

ASSESSMENT OF RIVER WATER QUALITY USING INTEGRATED CHEMICAL, BIOLOGICAL AND ECOTOXICOLOGICAL APPROACH THROUGH SATELLITE IMAGES VIA ML TECHNIQUES

Submitted in partial fulfillment of the requirements for the award of Bachelor of
Engineering degree in Electronics and Communication Engineering

By

DUGGEMPUDI HARISH REDDY (37130119)



DEPARTMENT OF ELETRONICS AND COMMUNICATION ENGINEERNING

SCHOOL OF ELETRICAL AND ELETRONICS

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

Accredited with Grade “A” by NAAC | 12B Status by UGC | Approved by AICTE

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APRIL – 2021



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DEPARTMENT OF ELETRONICS AND COMMUNICATION ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the Bonafide work of **DUGGEMPUDI HARISH REDDY (37130119)** who have done the project work as a team who carried out the project entitled "**Assessment of river water quality using an integrated chemical, biological and ecotoxicological approach through satellite images via ml technique**" Under my supervision from September 2020 to April 2021.

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Submitted for Viva voice Examination held on _____

Internal Examiner

External Examiner

DECLARATION

I DUGGEMPUDI HARISH REDDY (37130119) hereby declare that the Project Report entitled “Assessment of river water quality using an integrated chemical, biological and ecotoxicological approach through satellite images via ML technique” done by us under the guidance of Mr. V. KALIST, M.E is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in Electronics and Communication Engineering.

DATE: 15/04/2021

PLACE: Chennai

SIGNATURE OF THE CANDIDATE

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ABSTRACT

It is necessary to preserve the water resources to maintain the ecological balance and sustainable development. There is a lot of sources to contaminate the water bodies. The water quality assessment is mandatory to analyze whether it is appropriate for envisioned usages. The assessment of water quality is becoming an important but difficult task due to the complex mixture of pollutants. The traditional way of checking drinking water quality methods involves the manual sampling of waters followed by laboratory analysis. The Methodology used for monitoring the quality of the water also determines the Tendencies in the eminence of the aquatic milieu and how the quality of the water is polluted by the contaminants. Conventional surface water quality assessment methods are widely performed using laboratory analysis, which is labor-intensive, costly, and time-consuming. To such a problem, remote sensing has been a blessing because of its low cost, spatial continuity and temporal consistency, remote sensing applications in water resources management are quite essential and water quality parameters help in decision making regarding the further use of water-based on its quality. This research aims to monitor the quality of drinking water quality based on wireless sensor networks and different machine learning algorithms. For detecting and classifying the abnormal behavior of the drinking water, we use different types of machine learning algorithms on the collected data. The proposed work presented a comprehensive report on the current scenario of the water quality assessment which utilizing remote sensing and image processing techniques. The assessment of present as well future water resources, river dynamics, agriculture suitability, river dynamics, wetland inventory, climate models, surface water survey and management, and, flood mapping are some major areas that need information about the water. The capability to monitor the global water supply through satellite images is a great effort in the remote sensing community. The remote sensing of water can be described as observing water from a long distance and checking its availability, properties and quality of water. A thorough analysis of satellite images can

play a significant role in differentiating the changes in the earth areas between different changes of imaging. Scientists and researchers are putting their effort to design and develop tools and techniques that can help for analyzing the certain type of changes in the earth areas in a more rapid and easy manner. A tool is a set of various interactive steps to help in the analysis and identification process. There are numerous analysis applications for flood, agriculture and fuel type assessment. Uniformly, we can use these strategies to detect the water on the surface of the earth.

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List of Abbreviations

- RAM: Random access memory
- ROM: Read only memory
- GPU: Graphic processing unit
- PCS: Principal component analysis
- SVM: Support vector machine
- MODIS: Moderate resolution imaging spectroradiometer
- ANN: Artificial neural network
- DNN: Deep neural network
- RNN: Recurrent neural network
- LSTM: Long short-term memory
- GPM: Groundwater potential model
- GIS: Geographical information system
- AVHRR: NOAA advanced very high-resolution radiometer.

CHAPTER NO: 1

INTRODUCTION

Environmental issues are becoming increasingly important. Local authorities issued laws to regulate various kinds of pollution in order to protect the environment. In many instances, toxic substances were nevertheless released for many years, leading to strong contamination of poisonous gases. Cases of strong contamination are usually caused by waste being spilt in small bourns. Because of the scarcity of water, concentrations can become quickly high. When a flood takes place, pollutants move on to a wide area and cause soil contamination on the river banks. This happens also when river water is used for irrigation. Waste has been discharged into small rivers, leading to severe pollution of waters and soils. For many years, this situation has been considered a test site for various scientific studies aimed at improving the assessment methods and remediation techniques. Different approaches to this problem can be found in the literature. Chemical analyses of water samples are used to assess the levels of pollution using various methodologies, such as High-Performance Liquid Chromatography or Tandem Mass Spectrometry. Similar analyses have been performed on soils, applying standard procedures defined by the Law or by laboratory practice. Procedures such as Inductively Coupled Plasma-Mass Spectrometry or X-ray diffractometry are useful; however, they often require specific sample preparation.

In the last few years biomonitoring techniques have been applied, clearly showing the unhealthy status of both plant and animal life directly related to strong contamination. Our approach uses remote-sensing techniques to monitor vegetation in the proximity of river banks. From the Normalized. Difference Vegetation Index (NDVI), computed from visible and near-infrared satellite images, it is possible to assess the conditions of vegetation along the watercourse; an unhealthy status can be related to biological stress caused by pollution. Chemical measurements have been used for validation purposes. A “chemical index” has been defined, based on the concentration of various toxic substances sampled in different places, and compared with NDVI assessed in the same areas.

1.1 EXISTING METHOD

Water is one of the most important natural resources which is key to our life. Though most of the Earth area is filled with water, only a small amount of water is available for drinking purpose. Various water conservation techniques have been used till now. But the management of water resources is necessary for accomplishing this task in an effective way. Water quality detection through satellite images is one of the promising areas for conserving water through proper management. In this paper, we have reviewed various water detection techniques implemented by the researchers. Image processing is one of the significant parts of every remote sensing technique to get effective results.

The research review will help us to implement an effective technique for our research.

1.2 PROPOSED METHOD

A classification connection has been designed for classifying water quality degree using fish liver microscope images as a biomarker for assessing water pollution. The proposed approach consists of three main phases; pre-processing, feature extraction and classification phase.

Color histogram, color moments, and Gabor texture feature vectors are combined to extract feature and used as a PCA input for transformation. Finally, the SVM model is developed for water quality degree classification. Based on the obtained results, water quality degree classification accuracy is 94.2% using the SVM linear kernel function. This research is intended to highlight the capabilities of the usage of image classification technique based on the fish liver as a biomarker for water quality. We aimed at improving the understanding of fish liver as a biomarker and the effects of fish on water quality. In future work, we will enhance this method by applying it for classifying water quality degree using fish gills microscopic images as a biomarker to assessing water pollution.

Moreover, in order to improve the system accuracy, a larger number of training images per class should be used.

CHAPTER NO: 2

LITERATURE SURVEY

Mueller, N. et al. (2016) observed 25 years of Landsat imagery across Australia for accessing the information about the surface water. The tool used in the research named as WOFS (Water Observations from Space) helped to identify and to manage the surface resources water in Australia in a better way. A new way of information retrieval was possible through the maps generated using WOFS. The combination of large high-speed storage attached to supercomputer processors, and surface reflectance data in a standard grid arrangement has enabled the development of a single analysis that can be applied systematically through decades of data. Approximately 2×10^{13} observations and 184,500 scenes spanning over 27 years were used for the process. In this way, the continental map of the surface water was produced.

Klemas, V. and Pieterse, A (2015) proposed a technique for water resources detection in Arid and Semiarid Regions using the remote sensing. The condition of the soil degradation and desert areas was obtained through the internally consistent maps of arid regions. MCDM techniques were used to delineate potential ground zones. Satellite remote sensors and airborne sensors were used for the water detection.

Madhavan a, S., et al. (2017) tried to improve the dust detection techniques. In order to do so, multi-sensor measurements using the Aqua (A), Terra (T) and MODIS images with OMI (Ozone Monitoring Instrument) were used. The identification of the dust pixels was a simple task with the use of OMI-based aerosol type.

Arvinda, C. S., et al. (2016) used MODIS images in order to analyze the flood affected areas. Mean shift and SOM techniques were utilized for the flood assessment. The SOM algorithm was used before, during as well as after accessing the flood affected area images.

The flooded and non-flooded regions were differentiated through the ROC performance evaluation parameters. At last, the result of the study 1928 Himanshu Rana and Nirvair

Neeru shows that proposed method is effective enough to provide a clear view of the flood affected areas.

Baeye, M. et al. (2016) detected shipwrecks using ocean color satellite imagery in turbid water. They demonstrated that wrecks generate SPM (Suspended Particulate Matter) concentration signals that can be detected by using high- resolution ocean color satellite data like Landsat-8. Surface SPM plumes extended downstream for up to 4km from the wrecks, with the concentration ranging between 15 and 95 mg/l. Surface SPM plumes with fully submerged shipwrecks were observed by them, and they describe them regarding wrecks size and its geometry. So, SPM plumes were indicators that a shipwreck was exposed at the seabed and certainly not buried.

Gierach, M. M., et al. (2016) detected wastewater diversion plumes in Southern California. They examined the capabilities of multi-sensor satellite data to detect the 2006 HTP and 2012 OCSD wastewater diversions and their impact on water quality in the SCB. Data included ocean color from MODIS-Aqua and SST from ASTERTerra. The result from this was applied to the recent HTP diversion, which occurred from 21 September to November 2015 in response to the observation made during 2006 HTP diversion inspection.

Ovakoglo, G., et al. (2016) used MODIS satellite images for detailed Lake Morphometric. They presented a methodology for easy updating the bathymetry of a lake with large water level fluctuations using high temporal resolution satellite image. It seemed to be possible to produce the lake DDM, using a time series of shorelines digitized on the near infrared band of MODIS satellite images. Two versions of the DDM were produced to access the influence of seasonal water fluctuation. Their evaluation was small and attributed to seasonal water ponds and vegetation as well as natural sedimentation process.

The application of this was limited to the exposed part of the lake bottom; this methodology seems to be useful to cover the parts of the lake that were too shallow to survey by boat.

Rokni, K. et al. (2015) gave a new approach for surface water change detection. They introduced a new approach based on Integration of image fusion and image classification techniques for surface water change detection. The result shows the high performance by using the Gram Schmidt ANN and Gram Schmidt SVM approaches which provide a very high accuracy results; this approach has the advantage of producing a high-resolution multispectral image. In the end, the suggested approach has been proven to be effective³ in detecting the water surface changes of Lake Urmia, Iran.

Gupta, R., & Panchal, P. (2015) concentrated on cloud detection algorithm using Discrete Wavelet Transformation (DWT) and realization of data on NOAA, VIIRS Water Detection using Satellite Images Obtained through Remote Sensing 1929 and MODIS datasets with double threshold values, applied in the visible region of electromagnetic spectrum using pixel to pixel processing. The radiation in the microwave region is low and maximum at the visible region. Therefore, in this paper, computation is done in the visible region. DWT is STFT (Short Time Fourier Transformation). Equation (6) to Equation (12) show the mathematical operations of proposed algorithm. In this paper, images are categorized into different ecological surfaces such that water, soil, vegetation, snow. The proposed method can differentiate the cloud from clear regions. The comparison is made between existing method based on the color model, and proposed method was found to be better. Limitation of proposed method is that it faces some difficulties to differentiate between thick clouds and snow/Ice.

Sarp, G., & Ozcelik, M (2016) represented the changes that occurred in the Lake Burdur from the year 1987 to the year 2011. The images were obtained from the Landsat TM and ETM+ for detecting the changes. Support Vector Machine (SVM) classification and indexing, including the Normalized Difference Water Index (NDWI), Modified NDWI (MNDWI) and Automated Water Extraction Index (AWEI) were used to extract surface water from images. Overall SVM followed by MNDWI, NDWI and AWEI got the best result among all the techniques.

CHAPTER NO: 3

AIM AND SCOPE

River Water pollution is a global issue and whole world is facing worst results of polluted water. Major sources of River water pollution are discharge of domestic and agriculture wastes, population growth, excessive use of pesticides and fertilizers and urbanization. Bacterial, viruses and parasitic diseases are spreading through polluted water and affecting human health. It is suggested that there should be proper waste disposal system and waste should be treated before entering in to river. Educational and awareness programs should be organized to control the pollution. In developing reinforcement programmer, taking into account the specificity of each basin, special attention should be given to countries in EECCA and SEE, as these countries face the biggest challenges to reduce transboundary impact.

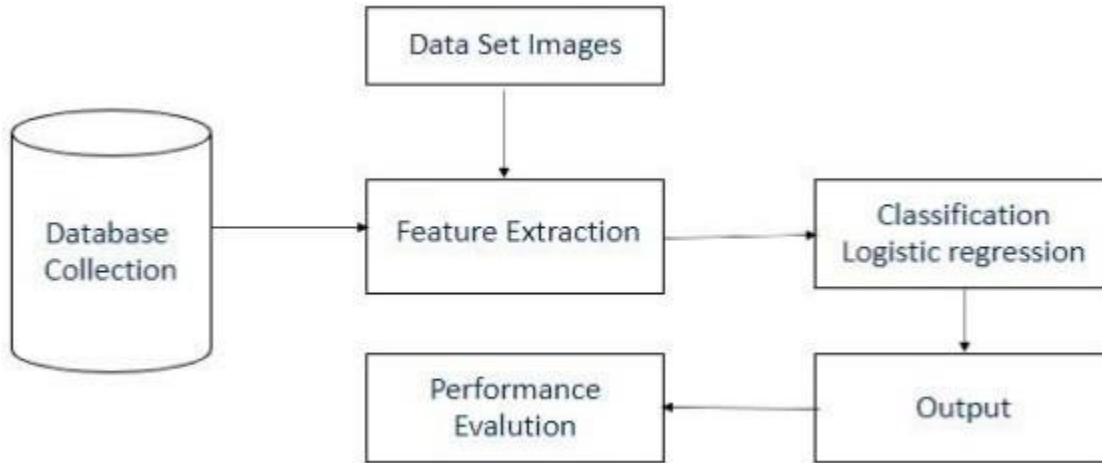
OBJECTIVE:

The proposed work introduces a survey of solutions that use various image processing tasks and machine learning concepts to detect pollution in river water. We carried out a useful analysis of various satellite sensors, image processing techniques, and classifiers used for classification of river water the following models are applied to water quality data: logistic regression, linear discriminant analysis, support vector machines (SVM), artificial neural network (ANN), deep neural network (DNN), recurrent neural network (RNN) and long short-term memory network and etc.

CHAPTER NO: 4

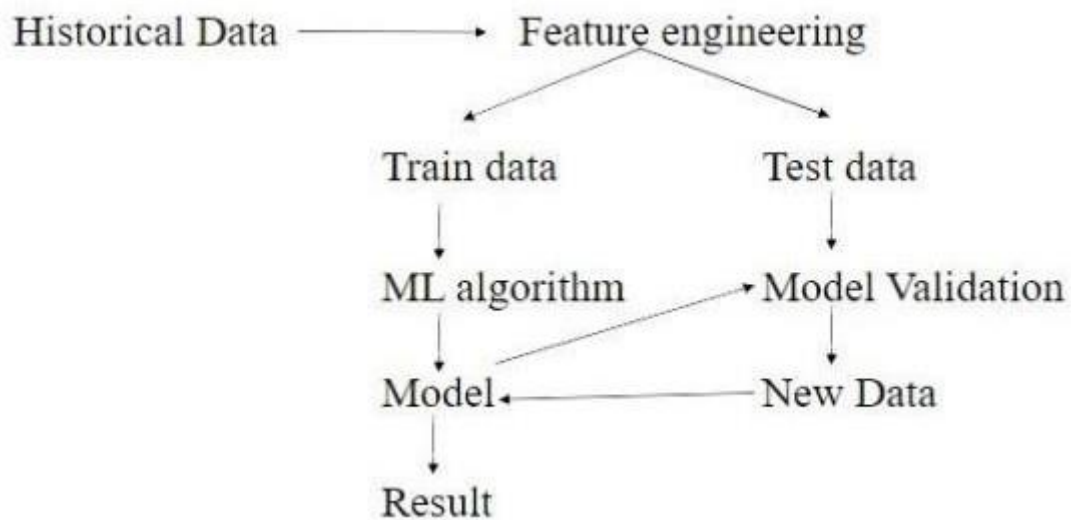
MATERIALS & METHOD

4.1



4.1 : Black diagram of water quality assessment by image processing

4.2 WORK FLOW



4.3 SOFTWARE REQUIREMENTS

- Tkinter
- OpenCV
- Scikit-image
- Spyder
- Anaconda Navigator

4.3.1 TKINTER

Tkinter is Python's de-facto standard GUI (Graphical User Interface) package. It is a thin object-oriented layer on top of Tcl/Tk. Tkinter is not the only GUI Programming toolkit for Python. It is however the most commonly used one. It is a standard Python interface to the Tk GUI toolkit shipped with Python. Python with tkinter outputs the fastest and easiest way to create the GUI applications. Creating a GUI using tkinter is an easy task. Moreover, Tkinter provides various controls, such as buttons, labels and text boxes used in a GUI application. These controls are commonly called widgets. These widgets are interactive and make Dynamism much attractive and efficient.

4.3.2 OPEN CV

Open-Source Computer Vision is a library of programming functions mainly aimed at real-time computer vision. It was originally developed by Intel's research center in Russia and now maintained by Itseez. The library is cross-platform and free for use under the opensource BSD license. It is a library of many inbuilt functions mainly aimed at real time image processing. Now it has several hundreds of image processing and computer vision algorithms which make developing advanced computer vision applications easy and efficient.

4.3.3 SCIKIT-IMAGE

Scikit-image is a collection of algorithms for image processing. It is available free of charge and free of restriction. It provides high-quality, peer-reviewed code, written by an active community of volunteers. scikit-image is a Python package dedicated to image processing and using natively NumPy arrays as image objects. Also, description on how to use scikit-

image on various image processing tasks is given, and insists on the link with other scientific Python modules such as NumPy and SciPy.

4.3.4 ANACONDA NAVIGATOR

Anaconda (Python distribution) Anaconda is a free and open-source distribution of the Python and R programming languages for Deep learning and machine learning related applications (Image Analysis, large-scale data, scientific computing, etc.), that aims to simplify package management and deployment.

4.3.5 SPYDER

Spyder is a powerful scientific environment written in Python, for Python, and designed by and for data analysts and image analysts. It features a unique combination of the advanced editing, analysis, debugging and profiling functionality of a comprehensive development tool with the data exploration. Formats of images such as Nifty, TIFF can be read on Spyder.

4.4 HARDWARE REQUIREMENTS

- Nvidia GPU 1080 TI
- RAM: 4 GB or more
- System type: 32- or 64-bit operating system
- Operating system: Linux, windows
- Processor: intel i5 3.60 Ghz or more

CHAPTER NO: 5

SUPERVISED AND UNSUPERVISED CLASSIFICATION METHOD

Advances in sensor technology for Earth observation make it possible to collect multispectral data in much higher dimensionality. In addition, multisource data also will provide high dimensional data. Such high dimensional data will have several impacts on processing technology it will be possible to classify more classes, more processing power will be needed to process such high dimensional data with large increases in dimensionality and the number of classes, processing time will increase significantly.

The analysis of remotely sensed data is usually done by machine-oriented pattern recognition techniques. One of the most widely used pattern recognition techniques is classification based on maximum likelihood (ML) assuming Gaussian distributions of classes. A problem of Gaussian ML classification takes long processing time. The long processing time leads to long computational time and as a result computational cost rise. This computational cost may become an important problem if the remotely sensed data of a large area is to be analyzed or if the processing hardware is more modest in its capabilities. The advent of the future sensors will aggravate this Rajiv Kumar Nath & S K Deb International Journal of Image Processing (IJIP), Volume (3): Issue (6) 360 problem. Hence, attention should be paid to extract detailed information from high dimensional data while reducing processing time considerably.

5.1 SUPERVISED CLASSIFICATION METHOD

The supervised classification is used to classify the satellite image of years (1992 and 2003) in three different classes namely blue color for water, green for the vegetation and aqua for dry land and these results are compared to find out the change in the Mancher

Lake of Pakistan. Report shows that number of points (Npts) selected for the sample region on the image and percentage (Pct) show the area of water, vegetation, and dry land.

Support Vector Machine with One-Against-One (1A1) and One-Against-All (1AA) techniques is used for land cover mapping of the Landsat Scene located at the source of River Nile in Jinja, Uganda. The bands used in this research consisted of Landsat's optical bands i.e., bands 1, 2, 3, 4, 5, and 7. The classes of interest were built up area, vegetation, and water. Table 3 gives a summary of the unclassified and mixed pixels resulting from 1A1 and 1AA classification. From Table 3 it is evident that the 1AA approach to multiclass classification has exhibited a higher propensity for unclassified and mixed pixels than the 1A1 approach. From Table 4, all accuracies would be classified as yielding very strong correlation with ground truth data. The individual performance of the SVM classifiers however show that classification accuracy reduced for the linear and RBF classifiers stayed the same for the polynomial and increased for the quadratic classifier.

The Bayesian supervised algorithm using the average intracluster distance within the fuzzy Gustafson-Kessel (GK) and Bayesian algorithm. The suggested algorithm uses the fuzzy GK algorithm in the form extended for the FCM. Different cluster distributions and sizes usually lead to sub optimal results with FCM. In order to adapt to different structures in data, GK algorithm used the covariance matrix to capture ellipsoidal properties of cluster. It makes classification of the remote sensing satellite image with multidimensional data possible. Fuzzy algorithm generally iterates the execution until there is almost no change in membership value.

The supervised classification technique using Gabor Filter for the textural attribute to the high-resolution satellite image. The author proposed a wavelet transform and Gabor filter-based texture analysis for the recognition of water bodies from satellite images including other object on Earth surface. The authors proposed two approaches namely pixel by pixel classification technique approach and object-oriented image analysis for classification of water bodies and other land cover in a satellite image. The authors proposed a mathematical morphological analysis approach for detecting water bodies

form satellite image. They also suggest chromaticity analysis for removal of atmospheric differences between images.

The spectral, spatial, and textural features for each region are generated from the thresholded image by dynamic thresholding. Then given these features as attributes, an unsupervised machine learning methodology called conceptual clustering (COBWEB/3) is used to cluster the regions found in the image into N classes—thus, determining the number of classes in the image automatically. This technique is applied successfully to ERS-1 synthetic aperture radar (SAR), Landsat Thematic Mapper (TM), and NOAA advanced very high-resolution radiometer (AVHRR) data of natural scenes. Figure shows an original SAR sea ice image that consists of packed ice with very dark, cutting linear structures (leads) and greyish regions (new ice or open water). Moreover, there are brighter, silky structures (possibly deformed first year ice) straining within the greyish regions.

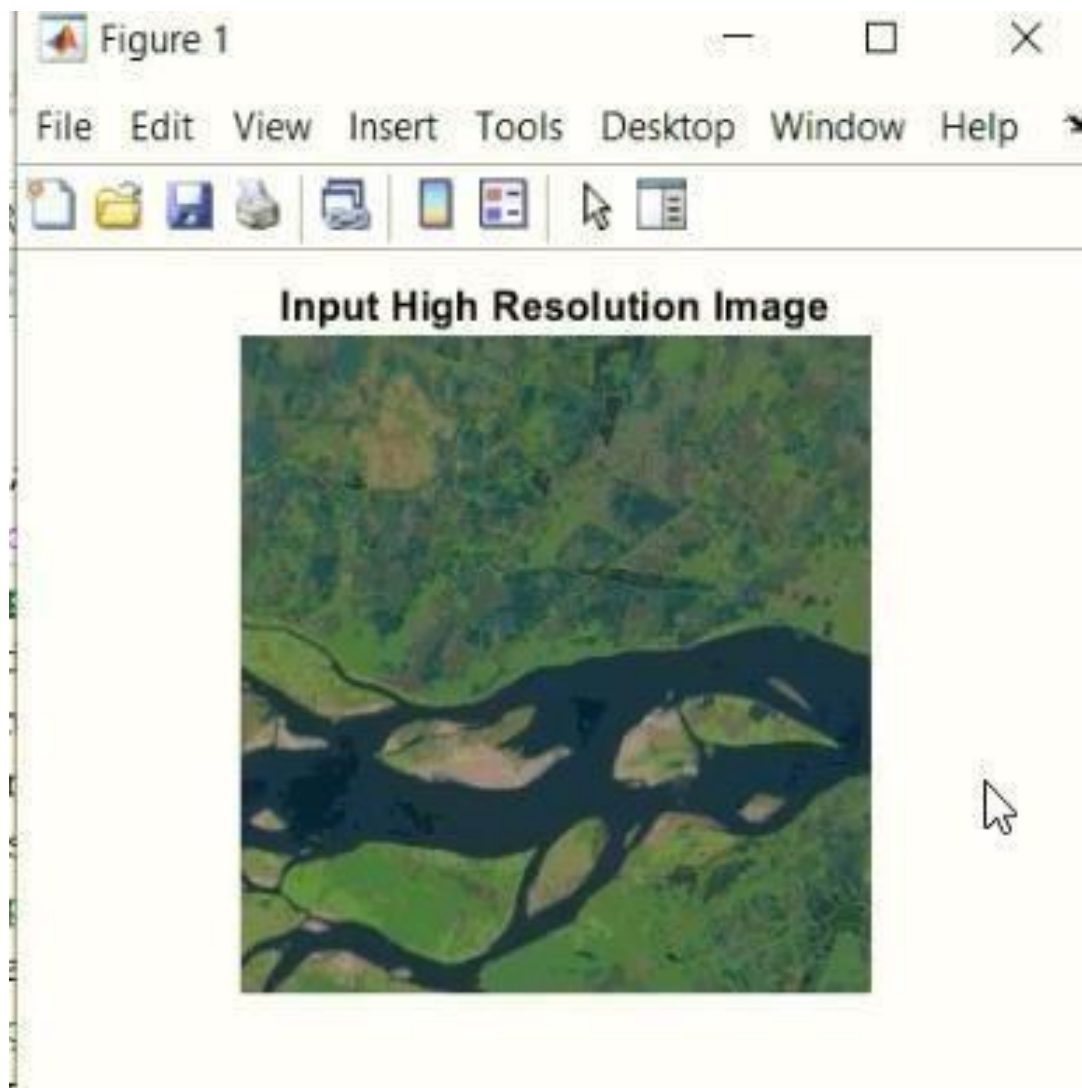
5.2 UNSUPERVISED CLASSIFICATION METHOD

The unsupervised classification in 15–30 classes was used for distinguishing between land and water (Fig 13). The 381 AVHRR scenes selected from the cloud algorithm were classified, using all channels. Extending back in time, Landsat data prior to 1985 and for the year 1986 was used for estimating flooding independently for 8 months (November 1972, May–June 1979, May– August 1984, November 1986). The Okavango Delta covers 4 Landsat scenes, and for each of these dates at least 3 Landsat scenes were available. If needed, the data gap (i.e., the 4th quadrant) was filled by dates with similar flooding patterns to the other.

Chapter No: 6

OUTPUT AND RESULTS

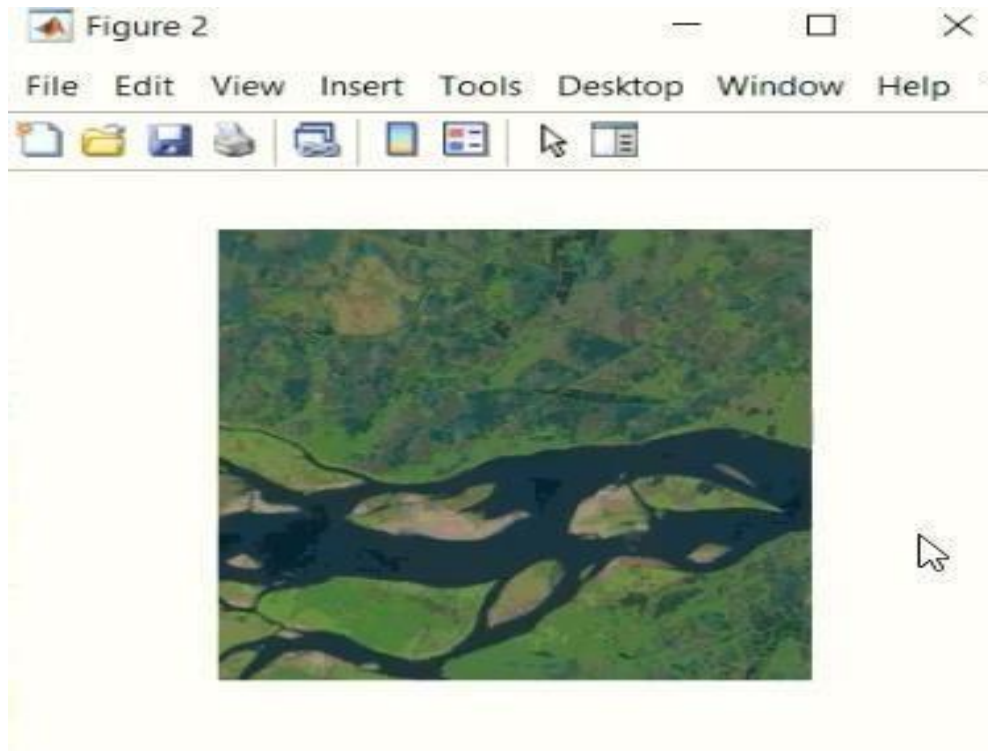
6.1:



6.1 : Input High resolution image

A low-resolution image is taken as an input and the same image is upscaled to a higher resolution which is the o/p.

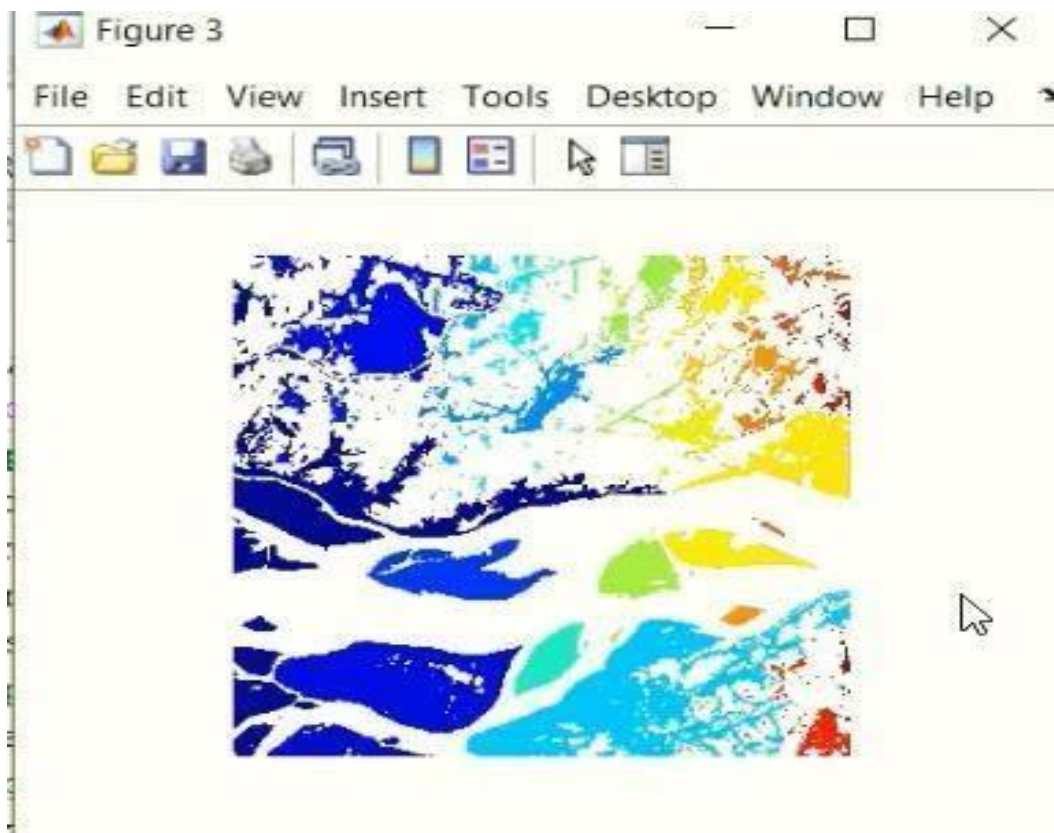
6.2:



6.2 : Input resized image

A new resized format (256*256) image with a high or low no of pixels must be generated. In the case of decreasing the pixel no's this usually results in a visible quality loss.

6.3:



6.3 : Image labelled by binary

Binary images are images whose pixels have only two possible intensity values..... Binary images are often produced by thresholding a grayscale or color image, in order to separate an object in the image from the background (RGB)

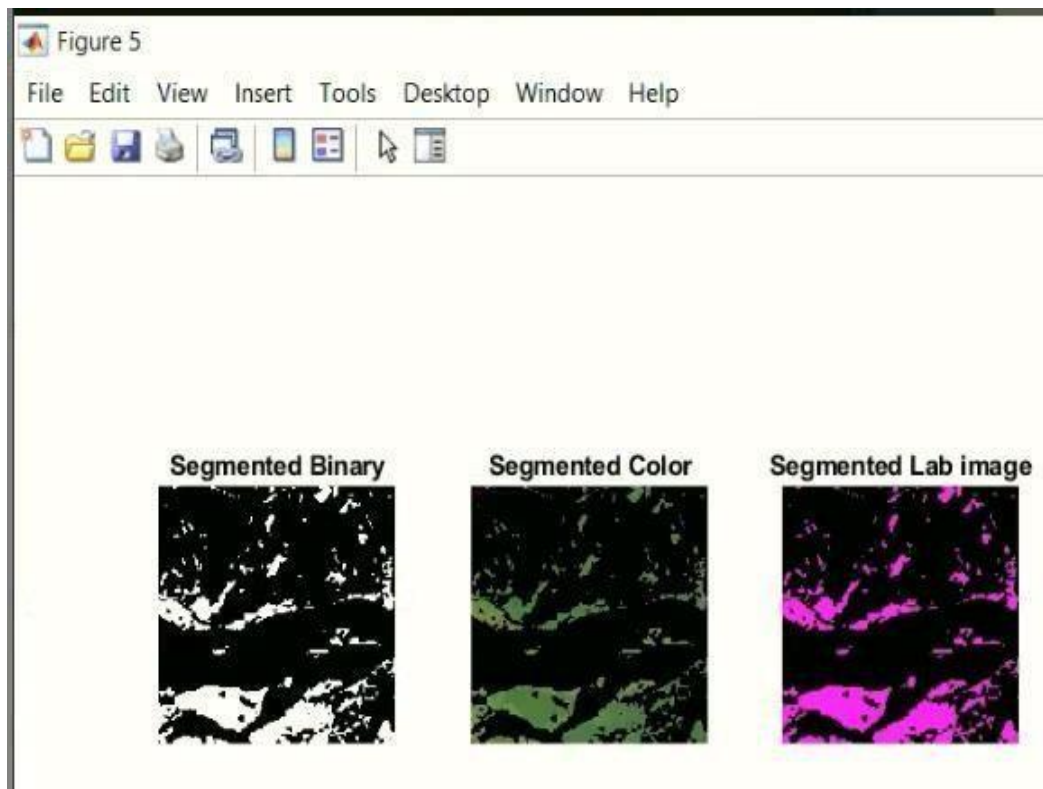
6.4:



6.4 : Image labelled by cluster index

Clustered index is a type of index where the table records are physically re-ordered to match the index. Clustered indexes are efficient on columns that are searched for a range of values. By doing this we can identify whether there is any error in the grey image or not.

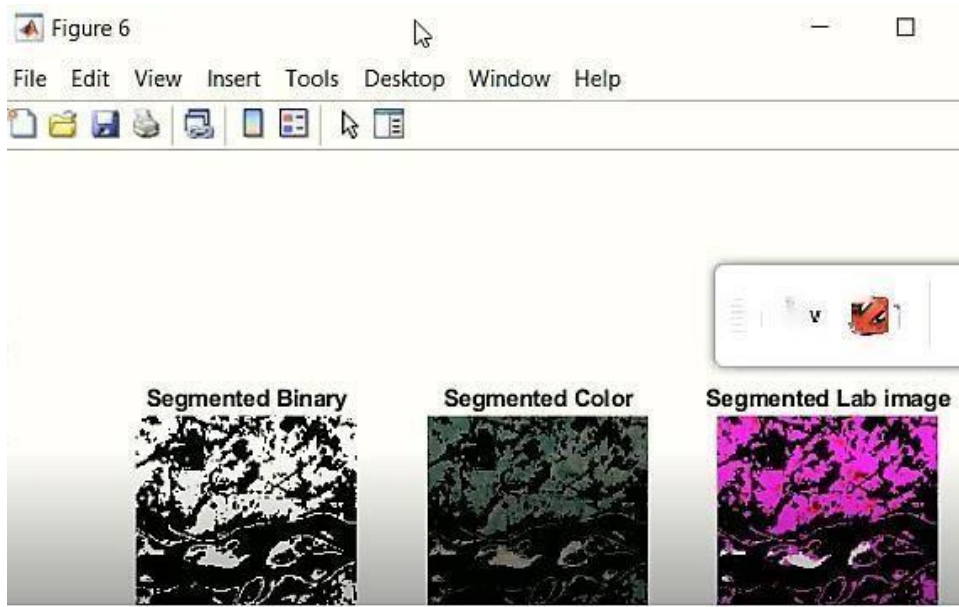
6.5:



6.5 : Segmentation

In the segmentation method each object of a single class in an image is highlighted with different shades to make them recognizable to computer vision. Now we want to turn our grey image into lab colors

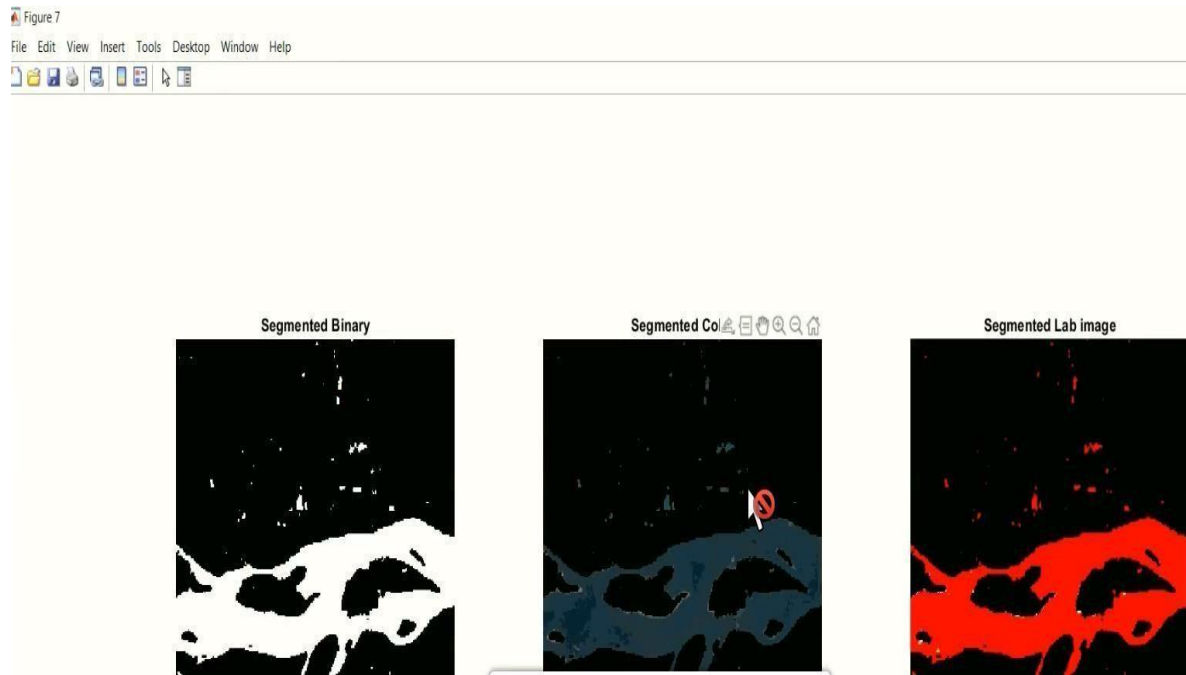
6.6



6.6 : Segmented lab images 1

Image Segmentation is the type of process by which a digital image is partitioned into various subgroups (of pixels) called Image Objects, which can reduce the complexity of the image, and thus analyzing the image becomes simpler. We Take the colors and repeat the clustering 4 times to avoid local minima it will be calculated as distance, sqeuclidean, replicates by using k means algorithm. Then we reshape the image by n rows and n cols

6.7:

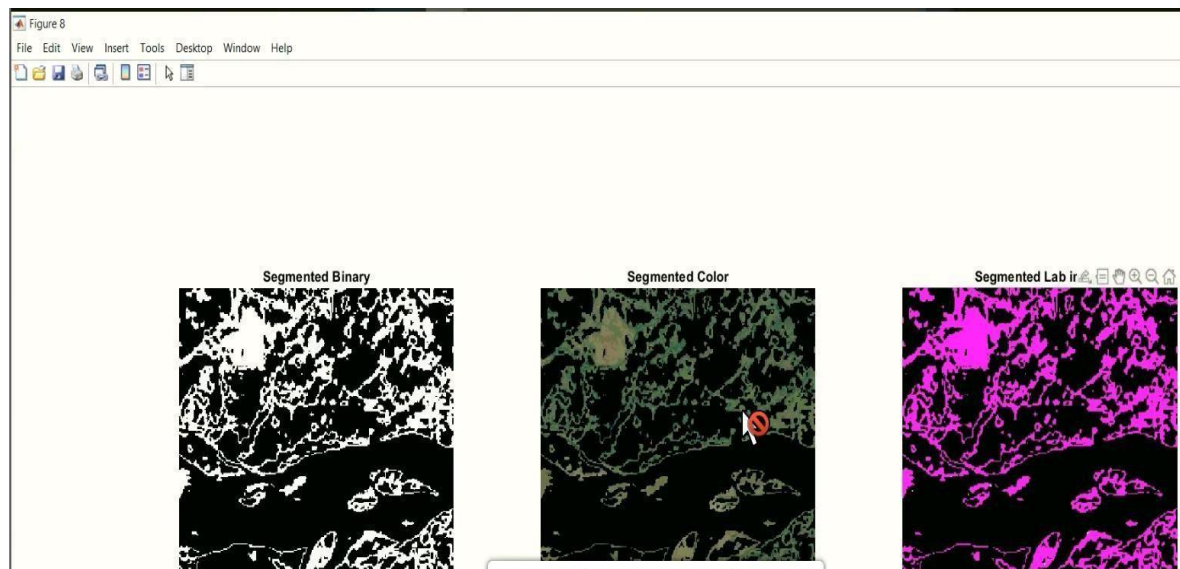


6.7 : Segmented lab images 2

For several lab segmented images, we have to use RGB colors. By using unsupervised endmember detection.

$R=1$, $g=2$, $B=3$...we get trained data image by using the values

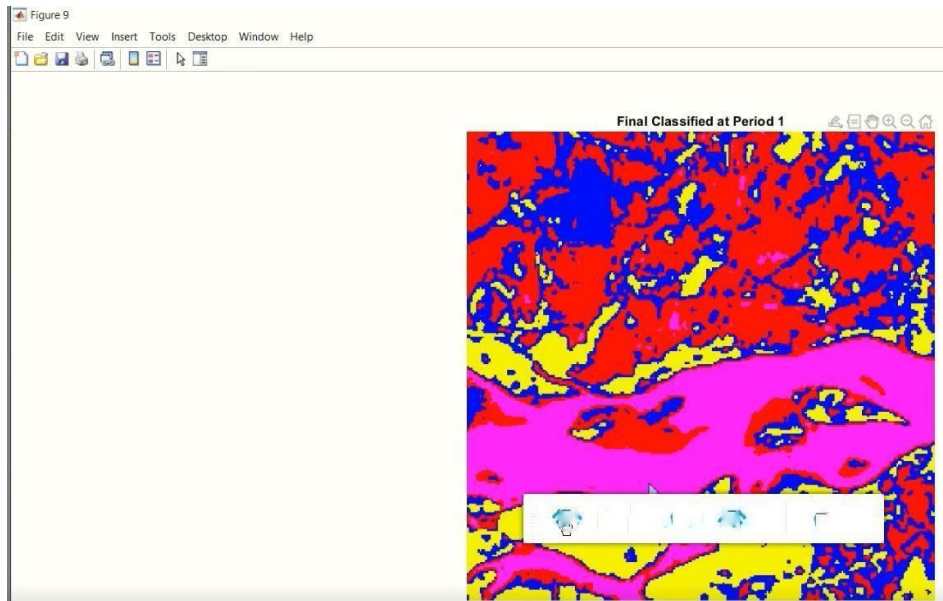
6.8:



6.8 : Segmented lab images 3

We use Gabor feature for RGB colors by no of scales and endmember using mean amplitude and MS energy...after that we use feature fusion method

6.9:



6.9 : Final Classified at period 1 F

After feature fusion method we set the 4 label lab colors to binary values. We set the values for red color = 1,0,0

Yellow color = 1,1,0

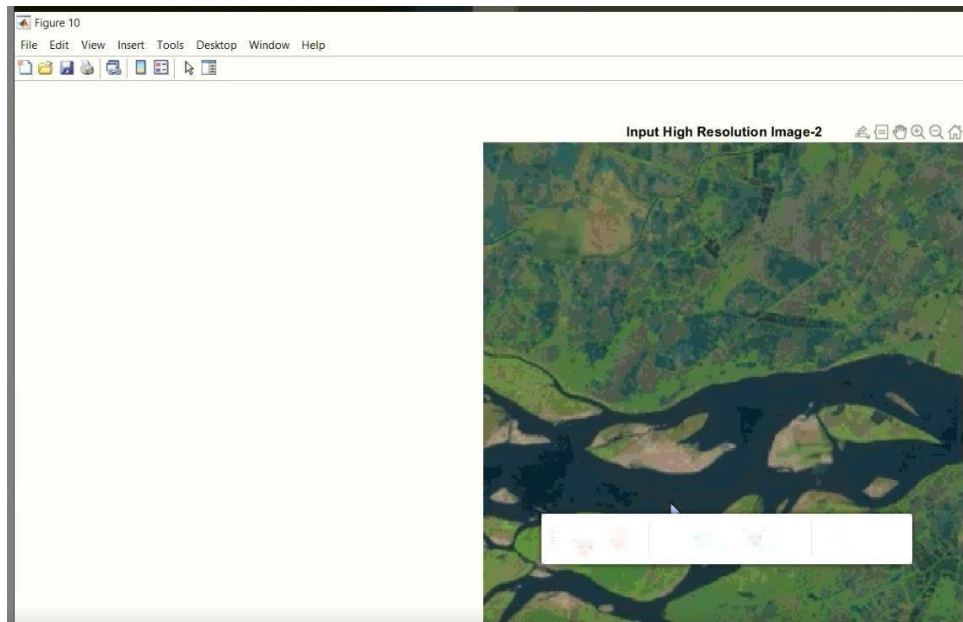
Green color = 1,0,1

Blue color = 0,0,1

Applying this we get the final classified image period 1

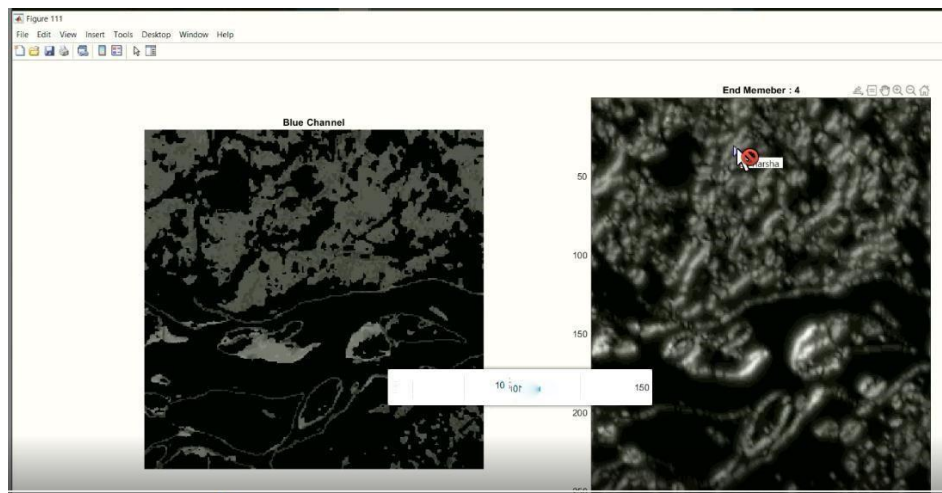
The same process from the starting need to be done again and again so that we can get the accurate reading and value of the water quality

6.10:

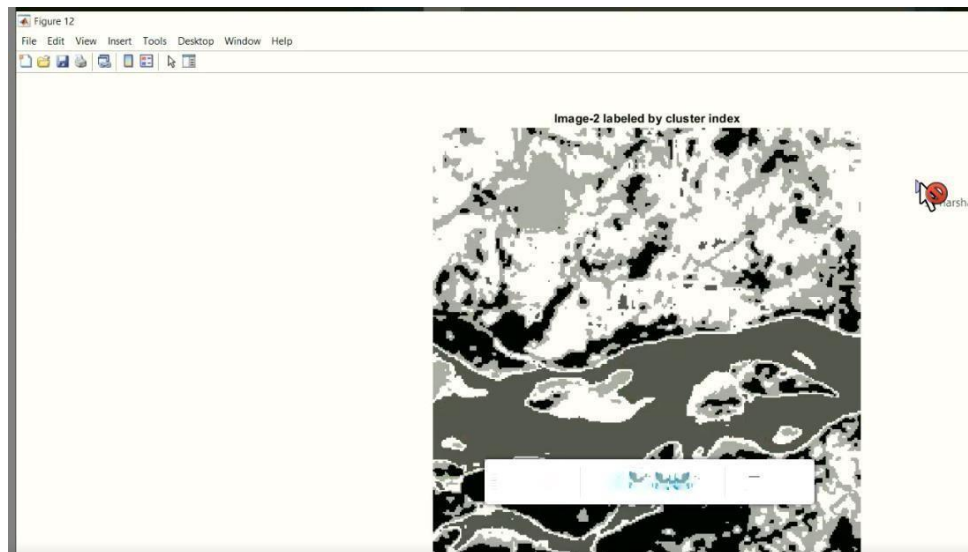


6.10 : Input high resolution image 2

6.11 : Input resized image 2

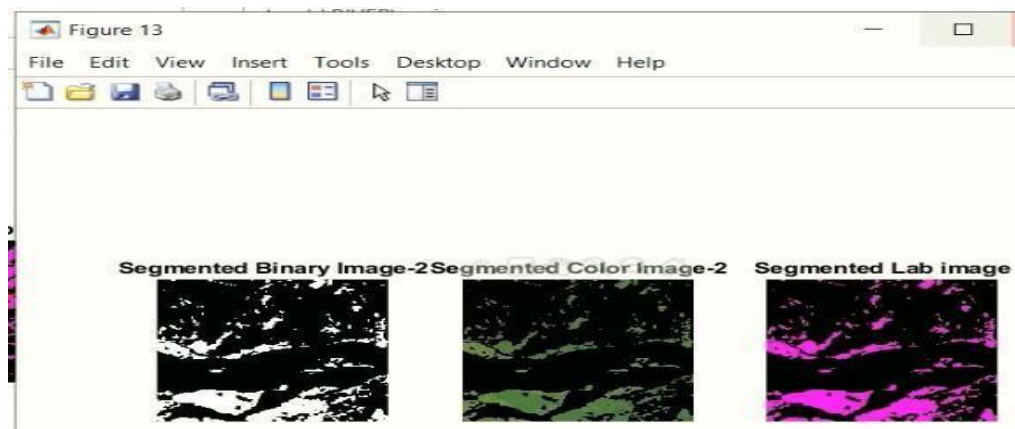


6.12:



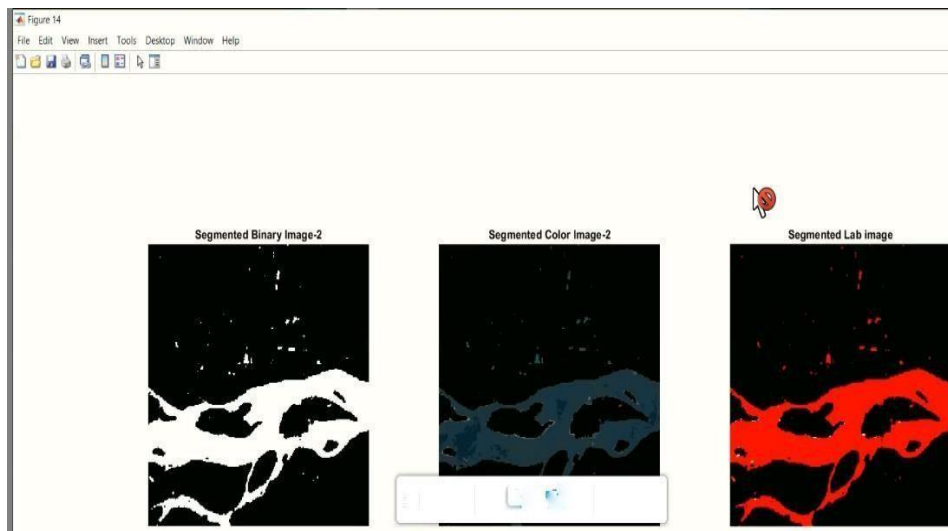
6.12 : Image 2 labelled by cluster index

6.13:



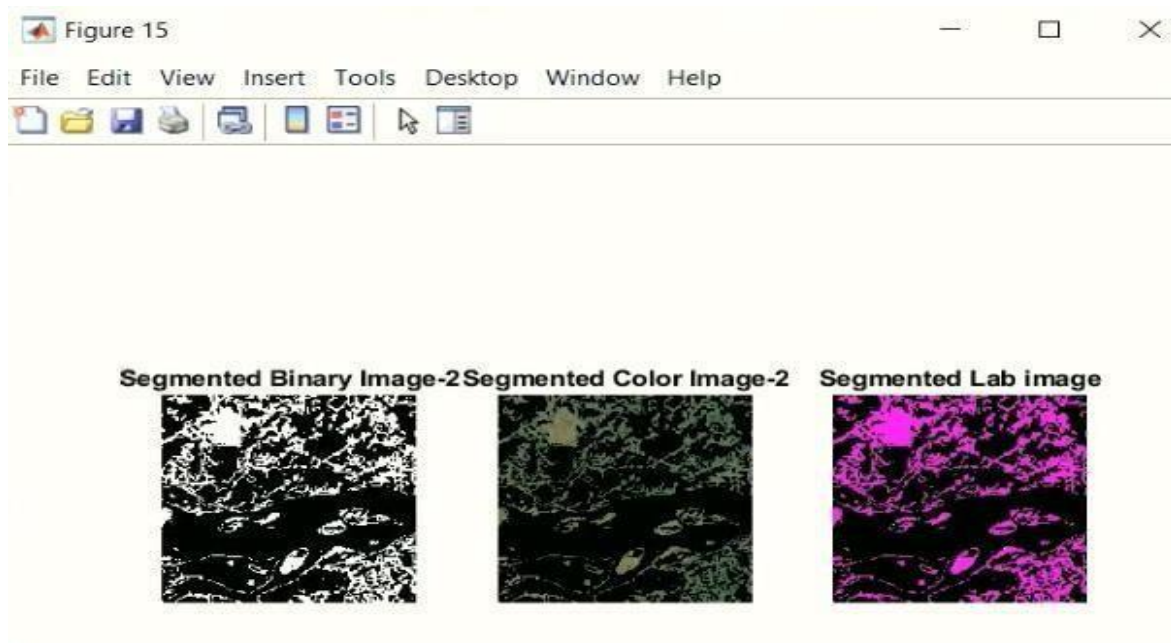
6.13 : Segmentation process starts

6.14:



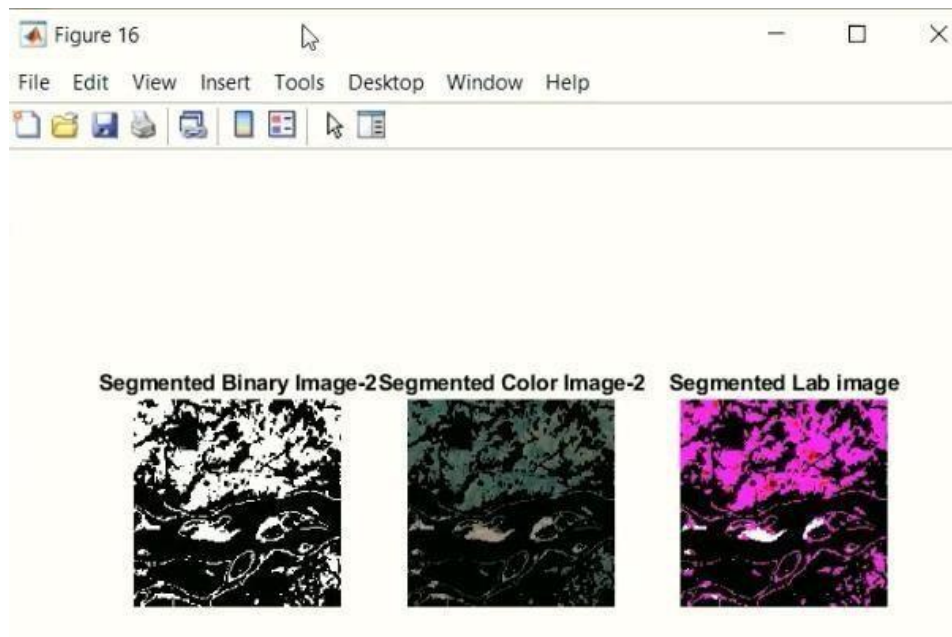
6.14 : Segmented lab image 1

6.15:



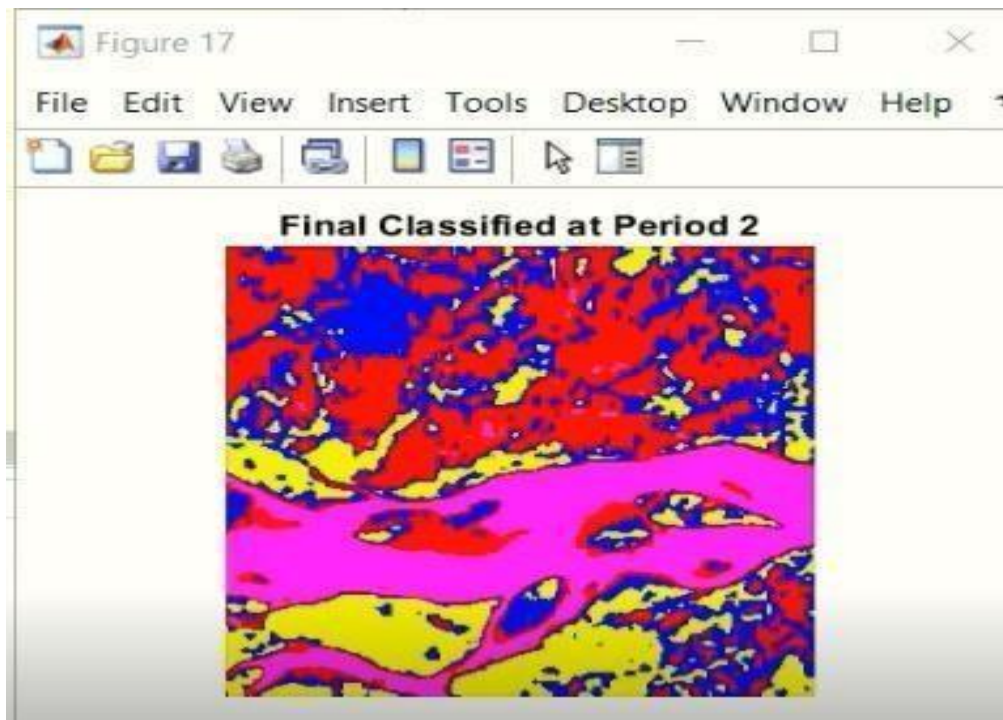
6.15 : Segmented lab image 2

6.16:



6.16 : Segmented lab image 3

6.17:



6.17 : Final classified at period 2

In the final classified image period 1 we took lab colored values $r=1$, $y=2$, $g=3$, $b=4$

We take the red colored image input value as species1 and title of the value is *Excoecaria agalloch*. We set the segmented image value to species 11 ... By applying +10 value for every color, we get the accurate polluted image and then we apply mortality rate, grow rate and pixel rate for Every color image to get accurate clear image of the area.

We take the yellow-colored image input value as species2 and title of the value is *ceriops decandra*..we set the segmented image value to species 21 ... By applying +10 value for every color, we get the accurate polluted image.

We take the green colored image input value as species3 and title of the value is *phoenix paludosa*..we set the segmented image value to species 31 ... By applying +10 value for every color, we get the accurate polluted image.

We take the blue colored image input value as species3 and title of the value is *avicennia alba*. We set the segmented image value to species 41 ... By applying +10 value for every color, we get the accurate polluted image.

At the end by calculating the mortality rate and reproductivity rate and grow rate and species images we get the clear output generated image.

CHAPTER NO: 7 TECHNIQUES

In this section, we will review the various techniques used in the satellite image processing for retrieving the information about the water. Various techniques have been adopted to get the high quality of pictures in order to get better information about the presence of water.

Standard supervised maximum likelihood classification

After obtaining the MODIS images from the NASA website, the images covering the Sindh province were classified. The standard supervised maximum likelihood classification was used for the images. In this way desired inundated class was translated into a shape file. Next, the visual interpretation was utilized for the inundated areas. To exert a different kind of info-layers, the shape file was intersected with the topographic maps.

The study areas used for the Research was the southern part of the Australia with an area of 140915 Km ranging 442 km from east to west and 579 km from north to south. Numerous data sources and software were used for the research. Information about the different info-layers was observed from the topographic maps. It includes the data from the railway track, rivers, boundaries, vegetated area, etc. The MODIS (Moderate Resolution Imaging Spectroradiometer) images were used with resolution comprising bands 1,2, and seven were retrieved and used as the main input to map the area which were overblown by flood.

The main technique which was used for estimating the num ber of affected people and the data obtained from the Pakistan, Federal Bureau of Statistics was District wise population density. Image Pre-Processing and the image pre-processing technique was used to prepare the images as an input for the satellite. The main pre-processing steps used in the techniques include atmospheric correction, co-registration, mosaicking, radiometric calibration, and resampling. The images were translated to the at-satellite radiance for the atmospheric correction and radiometric calibration. After that, each image

was transformed to at- Water Detection using Satellite Images Obtained through Remote Sensing 1931 satellite reflectance. The images containing the sun elevation and data acquisition rate were obtained from the Landsat header satellite. At last, the images were converted to surface reflectance from the at-satellite reflectance using the DOS (Dark Object Subtraction) method. The new images were then obtained by mosaicking to cover the entire study area. One image was used as a reference for the co-registration of multitemporal images. Root Mean Square Error (RMSE) was used to co-register the images. At last nearest neighbour method was utilized to resample the dataset as that of the size of the study area.

They delineated the potential groundwater zones through identification of the porosity indicators. It includes the vegetation, drainage pattern, drainage density, lineaments, etc. 1932 Himanshu Rana and Nirvair Neeru the tone, drainage pattern and texture characters were used to prepare the lithological map of the study area from the images obtained from Landsat TM. Various digital image processing techniques including the false color composite, band rationing, principal component analysis, filtering, and classification were applied to obtain high quality of images. Water Classification The water classification technique was utilized to analyse the areas of water. In this technique, N observations for each tile which is stored in AGDC were taken. The code 1 was used to define the pixel as water and code 0 to define the pixel as not water. The regression tree classification was used to obtain the water classification. The regression tree classification that uses normalized difference ratios (NDI) and Landsat Spectral bands.

Cells and 20 tiles used to develop training data for the model [N. Mueller, A. Lewis, D. Roberts, S. Ring, R. Melrose, J. Sixsmith and A. Ip] The figure shown above represents the 20 training tiles used as samples for the regression tree. Each tile was broken into an object for obtaining the training samples. After that object were classified manually into 26 different classes representing a different kind of water and non-water targets. The objects were selected based on the principle that only includes pixels of necessary class.

The adopted technique shows the positive result as it was able to clearly differentiate between the water and non-water bodies based on the water classification technique. Groundwater Potential Model (GPM) Weighted overlay technique was used for

implementing the GIS (Geographical Information System). The technique was used to determine the potential groundwater value. Each scale value of reclassified layer was multiplied by its weight to determine the potential groundwater value for a given area. At last, all the resulting cell values for were added to produce a final output representing the study area. The greater potential for groundwater was defined with the higher sum values. The presence of groundwater was classified into three categories including the low, moderate and high potential for the groundwater.

CHAPTER NO: 8

CHALLENGES, THE FUTURE AND CONCLUSIONS

8.1 CHALLENGES AND FUTURE

The distinction of colors between the shadows of tall buildings and calm water surface is still a challenge to the professionals. Therefore, it is difficult to get the exact information about water body in urban areas. To get the exact water in urban areas other similarity checks are required to be performed. Several algorithms were developed for extracting water body but none of them are accepted universally. Hence those are not applicable to various sensor images. Most of them are application specific. In future the development in the water body extraction algorithm is expected, so that the system will be automated for handling all types of sensor images and it will be combined with other tools to provide better information for flood, availability of underground water. These aspects are critical issue in developing countries. Sometimes, it is tedious to collect the ground data manually.

Conclusions: The first part of this paper introduced the importance of water body information, the motivations of performing water feature extraction and the major difficulties in water body segmentation. The paper describes the different types of satellites and sensors used in acquiring satellite images for extracting water feature. Some of the results are considered. Finally, an attempt has been made to conclude the current challenges as well as the future on water body extraction techniques.

8.2 CONCLUSION

Water is one of the most important natural resources which is key to our life. Though most of the Earth area is filled with water, only small amount of water is available for the drinking purpose. Various water conservation techniques have been used till now. But

management of water resources is necessary for accomplishing this task in an effective way. Water detection through satellite images is one of the promising areas for conserving the water through proper management. In this paper, we have reviewed various water detection techniques implemented by the researchers.

Image processing is one of the significant parts of every remote sensing technique to get effective results. the research review will help us to implement an effective technique for our research.

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ANNEXURE

Code

Clc;

```

Clear;

Close all;

Warning('off','all');

%% Get input image

[f,p] = uigetfile({'*.tiff;*.jpg;*.png'});

[~,filename] = fileparts(f);

F2=[f(1:end-6) '_2.jpg'];

FeatureFuseA=[];

% read input image

I1 = imread([p,f]);

% resizing to 256x256

I1=imresize(I1,[256 256]);

Figure,imshow(I1);

Title('Input High Resolution Image');

Reimg=I1;

Figure,imshow(Reimg);

Title('Input Resized Image');

Rgray=rgb2gray(Reimg); Pixel_labels1 = bwlabel(Rgray>100,8);

Figure,

Imshow(label2rgb(pixel_labels1),[]), title('image labeled by binary');

```

```
% converting to LAB color space
```

```
Cform = makecform('srgb2lab');
```

```
Lab_he = applycform(Reimg,cform);
```

```
Ab = double(lab_he(:, :, 2:3));
```

```
Nrows = size(ab,1);
```

```
Ncols = size(ab,2);
```

```
% Reshape
```

```
Ab = reshape(ab,nrows*ncols,2);
```

```
% No of classes
```

```
nColors = 4;
```

```
% repeat the clustering 4 times to avoid local minima
```

```
[cluster_idx, cluster_center] = kmeans(ab,nColors,'distance','sqEuclidean', ...
```

```
'Replicates',3);
```

```
Pixel_labels = reshape(cluster_idx,nrows,ncols);
```

Figure,

```
imshow(pixel_labels,[]), title('image labeled by cluster index'); Segmented_images =  
cell(1,4);
```

```
Rgb_label = repmat(pixel_labels,[1 1 3]);
```

```
I2 = im2double(I1);
```

```
Rr = I2(:,:,1);
```

```
Gr = I2(:,:,2);
```

```
Br = I2(:,:,3);
```

```
OutClassy=zeros(size(pixel_labels));
```

```
% spectral unmixing
```

```
Load TrainDataBase
```

```
For k = 1:4
```

```
    Tic
```

```
    Colorless=zeros(size(pixel_labels));
```

```
    Colorless(pixel_labels==k)=1;
```

```
Color = I1;
```

```
Bw = ones(size(color));
```

```
Color(rgb_label ~= k) = 0;
```

```
Bw(rgb_label ~= k) = 0;
```

```
Figure, Subplot(131);imshow(bw);title('Segmented Binary')
```

```
Segmented_images{k} = color;
```

```
Subplot(132);
```

```
Imshow(segmented_images{k});
```

```
Title('Segmented Color')
```

```
%% Color Features
```

```
I = im2double(segmented_images{k});
```

```
Lab = rgb2lab(I);
```

```
Subplot(133),
```

```
imshow(lab);title('Segmented Lab image')
```

```
R = I(:,:,1);
```

```
G = I(:,:,2);
```

```
B = I(:,:,3);
```

```
% unsupervised Endmember detection
```

```
[RmeanAmplitude, RmsEnergy] = gaborFeature(R, 4, 4,1); % 4 = number of scales, 4 =  
number of endmember
```

```
[GmeanAmplitude, GmsEnergy] = gaborFeature(G, 4, 4,2); % 4 = number of scales, 4 =  
number of endmember
```

```
[BmeanAmplitude, BmsEnergy] = gaborFeature(B, 4, 4,3); % 4 = number of scales, 4 =  
number of endmember
```

```
GaborAllmeanAmp=[mean(RmeanAmplitude) mean(GmeanAmplitude)  
mean(BmeanAmplitude)];
```

```
GaborAllmeanEnergy=[mean(RmsEnergy) mean(GmsEnergy) mean(BmsEnergy)];  
FeatureFuse(k,:)=[GaborAllmeanAmp GaborAllmeanEnergy];
```

Toc

% classification

% data=[FuseAllImg;FeatureFuse(k,[]);

For ii=1:length(FuseAllImg)

CoFeat(ii)=corr2(FuseAllImg(ii,:),FeatureFuse(k,[]);

End

[maxCla,classLabl]=max(CoFeat);

TestLab(k)=Labels(classLabl(1));

If Labels(classLabl(1))==1%red

Rr(bw(:, :, 1) == 1) = 1;

Gr(bw(:, :, 2) == 1) = 0;

Br(bw(:, :, 3) == 1) = 0;

I2 = cat(3,Rr,Gr,Br);

OutClassy(Colorless(:, :)==1)=1;

End

If Labels(classLabl(1))==2% yellow

```
Rr(bw(:, :, 1) == 1) = 1;
```

```
Gr(bw(:, :, 2) == 1) = 1;
```

```
Br(bw(:, :, 3) == 1) = 0;
```

```
I2 = cat(3, Rr, Gr, Br);
```

```
OutClassy(Colorless(:, :)==1)=2;
```

```
End
```

```
If Labels(classLabl(1))==3% green
```

```
Rr(bw(:, :, 1) == 1) = 1;
```

```
Gr(bw(:, :, 2) == 1) = 0;
```

```
Br(bw(:, :, 3) == 1) = 1;
```

```
I2 = cat(3, Rr, Gr, Br);
```

```
OutClassy(Colorless(:,l==1)=3;
```

```
End
```

```
If Labels(classLabl(1))==4%blue    Rr(bw(:,,1) == 1) = 0;
```

```
Gr(bw(:,,2) == 1) = 0;
```

```
Br(bw(:,,3) == 1) = 1;
```

```
I2 = cat(3,Rr,Gr,Br);
```

```
OutClassy(Colorless(:,l==1)=4;
```

```
End
```

End

Figure;imshow(I2)

Title('Final Classified at Period 1');

Image2;

% Species 1 -Excoecaria agallocha

Species_11=segmented_images{(TestLab==1)};

PixelRate11=double(Species_11>0);

Species_12=segmented_images_2{(TestLab2==1)};

PixelRate12=double(Species_12>0); Reproductivity12=abs(nnz(PixelRate11)-
nnz(PixelRate12))/length(PixelRate11(1));

GrowRate12=(nnz(PixelRate12)-nnz(PixelRate11))/length(PixelRate11(1));

If GrowRate12<0

GrowRate12=0;

End

MortalityRate12=abs(Reproductivity12-GrowRate12);

PSNR1=measerr(Species_11,Species_12);

Ssim1=ssim(Species_11,Species_12);

% Species 2 -Ceriops decandra

%

Species_21=segmented_images{(TestLab==2)};

PixelRate21=double(Species_21>0);

Species_22=segmented_images_2{(TestLab2==2)};

PixelRate22=double(Species_22>0);

Reproductivity22=abs(nnz(PixelRate21)-nnz(PixelRate22))/length(PixelRate21(1));

GrowRate22=(nnz(PixelRate22)-nnz(PixelRate21))/length(PixelRate21(1));

If GrowRate22<0

GrowRate22=0;

End

MortalityRate22=abs(Reproductivity22-GrowRate22);

PSNR2=measerr(Species_21,Species_22);

Ssim2=ssim(Species_21,Species_22);

% Species 3 -Phoenix paludosa

Species_31=segmented_images{(TestLab==3)};

PixelRate31=double(Species_31>0);

Species_32=segmented_images_2{(TestLab2==3)};

PixelRate32=double(Species_32>0); Reproductivity32=abs(nnz(PixelRate31)-
nnz(PixelRate32))/length(PixelRate31(1));

GrowRate32=(nnz(PixelRate32)-nnz(PixelRate31))/length(PixelRate31(1)); If

GrowRate32<0

GrowRate32=0;

End

MortalityRate32=abs(Reproductivity32-GrowRate32);

PSNR3=measerr(Species_31,Species_32);

Ssim3=ssim(Species_31,Species_32);

% Species 4 – Avicennia alba

Species_41=segmented_images{(TestLab==4)};

PixelRate41=double(Species_41>0);

Species_42=segmented_images_2{(TestLab2==4)};

PixelRate42=double(Species_42>0);

Reproductivity42=abs(nnz(PixelRate41)-nnz(PixelRate42))/length(PixelRate41(1));

GrowRate42=(nnz(PixelRate42)-nnz(PixelRate41))/length(PixelRate41(1));

If GrowRate42<0

GrowRate42=0;

End

MortalityRate42=abs(Reproductivity42-GrowRate42);

PSNR4=measerr(Species_41,Species_42);

Ssim4=ssim(Species_41,Species_42);

LastName = {'Excoecaria agallocha';'Ceriops decandra';'Phoenix paludosa';'Avicennia alba'};

GrowRate = [GrowRate12;GrowRate22;GrowRate32;GrowRate42];

```
MortalityRate = [MortalityRate12;MortalityRate22;MortalityRate32;MortalityRate42];
```

```
Reproductivity = [Reproductivity12;Reproductivity22;Reproductivity32;Reproductivity42];
```

```
PSNR_dB=[PSNR1;PSNR2;PSNR3;PSNR4];
```

```
SSIM=[ssim1;ssim2;ssim3;ssim4];
```

```
T = table(LastName,GrowRate,MortalityRate,Reproductivity,PSNR_dB,SSIM);
```

```
Disp(T)
```