A novel two-tier paradigm for labeling water bodies in supervised satellite image classification

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***Abstract*- The satellite images are the high dimensional data with huge spatial details which needs intelligent interpretation methods. The use of satellite images is more prevalent nowadays in many real time surveillance applications and it leads to the need of simple and accurate processing. The advent of machine learning classifiers improved the efficiency of satellite image applications. However, the ground truth data availability and spatial data labeling are certain serious limitations for supervised satellite image classification. Thus change monitoring models are highly dependent on unsupervised clustering methods with the compromised level of accuracy. This paper is focused on addressing the steps to overcome the above said ground truth validation, labeling and other feature discrimination issues in a supervised soft classifier model for simple change recognition of seasonal water bodies in satellite images.**

Keywords - Satellite Image; Labeling; Water body; Supervised learning; Change recognition.

I. INTRODUCTION

The satellite technology has revolutionized the life on earth right from a simple individual's routine life to complex governance decisions. Apart from communication and navigation purposes, deployment of satellite image based climate models could assist in monitoring the environmental deterioration which could directly affect the life on earth [1],[2]. The field work and surveys could bring insitu measurements that add more details to spatial images. however the manual labour and time consumption is quiet heavy when compared to that of satellite image based assessment. In order to evaluate the destruction or to assess the post hazard measures using satellite images, these highly intelligent models are in need.

The satellite image comprises of huge spatial details in every band of data with regard to urban, forestry and coastal structures. To facilitate the processing of huge dimensional data, with respect to volume and speedy decision, extraction of appropriate features with improved accuracy is must. The traditional methods for image classification such as Maximum likelihood approach, Principal component analysis (PCA), Linear discriminant analysis (LDA) etc- are highly dependent on the statistical features based on color, shape and texture of the objects [3],[4]. For better discrimination of an object under aerial examination, satellite images from different sensors on same temporal resolution may also be processed together. It would be highly helpful to use local descriptors based object examination with multiple sensor images in case of earthquakes, floods and landslides during the post hazardous events analysis for planning relief measures. Hence the use of local descriptors could overtake the performance of statistical descriptors in the upcoming big data realm where speed and volume benefits of complex data processing are the prime tycoon.

The local descriptors are found to be more highly robust than the global features that are been extracted from the clustered homogeneous objects of an image on overcoming the illumination and different viewpoint limitations. These initial detection of feasible feature points are followed with extraction of a region around those points comprising the details of geometrical and illumination variations [5]. These descriptors may be blob, edge or corner features. The local descriptors that are highly used in image classification tasks are Speeded Up Robust Features (SURF), Scale Invariant Feature Transform (SIFT) and HOG etc- [6],[7]. Other than these, local descriptors are widely used in localizing the corresponding points in image registration applications [8]. The rate of high discrimination levels could favor faster image classification in emergency and hazard scenarios. Even many navigation purpose applications depend on satellite image or non-commercial open street maps to position and regulate the vehicles [9].

In case of image classification, the traditional interpretation models on regression and statistical observations suffer with logical reasoning incompatibility. But a vibrant revolution occurred with these traditional models through addition of human level reasoning as a machine learning era. The multiple features extracted from images are optimized with reasonable feature selection methods in machine learning methods to achieve better accuracy [10]. However the results are still impractical towards the less efficiency in large scale data analysis due to training time and labeling limitations.

This paper addresses the issues on image labeling for supervised classification of spatial images through applying the proposed two-tier labeling scheme and further examines the effectiveness of labeling using the Histogram Of Gradients (HOG) features for change recognition of water bodies using notable supervised soft classifiers and the performance of the classifiers are evaluated using standard measures as explained in the following section II.

II. PROPOSED WORK

A. Study area selection

The Sambhar Lake in Rajasthan, India (26°58'N 75°05'E) is the chosen study area for the proposed model of change recognition in water bodies. For this proposed work 43 landsat-8 images of Sambhar lake from 2013 to 2016 has been chosen from the USGS explorer archive [11]. This is the largest inland salt water lake that accounts for highest salt production in India [12]. The climate conditions are hot since it is located in a highly drought prone region near to Thar desert of Rajasthan. Hence it is a suitable study area for tracing the changes in a water body using satellite images. The annual rainfall dataset for Rajasthan from 2013 to 2015 has been collected from the water portal of Rajasthan Government [13]. Apart from this spatial dataset, the list of weather stations in and around Sambhar lake, Rajasthan have also been collected.

B. Work flow of the proposed model

The proposed model includes different phases of processing for image labeling and feature extraction as shown in the following Fig. 1.

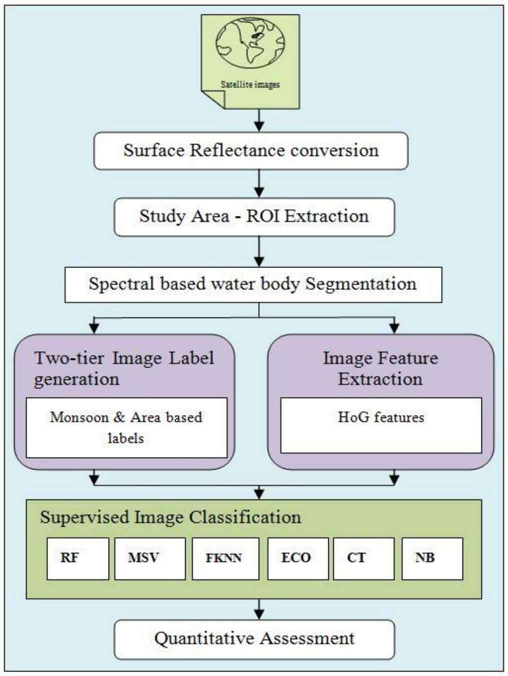

Figure 1. Proposed model architecture

Each Landsat 8 image consists of eleven spectral bands comprising of different spectral regions for specific purpose. The satellite images of same path and row has been selected to overcome the geometrical mismatches in the multi-temporal dataset. These images are in need to be scaled back to Surface Reflectance (SR) products through applying the atmospheric correction methods. Here, Dark Object Subtraction (DOS) method has been applied for SR conversion using Quantum GIS software (Geographic Information System). These SR products are then cropped to region of interest i.e Sambhar lake region using a standard shapefile as shown in Fig. 2. The shapefile of respective study areas can be generated using polygonal tracing in Google earth, however this proposed model applies the standard shapefile from the literature [14].

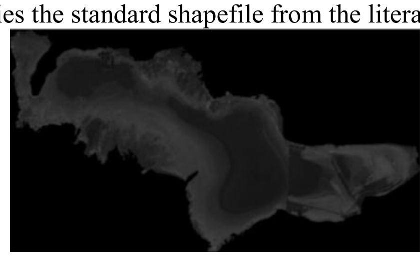

Figure 2. Sambhar lake in Rajasthan, India;

To have better visualization of satellite image bands, a false color composite (FCC) combining near infrared (NIR), green and blue bands is generated as shown in Fig. 3 where the land cover and water are depicted in red and green color respectively. Here, the region with salt sediments is made evident in brown color.

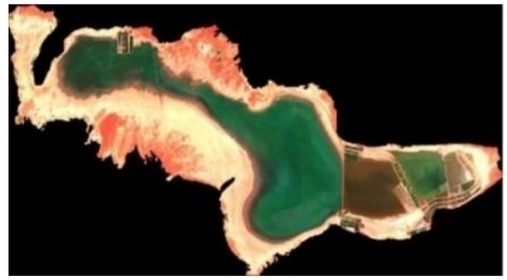

Figure 3. FCC of Sambhar Lake region.

The Satellite image interpretation models are generally facing certain challenges in obtaining image ground truth data and labeling. In case of spatial data research, the ground truth data generation using manual plots or ground surveys is highly laborious. Hence, the possible ground truth has been generated from the FCC image of sambhar lake using ImageJ software through masking and binarization as shown in Fig. 4 for validating the water segmentation results.

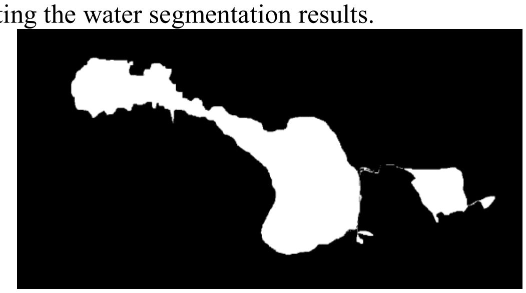

Figure 4. Ground truth of water body using ImageJ

C. Spectral based Water body segmentation

The satellite images are quite different from the other source of images since it includes different spectral bands of recorded wavelength of same object to be observed. Hence, the use of spectral indices, combining different bands bring better accuracy and less computational complexity than clustering methods. The combination of visual region of spectrum comprising blue, green and red bands with Infrared region of spectrum brings better discrimination of objects. The choice of combining the bands varies with respect to the type of object under examination based on their respective spectral reflectance curve exhibited. Among the widely used spectral indices for water extraction, the Normalized Difference Moisture Index (NDMI) which is a notable water index is used [15]. The Green and NIR spectral bands represented as b3 and b5 respectively are applied with band ratioing as in (1).

$$NDMI = \frac{(b3 - b5)}{(b3 + b5)} \quad (1)$$

The extracted water body using NDMI from October 2014 image is shown in Fig. 5 where this result clearly coincides with the green region of FCC.

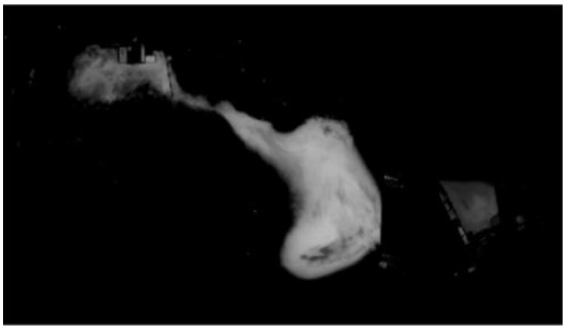

Figure 5. Spectral based water body segmentation

The acquired NDMI based water body segmentation has been quantitatively assessed using the possible ground truth data generated using ImageJ shown previously. The standard image quality metrics like Jaccard's coefficient (JC) and Correlation coefficient have been used to measure image similarity [16],[17]. The JC is termed for a ratio of two images where A and B are two different images to be compared as given in (2).

$$Jaccard\ Coefficient = \frac{|A \cap B|}{|A \cup B|} \quad (2)$$

The following results in Table I shows the significance of NDMI based water segmentation of october 2014 image, which is found to be similar to that of the ground truth data since the values remain close to 1.

TABLE I
WATER SEGMENTATION EVALUATION

Water segmentation	Jaccard Coefficient	Correlation coefficient
NDMI	0.8537	0.8334

The NDMI based water segmentation is relatively more accurate and less complex than existing segmentation approaches and also a leap towards fixing the gap of spectral importance being considered in soft classification based satellite image models.

D. *Two-tier image labeling based on rainfall data and area of water body*

The change recognition models using supervised learning needs target labels. The pixel based labeling using the signature file in GIS environment and certain semantic based pixel level labeling methods are the widely preferred satellite image labeling methods which would be a laborious and complex task [18].

Here, a two-tier image labeling method has been proposed considering the climatic variations acquired through performing a monsoon pattern analysis in tier-1 and the change of water body through assessing the area in tier-2 to recognize the severity of change in water body as shown in Fig. 6.

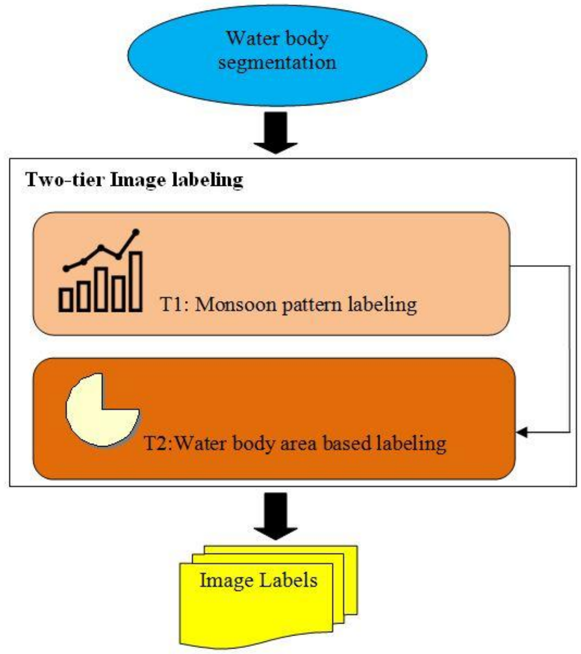

Figure 6. Proposed two-tier image labeling scheme

The sambhar lake has a distinct geographical location that includes the borders of three different districts of Rajasthan such as Ajmer, Nagaur and Jaipur. Through referring the geographical maps, three weather stations from the above said three districts around the lake have been identified to perform the monsoon pattern analysis.

Since the chosen study area is a seasonal lake with rainfall during the fixed monsoon period throughout all years, considering the rainfall data from nearest three stations is sufficient.

The annual rainfall observed in three stations for the specified three years using the collected rainfall data has been plotted in Fig. 7 to 9.

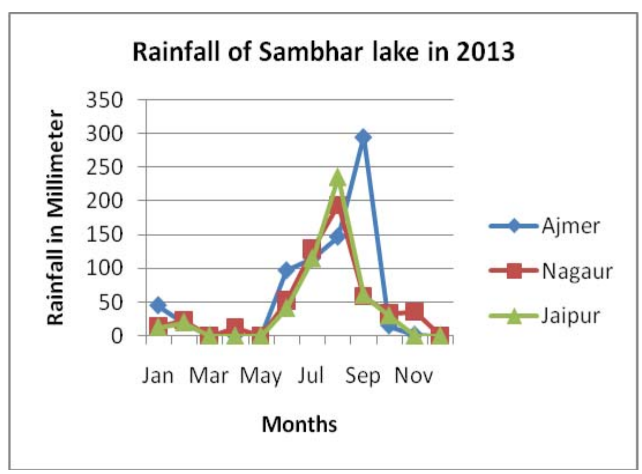

Figure 7. Monsoon pattern observation - 2013

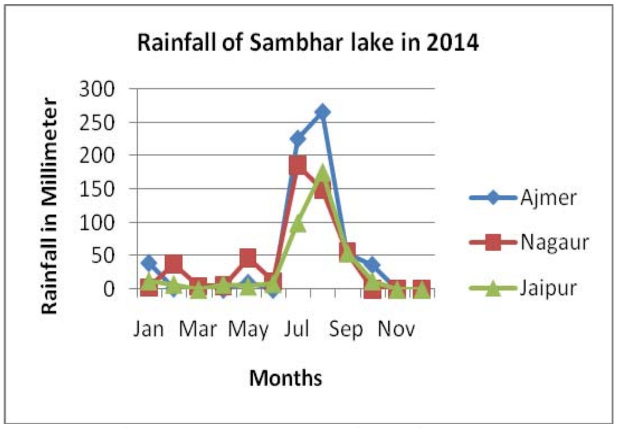

Figure 8. Monsoon pattern observation - 2014

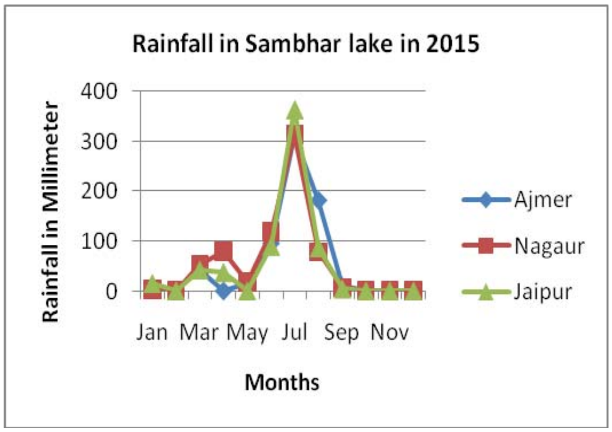

Figure 9. Monsoon pattern observation - 2015

On observing the above monsoon patterns, it is made evident that the sambhar lake region receives rainfall during June to October months of a year where July and August months record the highest rainfall. Hence, in tier-1 level, the images were labeled into two categories as monsoon and non-monsoon data based on the above monsoon pattern observations. Let tier-1 labels be 1 for Non-Monsoon (NM) data and 2 for Monsoon (M) data.

In the tier-2 level, the relative area of the water body along with the first tier labels are used for categorizing the data into 4 categories of water level such as (1) Under drought extremity, (2) Drought expectancy, (3) Average Water level and (4) Good Water level. The threshold values are determined using the maximum and median values of the water body area.

In order to compute the relative area of the water body, the extracted NDMI based water segmentation results are need to undergo a sequence of filtering and morphological operations to generate a closed component [19]. Initially the image is smoothened using gaussian filter and followed by the wiener filter for better boundary discrimination. This enhanced image is applied with contrast stretch limit method which exhibits dynamic stretching for effective binarization for brightness enhancement.

Further, bernsen thresholding which could offer shape based filtering with respect to maximum and minimum contrast values has been applied for binarization [20]. This binarized result of water body is applied with disk based morphological closing operation to achieve an effective closure of object as shown in Fig.10.

Figure 10. Closed component of water body

The closure of objects in image could favor grouping of pixels into limited no. of connected components. Further, the small water mass with less interest (i.e) outside the lake region in every image are removed by using minimum area threshold. In case of accurate spatial area assessment, the image calibration with image acquisition sensors needs to be considered which is slightly impossible in case of satellite image analysis. Hence, the relative area of the extracted body can only be measured through computing the no. of pixels in the water region.[21].

The above proposed labeling scheme can be applied for any seasonal water body for tracing the change events within a due course of time considering the appropriate climate data for first tier labeling. It aids soft computing based image classification for better decision making of change detection [22].

E. Image Feature Extraction

The improved discrimination of complex objects in images can be achieved using local descriptors which have been proved in many recent computer vision based object detection models. Different local descriptors with varied scale and geometrical orientation restricted models are applied for improving object detection. These local descriptors are the compact vector representation of the pixels along with the neighborhood in an image with respect to scale and other orientations observed. Here, in order to trace the change events of the water body, the HOG features has been extracted from the segmented water body. Each image has been represented as 1*81 size of HOG vector [23].

F. Supervised Learning for change recognition

The HOG vectors of 43 images and their corresponding image labels from two-tier architecture are used to evaluate the performance of supervised classifiers. The Fuzzy-K-Nearest Neighborhood (F-KNN), Multi-Support Vector Machines (MSVM), Error Correcting Output Codes (ECOC), Classification Tree (CT), Naive Bayes (NB) and Random Forest (RF) [24],[25],[26] are the chosen set of classifiers to trace the change events in Sambhar lake [27]. The performance evaluation results of the supervised learning with respect to different sets of k-fold cross validation are shown in the following Table II.

TABLE II
PERFORMANCE ANALYSIS OF SOFT CLASSIFIERS

HoG Features			
Classifiers	Accuracy	Kappa Coefficient	R^2
F-KNN	66.67	0.54	0.54
MSVM	**77.78**	**0.71**	**0.85**
ECOC	77.78	0.69	0.8
CT	55.56	0.40	0.65
NB	66.67	0.54	0.79
RF	55.56	0.39	0.73

On the extensive performance analysis of chosen supervised classifiers, it has been found that ECOC and MSVM outstands the other classifiers using HoG features.

III. CONCLUSION

The global water scarcity and other pollution threats bring importance of tracing the changes in water bodies. Hence, this paper briefs the purpose of deploying an efficient satellite image based model for tracing the change events of a water body. The results are feasible with HOG features on examining with the chosen set of classifiers. However, the use of large feature size in long term change detection can improve the efficiency much better. This process chain can be adopted to trace change events in any water body using Landsat 8 images susceptible to the data variations in tier 1 image labeling of monsoon pattern.

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