




An Assessment of Land Use Land Cover Using Machine Learning Technique

V. Pushpalatha¹, H. N. Mahendra^{2†} , A. M. Prasad³, N. Sharmila⁴, D. Mahesh Kumar², N. M. Basavaraju², G. S. Pavithra⁵ and S. Mallikarjunaswamy²

¹Department of Information Science and Engineering, JSS Academy of Technical Education (Affiliated to Visvesvaraya Technological University, Belagavi), Bengaluru-560060, Karnataka, India

²Department of Electronics and Communication Engineering, JSS Academy of Technical Education (Affiliated to Visvesvaraya Technological University, Belagavi), Bengaluru-560060, Karnataka, India

³Department of Computer Science and Engineering, Dayananda Sagar College of Engineering, Bengaluru-560078, Karnataka, India

⁴Department of Electrical and Electronics Engineering, JSS Science and Technology University, Mysuru- 570015, Karnataka, India

⁵Department of Computer Science and Engineering (AI-ML), RNS Institute of Technology (Affiliated to Visvesvaraya Technological University, Belagavi), Bengaluru- 560098, Karnataka, India

†Corresponding author: H. N. Mahendra; mahendrahn@jssateb.ac.in

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ABSTRACT

This research paper presents a comprehensive assessment of the built-up area in Mysuru City over the decade spanning from 2010 to 2020, employing advanced geospatial techniques. The study aims to analyze the spatiotemporal patterns of urban expansion, land-use dynamics, and associated factors influencing the city's built environment. Remote sensing imagery, Geographic Information System (GIS) tools, and machine learning algorithms are leveraged to process and interpret satellite data for accurate land-cover classification. The methodology involves the acquisition and preprocessing of multi-temporal satellite imagery to delineate and map the built-up areas at different time intervals. Land-use change detection techniques are employed to identify and quantify alterations in urban morphology over the specified period. Additionally, socio-economic and environmental variables are integrated into the analysis to discern the drivers of urban growth. The outcomes of this research contribute valuable insights into urbanization dynamics and land-use planning strategies, facilitating informed decision-making for sustainable urban development.

INTRODUCTION

Urbanization is an unequivocal global phenomenon, transforming landscapes and shaping the dynamics of human habitation (Aithal et al. 2012, Hosseiny et al. 2022, Mahendra et al. 2023c). The rapid expansion of built-up areas within cities has become a critical facet of this transformative process, necessitating a comprehensive understanding of its implications on the environment, society, and urban planning (Dash et al. 2015, Mahendra et al. 2023a). This research paper embarks on a meticulous investigation, employing advanced geospatial techniques, to assess the evolution of the built-up area in Mysuru City over the critical decade spanning 2010 to 2020.

Mysuru, a city steeped in historical and cultural significance, has undergone significant urbanization in recent years. The burgeoning population, economic activities,

and infrastructural developments have played pivotal roles in altering the city's physical fabric (Kanga et al. 2022, Mahendra et al. 2023d). The utilization of geospatial technologies, including satellite imagery, remote sensing, and Geographic Information Systems (GIS), provides an unprecedented opportunity to scrutinize and quantify the spatial and temporal dynamics of urban expansion (Mahendra et al. 2023, Firoz et al. 2016). This research endeavors to unravel the patterns, drivers, and consequences of the built-up area expansion in Mysuru, offering valuable insights for sustainable urban development strategies.

The significance of this study extends beyond the confines of Mysuru, as urbanization challenges are pervasive and multifaceted. By delving into the specific case of Mysuru, this research aims to contribute to the broader discourse on urban growth, aiding policymakers, urban planners, and researchers in formulating evidence-based

strategies for managing and mitigating the impacts of rapid urbanization. The integration of geospatial techniques allows for a nuanced analysis, enabling the identification of hotspots of development, encroachments, and potential areas for conservation or redevelopment (Kumar Jat et al. 2008, Mahendra et al. 2019).

As the world grapples with the repercussions of unchecked urbanization, understanding the dynamics of built-up area expansion becomes imperative for achieving sustainable and resilient cities. The insights garnered from this case study on Mysuru City serve as a microcosm, illustrating the intricate interplay between historical, cultural, economic, and environmental factors influencing urban growth. Through this research, we aim to provide a foundation for informed decision-making and policy formulation, fostering a balance between urban development and environmental preservation in the face of escalating urban challenges.

SIMILAR STUDIES IN THE PAST

In the literature, several studies have utilized geospatial techniques to assess the LULC classes of the study area. Dash et al. (2015) have to estimate the urban built-up area of Bangalore city and the latter quantifying urban expansion over 19 years. Ramachandra et al. (2012) applied remote sensing and spatial metrics to study the urbanization process in Mysuru, identifying a significant increase in built-up area. Usha et al. (2014) also used remote sensing and GIS technology to evaluate the growth of built-up areas in Udupi Taluk, highlighting the environmental impact of urbanization. Kanga et al. (2022) linked urban growth in Bangalore to changes in land surface temperature, revealing a significant increase in built-up areas. Shahfahad et al. (2020), in a study of Surat, found a rapid increase in both population and built-up area, with a strong positive relationship between population density and built-up area.

Prakash & Bharath (2020) conducted a case study of Bangalore for assessment of urban built-up using geospatial methods. The study results show that the eastern part of the city has urban volume development compared to the central business district. Aithal (2012) presented a dynamics assessment of LULC classes in Mysuru city between the years 1973 to 2009. The coalescence of urban areas occurred during the rapid urban growth from 2000 to 2009. Santosh et al. (2018) conducted a case study in Chikodi Taluk, Belagavi District, Karnataka, using a GIS-based multicriteria evaluation technique for urban development. Suribabu et al. (2014) conducted a case study on Thanjavur City, Tamil Nadu, India using remote sensing and GIS tools for evaluation of urban growth. The leapfrog sprawl dominates the study area in the study area.

Shahfahad et al. (2020) presented a case study of Surat City using multi-temporal Landsat data sets for the assessment of built-up density and urban expansion of fast-growing. The study results show that the growth rate of population and urban area are not identical to each other. Sharma et al. (2012) presented an urban dynamics change using geospatial techniques for the assessment of land consumption. The results show that land consumption is increasing rapidly with the exponential growth of the population. These studies collectively underscore the importance of geospatial techniques in understanding, and managing urban growth and highlight the need for ongoing assessment and planning to manage the impacts of urbanization in Indian cities.

STUDY AREA

Mysuru, also known as Mysore, is a city located in the southern part of the Indian state of Karnataka. Renowned for its rich cultural heritage and historical significance, Mysuru stands as a testament to the grandeur of the Wodeyar dynasty that ruled the region for centuries. The city is celebrated for its majestic Mysuru Palace, a stunning example of Indo-Saracenic architecture that attracts visitors from around the world. The palace, illuminated with thousands of lights during the annual Dasara festival, is a symbol of the city's royal past. Mysuru is also famous for its well-preserved heritage buildings, including the Jaganmohan Palace and the Chamundi Hills, which offer panoramic views of the city and house the Chamundeshwari Temple, a revered pilgrimage site.

Apart from its historical and cultural significance, Mysuru is recognized as an educational hub with a thriving academic environment. The city is home to prestigious institutions like the University of Mysore, which has played a pivotal role in shaping the educational landscape of the region. The serene surroundings and pleasant climate make Mysuru an ideal destination for students seeking a conducive learning environment. Additionally, the city is known for its yoga centers and wellness retreats, attracting enthusiasts from all over the world. Mysuru's unique blend of heritage, education, and wellness makes it a captivating study area that offers a holistic experience for residents and visitors alike. The map of the Mysuru city is shown in Fig. 1.

DATA USED

LISS-III (Linear Imaging Self-Scanning Sensor-III) is an advanced remote sensing sensor designed and developed by the Indian Space Research Organization (ISRO). It is part of the payload on board the Indian Remote Sensing (IRS) satellites, specifically designed for Earth observation.

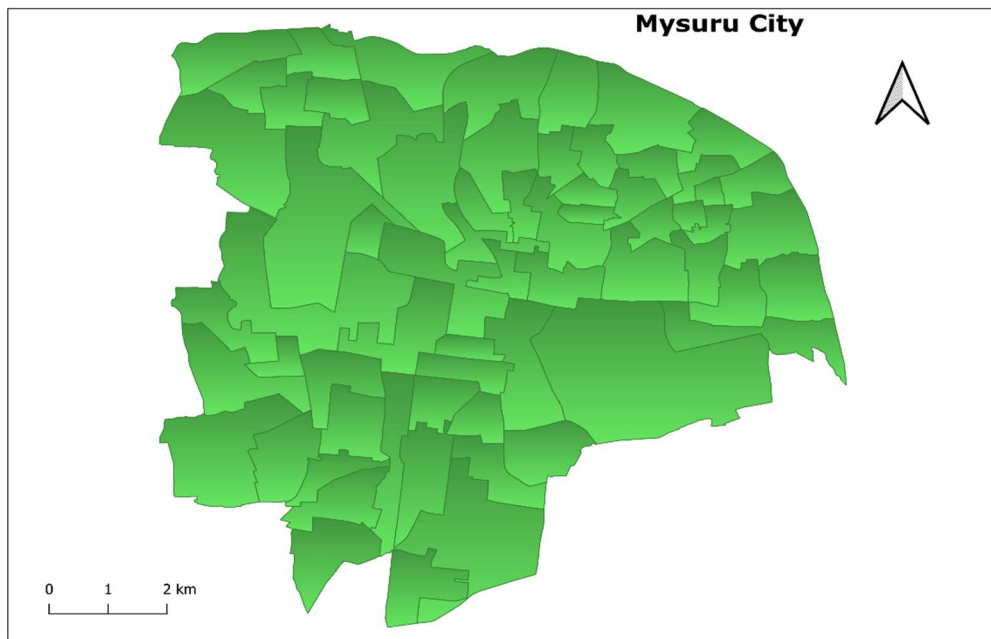


Fig. 1: Map of the Mysuru City.

LISS-III operates in the visible and near-infrared spectral bands, capturing imagery with a spatial resolution of 23.5 meters. The sensor's ability to acquire multispectral data makes it a valuable tool for land use and land cover (LULC) classification, as it can distinguish between different surface features based on their spectral characteristics.

In the context of LULC classification, LISS-III data proves instrumental due to its high spatial resolution, enabling the identification and mapping of various land cover types with greater detail. The multispectral capabilities allow for the extraction of valuable information about vegetation, urban areas, water bodies, and other land features. This data is particularly useful for monitoring changes in land cover, assessing environmental impacts, and supporting land management and planning initiatives. Researchers and decision-makers leverage LISS-III imagery to enhance their understanding of the Earth's surface, contributing to more effective land-use planning, resource management, and environmental conservation efforts.

MATERIALS AND METHODS

The research aimed to assess the built-up area in Mysuru City over a decade (2010-2020) using advanced geospatial techniques. The urban landscape is constantly evolving due to factors like population growth, urbanization, and infrastructure development. Understanding the temporal changes in built-up areas is crucial for effective urban

planning and sustainable development. The methodology followed in this work is shown in Fig. 2.

Study area and data collection: The study focused on Mysuru City, a rapidly growing urban center in India. Various geospatial datasets, including satellite imagery, aerial photographs, and land-use maps from 2010 and 2020, were collected. High-resolution images, acquired at regular intervals, formed the basis for the analysis, ensuring a comprehensive representation of land cover changes.

Image preprocessing: To enhance the accuracy of the analysis, the collected satellite imagery underwent rigorous preprocessing. This included radiometric and atmospheric corrections, image registration, and mosaicking. These steps aimed to standardize the data, reducing potential errors and ensuring consistency across the temporal dataset.

Land cover classification: A supervised classification approach was employed to categorize land cover types. Machine learning algorithms, such as Support Vector Machines (SVM), were utilized to train the classifier. Training samples were selected based on ground truth data, and the algorithm was fine-tuned to accurately identify built-up areas, distinguishing them from other land cover classes.

Change detection analysis: Change detection analysis was conducted to identify and quantify alterations in the built-up area between 2010 and 2020. This involved overlaying the classified land cover maps for the two time periods and extracting areas where changes occurred. The analysis aimed

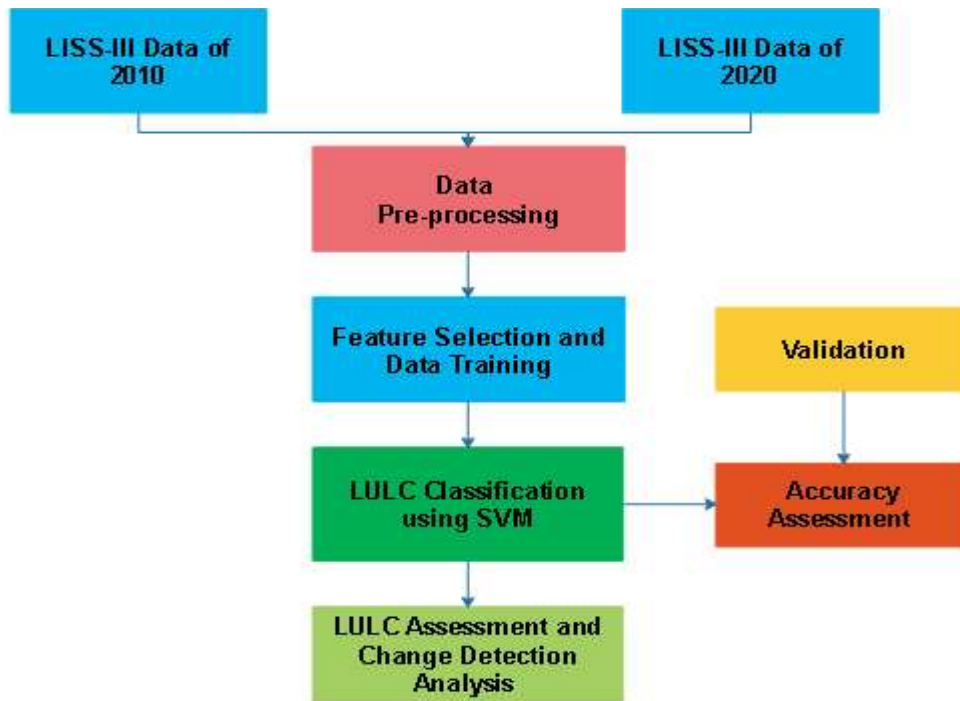


Fig. 2: Methodology followed in this work.

to identify expansion, contraction, and spatial shifts in the built-up zones.

Accuracy assessment: To validate the accuracy of the classification results, a rigorous accuracy assessment was carried out using ground truth data. This involved comparing the classified maps with independently collected reference data, assessing overall accuracy, producer's accuracy, and user's accuracy. The assessment ensured the reliability of the geospatial techniques employed in the study.

Spatial-temporal analysis: Spatial and temporal patterns of built-up area changes were analyzed to identify hotspots of urban expansion or decline. Geographic Information System (GIS) tools were employed to visualize and interpret the results, providing valuable insights into the dynamics of urban growth within Mysuru City.

SUPPORT VECTOR MACHINE (SVM)

Support Vector Machine (SVM) is a powerful machine learning algorithm widely employed in land use and land cover (LULC) classification tasks. LULC classification involves categorizing different types of land and surface cover, such as urban areas, water bodies, vegetation, and agricultural land, based on remotely sensed data (Mahendra et al. 2022). SVMs are particularly well-suited for this task due to their ability to handle high-dimensional data

and non-linear relationships between features (Davis et al. 2002).

One key strength of SVMs in LULC classification is their capability to find optimal hyperplanes that effectively separate different classes in the feature space. The algorithm aims to maximize the margin between classes, enhancing its generalization performance. In the context of LULC, this means SVM can delineate distinct land cover types with minimal overlap, resulting in more accurate classification maps. SVMs are robust in handling both binary and multi-class classification problems, making them versatile for LULC applications where multiple land cover classes need to be identified. The algorithm's ability to work with various kernel functions, such as linear, polynomial, and radial basis functions (RBF), allows it to capture complex patterns in the data. This flexibility is crucial when dealing with diverse and intricate LULC patterns across different landscapes.

SVMs are effective in handling imbalanced datasets commonly encountered in LULC classification. Land cover types may not be evenly distributed in remote sensing datasets, and SVMs can adapt to this by assigning appropriate weights to different classes, ensuring a balanced and accurate classification outcome. In comparison to some other machine learning algorithms, SVMs exhibit good generalization performance, meaning they can maintain their classification accuracy on new, unseen data. This is essential in LULC classification, where accurate predictions

on new satellite images or time-series data are crucial for monitoring land cover changes over time. SVMs may face challenges in handling very large datasets or those with high dimensionality. Additionally, parameter tuning is important for optimizing performance, and selecting the right kernel and regularization parameters requires careful consideration. Overall, Support Vector Machines remain a valuable tool in LULC classification, offering robustness, versatility, and the ability to discern complex patterns in remotely sensed data.

Support vector machines offer a robust and versatile approach to LULC image classification. Their ability to handle high-dimensional data, accommodate non-linear relationships, and provide interpretability makes them a valuable tool in extracting meaningful information from remote sensing imagery. As technology advances and the demand for accurate and timely land cover information grows, SVMs continue to be a relevant and effective choice for researchers and practitioners engaged in LULC mapping and monitoring. The classification function of the SVM is shown in Fig. 3 and represented in Equation (1)

$$f(x_i) = \begin{cases} 1 & \text{if } w \cdot x_i + b \geq 1 \\ -1 & \text{if } w \cdot x_i + b \leq -1 \end{cases} \quad \dots(1)$$

RESULTS AND DISCUSSION

LULC Classification

In this study, we employed geospatial techniques to assess the built-up area in Mysuru, focusing on LULC classes such as built-up, vegetation, water bodies, and others. The classification was performed using LISS-III satellite images for the years 2010 and 2020. The results reveal significant changes in the built-up area over the decade, providing valuable insights into urbanization trends in the region. The

classified map of the years 2010 and 2020 are shown in Fig. 4 and Fig. 5 respectively.

The analysis of the classified LISS-III images from 2010 and 2020 indicated a substantial increase in the built-up area within Mysuru city. The urban expansion is particularly pronounced, signifying the rapid growth and development experienced by the city over the studied period. Concurrently, a decline in vegetation cover and alterations in water bodies were observed, underscoring the dynamic nature of land use changes. These findings contribute to a comprehensive understanding of the urban landscape evolution in Mysuru.

Furthermore, the classification accuracy assessment demonstrated the reliability of the geospatial techniques employed in delineating LULC classes. The overall accuracy and kappa coefficient were calculated to validate the classification results for both years. The high accuracy values validate the robustness of the classification methodology and highlight its applicability for monitoring changes in built-up areas using remote sensing data.

LULC Assessment

The assessment of LULC in the city of Mysuru was conducted through the classified images of the years 2010 and 2020. The primary LULC classes considered for this study included built-up areas, vegetation cover, water bodies, and other land cover types. The results of the classification process revealed significant changes in the built-up area over the decade under consideration.

In the year 2010, the analysis indicated a notable extent of built-up areas concentrated in specific regions of Mysuru, with distinct patterns of urban development. The classification highlighted the distribution and density of infrastructure, residential, and commercial zones. In contrast, the 2020 LISS-III imagery exhibited a discernible

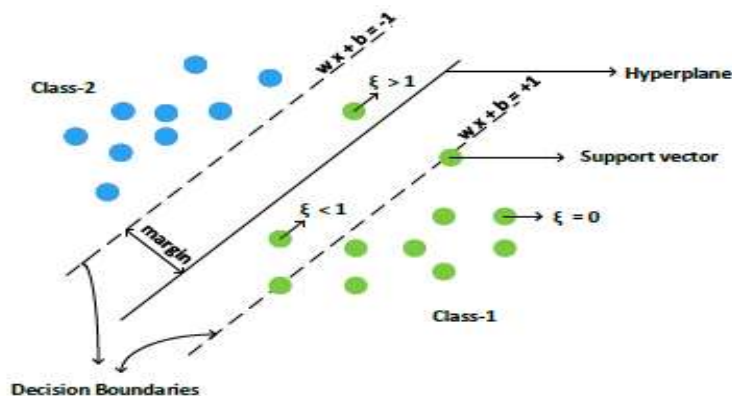


Fig. 3: Illustration of SVM classification function.

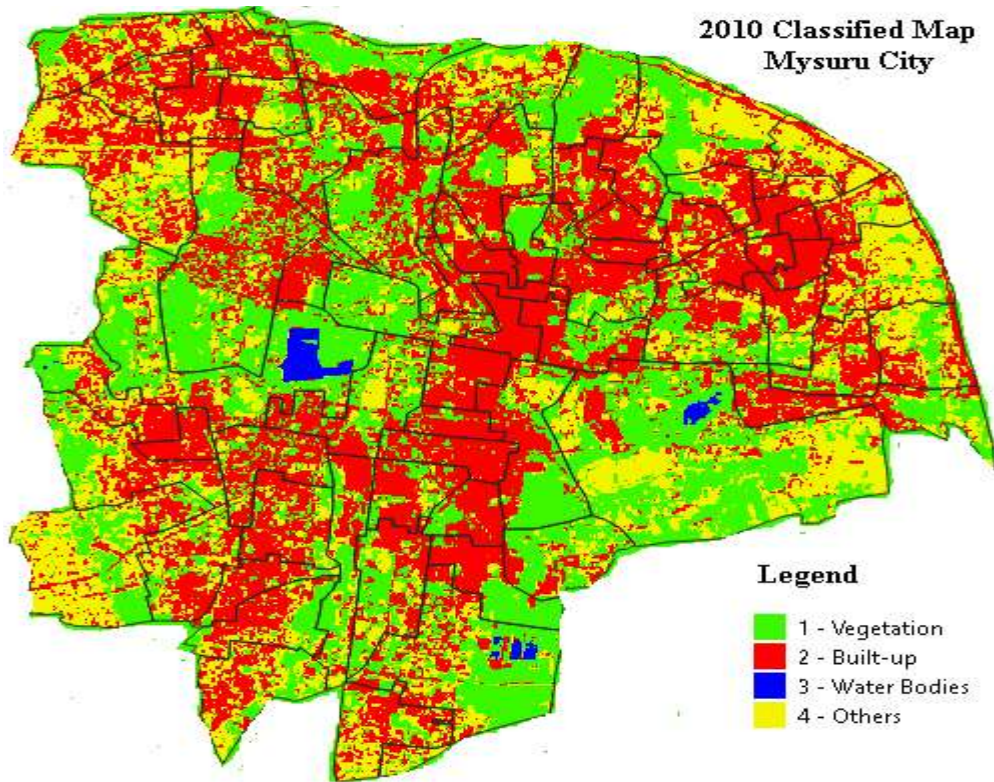


Fig. 4: Classified map of Mysuru city for the year 2010.

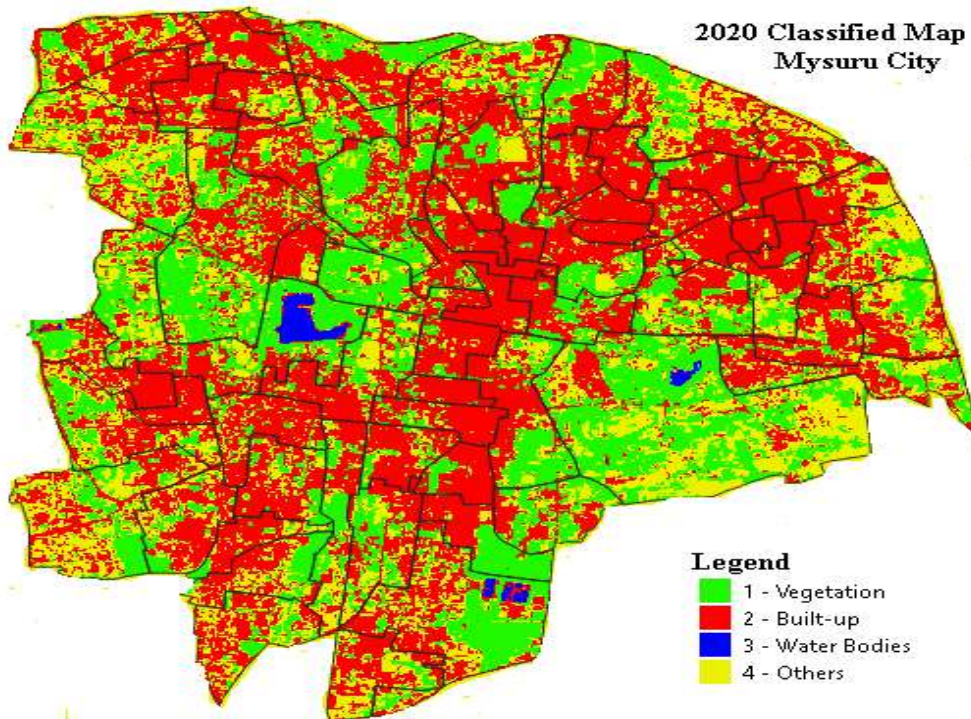


Fig. 5: Classified map of Mysuru city for the year 2020.

Table 1: LULC assessment of Mysuru city.

Class Name	2010		2020		Area difference (in Sq. km)	Change of Area in %
	Area (in Sq. km)	% Area	Area (in sq. km)	% Area		
Built-up	49.75	38.53	70.08	54.27	20.33	15.74
Vegetation	45.37	35.13	37.04	28.68	-8.33	-6.45
Water bodies	0.744	0.576	0.808	0.625	0.064	0.049
Others	33.25	25.75	20.38	15.78	-12.87	-9.97

increase in the built-up area, signifying urban expansion and potential changes in land-use policies. The results further underscored the need for sustainable urban planning to manage growth and maintain a balance between development and environmental preservation.

Furthermore, the LULC assessment demonstrated fluctuations in vegetation cover and water bodies. Changes in green cover were observed, reflecting alterations in the city's landscape due to factors such as deforestation, urbanization, or afforestation initiatives. Similarly, alterations in the extent and distribution of water bodies provided insights into the impact of urban development on hydrological patterns. The LULC assessment for the years 2010 and 2020 is shown in Table 1. The LULC assessment results of the year 2010 show the built-up area of 38.53%, vegetation of 45.37%, water bodies of 0.576%, and others of 25.75%. Similarly, the assessment results of the year 2020 show the built-up area of 54.2%, vegetation of 28.68%, water bodies of 0.625%, and others of 15.78%.

Change Detection Analysis

In this study, we conducted a comprehensive change detection analysis to assess the dynamics of the built-up area in Mysuru city over a decade (2010-2020) using a post-classification comparison technique. The change detection analysis between the years 2010 and 2020 is shown in Table 1.

Our analysis revealed significant changes in the built-up area of 15.74% of Mysuru city between 2010 and 2020. The built-up class exhibited a noticeable expansion, indicating urbanization and infrastructural development within the region. The expansion of built-up areas was spatially mapped and quantified, providing insights into the extent and distribution of urban growth over the decade. Concurrently, changes in vegetation cover of -6.45%, water bodies of 0.049%, and other land cover types of -9.97% were also identified and analyzed. These findings contribute to a comprehensive understanding of the urbanization dynamics and associated environmental impacts in Mysuru.

Furthermore, the change detection analysis facilitated the identification of specific areas undergoing rapid

transformation. Hotspot analysis was employed to pinpoint regions with the most pronounced changes in land cover, offering valuable information for urban planning and resource management. The results highlight the necessity of sustainable urban development strategies to mitigate the environmental implications of rapid urban expansion observed in Mysuru. Overall, the change detection analysis presented in this study serves as a valuable tool for policymakers, urban planners, and environmental researchers seeking to comprehend and address the evolving landscape of Mysuru city.

Accuracy Assessment

In comparing the classified maps with ground truth data, the overall accuracy of the built-up area classification for the year 2010 was determined to be 89.84% using confusion matrix, indicating a high level of precision in identifying urban and developed regions. Additionally, the kappa coefficient, a measure of classification accuracy that accounts for chance agreement, was found to be 0.878, further substantiating the reliability of the geospatial techniques employed. Similar accuracy assessment metrics were applied to the LISS-III images from 2020, revealing an overall accuracy of 88.28% and a kappa coefficient of 0.865. These results highlight the effectiveness of the geospatial techniques in consistently identifying built-up areas over the temporal span of the study. The confusion matrix constructed for a classified map for the years 2010 and 2020 is shown in Table 2 and Table 3 respectively.

Furthermore, individual class accuracies were examined to understand the performance of the classification across various land cover categories. The built-up class exhibited a high level of accuracy of 93.23%, demonstrating the robustness of the geospatial techniques in delineating urban environments. Additionally, accuracies for vegetation and water bodies were also assessed at 89.51% and 86.66% respectively for the 2010 classified map, providing insights into the reliability of the classification across diverse land cover types. The comparative analysis between the years 2010 and 2020 allowed for an assessment of changes in the built-up area over the study period, providing valuable information for urban planning and environmental monitoring.

Table 2: Confusion matrix for a classified map of 2010.

Classified Data	Class	Number of samples	Reference Data			
			Built-up	Vegetation	Water Bodies	Others
	Built-up	355	331	6	7	11
	Vegetation	410	10	367	14	19
	Water Bodies	240	8	13	208	11
	Others	275	10	12	9	244
Overall Accuracy: 89.84%			Kappa Coefficient: 0.878			

Table 3: Confusion matrix for a classified map of 2020.

Classified Data	Class	Number of samples	Reference Data			
			Built-up	Vegetation	Water Bodies	Others
	Built-up	355	326	8	9	12
	Vegetation	410	12	362	15	21
	Water Bodies	240	10	14	203	13
	Others	275	12	14	10	239
Overall Accuracy: 88.28 %			Kappa Coefficient: 0.865			

CONCLUSION

This research paper presents a comprehensive assessment of the built-up area in Mysuru City, Karnataka State, India, employing advanced geospatial techniques. Through meticulous analysis and application of remote sensing and GIS technologies, the study has yielded significant insights into the urban expansion dynamics over the past decade. The obtained results showcase an impressive overall accuracy of 89.84% for the year 2010 and 88.28% for 2020, underscoring the reliability and effectiveness of the employed methodologies. The research not only contributes to the understanding of urbanization patterns but also highlights the potential of geospatial techniques in urban planning and management, providing valuable data for policymakers, city planners, and researchers aiming to address the challenges associated with rapid urban growth.

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ORCID DETAILS OF THE AUTHORS

H. N. Mahendra: <https://orcid.org/0000-0003-3854-5500>