International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 09, September-2021

River Classification for Remote Sensing Imagery using SVM

A. Pranitha
Department of CSE
GNITS,Hyderabad
Telangana,India

Dr. D.V. Lalitha Parameswari
Department of CSE
GNITS, Hyderabad
Telangana, India

***Abstract*—River extraction accuracy is linked to agriculture, socioeconomics, the environment, and ecology. It aids in the early detection of major natural disasters such as floods, which result in huge loss of life and property.A large number of river-extraction approaches have been proposed as remote-sensing and information technologies have developed and become more prominent. KNN and PCA have traditionally been used to extract rivers. However, the majority of them are susceptible to noise interference and perform poorly in a huge data setting. A river extraction method based on Support Vector Machine is presented to address these issues.Image Classification is done using SVM. The river network was mapped using these technique with automatic feature extraction from a high-resolution Remote sensing image. To analyse performance indicators such as accuracy, IoU score, Kappa Coefficients, Recall, Precision and F1-score a research is conducted on SVM algorithm.**

***Keywords*—SVM,Remote Sensing Image,Image Classification**

I. INTRODUCTION

The lack of continuous, accurate river flow data is a major stumbling block to understanding water resource availability and hydrological extremes. This is especially true for rivers that are isolated, difficult to reach, morphologically dynamic, and hence rapidly changing. Over the last few decades, the state of global river discharge monitoring has deteriorated. This is despite the fact that these data are critical for river flow forecasting. Water resources in poorly gauged river basins may be strategic, but data collection can be difficult due to factors such as low accessibility, considerable seasonal variability, and the presence of huge wild animals in some parts of the world. When it comes to data collecting in locations like this, financial and physical resources aren't the only issue; changes in river geometry necessitate more frequent fieldwork to update stage discharge correlations than in other river systems.

River networks are dynamic in nature, shrinking, expanding, or changing their appearance or flow course over time as a result of many natural and human-induced processes. Changes in water bodies have an impact on other natural resources and human assets, as well as the environment. Changes in the volume of surface water frequently have major repercussions. Flooding can occur in extreme circumstances when surface water levels rise too quickly. As a result, efficiently detecting the presence of surface water, extracting its extent, quantifying its volume, and monitoring its dynamics is critical.

River dynamics can be seen more effectively using remote sensing equipment. Remote sensing is far more efficient than traditional in situ measurements since it can continuously scan the Earth's surface at numerous scales. Remote sensing data sets provides temporally frequent observational data and spatially explicit data of a variety of physical attributes about the Earth's surface, which can be used to map the extent of water bodies at regional or global scales, as well as to monitor their dynamics at regular and frequent time intervals. Such quick alterations could be revealed through remote sensing.These issues make it critical to look into data collection methods that reduce the reliance on empirical relationships between flows and permanent flow proxy observations (typically water levels), eliminate or reduce the need for contact with water during surveys and permanent observations, and finally, lower the costs of such observations.

II. LITERATURE REVIEW

Surface water identification using water indices has been extensively researched over the last few decades, and its capacity to distinguish water from background characteristics has been demonstrated. Digitizing by visual interpretation, single-band thresholding, multiple-band spectral water indices and target identification algorithms like constrained energy minimization (CEM) are some of the most widely used surface water extraction methods based on optical images.

A innovative method for retrieving information on storage fluctuations in any inaccessible place using Landsat data and digital elevation models (DEMs)[1]. The method, unlike other systems, does not require any in-situ measurements and is suitable for monitoring tiny, often undocumented irrigation reservoirs. It comprises of three steps towards recovery: I a 2-D dynamic classification of Landsat spectral band information to estimate water surface area;(ii) a 3-D reconstruction approach to account for clouds and Landsat 7 Scan Line Corrector failure; and (iii) a statistical correction of DEM data to represent reservoir topography.

Traditional manual digitising for shoreline extraction takes a long time and requires a lot of effort. Many studies on coastline detection from high-resolution satellite images have been conducted: unsupervised and supervised classification, segmentation, NDVI (Normalized Difference Vegetation Index), and NDWI (Normalized Difference Water Index) are just a few of the methodological aspects that have been considered and tested[2].

Remote sensing technology is rapidly evolving, and it now allows for autonomous extraction and dynamic monitoring of surface water bodies[3]. Sentinel-2 imagery has a higher spatial resolution and revisit frequency than other medium- and low-resolution remote sensing photos like Landsat and MODIS, making it more ideal for surface water extraction. Existing surface water extraction research using Sentinel-2 images is still mostly focused on the creation of water indices, which are easily influenced by shadows and built-up areas.

In 2018, it was proposed to use Visual Saliency Modeling for River Detection in High-Resolution SAR Imagery. There are four major steps in this process. SAR pictures are hierarchically over-segmented to superpixels during the superpixel synthesis and feature extraction process. The feature histograms are then extracted from the superpixels using a VF filter set, which consists of a DoG filter set and an SCC filter set. In the superpixel merging stage, feature histograms are quantized to lower their dimensions and increase the computing efficiency of the saliency extraction. By minimising a cost function, the corresponding optimum quantization parameters are learned from the labelled SAR data.The number of superpixels is then reduced using a merging method. This merging approach consists of two steps: histogram-based modelling and graph modelling. In the superpixel saliency extraction step, three saliency cues based on the specificity of the rivers in the SAR pictures, namely Local Region Contrast (LRC), Boundary Connectivity (BC), and Edge Density, are proposed to build a single layer saliency map (ED). BC is a metric that quantifies how certain a superpixel is that it is connected to the image borders.Saliency fusion is the final step of the procedure, in which the hierarchical saliency maps are treated as a tree-structured graphical model and an energy function is designed to generate an ideal full-resolution saliency map using a belief propagation algorithm[4].

With the help of aerial data and a four-step algorithm, the coastline may be automatically extracted[5]. After reducing noise distortion, the image is split into two parts (2016). The result is then analysed by morphological operators before being extracted and modelled using the Canny edge detection method.

A novel two-level machine-learning framework for recognising water kinds from urban high-resolution remote-sensing photos is proposed in this research[6].The framework is divided into two levels of interpretation: 1) water bodies are extracted at the pixel level using the water/shadow/vegetation indices, and 2) water kinds are identified at the object level using a collection of geometrical and textural properties. For image interpretation, both tiers use machine learning

Unsupervised water body extraction from GF-1 multispectral imaging is proposed using an automatic multifeature water body extraction (MFWE) method that integrates spectral and spatial features. The pixel region index (PRI), a spatial feature index that describes the smoothness in a local area surrounding a pixel, is discussed first. PRI can help the normalised difference water index (NDWI) discover important water bodies, which is especially useful in metropolitan areas[7].Parts of the water pixels along the boundaries, on the other hand, may not be included in significant water bodies; therefore, k-means clustering is used to group all of the water pixels into the same group as a guide map. To obtain the final water mask, the principal water bodies and the guiding map are blended (2019).

To choose water sample pixels, it first calculates the NDWI image using experimental photos. Second, it uses an improved spectral mixture analysis technique on the experimental image to extract water abundance for each pixel, and it segments the abundance image to extract water bodies at the global scale based on the selected water pixels[8].Third, it iteratively conducts water body extraction in multiscale local regions to refine the water bodies in a similar manner. Finally, when a stopping requirement is met, the final result of water bodies is acquired.

Due to increased urbanisation, especially in developing countries, water resources in metropolitan areas are gradually dwindling. As a result, precise extraction and automatic identification of water bodies are crucial and urgently needed for urban planning. Although various studies have been published on water-area extraction, few articles on the identification of urban water types have been published to our knowledge (e.g, rivers, lakes, canals, and ponds).

Using Sentinel-2 imagery and OpenStreetMap (OSM) data, an automatic surface water extraction approach based on the presence and background learning algorithm (ASWE-PBL) was developed.The OSM data are used as supplementary data to choose water samples automatically, and the PBL method is used to forecast the probability of water existence[9]. The modified normalised difference water index, the automated water extraction index, and the random forest classifier are used to compare ASWE-PBL to six typical study areas in China.

III. METHODOLOGY

A river extraction method based on Support Vector Machine is presented to address these issues. The river network was mapped using these techniques with automatic feature extraction from a high quality multispectral satellite picture.
The proposed methodology consists of five steps.Data Collection,Preprocessing, Feature Extraction, Model Training and Testing and Accuracy Evaluation.

Objectives :-

The following sub-objectives are formulated to attain the main goal:

(i)To extract automatic features for river network mapping.
(ii)To analyze the effectiveness of SVM classification algorithm for detecting river networks.
(iii)To evaluate different categorization techniques using performance indicators such as accuracy and kappa coefficients in a comparative research.

The modules are shown how to achieve the required outputs in this section. The course of image segmentation is depicted in Figure 1. The satellite image was first gathered and preprocessed to satisfy the specifications. A dataset is created, and SVM is used to map the river in the image.

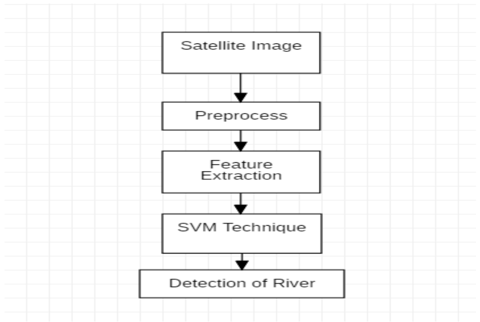


Fig 1. Flow of River Segmentation

- *Satellite Image*: This image was obtained from the National Research Space Center (NRSC) (National Remote Sensing Center).
- *Preprocessing*: To meet the standards, images are preprocessed.This data augmentation is carried out in order to expand the dataset.To mask the river portion of the image, image labelling is used.
- *Feature Extraction*: Gabor filters and canny edge detection are employed to extract the features.
- *SVM:* SVM image segmentation technique is used to map rivers in images.Read training images.Extract Features using gabor filter and edge detection.Read Labelled images (Masks).Get data ready for SVM. Fit a model with our training data.Save model for future use. Applying training model to predict the test images.
- *River detection:* After training with svm, a model is saved, and rivers are predicted in other photos using that preserved model.

IV. IMPLEMENTATION

A. Datasets Used

Data was collected by NRSC(National Remote Sensing Center).It was satellite image collected by cartosat satellite.The size of the image is 23GB.The supporting software to view the satellite image is ERADAS.

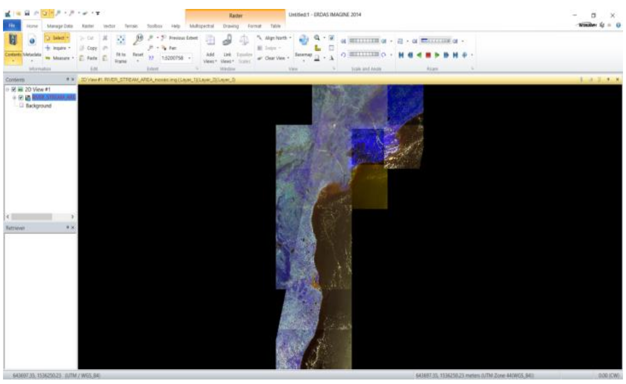


Fig 2. Remote Sensing Image In ERADAS

B. Data Preparation

Subset of Images:A subset is a portion of a larger image that has been downloaded. Because satellite data downloads typically cover a bigger area than interested in, it need to pick a specific portion of the broader image to work with.A smattering of photos are gathered from satellite images in such a way that the image includes both river and land areas. Each image subset is collected in a 512X512 dimension. River photos are manually captured in such a way that the river is visible and not obscured by clouds. Eradas Software is used to collect subset images.

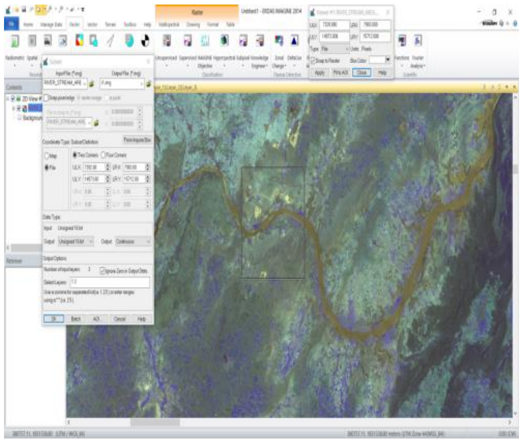


Fig 3. Subset of image in Remote Sensing Image

The above fig 3 shows the how the subset of images are collected using eradas software

Sample Dataset

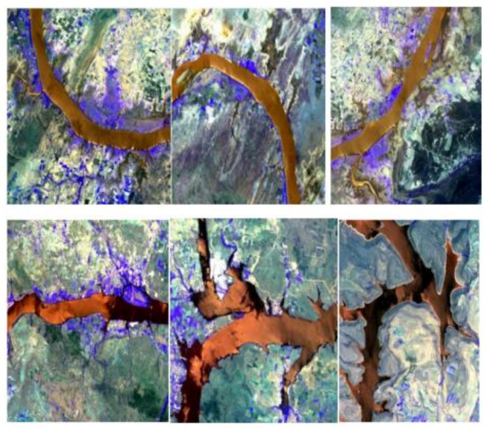


Fig 4. Sample Dataset

Total no of subset images =310

C. Image Labelling

Data labelling is a time-consuming activity that necessitates a lot of manual effort. Because there are so many different ways to annotate images. Boundary box, Polygonal Segmentation, Semantic Segmentation, 3D-Cuboids, Key-Point and Landmark are the different types. Because rivers do not have

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 09, September-2021

a certain shape and are not objects, semantic segmentation can be used to label the river and other classes in images.

Semantic Segmentation:

Semantic segmentation is a pixel-by-pixel annotation that assigns a class to each pixel in the image. River and non-river are two possible classifications, and each pixel has a semantic value.The APEER website allows users to add datasets and identify them with multiple classifications for semantic segmentation.

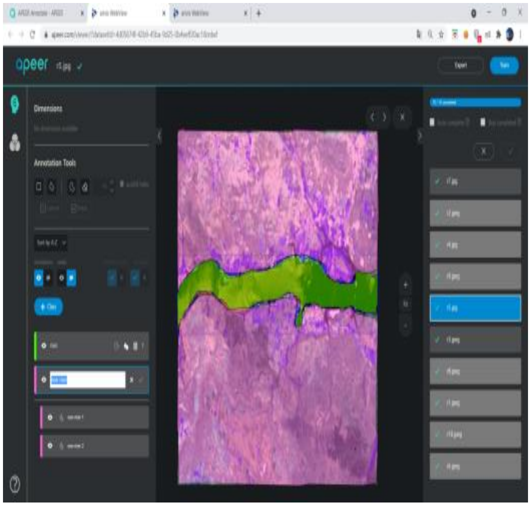


Fig 5. Image Labelling in APEER

D. Mask Images

Images are annotated manually. The images are classified in to two classes river class and non river class.

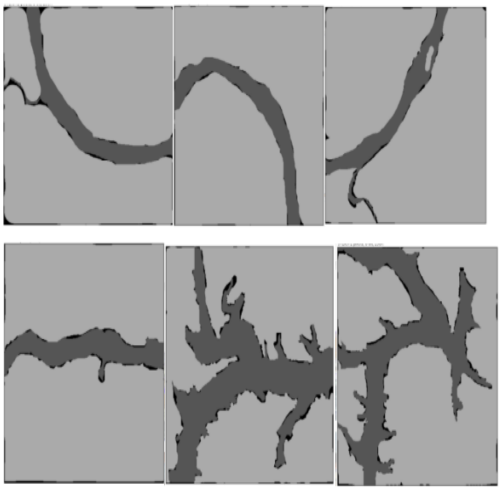


Fig 6. Sample Mask Images

E. Augmentation of Data

Deep Learning Techniques involves a larger amount of data for the model to be trained. Data augmentation is a strategy for adding slightly changed copies of current data or newly created synthetic data from existing data to expand the amount of data available. To increase the dataset, the original images are cropped, zoomed, and rotated (90° 180° 270°).

Total no of images=4960,Total no of Mask images=4960.

F. Image Segmentation using SVM

Voice recognition, tone recognition, text categorization, image classification, object detection, handwritten digital recognition, and data classification are some of the real-world applications. SVM is also regarded as one of the most well-known approaches for pattern and image classification. It is intended to differentiate two classes from a collection of training images, (x1, y1), (x2, y2),..., (xn, yn), where xi is in Rd, the d-dimensional feature space, and yi is in (-1,+1), the class label, with i=1..n.

Based on a kernel function, SVM creates the best separating hyper planes (K). All visuals with a feature vector on one side of the hyper plane are classified as class -1, while the others are classified as class +1. The two classification classes A and B are depicted in Figure 4.6. SVM iteratively generates the best hyperplane, which is then utilised to minimise an error. The goal of SVM is to find a maximum marginal hyperplane (MMH) that splits a dataset into classes as evenly as possible.

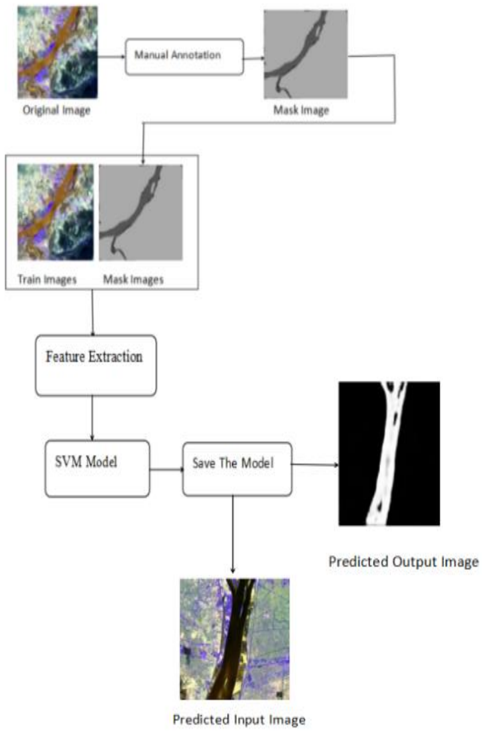


Fig 7. River Segmentation Using SVM

Figure 7 explains the image segmentation using SVM.First it reads training images.Extract Features using gabour filter and canny edge detection.Read Labeled images (Masks).Get data ready for SVM. Fit a model with our training data.Save

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 09, September-2021

model for future use. Applying training model to predict the test images.

a) Load dataset

To begin, import the required packages. After that, the dataset including river photos is loaded into the software. The images from the supplied path are read using theCv2.imread( ) function.

b) Create a DataFrame

To save the original image pixels, a DataFrame was built. This is the program's initial Feature.

c) Extraction of Features

Gabor Filter, Edge Detectors such as Canny Edge Detection, Prewitt Edge Detection, Sobel Edge Detection, Roberts Edge Detection, Roberts Edge Detection, and Scharr Edge Detection are used to extract other features. All of the additional features are added to the Data Frame.

d) Add Mask Images Dataset

After that, the dataset including river mask images is loaded into the application. The photos from the supplied path are read using the Cv2.imread( ) function. These image pixels are afterwards added to the Data Frame as well.

e) *Testing and Training*

Define the dependent variable for which a prediction is required (labels).The independent variables are then defined. After training the model, divide the data into train and test groups to ensure correctness. In different ratios, the input dataset is divided into training and testing sets, such as 60:40, 70:30, and 80:20 percent.

f) SVM Model

The method divides the data into classes by drawing a line or hyperplane. SVMs find a separation line (or hyperplane) between data of two classes as a first estimate. SVM is a machine learning method that takes data as input and, if possible, creates a line that divides the classes. The dataset includes images with both river and non-river sections.It is necessary to separate the river from the non-river portion (say positives from the negatives). As a result, the goal is to find an ideal line that divides this dataset into two groups (say river and background).The SVM method will locate the points from both classes that are closest to the line. Support vectors are the names for these points.

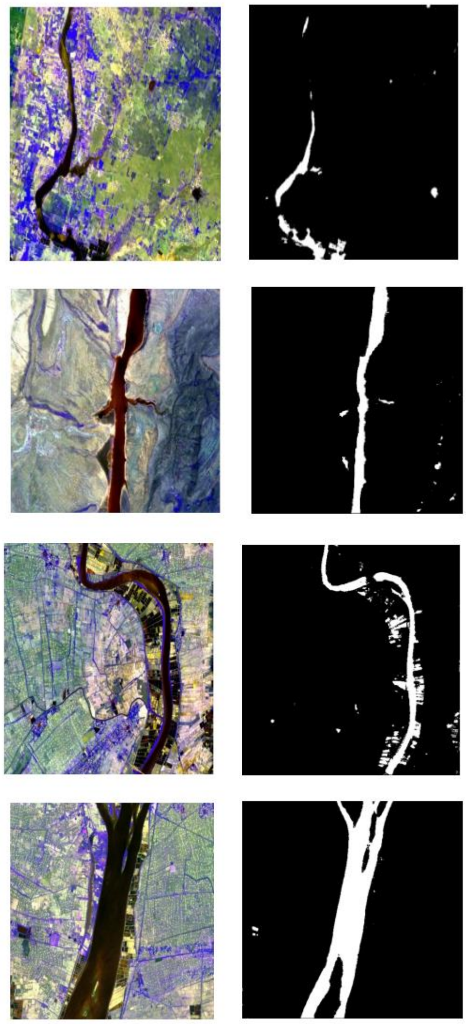
Now it'll calculate the distance between the line and the support vectors. This distance is referred to as the margin. The goal is to increase the profit margin as much as possible. The ideal hyperplane is the one for which the margin is the greatest.As a result, SVM seeks to create a decision boundary that is as wide asfeasible between the two groups (river and non-river section).On the training dataset, the model is built.Later, on the Testing dataset, Test Prediction is performed.

g) Save The Model

The model is saved in case it is needed again. Train the model on training images, test it on test images, and then deploy it on unknown images. Save the learned model to disc as a pickle string for future use in classifying further images.

V. RESULTS

Satellite Image was collected by NRSC(National Remote Sensing Center). The image was taken by Cartosat - 3 Satellite.This image consists of rivers and land area.SVM is used for image classification.To evaluate this classification technique performance measures like accuracy,IoU, kappa coefficients,persicion,recall and f1-score.



(a) (b)

Fig 8. SVM Results

Fig 8. shows the results of river segmentation from remote sensing images.(a)-Original image of remote sensing image.(b)-Segmented image of river output image formed using SVM.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 09, September-2021

TABLE I. Overall Accuracy Assessment IoU and Kappa Coefficient For SVM

Train-Test Split	Overall Accuracy	IoU Score	Kappa Coefficient
60-40%	75.56%	71.67%	0.72
70-30%	**89.29%**	**82.36%**	**0.86**
80-20%	80.11%	76.19%	0.77

A table is formulated for Overall accuracy,IoU and Kappa Coefficient along with testing and training percent for SVM.The better accuracy is achieved at 70% training and 30% testing.

TABLE II. Precision,Recall and F1-Score for SVM

	Precision	Recall	F1-Score
SVM	0.88	0.85	0.88

Table II shows the results of precision,recall and f1-score for SVM for 70% training and 30% testing model for predicting the river in the remote sensing images.

VI. CONCLUSION

The recognition of rivers in remote sensing images has always been a vital yet difficult problem. Various approaches for detecting rivers have been developed over the previous few decades with a lot of work.Accurate River extraction is linked to agriculture, socioeconomics, the environment, and ecology. It aids in the early detection of major natural disasters such as floods, which result in huge loss of life and property. A large number of river-extraction approaches have been proposed as remote-sensing and information technologies have developed and become more prominent. SVM image classification technique is used to recognise river networks from remote sensing images.Automatic feature extraction is achieved using this technique.

Although the proposed approach is effective in detecting water, it still has to be refined and improved. Because the images typically comprise both river and non-river parts, they must be built in such a way that they can categorise multi-class at a large size or on a worldwide scale. The width and length of the river must be estimated using various methods.

REFERENCES

[1] Avisse, Nicolas & Tilmant, Amaury & Muller, Marc & Zhang, Hua. (2017). Monitoring small reservoirs storage from satellite remote sensing in inaccessible areas. Hydrology and Earth System Sciences Discussions. 1-23. 10.5194/hess-2017-373.

[2] Basile Giannini, Massimiliano & Parente, Claudio. (2014). An object based approach for coastline extraction from Quickbird multispectral images. International Journal of Engineering and Technology (IJET) - ISSN: 0975-4024. Vol. 6. pp. 2698-2704.

[3] Cai, Y., Sun, G., Liu, B. “Mapping of water body in Poyang Lake from partial spectral unmixing of MODIS data” 2005 IEEE International Geoscience and Remote Sensing Symposium (IGARSS’05), Seoul, Korea, vol-32, 2005, pp-4539–4549.

[4] Sharma, R.; Tateishi, R.; Hara, K.; Nguyen, L. “Developing superfine water index (SWI) for global water cover mapping using MODIS data” Remote Sensing, vol-7, 2015, pp13807–13841.

[5] Paravolidakis, Vasilis & Moirogiorgou, Konstantia & Ragia, Lemonia & Zervakis, Michalis & Synolakis, Costas. (2016).”Coastline Extraction From Aerial Images Based On Edge Detection”.ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences. III-8. 153-158. 10.5194/isprsannals-III-8-153-2016.

[6] X. Huang, C. Xie, X. Fang and L. Zhang, "Combining Pixel- and Object-Based Machine Learning for Identification of Water-Body Types From Urban High-Resolution Remote-Sensing Imagery," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 8, no. 5, pp. 2097-2110, May 2015, doi: 10.1109/JSTARS.2015.2420713.

[7] Y. Zhang, X. Liu, Y. Zhang, X. Ling and X. Huang, "Automatic and Unsupervised Water Body Extraction Based on Spectral-Spatial Features Using GF-1 Satellite Imagery," in IEEE Geoscience and Remote Sensing Letters, vol. 16, no. 6, pp. 927-931, June 2019, doi: 10.1109/LGRS.2018.2886422.

[8] Y. Zhou, J. Luo, Z. Shen, X. Hu and H. Yang, "Multiscale Water Body Extraction in Urban Environments From Satellite Images," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 7, no. 10, pp. 4301-4312, Oct. 2014, doi: 10.1109/JSTARS.2014.2360436.

[9] Z. Zhang et al., "Automated Surface Water Extraction Combining Sentinel-2 Imagery and OpenStreetMap Using Presence and Background Learning (PBL) Algorithm," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 12, no. 10, pp. 3784-3798,Oct.2019, doi: 10.1109/JSTARS.2019.2936406.