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Research Article

Urban Sprawl: Analyzing Development and Change Detection Using GEE in Vijayawada

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Abstract

Vijayawada is an area undergoing rapid urbanization partly because of swift population growth and infrastructure developments. Nonetheless, effective planning in urban areas has been absent and this has led to environment degradation and socio-economic imbalance in a few areas in terms of lack of access to adequate resources and inequality of intake. The scope of the present project is to detect and analyze the urban sprawl phenomena in Vijayawada using GEE and the SVM algorithm. The study uses satellite data from 1990 until 2024, identifies critical drivers of urban growth, and offers spatial insights into supporting sustainable urban planning. The project incorporates land cover classification and change detection, which permits a holistic overview of development patterns over time. Further results suggest important land conversion in peri-urban areas that correlate with socio-economic factors and infrastructure developments. These would enable urban planners to outline policies that support growth in sustainable ways-that is, according to the Sustainable Development Goal (SDG 11) to build inclusive, resilient cities.

Keywords: Urban Sprawl, Vijayawada, Google Earth Engine, Support Vector Machine (SVM), Change Detection, Land Use Classification, Sustainable Urban Planning, SDG 11, Satellite Imagery, Socio -Economic Factors

1. Introduction

Urban sprawl without any regulation, the unchecked expansion of urban areas into rural as well as natural landscapes, is a growing menace that affects many countries across the world. Such conditions arise and continue unchecked mainly through high population growth, industrial development, and associated economy-generation activities without matching urban planning, thus creating a series of environmental and socioeconomic problems. Among many others currently exemplifying this condition is the case of Vijayawada, an emerging city in the increasingly developed state of Andhra Pradesh, India. In the last three decades, the city has undergone rapid urbanization owing to increased migration, infrastructure development, and its location as a hub for transport [1,2]. The expansion of urban areas has created new economic opportunities; however, it has also resulted in several adverse effects, such as the significant reduction of agricultural land, a decline in green spaces, and escalating environmental deterioration [3]. In the case of Vijayawada, rapid urban sprawl has exacerbated socio-economic disparities, leading to unequal access to resources and infrastructure across different parts of the city [4,5]. Addressing these challenges necessitates the implementation of sustainable urban planning strategies to mitigate the negative consequences of urbanization and promote equitable development.

Urban sprawl also poses severe environmental threats, including habitat fragmentation, biodiversity loss, and rising greenhouse gas emissions. The conversion of agricultural fields and forests into residential and commercial zones contributes to habitat destruction and soil degradation [6,7]. Moreover, unregulated urban expansion intensifies the urban heat island effect, elevating local temperatures, impairing rainwater absorption, and increasing risks of flooding and air pollution. Additionally, urban sprawl creates disparities in infrastructure distribution, with city centers becoming overcrowded and peri-urban areas lacking essential services [8,9]. A data-driven approach is essential to understanding the patterns and drivers of urban sprawl to address these challenges effectively.

This incorporates the use of Google Earth Engine (GEE)-based Support Vector Machine (SVM) algorithm to derive the outcome from residents in urban sprawl patterns within the study area of Vijayawada as examined by satellite imageries between 1990 and 2024 [10,11]. The study attempts to showcase places being developed rapidly to probe various socio-economic reasons behind such development and make informed assumptions on the possible future development of urban planning as well as for efficient resource utilization while at the same time, considering the reduced impacts of urban sprawl. This will help contribute to the future growth of Vijayawada in line with Sustainable Development Goal 11 (SDG 11), which deals with developing cities that are inclusive, safe, and sustainable [12]. This study proposes a framework for achieving balanced urban development by leveraging advanced technologies to deliver data driven insights that support informed decision-making for urban planners.

2. Literature Review

Urban sprawl, a defining feature of rapid urbanization, has become a pressing global concern, impacting both environmental sustainability and socio-economic balance. With cities expanding at an unprecedented rate, researchers are turning to advanced technologies like remote sensing, Geographic Information Systems (GIS), and machine learning to better understand urban growth, track land use changes, and identify key factors driving sprawl. This literature review explores the latest advancements (2020-2024) in urban sprawl analysis, highlighting the role of high-resolution satellite imagery, geospatial tools, and computational models. By examining recent studies, this review offers valuable insights into effective methodologies and approaches that can help shape sustainable urban planning and informed policy decisions in rapidly growing cities.

For instance, combined socio-economic indicators with satellite imagery to assess how unplanned urban expansion worsens social and economic inequalities. Their findings emphasize the urgent need for equitable development policies to counteract these disparities [11]. Similarly, focused on urban sprawl in India's smart cities, exploring how uneven development creates a gap between affluent and underprivileged areas. Their study also evaluated how effective smart city policies have been in addressing these issues [12].

On the environmental front, leveraged Google Earth Engine (GEE) to analyze the impact of urban sprawl on ecosystems. Their research revealed significant ecological damage, including deforestation and pollution, reinforcing the necessity for sustainable urban planning strategies [16].

Adding to this, demonstrated how machine learning models on GEE can serve as powerful tools for tracking large-scale urban expansion. Their study highlights how such technology can help policymakers identify critical intervention areas and enable more efficient monitoring of urban growth patterns [9]. push forward GIS-based tools integrated with machine learning to automate the detection of urban land cover, providing actionable insights into transitions in urban land and underlining the necessity for better land-use management in rapidly urbanizing regions [13]. apply cellular automata models and multi-temporal satellite data to simulate the trend of urban growth, predict rapid expansion of cities in peri-urban areas, and recommend policy interventions for sustainable growth [8]. apply high-resolution satellite imagery and object-based image analysis (OBIA) to investigate the urban expansion of China's peri-urban areas, which showed a rapid transformation of land use due to economic growth and infrastructure projects and underscores the need for sustainable planning [6]. Chakraborty and Maiti (2020) apply GIS and spatial analysis techniques to track urban sprawl in Kolkata, India, identifying population growth and poor urban planning as primary drivers of sprawl, resulting in unequal resource distribution and infrastructure access [7].

3. Proposed Architecture

3.1. Study Area

Vijayawada is a city in the Indian state of Andhra Pradesh located on the banks of the Krishna River in central Andhra Pradesh in Figure 1 and Figure 2. It is located 16°31' N latitude and 80°39' E longitude. The city has a tropical climate, hot summers & moderate winters. May and June experience maximum summer temperatures up to 47°C, while in winter, the temperature ranges from 20°C to 27°C. The region records an average humidity of 78% along with an annual rainfall of 103 cm as it receives both the southwest and northeast monsoons (IMD).

While the topography of the city is mostly flat, there are minor to medium hills sporadically around, giving rise to substantial coverage in other types of landscape. Which is a significant railway junction

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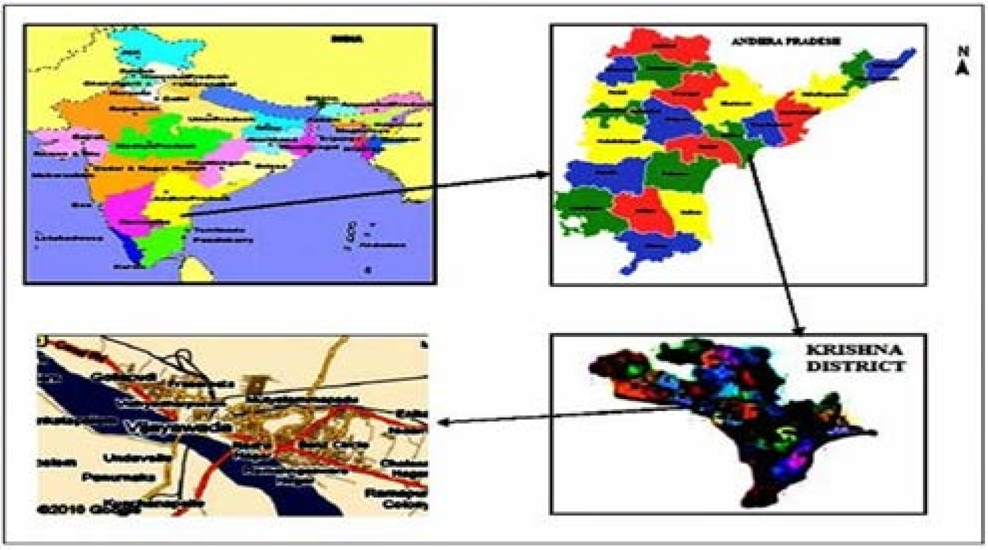

Figure 1: Location of Study Area

Figure 2: Satellite Images of Vijayawada City

3.2. Materials and Methods

3.2.1. Description of Dataset

The Land Use and Land Cover (LULC) Change Detection and Analysis System is designed to systematically detect and analyze changes in land use and land cover over time. The system integrates several components that contribute to seamless processing, analysis, and visualization of satellite imagery data.

The dataset used for land use and land cover (LULC) change detection and analysis spans over several decades, utilizing the satellite images from the Landsat missions to monitor changes in land cover and urban sprawl over time.

In 1990-1999, this system made use of United States Geological Survey imagery Landsat 5 in access through the Earth Engine API. This dataset's spatial resolution was 30 m, with bands B1 (blue), B2 (green), B3 (red), and B4 (near-infrared), which classified and monitored the development of changes in land covers of the 1990s. The period in 1990s focuses more on early detection signs for urban sprawl and a change in land covers.

The 2000-2009 period utilized the data from the USGS Earth Engine API for Landsat 5 with the same spatial resolution of 30 meters and the same spectral bands. During this period, the major objective was to detect urban sprawl and study the transitions in LULC, which occurred during the early 21st century, particularly in fast-developing urban regions.

Between 2010 and 2019, Landsat 7/8 satellite imagery, with a 30-meter spatial resolution and bands B1, B2, B3, and B4, was employed to analyze urbanization trends and their environmental effects. This decade-long dataset provided valuable insights, particularly in peri-urban areas where rapid infrastructure development and population growth led to significant shifts in land use.

For the most recent period, 2020, Landsat 8 imagery at the same resolution and spectral bands was used to assess ongoing land cover changes. The focus was on identifying patterns of urban sprawl and understanding how rapid urbanization has reshaped landscapes in recent years.

By systematically analyzing each time frame through remote sensing, this study offers a deeper understanding of urban expansion and its environmental consequences. These insights are crucial for informing sustainable urban planning and guiding responsible development strategies.

3.2.2. Description of Algorithms

The Support Vector Machine (SVM) algorithm is a powerful supervised learning method commonly applied in classification tasks, particularly in image classification and land cover analysis. In our urban sprawl analysis project for Vijayawada, SVM will be utilized within Google Earth Engine (GEE) to categorize satellite imagery into distinct land cover types, such as urban developments, vegetation, water bodies, and agricultural land. This classification will provide valuable insights into land-use patterns and support data-driven urban planning decisions. SVM operates by finding the optimal boundary, or hyperplane, that maximizes the separation of different classes in a dataset. The objective of SVM is to maximize the margin, which is the distance between the hyperplane and the nearest data points from each class. In this way, new data points are classified with a high degree of accuracy.

SVM is especially well-suited for this project because of several key advantages. There is great competency in handling complex class boundary problems, which is significant for distinguishing between similar class types in satellite images, and SVM is robust towards high-dimensional data, quite common in satellite imagery and multiple spectral bands that correspond to a high-dimensional feature space that SVM can really handle. It also provides the capability of processing nonlinear data using kernel functions; this is a benefit where land cover types, possibly in natural environments, cannot be simply separated through the use of simple boundaries. Lastly, SVM has performance even when it encounters insufficient training data as the former focuses on the support vectors, or critical points for separation, and does not rely on the total training data. These characteristics make SVM a powerful tool for land cover classification in satellite images and detection of urban sprawl in Vijayawada.

3.2.3. System Architecture

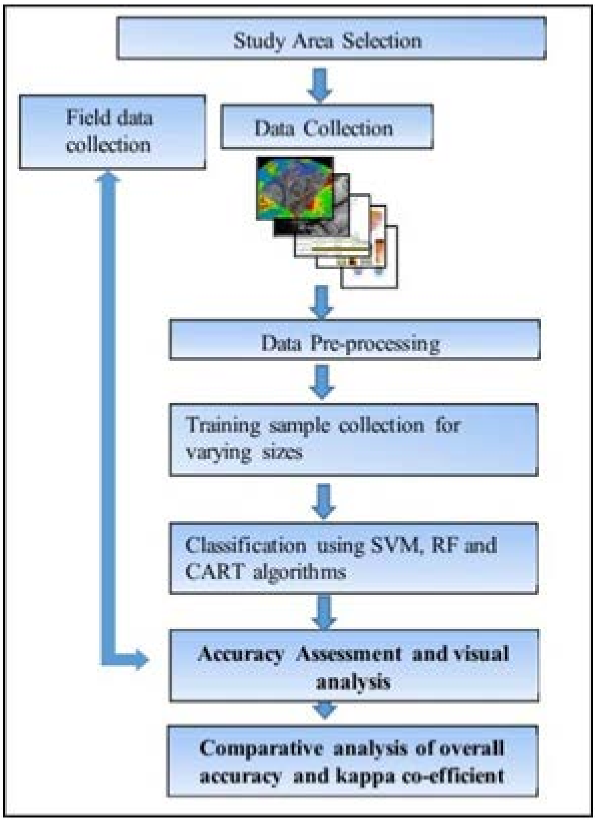

Figure 3: Architecture Diagram

In above Figure 3 it represents the architecture diagram which shows the flow of the project.

3.2.3.1. Data Collection (Landsat Imagery from GEE)
This module involves gathering satellite imagery data, specifically from the Landsat program, through Google Earth Engine (GEE). The data is used to analyse land cover and urban sprawl over time.

3.2.3.2. Data Preprocessing: Preprocessing of Satellite Imagery before the classification and change detection processes, there is preprocessing of the satellite images for quality and suitability analysis. These include:

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- **Cloud Masking:** It can be seen that cloud shadows and clouds affect the classification of land cover. With algorithms such as the Fmask (Function of Masking), these cloud and shadow pixels are then identified and excluded from further analysis.
- **Radiometric Calibration:** This step transforms the raw pixel values to the surface reflectance value to enhance the accuracy of the classification.
- **Geometric Correction:** All images from different time periods will be spatially aligned correctly with each other.
- **Band Selection:** Specific spectral bands are chosen according to the types of land cover under study. For instance, the Near Infrared (NIR) band is vital for analyzing vegetation, whereas the Red and Green bands are important for urban areas and water bodies identification.

3.2.3.3. Land Use and Land Cover Classification with SVM
The SVM algorithm for this classification process is one among the supervised machine learning methodologies that finds the most effective hyperplane in segregating data into classes or groups. SVMs have wide applications in remote sensing analysis because of its feature for handling high dimensional datasets along with classifying very complex patterns.

- **Training Data:** The SVM model is trained with ground truth data such as field surveys or reference maps. The data are composed of sample points of various land cover types (for example, water, urban areas, forests, agriculture).
- **Feature Extraction:** The spectral values obtained from the preprocessed satellite images are used as features for classification. Features are extracted from multiple spectral bands, such as the Red, Green, Blue, and NIR bands.
- **Classification:** Apply the SVM model to classify each pixel of the satellite image into predefined categories, such as Water, Bodies, Urban Areas, Agricultural Land, Forests, Barren Land, Vegetation. The trained SVM model then classifies the entire image and produces a categorized land cover map.

3.2.3.4. Change Detection: Change detection is a crucial method for understanding how land cover evolves over time. It involves comparing land cover data from two or more different time periods to pinpoint areas that have undergone significant changes. This process typically uses multi-temporal datasets, such as Landsat imagery from various years (e.g., 1990, 2000, and 2010). By analyzing these datasets, the system can identify patterns of land-use transformation, including urban growth, vegetation loss, or other notable land cover shifts.

3.2.3.5. Output and Visualization: The results of classification and change detection are presented in a clear and accessible graphical format. This is achieved through the Output and Visualization Layer, which includes:

- **Classified Maps:** The satellite image outputs are displayed as classified maps, showing various land cover types and their spatial distribution.
- **Change Detection Maps:** These maps highlight the areas that have experienced changes over time, such as urban expansion, deforestation, or other significant land cover alterations.
- **Charts and Graphs:** The system generates various visualizations, including area distribution charts, land-use trend graphs, and temporal changes in land cover proportions, providing detailed insights into the identified changes.

3.2.4. Confusion Matrices and Accuracy Metrics
These are used to evaluate the accuracy of the classification results, providing quantitative insights into the performance of the SVM model.

This is an LULC change detection and analysis system integrating advanced remote sensing technologies, machine learning algorithms, and an interactive user interface. It processes large satellite datasets efficiently, applies the SVM algorithm for classification, and provides visual and quantitative outputs to assist in informed decision-making for sustainable urban planning.

4. Results and Discussion

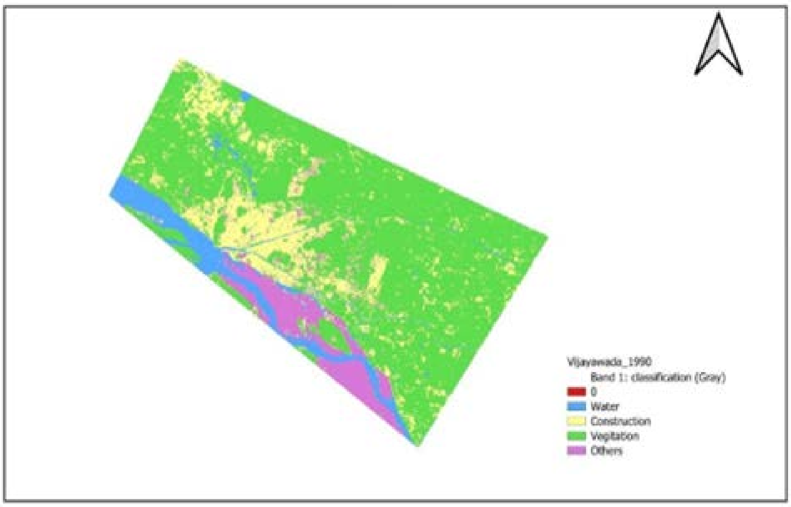

Figure 4.1: Image Classification (1990-1999)

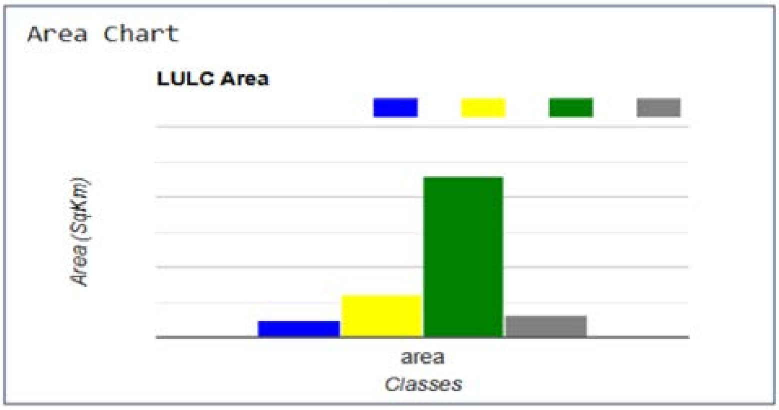

Figure 4.2: LULC Area Chart (1990-1999)

In the above figure 4.1 and figure 4.2 represents the LULC analysis of the region indicates that agriculture is the dominant land use type, covering approximately 65.65% of the total area (114.642 sq km). This indicates that agricultural activities play a crucial role in the region's economy and land utilization. Construction areas, including urban and built-up zones, account for 17.54% of the land (30.638 sq km), indicating significant urbanization and infrastructure development.

Water bodies, although significant, cover only 7.26% of the region (12.691 sq km), indicating a meager amount of water resources available in the region. Other areas make up 9.15% of the region (16.006 sq km), which include barren or uncategorized land, hence a small fraction of the total area. This categorization indicates a wide variation in land usage and different levels of urbanization, agricultural activities, and natural resources in the region.

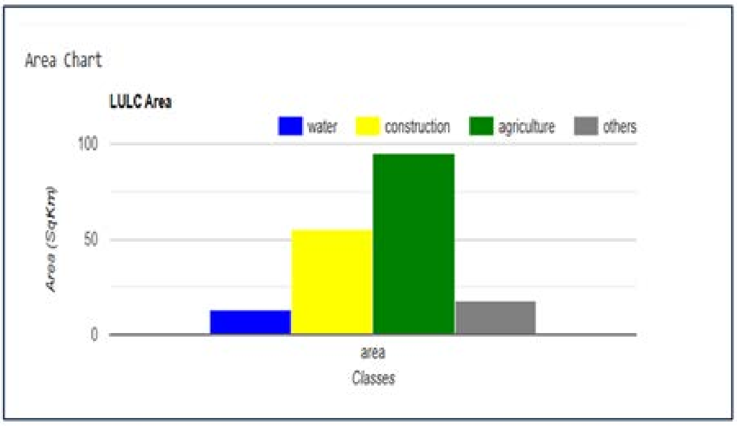

Figure 5.1: Image Classification (2000-2009)

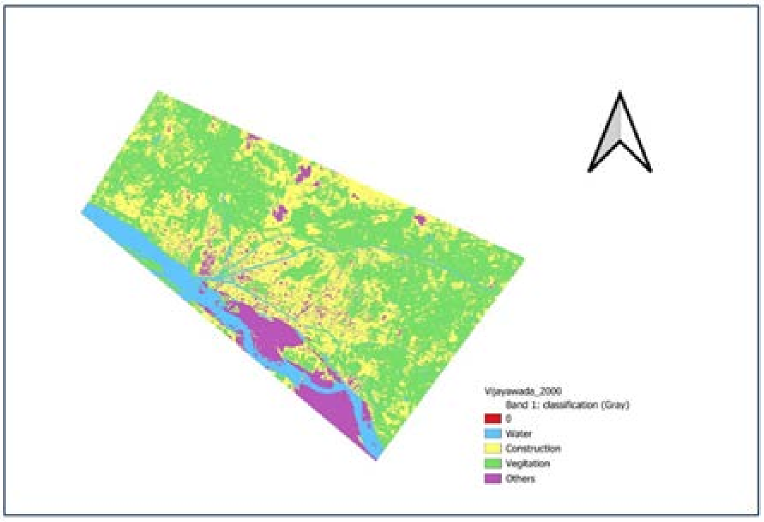

Figure 5.2: LULC Area Chart

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In the above figure 5.1 and figure 5.2 represents the LULC analysis of the period 2000-2009 shows that agriculture is the dominant land use, covering 52.87% of the area, which is 95.063 sq km, and the dominant one in the region. Urban development, with construction areas, occupies 30.86% of the land, which is 55.520 sq km, showing significant growth during this period. The water bodies are minimal and only occupy 7.17%, which is 12.893 sq km, indicating limited water resources. There remain others of 9.83% or 17.696 sq km "Others", which constitutes lands without categories or as empty.

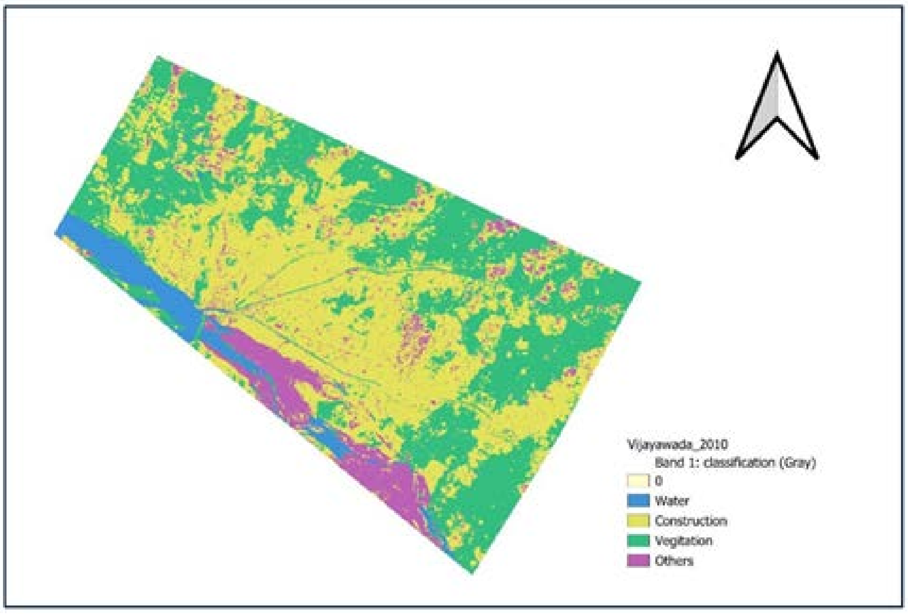

Figure 6.1: Image Classification (2010-2019)

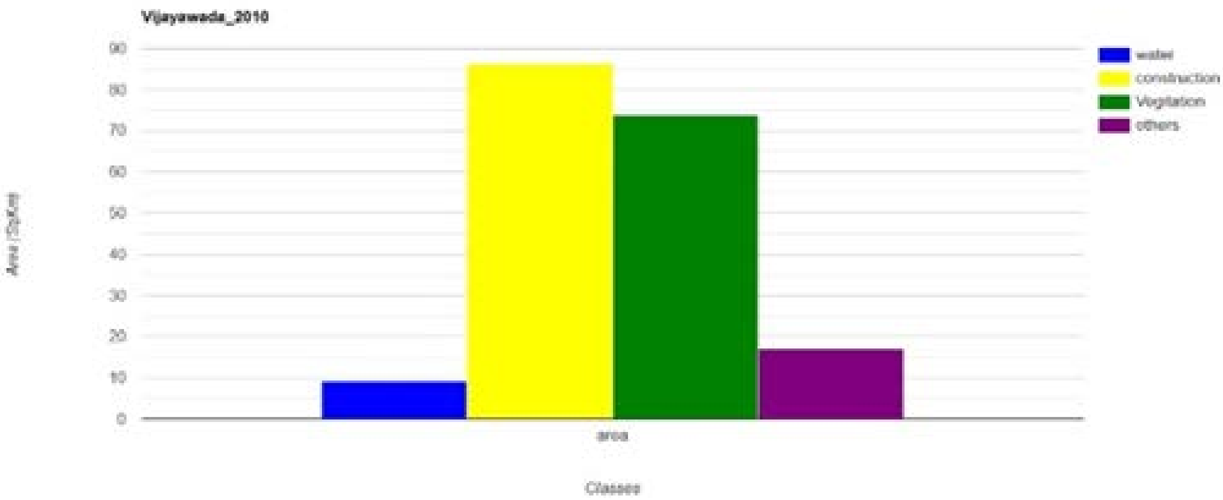

Figure 6.2: LULC Area Chart

In the above figure 6.1 and figure 6.2 represents the LULC analysis of the region reflects that the construction areas have the maximum share, covering 52.11%, which are extensive urban development areas equivalent to 84.938 sq km. Agriculture comprises 36.76% (59.950 sq km), thus showing an important share of land is used for agriculture. The water bodies are only at 5.15% (8.387 sq km), signifying little water resources in the area. The remaining 20.14% (32.856 sq km) is categorized as "others," which includes natural or uncategorized lands, representing a notable fraction of the total area.

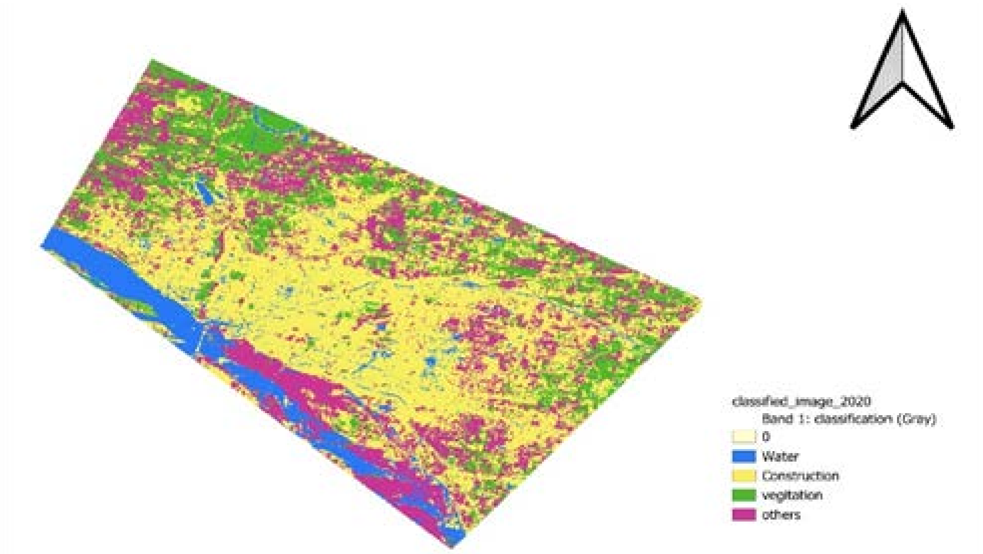

Figure 7.1: Image Classification (2010-2020)

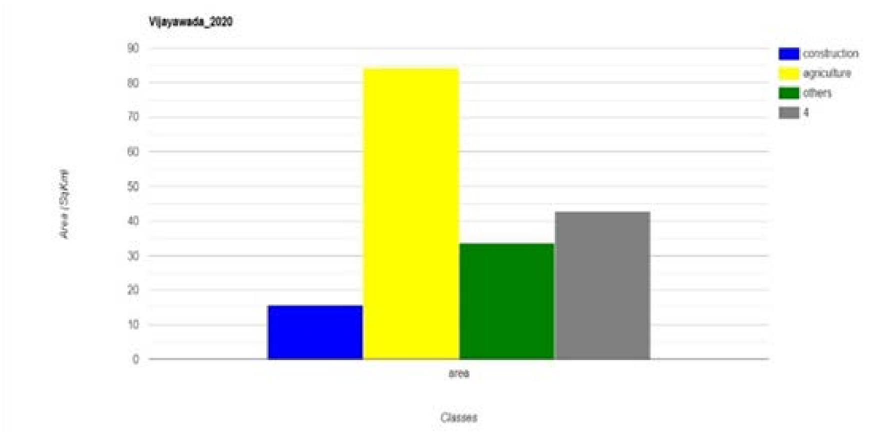

Figure 7.2: LULC Area Chart

In the above Figure 7.1 and Figure 7.2 represents the LULC analysis for 2020 reveals continued rapid urban growth, with construction areas increasing to 52.11% (84.938 sq km) of the total land, highlighting significant urban expansion. Agricultural land remains substantial at 36.76% (59.950 sq km), though it shows a slight shift. Water bodies have seen a sharp decline, covering only 5.15% (8.387 sq km), indicating a reduction in available water resources. Others" category has only increased to 20.14% (32.856 sq km) indicating an increase in natural or unclassified land masses.

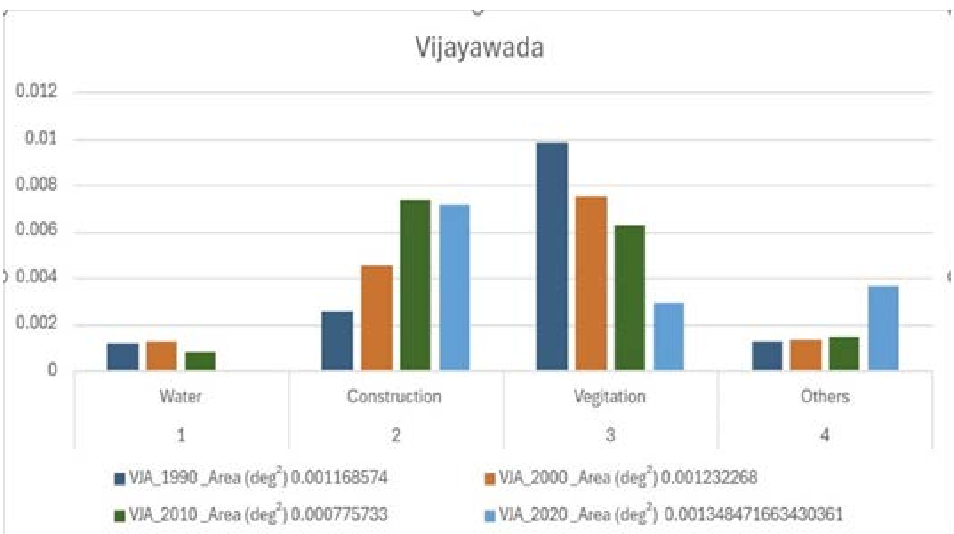

Figure 8: Histogram Comparing the LULC Classes between 1990 and 2020

In Figure 8 represents the LULC analysis between 1990 and 2020 reveals significant changes in land use patterns. Water coverage has remained relatively low, with a small fraction of the total area dedicated to water bodies in both years. The percentage of water area in 2020 was around 5.15%, showing little to no significant increase over the past few decades, possibly due to limited urbanization or climate factors. Urbanization, which expresses construction, has experienced a considerable increase. Urban areas had covered 52.11% (84.938 sq km) of all the land in 2020, which was by far a significant increase over 1990. Such an increase shows a gross expansion of urban development year after year. Agricultural areas, which probably comprised much more in 1990, have reduced to about 36.76% (59.950 sq km) by 2020, probably due to encroachment by towns and changes in land uses. The "others" category is natural or unclassified lands which, in 2020, occupied 20.14% of 32.856 sq km indicating a rather stable quantity of natural or unused lands irrespective of urban and agricultural change.

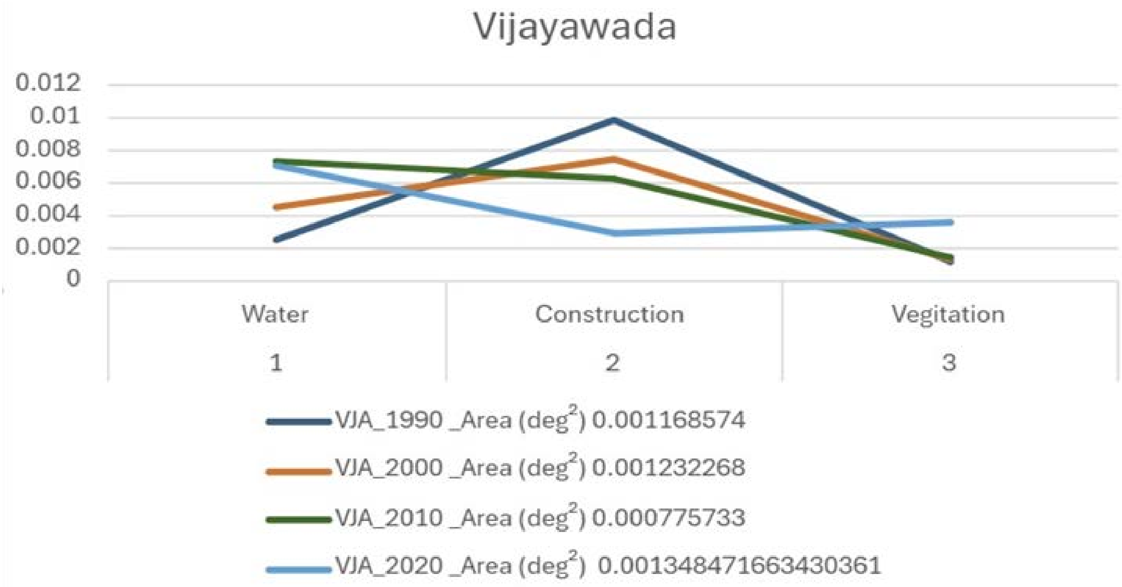

Figure 9: Land Use and Land Cover and Change Detection Analysis

The above Figure 9 tells about the change detection analysis is used for monitoring and measuring the change in LULC of Vijayawada from 1990 to 2020. The comparison of the changes in Landsat satellite images during these decades revealed water bodies, cultivated lands, construction areas, and other land types, in which shifts like urban expansion, reduction in agricultural areas, and how urbanization affects natural resources could be noticed. This insight allows better comprehension of the dynamics and the environmental changes that occur due to urban sprawl in the region.

The bar graph of each year show the great change in the land use of Vijayawada over three decades. In 1990, it was seen that the land use was predominantly agricultural with many areas given over to farmland. Other land uses, such as water bodies and construction zones, urban

Areas were minimal, and thus, it reflected that growth was still in the starting stages. Till 2000, the scenery of growth started when built up areas expanded due to increase in population and growth of infrastructure. Agricultural areas decline gradually during this time as they announced the commencement of urban sprawl.

Urbanization, however, increased considerably by 2010 as visible in the construction and areas of urbanization. Farmland continued its decline with significant and fast conversion during this decade to feed the growing city. Water bodies showed hardly any change signifying some resilience of aquatic environments. By 2020, Vijayawada had gone completely towards a heavy-urbanized landscape with built-up areas dominating the landscape. Agriculture had shrunk further, and undeveloped land was remarkably reduced, underlining the widespread impact of urban sprawl on the region.

5. Conclusion

Vijayawada is the third largest and a commercial capital of Andhra Pradesh. Vibrant rapid urbanization in the region results in extreme land use/cover changes. Since its relation to sustainable development, issues of urban sprawl demand effective planning and resource allocation towards balanced growth. This paper presents an attempt to analyze and understand the observed changes in land use and sprawl in Vijayawada using remote sensing techniques and Landsat satellite imagery for the period 1990 to 2020. In this given study, supervised classification methods were used for classifying land use into major categories like urban, water bodies, agricultural land, barren land, and vegetation. The analysis shows a huge increase in urban areas over the decades at the cost mainly of agricultural and barren lands. Urban expansion is a growing pressure for infrastructure and consumptive uses due to the population pressure. On the contrary, declining arable land reflects the tough challenges in sustainability of food security and environmental balance. Results draw a conclusion that, apart from all these, proper attention should be provided to the constant monitoring and analysis of trends in urban growth. The application of a change detection analysis becomes crucial in understanding the ever-changing patterns of urbanization and its implications. This research may be very helpful to policymakers, urban planners, and other stakeholders in setting up planning strategies for the sustainable development of an urban area. It ensures there is a balance between conserving natural resources and the growth of an urban area. Thus, justly proportioned infrastructure equities allow residents' lifestyles while retaining environmental integrity in the city.

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