Vision-Based satellite Imagery for riparian and forest Ecosystem classification

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***Abstract*— This Paper analyzes changes in the riparian area of Koyna wildlife sanctuary and the forest area of Tadoba Andhari reserves using remote sensing technology over a ten-year period from 2014 to 2023. Satellite imagery was segmented based on vegetation and color, and area and perimeter were calculated to determine changes. Results show fluctuations in vegetation cover, highlighting the dynamic nature of these ecosystems. The data collected indicates a decrease in the area and perimeter of both ecosystems, emphasizing the need for sustainable land use and resource management decisions. These findings provide valuable information for conservation efforts and management strategies to maintain the health and diversity of these ecosystems. This study highlights the importance of promoting sustainable land use practices and resource management decisions for the long-term health and diversity of these ecosystems.**

Keywords*— *Riparian, Forest, Satellite, Vegetation.

I. INTRODUCTION

Satellite image has proven to be a valuable tool in the classification of riparian and forest ecosystems. With the advancement of faraway sensing generation, high-decision satellite imagery for pictures can now provide detailed information about the Earth's surface, making it possible to accurately map andmonitor the distribution of different types of vegetation and land cover. Our studies suggests that professionals' expertise does not vary semantically, but that statistics tends to be related. The experiments done showed that the scale of words and the velocity at which phrases are retrieved from reminiscence varies among people with unique historical past know-how. The findings of our take a look at may also help to provide higher, customized instructions to users in extraordinary regions and aid the improvement of a extra interactive dialog between the person and an intelligent tutoring machine. One example of a successful application of satellite imagery for forest and riparian surroundings classification is the have a look at via (Tarasova et al., 2000), which used satellite records to map land cover and plant life types inside the USA. The results of this study showed that satellite imagery can provide a highly accurate and cost-effective means of mapping the distribution of riparian and forest ecosystems at a regional scale. Another example is the take a look at through (Dale et al., 2001), which used satellite imagery for data to map land cowl and vegetation sorts inside the Brazilian Amazon. The results of this work show that the distribution of different vegetation types, such as forests, savannas, and agricultural fields, throughout vast and intricate tropical ecosystems can be precisely mapped using satellite data.

II. LITERATURE SURVEY

Johansen et al. research examined the ability of high spatial decision satellite picture statistics to differentiate structural tiers of flowers in riparian forested ecosystems, the usage of the British Columbia Terrestrial Surroundings Mapping scheme. The results showed that most structural types of vegetation may be distinguished, and window sizes of 3×3 pixels and 11×11 pixels have been the maximum suitable for photo texture calculations. [1]. Rivas-Fantino et al. researched that the RSQI is a devicefor tracking riparian first-rate without fieldwork, with an accuracy of ninety-two% and a kappa index fee of 0.88. It quantifies and identifies areas which can be extra inclined or in a worse state of affairs, with satisfactory circumstance similar to stretches of flowers with top-quality cowl, top connectivity with the adjacent woodland environment, and very little presence of invasive plants. [2]. The paper how appropriately floristically described woodland types in lowland tropical rain forests in Peruvian Amazonia may be diagnosedby the use of far-off sensing information (Landsat ETM+ satellite imagery for photo and STRM elevation version) [3]. K.Housni presents a method for classifying high-resolution urban satellite images using a combination of Support Vector Machines (SVM) and Graph Cuts The method consists of two stages: an SVM classifier is trained on labeled training samples and a Graph Cuts algorithm is usedto refine the classification results SVM give 96.05% Accuracy.[4]. Tarasova and Smirnova use maximum probability, decision Tree, and Neural network techniques for the classification of riparian zones using satellite images

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and they got an accuracy of 96.09%, 86.54 %, 94.51% respectively [5]. Strasser, Thomas discusses conceptual factors and initial effects of a workflow assessing habitat distribution and fantastic via the use of item-primarily based photo assessment in a riparian woodland. Also, They developed a workflow-based strategy for automated habitat delineation and assessment, using a hierarchical class modeling scheme and 8-band WorldView-2 imagery for this Analysis they uses Support Vector Machine (SVM) Model and they got 87% Accuracy as a result [6]. Walker et al. compare the use of ALOS/PALSAR and Landsat remote sensing statistics resources for mapping forest and land cover in the ALOS/PALSAR provided more accurate results for certain land cover types, The paper emphasizes the importance of using multiple data sources to improve accuracy and reliability. The accuracy they got was as Landsat spectral 89.2%, Ancillary 89.5%, PALSAR spectral 80.7% Ancillary 84.7 [7] The Paper shows the Approach to the detection of buildings on satellite images they discuss Many methods of building detection one of them is Hough remodel used to extract the bounds and detection of square buildings within the work like this overall detection is done for this use Spectral Graph Theory technique and this method gives an 89% Accuracy [8] Neware, Rahul, and Amreen Khan presents a classification and segmentation of the image into its land cover type also in this paper they discuss the classification strategies utilized in far-flung sensing for satellite pics, such as Object-based, Supervised and Unsupervised. Supervised classification is used due to its high accuracy [9]. The paper proposes a hybrid approach forsatellite image classification that combines various techniques such as Fuzzy C-mean clustering, help Vector system (SVM) category, The performance assessment is primarily based on outside and internal metrics such as correctness, DB index, and MSE. MSE gives a 95.8% accuracy as a result [10]. Kasper et al. evaluated the usage of IKONOS and Landsat-7 ETM+ imagery to map riparian flower fitness signs in Keel bottom Creek, Queensland, Australia. For mapping indicators of riparian flora, the writer used IKONOS fifty four.56% and Landsat ETM+ Imagery method to test Accuracy. [11]. Peerbhay, Kabir, et al.the mixing of LiDAR with minimal noise fraction (MNF) records produces the excellent trojan horse weed detection price (DR) and fake tremendous price (FPR). This observe has proven the capability of mixing hyperspectral statistics with LiDAR-derived top to exactly map (83%) the incidence[12]. T. Strasser et al. used object-primarily based photo analysis strategies to autonomously delineate wooded area habitats and check habitat pleasant in the Salzach river floodplain. the principle pillar of the workflow changed into the usage of an item feature library (OFL) to calibrate the method of information extraction and estimations. They used the Habitat elegance Modeling method for habitat quality monitoring in the riparian forest they got 86.93% Accuracy using this technique[13]. Veronique PRINET et al. Introduce a new approach to the type of curvilinear networks, which is the major hobby for image indexing and picture matching. the primary concept is to apply a choice tree taking into account a priori understanding, and the resulting community is encoded as a graph with a multi-scale description [14]. Dunham et al. Investigated the connection among the Palmer Drought Severity Index and high-quality flowers sorts via the derivation of vegetation indices from Landsat 7 ETM+ information. three flora indices were selected SAVI, Tasseled Cap, NDVI respectively [15]. The paper evaluated the effect of satellite images for laptop photograph spatial decision (30 meters from Landsat and 1 meters from digital Globe) on land use class and ordinary suspended solids load estimates from the Soil and Water assessment device general suspended solids technique offers accuracy as 82.3%. [16]. Nejad et al. predicted normalized difference moisture index and land floor temperature the use of facts from Landsat 8 and MODIS within the Karun riparian woodland in the Khuzestan province of Iran Accuracy rate of (LST) is ninety five%.[17]. within the Paper detecting waterways and wetlands in Texas, plant life studied covered large reeds, Waterhyacianth, and massive salvinia. outcomes showed that quick hen imagery can be used efficiently to map infestations of these three weeds. [18]. Chen et al. presented an approach for mangrove mapping and change detection analysis for this analysis they mainly stated the NDVI, and NDWI techniques for Mapping [19]. This study used satellite pix to degree tree greenness at some stage in spatial and temporal gradients of salmon fertilization outcomes in regions. For this, they finished two case research on the lower Fraser River, the principal coast. [20]. Philippe et al. Give the Joint studies Centre's wood mission satellite-derived plants Map of crucial Africa, The digital photograph processing and geographical statistics structures techniques have been used to convey collectively a cartographic map product work is persevering with to beautify the map the use of new satellite sensors, along side JERS, ATSR [21]. Lee et al. evaluated the reduction impact of nonpoint supply pollution by way of applying quality control practices (BMPs) to a 1.21 km2 agricultural watershed with the usage of a SWAT (Soil and Water evaluation device) version. For discount, they s used NPS pollution via applying BMPs to the usage of the SWAT version. [22]. The paper states that Deep learning (DL) has great potential to outperform existing classification methodsand obtain more accurate classification maps. they used CNN and SVM models for classification they got 84.5% Accuracy for CNN and SVM 87% [23]. Kanniah et al. used Landsat satellite imagery pix to analyze the changes over a length of 25 years of mangrove areas in Iskandar Malaysia (IM). For this they used two techniques MLC and SVM they got accuracies of ninety-four. 61% 88. sixty two% respectively. [24]. Komura et al. developed a method for the delineation of tree crowns For this classification they used NDVI and RDI techniques according to them NDVI isn't always enough for a category of plant life, so RDI is used to increase the Classis of classifiable vegetation [25].

III. METHODOLOGY

The Block diagram of proposed system involves several primary steps which are Shown in the below Fig 1. So firstly, project begins with the Collecting of satellite imagery, which is pre-processed to improve its quality and remove noise. The images are then classified into two categories: riparian ecosystems and forest ecosystems. The riparian ecosystem classification and the forest ecosystem classification steps involve identifying vegetation in the images and segmenting it using thresholding and contour detection. Depending on the features of the image, the forest ecosystem classification stage may require applying different criteria or methodologies. The output of the project includes the Riparian and forest Area analysis by the classification steps.

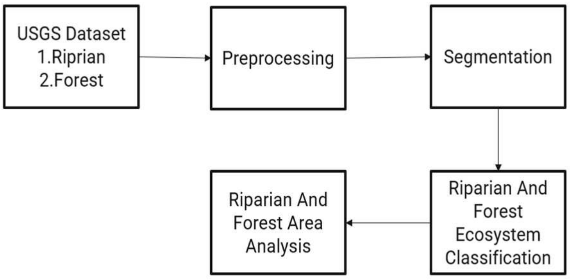

Fig 1. Block diagram of RAFEC system

A. Dataset

The dataset used in our project consists of satellite images of Riparian and forest area as shown in Fig 2 and 3, collected from the USGS earth Explorer of the (Koyna Wildlife Sanctuary) for riparian and Tadoba Andhari Tiger Reserve for Forest over a period of 10 years. USGS Earth Explorer is a web-based application that allows us to search, preview, and download satellite, aerial, and other remote sensing data. USGS is a reliable source of satellite imagery. The purpose of the dataset is to support the vision-based classification of riparian and forest ecosystems. We specifically used Landsat images for the riparian and forest classification task. The images cover various areas of the Koyna Wildlife sanctuary and Tadoba Andhari. The dataset contains images of resolution 1024 × 1044, ranging from 30 meters to 60 meters, depending on the Landsat satellite used. For obtaining a result of 10 years of ecosystem for riparian and Forest areas, we have used ten images from 2014–2023 from February's month each into dataset.

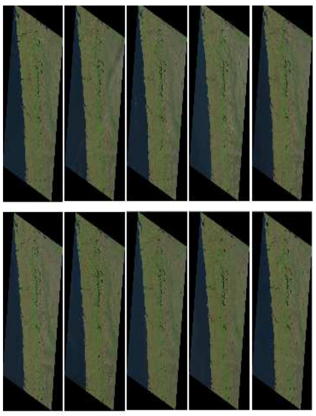

Fig.2. Dataset of Koyna wildlife for year 2014-2023

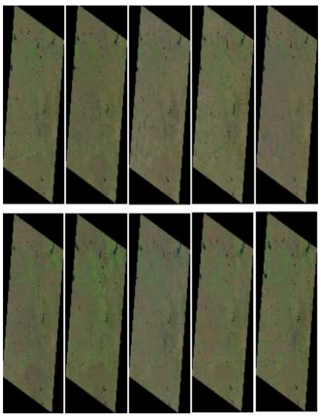

Fig.3.Dataset of Tadoba Andhari for year 2014-2023

B. Segmentation

"Segmentation" is the automatic and ideal grouping of image pixels or the division of a landscape into spectrally homogenous and geographically different sections or image objects. A method used in image processing to separate objects or regions according to their color or hue is called color-based segmentation. It entails converting an input image into a color space, like RGB or HSV, and then using a threshold to produce a binary mask that emphasizes the pixels with colors falling inside a certain range. We used color-based segmentation to identify vegetation in the input images. This is done by first converting the images from the BGR color space to the HSV color area, which separates the color facts into hue, saturation, and value channels. Then defines a range of green hues in the HSV color space using lower and upper bounds and applies a threshold to the hue channel to create a binary mask that highlights the pixels with green colors. This mask is then used to filter out non-vegetation regions in the image, making it easier to identify and analyze the vegetation cover in the riparian area. It includes additional steps to reduce noise and refine the segmentation results, such as applying a median filter and opening a morphological operation.

C. Algorithm dor vegetation and segmentation

Algorithm 1 Riparian Vegetation Segmentation

Require: Image dataset directory
1: Set lower and upper threshold
    lower_green ← [40, 40, 40]
    upper green ←|[70, 255, 255]
2: Set kernel size for median filter and morphological operation
    median_kernal_size ← 5 * 5
    opening kernal size ← 5 * 5
3: Create output directories for segmented images
4: **for** each filename in the list **do**
    I. Load the image
    II. Convert image to HSV color space
    III. Apply threshold to HSV image
    IV. Apply a median filter with 5* 5 kernel size
    V. Apply an opening morphological operation
    VI. Convert the Binary Mask to Color image
    VII. Find the Contour of the Vegetation Mask
    VIII. Draw the contours of the segmented image
5: **end for**
6 : Find the area and perimeter for Vegetation
7: end

D. Flowchart for calculating area and parameter

To calculate the area and perimeter of vegetation in an image, the process involves several steps as shown in the Fig 4. First, the input image is converted to grayscale and thresholding is applied to make it easier to detect the contours of the vegetation. Then, using findContours() function, the contours of the vegetation are identified. For each contour detected, it is drawn on the image and its area and perimeter are calculated using contourArea() and arcLength() functions. The areas and perimeters of all the contours are then summed up to obtain the total area and perimeter of the vegetation in the image. Finally, the total area and perimeter are printed to the console. By following these steps, accurate quantification of the vegetation in an image can be obtained, providing important information for analysis and research purposes.

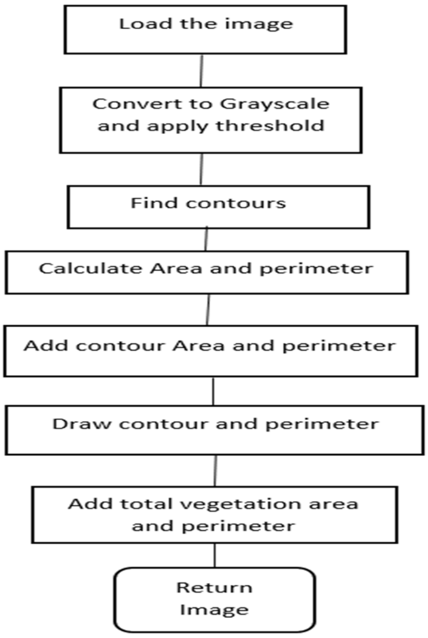

Fig.4. Flow diagram for calculation of area and perimeter

E. Functional diagram

Fig 5 shows a functional diagram of our proposed system which involves several steps. First, we convert the input images to the HSV color space. This color space represents colors based on three dimensions: hue, saturation, and value. Hue represents the color itself, including red, blue, green. Saturation represents the intensity or purity of the shade, and value represents the brightness of the color. Next, we set a threshold for the lower and upper bounds of the green color. We use 40 40 40 for the lower_green bound and 70 255 255 for the upper_green bound. Then, we perform morphological operations on the binary images. The main purpose of the morphological opening operation is to remove small or isolated areas in the binary mask. The resulting image after each step is shown in Fig. 3. After that, we draw the contours of the vegetation zone to evaluate the vegetation area. We then perform color-based segmentation, which is a method used in image processing to separate objects or regions according to their color or hue. Finally, we obtain the segmented image, and we calculate its area and perimeter for analyzing the changes.

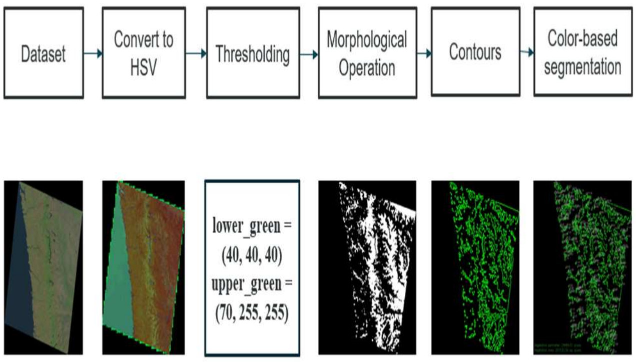

Fig.5. Functional diagram of RAFEC system

IV. RESULT AND DISCUSSION

The result of our analysis of the forest and riparian ecosystems showed fluctuations in vegetation area and pixel count over the 10-year period studied. In this section, will discuss these findings in more detailed and explore their implications for local land management and conservation initiatives.

A. Riparian Area Analysis

For the riparian ecosystem of Koyna Wildlife Sanctuary, our analysis revealed fluctuations in the vegetation area and the number of pixels that make up the vegetation over the 10-year period. The results show a peak in vegetation area in 2015, with an increase from 201532.50 sq. pixels in 2014 to 173149 sq. pixels in 2015, followed by a decline in subsequent years, with a low point in 2018 at 145998 sq. pixels. However, the area covered by vegetation has grown in recent years Fig 6 shows that the area appears wide in some years and partly narrow in others, such as in 2014 when it is wide and narrow in 2018, This indicates that the amount of vegetation in the riparian ecosystem can vary over time, with potential implications and overall health. Our study highlights the importance of regular monitoring and conservation efforts to maintain the riparian ecosystem's vegetation and biodiversity, which is crucial for the ecosystem's long-term survival and the well-being of the species that depend on it. Table 1 summarizes the changes in vegetation area and pixel count in the riparian ecosystem, with up and down arrows indicating increases and decreases, respectively. It is important to note that the peaked area in 2015 was a significant increase from the previous year and may have been influenced by environmental factors such as rainfall or temperature.

TABLE I. VEGETATION AREA AND PERIMETER OF RIPARIAN AREA

Sr. No	Year	Area	Perimeter
1.	2014	201532.50 sq. pixel ↑	29984.01 pixel ↑
2.	2015	173149.00 sq. pixel ↓	26796.90 pixel ↓
3.	2016	150078.50 sq. pixel ↓	25532.41 pixel ↓
4.	2017	164911.50 sq. pixel ↑	26784.61 pixel ↑
5.	2018	145998.00 sq. pixel ↓	24200.95 pixel ↓
6.	2019	133833.00 sq. pixel ↓	22879.41 pixel ↓
7.	2020	152577.00 sq. pixel ↑	26163.81 pixel ↑
8.	2021	164505.50 sq. pixel ↑	28152.82 pixel ↑
9.	2022	144204.00 sq. pixel ↓	25460.58 pixel ↓
10.	2023	140745.50 sq. pixel ↓	25915.29 pixel ↓

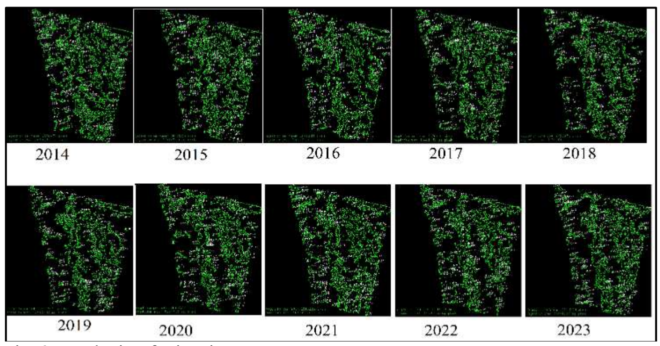

Fig.6. Analysis of Riparian Area

B. Forest Area Analysis

Our investigation showed that the vegetation area and the quantity of pixels that make up the vegetation varied over the 10-year period for the forest ecosystem in Tadoba Andhari Reserve. The results show a peak in vegetation area in 2017, with 797427.50 sq. pixel, followed by a decline in subsequent years, with a low point in 2022 at 667139.50 sq. pixel. However, the area covered by vegetation has grown in recent years, reaching 820951.50 sq. pixel in 2023. The up and down arrows in Table 2 depict these variations in the vegetation area and the number of pixels required to depict the vegetation, also from Fig 7 will see that in year 2015 vegetation area is looking wide and in 2020 it's looking partly. These findings demonstrate that the amount of vegetation in the forest ecosystem can vary over time, with potential implications for the ecosystem's health and biodiversity. Therefore, our study highlights the need for regular monitoring and conservation efforts to maintain the forest ecosystem's vegetation and biodiversity.

TABLE II. VEGETATION AREA AND PERIMETER OF FOREST AREA

Sr. No	Year	Area	Perimeter
1.	2014	763685.50 sq. pixel ⇧	34665.03 pixel ⇧
2.	2015	774264.00 sq. pixel ⇧	42805.55 pixel ⇧
3.	2016	728104.00 sq. pixel ⇩	43220.15 pixel ⇩
4.	2017	797427.50 sq. pixel ⇧	26909.54 pixel ⇧
5.	2018	507974.50 sq. pixel ⇩	42228.36 pixel ⇩
6.	2019	709725.50 sq. pixel ⇧	40079.79 pixel ⇧
7.	2020	779496.50 sq. pixel ⇧	24862.09 pixel ⇧
8.	2021	770798.50 sq. pixel ⇩	35424.25 pixel ⇩
9.	2022	667139.50 sq. pixel ⇧	32170.59 pixel ⇧
10.	2023	820951.50 sq. pixel ⇧	33246.17 pixel ⇧

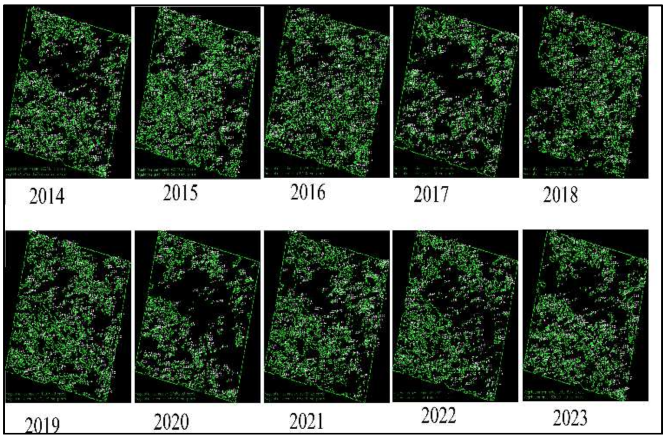

Fig.7. Analysis of Forest Area

CONCLUSION AND FUTURE SCOPE

Color-based segmentation is a useful technique for identifying and analyzing vegetation cover in riparian areas. This can be crucial when utilizing satellite data to categorize riparian and Forest ecosystems, as these ecosystems frequently contain distinctive vegetation that can be found and studied using remote sensing methods. We have observed an analysis of riparian and forest areas from Table 1 and 2 that how the ecosystem changes over time and gain insight into the variables as in year 2014 Riparian vegetation area is peaked to 201532.50 sq.pixel but deemed in year 2019 up to 133833 sq.pixel, also in 2022 to 144204 sq.pixel and For forest it's peaked in recent year 2023 up to 820951.50 sq.pixel and it is observed that it is decreased in year 2018 up to 507974 sq.pixel and this is also indicated by UP and Down arrow's to understand the changes also from Fig 6 and 7 from images will see that the wide and narrow effect for this above mentioned year's , that may be driving these changes, such as climate change, land use practices, or natural disturbances, by applying the color-based segmentation technique to a dataset of satellite images gathered over a ten-year period 2014-2023. With the help of this technology, we can track changes in vegetation cover, assess the health and richness of riparian and forest ecosystems through time, and provide information that is useful for managing and conserving ecosystems. It also emphasizes how crucial it is to use sophisticated remote sensing methods, including color-based segmentation, to extract useful information from satellite imagery and support reasoned decisions for managing and conserving ecosystems.

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