Identifying Deforestation using fair classical Image Processing Techniques

Applied Digital Image Processing
Fall 2023

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December 10, 2023

1 Abstract

Satellite imagery stands as a pivotal tool, progressively evolving to provide insightful information and monitor various topological transformations. Despite its substantial capabilities, there is an underutilization due to a lack of guidance on effective tool utilization. This research addresses this gap by offering insights into selecting suitable platforms and providing essential information about the monitored area, facilitating efficient tracking of deforestation or afforestation. Instead of relying on the complex and data-intensive Normalized Difference Vegetation Index (NDVI) method, this study adopts a pragmatic approach using clustering methods.

Through experimentation, even with a simple screenshot of the targeted area, the proposed method yields accurate approximations, proving effective in tracking deforestation activities. This research establishes a streamlined and accessible methodology for monitoring environmental changes, fostering sustainable practices through a straightforward and reliable clustering approach.

2 Introduction

In the context of our present ecological challenges, addressing and raising awareness about global warming stands as a paramount imperative. Given the limitations in resources and the potential reluctance of governing bodies to prioritize this issue adequately, it becomes essential to pioneer a systematic approach for monitoring, reflecting upon, and mitigating these environmental changes.

Our primary objective is to institute a meticulous process for the collection and analysis of satellite imagery. Subsequently, we intend to apply various advanced methodologies and mathematical algorithms to these images. This multifaceted approach serves a dual purpose: it helps in our ability to fairly analyze and document alterations in land topography brought about by climate change upto an approximate degree, while also diminishing our reliance on local authorities and potential vested interests that may obstruct progress in this crucial area.

By implementing this approach, we aspire to foster greater transparency, accountability, and data-driven decision-making in the quest to combat global warming. Moreover, this initiative carries the potential to engage and enlighten the public about the pressing need for environmental conservation, ultimately leading to a more sustainable and resilient future for our planet as we try to compare and contrast different classical digital image processing techniques with the current state of the art method.

Our project aims to utilize the capabilities and functionalities of classical digital image processing for the purpose mentioned above that can be done using satellite imagery and images from Google Earth. Deforestation is a major contributor towards the global boiling, as environmentalists term it now (instead of global warming). The monitoring system can contribute towards helping the relevant stakeholders to make better informed decisions through sustainable development. [1]

3 Literature Review

This section entails a review of the previous work done in the scope of detecting deforestation using different types of satellite imagery. Most of the techniques use remote sensing, i.e., making use of the satellite imagery to detect image change and deforestation. While the methods in section 3.1 and 3.2 work on single band images, section 3.3 and onwards work on multi-band images which is the current state of the art procedure.

Our project aims to bring classical techniques and compare their results with the more accurate methods to see if the classical methods can be used to have a fair estimate of the deforestation since the acquisition of multi-band satellite imagery and the pre-processing required is cumbersome and cannot raise public awareness.

3.1 Image Clustering

Content Based Image Clustering (CBIR) is a method used to group or classify objects into different classes which have similar properties. These classifying of images help us study different characteristics of

FCM (Fuzzy C-mean) [2] is one of the most common form of image clustering and it is the based on the principle of fuzzy classification. In fuzzy C-mean clustering pixels with identical properties will be grouped into to same categories or clusters.

The input images of the fuzzy C-mean clustering, where Gray scale images and the cluster centers were computed automatically by the function itself. Once the cluster center was found and fixed, the next stage was setting the rules for fuzziification. That is if-then rules are given below assuming that the three cluster values are cluster 1, 2 and 3.

- If pixel (i,j) is less than Cluster-1, center make it black(0)
- If pixel (i,j) is greater than cluster-3 center make it White (1).
- Else make pixel (i,j) in between black and white (0.5).

The FCM algorithm continuously upgrades and moves this cluster centers iteratively to the ideal or right position. So by continuous moving of initial cluster centers, it precisely clusters the image into different regions and groups the accuracy of the membership grades of each groups [Cite3 in 23 in Doc].

3.2 Otsu Method on color spaces

The Otsu Method [3] is seperating or dividing of images into different clusters or regions based on common properties and/or differences between other regons properties. One property out of the many could be applied to separating images into regions is pixel intensity.

So we normally can segment images into different regions through thresholding or separating the pixel levels into different scales. These different thresholding scales create different regions corresponding to the pixel intensity values.
A simple example can be thresholding a gray scale image pixels into two regions, by transforming the gray scale image into binary image, which will consist of only two regions, namely either the black or white.

If $G(x, y)$ is a threshold version of $f(x, y)$ at some global threshold T,:

$$G(x,y) = \begin{cases} 1 & \text{if } f(x,y) \geq T \\ 0 & \text{otherwise} \end{cases}$$

This method has been used with color spaces like HSV (Hue, Saturation, Intensity), and L*a*b* to identify areas of deforestation that we will further see in the methodology section.

3.3 NDVI Method

The Normalized Difference Vegetation Index (NDVI) is widely employed for vegetation assessment by gauging the abundance of vegetation cover on land. The principle underlying NDVI hinges on the capacity of chlorophyll in plants to absorb red and blue light while reflecting near-infrared (NIR) and green light. Landsat imagery, sourced from diverse satellites, particularly Landsat 7 and 8, has been instrumental in acquiring data for the wavelengths absorbed by vegetation. With an operational history spanning over two decades, Landsat satellites have been optimized to furnish data primarily centered on land cover and vegetation dynamics based on surface reflectance.

The utilization of Surface Reflectance products further refines this process by providing an estimate of spectral reflectance at ground level, effectively negating the impact of atmospheric scattering or absorption that could otherwise distort measurements. This approach ensures the accuracy and reliability of NDVI data in discerning variations in vegetation over time. The Landsat were further the preferred choice as among the many other satellites with the same idea developed for monitoring the land changes, Landsat is the only of the few remaining satellites which has the data for such an extended time.

Originating in the 1970s, the utilization of the Normalized Difference Vegetation Index (NDVI) has undergone a transformative evolution. Initially designed for vegetation detection, it has progressed to become an invaluable tool for monitoring and predicting vegetation health and growth. This comprehensive methodology has found substantial application in environmental monitoring, notably in the Brazilian forest [4]. Employing the Random Forest model, historical NDVI data has been meticulously analyzed to not only comprehend the past growth patterns of the Brazilian forest but also to project future developments. Using the GEEE platforms to extract the utilize the data available, the data was then processed and checked against the Random Forest algorithm to monitor the changes over the years, and see the future vegetation prospects based on this idea.

The versatility of NDVI extends to pattern monitoring, exemplified by the Mimbo forests [5]. In this context, the NDVI method served as a robust metric for quantifying deforestation. Incorporating regression analysis into the evaluation of identified patterns has not only facilitated a nuanced understanding of past deforestation trends but also augments the capability to predict future vegetation dynamics within the Mimbo region.

4 Methodology

As undergraduate students with limited knowledge and expertise, we were not able to come up with a novel idea. However, keeping in mind the techniques learned in the course of Applied Digital Image Processing, we implemented the methods that have been used for detecting deforestation in the papers cited above.

4.1 Image Clustering

This classifying of images into groups help assist study different characteristics of the image like better flow, pattern changes and similarity of events or phenomenon. Further clustering of images gives clusters or regions with detailed and concise information and the content of the images which ease the task of asserting this regions of clusters.

The Fuzzy C-Means (FCM) clustering method [2] is based on minimizing the following objective function:

$$J_m = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^m \cdot \|\mathbf{x}_i - \mathbf{v}_j\|^2 \tag{1}$$

Here's a breakdown of the terms:

- J_m is the objective function to be minimized.
- n is the number of data points.
- c is the number of clusters.
- u_{ij} is the degree of membership of data point $\mathbf{x}_i$ to cluster j.
- m is a weighting exponent, usually set to 2 for FCM.
- $\mathbf{v}_j$ is the centroid of cluster j.
- $\|\mathbf{x}_i - \mathbf{v}_j\|^2$ is the Euclidean distance between data point $\mathbf{x}_i$ and the centroid $\mathbf{v}_j$.

The objective is to find the membership values u_{ij} and cluster centroids $\mathbf{v}_j$ that minimize the objective function. The degree of membership u_{ij} indicates the fuzzy assignment of data point $\mathbf{x}_i$ to cluster j, with higher values indicating stronger membership.

4.2 Otsu Method

The method involves finding an optimal threshold that minimizes the intra-class variace of pixel intensities:

$$\sigma_w^2(t) = w_1(t) \cdot \sigma_1^2(t) + w_2(t) \cdot \sigma_2^2(t) \tag{2}$$

Where:

1. t is the threshold value.
2. $\sigma_w^2(t)$ is the weighted sum of the variances of the two classes spearated by the threshold
3. $w_1(t)$ and $w_2(t)$ are the probabilities of the occurences of the two classes separated by the threshold.
4. $\sigma_1^2(t)$ and $\sigma_2^2(t)$ are the variances of the two classes separated by the threshold.

The goal here, is to find the threshold value t which effectively spearates the image into two classes, that minimizes the intra-class variance and maximizes the inter-class variance. [3]

4.3 NDVI Method

The implementation of the NDVI ratio to check the absorbed and reflected wavelengths from a particular region and is then used for the formula

$$NDVI = (NIR - RED)/(NIR + RED) \tag{3}$$

Where NIR corresponds to the near-infrared wave. These individual wavelengths are calculated at each point for a pixel and is then used to monitor the type of vegetation. The $NDVI$ yields a value ranging from -1 to 1 where -1 – 0 indicated dead plants or inanimate objects, 0 – 0.33 are considered as healthy plants, 0.33 – 0.66 were considered as moderately healthy plant and 0.66 – 1 were considered as healthy plants.

Utilizing these values the previous approaches as mentioned plotted an image identifying the regions which had a healthy vegetation and which did not. Different images for each time were generated and showed as a visual representation to the console.

5 Implementation

The implementation of the sections discussed below can be found on our Github repository [6]

5.1 Image Clustering

Our code implements the Fuzzy C-Means (FCM) clustering algorithm for image segmentation, focusing on feature detection, especially in identifying vegetation. We start by initializing a membership matrix, a crucial part of FCM, where each entry signifies the pixel's association degree with each cluster, capturing the uncertainty in pixel assignments during clustering. The iterative refinement of cluster centers and the membership matrix is then executed through a structured process.

Initially, cluster centers are set by randomly selecting data points from input samples (X), and the membership matrix is initialized using the initialize membership_matrix_function. This function assigns and normalizes random values, ensuring they collectively sum to 1 for each data point. The iterative phase continues until convergence or a specified number of iterations. In each iteration, the cluster centers are updated through the `update_cluster_centers` function, calculating new centers based on the current membership matrix, input data (X), and a fuzziness parameter.

Simultaneously, the `update_membership_matrix` function recalculates the membership matrix based on the updated cluster centers, input data (X), and the fuzziness parameter. Convergence is determined by assessing changes in cluster centers and the membership matrix against a defined tolerance. If criteria are met, the algorithm terminates; otherwise, it continues. The final output consists of refined cluster centers and a membership matrix, capturing patterns within the input data. This ensures the algorithm stops iterating when updates reach a satisfactory precision level.

The update of cluster centers involves computing a weighted average of data points based on the membership matrix, while the membership matrix is updated by recalculating the degree of association between data points and clusters. Convergence is determined by evaluating changes in cluster centers and the membership matrix. In image processing, the code utilizes the LAB color space, extracting the L channel representing luminance. The L channel's pixel values are rescaled and used as input for FCM clustering, resulting in a segmented image. The code further aids in identifying areas with high intensity, indicating potential vegetation. Overall, this implementation clarifies the FCM algorithm's application in image segmentation.

5.2 Otsu Method

The provided code utilizes the Otsu thresholding method to segment images in different color spaces: HLS (Hue, Saturation, Intensity), HSV (Hue, Saturation, Value), and LAB (Luminance, Green-Red, Blue-Yellow). The algorithmic explanation for the Otsu method in each color space is detailed below:

HLS Color Space: The code begins by converting the input image to the HLS color space and then splits it into three channels: Hue (H), Saturation (S), and Intensity (I). Otsu thresholding is independently applied to each channel, determining optimal threshold values based on the channel's pixel intensity histogram. Binary images are created for the Hue and Saturation channels, showcasing the segmented regions.

HSV Color Space: Similarly, the input image is converted to the HSV color space, and the image is split into three channels: Hue (H), Saturation (S), and Value (V). Otsu thresholding is individually applied to each channel, leading to the creation of binary images. The resulting segmented regions are displayed for the Hue and Saturation channels.

LAB Color Space: The code then proceeds to convert the input image to the LAB color space, splitting it into three channels: Luminance (L), Green-Red (a), and Blue-Yellow (b). Otsu thresholding is independently applied to each channel, determining optimal thresholds based on pixel intensity histograms. Binary images are generated for the Luminance, Green-Red, and Blue-Yellow channels, displaying the segmented regions.

In each color space, the Otsu thresholding method is employed to find optimal thresholds that maximize variance between foreground and background pixel classes. The resulting binary images highlight segmented regions, providing a visual representation of the segmentation outcomes.

Additionally, the code includes post-processing steps where the segmented regions meeting specific criteria are highlighted in red. This enhancement offers a clearer visual indication of the identified segmented areas.

5.3 NDVI Method

Two TIF files, corresponding to different spectral bands of satellite imagery, are loaded using the `rasterio` library. The red and near-infrared (NIR) bands are read as NumPy arrays, denoted as `red_band` and `nir_band`.

The script computes the band difference by subtracting the NIR band from the red band, resulting in the band difference. Additionally, the script determines the dimensions (height and width) of the image.

Using `np.any()`, the code checks for non-zero values in the red band. If non-zero values are present, the script identifies the index of the first non-zero value.

NDVI is calculated using the equation 3 in Section 4.3. The NDVI values are clipped to ensure they fall within the range $[-1, 1]$. A threshold value (e.g., 0.2) is defined to distinguish areas with high and low NDVI values.

Binary masks, namely `high_ndvi_mask` and `low_ndvi_mask`, are created to highlight areas with high and low NDVI values based on the defined threshold.

Images are generated to highlight areas with high and low NDVI separately. High NDVI areas are depicted in green, and low NDVI areas are depicted in red in the respective highlight images.

The script combines the high and low NDVI highlight images into a single RGB image (`highlight_image`). In this representation, high NDVI areas appear in green, low NDVI areas in red, and other areas in black.

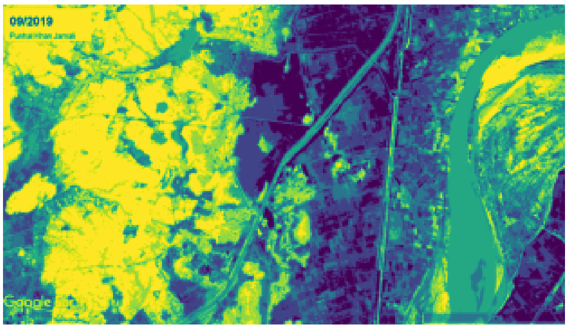
This script effectively processes satellite imagery, calculates NDVI, and visually represents areas with varying levels of vegetation health.

6 Experimental Results

We used the methods and implemented them on the images of Punhal Khan Jamali, Each of our code were executed and timed appropiately. Where analysis was done not by only varying the parameter values but also working principle of each code with varying image types and the type of landscape provided to it as well. Each method would be discussed and the type of result that it had provided with.

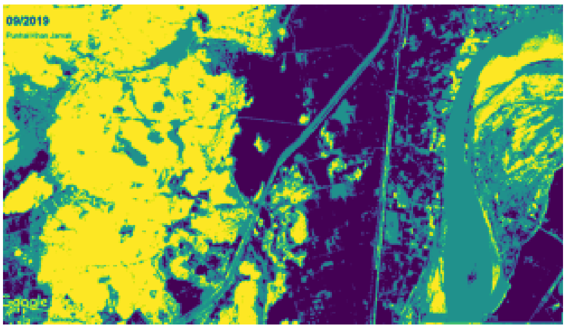
The Clustering method had a controllable factor of the number of clusters which would be required to be taken for. Increasing the number of clusters would only increase the amount of variations of the classes of pixels to be grouped and formed for the image. This would lead to an inconsistency as the code works on the idea of the green pixels being seperately and would lead to the different shades of green being grouped in different clusters. Where if we were to take this for different images, each would lead to a different normalized binary value. Thus, standardization would not only be hard but also difficult to maintain without using a machine learning model where for a large data set it would be trained for and then checked against each. Figure 1a below shows when we use the number of clusters to be 6 and followed by 1b showing the same image but for 3 number of clusters. Thus, after more trial and errors, 3 was found to be the closest number of clusters for which the most accurate clustering method could be deployed with the best vegetation detection possible.

However an important point to further note is also the idea of image and its

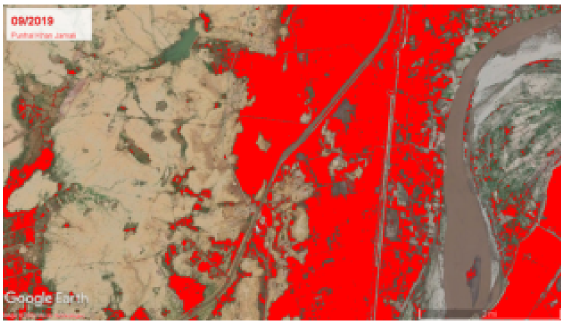


(a) Figure 1a.1: For 6 number of clusters

(b) Figure 1a.2: Impact on the real image



(c) Figure 1b.1: For 3 number of clusters



(d) Figure 1b.2: Impact on the real image

Figure 1: Changing the number of clusters in FCM

resolution. A low resolution image could result in the mixture of clusters where different pixels could be grouped for the wrong clusters leading to a little deviation of identifying the wrong area for the vegetation. Such as in fig 2 below where different areas were being identified as the area of vegetation even though they were not (extra areas marked with red).

The NDVI method was the most reliable method as discussed before due to its implementation being reliant on extremely accurate information provided by the satellite. However, for an individual to only include a diagram or to get a rough estimate would be required to extract the information by first getting the individual bands. The file size of the images themselves are very large due to the aspect of high quality data as compared to the clustering method where only a screen shot would also suffice, the process of getting the data would be a little hard to navigate.

Followed by the selection of the satellite and ensuring the given satellite would have the up to date data or not. Where the time taken to handle each data image would almost near to the time being taken by clustering.

Thus this results in the following analysis for each of the methods below where the time taken for each to run is shown below

Method Used	**Time Taken for CPU (s)**
NDVI	12.5625
Clustering	12.421875
Otsu	0.015625

Table 1: Time taken for different methods on CPU.

It is observable based on the table 1 above where the time taken for each NDVI and Clustering is almost equal, clustering would still be giving an estimate as compared to the NDVI method. However based on the technique and idea used to get information and the idea of automation, clustering would give a good estimate while having the idea of getting incorporated with automation tasks which involve only taking the screen shot of the map as compared to NDVI where automation would also be complicated as the selected files would have to contain the required bands. Thus, both the ideas could also be used to track forestation as seen in Figure 3 where the red area identifies the area of deforestation and blue identifies the area of afforestation. Where with some additional changes, it could further be improved to the extent where the area of deforestation and afforestation could also be found.

The Otsu method would not be regarded in this case as the idea of Otsu revolves around the varying image properties where it was for varying images different channels were being to identify the area of forestation or not and relied heavily on the user identifying which would be more appropiate rather than the idea of automating it for any image it would be given. Thus, even though it would be useful in some aspects but in the larger aspect it would not be useful to us.

(a) Deforested area (b) Amount of vegetation detected

Figure 2: Blur image being used

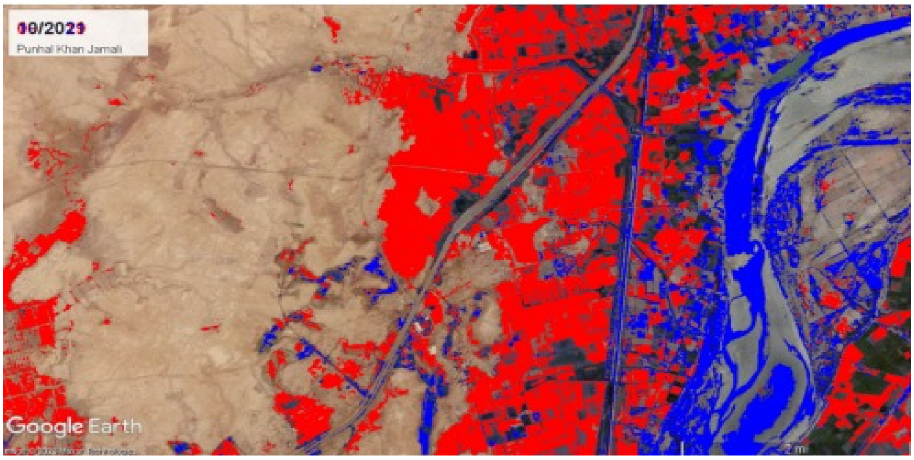


Figure 3: afforestation: Blue, deforestation: Red

7 Conclusion

Upon analyzing the outcomes derived from each experimental result, we can confidently assert the efficacy of Fuzzy C-Means (FCM) as a robust method for vegetation identification within a given area. Notably, this approach stands out due to its versatility in accommodating diverse image formats such as JPEG, TIFF, PNG, and others, setting it apart from methods like Normalized Difference Vegetation Index (NDVI) that necessitate images from each band. Our comprehensive examination leads us to conclude that FCM clustering serves as a compelling alternative, offering valuable insights into the extent of forestation. This approach eliminates the need for intricate satellite selection and the handling of large data files associated with extremely high-resolution band-specific images. The simplicity and accuracy of FCM make it a practical choice for assessing vegetation cover in diverse environmental contexts. However, there are limitations to this approach, firstly being the less accurate dataset as we use Google Earth images instead of the multi-band satellite images that are dedicated to the identfication of the topology and Earth's natural resources. Secondly, we could not come up with a way of quantfying the accuracy of the classical methods with the NDVI method which uses multi-band imagery, and thus a quantitative comparison becomes virtually impossible.

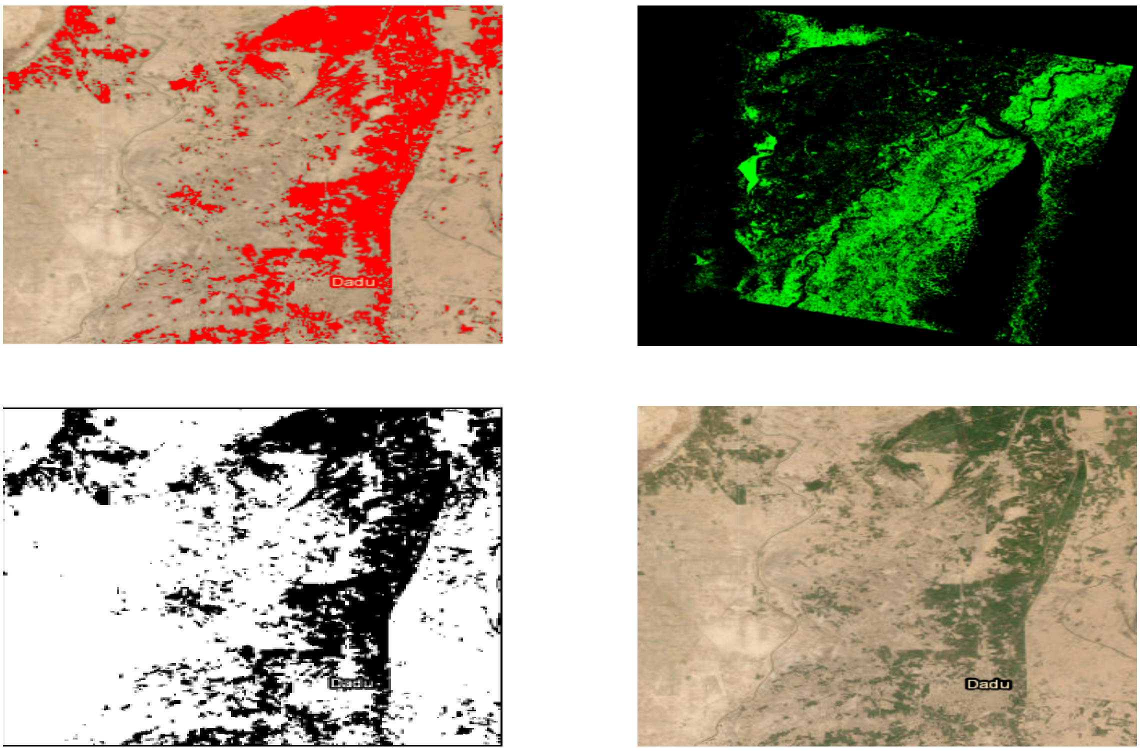


Figure 4: Vegetation detected using different methods

8 Acknowledgements

We thank our course instructor, Dr. Muhammad Mobeen Movania, for his guidance and support throughout the course.

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