# River Water Level Prediction in Satellite Images using Support Vector Machine

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## ABSTRACT
In recent days, the impact of satellite image processing in various researches is greater because of the wide variety of applications in astronomy, GIS, Agriculture monitoring and Disaster management. Besides other, the disaster management is important, since it is very useful in protecting the living beings. In this paper, river water level identification is done using support vector machines. In order to achieve this, the input satellite image is preprocessed and subsequently the segmentation is carried out with the aid of the anisotropic diffusion segmentation. Support Vector Machine (SVM) is utilized to identify the river spot in the input image in which contains land also and then the morphological operation is utilized to smooth the image. Consequently, in the testing phase, the image is tested with the SVM for water region identification and also another one SVM is utilized for the identification of the river stage.

## General Terms
Satellite Image Processing, Neural Networks

## Keywords
Satellite Image Processing, river stage, Support Vector Machine (SVM), morphological operation

## 1. INTRODUCTION
Terrestrial waters represent less than 1% of the total amount of water on Earth [14]. However, they have a crucial impact on terrestrial life and human needs, and play a major role in climate variability [2]. It is becoming increasingly clear that water resources represent one of the most important issues facing humans, as water is the building block of all societies [3]. Climatically driven, seasonal changes in river water levels (river stages) govern a wide range of hydrologic, geomorphological and ecological processes [8] [10]. Measurements of water levels in the main channels of rivers, upland tributaries and floodplain lakes are necessary for understanding flooding hazards, methane production, sediment transport and nutrient exchange [1]. However, because of increasing population, industrialization, and dependence on irrigation, infrastructure deficiencies, and the inherent high variability of precipitation and discharge, water resource scarcity (from occasional to chronic) is already common in many regions of the world, and can be expected to become more acute[5]. When water problems extend beyond the borders of local communities, the river basin is generally seen as the most appropriate unit for analysis, planning, and institutional arrangements [11].

Difficulties in obtaining data consistently and accurately from remote regions are impractical in some cases. As a result, remote sensing of rivers, wetlands, and lakes is recognized as an additional useful source of water resource information [16]. Spatial information technology (SIT) i.e. remote sensing (RS), geographical information system (GIS) and global positioning system (GPS) has proved to be an efficient tool in delineation of drainage pattern and water resources management and it's planning [9][17].The growing availability of multi-temporal satellite data has increased opportunities for monitoring large rivers from space. A variety of passive and active sensors operating in the visible and microwave range are currently operating, or planned, which can estimate inundation area and delineate boundaries. Radar altimeters show great promise for directly measuring stage variation in large rivers [18]. Multispectral imagery has been used as the data source for water and land observational remote sensing from airborne and satellite systems. [7]. Spatial and temporal patterns of inundation areas can be inferred from multi-temporal satellite images: visible/infrared (IR) or Synthetic Aperture Radar (SAR) sensors are used to delineate floodplains [13]. Imagery from spaceborne platforms such as synthetic aperture radars (SAR), passive microwave sensors, and Landsat thematic mapper (TM), have been used to map the extent of inundation [6].

Remote sensing techniques are widely used to collect information on the qualitative and quantitative status of natural resources in protracted areas [4][20]. Three possible approaches to estimating river discharge from satellite-based data can be summarized as follows:

- With the help of a hydraulic equation, or rating equation, estimate river discharge from the measurement of hydraulic variables from satellite and/or other remotely obtained information.
- Measure water level variation by using radar altimeter data or the interferometric radar technique and then convert it to river discharge on the basis of a rating curve between satellite-derived "water level" and ground-measured discharge.
- Correlate satellite-derived water surface areas with ground measurements of discharge, and then infer river discharge from satellite data on the basis of the water area–discharge rating curve [12].

Understanding of the flooding dynamics and hydrological exchange between rivers and related floodplains relies on measurements of water levels recorded at gauging stations along a main channel. But most remote river basins have only a few gauging stations and these tend to be restricted to large river channels. Although radar remote sensing techniques using interferometric phase measurements have the potential to greatly improve spatial sampling, the phase is temporally incoherent over open water and has therefore not been used to determine water levels [8]. For nearly all wetlands, however, the lack of floodplain stage recording devices results in poorly constrained estimates of floodplain water storage [15] [19].

## 2. RELATED WORK

A handful of researches are available and they are reviewed below. Kalaivani *et al*. [21] have analyzed to determine the stage of the water level. Three phases involved in this work were the training phase, analysis phase and the testing phase. In the training phase, two ANNs were trained. One network was for the identification of water regions and the other was for analyzing the status of the river. In the testing process, the input raw river image was denoised and morphological operation was carried out on the denoised image. After that the river image was segmented into water regions with the aid of the ANN. Finally in the analysis phase, the stage of the river water was identified whether the river was in draught, normal or flood stage.

Hostache *et al*. [22] have provided distributed water levels from SAR images. Furthermore, in view of improving numerical flood prediction, a variational data assimilation method (4D-var) using such distributed water level has been developed. This method combined an optimal sense remote sensing data (distributed water levels extracted from spatial images) and a 2D shallow water model. They also derive water levels with a ±40 cm average vertical uncertainty from a RADARSAT-1 image of a Mosel River flood event. Shah *et al.* [23] have presented the methods like edge detection, thresholding, image erosion and other color and feature extraction algorithms to extract water content (river). The algorithms used here includes, K means clustering algorithm, Hill Climbing Algorithm, Color histogram and image thresholding. Here, the condition of river like normal, drought or flood is also predicted by visual inspection of the processed satellite image. Powell et al.[24] have demonstrated an approach for mapping saltcedar along 50-km of the Bighorn River in Montana using ASTER (Advanced Spaceborne Thermal Emission and Reflectance Radiometer) imagery and a Random Forests classification tree modeling approach. They modeled the continuous probability of saltcedar presence and evaluated optimal threshold levels in terms of omission and commission error. Reasonable classification accuracy was achieved for some management purposes.

Seng Mah *et al*. [25]have discussed the hydraulic models that was successfully identified the weaknesses and areas for improvement with respect to flooding in the Sarawak River system, and can also be used to support decisions on flood management measures. They have demonstrated a theoretical flood management framework inferred from Sarawak River modeling outputs.

Goswami [26] has discussed the Majuli island has lost a considerable part of its total geographical area due to severe erosion caused by the Brahmaputra river and its tributaries. The island has also been witnessing gradual morphological changes, particularly, after the devastating Assam earthquake of 1950.

Rawat *et al*. [27] have analyzed the morphometric parameters of third order sub basins (TOSBs) special reference to natural hazard vulnerability assessment through integrated GIS database modeling on geo-informatics and morphometry-informatics modules. The Dabka River Basin (DRB) constitutes a part of the Kosi Basin in the Lesser Himalaya, India in district Nainital has been selected for the case illustration.

## 3. PROPOSED MECHANISM

Determining the stage of a river is a huge process and also vital one too. The process of identifying the stage of a river with the aid of a satellite images is a tedious process, because the satellite images are the images which are remotely sensed. Hence by utilizing these images the stage of a river is identified. In our previous works [21] and [29], we utilize the Back Propagation Network (BPN)and Radial Basis Feed Forward Network (RBFNN) respectively. In this work, we utilize the Support Vector Machine [28] and the proposed mechanism is detailed below.

### 3.1 Preprocessing Phase

In this preprocessing phase, the input satellite image is initially preprocessed for the further process and firstly the input image $\mathrm{Im}$ is obtained from the database $Db$. The image is of dimension $X \times Y$ where $0 \le x \le X-1; 0 \le y \le Y-1$. Initially the image $\mathrm{Im}$ is applied with the filter in order to remove the noise for the betterment of image. Once the image is get rid of the noises then the image is converted to the LAB color space because converting all the images in the same color space assists to obtain the proper output and also to obtain keen information. The following set of equations show the formulas for the conversion of RGB color image into CIE Lab color space [30].

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072167 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} * \begin{bmatrix} r \\ g \\ b \end{bmatrix} \tag{1}$$

$$L* = \begin{cases} 116*(Y/Y_n)^{1/3} - 16, & for\ \ Y/Y_n > 0.008856 \\ 903.3*Y/Y_n, & otherwise \end{cases} \tag{2}$$

$$a* = 500*(f(X/X_n) - f(Y - Y_n)) \tag{3}$$

$$b* = 200*(f(Y/Y_n) - f(Z - Z_n)) \tag{4}$$

Where $f(t) = \begin{cases} t^{1/3} & for \quad t > 0.008856 \\ 7.787 * t + 16/116 & \text{otherwise} \end{cases}$.

Here $X_n$, $Y_n$ and $Z_n$ are the tristimulus values of the reference white. After the conversion of color space then the image $\mathrm{Im}$ is now in the CIELAB color space and then this image is utilized for the process

Then the LAB color spaced image is applied with the anisotropic diffusion segmentation. In this segmentation process the non-linear diffusion segmentation mechanism is utilized. The segmentation is the process in which the digital image is fragmented into certain regions, so that we can obtain the information of the regions clearly rather than processing a raw image. Anisotropic diffusion segmentation is a family of continuous partial differential equations, which incorporate both the physical processes of diffusion and the Laplacian. The following eqn details the segmentation process.

$$\frac{\partial \mathrm{Im}}{\partial t} = div(c(x,y,t)\nabla \mathrm{Im}) = \nabla c.\nabla \mathrm{Im} + c(x,y,t)\Delta \mathrm{Im} \qquad (5)$$

Where $\Delta$ indicates the Laplacian, $\nabla$ stands for the gradient, $div$ is the divergence operator and $c(x,y,t)$ is the diffusion coefficient. $c(x,y,t)$ manages the rate of diffusion and is typically selected as a function of the image gradient so as to conserve edges in the image. Thus the segmentation process is completed over the aid of anisotropic diffusion segmentation and we obtain $\mathrm{Im}_{seg}$. After segmentation process the segmented regions are put into the process in order to identify the watered regions.

**Binarization:** The segmented image $I_{sgm}$ is then converted to the binary image which is then utilized for the further processes. In this binarization process, the converted LAB color spaced image is given as the input and the following pseudo code details the conversion process

**Input:** Segmented image $\mathrm{Im}_{seg}$, threshold $thresh$

**Output:** Binarized image $\mathrm{Im}_{br}$

**Steps:**

Convert the image into grayscale image with the following formula

$$\mathrm{Im}_{gray} = \frac{(L + a + b)\mathrm{Im}_{seg}}{3}$$

*For* all pixels $p_{xy}$ in the segmented image $\mathrm{Im}_{gray}$

*If* $p_{xy} \geq thresh$ *then*

Set $P_{xy} = 1$

Here in this pseudo code $thresh$ is the global threshold parameter. Hence the converted binary image $\mathrm{Im}_{br}$ is attained.

**Smoothing of image through morphological operation:**

The morphological operation is utilized to smooth the image for acquiring the keen information. The impacts of the morphological operation are on the application and for example machine vision and object detection which may utilize to identify the structure of an image. Morphological operation is utilized to detect objects or boundaries presented in an image. This operation is applied on the $\mathrm{Im}_{br}$ which is the obtained image. For this process, we utilize the 'imclose' operation that morphological closes the image and here $st$ is the structuring element here that is disc here. The following eqn details the process.

$$\mathrm{Im}_{br} \bullet st = (\mathrm{Im}_{br} \oplus st) \ominus st \qquad (6)$$

**Thresholding to remove the surplus regions:** The remote sensing images capture the river area as well as land hence the watered area must be identified for that we take out the surplus region through the thresholding operation that eliminates land area as well as the small watered regions. The pseudo code for the above process is explained in detail below.

**Input:** morphology applied image, t

**Output:** thresholded image

For $\forall\, \mathrm{Im}_{seg}$ in $\mathrm{I}m$

For $\forall\, \mathrm{p}_{xy}$ in $\mathrm{Im}_{seg}$

If $\mathrm{p}_{xy} \leq \mathrm{thresh}$ then

$\mathrm{p}_{xy} = 255$;

End If

End For

End for

In the above pseudo code for thresholding process, the pixel value larger than the threshold is measured and the remaining pixel values are altered to the value 255 to mark the small watered regions as white and hence we obtain the mandatory watered regions in order to identify the stage of the river

**Suppression:** The suppression is the process of eliminating the surplus regions and then the residual watered regions are taken into consideration and the resultant image is marked with the watered regions Here the outcome image is $\mathrm{Im}_{wr}$ which is the original image marked with the watered regions that is essential to identify the stage of the river.

Subsequent to this process, this image is utilized to identify the stage of the river.

### 3.2 Training Phase

In this phase, the watered regions identified images such as $\mathrm{Im}_{wr}$ are trained in order to identify the stage of the river. In our previous works we have utilized the training algorithm BPN [21] and RBFNN [29]. In this work, we utilize Support Vector Machine (SVM) for identifying the stage of the river. The Support Vector Machine (SVM) is a state-of-the-art classification method introduced in 1992 by Boser, Guyon, and Vapnik [31]. In this training phase the watered region identified images are used to train the SVM in order to identify the watered regions in the river image. The following details the error minimization process for the SVM. SVMs related to the generalized linear classifier's family. SVMs are also regarded as a special case of Tikhonov regularization. A peculiar property is that they have diminished the empirical classification error and increase the geometric margin at the same time. Therefore, they are termed as maximum margin classifiers. The SVM training intends to minimize an error function that is given as

$$\arg\min \rho \sum_{j=0}^{n_s'-1} \alpha_j + 0.5\omega^T.\omega \qquad (6)$$

with the following constraints,

$$C_j(\omega^T \delta(\hat{Z}_j) + \beta) \geq 1 - \alpha_j \qquad (7)$$

and

$$\alpha_j \geq 0 \qquad (8)$$

In Eq. (6), $\rho$ is the penalty constant, $\alpha$ is a parameter that handles the data and $\omega$ is a matrix of coefficients. In the constraints given in Eq. (7) and (8), $C_j$ is the class label of the $j^{th}$ watered region dataset, $cn$ is a constant and $\delta$ is the kernel that transforms the input data to the feature space. Hence, by minimizing the error function, the SVM learns the training gene dataset $\hat{Z}$ well and so that it can classify the images' watered region that is similar to the training set and also another SVM is utilized to identify the stage of the river. In this SVM the identified watered regions are given as training set their length is the measuring element here. This SVM is measured with the aid of a threshold that is length here if the length of the watered regions that are above or below or approximately equal to the threshold.

For $\forall L$ of watered regions of different images

If $L > thr$ then

Stage='Flood'

Else If $L < thr$ then

Stage='Draught'

Else If $L \approx thr$ then

Stage='Normal'

End If

End If

End If

### 3.3 Testing Phase

In this testing phase, initially the image is given as input to this system and initially the image is applied with the preprocessing mechanisms such as denoising, color space conversion, binarization, smoothing, thresholding and suppression that are discussed in the preprocessing phase. After completing this, the image is provided to the first SVM in order to observe the watered regions and then these regions are utilized to identify the stage of the river. In another SVM the length of the identified watered region is utilized to identify the stage of the river. Thus this system identifies the stage of the river with the aid of a raw satellite image.

## 4. RESULTS AND DISCUSSION

Our proposed technique is utilized to predict the stage of the river water level and that is implemented using the platform of MATLAB (version 7.10). Our proposed methodology was evaluated with different images of river obtained publicly available.

**Table 1. Performance parameters calculated for SVM**

| Stage of river | TP | TN | FP | FN | Sensitivity | Accuracy | Specificity |
|---|---|---|---|---|---|---|---|
| Normal | 2 | 4 | 0 | 0 | 100 | 100 | 100 |
| Draught | 2 | 3 | 1 | 0 | 100 | 83.33 | 75 |
| Flood | 1 | 4 | 0 | 1 | 50 | 83.33 | 100 |

The various parameters that are calculated and compared include true positive, true negative for all three stages drought, flood and normal, sensitivity, specificity, accuracy, False positive rate, positive predictive value, negative predictive value, False discovery rate and Mathews correlation coefficient.

The performance parameters that are calculated are tabulated in table 1 and table 2 and the images of the river after passing through the various stages are shown below.

**Table 2. Other Parameters to measure the performance of SVM**

| Stage of river | FPR | PPV | NPV | FDR | MCC |
|---|---|---|---|---|---|
| Normal | 0 | 100 | 100 | 0 | 57.73 |
| Draught | 25 | 66.66 | 100 | 33.33 | 54.77 |
| Flood | 0 | 100 | 80 | 0 | 28.28 |


**Figure 1. Original Satellite River Image**

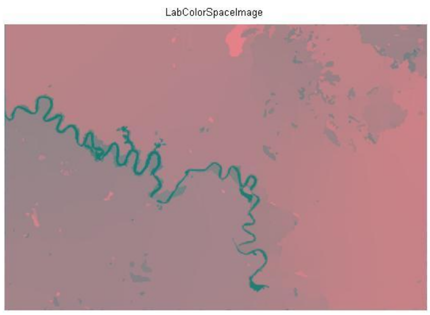


**Figure 2 Color space converted River Image**

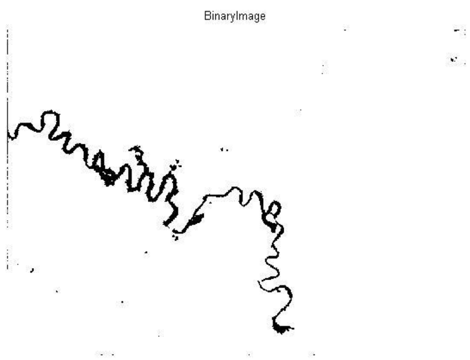


**Figure 3. Binary form of the input River Image**

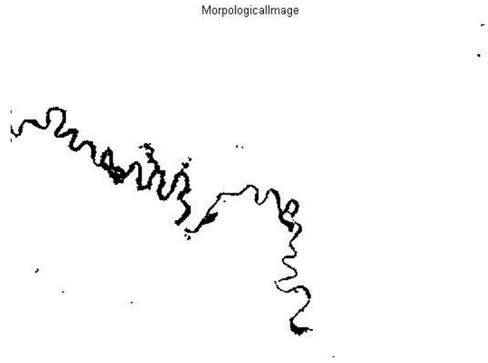


**Figure 4. Morphological operation applied input River Image**

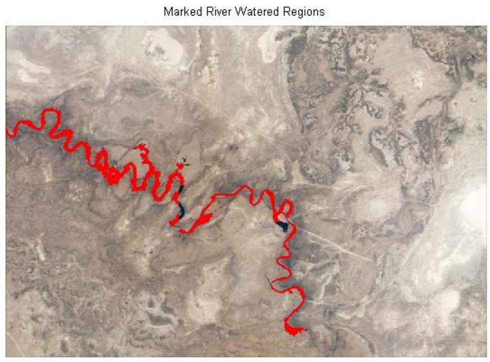


**Figure 5. Watered Region marked in the original River Image**


**Figure 6 Stage of the original River Image**

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