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Analysing vegetation cover of an area using established Green Index from Satellite Image

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***Abstract*—** In present day scenario decrease in tree count or vegetative area is one of the major challenges to humanity. Identification of vegetative area and analysing the density of forest cover is one of the fields in remote sensing. Manually detecting the vegetation change effectively and accurately is quite time consuming. Hence comes the need of automated system which identifies area of forest cover, analyses its density and makes a comparison of its vegetative cover of an area over a certain time period. This paper establishes a parameter 'Green Index' to identify forest cover of an area. Satellite images are used to monitor any change. The spectral index NDVI (Normalized Difference Vegetation Index) is used to calculate green index of an area from satellite image. Histogram is plotted for different wavelengths (Red, Green, and Blue) versus different area (Forest, Desert, Sea and Snow area) to compare its green index.

***Keywords*—** Green Index, Vegetative cover, NDVI, Satellite images.

I. INTRODUCTION

In various government, environment and military applications, automatically detecting changes based on satellite images is of utmost importance. Detection of change is the process of identifying the object state by observing it different times. Change detection is widely used in various applications such as vegetation monitoring, land use change analysis and also used in deforestation assessment, etc. Automated system is preferred over manual identification of these changes because of efficiency and accuracy.

Satellite images are used as dataset for identifying forest, desert, sea and snow covered area. The reflected radiation obtained from RGB satellite image to identify and analyse the vegetation cover of an area.

Introduced in the early seventies, the parameter Normalized Difference Vegetation Index, or NDVI, is a very popular tool in the remote sensing community dealing with agricultural monitoring [1]. This paper establishes a parameter i.e. Green index to measure forest cover of an area.

In this paper Section I contain introduction specifying need of the work and its importance in present scenario. Section II defines various related work in this field. Section III explains the algorithm and steps of implementing the technique. Section IV describes the result and its performance rate. Section V concludes the research work.

II. RELATED WORK

Land cover classification and change detection is a well-studied problem in the domain of remote sensing. Several research works have been done in this field. Various machine learning algorithms have been used to identify the land cover and its change over a period of May 1998 to May 2011 using Landsat data [2]. In this approach, spectral indices of image data are generated after pre-processing it. Several CVA studies were summarized by Johnson and Kasischke [3]. They aimed to demonstrate that CVA is a helpful way to detect change. Mas [4] contrasted six distinct techniques of detection of changes on Landsat MSS imagery in his research. These techniques are image difference, NDVI difference, PCA, direct classification, following classification data, image enhancement and subsequent classification. In identifying modifications, he found that the technique of image enhancement and classification is better than the remainder. In a research [5], variations of the well-known vegetation index (VVI) ratio and the standardized vegetation difference index (NDVI) to identify changes on Ikonos satellite images of very elevated resolution is presented. The remote sensing satellite collects the radiations reflected by the earth. An RGB image consists of three bands red, green and blue band. Therefore for many scientific and academic purposes, hyper spectral images consisting of many bands can be used [6] .The vegetation index method was developed due to the distinctive spectral features of green vegetation in visible and near-infrared wavelengths. This green vegetation has relatively low reflectance in visible wavelength and high reflectance in near infrared spectrum (0.7 – 1.3 micrometers) while other surface types, such as bare soil and water, have similar reflectance in both spectrums. Healthy and fully developed vegetation canopy tends to have less reflectance at red spectrum and higher reflectance in near-infrared spectrum as compared to under-developed canopy condition [7]. The unsupervised method of change detection using k means clustering is discussed in [8]. The Unsupervised kernel methods are discussed in [9]-[12]. Kernel-based change detection methods and Bayesian criterion is given in [13] to improve change detection accuracy and efficiency. Kernel analysis is also called as a pattern analysis algorithm. Region based change detection is discussed in [14]. Traditional change detection techniques are based on the images of multiple dates using principal component analysis, change vector analysis or cross correlation analysis and image subtraction. If the changes are detected in space using spectral signature one can analyse the change features with the image

III. METHODOLOGY

Long-term surveillance of vegetation with worldwide remote sensing systems is critical to gaining a better knowledge of agricultural change procedures over lengthy periods of time. This refers specifically to sub-humid to semi-arid ecosystems where it is only possible to detect agricultural changes in grazing lands based on long-term sequence [15]. In the spectral region of photo synthetically active radiation (PAR), live green plants absorb solar radiation, which they use as a source of energy in the photosynthesis process. NDVI is calculated from visible and near-infrared light of the vegetation-reflected. Leaf cells disperse solar radiation (i.e. reflect and transmit) in near-infrared spectral region. In this paper, we have established a greenness index which can be used to identify the type of vegetation (i.e. dense forest, desert area, sea or ocean and snow covered area) cover on a land.

In this paper a greenness value is established for sub-humid to semi-arid ecosystems using the below algorithm. The proposed algorithm to calculate greenness index from an image is as follows:

Input: Image of Dimension [m] [n] [3]

Output: Predicting vegetation cover of an area.

Algorithm:

1. Input satellite image of an area in RGB format with dimension as Image[m][n][3].
2. Flatten the input image to a new dimension as Image[m*n][3].
3. Calculate new R'G'B' for each pixel in image a

   R' = R / (R+G+B)

   G' = G / (R+G+B)

   B' = B / (R+G+B)

4. Calculate greenness for each pixel as

   Greenness = 2G' - (R' + B')

5. Calculate mean greenness in a given image.

   Mean Greenness = Total Greenness / No of pixels in image

6. Predict the density of vegetation of an area from the greenness index established.

The algorithm is applied on satellite images collected from Google Pro Earth of resolution 1280 X 720. Table 1 describes the details (its latitude, longitude and scale) of image dataset.

Table1 Description of dataset

Geographical Area	Latitude	Longitude
Amazon Basin	3°27'50.10"S	62°12'57.17"W
Congo Basin	1°01'45.97"S	17°44'18.57"E
Kinubalo (Malayasia)	5.9804° N	116.0735° E
Mt Leuser National Park (Sumatra)	3.7742° N	97.2437° E
Sundarban	21°56'55.69"N	89°11'08.05"E
Daintree Rain Forest (Australia)	16.1700° S	145.4185° E
Sahara	23°31'49.82"N	26°15'01.15"E
Kalahari	25.5920° S	21.0937° E
Arabian Desert	21°28'50.18"N	47°55'48.62"E

Thar Desert	27°29’22.04”N	70°36’17.56”E
Auatralian Desert	21°31’24.81”S	131°55’10.73”E
Syrian Desert	34°21’16.11”N	38°39’39.47”E
Antarctica	82°49’10.40”S	134°59’28.85”E
Greenland	72°18’11.40”N	42°22’19.55”W
Pacific Ocean	13°02’50.11”N	172°56’27.11”E
Bay of Bengal	11°07’02.19”N	88°10’36.53”E
Indian Ocean	31°36’16.71”S	81°33’34.60”E
Atlantic Ocean	27°43’43.26”N	34°44’21.21”W
Kolkata, India	22.5726° N	88.3639° E
Delhi, India	28.6139° N	77.2090° E
Mumbai, India	19.0760° N	72.8777° E
Chennai, India	13.0827° N	80.2707° E
Tokyo, Japan	35.6762° N	139.6503° E
Beijing, China	39.9042° N	116.4074° E
New York, USA	40.7128° N	74.0060° W

IV. Results and Discussion

The greenness value calculated as per the proposed algorithm for various regions are described below.

Table2 Calculated greenness of different forests in the world.

Forest Names	Calculated Greenness value
Amazon Basin	0.3353
Congo Basin	0.2873
Kinubalo (Malayasia)	0.3971
MtLeuser National Park (Sumatra)	0.3793
Sundarban	0.275
Daintree Rain Forest (Australia)	0.2665

Table3 Calculated greenness of desert area in the world.

Desert Names	Calculated Greenness value
Sahara	-0.0061
Kalahari	0.0015
Arabian Desert	-0.0013
Thar Desert	0.0183
Auatralian Desert	-0.0756
Syrian Desert	-0.0067

Table4 Calculated greenness of snow covered area in the world.

Snow Desert Names	Calculated Greenness value
Antarctica	-0.02185
Greenland	0.0049

Table5 Calculated greenness of different Sea and Ocean in the world.

Sea and Oceans	Calculated Greenness value
Pacific Ocean	-0.1044
Bay of Bengal	-0.1106
Indian Ocean	-0.1003
Atlantic Ocean	-0.0918

Table6 Calculated greenness of different urban area in the world.

Urban Area	Calculated Greenness value
Kolkata, India	-0.0617
Delhi	0.0264
Mumbai	0.0291
Chennai	0.0421
Tokyo	0.00401
Beijing	0.0394
New York	0.0334

Table6 Calculated mean greenness of different geographical areas.

Areas	Mean Greenness value
Forest	0.323417
Desert	-0.01165
Snow Area	-0.00848
Sea and Ocean	-0.10178
Urban area	0.016101

From Table 2, 3, 4 and 5 a greenness scale can be derived. Table 6 describes mean greenness index.

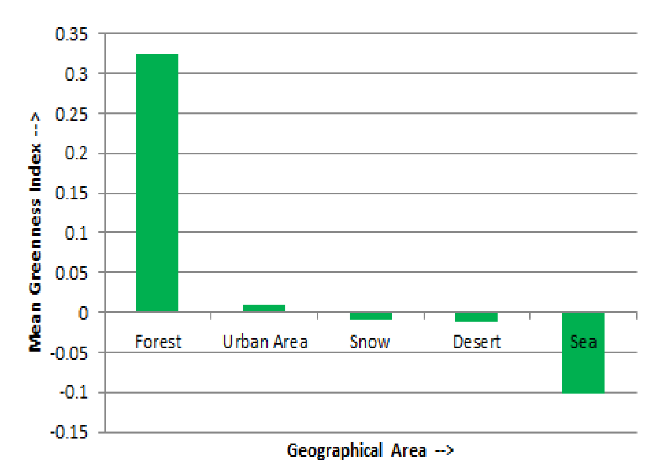

Figure1 Mean Green index for different geographical area.

So from our output data it is clearly visible that every geographical region has its own greenness index. Here forest region has high green index whereas the regions without green coverage (i.e. snow-capped areas and desert areas) fall highly short on the greenness index. It is cleared from our output that every geographical region has its own unique greenness index, which can be relied further to identify the nature of a given geographical region.

V. Conclusion and Future Scope

In this present age one of the major concerns is to protect our sustenance by protecting the vegetation cover throughout the world. Various techniques have been established to identify vegetation and its changes over time period. This paper suggests an appropriate method to establish a green index that can be used for detecting presence of vegetation from satellite image. This technique can even be used to detect the change in vegetation cover over the time from satellite images. In absence of NIR cannels data in the satellite images, we can use this technique to calculate the density of vegetative cover present in a given geographical area.

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