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**SATELLITE MULTISPECTRAL REMOTE SENSING IMAGE****Sangeetha.V<sup>1</sup>, Aishwarya.C.G, Apoorva.T.M<sup>2</sup>**<sup>1</sup> Associate Professor, Department of CSE, K S Institute of Technology, Bengaluru, India.<sup>2</sup> UG 8<sup>TH</sup> Sem Students, Department of CSE, K S Institute of Technology, Bengaluru, India**ABSTRACT**

The spectral classes of the imagery are finally translated into the different feature types in the image interpretation process (image processing). Presently, classification of all feature types is a manual process. Local and global climatic variability and change is inevitable which makes satellite imagery redundant in a short span of time. Due to the above stated reasons, we need an efficient and fast automatic feature extraction algorithm for better observing and organization of the resources of Earth. This paper is a study of different technique to extract urban built-up, land/vegetation and water features from Enhanced Thematic Mapper Plus (ETM+) (Landsat 7) imagery. The study selected three indices, Normalized Difference Built-up Index (NDBI), Normalized Difference Water Index (NDWI), and Normalized Difference Vegetation Index (NDVI) to represent three major features on Earth: built-up land, open water body, and vegetation, respectively. Consequently, the seven bands of an original Landsat 7 image were reduced into three thematic-oriented bands derived from above indices, which were combined to compose a new image

**Keywords:** Automation, Remote sensing, Landsat, Spectral index ratio, Feature extraction.**I. INTRODUCTION**

Sustainability of water resources is one of the critical factors in maintaining human civilization as it exists today. But with the current trend in modifications in the land cover of the world, more so in the populated developing countries, the long-term sustainability of water resources is a question. Mapping and regular monitoring of surface water bodies for the availability of water resources at river basins/sub basins, regional, state and country level is an important aspect of water resources planning and management in India[1]. Urban spatial areas have expanded in an accelerated speed during the last five decades, and rates of urban population growth are higher than the overall growth in most countries because urban areas are the locus of economic activity and transportation nodes. Expanded urbanized areas have encroached on surrounding valuable natural lands such as paddy fields, forestlands, or wetlands. Urban areas are dominated by built-up lands with impervious surfaces, and therefore the conversion of the nature lands into these impervious built-up lands may have significant impacts on the ecosystem, hydrologic system, biodiversity, and local climate which can result in the negative aspects such as the urban heat island phenomenon. As water gets depleted with every passing minute, so does our ability to find more water resources for consumption. This calls for quick factual statistics of water resources. The study of urban spatial expansion and

the resultant urban heat island phenomenon always needs accurate data on urban built-up areas such as the size, shape, and spatial context. Therefore, a technique is required to quickly reveal the data. Timely availability of the data is of great importance for urban planners, water resource planners and decision makers. Satellite remote sensing data provide a synoptic coverage of fairly large areas at frequent intervals, enabling thereby to monitor the features and capture their geospatial and temporal variability; thus helping in the assessment of inter/intra-annual variations in feature spread. Using Enhanced Thematic Mapper Plus (ETM+) (Landsat 7) optical imagery, spatio-temporal information on features has to be generated and conserved by developing an automatic feature extraction algorithm. The algorithm will then enable quick processing of data and dissemination of feature information through a web-enabled information system. Landsat 7 sensors provides data eight bands but we primarily use four spectral bands, namely Green, Red, Near Infrared (NIR) and Short Wave Infrared (SWIR) regions of electromagnetic spectrum. The present study aims at automated feature mapping which encompasses spectral characterization of various types of water bodies, vegetation areas, urban areas and development of spectral relationships and algorithm for the extraction of such features that facilitates quick processing.

## II. RELATED WORK

### **A. Mapping land water and energy balance relations through conditional sampling of remote sensing estimates of atmospheric forcing and surface states**

Mapping land water and energy balance relations through conditional sampling of remote sensing estimates of atmospheric forcing and surface states[2]. In this study, the new mapping estimation methodology for the parameters that link the land water and energy balance is developed and applied. Parameters of water and energy balance components are estimated by developing objective functions that link atmospheric forcing (precipitation and incident radiation) and surface states (soil temperature and moisture). Because data products on these four variables are now available based on remotely sensed measurements, the approach is suitable for mapping across diverse landscapes. This estimation approach is based on conditional averaging of heat and moisture balance equations on land surface temperature and moisture states, respectively. The uncertainty of the estimated parameters is obtained through the inverse of Hessian of the cost function, which is an approximation of the covariance matrix. The developed methodology is distinct from traditional calibration because it does not need flux information (e.g., problematic drainage and evapotranspiration data) to estimate the parameters. Only forcing data (e.g., precipitation and incoming radiation) and state data (e.g., soil moisture and soil surface temperature) are required as the input data in this estimation methodology. The method was implemented at point scale using synthetic data and field site data from various sites across northern United States [Farhadi, 2012; Farhadi et al., 2014]. In this paper, the feasibility of this parameters estimation and mapping technique is demonstrated over the Gourma region in West Africa.

### **B. Land Surface Water Mapping Using Multi- Scale Level Sets and a Visual Saliency Model from SAR Images**

A novel water segmentation method[3] was proposed based on the integration of multi-scale level sets and a visual saliency model, as follows, (1) To improve the accuracy and efficiency of water extraction, the classic Itti model is first introduced to detect the SWR. After that, the level set method can be applied only to these regions, and at the same time, the visual saliency map can be used for initializing the zero level set function. Thus, we can detect water regions rapidly using Itti model and we can accurately segment water from those regions using level sets; (2) The classical Itti model is not designed for SAR water images, thus, an improved visual saliency attention model was presented. First, we replace the color images in the Itti model with textured images, which are generated using the gray-level co-occurrence matrix (GLCM) algorithm.

### **C. A Comparison of Land Surface Water Mapping Using the Normalized Difference Water Index from TM, ETM+ and ALI**

They calculated eleven different normalized difference water indexes (NDWIs) based on the green, near-infrared (NIR), and shortwave-infrared (SWIR) bands of Earth Observation-1 (EO-1) Advanced Land Imager (ALI), Landsat Thematic Mapper (TM), and Landsat Enhanced Thematic Mapper Plus (ETM+) sensors[4]. The results of this quantitative analysis show that (1) the NDWI model based on the green band (Band 4: 0.520–0.605  $\mu\text{m}$ ) and the SWIR band (Band 9: 1.550–1.750  $\mu\text{m}$ ) of the ALI sensor, namely NDWIA4,9, is the best indicator for land surface water (LSW) mapping; (2) using Bands 4 and 9 of the ALI sensor to produce an LSW map will obtain the best effect, followed by Bands 4 and 8 (1.200–1.300  $\mu\text{m}$ ), Bands 4 and 10 (2.080–2.350  $\mu\text{m}$ ), Bands 4 and 7 (0.845–0.890  $\mu\text{m}$ ), and Bands 4 and 6 (0.775–0.805  $\mu\text{m}$ ). The results of this paper also show that Xu's NDWI performs better than McFeeters's NDWI on water body information enhancement and LSW mapping. The indexes using the green band (0.520–0.605  $\mu\text{m}$ ) and the SWIR band (1.550–1.750  $\mu\text{m}$ ), that is Xu's NDWI, are the most efficient indices for detecting water body information and for mapping water bodies. Specifically for the EO-1 ALI sensors, we recommend NDWIA4,9, for detection of LSW body features, such as open water body information extracting, flood disaster monitoring, flood disaster risk assessing, wetland mapping, LSW mapping, and identification of other water body features.

### **D. Automated Water Extraction Index: A new technique for surface water mapping using Landsat imagery**

Using Landsat 5 TM data, they introduced a new automated water extraction method (AWEI) and compared its per-pixel and sub pixel accuracy and threshold stability with that of the MNDWI and ML classifiers[5]. AWEI significantly improved accuracy in areas where shadow and other dark surfaces were the main sources of classification errors. A sub-pixel analysis of errors at the edges of water bodies revealed that the AWEI classifier was relatively more accurate in classifying edge pixels compared to the MNDWI and ML classification methods. Besides, the optimal threshold of AWEI was shown to be less variable with images of different locations and times compared to that of MNDWI. Therefore, AWEI is proposed as an alternative and improved water index, especially in extracting water information from areas where noisy results are expected because of the presence of shadows and built-up surfaces. This new method would also be suitable for surface water change detection studies since it classifies edge pixels with high accuracy and with a stable threshold.

### **E. Automatic extraction of Tide-Coordinated shoreline using Open Source Software and Landsat imagery**

In this paper they have proposed a methodology for extracting a tide-coordinated shoreline from two Landsat-8 images corresponding to low and high tidal conditions[6]. Assuming that the beach slope remains constant between a given time period for which we have two images corresponding to a low tide and a high tide we have proposed a methodology to interpolate a tide coordinated shoreline for a given tidal height. The results have shown that an automatic tide-coordinated extraction method can be efficiently implemented using free available remote sensing imagery data (Landsat 8) and open source software (QGIS and Orfeo toolbox) and python scripting for task automation and software integration. Further developments will include: i) the implementation of an automated procedure for topological error detection and correction and ii) the use of a distance metric to evaluate numerically the interpolated tide-coordinated shoreline and the instantaneous shoreline.

## **III. SYSTEM DESIGN**

We began to work with Java as it is widely used in all our applications today. Unfortunately, we were unable to download necessary library files such as media.wrapper class for image extraction, rasterization, etc. Hence, we searched for alternatives. Python programs when compared to Java programs are 3-5 times shorter. This is because of the Python's built-in high-level data types and its dynamic typing. For instance, a Python programmer need not have to waste time to declare the types of arguments or variables and Python's powerful polymorphic list and dictionary types. Because of the run-time typing, Python's run time works harder than Java's. Thus, Python was used instead of Java. Satellite imagery in our study has been obtained from Landsat 7 or Landsat Enhanced Thematic Mapper Plus (ETM+). These images consist of 8 spectral bands with a spatial resolution of 30 meters for Bands 1 to 7. The resolution for Band 8 (panchromatic) is 15m. All bands can collect one of the two gain settings namely high or low for increased dynamic range and radiometric sensitivity, while Band 6 collects both high and low gain for all scenes. Approximate scene size is 170km north-south by 183km (east-west). Out of the 8, we have made use of 4 bands of the ETM+ satellite images, that is, Band 2, band 3, Band 4 and Band 5. For each spectral ratio index, we have calculated a difference between two of the four distinct bands of the ETM+ bands.

## **IV. IMPLEMENTATION**

System requirements consist of both hardware and software. Hardware requirements we have used are as follows:

- Intel i3 or above
- 4GB RAM
- 1GB graphic card (or above) for clearer image

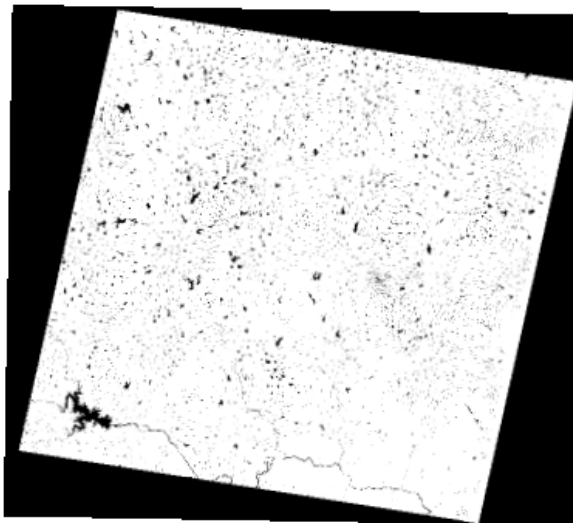
The Open Source Geospatial Foundation (OSGeo): OSGeo is a non-government non-profit organization. Its mission is to support and promote the development of open geospatial technologies and data.

The implementation is given in the form of the following algorithm:

```
import libraries
Open images
{
extract bands for that spectral image(rasterization)
    for ndwi, extract band2 and band4
    for ndvi, extract band3 and band4
    for ndbi, extract band4 and band5
calculate the spectral ratio indices if index value for both bands > 0
{
    calculate min and max values of ratio of each pixel display output image based on min, max values
}
}
```

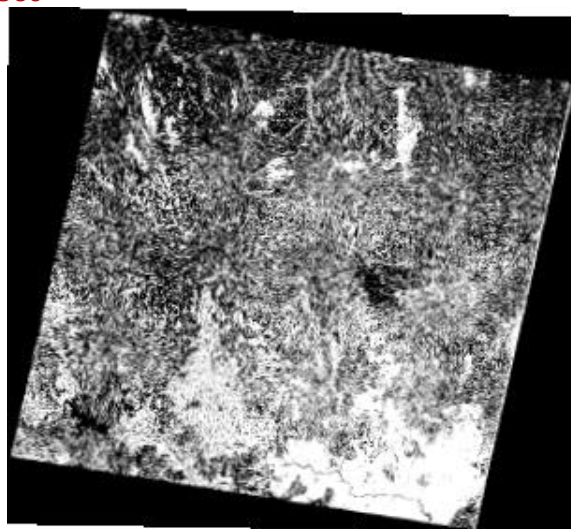
## V. RESULTS

The jpeg image we generate after computing the index for extraction of water bodies is given in figure 3. It gives all the water bodies, small or big, turbid or clear, within the scene size of 183km by 170km of ground area.



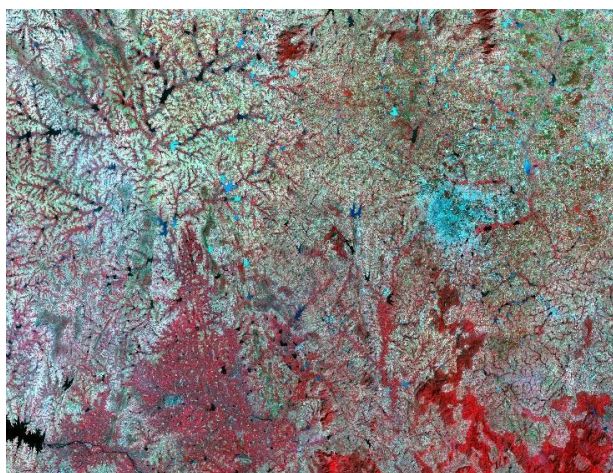
*Figure 1: All water bodies extracted from the satellite image.*

The jpeg image we generate after computing the index for extraction of vegetation is given in figure 4. It displays all classes of vegetation, barren or agricultural or non-agricultural, within the scene size of 183km by 170km of ground area.



*Figure 2: Image shows all vegetation types in that area.*

Testing and evaluation of these images was done at ISRO, Bangalore using ERDAS Imagine software. When we stacked up these images in RGB format (which is readable with naked eyes), we obtain the image shown in figure 3



*Figure 3: This is what the satellite image looks like in RGB format after all the bands have been stacked up and evaluated using ERDAS Imagine software.*

## VI. CONCLUSION

Spatio-temporal information across inter/intra-seasonal variation in surface water bodies is a valuable tool for better water resources planning and management. With the advent of spatial information technologies, namely Remote sensing and GIS, a number of satellite missions are providing the synoptic coverage of larger areas with high repetivity to generate spatio-temporal information on water bodies. In view of the existing limitations in image classification methods for quick extraction of water bodies, an algorithm to automatically extract water pixels from satellite image has been developed for IRS AWiFS sensor data. The methodology presented in this study was implemented on a large number of datasets of India after validation. The evaluation of the algorithm with other sensor data such as ResourceSat-1 LISS III, Landsat ETM, and ASTER showed satisfactory results. However, minor modifications may be required for application of the algorithm for global/national scale implementation to account

for the lower radiometric resolution of these sensors. The spatio-temporal information on water spread area was derived using the automatic extraction algorithm for India during May 2004, June 2005, July 2006 and Aug. 2007 representing the crop seasons (kharif, rabi, and summer). Further, this information would also be useful for disaster management support systems dealing with drought and flood databases and in studies related to the effect of climate change. The results (spatio-temporal maps) are published on the web site Bhoosampada of NRSC (www.nrsc.gov.in). The results of the present study are useful to enable the development of web-based water bodies information generation and dissemination system in near-real-time mode.

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