Surface Water and Vegetation Analysis using Satellite Images

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***Abstract*—Performing satellite image analysis by combining novel image processing and Machine Learning/Deep Learning techniques can give us meaningful insights about the impactful natural events that can affect human life. One of the popular uses of these images is in analysing the planet's surface water dynamics and subsequently it's effects on the vegetation/ecology over a study area. Monitoring the flow rate of surface water bodies and keeping track of vegetation is important as it helps to gauge the impact of human activities and their roles in climate change. In this project, we create an interactive tool for accessing the Landsat-8 satellite images.**

***Index Terms*—Remote Sensing; Landsat-8; Surface Water; Vegetation Analysis; Google Earth Engine; Automated Time Series**

I. Introduction

Petabytes of Satellite imagery data is generated everyday that map the physical, chemical and ecological events of our planet. They allow us to study the past and present state of the surface and can allows us to predict their future transformations, helping us in understanding climate change and natural phenomenons. The act of acquisition of information of an object or a phenomenon without getting in physical contact with it, is known as remote sensing.

Remote sensing has significantly contributed to the creation of huge datasets of satellite imagery. Although this data has been available to the public for quite some time, the technological advancements in processors and GPUs in recent years have made the analysis of these datasets possible for scientists and enthusiasts across the world. Moreover, the improvements in image processing techniques have also fueled the predictive analysis of events like cloud movements, forest fire paths, monsoon patterns etc from satellite imagery.

In the following section we explain some of the jargons in remote sensing and also talk about some software tools such as Google Earth Engine, ArcGis as well as artefacts and satellites like Lidar sensors, LANDSAT-8, Resourcesat-1,2, Sentinel-1,2. The subsequent section talks about popular classification and processing techniques for satellite images. We then present a case study

Finally, we discuss the applications of these techniques and how they help in analysing Surface Water Dynamics, Vegetation Patterns, Land Use Land Cover(LULC) and Ecological studies.

II. Tools & Techniques in Remote Sensing

A. Definitions

- **Multispectral/Hyperspectral:** Multispectral imaging refers to acquiring visible, short-wave infrared, and near infrared images in several broad wavelength bands and combining it in a single image. Since different objects reflect or absorb rays in different wavelengths, it aids object identification. Multispectral imagery is useful to discriminate land surface features and landscape patterns Hyperspectral imaging on the other hand, refers to the acquisition of images in over one hundred contiguous spectral bands. Hyperspectral imagery allows for materials' identification and characterization.
- **True Colour Composites vs False Colour Composite:** True Colour Composite images are the images that resembles what would be observed naturally by the human eye: water is blue to black, vegetation appears green and bare ground appears light gray and brown. The red, blue and green bands of the images are displayed over the corresponding RGB pixels of the screen.
  False Colour Composites are images produced using bands other than visible red, green and blue as the RGB components of the display. These images allow us to visualize wavelengths that cannot be seen by the human eye.

Fig. 1. True Colour Composite(Left) vs False Colour Composite(Right)

- **Spatial Resolution:** It refers to the smallest size of the detail that can be represented in an image. For eg. An image with 30 meter spatial resolution means that a single pixel represents an area on the ground that is 30 meters across.
- **Layer Stacking:** Layer Stacking is a process in which we combine multiple image and convert it to a single image for processing, i.e. all the different bands(wavelengths) that are captured by the satellite are stacked to create a single image. The dimensions and spatial resolution of the different band images should be the same to perform layer stacking.
- **Revisit Time:** Revisit time refers to the total time between two successive observations of a region of interest, i.e. the time taken by a satellite to 'revisit' a particular region of interest.
- **Vegetation Index(VI):** A vegetation index (VI) refers to the spectral calculation of two or more bands of light that highlight certain vegetative properties. In a field of crops, it allows the viewer to make multiple comparisons of the photosynthetic activity across the region of interest.

  The Normalised Difference Vegetation Index (NDVI) is one of the most widely used vegetation index that quantifies vegetation presence, health or structure. It is calculated using the Near Infrared Red (NIR) and Red bandwith of the spectrum. Healthy vegetation reflects light strongly in the NIR part of the spectrum and absorbs light in red part of the visible spectrum for photosynthesis. A high ratio between light refected in the NIR part of the spectrum and light reflected in the red part of the spectrum would represent areas that potentially have healthy vegetation. It is worth noting that different plant species absorb light in the red part of the spectrum at different rates. The same plant will also absorb light in the red band differently depending on whether it is stressed or healthy, or the time of year. It is often used over large areas as an indication of land cover change.

  $$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

  . For example, a pixel with an NDVI of less than 0.2 is not likely to be dominated by vegetation, and an NDVI of 0.6 and above is likely to be dense vegetation.

B. Tools and Artefacts

1) GIS: Geographic Information System(GIS) are computer systems that are used for capturing, storing, checking and displaying remote sensing data. GIS technology helps in comparing and contrasting geotagged information and can also include data about people such as population or income level. They can also include information about landscapes, terrains, vegetations, types of soil as well as schools, roads, power lines, factories etc. Some popular GIS tools are ArcGIS, Google Earth, Google Maps, Maptitude etc.

2) Google Earth Engine: Google Earth Engine(GEE) is a full cloud based GIS that acts as a collection of multipetabyte public satellite data catalog, compute infrastructure, Geospatial APIs and an interactive app server. GEE provides an Earth Engine Explorer which is a lightweight geospatial image data viewer with access to a very large set of regional as well as global datasets made available by different space agencies, government bodies or data aggregators.

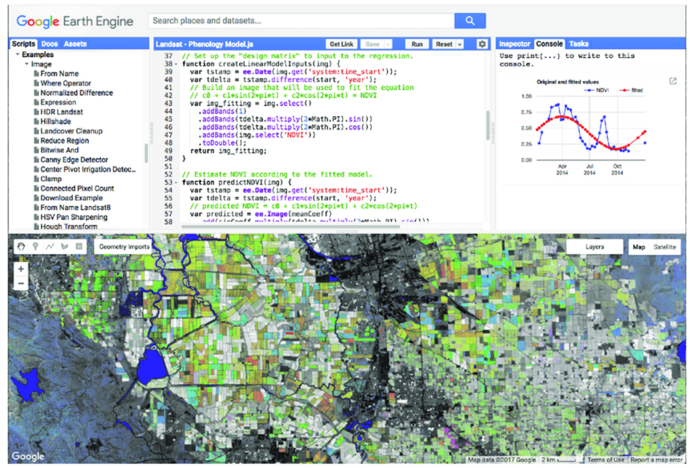

Fig. 2. Earth Engine Explorer

GEE also provides a Python API to access the Earth Explorer, that can be used to create satellite image datasets, utilised by Deep Learning frameworks like Tensorflow.

3) LIDAR: Light Detection and Ranging(LIDAR) is an advanced remote sensing method that is used to create 3D representation of the surroundings using light in the form of pulsed laser. The target objects are illuminated by the laser lights and the reflections are captured by the light sensors. The differences in the laser return times and their wavelengths can then be used to calculate the 'depth' data that are turned to 3D model of the target. LIDAR enjoys widespread terrestrial, airborn and mobile applications.
Airborne LIDAR sensors are used to create topographical and terrestrial maps, helping scientists map the surface irregularities of our planet.

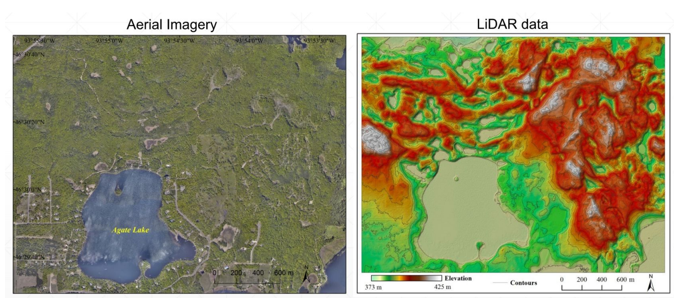

Fig. 3. Real image vs LIDAR

4) LANDSAT 8 Satellite: Landsat 8 is a remote sensing satellite launched by NASA and USGS (United States Geological Survey) ”to 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. It is the eight iteration in the Landsat program ensuring continual collection and availability of the longest collection of multispectral images.

Fig. 4. Landsat 8

Bands	Wavelength (micrometers)	Resolution (meters)
Band 1 - Coastal aerosol	0.43 - 0.45	30
Band 2 - Blue	0.45 - 0.51	30
Band 3 - Green	0.53 - 0.59	30
Band 4 - Red	0.64 - 0.67	30
Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
Band 6 - SWIR 1	1.57 - 1.65	30
Band 7 - SWIR 2	2.11 - 2.29	30
Band 8 - Panchromatic	0.50 - 0.68	15
Band 9 - Cirrus	1.36 - 1.38	30
Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100
Band 11 - Thermal Infrared (TIRS) 2	11.50 - 12.51	100

Fig. 5. Landsat 8 Operational Land Imager (OLI) and Thermal Image Sensor (TIRS) Information

It operates in the visible, thermal infrared, short wave infrared and near-infrared spectrums and captures more than 700 scenes a day. The Landsat program has powered decades of studies in agriculture, cartography, geology, forestry, regional planning, surveillance and education.

5) Resourcesat-1 Satellite: Resourcesat-1 is the 10^{th} iteration of IRS series of satellites built by ISRO possessing advanced remote sensing capabilities.

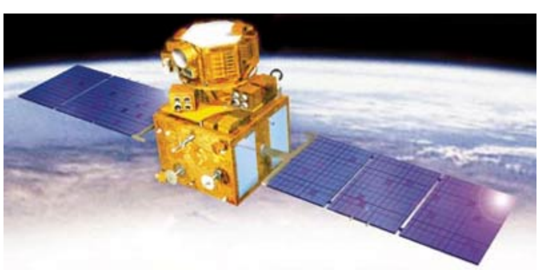

Fig. 6. Resourcesat-1

Resourcesat-1 carries three cameras. The first one is a high resolution camera that operates in three spectral bands in the Visible and Near Infrared Region (VNIR) with 5.8 metre spatial resolution. The second one is a medium resolution Linear Imaging Self Scanner (LISS-3) operating in three spectral bands in VNIR and one in Short Wave Infrared (SWIR) band with 23.5 metre spatial resolution. And the third is an an Advanced Wide Field Sensor (AWiFS) operating in three spectral bands in VNIR and one band in SWIR with 56 metre spatial resolution.

Spectral Band	Wavelength	Resolution
Band 1	0.52 - 0.59 µm	23.5 m
Band 2	0.62 - 0.68 µm	23.5 m
Band 3	0.77 - 0.86 µm	23.5 m
Band 4	1.55 - 1.70 µm	23.5 m

Short Wave Infrared bands for LISS-3

Spectral Band	Wavelength	Resolution
Band 1	0.52 - 0.59 µm	56 m
Band 2	0.62 - 0.68 µm	56 m
Band 3	0.77 - 0.86 µm	56 m
Band 4	1.55 - 1.70 µm	56 m

AWiFS Spectral Bands

Fig. 7. Resourcesat-1 Band Information

Resourcesat-2 is the successor of Resourcesat-1 in the IRS series of satellite. These satellites help ISRO catalogue high resolution images of the India subcontinent with great details and help in remote analysis of changes in vegetation or river bodies with immense accuracy.

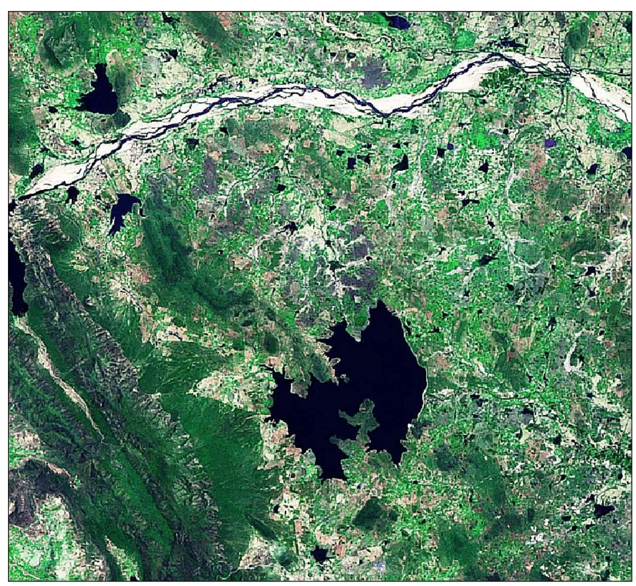

Fig. 8. Resourcesat-2 image of a part of Krishna Basin, India in TCC

III. Case Study: Automated Land Cover Mapping Using Random Forest

In the following case study, we perform train a classifier that automatically maps the Land Cover given a multispectral LANDSAT 8 image.

A. Geemap Installation

Geemap is a python package which is mainly used for interactive mapping with the help of Google Earth Engine, ipywidgets and ipyleaflet. Google Earth Engine is a cloud computing platform used for studying geospatial information. Recently Google Earth Engine has become commonly used in the geospatial community and it has allowed the establishment of multiple environmental applications at global , regional and local scales.

B. Modeling

Traditional Machine Learning algorithms running in Google Earth Engine is used to handle supervised classification by the 'classifier' package. CART(Classification and Regression Tree), Random Forest, Naive Bayes and SVM are the classifiers included.
Here since we use landsat-8 imagery, features include the seven spectral bands and the 20 labels exist based on USGS National Land Cover Database (NLCD). For the purpose of training the training dataset we use smileCART classifier.

C. Training Data

Generating the training dataset can be done in several ways, which includes:-

- Draw a shape (e.g.,triangle) on the map and use region = Map.user_roi
- Define a geometry, such as region = ee.Geometry.Rectangle([-122.6003, 37.4831, -121.8036, 37.8288])
- Create a buffer zone around a point, such as region = ee.Geometry.Point([-122.4439, 37.7538]).buffer(10000)

The high-resolution images were thoroughly examined and was used to find which among the 20 classes showed at each Landsat pixels(Open water, Snow, Developed Open Space, Developed Low Intensity etc.) to act as training data. We have used the USGS National Land Cover Database (NLCD) to create label dataset for training

D. Model Validation

In order to do accuracy assessment in Google Earth engine, we need to reclassify the class values which are now (11,12,21,22,23 etc.) to consecutive integers ie; starting from zero to number of classes present. Since it is 20, class values will be reclassified to 0-19. Then we can still use the same land cover pallet. For accuracy assessment you need to do training and testing, we can use the points to find the values in the seven spectral landsat bands. Dataset needs to be split into 70% for training purpose and 30% for prediction. Once we have the training and testing dataset we can use it to do classification. Accuracy assesment can be done using a function called confusionMatrix(). According to it's training data, confusionMatrix() calculates for the classifier a 2D confusion matrix. This function is applied on the classifier, thus you get the training accuracy. The diagonal elements in the matrix represents those predicted correctly and the rest represents those represented incorrectly. Number of rows and columns will be same as that of number of classes which is 20. To find overall accuracy we need to apply accuracy() on the result of training accuracy.

Fig. 9. Labels according to USGS National Land Cover Database (NLCD)

$$OverallAccuracy = \frac{Sum\ of\ numbers\ in\ diagonal\ line}{Sum\ of\ all\ numbers\ in\ the\ matrix} \tag{2}$$

So here 5000 data points were taken out of which we get 95% overall accuracy. This is high considering we used 70% of dataset for training. The Kappa Coefficient is generated using kappa(), it is calculated to find the accuracy of the classifier. The value of Kappa Coefficient ranges between -1 to 1, higher the value more better.
Producer's Accuracy and Consumer's Accuracy can also be calculated using producersAccuracy() and consumersAccuracy(). Producer's Accuracy is found by complementing Omission Error.
Producer's Accuracy = 100%-Omission Error

The Consumer's Accuracy is found by complementing Commission Error,
User's Accuracy = 100%-Commission Error

```
In [32]: train_accuracy = classifier.confusionMatrix()

In [33]: train_accuracy.getInfo()

Out[33]: [[280, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
          [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
          [0, 0, 156, 6, 1, 0, 0, 4, 0, 0, 0, 0, 0, 0, 0, 0, 1, 21, 0, 0],
          [2, 0, 2, 440, 4, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 10, 0, 0],
          [0, 0, 1, 15, 197, 3, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0],
          [2, 0, 1, 3, 6, 89, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0],
          [0, 0, 0, 0, 0, 0, 11, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0],
          [0, 0, 2, 2, 0, 0, 0, 192, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 0],
          [0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
          [0, 0, 0, 0, 0, 0, 0, 2, 0, 9, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
          [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
          [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0],
          [0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 29, 0, 0, 0, 0, 5, 0, 0],
          [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
          [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
          [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
          [1, 0, 3, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 92, 12, 0, 0],
          [2, 0, 1, 3, 0, 1, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1740, 0, 0],
          [0, 0, 1, 2, 0, 0, 0, 6, 0, 0, 0, 0, 0, 0, 0, 0, 0, 4, 54, 0],
          [0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0]]
```

```
In [44]: test_accuracy.producersAccuracy().getInfo()

Out[44]: [[0.9664429530201343],
          [0],
          [0.15217391304347827],
          [0.6030927835051546],
          [0.3258426966292135],
          [0.5434782608695652],
          [0],
          [0.6190476190476191],
          [0],
          [0],
          [0],
          [0],
          [0],
          [0],
          [0],
          [0],
          [0.10416666666666667],
          [0.9098984771573604],
          [0.16],
          [0]]
```

If we get the accuracy of any classes as 0 it means the class doesn't exist in the part of image we chose.
For accuracy assessment on validation dataset, we can use errorMatrix(). This is going to produce a confusion matrix similar to the one before. Now overall accuracy can be calculated in similar way as before.

We observed that this was lesser than that of training dataset, as the testing overall accuracy is 71% and that of training dataset is 95%. This is within our expectation. Further kappa coefficient, producer's accuracy and customer's accuracy can be found.

IV. Applications of Remote Sensing

A. Estimating Vegetation Cover

The key factor in determination of vegetation is chlorophyll. Unlike other pigments, it strongly absorbs red and reflects green, hence leaves are green for naked eyes. However it strongly reflects very near-infrared (VNIR) and hence glows brightly in VNIR lenses. // Unlike vegetation which strongly reflects Near Infrared Red(NIR), water strongly absorbs NIR. Hence in our FCC image created using Red, Green and NIR, lower reflectance regions are likely to be water and higher reflectance regions(with more NIR value) are likely to be vegetation. In Fig.10, we've represented NIR in blue for the False Colour Composite (FCC). We can see the parts of the image that are blue are estimated to be vegetative areas

```
In [45]: test_accuracy.consumersAccuracy().getInfo()

Out[45]: [[0.9664429530201343,
          0,
          0.2545454545454545,
          0.5318181818181819,
          0.3625,
          0.5952380952380952,
          0,
          0.5148514851485149,
          0,
          0,
          0,
          0,
          0,
          0,
          0,
          0,
          0.25,
          0.8327526132404182,
          0.25,
          0]]
```

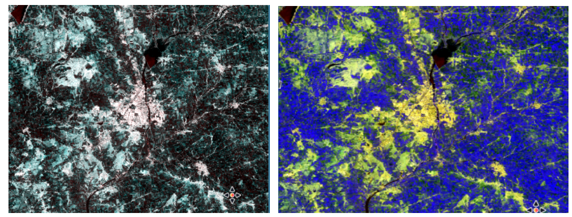

Fig. 10. Bareilly TCC (left) vs FCC (right)

(comparing with the TCC on the left). The leaves are reflecting the NIR light from the sun which is being captured by the satellite's cameras.
There's a way to quantify these pixels and estimate the vegetation cover, using vegetative indices. For our analysis, let's use NDVI as our vegetative index.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{3}$$

We calculate this value for each pixel of the image and find the NDVI plot (Fig.11). NDVI ranges from -1 (for water), 0 (for land/urban), +1 for vegetation.

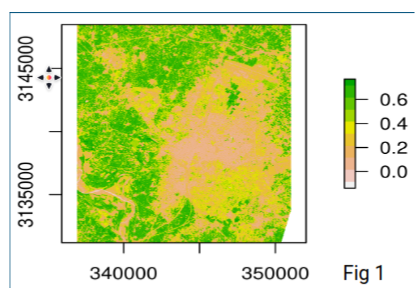

Fig. 11. Bareilly NDVI plot

We can do further analysis on the NDVI plots using ML/DL techniques for automatically classifying the region into clusters of sparsely vegetated, moderately vegetated or heavily vegetated areas. Let's perform K-Means clustering on the obtained NDVI plot.

K-Means has classified each NDVI values into 10 clusters. We then represent the clusters on the plot and can estimate the vegetation cover of a region. We can further create a histogram of the NDVI values.

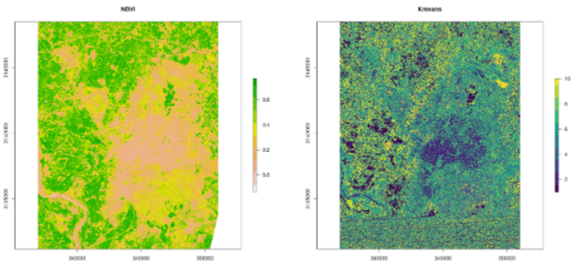

Fig. 12. Bareilly NDVI K-Means Classification (k = 10)

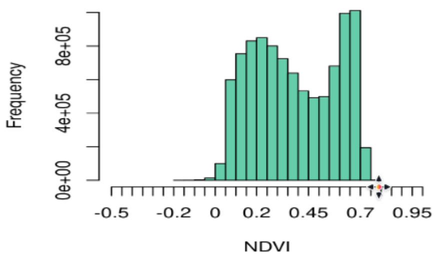

Fig. 13. Bareilly NDVI histogram

NDVI histogram of any region tells us a lot about that region. Healthy vegetation reflects light strongly in the NIR part of the spectrum and absorbs red light for photosynthesis. High ratio between light reflected in the NIR part of the spectrum and light reflected in the red part of the spectrum would represent areas that potentially have healthy vegetation. A right skewed histogram denotes heavy vegetation in the area (like forests), and a left skewed histogram usually indicates presense of water bodies.

B. Surface Water Dynamics

Surface water dynamics analysis relates to remote sensing studies of the water bodies in the area of interest. Ground reality and on site analysis of water bodies can incur massive project costs. Remote sensing techniques can supplement the need to be physically present in the area. We can compare the flow of a water body over many years, estimate oncoming droughts and also relate the changes in water table with the vegetation over the area, all done remotely.
Similar to NDVI, the water quantity in a region can be estimated with an index called Normalized Difference Water Index (NDWI). NDWI is remote sensing index related to gauging liquid water and can refer to two instances. One is used to monitor changes in water content of leaves, using near-infrared (NIR) and short-wave infrared (SWIR) wavelengths.

$$NDWI = \frac{(NIR - SWIR)}{(NIR + SWIR)} \tag{4}$$

Another is used to monitor changes related to water content in water bodies, using green and NIR wavelengths.

$$NDWI = \frac{(Green - NIR)}{(Green + NIR)} \tag{5}$$

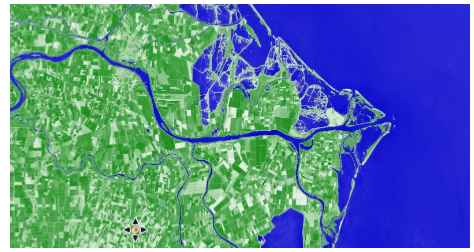

Fig. 14. NDWI Plot for Italian Coast

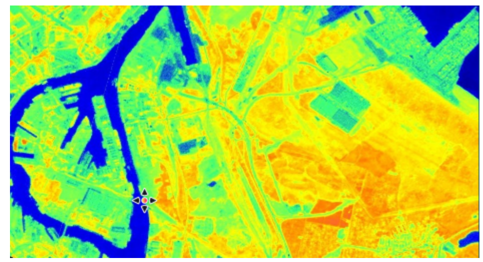

Fig. 15. NDWI (leaves water content) for Rome

We can compare the two NDWI indices in the above image. In the NDWI plot for Italy, the water bodies are marked in blue. In the other NDWI plot of Rome, greenish-bluish hue represents the leaf water content.
In Fig.16, we've plotted the NDWI values for Maharashtra comparing them for 2010 and 2015. Blue regions represent observed water bodies, rivers, reservoirs. More reddish pixel value indicate drier land/barren land.

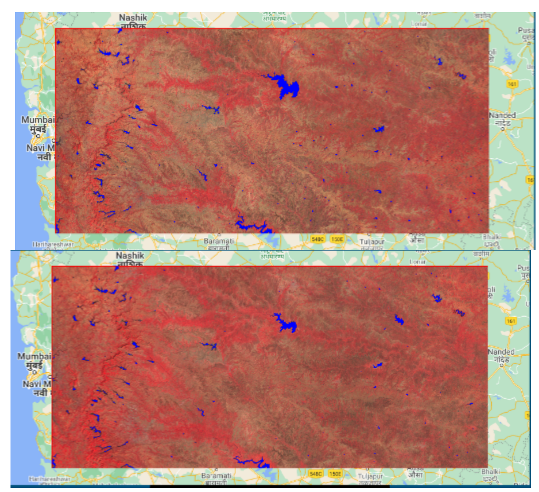

Fig. 16. Maharashtra NDWI plots 2010(top), 2015(bottom)

Maharashtra witnessed the worst droughts in 2015, and this can be observed in the NDWI plot. Shrinkage/disappearance of water bodies shown in blue indicate severed drought conditions in the region. A shrinkage in water table severely affects the vegetation in the area. Fig.17 represents the NDVI plots for 2014 and 2015. We've set a threshold of 0.3 for the NDVI, i.e. the green colour represents vegetation starting

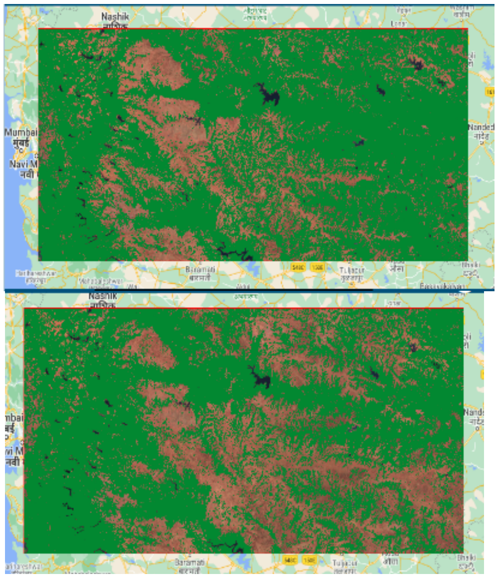

Fig. 17. Maharashtra NDVI plots 2014(top), 2015(bottom)

from shrubs, grasslands to thick forests. We can observe the significant decline in vegetation of the state in just one year due to vegetation.

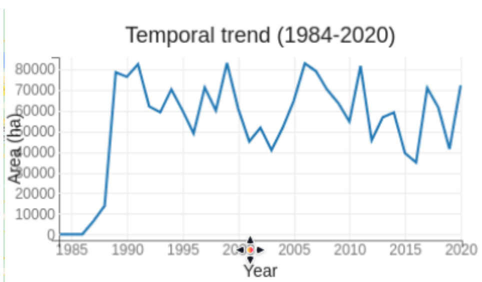

Fig. 18. Real image vs LIDAR

Plotting a line chart (Fig.18) for the NDWI values over a range of years, we can see that the values supplement the hypotheses of droughts in Maharashtra over 2015-16. LANDSAT 8, the satellite whose images we're using, effectively started recording the images of the region after 1990 and hence the study starts after 1990. We see the lowest dip between 2015-16 i.e. the lowest presence of water in a period of two decades was recorded in 2015.

Surface water dynamics studies help in tracking changes in flow of water bodies over the years. They help us gauge the effects of floods, inundations and droughts on human settlements. We can viasualize effects of water bodies on the ecology of an area and how climate change has affected our planet.

V. Summary

In this paper, we've elaborated the various tools, artefacts and techniques used in remote sensing. Availability of cheap computing and storage resources as well as processing power has massively helped in making remote sensing accessible to all. It has allowed us to gather massive amounts of data of our planet, enabling us to visualise the effects that natural or human activities have on the land we share. Augmenting remote sensing with Image processing and Artificial Intelligence can help in creating sustainable goals for our progress and can eliminate the problems that we face today.

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