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Leveraging HPC for Analysing Changes In Urban Green Spaces With An Image Data Fusion Approach

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ABSTRACT**—** Analysis of Urban Greenspace dynamics, emphasises the future growth trajectories of city's urban areas. Land Use Land Cover (LULC) is also an effective part of the Urban Area. For finding Urban Greenspace there are many parameters like Land Use Land Cover (LULC), Land Surface Temperature, Carbon Storage etc. which are directly connected with Urban Green Space (UGS). This paper focuses on the assessment of the changes in green space through spatio-temporal data, derived from satellite images, by employing Support Vector Machine(SVM) classification algorithm. Key frequency bands of this research include the integration of Near Infrared (NIR) band, Red and Green bands. Leveraging the high spectral resolution of the moderate images Spectroradiometer MODIs dataset in conjunction with high spatial resolution of LANDSAT 7 dataset we have arrived at the calculation of Normalized Difference Vegetation Index (NDVI). This methodological framework facilitates the quantification of total green space area within the Ahmedabad region, enabling the monitoring of spatial changes over time and similarly change in the NDVI of the region. The findings of this research indicate a significant reduction in overall green space, with a decrease of approximately 50% over a decade. This paper discusses the implication of these findings and the effectiveness of the proposed analytical platform for urban greenspace assessment, Normalized Difference Vegetation Index(NDVI) and change detection.

Keywords—Urban Green Space (UGS), Land Use and land Cover (LULC), Remote Sensing, Machine Learning, Support Vector Machine (SVM)

I. INTRODUCTION

Land use refers to the utilization of Earth's land resources for different human activities, whereas land cover is the biophysical cover over Earth's surface by built-up spaces, agricultural farmland, green pastures, forests, water bodies etc. [1] Urbanization is the prime contributor to anthropogenic driven Land Use Land Cover changes, extending and densifying existing urban area. Urbanization involves the mass migration of people towards urban areas search for better job education and health care opportunities [2]. Urbanization expands existing city boundaries, transforming forests, croplands and wetlands into built-up areas containing residential, commercial and industrial buildings and supporting infrastructure like roads, bridges, parks, play - grounds etc.

This study focuses on tracking changes in urban green spaces in Ahmedabad using advanced computing and multiple satellite images. Identifying green areas in cities filled with buildings, factories, and roads is challenging. As cities grow, green spaces often shrink, but these areas are important for reducing air and noise pollution and helping with mental well-being, as noted in earlier research [6].

Recent improvements in high-performance computing (HPC) [7]. Have made it possible to analyze images on a large scale, which is useful for studying green spaces globally [8]. Combining data from different satellite sources [9] has shown to be effective for green space analysis. However, relying on just one satellite's data often doesn't provide enough information for traditional assessment methods, highlighting the need for better data fusion techniques.

In India, there is increasing research using geospatial data [10][11], but the use of satellite data fusion and HPC specifically for studying green space changes is still a relatively new area. This study aims to address that gap by using advanced technology to improve how to monitor urban green space, which can help with better city planning and environmental management.

II. LITERATURE REVIEW

Urban Green Spaces, UGS, are essential components of urban ecosystems, providing numerous benefits for human health; environmental sustainability and social wellbeing [15]. However, the rapid urbanization process has led to the degradation and loss of UGS, resulting in negative impacts on urban environments[4] Land Use Land Cover (LULC) changes are a significant driver of UGS loss, with built-up areas expanding at the expense of natural habitats[7]

Remote sensing and geographic information systems (GIS) have emerged as valuable tools for monitoring and analyzing LULC changes and UGS dynamics[3]. Studies have employed various remote sensing data sources, including Landsat[4][10] and high-resolution images[15] to assess LULC changes and UGS patterns. GIS-based analysis has also been used to evaluate the impact of LULC changes on UGS [18]

Machine learning algorithms, such as support vector machines (SVM) and artificial neural networks (ANN), have been applied to LULC classification and UGS mapping[4][15] However, these methods often require manual feature engineering and may not full capture the complexities of LULC changes[9]. Deep learning (DL) methods have shown promise in LULC classification and UGS mapping, with convolutional neural networks (CNNs) and recurrent neural networks (RNNs) being widely used[15]. However, DL methods often require large datasets and may not generalize well to new environments[4]

The integration of feature engineering and DL methods has been proposed as a solution to improve LULC classification and UGS mapping accuracy[17]. Feature engineering techniques, such as false colour image synthesis and vegetation indices, can enhance the spectral information of remote sensing images and improve DL model performance[15].

Ablation experiments have been conducted to evaluate the effectiveness of different DL architectures and feature engineering techniques (Results have shown that the integration of feature engineering and DL methods can improve LULC classification and UGS mapping accuracy[16]

In conclusion, the literature review highlights the importance of UGS in urban ecosystems and the need for accurate LULC classification and UGS mapping. Remote sensing and GIS-based analysis have emerged as valuable tools for monitoring and analyzing LULC changes and UGS dynamics. Machine learning and DL methods have shown promise in LULC classification and UGS mapping, but require careful consideration of feature engineering and model selection.
Support vector machines (SVMs) are the classification method used in this study because studies have shown that they perform well with satellite imagery [10] The various classification algorithms and classifications for satellite photos are compiled in Table 1 Algorithms for supervised land cover classification and identifying changes over time were diverse[11]. Urban green spaces are crucial components of cities because tree leaves help capture dust, lessen air environmental damage, and reduce vibration, which has become a major issue in urban areas [6].

1. III. METHODOLOGY

Study Area:

The Ahmedabad city is positioned at a latitude of 23°03′ N and longitude of 72°58′ E sitting about 56 meters above sea level. Ahmedabad has a hot, semi-arid climate, receiving around 800 milli meters of rainfall.
The population of Ahmedabad has increased a lot over the past years, going from 2.76 million people in 1971 to 7,21 million in 2011, according to the Census of India. It was estimated that the population would reach about 9.78 million by 2021. With around 11,948 people living in each square kilo-meter, the city faces challenges due to this rapid growth.
This Fast Increase in Population can create problems for the city’s development, so it is important to have smart and sustainable plans to protect its heritage and culture. These efforts are essential for improving Ahmedabad's image both in India and around the world, ensuring that the city can handle its growing population while keeping its historical and cultural identity intact.

Fig 1.1 Ahmedabad City

Fig. 1.2 Area of interest marked on Google Earth.

Proposed Methodology

The study involves satellite image classification using SVM and spatio-spectral fusion of satellite image data. The Spectral and spatial information from two different datasets can significantly improve the accuracy of the classifier in the process of green space identification.

The spatial information can provide information about the shapes of man-made or natural objects in the images, while the spectral resolution can represent features of various colours based on their reflectance in distinct wavelength ranges. Multispectral satellite images need to be pre-processed before applying any algorithms as unprocessed data often leads to misclassification. This spatial and spectral information fusion approach reduces the labelling uncertainty and salt and pepper noise. In the present study, cloud masking is performed on the satellite images prior to classification.

Pre-processing

Pre-processing includes removal of noise from satellite images of the Landsat 7 dataset,
performed as follows:

Function: Masking Clouds(images)
{
1.Input: Satellite images with multiple bands.
2. Output: Satellite images with masked clouds.
3.Bands (‘B1’, ‘B2’, ‘B3’,’B4’,’B5’,’B6’,’B7’,’pixel_qa’)
4. qa=images. Select (‘pixel_qa’);
//if the cloud bit 5. Is set and the cloud confidence 7.is high // or the cloud shadow bit is set (3) , then it’s a bad pixel.
5. cloud mask = qa.bitwise and (Bit_1<< Bit_5) And (qa.AND (Bit_1 << Bit_7))
6.OR (And(Bit_1 << Bit_3));
7.// Remove edge pixels that don’t occur in all bands
8. // mask the images with masks used here.
9. MAskedimage = image.apply (cloudmask)
10. Return (Masked image)
}

Support Vector Machine

Support vector machine algorithm is one of the popular machine learning algorithms for Supervised Linear algorithm. The idea is to consider large satellite images with pixels in this larger satellite images area associated with the original images and apply the SVM classifier to this new set of data points in the largest satellite image area. This will produce a linear decision boundary in the enlarged satellite images area. This will produce a linear decision boundary in the original satellite images area. With this approach, the nonlinear boundaries are reduced by separating the satellite images into a linear one and using the classification algorithm to classify the pixel in the images.
Suppose (x1, y1) .... (xN, yN) are our training data points xi is a p-dimensional vector. Each xi is a p-dimensional vector

$$p = f(\beta n)$$

Where n is the number of bands in the images, and β gives the images dimensions. The feature space is denoted Sp, while Si is the satellite image. We have to enlarge Sp by mapping each pixel, x to a vector in SM, which is a large space.
Let f: Sp to SM be given by

$$f(x) = (f1(x1), f2(x2) \ldots\ldots fM(x))$$

Where fi from Sp
→ SM are some functions and fi are called the basic functions.

If f(x1), f(x2) .... f(xN) is our original set of points,
(f(x1), y1) .... (f(xN), yN) Є SM

(f(x1), y1) ...(f(xN), yN) is our new training dataset.
Using the new training set in the new feature space, SVM classifier is applied and a hyperplane in SM that softly separates points f(x1) through f(xN). For training the SVM, high spectral resolution images data from the MODIS dataset is used and then downscaled to the Landsat & dataset which has high spatial resolution.

Spectral fusion approach for classification

This paper adopts a spectral fusion approach to green space assessment, as shown in Fig. The approach is based on the spectral fusion of the MODIS and Landsat 7 datasets- similar to the methodology explained by Gallagher et al. (2018). Classification is performed on the fused data using the SVM to monitor green space changes over a particular Time Period.

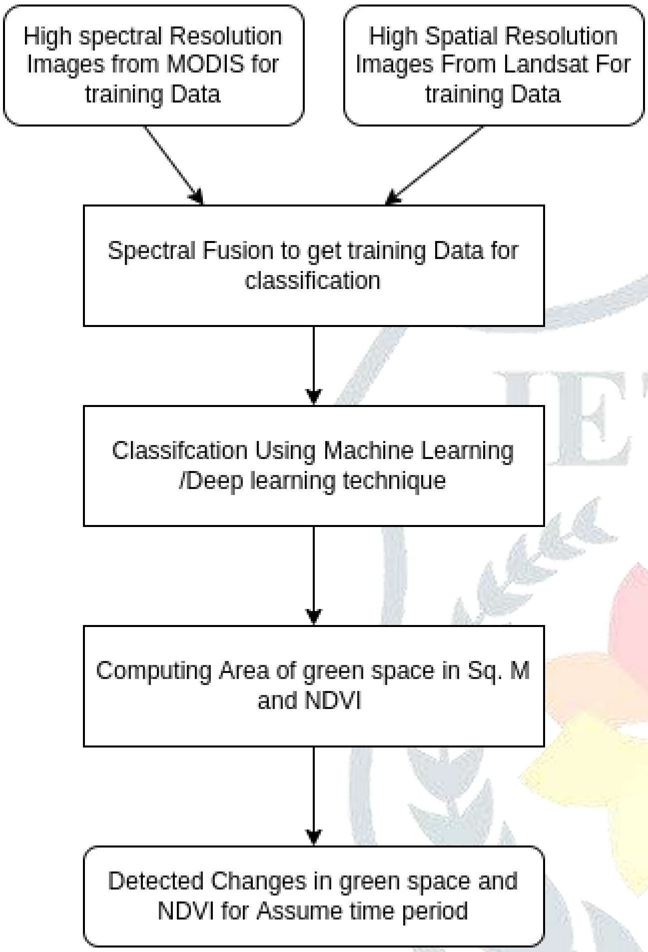

Fig-2 It is Workflow diagram for finding NDVI and Greenness in particular Area

Function: Spectral_fusion(image)
{
1. Bn = select bands from satellite images
2. High_Spectral _ images from MODIs dataset
3. High_Spatial_images form LANDSAR dataset
4. Training_dataset_features = (Bn from MODIS)
5. Out = Classify (images, training_dataset_features, training_data, SVM)

// calculate area of green space of output images
(6) Calculate _area (out);
(7) Testing _dataset_features (Bm from LANDSAT)
(8) Calculate_change_from_area (year1, year2);
}

III. Result and Analysis

This section discusses an experiment that looks at how well a method called fusion can classify different types of land, particularly green spaces. The results of this analysis are shown through various charts and figures.

Computing Platform and Experimental Setup

For this experiment, we utilized two primary tools: Google Collaboratory and Google Earth Engine. Google Collaboratory is a free online platform that enables users to write and share Python Code in a notebook format. It also allows for easy saving of work in google drive. A notable feature of this tool is its ability to leverage powerful hardware, such as Graphics Processing Units (GPUs) and Tensor Processing Unit (TPUs), which enhance Processing speed and efficiency. This capability supports extended periods of continuous operation, making it ideal for handling complex computations

Google Earth Engine is a robust tool that provides access to a vast array of geospatial data, including extensive satellite imagery from sources like Landsat and MODIS over many years. This Platform simplifies the visualization of data and facilitates the downloading of intermediate results for further analysis. Together These tools create a powerful environment for conducting our experimental analysis.

Dataset Used

For this research, a specific dataset called MODIS MOD13Q1 is used, which provides detailed information about vegetation at a resolution suitable for analysing changes over time. This dataset combines data from two satellites and selects the best quality images from a set time period. It has information dating back several years.
We also used the Landsat 7 dataset, which has a finer resolution and contains data from several years ago to the present. This dataset has been corrected for atmospheric effects, making it more reliable for analysis. Our research specifically looks at data from a significant time frame to understand changes in green spaces in the Ahmedabad area.
For analysing green spaces, pixel-based and band-based classification methods have been used. In pixel-based classification, we compare individual pixels in the satellite images to a set of training pixels whereas in band-based we use 3 bands viz. Near Infrared (NIR) band (band 5), Red (band 4) and Green bands (band 3).

Result Analysis

Tabel-1: Landsat and MODIS bands with bandwidths.

Landsat Band	**Bandwidth (µm)**	**MODIS Band**	**Bandwidth (µm)**
Band 1	0.45 to 0.52	Band 1	0.47 to 0.53
Band 2	0.52 to 0.60	Band 2	0.54 to 0.61
Band 3	0.60 to 0.69	Band 3	0.63 to 0.69
Band 4	0.76 to 0.90	Band 4	0.75 to 0.89
Band 5	1.55 to 1.75	Band 5	1.30 to 1.35
Band 6	1.04 to 1.25	Band 6	1.62 to 1.65
Band 7	2.09 to 2.35	Band 7	2.10 to 2.15

Proposed work analyses the green space changes in the Ahmedabad area, which include a particular area of Ahmedabad. Over a period 2015 to 2025, the amount of green space in the region has significantly declined, with a notable decrease of nearly half, except for a slight increase observed between 2022 and 2024. The study employs spectral fusion methods to classify and quantify the green spaces, achieving a high accuracy rate.

The results indicate substantial reduction in green space, with the spectral fusion approach yielding an accuracy higher than previous studies. Various figures illustrate the changes in green space over the years, the accuracy of different dataset using Support vector machine (SVM) algorithm. Additionally, the number of images used for classification each year is highlighted.

This is inferred that Machine learning techniques, particularly the spatio-spectral fusion approach, effectively analyse green space changes, with visual representations indicating positive and negative changes in green areas across Ahmedabad urban area.

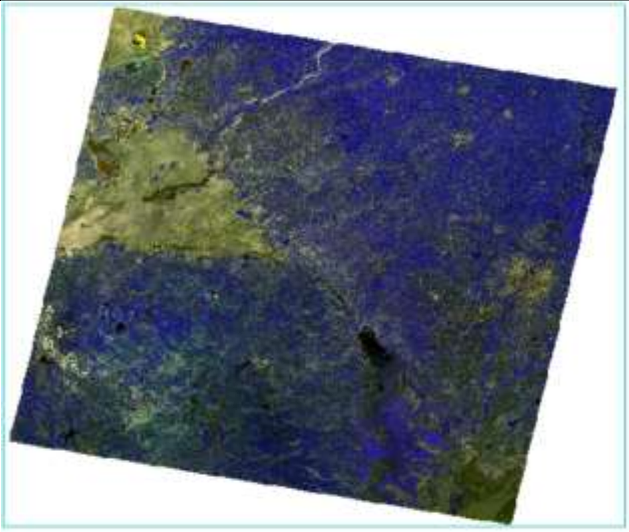

Fig-3. Image in the year 2020 for (NDVI) with Data Ignore Value as Zero.

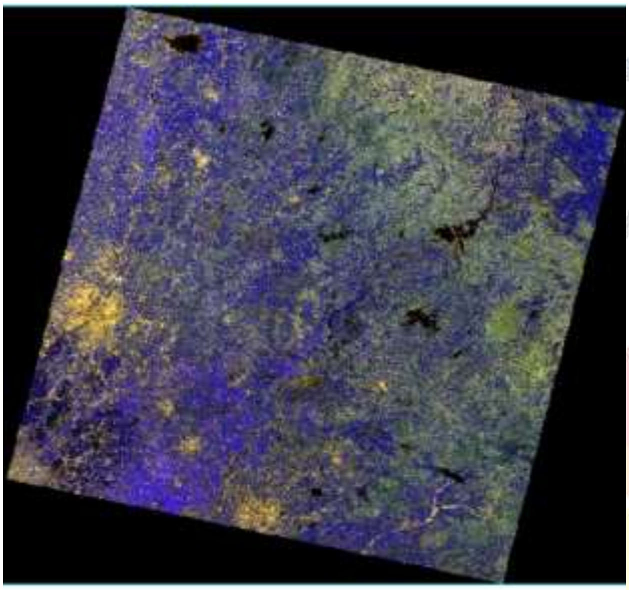

Fig-4 Image in the year 2024, for NDVI without Data Ignore Value. Blue Colour Show the Vegetation of Interested Area.

The proposed work also demonstrates green space changes in the Ahmedabad and Ahmedabad Urban Area based on fusion of high spectral resolution and high spatial resolution images. As shown in Fig.1 there is calculated Normal Difference Vegetation Index (NDVI) with Data Ignore Value as Zero for the year 2020 and in Fig.2 Calculated NDVI without Data Ignore Value for the year 2024. In NDVI shown with classification of images and selected Band i.e. Band 3 and Band 4. Blue Colour Show the Vegetation of Interested Area.

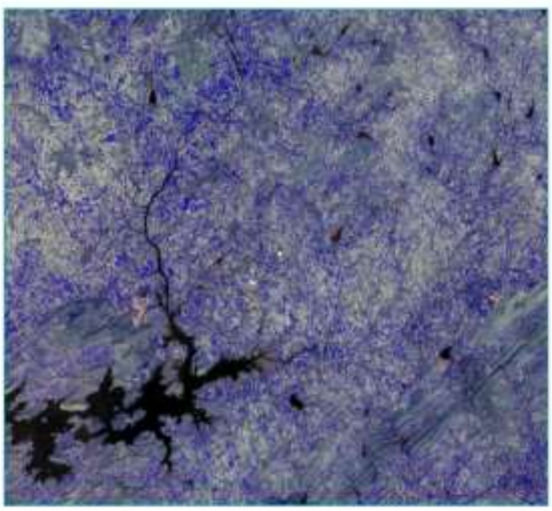

Fig-5. Calculated NDVI Using Band 5 only for subsets Present UGS Calculated in the subset of the image of Fig 4 with band wise classification.

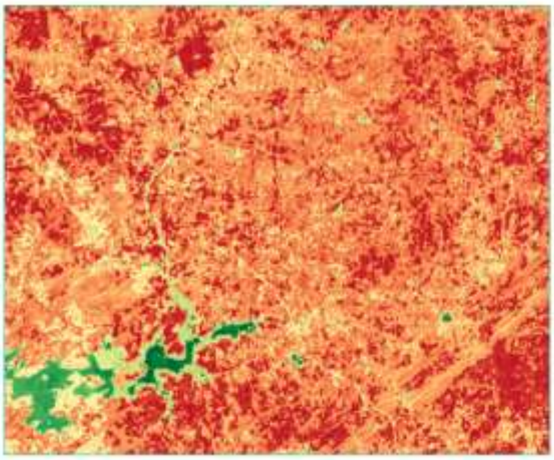

Fig.6: Present UGS Calculated in the subset of the image of fig 5 with band wise classification.

Image in Fig-5 visualises the calculated NDVI with Using Band 5 only for subset of area with pixel classification. Fig. 4 shows the calculated Urban Green Space (UGS) in the subset of the image of Fig. 4 which has band wise classification. Similarly, Urban Green Space (UGS) in the subset of the image of Fig. 4 with pixel wise classification is shown in Fig 6..

Fig 7: Present UGS Calculated in the subset of the image of Fig 5 with pixel wise classification.

V. Conclusion:

Objective of the proposed work is to demonstrate greenness , Urban Green Space, of an urban area using HPC and data fusion approach. From results with Fig 4 & 5, it is thus demonstrated for the year 2025. First, google earth image of Ahmedabad city is acquired and then using data sets, green space is calculated using the subset of the image of Fig 3 with 2 different approaches i.e. band wise classification and pixel classification.

It is found that there is a significant reduction in green space of the Urban area of Ahmedabad over one decade. Normalized Difference Vegetation Index (NDVI) is reduced and it shows the reduction in green space in a subset of urban area.

The results obtained from this work can be extended to improve green space coverage in the city. Additionally, deep learning approaches can also be used to improve the performance of the system. The results may help the Town Planning department of the governments to increase NDVI and Urban Green Space.

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