

Satellite Image Analysis

Lohith Ramesh^a, Nithin Jain^b, Rithvik. B. Reddy^c

^aLohith Ramesh, Bristol, United Kingdom

^bNithin Jain, Bengaluru, India

^cRithvik. B. Reddy, Boston, USA

Abstract

Satellite image processing is an important area of research nowadays due to its wide range of applications. Researchers and scientists have paid attention to satellite image processing to capture information from them. Satellite image analysis poses a great challenge to researchers due to high variability, low resolution, and large data on satellite images. A lot of work has been done for satellite image analysis that covers the research from the classification of hand-crafted features to applying high-performance computing on satellite images. The researchers have achieved great success in satellite image analysis. However, a systematic review, which will lead researchers to identify the problem and contribute to this field, is missing. In the presented chapter, an attempt has been made to present a detailed review of the various steps of satellite image processing, classification and available databases. This chapter will give an impetus towards further research in this field and will provide a baseline to research in the field of satellite image processing.

Keywords: Satellite Image Processing; Remote Sensing; Google Earth Engine (GEE); Landsat Program; Sentinel Satellite; Normalized Difference Vegetation Index (NDVI); Image Classification; Feature Extraction; Spectral Resolution; Spatial Resolution; Time-Series Analysis; Multispectral Imaging; Hyperspectral Imaging; Change Detection; Land Cover Mapping; Vegetation Health Monitoring; Deforestation Monitoring; Urbanization Analysis; Disaster Management; Precision Agriculture; Forestry Monitoring; Environmental Monitoring; Cloud Computing in Remote Sensing; Big Data Analytics in Earth Observation; AI and Machine Learning in Remote Sensing; Image Enhancement; Data Visualization in Remote Sensing; Cloud Removal in Satellite Imagery; NDVI-based Crop Analysis; Quantum Algorithms in Remote Sensing.

Nomenclature

NDVI - Normalized Difference Vegetation Index, a measure of vegetation health using satellite imagery.

GEE - Google Earth Engine, a cloud-based platform for geospatial analysis.

Landsat - A series of Earth observation satellites managed by NASA and USGS.

Sentinel-2 - A satellite mission by the European Space Agency for Earth observation.

Remote Sensing - The process of acquiring data about Earth's surface using satellites or airborne sensors.

Spectral Resolution - The ability of a satellite sensor to differentiate between different wavelengths of light.

Spatial Resolution - The size of the smallest feature that a satellite image can capture.

Radiometric Resolution - The ability of a sensor to detect variations in brightness levels.

Temporal Resolution - The frequency at which a satellite revisits and captures data for the same location.

Change Detection - The process of identifying changes in land use or vegetation over time using satellite images.

Image Classification - The categorization of pixels in satellite images into meaningful land cover types.

Big Data in Remote Sensing - The handling and processing of large-scale satellite datasets.

Multispectral Imaging - Capturing image data at different wavelengths of the electromagnetic spectrum.

Hyperspectral Imaging - A technique that collects and processes information across a large number of spectral bands.

Feature Extraction - IDENTIFYING and isolating significant features from satellite images for analysis.

Cloud Masking - The process of removing cloud interference from satellite imagery.

Land Cover Mapping - The classification of land into different categories such as urban, forest, or water bodies.

Time-Series Analysis - Analyzing changes in satellite images over different periods.

False Color Composite - A visualization technique where non-visible bands (such as infrared) are displayed as colors.

Vegetation Index - A quantitative measure of vegetation health derived from spectral reflectance.

Pixel-Based Classification - A classification method that assigns categories to individual pixels.

Object-Based Classification - A technique that groups pixels into meaningful objects before classification.

Cloud-Free Compositing - Merging multiple satellite images to remove cloud-covered areas.

1.1. Introduction

At present, tabular and time-series data, Data Scientists or Data Analysts can also draw information and insight from image data. This will demonstrate satellite image analysis using Google Earth Engine, referred to as Earth Engine. Satellite images are raster data, just like any image. What makes them different is that satellite images have spatial attributes. Each pixel represents a location in the real world. Analyzing satellite images means we are going to get information on what is in our study area. The science focusing on studying this field is Remote Sensing.

The growing demand for natural resources has caused major environmental impacts and is changing landscapes everywhere. Conversion of land cover due to human use is one of the key factors behind greenhouse gas emissions and biodiversity loss. The spatial quantification of land use and land cover change allows societies to understand the extent of these impacts. Satellites are required to generate land cover products since they provide a consistent, periodic, and globally reaching coverage of the planet's surface. Thus, satellite-based land cover products are essential to support evidence-based policies that promote sustainability.

The integration of historical map classification and satellite images is a novel attempt to detect the everchanging land/water features on the earth. Satellite images captured over some time on a specific region are used to identify the increase/decrease in the region. These data are further used to create accurate maps for all practical applications. Satellite image processing is one of the significant computational methods that finds application in military, agriculture, natural disaster prevention, natural resource identification and so forth. However, satellite image processing is extremely complex due to the large dimensions of the satellite images. Remote sensing images contain a large amount of information, and if the image quality is not good or if the image analysis does not use an optimum feature set, then the impact of the remote sensing application for which the technique is used may not be fully utilized. The visual interpretation of remote sensing images utilizes different elements of interpretation such as shape, hue, tone, texture and so forth. Manual interpretation is limited to analyzing only a single image at a time due to the difficulty in multiple image interpretation. Manual interpretation is subjective, and time for visual classification depends mainly on the image quality. So, image processing tools play a major role in applications about remote sensing. Remote sensing methods are considered as a complementary tool in various applications due to the wide range of areas the images can cover. The usefulness of satellite images to remote sensing applications depends on the accuracy of the techniques. A good understanding of how well the image processing techniques perform will help in deciding the best choice of methods for various applications.

With the enhancement of technology, the demand for near-real-time monitoring and visual images for use in emergency services and the public in the case of a natural disaster is increasing. Recent advancements in earth monitoring satellites are making their way towards use in such applications. Methods are thus being developed to utilize the available data effectively to make sure that the best possible intelligence is available to emergency services and decision makers on time. While a vast amount of digital satellite and aerial imagery is available, the real challenge is in the analysis of raw images, extraction of useful information with high accuracy and applying it to real world decision making and applications.

Even though there are various image processing techniques available, conventional methods need to be critically reviewed, and image understanding concerning features of interest is important. With the advances in artificial intelligence and machine learning, there is an improvement in the extraction of detailed features from high-resolution aerial imagery. The fin different layers are utilized for developing various image processing techniques. Several methods have already been explored to process satellite images efficiently. Still, there is plenty of room for performance improvement of the conventional system. A detailed understanding of the conventional methods is extremely necessary to develop new automated systems for satellite image processing. In this work, an exhaustive survey is presented on the various aspects/applications of satellite image processing.

The pros and cons of the methods are also presented, which will aid in developing novel solutions for the current problems in satellite image processing.

The emergence of cloud computing services capable of storing and processing big EO data sets allows researchers to develop innovative methods for extracting information. One of the relevant trends is to work with satellite image time series, which are calibrated and comparable measures of the same location on Earth at different times. These measures can come from a single sensor like MODIS or by combining various sensors like Landsat 8 and Sentinel-2.

A multiyear time series of land cover attributes enables a broader view of land change. Time series capture both gradual and abrupt changes. Researchers have used time series in applications such as forest disturbance, land change, ecological dynamics, agricultural intensification, and deforestation monitoring. Satellite image analysis has become an increasingly important tool for understanding and monitoring our planet.

Satellite images provide a wealth of information about the Earth's surface, from natural features such as forests, oceans, and mountains to human activities such as agriculture, urbanization, and industrial development. By analyzing satellite images, we can gain insights into a wide range of environmental, social, and economic phenomena and monitor changes over time.

One key technique used in satellite image analysis is the calculation of the Normalized Difference Vegetation Index (NDVI). The NDVI is a measure of vegetation health and density based on the differential absorption of red and near-infrared light by plants. It is calculated as the ratio of the difference between near-infrared and red reflectance to their sum, and ranges from -1 to +1, with higher values indicating greater vegetation density and health. The NDVI is widely used for a variety of applications, including monitoring crop health, mapping vegetation cover, and detecting land use and land cover changes.

To perform satellite image analysis using NDVI, a variety of satellite data sources can be used. One commonly used source is Landsat, a series of Earth observation satellites operated by the United States Geological Survey (USGS). Landsat collects images at a spatial resolution of 30 meters, with a revisit time of 16 days, making it a useful tool for monitoring changes over time. Other sources of satellite data include Sentinel-2, a European Space Agency (ESA) satellite that collects images at a higher spatial resolution of 10 meters, with a revisit time of 5 days.

Satellite image analysis typically involves several key steps, including data acquisition, pre-processing, image enhancement, feature extraction, and data visualization. In the data acquisition stage, satellite images are obtained from the relevant data archive, such as the USGS Earth Explorer or the ESA Sentinel Hub. The images are then pre-processed to correct for atmospheric effects, such as haze and cloud cover, and to convert the raw data into a usable format, such as radiance or reflectance.

Once the data has been pre-processed, image enhancement techniques can be used to improve the quality and visibility of the images. Common enhancement techniques include contrast stretching, color balancing, and histogram equalization. These techniques can help to bring out important features in the images and improve their interpretability.

After image enhancement, feature extraction techniques can be used to identify and quantify specific features in the images, such as vegetation cover, water bodies, and urban areas. These techniques can include spectral analysis, texture analysis, and machine learning algorithms. The NDVI is a key feature that can be extracted from satellite images to assess vegetation health and density.

Finally, data visualization techniques can be used to present the results of satellite image analysis in a meaningful and intuitive way. Common visualization techniques include color maps, 3D visualizations, and time series graphs. These techniques can help to highlight patterns and trends in the data and communicate the results to stakeholders and decision-makers.

Overall, satellite image analysis using NDVI is a powerful tool for monitoring and understanding our planet. By analyzing satellite images, we can gain insights into a wide range of environmental, social, and economic

phenomena and monitor changes over time. With advances in satellite technology and data processing techniques, satellite image analysis is becoming an increasingly important tool for environmental monitoring, disaster response, and sustainable development.

1.2. Proposed System

This process aims to analyze images and return the Normalized Difference Vegetation Index (NDVI) using Landsat 8 images, too. NDVI is an index commonly used in satellite image analysis to get basic information on vegetation distribution. Then, the NDVI values are divided into 5 classes and mapped. Finally, show how to export the result.

1.3. Objectives

- Selecting the region of interest (ROI) or area of interest (AOI).
- Obtaining the Landsat satellite images of the region of interest for the given period.
- Filtering the obtained image and obtaining the composite image.
- Compute the NDVI and display the NDVI raster in green-yellow-black gradation.
- Obtaining the classified NDVI.

2.1 Literature Survey

1. LP Aswathi, K Anoop, "An Efficient Content Based Remote Sensing Image Retrieval Using Artificial Neural Network", 2020 International Conference on Smart Electronics and Communication (ICOSEC), pp.610-614, 2020.

Abstract - Remote sensing is being used in different fields, such as agriculture, research, etc. Remotely sensed images contain complex visual contents. This paper explains the content-based remote sensing image retrieval using ANN. In the remote sensing method, the sensors, which will be fixed on an aircraft or satellite, are used for capturing remote sensing images. Due to the increase in the use of remote sensing technology and the number of satellites used, the volume of image datasets is increasing exponentially. Content-based remote sensing Image Retrieval is used to reduce the difficulty in managing large volumes of earth data.

2. Manuel Henriques, Duarte Valério, Rui Melicio, "Fractional Order Processing of Satellite Images", Applied Sciences, vol.11, no.11, pp.5288, 2021.

Abstract - Nowadays, satellite images are used in many applications, and their automatic processing is vital. Conventional integer grey-scale edge detection algorithms are often used for this. This study shows that the use of color-based, fractional order edge detection may enhance the results obtained using conventional techniques in satellite images. It also shows that it is possible to find a fixed set of parameters, allowing automatic detection while maintaining high performance.

3. K. Jagruth, V. M. Manikandan, Ravi Kant Kumar "Water Body Identification from the Satellite Images using Color Component Analysis with Morphological Operations" IEEE publications, July 2021, vol 04, Pp: 05

Abstract - Many countries, including India, are frequently affected by natural disasters like floods. In general, predicting natural disasters accurately is very difficult, but advanced technologies can be utilized to overcome such difficulties or to reduce the impact of natural disasters. Satellite image processing is one of the efficient ways to detect water bodies in earth regions, which may help the agriculture industry or to identify the flooded regions. In this paper, we propose a scheme to identify the water bodies from the satellite images, which will be useful for various applications. During our research, we created a set of water body images by cropping satellite images. The properties of the water body regions were analyzed using an algorithm and computed a set of possible threshold values for the pixels representing the water bodies. The threshold values obtained from the analysis of „water body images' are used in the proposed algorithm to identify water bodies in any given image. A sequence of morphological operations is introduced to refine the results that are obtained through pixel color component analysis. The result analysis is carried out on a set of satellite images, and it achieved good results.

4. Kyu-Yul Lee, Jae-Young "SimCloud Removal of Satellite Images Using Convolutional Neural Network with Reliable Cloudy Image Synthesis Model" 2019 IEEE International Conference on Image Processing (ICIP).

Abstract - Cloudy pixels in satellite images degrade the visibility of captured surface structure. We propose a novel cloudy image synthesis model and develop a cloud removal algorithm using a convolutional neural network. We extract the cloud masks from real cloudy satellite images and real sky images with clouds. Then, we investigate the characteristics of real cloudy images and devise a reliable cloudy image synthesis model that considers the background surface color, misalignment of channel images, and blur in clouds. We train a hierarchical cloud removal network using the synthetic cloudy images. Experimental results demonstrate that the proposed algorithm removes the clouds from cloudy satellite images faithfully and outperforms the existing methods.

5. Tongying LI, Hongbo ZHU "Research on Color Algorithm of Gray Image Based on a Color Channel". IEEE publications and 2020 Chinese Control and Decision Conference (CCDC), vol 08, pp: 03

Abstract - Traditional grayscale image colorization methods generally have problems such as distortion and inaccuracy, such as pseudo color enhancement and false color processing. This paper uses a more accurate and better color implementation algorithm. First, the source image and the target image are converted from the RGB channel into the $\lambda\beta$ channel, and then the similarity of the pixels in the source image is determined and compared by comparing the similarities of the pixels between the two images, and then the target image is colored. transfer. Finally, the image can be converted from the $\lambda\beta$ space to the RGB space. This paper elaborates on the theoretical basis, formula steps, program implementation, and superiority of the algorithm compared with traditional image processing methods.

3 Methodology

3.1 Introducing Google Earth Engine (GEE):

Google Earth Engine is a cloud-based geospatial analysis platform that enables users to visualize and analyze satellite images of our planet. Scientists and non-profits use Earth Engine for remote sensing research, predicting disease outbreaks, natural resource management, and more. Your students can access this information to join the discussion and become data scientists themselves.

Google Earth Engine brings together more than 40 years of historical and current global satellite imagery, along with the tools and computational power necessary to analyze and mine that vast data warehouse. As a planetary-scale platform for environmental data analysis, it is an invaluable tool to deepen the knowledge of the implications of climate change and much more. The Time-lapse project shows the power of Earth Engine by creating an interactive viewer showing cloud-free, global land coverage changes across 32 years.

3.1.1 Setting up the Google Earth Engine:

The steps below demonstrate how to open Earth Engine and execute a script that displays an image.

1. Create an account in Google Earth engine.
2. Open the Earth Engine Code Editor.
3. If there is any specific region to analyze, then we can select a particular region.
4. Navigate to the scripts tab located on the far left of the Code Editor and enter the code.
5. Under “Image Collection,” select “Filtered Composite.”
6. Click on the RUN button to execute the code.

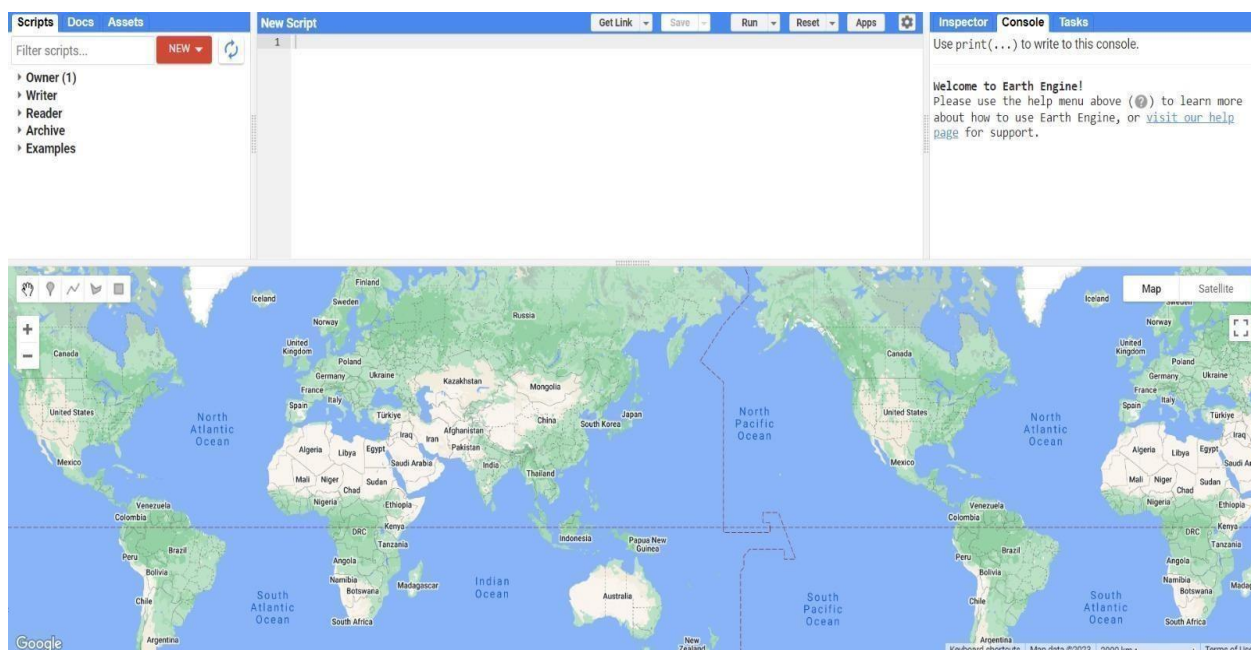


Fig 1: Google Earth Engine

3.2 Landsat Program:

The Landsat Program is a series of Earth-observing satellite missions jointly managed by NASA and the U.S. Geological Survey.

In 1972, in cooperation with NASA, the Earth Resources Technology Satellite (ERTS-1) was launched. It was later renamed Landsat 1. Additional Landsat satellites have been launched to bring the world an archive of remote sensing data. Currently orbiting and active satellites are Landsat 8 and Landsat 9.

NASA and USGS are already planning the development of the follow-on SLI missions, including Landsat Next, the successor mission to Landsat 9.

Landsat satellites have the optimal ground resolution and spectral bands to efficiently track land use and to document land change due to climate change, urbanization, drought, wildfire, biomass changes (carbon assessments), and a host of other natural and human-caused changes.

The Landsat Program's continuous archive (1972-present) provides essential land change data and trending information not otherwise available. Landsat represents the world's longest continuously acquired collection of space-based moderate-resolution land remote sensing data. Landsat is an essential capability that enables the U.S. Department of the Interior to wisely manage Federal lands. People around the world are using Landsat data for research, business, education, and other activities.

3.2.1 List of Satellites in Landsat Program:

Name of Satellite	Launch Year
Landsat 1	1972
Landsat 2	1975
Landsat 3	1978
Landsat 4	1982
Landsat 5	1984
Landsat 6	1993
Landsat 7	1999
Landsat 8	2013

3.2.2 Sentinel V/S Landsat Satellite:

Spatial resolution:

Spatial resolution is the size of the smallest feature that a sensor can detect on the ground. It is usually measured in meters or kilometers per pixel. For example, a sensor with a spatial resolution of 10 meters can distinguish objects that are at least 10 meters apart. A higher spatial resolution means more detail and clarity but also more data and storage. Landsat sensors have a spatial resolution of 15 to 60 meters, depending on the band. Sentinel sensors have a spatial resolution of 10 to 50 meters, depending on the band and the mode.

Spectral resolution:

Spectral resolution is the number and width of the spectral bands that a sensor can record. Each band corresponds to a range of wavelengths of the electromagnetic spectrum, such as visible light, infrared, or microwave. Different bands can reveal different information about the surface features, vegetation, water, or atmosphere. A higher spectral resolution means more bands and more diversity but also more complexity and noise. Landsat sensors have 8 to 11 bands, covering the visible, near-infrared, shortwave infrared, and thermal infrared regions. Sentinel sensors have 13 to 25 bands, covering the visible, near-infrared, shortwave infrared, and microwave regions.

3.3 Introducing NDVI:

NDVI, or Normalized Difference Vegetation Index, is a remote sensing method that uses the reflectance of light in the visible and near-infrared (NIR) wavelengths to determine the amount and health of vegetation in an area. NDVI is widely used in agriculture, forestry, and ecology to monitor the growth and health of vegetation and to identify areas of stress or damage. NDVI values can also be used to map and classify vegetation types and to detect changes in vegetation cover over time.

Simply put, the Normalized Difference Vegetation Index is an indicator of a plant's health entirely based on how the cell structures reflect the different light waves in visible and near-infrared bands.

In other words, it aids in detecting and quantifying the presence of live green vegetation based on how objects interact with light. To understand the plant's health condition, one needs to compare the absorption and reflection values of red and NIR (near-infrared) light. Here is where NDVI comes into the picture.

How is NDVI calculated?

Plants have a unique reflectance characteristic; they reflect more near-infrared (NIR) light and absorb more visible light. When plants are healthy, they have a high chlorophyll content, which allows them to absorb more light in the red region of the spectrum and reflect more light in the NIR region. So NDVI uses this characteristic of plants to differentiate healthy vegetation from non-vegetation or unhealthy vegetation.

NDVI is calculated by subtracting the reflectance of the NIR band from the reflectance of the red band and then dividing that value by the sum of the reflectance of the NIR and red bands. NDVI values range from -1 to 1, with -1 indicating no vegetation, 0 indicating bare soil or water, and values closer to 1 indicating greater amounts and healthier vegetation.

In mathematical terms, comparing the red and near-infrared light signals can help differentiate between healthy and sick plants or distinguish non-plants from plants.

Look at the formula below for the evaluation of NDVI:

$$\text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red}) \quad (1)$$

Now, the values range from -1 to +1. A higher or more positive value indicates greater plant vigor and general health. Generally, healthy vegetation, which contains a good measure of chlorophyll and cell structures, tends to absorb a significant amount of visible light while reflecting NIR light. On the other hand, unhealthy vegetation does the opposite; it reflects more visible light while absorbing the NIR light. NDVI allows differentiating vegetation from non-vegetation or unhealthy vegetation using the unique reflectance characteristic of healthy plants and thus allows monitoring the growth and health of vegetation and identifying areas of stress or damage.

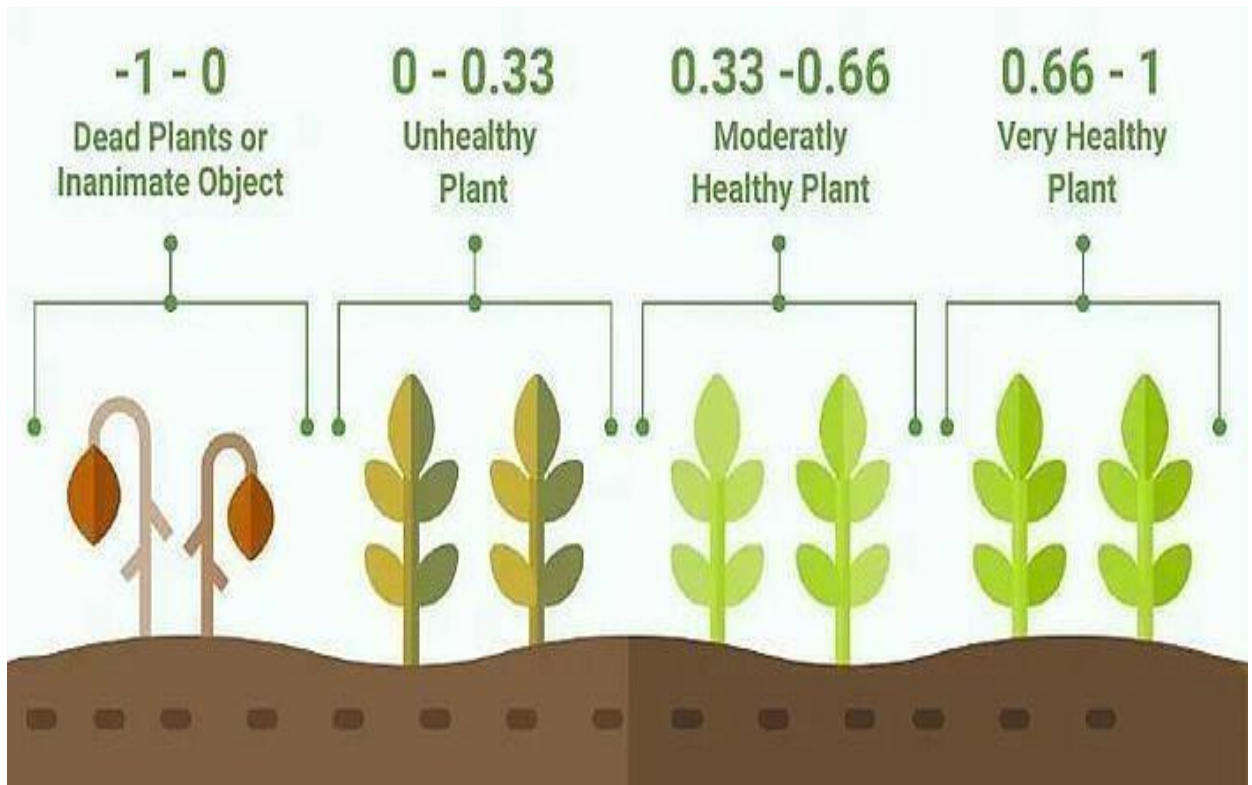
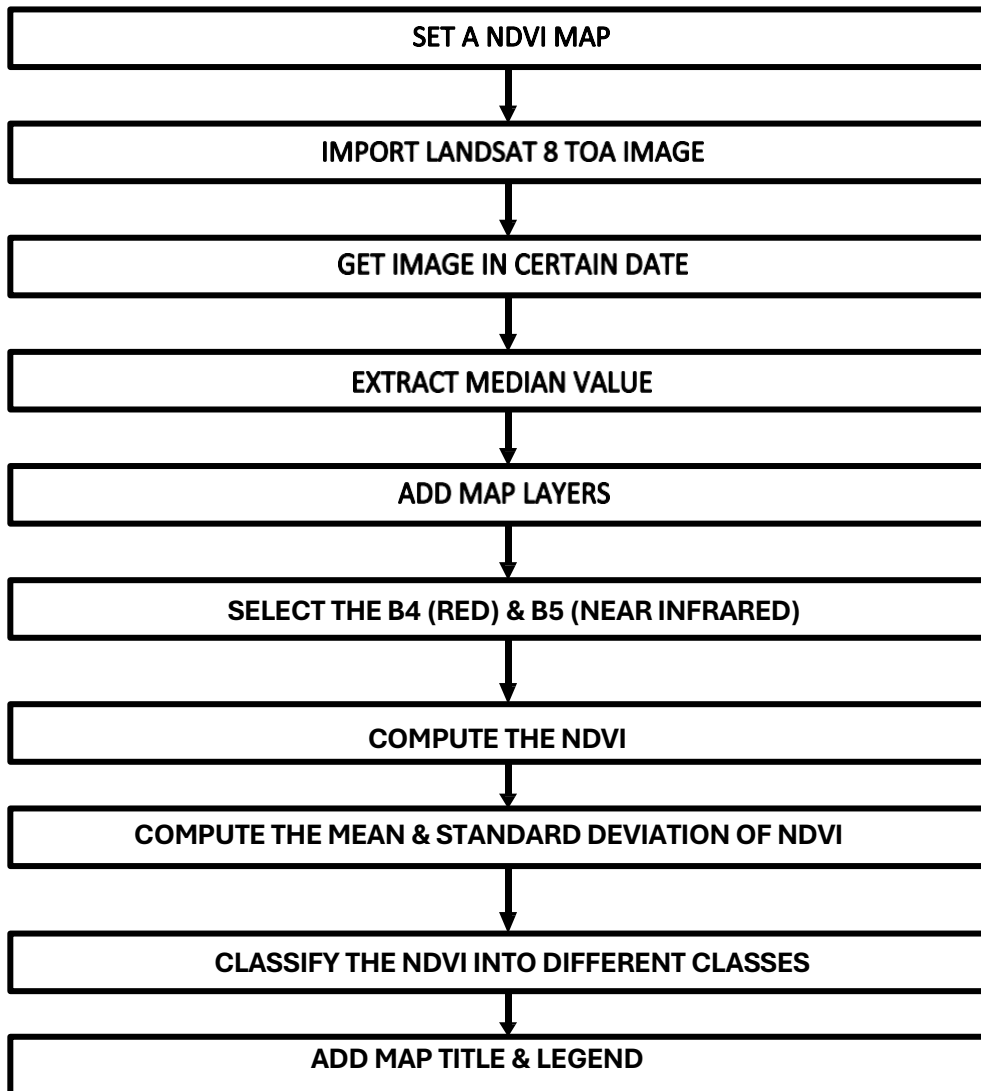


Fig 2: Normalized Difference Vegetation Index (NDVI)

4 Design and Implementation

4.1 Proposed System:



- Firstly, we decided the study area to analyze the image for NDVI. The red square is drawn to set the boundary of the study area.
- Then, we import Landsat 8 image collections for the study area. Landsat 8 images are available from 2013 until now. The loaded images are clipped using the red square and named “composite”.
- Now, we can visualize the image with composite bands 6, 5, and 4. This is the best composite to show vegetation in false color.

- The NDVI raster is displayed in green-yellow-black gradation. The green color represents a higher NDVI value, followed by the yellow color, and the black color represents the lower NDVI. Notice that the water body, like the sea, has a black color. The land has mostly a yellow color and a little green color. The pixel value can be identified using “inspector”.
- We then compute the overall average and standard deviation of the NDVI values.
- A better way to understand the NDVI result is by classifying the values. Here, we classify the NDVI values into 5 classes. Each class is symbolized with different colors. These classes are associated with the land cover.
- The next step is to add the map title and legend. The map title is “Map of NDVI”.
- Then we create the content of the legend, where we create the color boxes and set the box height and width and then create labels.
- Water is symbolized in brown color because of its lowest NDVI value.
- Settlements and aquaculture with NDVI values ranging from 0 to 0.2 are symbolized in orange.
- Yellow and light green classes are crops. Crops in the green class have higher NDVI than crops in the yellow class. This can mean that crops in the green class have higher density and higher yield or are healthier than those in the yellow class.

5 Results and Conclusion

5.1 Results:

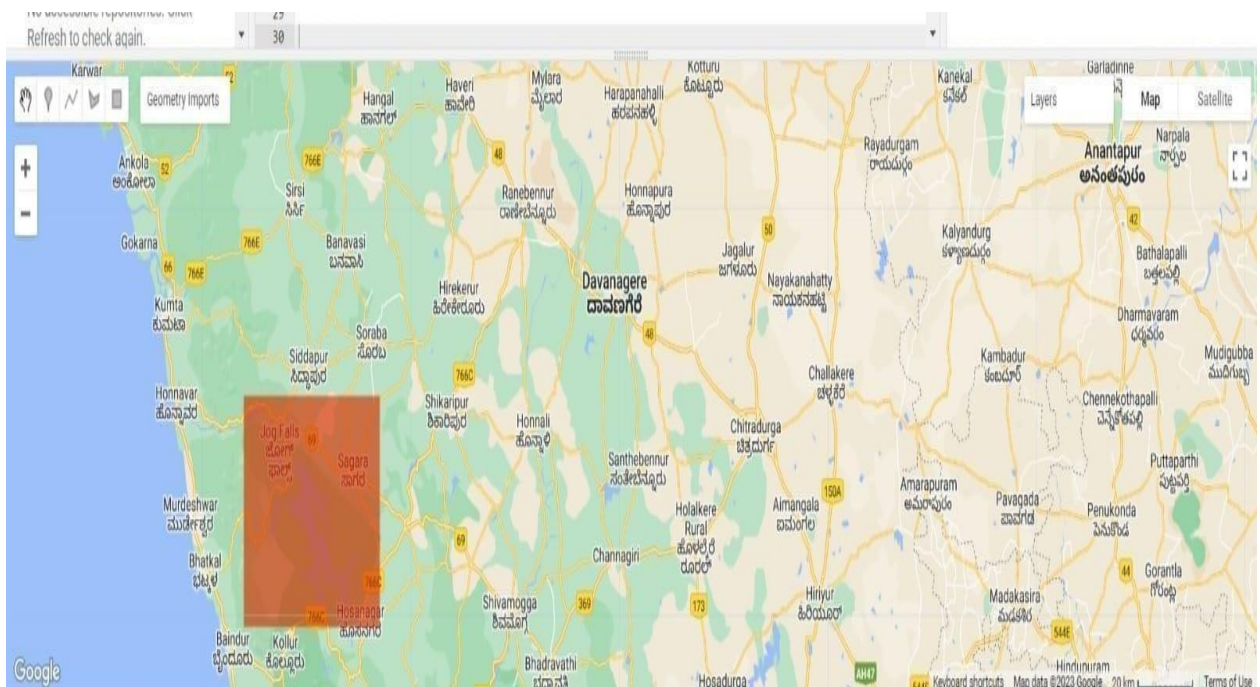


Fig 3: Region of Interest

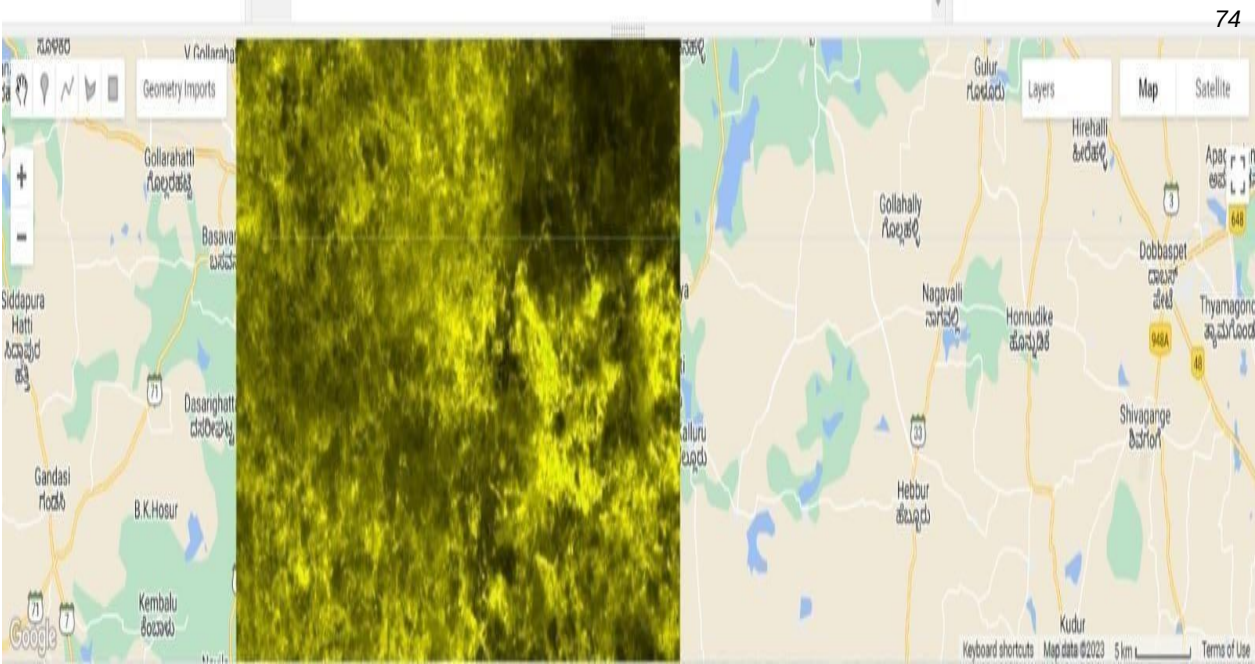
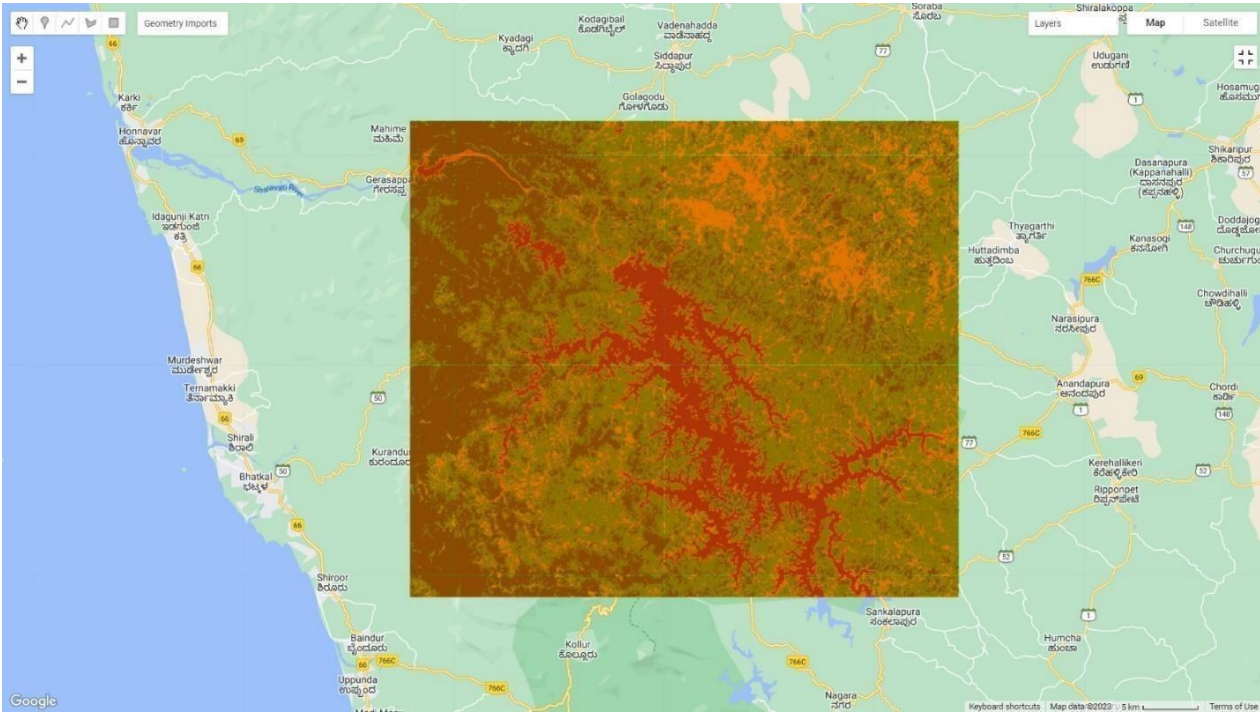


Fig 4: Continuous NDVI Image



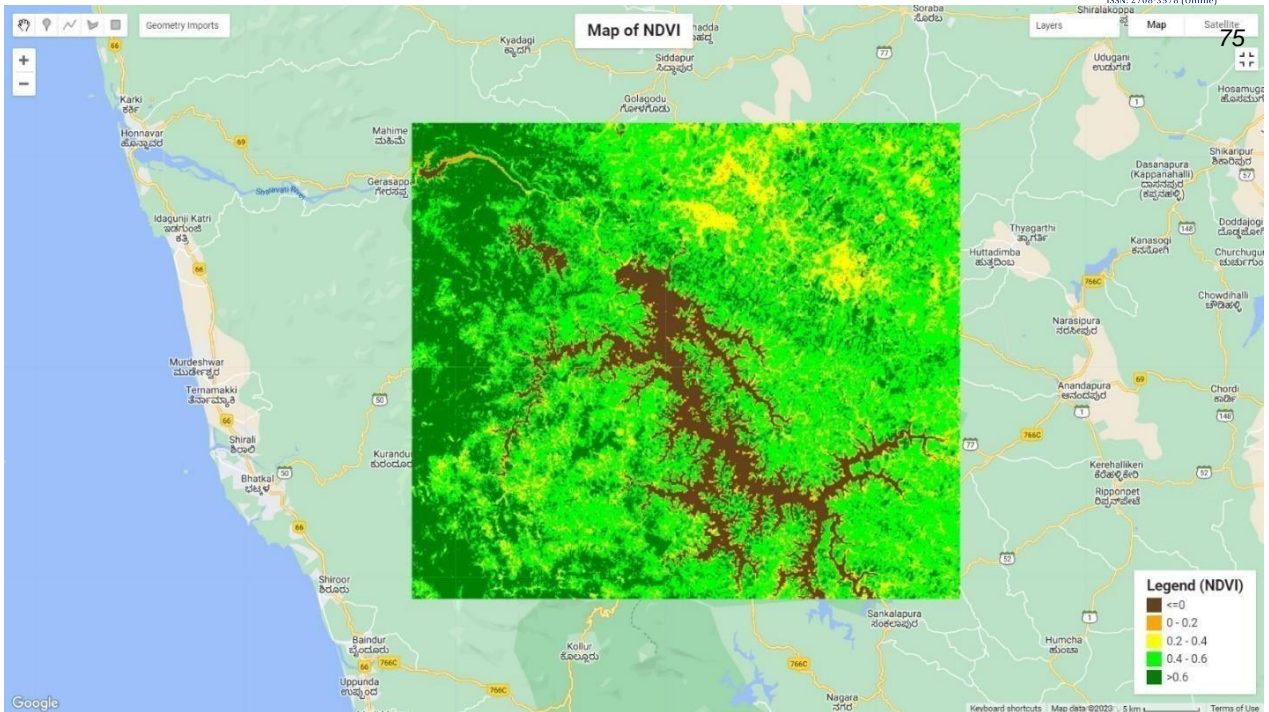


Fig 5: Classified NDVI Image

5.2 Conclusion:

In this study, a detailed review of the image processing techniques for satellite image analysis is presented. This work attempts to provide an insight into the importance of image processing techniques in remote sensing applications. A roadmap of the research activities in various image processing stages has been explained with relevance to remote sensing applications. With the emergence of technology and the frequent availability of satellite imagery, image processing in remote sensing is a topic of growing interest. The survey explores various image processing techniques and points out the advantages and limitations associated with these methods. Further, the techniques specific to various applications are discussed, and the performance measures are explained. Low contrast of satellite imagery, improper threshold selection for image segmentation, and misinterpretation of image pixels as part of change detection are some of the challenges in image processing. The complexity of satellite images further poses a difficulty in real-world classification applications and can be solved by involving computationally intelligent paradigms.

The quality of the input image and the complexity of image features are some factors responsible for deciding the image processing technique to be applied. Research is currently being extended into hybridized image processing techniques to improve the robustness of the existing techniques. The future work can be extended to apply the explained techniques in various practical areas in remote sensing and extending the implementation of quantum algorithms for remote sensing applications.

6.1 Applications

The Normalized Difference Vegetation Index (NDVI) is a widely used remote sensing technique with a variety of applications in agriculture, forestry, and environmental monitoring. Some specific examples of how NDVI is used in these fields include:

1. NDVI in Agriculture

NDVI is commonly used to monitor the health and productivity of crops. It can help farmers identify areas of the field that may be stressed or experiencing nutrient deficiencies and can be used to optimize irrigation and fertilization practices. NDVI can also be used to monitor the growth and development of crops over time and to estimate yields.

NDVI can also be used in precision agriculture, which is the use of technology to optimize crop management decisions. NDVI values can be used to identify variations in crop growth and health and to target specific management practices, such as fertilization and irrigation, to areas of the field that need it most. This can lead to more efficient use of resources and can improve crop yields and quality.

2. NDVI in Forestry

NDVI can be used to assess the density and health of forests and to monitor changes in forest cover over time. It can help identify areas of the forest that may be experiencing stress or damage due to pests, diseases, or other factors. NDVI can also be used to estimate the biomass and carbon sequestration potential of forests. NDVI can be used to monitor the health of forests over large areas by detecting changes in vegetation cover, such as changes in canopy cover, leaf area index, and biomass.

NDVI can be used to detect changes in forest structure, such as changes in the density of trees, and to identify areas of forest regeneration. NDVI can also be used to monitor the effects of forestry management practices, such as clear-cutting, thinning, or prescribed burning, on forest growth and health.

3. NDVI for Environmental Monitoring

NDVI can be used to monitor the health and productivity of vegetation in natural ecosystems, such as grasslands, savannas, and wetlands. It can be used to detect changes in vegetation cover due to human activities or natural events, such as deforestation, land use change, and drought. NDVI can also be used to monitor the recovery of vegetation after disturbances, such as fires or floods.

NDVI can be used to detect changes in vegetation cover, such as changes in canopy cover, leaf area index, and biomass. NDVI can also be used to detect changes in ecosystem structure, such as changes in the density of vegetation, and to identify areas of ecosystem regeneration.

NDVI can also be used to monitor the effects of environmental management practices, such as restoration, conservation, or reforestation, on ecosystem health. NDVI values can be used to identify areas that are recovering well from management practices and to detect areas that are not recovering as well.

4. NDVI aids in tracking Crop Health.

Most scientists and agronomists prefer NDVI as an ideal tool for tracking crop health. Primarily, they capture a series of NDVI maps to keep a close check on crop health. It is applicable during the growing season and from year to year.

These NDVI values, when averaged, can help determine the normal growing conditions of crops in a particular area and at a given time of the year.

NDVI data can be used to identify nutrient deficiencies in crops. For example, low NDVI values in certain areas of the field may indicate that the crops in those areas are experiencing a deficiency of a specific nutrient, such as nitrogen or phosphorus. This information can help farmers to target fertilization practices to address the deficiency and improve crop health.

5. NDVI helps Agronomists develop Variable Prescription Maps

With NDVI maps, agronomists and other stakeholders can identify nutrient deficiencies, conduct the much-needed ground-truthing, and then upload the data on a farm ERP solution like Crop in, a revolutionary in promoting and making precision farming possible.

NDVI data can be used to optimize irrigation schedules by identifying areas of the field that are most in need of water. For example, if NDVI values are lower in certain areas of the field, this may indicate that the crops in those areas are stressed and may benefit from additional irrigation.

Consequently, farmers and farming companies need not spend extra anymore. With data-backed advisories from agronomists, they can spray, and seed only as needed to save time, money, and resources significantly.

6. NDVI helps Scout Fields Faster

The traditional physical process of assessing or tracking a field can be more detrimental to the crops. Plus, it is time-consuming and labor-intensive. On the other hand, with NDVI, you can identify the problem areas sooner and take the necessary steps to improve crop health and yield. An absolute win-win situation for both the farmer and the associated brand!

7. NDVI helps identify crop problems sooner.

NDVI also helps agronomists identify stressed crops up to 2 weeks before the naked eye can see. Since crop stress is more apparent in the near-infrared light spectrum than in the visible one, it can aid growers to eliminate pests, diseases, fungi, and arid conditions sooner. In addition, consistently low NDVI values at the same place every crop cycle could indicate problems with drainage, soil pH, or even soil compaction.

Therefore, NDVI is now an indispensable part of precision farming that plays a direct role in maintaining crop health and yield. Crop in, a pioneering Agri-tech SaaS-based solution provider, acknowledges this aspect and has developed smart farming solutions that embrace and leverage the benefits of this versatile vegetation index.

8. NDVI helps indicate drought situations.

NASA made a case for using NDVI as an indicator of drought. NASA writes on its website, "more a plant is photosynthesizing, the more it is being productive". Conversely, the less sunlight the plant absorbs, it isn't productive." This gives us NDVI values over a period. When averaged, the NDVI values give a region's absorption/reflection capacity. Thus, NDVI indicates the health of the vegetation in that area compared to the average.

Armed with 20 years of NDVI data over the entire globe, NASA can now compare today's NDVI with the 20-year average to reveal if the productivity of a particular region is more, less, or the same. A region which is shown reduced plant growth characterized by lower NDVI values compared to average could be labeled as "in drought." Not always, though. Cloud cover and extreme cold can also cause lower-than-normal NDVI.

6.2 Limitations

1. Data collection becomes difficult if the sky is cloudy.
2. Exact height of any region or object cannot be calculated.
3. Development of satellite images incur high cost due to use of highly advanced technology.

4. NDVI is sensitive to variations in atmospheric conditions, such as clouds, haze, and aerosols, which can affect the reflectance of light in the visible and near-infrared (NIR) wavelengths. This can lead to errors in NDVI values and make it difficult to accurately interpret NDVI images.
5. NDVI can also be affected by sensor characteristics, such as spatial resolution, spectral resolution, and radiometric resolution, which can influence NDVI values.
6. The NDVI values can be affected by the sun angle, and NDVI values can change depending on the time of day or the time of year when the images are acquired.

Future Scope

Due to advances in image processing and related technologies, there will be millions and millions of robots in the world in a few decades, transforming the way the world is managed. Advances in image processing and artificial intelligence will involve spoken commands, anticipating the information requirements of governments, translating languages, recognizing, and tracking people and things, diagnosing medical conditions, and performing surgery. The future trend in remote sensing will be towards improved sensors that record the same scene in many spectral channels.

Currently, NDVI data is often collected at regular intervals and analyzed retrospectively. In the future, there may be more efforts to use NDVI data in real time, enabling farmers and other users to make more timely and informed decisions.

The future of NDVI technology is likely to involve further advancements in sensor technology, such as the use of hyperspectral and multispectral sensors, which can provide more detailed and accurate information about vegetation. Additionally, the integration of NDVI technology with other data sources, such as weather and soil data, will enable more sophisticated analyses and applications, such as precision agriculture and monitoring of ecosystem health. With the increasing use of UAVs and satellites, NDVI will be available to more people, making it more accessible, cost-effective, and efficient.

References

1. Ping, X.; Bingqiang, C.; Lingyun, X.; Jingcheng, Z.; Lei, Z.; Hangbo, D. A new MNF– BM4D denoising algorithm based on guided filtering for hyperspectral images. *ISA Trans.* 2019, 92, 315–324.
2. Chang, Y.C. A flexible contrast enhancement method with visual effects and brightness preservation: Histogram planting. *Comput. Electr. Eng.* 2018, 69, 796–807.
3. Suresh, S.; Lal, S. Modified differential evolution algorithm for contrast and brightness enhancement of satellite images. *Appl. Soft Comput. J.* 2017, 61, 622–641.
4. Singh, H.; Kumar, A.; Balyan, L.K.; Singh, G.K. A novel optimally weighted framework of piecewise gamma corrected fractional order masking for satellite image enhancement. *Comput. Electr. Eng.* 2019, 75, 245–261.
5. Tang, S.; Wu, B.; Zhu, Q. Combined adjustment of multi-resolution satellite imagery for improved geo-positioning accuracy. *ISPRS J. Photogramm. Remote Sens.* 2016, 114, 125–136.
6. Vijayaraj, V.; Bright, E.A.; Bhaduri, B.L. Rapid damage assessment from high resolution imagery. *Int. Geosci. Remote Sens. Symp.* 2008, 3, 1445–1448.
7. Yuan, X.; Chen, S.; Yuan, W.; Cai, Y. Poor textural image tie point matching via graph theory. *ISPRS J. Photogramm. Remote Sens.* 2017, 129, 21–31.
8. Sedaghat, A.; Mohammadi, N. Uniform competency-based local feature extraction for remote sensing images. *ISPRS J. Photogramm. Remote Sens.* 2018, 135, 142–157.
9. Rathore, M.M.U.; Ahmad, A.; Paul, A.; Wu, J. Real-time continuous feature extraction in large size satellite images. *J. Syst. Archit.* 2016, 64, 122–132.
10. Zhang, L.; Sun, Q. Saliency detection and region of interest extraction based on multi-image common saliency analysis in satellite images. *Neurocomputing* 2018, 283, 150–165.

Appendix A. Supplementary Data and Figures

1. **List of Satellites in the Landsat Program** – A table summarizing all Landsat satellites, their launch years, and key specifications.
2. **Sentinel vs. Landsat Comparison Table** – A detailed comparison of the spatial, spectral, and temporal resolution of Sentinel and Landsat satellites.
3. **NDVI Calculation Formula & Example** – The NDVI formula with a sample calculation.
4. **Additional Figures** – Any large or supplementary figures such as:
 - Region of Interest (ROI) Selection (Figure 3)
 - Continuous NDVI Image (Figure 4)
 - Classified NDVI Image (Figure 5)

Appendix B. Google Earth Engine (GEE) Script

```
// Load the Landsat 8 Image Collection
var landsat = ee.ImageCollection("LANDSAT/LC08/C01/T1_TOA")
  .filterBounds(ee.Geometry.Rectangle([xmin, ymin, xmax, ymax])) // Define Region of Interest
  .filterDate('YYYY-MM-DD', 'YYYY-MM-DD') // Define Date Range
  .median(); // Composite Image

// Compute NDVI
var ndvi = landsat.normalizedDifference(['B5', 'B4']).rename('NDVI');

// Define Visualization Parameters
var ndviParams = {
  min: -1,
  max: 1,
  palette: ['black', 'yellow', 'green']
};

// Display NDVI on Map
Map.centerObject(landsat, 10);
Map.addLayer(ndvi, ndviParams, 'NDVI');

// Export NDVI Image
Export.image.toDrive({
  image: ndvi,
  description: 'NDVI_Image',
  scale: 30,
  region: ee.Geometry.Rectangle([xmin, ymin, xmax, ymax]),
  fileFormat: 'GeoTIFF'
});
```

Explanation of the Script:

1. **It loads Landsat 8 images** and filters them based on the **Region of Interest (ROI)** and **date range**.
2. **Compute NDVI** using the standard formula:

$$\text{NDVI} = (\text{NIR-Red}) / (\text{NIR+Red})$$

where:

- B5 (Near Infrared)
 - B4 (Red Band)
3. **Visualizes NDVI** using a color scale (black = low NDVI, green = high NDVI).
 4. **Export the NDVI image** as a GeoTIFF file for further analysis.