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# Detection of Bare Soil and Determination of Plant Health using NDVI and VARI Algorithm

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**ABSTRACT:**

Agriculture is one of the primary occupations in India. Various methods and technologies are used to carry out precision agriculture. Countries around the world are faced with land use /land cover change due to various factors such as rapid population growth, increased demand for agricultural productivity, and change in climatic characteristics. Land cover change needs to be addressed through monitoring and management. Along with this, detection of crops health is also a major need of the farmers which is satisfied using different machine learning algorithms. Traditional method of checking plant health is through visualization but this method is not so relevant in detecting the diseases associated with plants. So we can provide a better alternative, fast and accurate detection by using Machine learning algorithms which can be more reliable than some other old methods. This paper throws light on various methods used for monitoring the plant health and detecting land cover areas using NDVI and VARY Algorithms. Satellites play a huge role when it comes to providing the real time images to carry out such studies and research . It has been found by various researchers that one of the major applications for hyperspectral imaging is plant health detection and monitoring.

**Keywords**: Agriculture, Machine Learning, Land use - Land cover, Crop health detection, NVDI, VARI

## I. Introduction

The science of training machines to learn and produce models for future predictions and precision agriculture is widely used, and not for nothing. Agriculture plays a critical role in the global economy as being the most primary occupation. With the continuing expansion of the human population, understanding worldwide crop yield is central to addressing food security challenges and reducing the impacts of climate change. Crop yield prediction is an important agricultural problem. The Agricultural yield primarily depends on weather conditions (rain, temperature, etc), pesticides and fertilizers. Accurate information about history of crop yield is important for making decisions related to agricultural risk management and future predictions. Cuisine varies greatly around the world, but the basic ingredients that sustain humans are pretty similar be it wherever around the world. We eat a lot of corn, wheat, rice and other simple crops. India ranks second worldwide in agricultural outputs. The history of Agriculture in India goes back to Indus Valley Civilization. As per 2018, agriculture employed not only more than 50% of the Indian workforce but also contributed 17–18% to the country's GDP. According to the latest report, agriculture is the primary source of livelihood for 58% of the population in India . In 2013,India exported $38 billion worth of agricultural products which made it the seventh largest agricultural exporter worldwide and the sixth largest net exporter. There are various techniques used to increase the yield of crops in precision farming. To detect the area already being used for farming and uncovered land NDVI algorithms are used ,while to detect crop health and used of fertilizers and pesticides amount other machine learning algorithms are used. Various other grounds were also covered in agricultural researches such as Evaluation of soil moisture using remote sensing technology ,detection of weeds and wheat using image processing and biotechnology in agriculture and its relation to the sustainable agriculture.

The main approach adopted in practice for detection and identification of plant diseases is naked eye observation of experts. The decision making capability of an expert also depends on his/her physical condition, such as fatigue and eyesight, work pressure, working conditions such as improper lighting, climate etc. That's why this is not a proper way and also time consuming. It might be expensive as continuous monitoring of experts in large farms. So, we need a fast way and remote sensing form to detect the uncovered farm area and monitor the plant's health.

Our system consists of a mobile application, which will enable the farmers to take images of plants using their mobile phones and send it to a central server where the central system in the server will analyse the pictures based on visual symptoms using image processing algorithms in order to measure the plant health based on the chlorophyll present in it. An expert group will be available to check the status of the image analysis data and provide suggestions based on the report and their knowledge, which will be sent to the farmer as a notification in the application. It will also help the farmer to monitor the plant health by keeping their previous record saved in their individual profiles with their current status.

In order to make this facility easily available we have also linked our application to our website.

## II. RELATED WORK

1. L. Valderrama-Landeros , F. Flores-de-Santiago, J. M. Kovacs, F. Flores-Verdugo [7] (2018) carried out the research in Mexico, over an area covered with mangrove forests. The dataset mainly consisted of images collected from Landsat-8, SPOT-5, Sentinel2 and WorldView-2 satellites. Results shown that to classify and monitor environmental variability in mangrove forests, optimal spatial resolution from remote sensing data is required. It was found difficult to differentiate among the plant species present in the mangrove forests due to similarities in the reflectance properties of the plants. In the study, NDVI was less accurate due to the conditions under which the research was carried out, however, this does not question the applicability and capability of NDVI in any manner. The accuracy varied between 64% and 93%, with the variation of the images used from different satellites. This study stated that the use of the WorldView-2 satellite is the most effective when it comes to mapping the spatial distribution of mangrove species at regional scales. This study shows that very-high spatial resolution multispectral imagery from WorldView-2 data can effectively map the spatial distribution of mangrove species at regional scales. Contrary, very small and dense clusters (i.e., islands) of mangrove forests along the tidal creeks will not be identified from moderate-resolution satellite data such as Landsat-8, SPOT-5, and Sentinel-2.

2. The study area of the research carried out by Sabelo Madonselaa, Moses Azong Cho, Abel Ramoelo, et al. [8] (2018) stretches across the KwaZulu-Natal (KZN), Mpumalanga and Limpopo provinces of South Africa, within the broader savannah woodland belt. The main aim of the research was to identify tree species within randomly placed sampling plots and quantify local species diversity (αdiversity) in the region using the common measure of diversity i.e. Shannon index. This study explored the relationship between woody canopy cover (WCC) and tree species diversity. Data was collected over a period of 4 months, march, april, may and july. During this period the NDVI signal is influenced by woody canopy foliage and also by green herbaceous vegetation which would maintain high green biomass. The results of this study indicate that Landsat derived NDVI, particularly in March, has a higher relationship with tree species diversity when compared to woody canopy cover (WCC). The study showed a significant positive relationship between WCC and tree species diversity in southern African savannah. In essence the NDVI signal captures total vegetation productivity within savannah woodland and therefore has a higher explanatory power than woody canopy cover.

3. Instead of using satellite imagery, authors T. Duana,b , S.C. Chapmana,c , Y. Guo and B. Zhenga [9] (2017), used an unmanned aerial vehicle equipped with a camera and a hand-held sensor (e.g. GreenSeeker) for the dynamic monitoring of NDVI in wheat agronomy. Authors decided to use unmanned aerial vehicles because of the difference in altitude. The estimation of the NDVI can be used as a reference index for the dynamic monitoring of the biomass change during the growth season of wheat. Here they developed an efficient workflow to dynamically monitor the NDVI change over the wheat growing season. This study was carried out over a period of two months to carefully observe the variation in NDVI with time. In the original research, the Red wavelength range was 620–700 nm and the NIR was 750–950 nm. The reconstructed 5 band mosaic TIF provided the Red and NIR information with peaks at 668 nm and 840 nm wavelengths, with 10 and 40 nm full width half maximum bandwidths, respectively. NDVI around the flowering period had the higher correlation with final yield after adjusting with ground coverage, which indicates how data fusion from multiple sources can provide more insight into adaptation mechanisms of crops.

4. According to the researchers Feng Tian , Martin Brandt , Yi Y. Liu , Aleixandre Verger , Torbern Tagesson , Abdoul A. Diouf , et al. [10] (2016), the use of optical remote sensing provides a unique way of achieving a full coverage of global drylands. The study area was located in the semi-arid sahel zone of Senegal, which was then separated into three zones of annual rainfall. In order to have a better understanding of the vegetation optical depth (VOD) responses to herbaceous and woody compositions, they compared VOD spatial patterns and seasonal variations to NDVI over the study area. In this study, VOD was proven to be an efficient proxy for green biomass of the entire vegetation stratum, similarly the seasonal matrices of NDVI are still well suited for monitoring of green vegetation. In this study, the annual sum of VOD was found to perform well due to possible linkage between water content in the persistent part of the woody plants during dry season and foliage production during the growing season. VOD was found to be less sensitive to vegetation species composition in monitoring dryland biomass production as compared to greenness measures derived from visible/near-infrared parts of the spectrum.

## III. DATASET AND SOURCES

Some part of our research data was retrieved from LandLook viewer, The official website of the US government which has a library of the images by satellite landsat-8. The data obtained was in .tiff format and it was already splitted into various bands, which made it easier for us to implement the Algorithms. For our system, the user can either use a drone to capture farm images or he can use a normal mobile phone camera to upload the image. The image should be in .png format or .jpg format. Image should have all the three bands i.e. red band, blue band, and green band.

All paragraphs must be indented.  All paragraphs must be justified, i.e. both left-justified and right-justified.

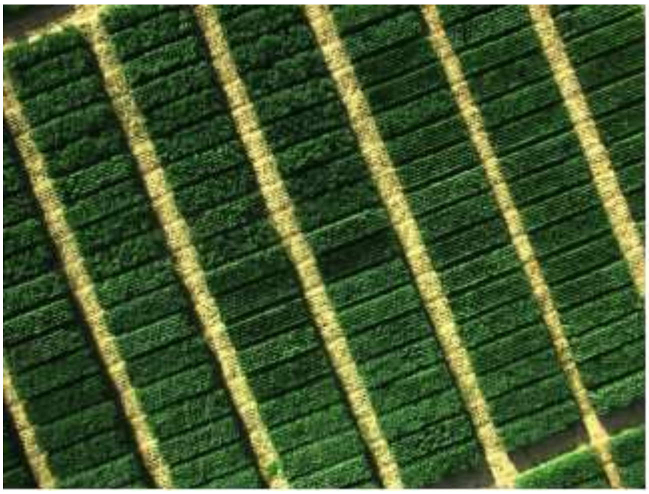

Fig. 1. Sample Input Image

The images can be either of the large portion of the farm, as shown in Fig 1. Or it can be of an individual plant. The images need to be clear for better processing and better results. After the processing, the resulting images will be saved in the .png format.

## IV. ALGORITHMS IMPLEMENTATED

*1.NDVI*

NDVI is calculated in accordance with the formula: NDVI= (NIR - RED)/(NIR + RED).-- eq (1)

NIR – reflection in the near-infrared spectrum, RED – reflection in the red range of the spectrum. According to this equation, the density of vegetation (NDVI) at a certain point of the image is equal to the difference in the intensities of reflected light in the red and infrared range divided by the sum of these intensities.

This index defines values from -1.0 to 1.0, basically representing greens, where negative values are mainly formed from clouds, water and snow, and values close to zero are primarily formed from rocks and bare soil. Very small values (0.1 or less) of the NDVI function correspond to empty areas of rocks, sand or snow. Moderate values (from 0.2 to 0.3) represent shrubs and meadows, while large values (from 0.6 to 0.8) indicate temperate and tropical forests. Crop Monitoring successfully utilizes this scale to show farmers which parts of their fields have dense, moderate, or sparse vegetation at any given moment.

Put simply, NDVI is a measure of the state of plant health based on how the plant reflects light at certain frequencies (some waves are absorbed and others are reflected).

Chlorophyll (a health indicator) strongly absorbs visible light, and the cellular structure of the leaves strongly reflect near-infrared light. When the plant becomes dehydrated, sick, afflicted with disease, etc., the spongy layer deteriorates, and the plant absorbs more of the near-infrared light, rather than reflecting it. Thus, observing how NIR changes compared to red light provides an accurate indication of the presence of chlorophyll, which correlates with plant health.

*2.VARI*

The Visible Atmospherically Resistant Index (VARI) was designed and tested to work with RGB sensors. VARI is a measure of "how green" an image is. VARI is not intended as a substitute for an NIR camera, but it is meaningful when working with non-NDVI imagery. RGB images with the 65 VARI algorithm applied make it possible to detect areas of crop stress in a field. VARI is given by the formula VARI=(Green - RED)/(Green + Red - Blue) -- eq (2)

VARI works on RGB images. It uses 3 bands present in the image to calculate the index. VARI was designed and tested to work with RGB data rather than near-infrared (NIR) data. Unlike NDVI, VARI does not need near-infrared band

## V. METHODOLOGY EMPLOYED

The images used by our system have to be uploaded by the user. The images can be clicked by a drone or a normal smartphone camera. The images have to be in RGB images and in the format of .jpg and .png. After the images are uploaded by the user, these images are run under a python script. This script implies the above mentioned algorithms on the images. These algorithms apply their formula on each pixel, hence each pixel is having a different value.

After the algorithms are implemented, these pixel values are given out in the form of an array. Using the matplotlib library, these pixel values are plotted on a color map, which gives us our resulting image.

Values which are greater than one, indicate the presence of plants. Also, greater the number, higher the health. Hence for all the pixels having values greater than 1, when mean is calculated, the resulting value gives us the overall health of the plants present in the image or whole farm. This will give the user or the farmer an idea about the health of the plants in his farm, which will then help him to implement various agricultural techniques to get a better yield off his farm.

## V. RESULTS

Our system applied both the above mentioned algorithms on the above mentioned sample image, and the results that were obtained were quite satisfactory. When NDVI algorithm was implemented, the following result was obtained.

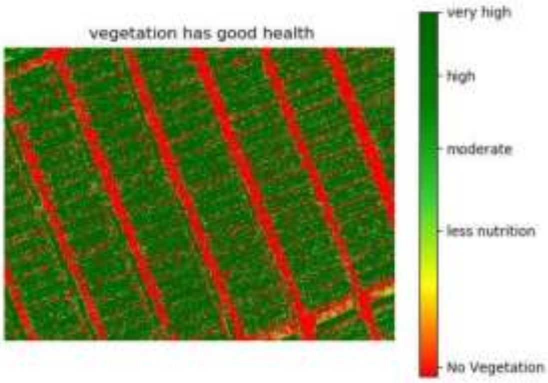


Fig.2. Results of NDVI Algorithm

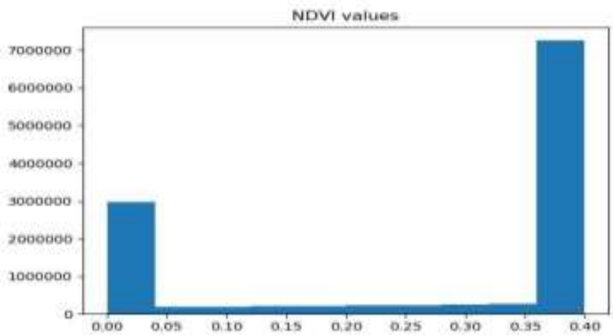


Fig.3. Histogram of values obtained from NDVI Algorithm

When the VARI algorithm was implemented on the same image, following was the result that we obtained.

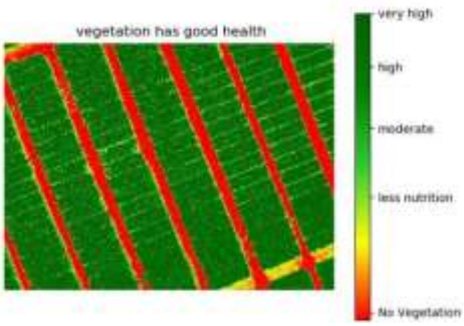


Fig.4. Results of VARI Algorithm

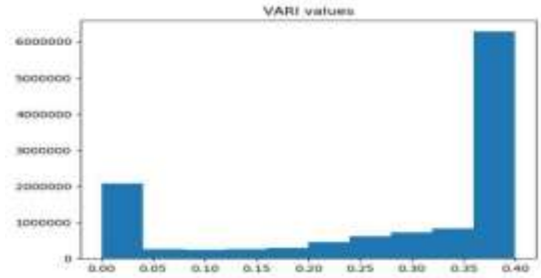


Fig.5. Histogram of values obtained from VARI Algorithm

The mean value obtained by implementing NDVI algorithm was found to be 0.35630289217371525 and that of VARI algorithm was found to be 0.33381966992694134. Which means that both of these algorithms have almost 94% similarity. Which means that the NDVI algorithm, which is always highly spoken of, has a good substitute, which can be used whenever obtaining the near infrared images is a constraint.

## V. CONCLUSION AND FUTURE WORK

The systems which already exist have quite a few shortcomings . So We have tried to overcome those shortcomings to a certain extent and tried to find an efficient solution for those shortcomings. The NDVI algorithm requires the image to be either captured by a satellite or by a multispectral camera with the help of a drone. Satellite captured images are not available for use publicly, and multispectral cameras and drones are way too expensive which will not be affordable by middle class farmers. With our system, These algorithms can work on images that are captured using a normal drone or a mobile phone camera too. With our system, the total cost required is very minimal, which a farmer can afford easily. As like existing systems our system does not need any fancy software or hardware tools. This works even on a normal mobile phone. With our system, images can be clicked using a normal camera, without the need of fancy multispectral cameras.

In future, we are planning to work with drone experts, with their help farmers will be able to capture the pictures of their whole farm at once, at a minimal rate. A separate portal will be added in our system for the drone experts, where they can register themselves and mention what type of drones or tools they have. Farmers who are in need of drone experts, can search for them in this portal and contact them accordingly. Also based on the quality and health of the plants in their farm we are planning to advise and educate farmers about which agricultural methods should they use to get a better yield off their farm. We are also planning to integrate this system with a drone, and make it a IOT based project. A drone that will calculate the health of the plants on the go, which will be very affordable cost wise.

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