes in LULC between the years 1995-2001, 2001-2007, 2007-2014 and 2014-2022. Four separate intervals were created, and for each interval, new thematic layers were generated to represent the changes in LULC. Additionally, a change matrix was also constructed to offer statistical information on the transitions or variations that happened from one LULC class to another during the specific period. The analysis has discovered the increases and losses in each LULC class. This information was then used to create a change map, which visually represented and analysed the spatial changes that occurred between the two periods.

The dynamic degree method, on the other hand, measures the extent of disparities in the area of land use over a specific time interval. To quantify the rate of change in LULC classes, the land use dynamic index was calculated using the following equation (Eq. 1) [18].

$$K = \frac{U_b - U_a}{U_a} X \frac{1}{T} X 100$$

The magnitude of Land Use Land Cover change for a particular category, designated as K, is computed using the initial area 'a' and the final area 'b' of land use or land cover over the selected time period. The total duration of the study is denoted as T.

Urban expansion quantification

Finally, to measure the spatial range of built-up growth in and surrounding Mysuru, the built-up density has been calculated using a multi-ring buffer of 1 km intervals. The built-up layer

Table 1. Details of satellite imageries used in the study

Mission	Sensor	Acquisition Date	Spatial Resolution	Path/Row
Landsat 5	TM	22-01-1995	30 m	144/051, 144/052
Landsat 5	TM	12-03-2007	30 m	144/051, 144/052
Landsat 7	ETM +	03-03-2001	30 m	144/052
Landsat 8	OLI TIRS	06-03-2014	30 m	144/052
Landsat 8	OLI TIRS	05-03-2022	30 m	144/052

of different years has been clipped using a buffer distance of 1 km intervals to measure the compactness of the built-up area concerning the buffer area.

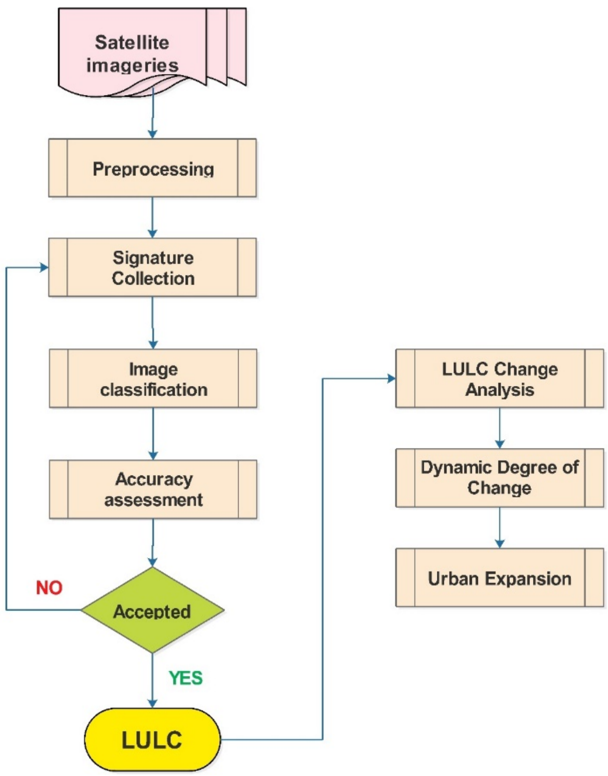

Fig. 2. Methodology flow diagram used in the study

Results and discussion

Land use land cover

The land use and land cover maps for the study area in the years 1995, 2001, 2007, 2014 and 2022 were derived through supervised classification of the Landsat images. The classified image (Figure 3) reveals the presence of five distinct categories of LULC in the study area. These categories include built-up areas represented in red, open land in brown, agricultural land in yellow, vegetation in green and water bodies in blue. The visual analysis of the classified image depicts a consistent pattern of land use and land cover transformation taking place in Mysuru from 1972 to 2018. This observation highlights the dynamic nature of land utilization and underscores the significance of monitoring and understanding LULC changes over time.

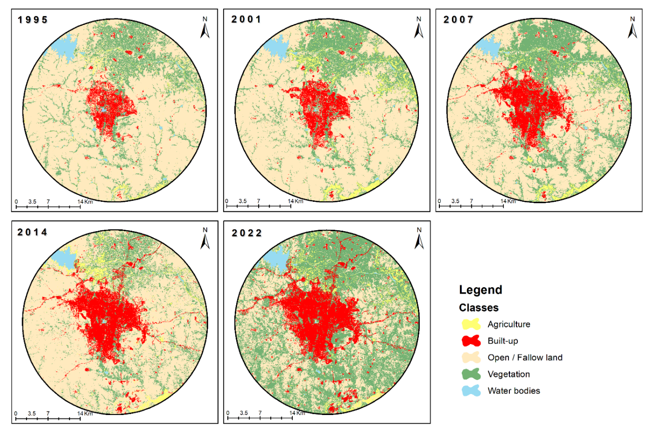

Fig. 3. Land use and land cover of Mysuru in the years 1995, 2001, 2007, 2014 and 2022

Classification accuracy assessment

The accuracy assessment intends to assess the degree to which the classes in the classified image align with the reference image or ground truth. To achieve this objective, a confusion matrix was generated to evaluate the precision of the classified image, illustrated in Table 2 . The overall accuracy of the classified images for the years 1995, 2001, 2007, 2014 and 2022 was determined to be 91.74%, 92.04%, 92.42%, 92.13% and 91.15% respectively. These accuracy measures indicate the overall reliability and correctness of the classification outcomes.

Table 2. Summary of the error matrix depicting classification accuracy of satellite imageries of Mysuru

Year	Accuracy	Classes					Overall Accuracy	Overall Kappa
		Built-up	Open/Fallow land	Agricultural	Vegetation	Water bodies		
1995	Reference Total	35	49	46	52	36	91.74	0.88
	Classified	35	47	51	50	35		
	Correctly Classified	32	44	42	47	35		
	User's Accuracy (%)	91.43	93.62	82.35	94	100		
	Producer's Accuracy (%)	91.43	89.80	91.30	90.38	97.22		
	Kappa	0.91	0.9	0.91	0.9	0.91		
2001	Reference Total	47	48	50	51	30	92.04	0.90
	Classified	47	46	55	49	29		
	Correctly Classified	44	43	46	46	29		
	User's Accuracy (%)	93.62	93.48	83.64	93.88	100		
	Producer's Accuracy (%)	93.62	89.58	92.00	90.20	97		
	Kappa	0.94	0.92	0.92	0.92	0.95		
2007	Reference Total	52	53	48	48	36	92.42	0.89
	Classified	52	51	53	46	35		
	Correctly Classified	49	48	44	43	35		
	User's Accuracy (%)	94.23	94.12	83.02	93.48	100		
	Producer's Accuracy (%)	94.23	90.57	91.67	89.58	97.22		
	Kappa	0.84	0.87	0.90	0.90	1		
2014	Reference Total	43	49	48	48	33	92.13	0.88
	Classified	43	47	53	46	32		
	Correctly Classified	40	44	44	43	32		
	User's Accuracy (%)	93.02	93.62	83.02	93.48	100		
	Producer's Accuracy (%)	93.02	89.80	91.67	89.58	96.97		
	Kappa	0.95	0.95	0.84	0.96	0.80		
2022	Reference Total	41	47	44	49	31	91.15	0.88
	Classified	41	45	49	47	30		
	Correctly Classified	38	42	40	44	30		
	User's Accuracy (%)	92.68	93.33	81.63	93.62	100		
	Producer's Accuracy (%)	92.68	89.36	90.91	89.80	96.77		
	Kappa	0.97	0.83	0.87	0.75	1.00		

The Kappa coefficient values for the images range between 0.88 and 0.90. The Kappa coefficient is a statistical metric that evaluates the concurrence between the classified image and the reference data, considering the extent of agreement that might arise by random chance. In land use and land cover classification, an accuracy level of at least 85% is commonly accepted as the minimum threshold for acceptable classification results [31].

From Table 2 , it can be observed that the accuracy of the classification varies across different years and classes. Generally, the user's and producer's accuracies were high, ranging from 81.63% to 100%, indicating a good level of classification performance. The overall accuracies range from 91.15% to 92.42%, indicating a high level of overall classification accuracy. The Kappa coefficients also indicate a substantial level of agreement amongst the classified images and the location data, with values ranging from 0.88 to 0.90. During the study period from 1995 to 2022, it was observed that the accuracy of identifying built-up land steadily improved. Similarly, the accuracy of detecting water bodies consistently remained at a high level, demonstrating a reliable and consistent performance. Conversely, the accuracy of agricultural land has diminished due to the challenge posed by mixed pixels within the study area. Open/fallow land mixed up with the agricultural land and vegetation has noticeably reduced the accuracy of agricultural area. The classification accuracies were deemed satisfactory as all recorded accuracy values exceeded 90% for all the years, indicating a high level of accuracy across the board. In summary, the classification was deemed practical as it achieved an agreed-upon value for both overall accuracy and overall Kappa coefficient, indicating a satisfactory level of performance.

LULC change analysis

Land use and land cover area of Mysuru and the surrounding area for the year 1995-2022 has been presented in Table 3 . The land use and land cover of Mysuru were observed to undergo persistent changes over time. This change is especially noticeable in the case of built-up land, which exhibits a clear upward trend in terms of growth. The built-up land class demonstrates consistent growth throughout the entire period. Starting at 6,063.90 ha in 1995, it steadily expands to 8,226.47 ha in 2001. The rate of growth rate intensifies, with a significant leap to 12,944.63 ha in 2007. Further, the trend continues, reaching 20,312.57 ha by 2022. This growth can be attributed to the demographic shift and the diversification of economic activities within the city. The nearness of Mysuru to the city of Bangalore has played a noteworthy role in driving these changes. The built-up area has expanded spatial from the CBD of the city to the surrounding area (Figure 3). The expansion of urban sprawl becomes particularly evident after the year 2007, with a significant upsurge in built-up lands. The present expansion is largely facilitated by the development of transport infrastructure, which contributes to the quick growth of urbanization and the spread of built-up land.

The area dedicated to agriculture experienced fluctuations throughout the years. It saw an increase from 3186.09 hectares in 1995 to 5728.33 hectares in 2001. However, there was a decline in agricultural land from 2001 to 2007, subsequently, it started increasing again in 2014 and 2022. The agricultural area was also classified under the fallow land category, as most of the agricultural area during summer (March) was left uncultivated in Mysuru. The reduced agricultural land is also substantiated by the fact that the majority of farmers hold agricultural land of less than one hectare [1]. This has also contributed to the extravagant increase in the open/fallow land group in the study area. The total area of open/fallow land has decreased from the year 1995 to 2022. In 1995, open/fallow land covered 90744.21 ha. By 2022, this number had decreased to 42745.47 ha. This decrease is likely due to a combination of factors, including urbanization, population growth, and changes in agricultural practices. The vegetation class demonstrates fluctuations over time. The area increases from 22760.54 ha in 1995 to 25511.06 ha in 2001. However, it declines to 32869.55 ha in 2007 and further decreases to 19092.64 ha in 2014. Surprisingly, there is a substantial rebound with a significant expansion to 54858.25 ha in 2022. These fluctuations may be due to factors such as changes in land management practices, conservation efforts, or ecological restoration initiatives.

The total land under water bodies, such as lakes, streams, and reservoirs, shows relatively minor fluctuations. It decreases slightly from 2867.36 ha in 1995 to 2229.76 ha in 2022. These variations could be inclined by factors such as water management practices, climate variations, or human interventions affecting water bodies. Figure 4 displays the area share of various LULC categories for different years in per cent for Mysuru. The River Cauvery and KRS reservoir in the northern and Kabini River in the southern directions and several small lakes in the city represent the water bodies in the study area. The agricultural lands can be seen mainly concentrated surrounding these waterbodies both in the north and south of the city (Figure 3). The vegetation area was seen fluctuating, sometimes overlapping with open/fallow land due to natural growth in the abandoned agricultural area. This can be evident in Figure 4 , where the drop in open/fallow land area is compensated by increasing vegetation. One possible reason for the abandonment of agricultural fields is the changing nature of economic activities. This shift may lead to a decreased focus on agricultural practices and a subsequent decline in the utilization of agricultural fields.

To delve deeper into the examination of land use and land cover alterations between 1995 and 2022 in Mysuru, the dynamic degree index of change is utilized. This index quantifies the magnitude of shifts in land use categories over

Table 3. ULC area in hectares for Mysuru during the years 1995, 2001, 2007, 2014 and 2022

Classes	Area (ha)				
	1995	2001	2007	2014	2022
Agriculture	3186.09	5728.33	3337.99	5358.43	5476.16
Built-up	6063.90	8226.47	12944.63	16615.06	20312.57
Open/Fallow	90744.21	83928.96	74507.54	82695.53	42745.47
Vegetation	22760.54	25511.06	32869.55	19092.64	54858.25
Water bodies	2867.36	2226.11	1962.58	1860.63	2229.76

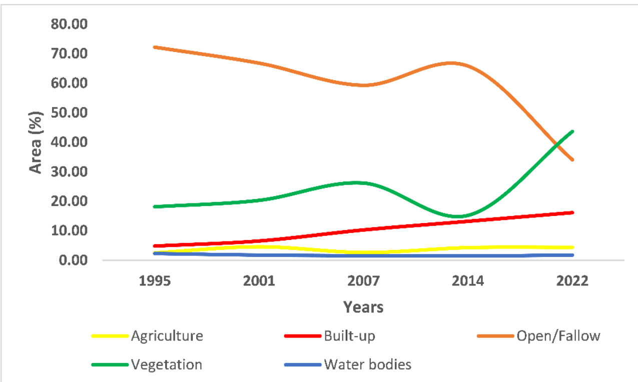

Fig. 4. Area share of different LULC categories in Mysuru for the years 1995, 2001, 2007, 2014 and 2022 shown in per cent

a defined period. A positive value for the dynamic degree of land use signifies progressive change, while a negative value indicates regressive change. The dynamic degree of LULC variation for Mysuru (Table 4) shows that the built-up land use class indicate progressive changes in all periods analysed. The built-up class has the maximum dynamic degree change, with an overall increase of 8.70%. Although the periodical rate of built-up area growth has decreased since 2007, the absolute increase remains highly noticeable. The growth is particularly visible towards the southern and northeastern directions of the city. Between 1995 and 2022, the vegetation area increased by 5.22%. This increase has been driven by several factors, including reforestation efforts, the desertion of agricultural land, and the natural succession of vegetation.

The agricultural land class has contracted the most, with a dynamic degree of -2.66. This is likely due to a combination of factors, including the decline of traditional farming practices, the increase of built-up areas, and the conversion of agricultural land to other uses. The open/fallow land class has experienced negative growth, with a dynamic degree of -1.96. This is likely due to the fact that this land class is often used for grazing or other agricultural purposes, which tend to fluctuate with the seasons. There has been a slight decrease in the extent of water bodies, which has reduced by 0.82%. The marginal decrease in the dynamic degree of water bodies is mostly accredited to the presence of rivers, which constitute the largest proportion of the water body category. Overall, the landscape of the region has experienced important variations over the last 27 years.

LULC transition matrix

The post-classification change matrix was formulated by spatially intersecting distinct land use and land cover maps to evaluate the transitions between various categories during different time intervals. This matrix provides a quantitative analysis of the fluctuations in land use and land cover over the years (Tables 5, 6, 7 and 8). The tables display the horizontal values indicating the additional area due to the alteration from one category to another, and the vertical values representing the area contracted by the conversion from one class to another. The transverse values in the table represent the unaffected area for each LULC zone.

From 1995 to 2001, open/fallow land contributed significantly to the built-up land trailed by vegetation and agricultural land. The open/fallow land, which typically consists of unused or uncultivated areas in Mysuru, often becomes the target for urban expansion and development. As the city grows, there is a higher demand for residential, commercial, and industrial spaces, leading to the transformation of open/fallow land into built-up areas. A comparable tendency can be seen to continue for the period of 2001-2007, 2007-2014 and 2014-2022 period as well (Tables 6, 7 and 8). From 2007 to 2014 the contribution of vegetation to built-up areas has increased significantly to 1552.77 ha, denoting increased investment in transportation infrastructure and large-scale projects in Mysuru. The exaggerated increase can also be credited to classification errors that might have crept in between agricultural and vegetation categories. The agricultural area has remained a marginal contributor to built-up growth as an agricultural activity constitutes the core traditional economic activity in Mysuru. Water bodies have also contributed to a minimal area of built-up land in Mysuru. The vegetation land, which has increased significantly throughout the study period has been contributed largely by open/fallow and agricultural land. The shift in economic activity has led largely to the fallowing of the land and the growth of natural vegetation in the empty lands. This can also be observed in the synonymous contribution of vegetation and open/fallow land

Table 4. Dynamic degree of change statistics of different LULC classes in Mysuru for different periods

Classes	Dynamic Degree (%)				
	1995-01	2001-07	2007-14	2014-22	1995-2022
Agriculture	13.30	-6.95	8.65	0.27	2.66
Built-up	5.94	9.56	4.05	2.78	8.70
Open/Fallow	-1.25	-1.87	1.57	-6.04	-1.96
Vegetation	2.01	4.81	-5.99	23.42	5.22
Water bodies	-3.73	-1.97	-0.74	2.48	-0.82

towards agricultural areas in different periods. The water bodies have remained constant more or less during the study period, with a major portion of the transition towards agricultural and open/fallow land.

Figure 5 a, 5b, 5c and 5d represents the spatial conversion of land use and land cover in Mysuru for the year 1995 to 2001, 2001 to 2007, 2007 to 2014 and 2014 to 2022 respectively. Observing the figures reveals that within the city's central zone, the expansion of built-up areas predominantly originates from the vegetation class. Conversely, in the periphery of the city, the growth of built-up areas is primarily attributed to open/fallow and agricultural regions. The expansion of transport infrastructure and linear expansion is particularly visible since the year 2007 in Mysuru. During 2014 and 2022 (Figure 5 d) the transition into the vegetation category is dominant across Mysuru due to rapid land use and socio-economic variations. Increased concentration of built-up land in the south near Nanjangud is becoming apparent as well during the 2014-2022 period.

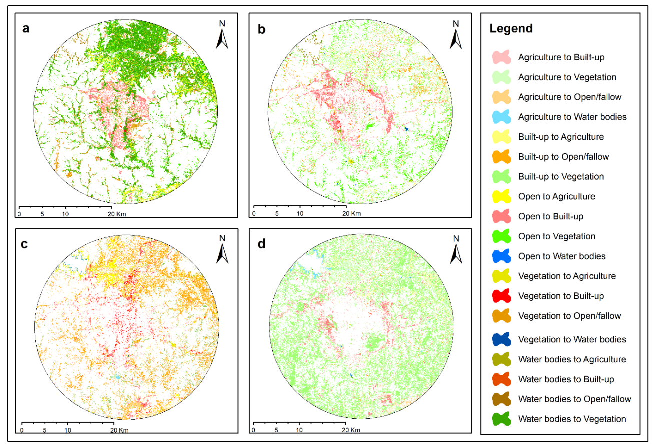

Fig. 5. 5 LULC transition in Mysuru during a. 1995-01, b. 2001-07, c. 2007-14, d. 2014-22

Urban growth analysis

To measure the spatial dispersal of built-up density in Mysuru for the different years from 1995 to 2022, the concentric buffer-based built-up density is measured (Figure 6 a-b). It can be seen from the descending curves of Figure 6 b that the concentration of the built-up area generally declines towards the periphery. However, the rate of decrease is not constant. The central part of the city exhibits a dense concentration of built-up areas, with a density of over 75 per cent persisting within a range of 6 to 8 km from the CBD. Eventually, there is a gentle sloping of the density curves from a distance of 8 km towards the fringe of the city. From a distance of 14 km from the CBD of Mysuru the density is reduced to 10 per cent and the curves become flat. The distance between curves representing periodical built-up growth maintains a uniform distance except for the years 2001 to 2007, during which there was a substantial increase in the built-up land.

Figure 6 a demonstrates a constant accretion of the built-up land in Mysuru during the study period. The growth is particularly significant in closer buffer distances, indicating more concentrated urban development and higher population density near the city centre. As the buffer distance increases, the built-up density tends to spread out, reflecting urban expansion and suburban development. The rural-urban conversion at the margin of the city remains evident by increased built-up accretion at the periphery over the years. This information provides insights into the spatial dispersal and density of built-up areas in Mysuru, which can be useful for urban planning and land management purposes.

Conclusion

In the current study, a comprehensive dataset of land use and land cover was generated meant for Mysuru, India, utilizing a series of Landsat satellite images spanning a period of 27 years, ranging from 1995 to 2022. The study has helped to effectively monitor, enumerate, and designate the fluctuations in land use and land cover over the time, with a particular focus on variations in built-up areas. This allowed us to identify and analyse the inclinations and patterns of urban expansion. The present work employed a mixture of remote sensing and GIS techniques to accurately capture and analyse the quantitative aspects of LULC modification and the intricate details of built-up expansion.

The study has identified dynamic changes in the LULC of Mysuru from 1995 to 2022 caused by a sweeping surge in built-up area. The study unveiled a notable escalation in

Table 5. ULC transition matrix (area in ha) from 1995 to 2001 in Mysuru

	LULC 2001						Grand Total
	LULC Classes	**Agricultural land**	**Built-up**	**Open / Fallow land**	**Vegetation**	**Water bodies**	
LULC 1995	**Agriculture**	1675.68	57.90	610.78	806.90	34.83	**3186.09**
	Built-up	3.14	4706.86	1051.48	302.43	0.00	**6063.90**
	Open/Fallow land	2218.37	3244.81	77566.06	7712.98	0.90	**90743.13**
	Vegetation	1634.18	213.59	4410.78	16497.40	4.32	**22760.27**
	Water bodies	196.96	3.31	289.86	191.18	2186.05	**2867.36**
	Grand Total	**5728.33**	**8226.47**	**83928.96**	**25510.88**	**2226.11**	**125620.76**

Table 6. ULC transition matrix (area in ha) from 2001 to 2007 in Mysuru

	LULC 2007						Grand Total
	LULC Classes	**Agricultural land**	**Built-up**	**Open / Fallow land**	**Vegetation**	**Water bodies**	
LULC 2001	**Agricultural land**	2486.92	27.73	566.50	2581.51	65.67	**5728.33**
	Built-up	0.00	8226.47	0.00	0.00	0.00	**8226.47**
	Open / Fallow land	128.43	4343.84	70384.66	9027.00	45.03	**83928.96**
	Vegetation	584.63	339.08	3405.46	21126.30	55.59	**25511.06**
	Water bodies	138.01	7.50	149.94	134.37	1796.29	**2226.11**
	Grand Total	**3337.99**	**12944.63**	**74506.55**	**32869.19**	**1962.58**	**125620.94**

Table 7. ULC transition matrix (area in ha) from 2007 to 2014 in Mysuru

	LULC 2014						Grand Total
	LULC Classes	**Agricultural land**	**Built-up**	**Open / Fallow land**	**Vegetation**	**Water bodies**	
LULC 2007	**Agricultural land**	1652.55	33.45	1262.67	313.34	75.98	**3337.99**
	Built-up	0.00	12944.63	0.00	0.00	0.00	**12944.63**
	Open / Fallow land	1268.85	2084.12	67974.20	3089.34	91.02	**74507.54**
	Vegetation	2115.66	1552.77	13454.69	15686.54	59.89	**32869.55**
	Water bodies	321.37	0.09	3.96	3.42	1633.75	**1962.58**
	Grand Total	**5358.43**	**16615.06**	**82695.53**	**19092.64**	**1860.63**	**125622.29**

Table 8. ULC transition matrix (area in ha) from 2014 to 2022 in Mysuru

	LULC 2022						
	LULC Classes	**Agriculture**	**Built-up**	**Open / Fallow**	**Vegetation**	**Water bodies**	**Grand Total**
LULC 2014	**Agriculture**	2259.54	162.27	805.28	1672.35	458.99	**5358.43**
	Built-up	0.00	16615.06	0.00	0.00	0.00	**16615.06**
	Open / Fallow land	2523.71	3434.20	41049.36	35671.24	16.92	**82695.44**
	Vegetation	603.83	100.52	877.79	17493.14	17.37	**19092.64**
	Water bodies	89.08	0.52	13.05	21.51	1736.48	**1860.63**
	Grand Total	**5476.16**	**20312.57**	**42745.47**	**54858.25**	**2229.76**	**125622.20**

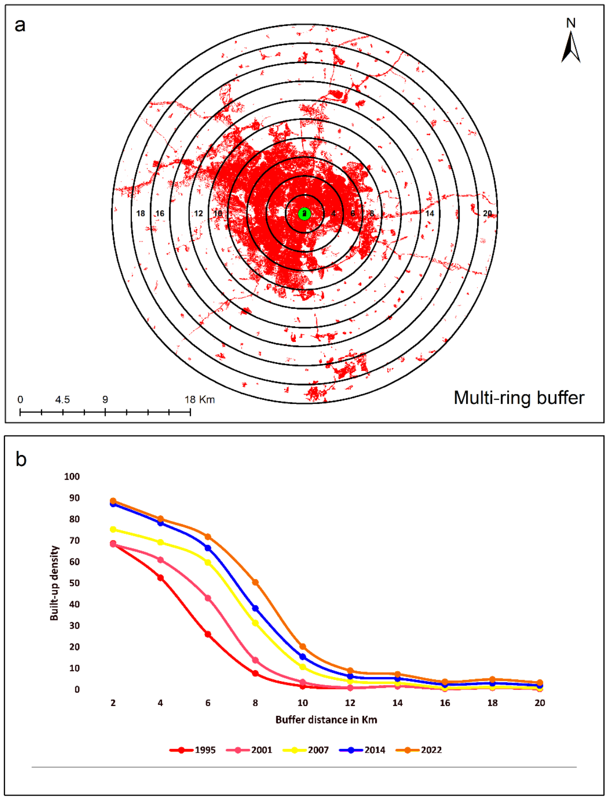

Fig. 6. Spatial extension of the built-up area in Mysuru a. 2 km buffer around CBD b. built-up density graph

the expanse of built-up land, manifesting an augmentation of more than 235 percent between the years 1995 and 2022. The examination of the LULC variation matrix highlights that the growth of urban areas has been predominantly fuelled by the conversion of open/fallow, vegetation and agricultural land. These land categories have made substantial contributions to the general urban growth observed in Mysuru. The increasing trend of open/fallow land conversion to built-up areas signals drastic socio-economic changes leading to urbanisation in the study area. The shifting from agricultural to secondary and tertiary activities can be inferred from the changing LULC trends in Mysuru. In the region, a distinctive radial pattern of built-up growth can be observed, originating from the centre. This expansion can be attributed primarily to the formation of production centres and the expansion of various infrastructure amenities in Mysuru. The results of the present work highlight the phenomena of rapid built-up growth and emergence of mid-sized Indian cities as hotspots of imminent urban growth in India.

Mysuru, a medium city in the southern state of Karnataka, is experiencing rapid urbanization. The city's population has increased by more than 50% in the past 20 years, and it is anticipated to remain growing at a similar rate in the upcoming years[14]. Cities such as Mysuru, which are experiencing rapid urbanization, hold the potential to accommodate a significant share of the India's upcoming urban residents[32]. Rapid pace of urbanization poses a substantial risk to sustainable development. The consequences of hazardous LULC change are multi-faceted, affecting the environment, social and economic aspects of urban centres. Consequently, there is a pressing requirement to implement sustainable urban management strategies to ensure the well-being and long-term viability of these cities. The conclusions of this study aid as a valuable foundation for future research in this field, considering the current situation on the ground in Mysuru. By shedding light on the prevailing conditions and challenges associated with rapid urbanization in the city, this study sets the stage for further investigations and inquiries.

References

1) Uma SM, Shankar B, Rego J. An Overview of Agriculture in Mysore District: Proposal of an Agriculture Hub in Mysore City. *International Journal of Recent Technology and Engineering*. 2021;10(4). Available from: https://www.ijrte.org/wp-content/uploads/papers/v10i4/C64810910321.pdf.
2) Singh B, Venkatramanan V, Deshmukh B. Monitoring of land use land cover dynamics and prediction of urban growth using Land Change Modeler in Delhi and its environs, India. *Environmental Science and Pollution Research*. 2022;29(47):71534–71554. Available from: https://doi.org/10.1007/s11356-022-20900-z.
3) Bhatta B, Saraswati S, Bandyopadhyay D. Quantifying the degree-of-freedom, degree-of-sprawl, and degree-of-goodness of urban growth from remote sensing data. *Applied Geography*. 2010;30(1):96–111. Available from: https://doi.org/10.1016/j.apgeog.2009.08.001.
4) Pradhan, Charan K. Unacknowledged Urbanisation: The New Census Towns in India. *Exploring Urban Change in South Asia*. 2017;48:39–66. Available from: https://mpra.ub.uni-muenchen.de/41035/2/Unacknowledged_Urbanisation.pdf.
5) Laidley T. The Problem of Urban Sprawl. *Contexts*. 2016;15(3):74–77.
6) Freeman L. The Effects of Sprawl on Neighborhood Social Ties:<i>An Explanatory Analysis</i>. *Journal of the American Planning Association*. 2001;67(1):69–77. Available from: https://doi.org/10.1080/01944360108976356.
7) Han L, Zhou W, Li W, Li L. Impact of urbanization level on urban air quality: A case of fine particles (PM 2.5) in Chinese cities. *Environmental Pollution*. 2014;194:163–170.
8) Mundoli S, Manjunath B, Nagendra H. Effects of urbanisation on the use of lakes as commons in the peri-urban interface of Bengaluru, India. *International Journal of Urban Sustainable Development*. 2015;7(1):89–108. Available from: https://doi.org/10.1080/19463138.2014.982124.
9) Garouani AE, Mulla DJ, Garouani SE, Knight J. Analysis of urban growth and sprawl from remote sensing data: Case of Fez, Morocco. *International Journal of Sustainable Built Environment*. 2017;6(1):160–169. Available from: https://doi.org/10.1016/j.ijsbe.2017.02.003.
10) Das S, Angadi DP. Land use-land cover (LULC) transformation and its relation with land surface temperature changes: A case study of Barrackpore Subdivision, West Bengal, India. *Remote Sensing Applications: Society and Environment*. 2020;19:100322–100322. Available from: https://doi.org/10.1016/j.rsase.2020.100322.
11) Fertner C, Jørgensen G, Nielsen TAS, Nilsson KSB. Urban sprawl and growth management – drivers, impacts and responses in selected European and US cities. *Future Cities and Environment*. 2016;2(0):9–9. Available from: https://doi.org/10.1186/s40984-016-0022-2.
12) Guin D. Contemporary perspectives of small towns in India: A review. *Habitat International*. 2019;86:19–27. Available from: https://doi.org/10.1016/j.habitatint.2019.02.003.
13) Hegazy IR, Kaloop MR. Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt. *International Journal of Sustainable Built Environment*. 2015;4(1):117–124. Available from: https://doi.org/10.1016/j.ijsbe.2015.02.005.
14) Sastry GS. Urbanisation in a Forward Looking State of India: Patterns, Issues and Policy. 2006. Available from: https://pdfs.semanticscholar.org/7dff/fa9ae07e88d046df7c55755f48abb03d7bc5.pdf?_ga=2.
15) Sanke S, Vittal I, Dobbs R, Mohan A, Gulati A, Ablett J, et al. India's urban awakening: Building inclusive cities, sustaining economic growth. 2010. Available from: https://www.mckinsey.com/featured-insights/urbanization/urban-awakening-in-india.
16) Vaddiraju AK. Challenges of Urbanization in South India: Diverse Patterns and Different Trajectories. *Journal of Leadership Accountability and Ethics*. 2022;19(1). Available from: https://www.researchgate.net/publication/359161647_Challenges_of_Urbanization_in_South_India_Diverse_Patterns_and_Different_Trajectories.
17) Aithal BH, Setturu B, Sreekantha S, Durgappa S, Ramachandra D. Spatial patterns of urbanization in Mysore: Emerging Tier II City in Karnataka. In: Proceedings of NRSC User Interaction Meet- 2012. 2012. Available from: https://wgbis.ces.iisc.ac.in/energy/water/paper/nrse_mysore/mysore_nrsc.pdf.
18) Sowmya DR, Shenoy D, Venugopal KR. Remote Sensing Satellite Image Processing Techniques for Image Classification: A Comprehensive Survey. *International Journal of Computer Applications*. 2017;(11):161–161. Available from: https://ijcaonline.org/archives/volume161/number11/27193-2017913306/.
19) Asokan A, Anitha J, Ciobanu M, Gabor A, Naaji A, Hemanth DJ. Image Processing Techniques for Analysis of Satellite Images for Historical Maps Classification—An Overview. *Applied Sciences*. 2020;10(12):4207–4207. Available from: https://doi.org/10.3390/app10124207.
20) Thenkabail PS. Remotely Sensed Data Characterization, Classification, and Accuracies. Boca Raton. Taylor & Francis Group. 2016.
21) Jensen JR, Cowen DC. Remote Sensing of Urban/Suburban Infrastructure and Socio-Economic Attributes. 1999. Available from: https://www.asprs.org/wp-content/uploads/pers/99journal/may/1999_may_611-622.pdf.
22) Jensen JR. Introductory Digital Image Processing A Remote Sensing Perspective. 2005. Available from: https://dl.acm.org/doi/book/10.5555/526335.
23) Lillesand TM, Kiefer RW, Chipman JW. Remote Sensing and Image Interpretation. JohnWiley & Sons, Inc. 2015.
24) Alberti M, Weeks R, Coe S. Urban Land-Cover Change Analysis in Central Puget Sound. 2004. Available from: https://pdfs.semanticscholar.org/d2b6/43acab0679224b1071616f2be56305e2449c.pdf.
25) Harris PM, Ventur SJ. The integration of geographic data with remotely sensed imagery to improve classification in an urban area. 1995. Available from: https://www.asprs.org/wp-content/uploads/pers/1995journal/aug/1995_aug_993-998.pdf.
26) Manandhar R, Odeh IO, Ancev T. Improving the Accuracy of Land Use and Land Cover Classification of Landsat Data Using Post-Classification Enhancement. *Remote Sensing*. 2009;1(3):330–344. Available from: https://doi.org/10.3390/rs1030330.
27) Congalton RG, Green K. Assessing the Accuracy of Remotely Sensed Data: Principles and Practices (2 ed.). Boca Raton. CRC Press. 2008. Available from: https://doi.org/10.1201/9781420055139.
28) Ismail MH, Jusoff K. Satellite Data Classification Accuracy Assessment Based from Reference Dataset. *International Journal of Geological and Environmental Engineering*. 2008;2(3):23–29. Available from: https://www.semanticscholar.org/paper/Satellite-Data-Classification-Accuracy-Assessment-Ismail-Jusoff/d5e03bd3a3454bb7cd3757b4a406c1f01d113100.
29) Foody GM. Status of land cover classification accuracy assessment. 2002. Available from: https://doi.org/10.1016/S0034-4257(01.
30) Hassan Z, Shabbir R, Ahmad SS, Malik AH, Aziz N, Butt A, et al. Dynamics of land use and land cover change (LULCC) using geospatial techniques: a case study of Islamabad Pakistan. *SpringerPlus*. 2016;5(1). Available from: https://doi.org/10.1186/s40064-016-2414-z.
31) Anderson JR, Hardy EE, Roach JT, Witmer RE. US Geological Survey. 1976. Available from: http://pbcgis.com/raster/anderson.pdf.
32) Sastry GS. A model for sustainable urbanisation: the case of Karnataka. *Journal of Social and Economic Development*. 2009;(2):11–11.