International Journal of Scientific Engineering and Technology (ISSN : 2277-1581)
Volume 2 Issue 5, pp : 404-410 1 May 2013

Rainfall Water Runoff Determination Using Land Cover Classification of Satellite Images For Rain Water Harvesting Application

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I. Abstract:

In country like India where an amount of precipitation is limited to specific period (monsoon season) and if not utilized, water becomes a scary resource. At this same time the present statistics about the average water table in the country indicates a rapid fall in the level. There is an immense need to make a proper utilization of water and increase in ground water level by means of rain water harvesting techniques. This paper presents an approach for determining the water runoff from a particular built-up area based on the satellite image of that area. The process involves segmentation and classification of satellite images. The classification is mainly done using texture analysis techniques. The satellite image is classified into various classes like built up region, soil region, grass region and water region. The area under built up region is computed, then based on the relationships between the surface type and the rainfall, the water runoff is computed; which in turn is used for the design and development of rain water harvesting system.

II. Keywords:

Land use and Land cover classification, K-means, Image Segmentation, Textural analysis, Water runoff, Pavement runoff, urban area, color image segmentation.

III. Introduction:

Human race has always indulged in wars over the natural resources. Over the ages, the only difference between these wars was 'what was the natural resource?' As astonishing as it sounds, brilliant minds of world think that in next war that 'natural resource' will be the 'water'.

In the world, almost one-fifth of world's population (about 1.2 billion) lives in area where water is scare [1]. According to United Nation (UN) report, water use rate has been increased at more than twice of population increase in last century. In the same report, they have estimated that, by current rate of consumption, by 2025, 1800 million people will be living in countries or regions with absolute water scarcity, and two third of world population could be under stress conditions[2].

In India, situation is not so different. The thirst of water for India's rapid development is growing day by day. In spite of adequate average rainfall in India, there is large area under the less water condition/drought prone. In 2012, 64% of total districts in India (400 of total 627) experienced drought-like situation. Situation in 2013 is not optimistic from any point of view.

The normal annual rainfall precipitation in the country is estimated to be 400 million hectare-meters (Mha-m) of water. Out of this, 115 Mha-m enters surface flows, 215 Mha-m enters the ground, and 70 Mha-m is lost to evaporation. Only 25 Mha-m is finally used through surface irrigation which constitutes merely 6 per cent of the total water available through rain and from flows from outside the country (20 Mha-m)[4].

One of the reasons for the poor utilization of rain-water in India is the high concentration of rainfall over a few months. About 74 per cent of the rainfall is received during the south-west monsoon period of June to September. Besides this, the distribution of rainfall is also geographically highly uneven. Only 8 per cent of the country receives very high/assured rainfall of above 2000 mm, and another 20 per cent receives high rainfall of 1150 to 2000 mm. The rest of the country, that is, 72 per cent, is in the low, dry, or medium rainfall range of less than 1150 mm, with 30 per cent area particularly dry at below 750 mm[3][4].

States	May 1999-May2000		May 2000-May 2001	
	Fall in water table level			
	2-4 meters	4+ meters	2-4 meters	4+ meters
	Number of districts			
AP	8	6	5	3
Maharashtra	11	6	12	3
MP	3	2	23	11
Rajasthan	All Except 5	14	NA	NA
Punjab	2	1	6	0
Haryana	3	2	3	1
UP	6	4	11	6
Bihar	4	-	NA	NA
W. Bengal	3	2	NA	NA
Orissa	2	1	NA	NA
Assam	4	-	5	1
Gujarat	All Except 4	9	NA	NA
Karnataka	8	3	4	2
Tamil Nadu	13	6	16	10

Table 1 Water table levels

The situation of acute drops in the water tables is highlighted by Table 1. Water table falls of over four meters per year are seen in a large number of districts. There appears to be a wide-spread need to explore the possibilities of rainwater harvesting to alleviate the decline in water tables [2].

With this horrified scenario rain harvesting has become the necessity. Hence we wanted to tackle this problem with completely different albeit novel approach. Since last two decades land use and land cover classification has seen huge development because of development in remote sensing satellite technology. Till now satellite images have been used in practical applications such as urbane land cover application [5] [6], urbane planning [7], classification of urbanized areas within sensitive coastal environments [8], land use and land change in the ecotone of agricultural-animal husbandry [9], to study forest dynamics [10].

In this paper, we are proposing a scheme for computing the rainwater runoff from the areas like rooftops for the purpose of rainwater harvesting using land cover classification from satellite images. In this scheme the regions in the satellite images are segmented and classified using famous K-means algorithm. From the class related to residential areas, built up areas are separated and areas under each region are computed. Based on the area of this hard surface the water runoff is computed based on the rain fall. This estimation can be used to design rainwater harvesting schemes for water percolation and recycle/reuse. An attempt is also made to use this scheme for Google earth images in order to make the tasks simpler.

IV. Literature Survey:

Land use and land cover classification has taken huge leap in development since high quality image data became available.

First goal of our proposed scheme was to work on segmentation of satellite image. Tai-Sheng Wang et.al [11] have worked on Land use

and land cover classification; for classification they have extracted pixel form ground images and trained them using Back Propagation Neural Network (BPN). They attained accuracy of 63.5% after 100 runs. (Obviously, accuracy will improve, as we will increase training data).

Maximum Likelihood is the most popular classification method, and well-known for the analysis of satellite images [18]. In addition, it is also widely applied in land cover classification and monitoring of the land use changes [19, 20].This method is based on a normal Gaussian data distribution of that particular data with pixels allocated to the most likely output class. The basic theory assumes that the input bands have normal distribution and these probabilities are same [21]. However, K. C. Tan *et.al* [12], have presented clear cut reason for not using maximum likelihood classifiers as it has accuracy of 80.5% as compared to Neural Network which has accuracy over 93%.

Zhen Lei *et.al* [13], have worked on speed and accuracy of algorithms such as Texton Forest (TF), Conditional Texton Forest (CTF), Markov Random Field (MRF), Support Vector Machine (SVM) and they have conclusively proved that CTF method shows an advantage on accuracy over the alternative methods. While discussing about speed, they have stated thet CTF has almost the same speed as TF however it is several times faster than MRF and hundreds of times faster than SVM. On the other hand, CTF training is slightly slower than TF and SVM. MRF does not need much time for training.

Teodor Costăchioiu *et.al* [14], researchers have given whole new perspective for land use and land cover classification. Unlike most of other researches they have not used neural network; instead they have used Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI) method on Landsat satellite images. This paper gave us confidence that land use and land cover classification can be performed without a use of neural network which will reduce time and computational complexity; in the proposed work we are maintaining the accuracy.

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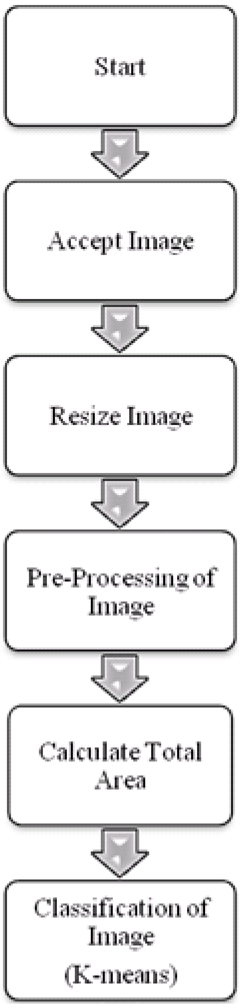
The limitation of NDVI, NDBI method is that this method can be used only on Landsat images; where images have 7 thematic bands. In our proposed scheme we are stressing more on generalized approach in which availability of a satellite image should not be point of concern i.e. we wanted our algorithm to work on all types of color satellite images.

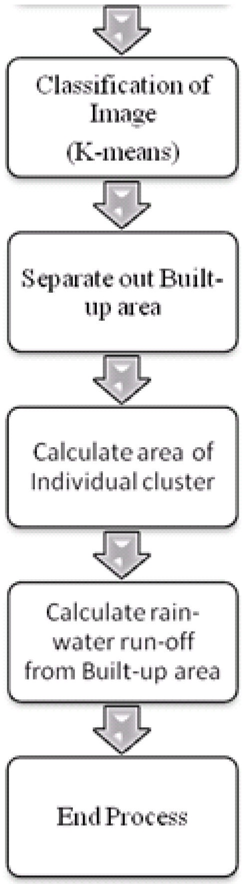
Chinki Chandhok [15] has given K-means clustering algorithm which is used for color image segmentation. He has conclusively proved that using K-means clustering algorithm we can computational complexity by avoiding feature calculation for every pixel in the image and this algorithm can be worked on images where clusters are not well separated. In addition to these advantages, K-means algorithm does not fail on account of accuracy.

In this way, after going through large number of papers we conclude that K-means algorithm can be better option for the segmentation.

V. Proposed Scheme:

A. Flowchart:





B. K-means algorithm for segmentation:

K-means is clustering algorithm used to determine natural spectral grouping in given set of data. K-means is unsupervised clustering algorithm which classifies given set of data into multiple classes. Here number of classes is defined by the user. Classification takes place based on inherent distance between any two points from each other in data set. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. The dataset is partitioned into K clusters. K-means algorithm considers that each object has its own location in space. Algorithm puts every data point in a cluster such that; that point would be close to every other point in his cluster and as far as possible from every other point from other clusters. [16] [17]

Euclidean distance metric is being used in the K-means algorithm. For each data point its Euclidean distance from original cluster is calculated. If that distance is low which means data point is closest to cluster then leave it in that cluster only.

If that distance is not closest then move that data point to closest cluster. This process is repeated until and unless process arrives at a point where no data point is being moved from one cluster to other cluster. At this point clustering ends. As K-means approach is iterative, it is computationally intensive and can be treated as unsupervised training areas[15]. For algorithm L*a*b* color space has been used. The L*a*b* color space (also known as CIELAB or CIE L*a*b*) enables us to quantify visual differences. The L*a*b* color space is derived from the CIE XYZ tristimulus values. The L*a*b* space consists of a luminosity layer 'L*', chromaticity-layer 'a*' indicating where color falls along the red -green axis, and chromaticity-layer 'b*' indicating where the color falls along the blue-yellow axis. Range of ‘L*’ layer goes from 0 to 100 whereas range of ‘a*’ and ‘b*’ goes from -128 to 127. All of the color information is in the 'a*' and 'b*' layers. We will measure the difference between two colors using the Euclidean distance metric. Since the color information exists in the 'a*b*' space, our objects are pixels with 'a*' and 'b*' values. Use K means to cluster the objects into required number of clusters using the Euclidean distance metric.Thus image is classified into regions using K means algorithm.

C. K-means algorithm result:

Fig.1. Original Satellite image

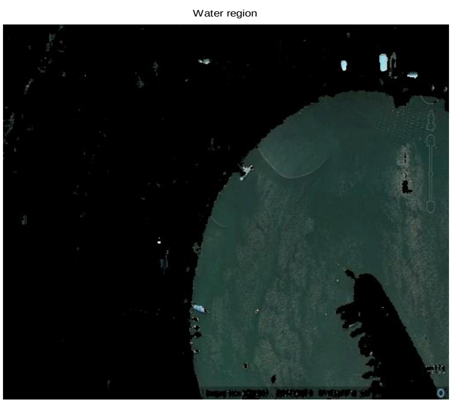


Fig.3. Water region

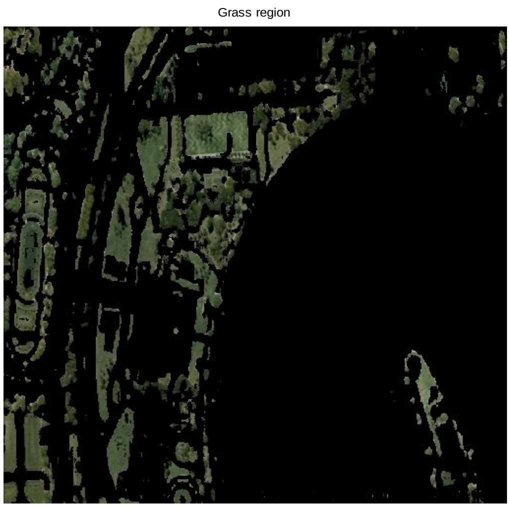


Fig.5. Grass region

Fig.2. Image Labeled by Cluster Index

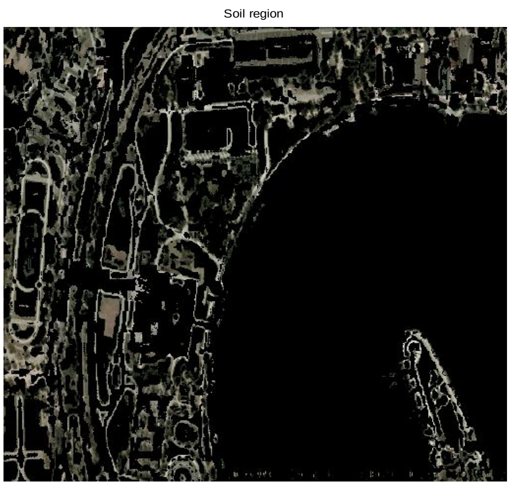


Fig.4. Soil region

Fig.6. Built up region

As evident from output images, output for all regions is accurate. Soil area in this image is fairly scattered over entire image still K-means algorithm has successfully managed to classify soil region; which is proof of accuracy of algorithm.

D. Area calculation:

After classification of an image, area under each cluster is calculated. For that purpose, total area has been taken from Google image using 'scale' option. Then to calculate individual cluster area, number of pixels in each cluster has been calculated. Using total number of pixels in an image and pixels present in each clustered image, percentage of each cluster in an image has been computed. These percentages along with the total area under image have been used to calculate area under each cluster.

E. Calculation of water runoff from built up area:

To calculate water runoff from built up area we have used following equation:

$$Q = \frac{K \times i \times A}{36}$$

…(1)

Where,

Q = Peak flow in Cumec.

i = Rainfall intensity in cm/hr.

A = Catchment area in hectares.

K = runoff coefficient. [22]

Now using rainfall intensity and built up area that has been already calculated; water runoff has been computed using given formula.

F. Study area description:

We have taken study area near Jaipur, Rajsthan, India. Google Earth image of area near Jaipur is taken. This image covered area around latitude 26º 54' 33.27'' N and longitude 75º 47' 01.79'' E. Study area approximately covers 417150 meters square, which is 0.417 KM^2.

Satellite image of study area:

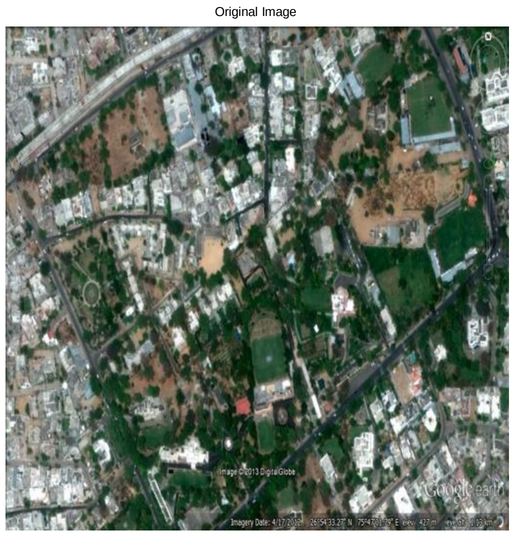


Fig.7. Original Satellite image of study area

While taking image from Google Earth we have taken some parameter of satellite image.

City - Jaipur

State - Rajsthan

Country - India

Latitude - 26º 54' 33.27'' N

Longitude - 75º 47' 01.79'' E

Elevation - 427 meter

Eye altitude - 1130 meter

Length - 810 meter

Breadth - 515 meter

Here we would like to mention that, although specific image has been used to test the results of proposed scheme; this algorithm works on any kind of satellite images subject to change in quality of an image.

G. Result:

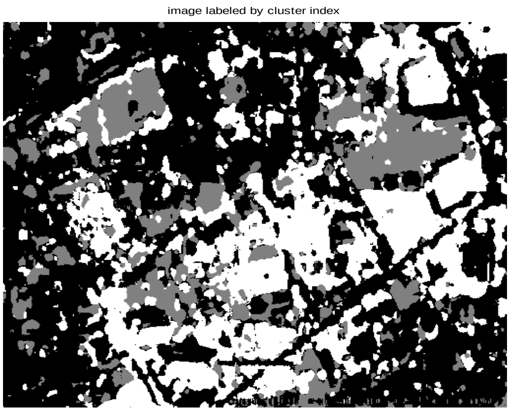


Fig.8. Image Labeled by Cluster Index

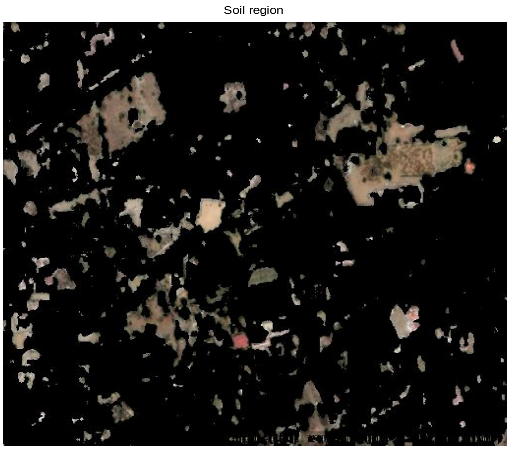


Fig.12.Soil region

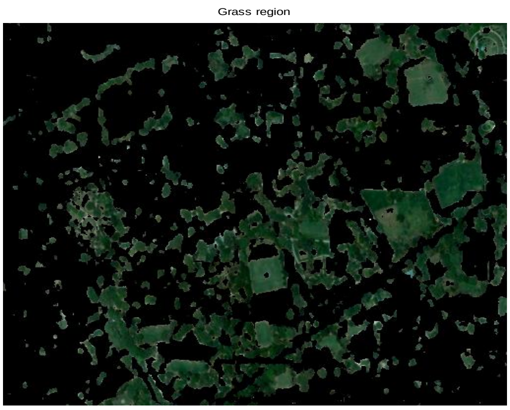


Fig.9.Grass region

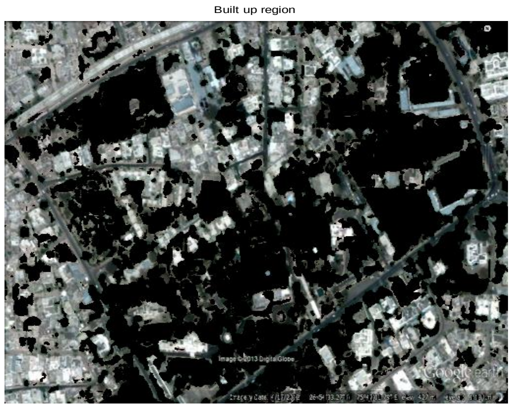


Fig.11.Built-up region

H. Table of Area calculation:

Using Length and Breadth we have calculated total area. Then using that area and percent of pixels for each cluster present in image we have calculated area under each cluster.

Class	Area (meters2)
Total Area	417150
Area under Soil Region	63583.61
Area under Grass Region	128368.66
Area under Built-up Region	225197.73

Table 2 Area Under Each Cluster

I. Water runoff calculation:

Now to calculate water runoff using equation (1), we have,

$K = 0.65$

$A = 225197.73$ meters

$i = 0.1$ cm/hr (assumed)

Thus water runoff (Q) is 0.04 cubic meter per second. Which means when 0.1 cm/hr rain will fall on study area; water runoff of 0.04 cubic meters per second will take place.

J. Software and Image details:

For this project we are using MATLAB version R2012a as software for computation of algorithm. As mentioned above, this algorithm works for all kinds of satellite images, we are using Google Earth Image in our project.

VI. Conclusion:

This proposed scheme presents a model for calculation of water runoff using land cover classification of satellite images. In the process K-means algorithm has been used for classification of satellite images, which was chosen because of its excellent accuracy. Once classification of satellite image was performed area under built up region is computed and using that area and rainfall; water runoff is calculated.

In this way proposed scheme gives us a way to calculate water runoff using techniques of image processing which in turn is used for development of rain harvesting system.

VII. Acknowledgement:

We would like to express our gratitude towards Prof. Dhonde and Prof. Ms. Ulka Joshi (Civil department, Vishwakarma Institute of Information Technology) for their wholehearted support and guidance.

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