USE OF A DEM AND NDVI TIME SERIES TO MAP AND MONITOR HORTICULTURAL AREAS IN TIGRAY, AS INPUT FOR A BETTER-INFORMED FOOD SUPPLY CHAIN

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August 2021

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Thesis submitted to the Faculty of Geo-information Science and Earth Observation of the University of Twente in partial fulfilment of the requirement for the degree of Master of Science in Spatial Engineering.

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DISCLAIMER

Abstract

This paper identifies, maps, calculates the percentage, and monitors the presence of horticultural crops within small clusters of fields in Tigray.

First NDVI time series were used to select the possible are of interest (AOI). The first approach was with the perception that higher NDVI values during the dry season can possibly represent horticultural areas and can be used to square the desired results. But the first approach has later proven that it is not possible to identify horticultural areas based on NDVI only. Hence, DEM with additional selection parameters was used, to get the possible area of interstates. After having those desired areas of interest, the NDVI time series were used to Further limit potential areas of interest and lead to the final AOI's. This was done by using the unsupervised classification of the extracted areas from DEM and the Pre-Processed NDVI-data (DN values) image from 20 years Spot-VGT + PROBA-V NDVI-data.

After acquiring the final AOIs the percentage of each AOIs that is covered by horticulture was also calculated. This was done by pixel level, by creating random points of 1km pixels for each specific NDVI-class in ArcMap and checking how much percentage of that pixel is covered by horticulture on google earth image. Resulting in most of the classified classes containing less than 40% of horticulture. This was followed by monitoring for the selected clusters of fields that containing greater than 40% of horticulture. This was done by assessing their temporal NDVI-patterns, which periods crops were grown, and what their performance was. All final AOIs show higher NDVI values during Kiremit, which is the rain season of the region. In most of the classes that have a higher percentage of availability of horticulture, their NDVI values during the dry season are relatively higher. This is done for the year (covering 2010 to 2019).

Acknowledgment

This is my favorite part of this whole paper, because I have so much to be thankful for and so many people, I want to send my gratitude to. This time I was not lucky enough to work on my thesis with all my energy and spirit because the war on Tigray broke out in the midst of my thesis, and I was not able to reach my family. But against all odds I am here. I would like to say congratulations to my family, who are eagerly waiting for me to finish this masters and send my gratitude for always being so proud of me and believe in me more than I can ever be proud and believe in myself. You have done everything for me, anything that is good in me is because of you. Everything!

I wish it was easy and I could call and tell you I have finished or invite you to my graduation, but I know you have me in your heart, as I have you in mine. To my boyfriend, thank you for constantly reminding me that even when we are in these darkest moments, the fact that the "Holy Spirit" is within us is always the reality, and for always being there.

I would like to send my deepest gratitude to my supervisors Dr. ir. Kees de Bie and drs.ing. M. Huesca Martinez, for always being there. Literally, for teaching me something I didn't know before and for doing that with all the patience, because I know it was not easy. Kees thank you for not giving up on me. Marga, thank you for making it easier and for being kind to me.

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I am proud!

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1. Background

Agriculture in Ethiopia is the key pillar of the country's economy, and many lives are dependent on it. Out of the Gross Domestic Product (GDP) of the country, agriculture covers about 46.3 percent, and it supports 83.9 percent of exports and 85 percent of the country's total jobs. Many other economic activities also rely on agriculture. Some of them are agricultural goods marketing, manufacturing, and shipping (FAO, 2010). Unfortunately, agriculture in Ethiopia is afflicted by unreliable rainfall, soil erosion caused by overgrazing, and deforestation (Gebreselassie, Kirui, & Mirzabaev, 2016). High taxation rates and poor infrastructure are making it difficult and costly to sell products beyond the local markets. Agriculture remains the country's biggest resource and plays a critical role in the entire economy (OECD, 2007; Welteji, 2018) In Ethiopia over 80% of the land is held by smallholder farmers for agriculture production (Neigh et al., 2018), with many occupying 1 ha or less (Jayne, Chamberlin, & Headey, 2014).

For smallholder farmers in Ethiopia, vegetables are the most beneficiary of horticultural produce as they are among the sources of food, income, and rural employment. The market however lacks distribution facilities, market information systems and marketing access (Megerssa, Negash, Bekele, & Nemera, 2020). It also suffers from seasonality of supply, lack of quality, high perishability, and poor performance of the vegetable market. (Amare, 2019; Trienekens, 2011)

Zooming into the study area Tigray, the most northern region of Ethiopia, encounters the aforementioned problems including low average annual rainfall, it suffers from unpredictable drought during the dry seasons (Gebrehiwot & Van Der Veen, 2013).

Despite several attempted solutions, it has been difficult to incorporate modern and advanced value chains and engage stakeholders and additional actors such as traders and middlemen brokers (ISSD Tigray, 2019). All in all, lack of well-organized markets results in farmers selling their products to middlemen at exploitative prices. Farmers will have less profitability and the brokers take the biggest share of the whole transaction (Amare, 2019). The lowering of prices results in the farmers' frustration and with an increased number of brokers in the market, the exploitation continues to lower the price of the agricultural products resulting in making the situation worse and hence the problem is wicked. In the same token, the market became too dependent on individuals than an organized system of trading. During the first months of the Covid pandemic for example, a large amount of tomato produced by farmers in the Raya region had to go to waste for lack of direct access to the market.

To create a more reliable market system and strengthen the supply chain, identifying crop growth in an area is important. Actors that work on market dissemination like the

Agricultural Transformation Agency, government ministries, agencies like TAMPA (Tigray Agricultural Marketing Promotion Agency) can make use of this data to plan and organize the distribution of the products in the market. However, production estimates and identification of produce availability in heterogeneous clusters of fields or smallholder farming systems is mostly done either using traditional methods like word of mouth or using labor-intensive surveys that are not sustainable, easily scalable, nor exhaustive (Lambert, Traoré, Blaes, Baret, & Defourny, 2018).

Technological advancement has brought advanced solutions in the areas of remote sensing to improve efficiency and timeliness of the processes mentioned above. Remote sensing information allows detecting and monitoring the physical characteristics such as the terrain of a land, type of soil and water capacity of an area. It provides valuable insights and data about Earth systems through satellite sensors or airborne sensors (Earthdata, 2021). Remote sensing applications can be used to solve challenges in smallholder farms and heterogeneous small clusters of fields such as the one depicted in figure 1 below. Recent improvements in high spatial resolution earth observation opens up new possibilities to work in smallholder systems (Delrue et al., 2013).

Figure 1: Cluster of very small, cropped fields along streams, Agula, Tigray, Ethiopia. Image was taken October 6, 2019, via google earth.

Nowadays there are many satellites available. Among them, PROBA-V is a global vegetation monitoring satellite. It provides data with a 100 m to 1 km spatial resolution and a daily to 10-day temporal resolution. PROBA-V plays a key role in monitoring those clusters of small fields as shown in figure above (Dierckx et al., 2014). PROBA-V has high temporal resolutions which are suitable for crop mapping and change detection (X. Zhang, & Wu, 2016). Still, it has a coarse spatial (i.e., 1 km, 300 m, 100 m) resolution, and this makes it hard to know the variability of crops, especially in small patches.

Figure 2: Map of small clusters farming areas, same area during two different years, both during the dry season Tigray, Image taken 2015 and 2018 respectively via google earth.

Normalized Difference Vegetation Index (NDVI) time series from PROBA-V were applied to identify the type of the area such as cluster of trees, land use, evergreen shrub/bush lands (T.Zhang et al., 2017). Figure 2 shows the greenness of the same area at different times represented by the NDVI time series. Figure 3 represents NDVI time series associated with profiles that show greenness during the dry and wet season. Figure 4 shows the spatial distribution of NDVI during the year (2010 -2019) throughout the study site in Tigray with wet and dry season samples.

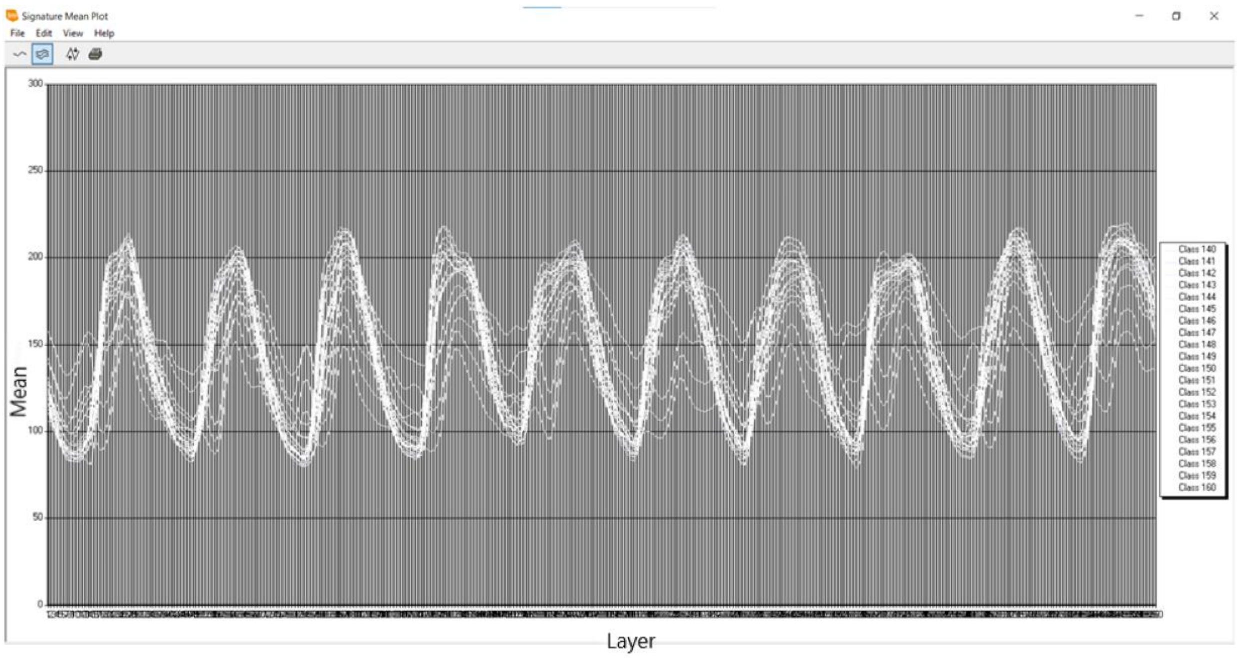


Figure 3: Signature profile of DN-values using PROBA-V, that shows greenness during the dry and wet seasons, from the year 2010-2019, in Tigray.

Using the latest images, hyper-temporal images available, information of the cluster fields can be acquired.

DEMs which are raster files with elevation data for each raster cell can be used for hydrologic, geologic, geomorphic and landscape analysis (Sitabi, 2015).

This can lead to extract information about small clusters of fields at a 10-day interval. This information can then be integrated and used to support and suggest efficient alternatives of the supply chain.

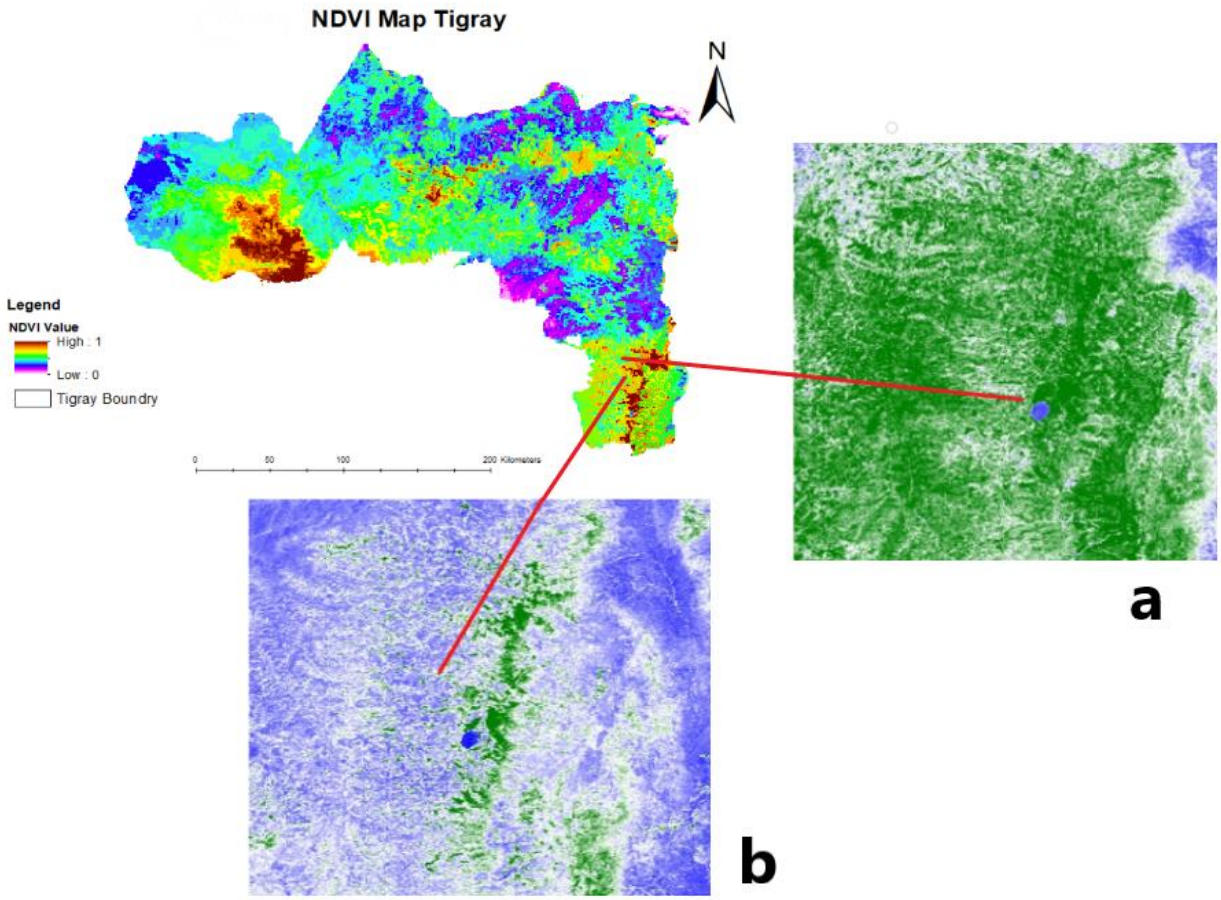


Figure 4: Sentinel-2 NDVI Data of year 2017-2019, Tigray, with samples of wet (Kiremt) season (a) and dry (Hagai) season (b), green areas of (a) and (b)showing higher NDVI values. This map was produced using google earth engine (GEE)

Furthermore, spatiotemporal analysis was conducted for monitoring purposes.

This information of the horticulture availability can be applied to establish and provide improvement of accessibility of agricultural products, that engages stakeholders and minimizes the actors involved in the process. This can also result in selling products at a fair price.

This paper will identify, map, and monitor the presence of horticultural crops within small clusters of fields. Since it was not easy to identify and map horticultural areas using only NDVI values from PROBAV, DEM was used to first identify and detect clusters of smaller fields. using DEM and then further improvement and refining of the areas of interest was conducted using NDVI time series. This research targets small farmlands (Figures 1 & 2) and fields managed by farmers that are in the rural parts of Tigray and have low income partly due to lack of access to market.

2. Research aim and Objectives

2.1 Problem Statement

Insufficient information about crop availability and whereabouts affects the supply chain in Tigray. Especially when products are in remote locations and smallholder farmers, the capacity of getting market access is less and this is a challenge. In addition, different parties that are involved in the supply chain use such information to sell products at an expensive price than the real price of the product by creating a longer supply chain. This makes the whole situation a wicked problem. This research proposes detecting and mapping the horticultural products and monitoring their availability using PROBA-V and remote sensing techniques.

2.2 The main objective

The main objective of this research is to identify, and map irrigated small horticultural areas along with major streams in Tigray, and to monitor over time when a cluster of fields was cropped at what performance level.

2.3 Sub-objectives

1. Map for Tigray, through using a 30m resolution Digital Elevation Model (DEM), potential horticultural areas that are (i) relatively flat and (ii) within a specific distance and height from major streams (as a potential source of irrigation water)
2. Further limit the above extent using 1km resolution NDVI time series from 2010 to 2019 as derived from SPOT-VGT and PROBA-V images, to areas that are possibly cropped
3. Use Google Earth to survey the remaining areas (AOIs) and estimate for them the fractions (%) of clustered fields they contain and that are likely horticultural areas
4. Monitor for selected clusters of fields identified in (3), through assessing their temporal NDVI-patterns, which periods crops were grown and what their performance was (covering 2010 to 2019)

2.4 Research Questions

Research Question 1 for Sub-objective 1.
Which AOI were derived from DEM?
Research Question 2 for Sub-objective 2.
To what extent can 1km resolution NDVI time series help identify horticultural areas?
Research Question 3 for Sub-objective 3.
What percentage of each AOIs is covered by horticulture?
Research Question 4 for Sub-objective 4.
Is there any temporal variability in the selected horticultural areas for the year (2010-2019)?

2.5 Hypothesis

Spot-VGT and PROBA-V have produced effective satellite data to map and monitor clusters of small horticultural fields.

3. Conceptual diagram

The geographical boundary of the system is Tigray, Ethiopia, where the small-scale horticultural production areas are located. The elements of the system consist of the small horticultural fields, and the irrigation system. The farmers including associations are the main actors that manage the land and carry out cultivations starting from land preparation to harvesting. In the system there is water availability which affects the growth of horticultural crops. Moreover, different stakeholders play a key role in this system, though the eventual benefits of this research being to producers and consumers, results of the study are expected to support all stakeholders directly or indirectly (Figure 5).

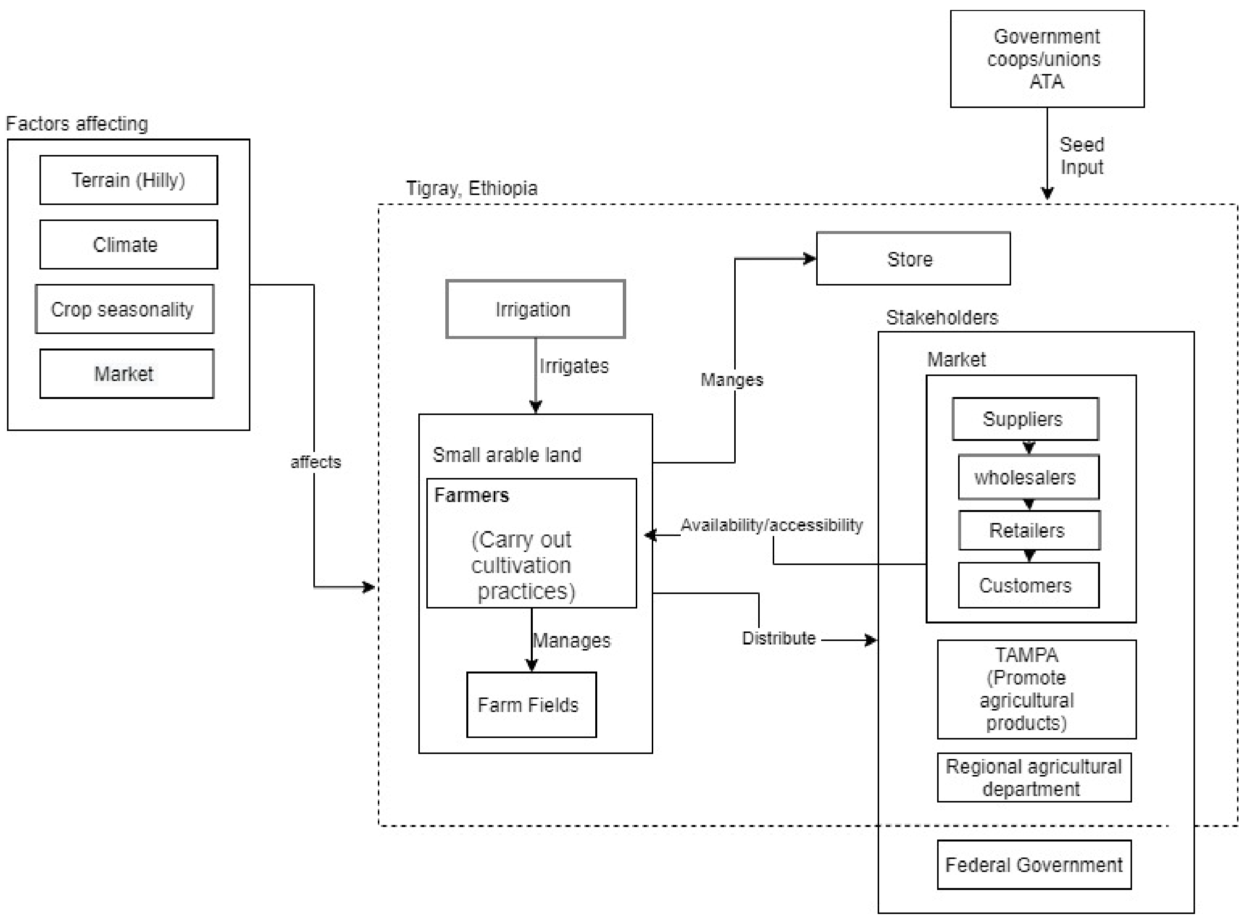


Figure 5: Conceptual diagram of the study

3.1. Literature review and analysis

Different scientific literature is used to complete this research. Previous works were studied to get insight into what attempts had been made to identify the horticultural field using remote sensing data. The literature may also help find relevant data that will be useful for analysis.

4. Methodology

4.1 Study area

The geographical location of the study area is in Tigray, Northern Ethiopia located approximately at 12–14° N and 36–39° E (Figure 6). Tigray consists of over 41,000 km2 (4.1 million ha), with over four million inhabitants. It is approaching the full extent of available arable land in the more productive highlands of the region (Neigh et al., 2018).
The climate gradient in Tigray varies from cool, moist upland areas in the west to dry, open lowland savannas that lead to desert lands in the east. As a result, the productivity decreases from the west to the east, and it closely follows the precipitation gradient. However, due to elevation of 2000 to 4000 m above sea level, the climate is considered temperate and experiences two growing seasons (Neigh et al., 2018). The long rains occur roughly from June to September (i.e., Kiremt) and the short rains occur from March to May (i.e., Belg). There are four different growing seasons. Tsidia/Kiremt (stays from June to September and is the rainy season), Hagai (January to March), Azmera (April to June), and Kewua (October to December) is the harvest season. Agriculture in Tigray depends on the Kiremti Meher (long) rains that last from June to September (Taffesse, Dorosh, & Asrat, 2011b; Vrieling, De Leeuw, & Said, 2013).

Particular irrigated crops in Tigray include vegetables (e.g., red peppers, cabbage) and root crops (e.g., onions, potatoes) (Taffesse, Dorosh, & Asrat, 2011a). The market of agricultural products is based on the traditional value chain system (as shown in Figure 7) consisting of many actors in between. Mainly, the supply chain contains different actors and unproductive market participants that make the chain longer (Amare, 2019).

a

B

Figure 6: Map of Ethiopia (a) and Tigray Region (b) from Google earth

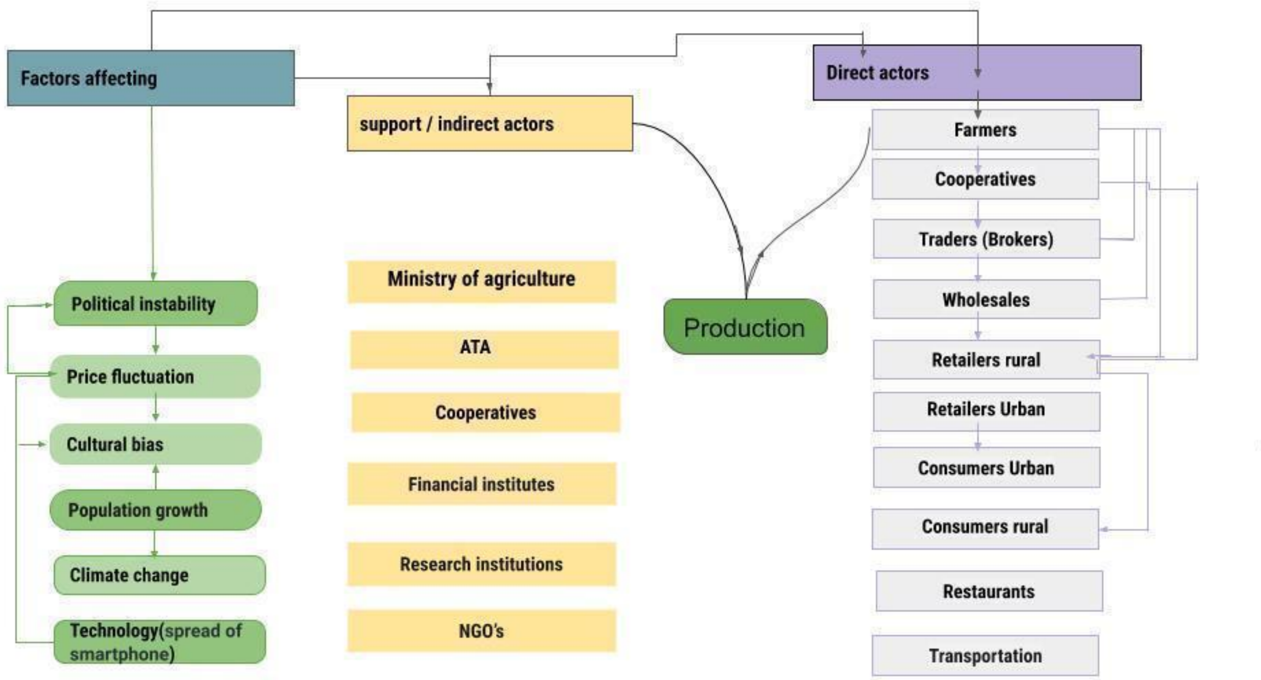


Figure 7: Traditional value chain system

4.2 Data

4.2.1 Remote-sensing data

4.2.1.1 PROBA-V

This study uses remote sensing data of hyper-temporal images from the PROBA-V satellite, launched by the European Space Agency (ESA). PROBA-V contains four spectral bands blue (centered at 0.463 μm), red (0.655 μm), near-infrared (NIR, 0.837 μm), and short-wave Infrared (SWIR, 1.603 μm). PROBA-V has a temporal resolution of 10 days and coarse spatial resolution (i.e., ≃ 1 km). The dataset product is PROBA-V Level 3, which contains images taken from 2010 - to 2019, containing 378 images. The PROBA-V was obtained from the ITC Repository Copernicus_VGT_PROBA_3rd_Catalogue_NDVI in 1km spatial resolution.

It should be noted that hyper-temporal images of the year 2010 - 2019 from the PROBA-V are taken to get the correct representation of agro-ecological zones of land use and land cover.

4.2.1.2 Landsat

Landsat imagery from google earth was used in this study for validation purposes.

4.2.2 Ancillary data

4.2.2.1 Spatial data layer

30m of DEM is used from WorldGrids.org.

Table 1:Summary of the ancillary data will be used for this research

Layer	Format	Source
DEM	Raster	WorldGrids.org

4.3 Software

Different software are used to process, analyze, interpret, and visualize the data. These are shown in Table 2.

Table 2: Software to be used during the research

Software	Description
ERDAS	Image processing,
GDAL	To set the directory to save further files
ENVI	Image processing (smoothing)

Microsoft word	Report and proposal writing
Microsoft PowerPoint	Proposal presentation
Microsoft excel	Export signature profile, export point values and create graphs
ArcMap	Visualization, Design Map
Miro	Conceptual diagram development
Google chrome	Downloading satellite images from PROBA - V
Diagrams.net	Diagram software and flowchart maker

4.4 Research Method

The method is divided into 5 main steps. (1) AOI selection using time series, (2) Identifying potential AOI using DEM, (3) Select AOI using DEM + NDVI (4) Estimating the percentage fraction of each final AOIs, (5) Spatiotemporal analysis for monitoring and validation was also conducted in each step. Figure 9 shows the general flowchart of this work. In this research, DEM analysis and NDVI temporal profiles are used to identify the AOI, which covers horticultural fields along rivers in relatively flat areas. Also, with irrigation options and water supply. The AOIs were validated with Landsat from google earth. As a result, the expected AOI of this research, which are small horticultural irrigated areas, found along streams easily accessible to market areas, were selected. However, it is important to know that this is low spatial resolution data and might lead to loss of vital information. Hence, why estimating the percentage of each class and validating the final AOI's was required.

4.5 Research flowchart

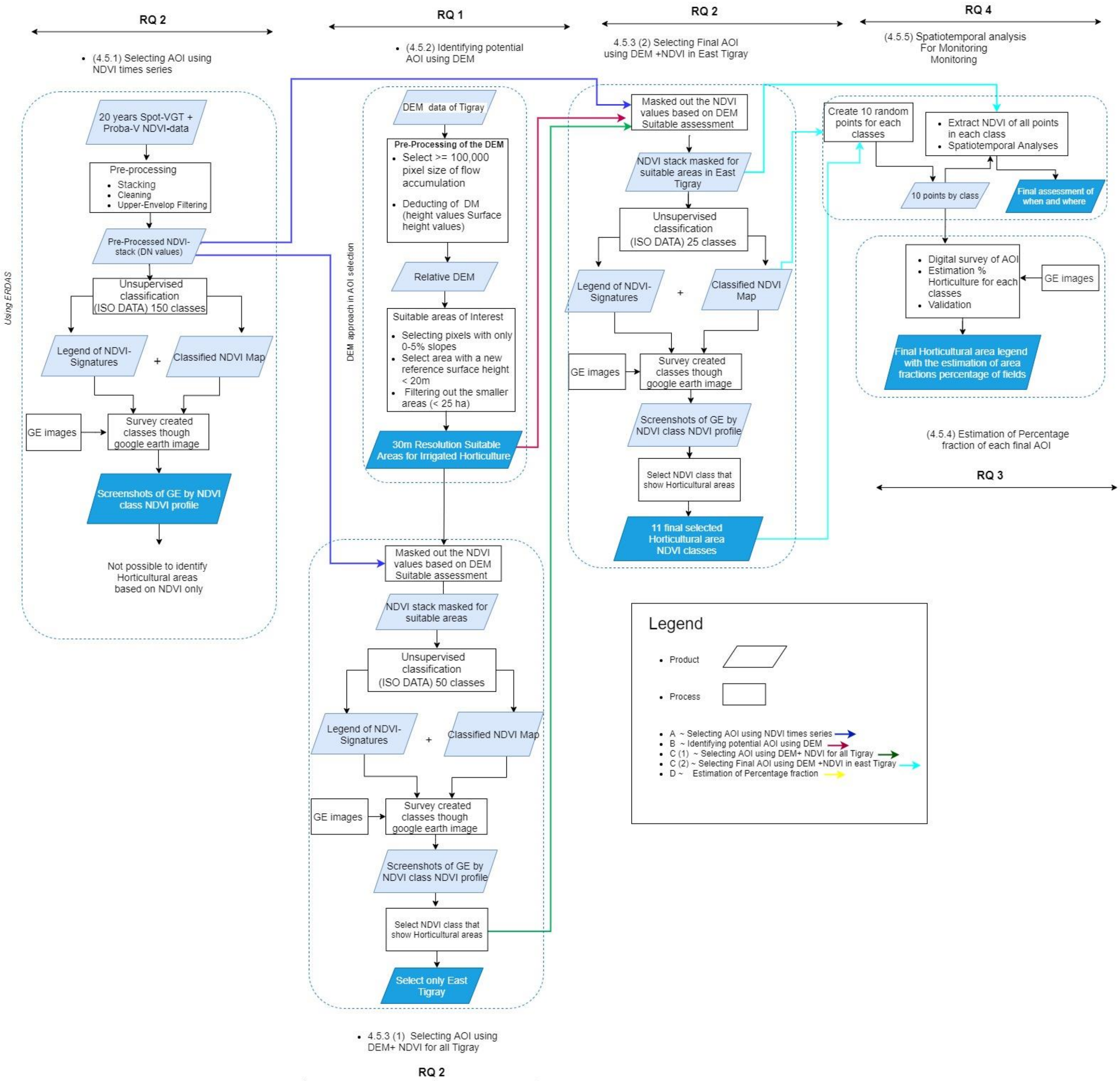


Figure 8: Analytical framework

4.5.1 Selection AOI using NDVI time series

PROBA-V data was used to map the availability of horticultural production areas and extract the main AOI for this research.

4.5.1.1 PROBA-V Preprocessing

Normalized Difference Vegetation Index	$NDVI = \frac{NIR - RED}{NIR + RED}$	$NDVI = \frac{B8 - B4}{B8 + B4}$

Firstly, hyper-temporal NDVI images from the PROBA-V satellite were used. The pre-processing methods for PROBA-V were done using ERDAS. This includes Image correction and projection, retrieving data using GDAL, stacking images, rescaling/ cleaning the NDVI stacked image, applying Savitzky Golay filter (Iterative Upper Envelope Smoothing) to smoothen and reduce noise in NDVI stacked image.

4.5.1.2 NDVI approach in AOI selection

Having high NDVI values indicates healthier plants and low NDVI values indicates less or no vegetation. (Allawai & Ahmed, 2020). This way NDVI helps identify vegetation and provides information about its health and vitality.

After stacking and cleaning the NDVI image, an unsupervised classification was conducted. In a first approach, AOIs were defined using NDVI profiles from the unsupervised classification. Since the area contains small fields and to be as accurate as possible, 160 classes are used. After exploring the results with Landsat from google earth, it was realized that some of the NDVI profiles that met the criteria of being horticultural crops were not identified as such in Landsat imagery. In the second approach, DEM information was considered as explained below

4.5.2 Identifying potential AOI using DEM

4.5.2.1 DEM approach in AOI selection

DEM, Slope, and water accumulation were used to identify potential AOI and NDVI profiles to select the definitive AOIs within the potential AOIs. Potential AOIs were found along streams as well as in flat areas which are the criteria selected in this second approach.

Final AOI were selected based on areas that presented high NDVI profiles during the dry season. DEM approach includes, raster calculator, extraction, clipping, cropping etc.

4.5.2.2 Steps that are taken to filter flat areas of interest using DEM

Different steps were taken to filter flat areas around the streamline with flow accumulation that can be used for irrigation during the dry season. Steps include adding the SRTM DEM and hillside with 30m resolution, Removal of null values, filling sinks, creating flow direction and flow accumulation. The water accumulation threshold was set at a higher pixel value, to be able to see the higher flow accumulation areas. It was expected that irrigations were found in areas with higher accumulation flow. Thus, the pixel value of the low threshold was set at 100,000 and the higher threshold was set at pixels depending on the available cells that flow to a certain area. This lower pixel size was selected by calibrating with the available image in google earth and trial and error.

The small fields with >=100,000 pixels of water accumulation and < 20m height above the height of the nearby river were exacted (Figure 10), and the results were compared with the generated NDVI values to select only the 1km NDVI-pixels that overlap the AOI.

Using ERDAS DEM values of the flow accumulation of pixels above 100,000 is extracted. Those are loaded into the Terrain Surfacing Tool and created a new reference surface (same pixel sizes) through rubber sheeting that goes exactly through those rivers of (FA > 100,000). This is to create the "zero" level by deducting from the actual DEM the new reference surface. Then all rivers turn to a 0-height.

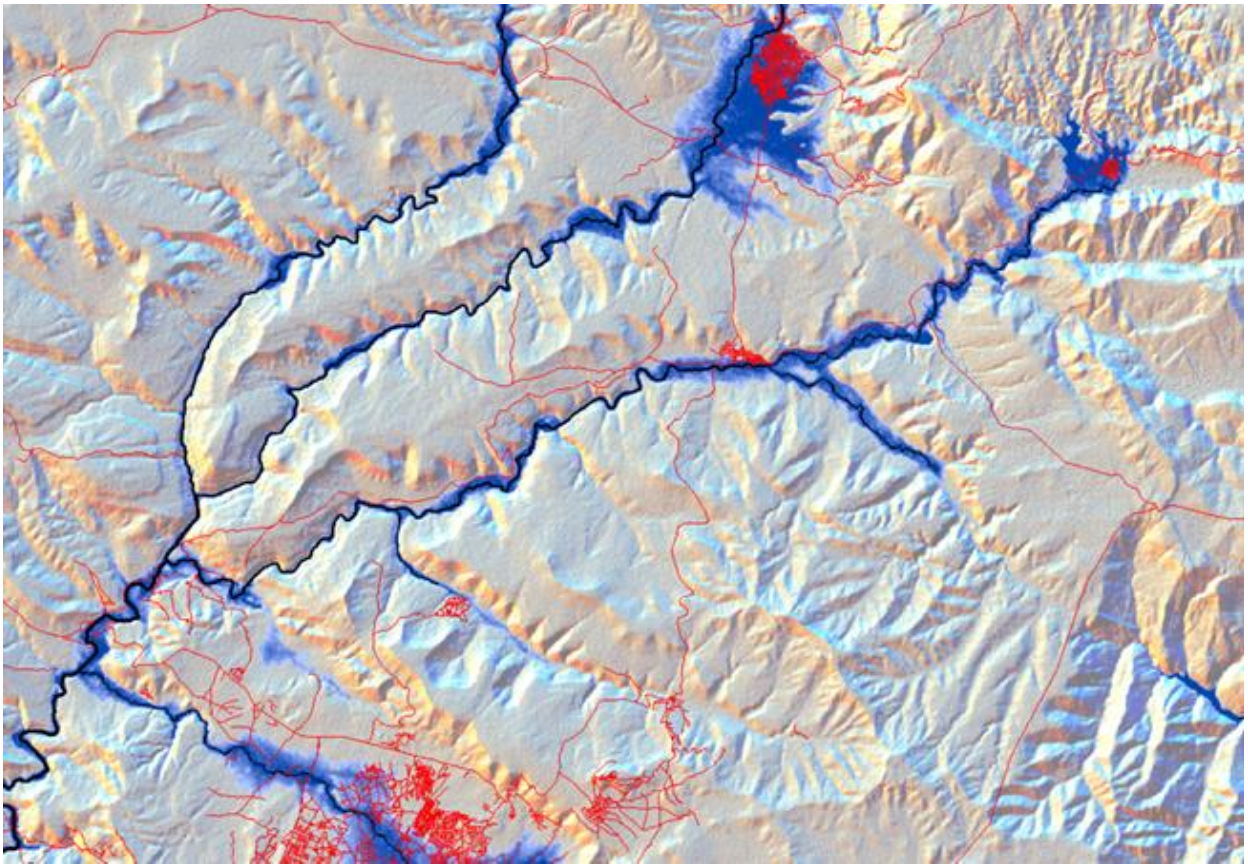


Figure 9: In blue showing -- All areas close to the river system with flow accumulation > 100000 and that have less than 20m height above the height of the nearby river.

Then pixels with only 0-5% slopes and with a new reference surface height < 20m were selected. The majority filter on the results of the map was done twice to make it smoother.

4.5.3 Selecting AOI using DEM+ NDVI

4.5.3.1 Selecting AOI using DEM+ NDVI for all Tigray

After selecting the potential AOIs based on the DEM information, it was used in the NDVI profile to select definitive areas. The goal is to classify just the pixels within DEM polygons.

Then, the NDVI values of the selected potential AOIs were classified in 50 classes applying the previous mask defined by the DEM polygons because it is only required to classify pixels within them. 50 classes are less than the previous 160 classes; however, the target areas are already narrowing down based on the additional criteria, hence 50 class is optimal. Next, the result of each class was explored with google earth image and decided if the classes can be considered as AOI's. Then, final AOI's were selected.

4.5.3.2 Selecting AOI using DEM+ NDVI for East-Tigray

In this section the same approach as the above 50 classes for our Tigray was used. The only difference is that, here only east Tigray was selected. The areas of East Tigray that were generated by DEM during the suitable assessment and the NDVI values of those areas were masked out and classified in 25 classes. Each class was explored in google earth image and decision was made to include the areas as a final AOI or not.

4.5.4 Estimating the Percentage fraction of each final AOI

Finally, to further specify the whereabouts of the horticultural fields the amount of horticulture in each class of those final AOI's by percentage (%) using NDVI was estimated. To estimate the required fractions, random sampling of each NDVI-class was used. 10 random points of 1km pixels for each specific NDVI-class were used, and then visually estimated the % of each class. After estimating % of each 10 points per each class, the average of those numbers was taken as the percentage of the specific class. To cross check the estimated percentages of each class, manual sampling of three classes was taken, and polygons were drowned in the areas that are covered by horticulture and areas of those polygons were measured. The numbers are not exactly the same, but it shows the approximations.

4.5.5 Spatiotemporal analysis For Monitoring

4.5.5.1 Steps followed for Spatiotemporal analysis

The stacked PROBA -V image of the year 2000-2020 was used to extract the selected final AOI's to get the stacked NDVI of only those AOI's using ArcMap.

Random points were created, on the top of the extracted AOI stacked image. In the ArcMap, it was set to use 10 points in one polygon with a distance of 100 meters from each point. Using the multi values tool, values were extracted to points. The output field name was set to “B_ “to represent the bands.

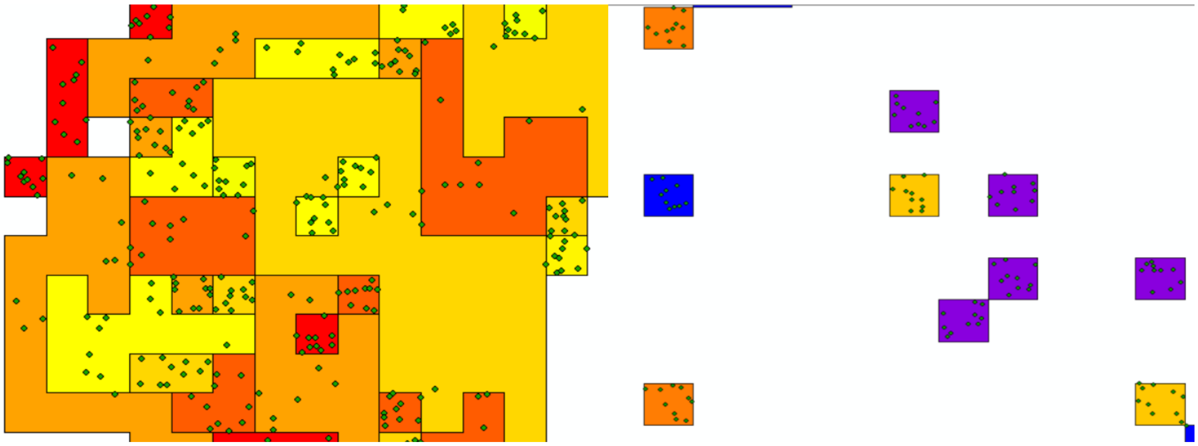


Figure 10: Zooming into the stacked AOI's shows the with random points

4.5.5.2 Steps taken to get NDVI data of the three zonal polygons

Selection by attribute from the region shapefile was used to get the Zone based boundary and export it as a separate shapefile for the selected zone. To get the random sample points that intersect the given zone boundary selection by location was applied and exported to new zone-based random sample points. JOIN_ONE_TO_ONE was made between the NDVI and Zone-based random sample points using spatial join.

Then, the NDVI data of the pixels within final AOIs were extracted to excel. In one polygon it is possible to find more than one same class value. And, since random points were set to 10, and if we expect the same class to appear many times, the expected result would be [Y*10]. Y being the number of classes that can appear in one polygon. However, whenever the results are similar or the difference is insignificant, the average of the random points of each class were taken.

Furthermore, all the areas and classes that fall within the polygons of Ma'ekelawi, Misraqawi and Debubawi zone were listed. Then, classes inside each polygon of the east boundaries were selected to see which zonal area contains similar class and NDVI values. The classes that appear in two or more areas of each polygon and classes that appear only in one were all compared and analyzed, and graphs were drawn.

It is important to note that, only areas greater than 40% percentage fraction cover of horticultural fields were taken to see the spatiotemporal differences of each class within the three Zonal polygons.

4.6 Validation

Exploring the AOI of PROBA-V and validation had taken place by overlaying the selected areas on google earth image and analyzing if the areas are horticultural lands.

5. Results

5.1 Selection AOI using NDVI times series

5.1.1 PROBA-V Preprocessing

Cleaned, smoothed, and stacked image was generated

5.1.2 NDVI approach in AOI selection

The below profiles are the results of NDVI values from the year 2010 - 2019 data of the Tigray Region, which was classified in 160 classes. The cell structure of a plant reflects most of the near-infrared light while the chlorophyll pigment of a healthy plant absorbs most of the visible red light. This implies that high photosynthetic activity, which is associated with dense vegetation, will have less reflectance in the red band and higher reflectance in the near-infrared band. Using those values, vegetable cover can be directed and analyzed.

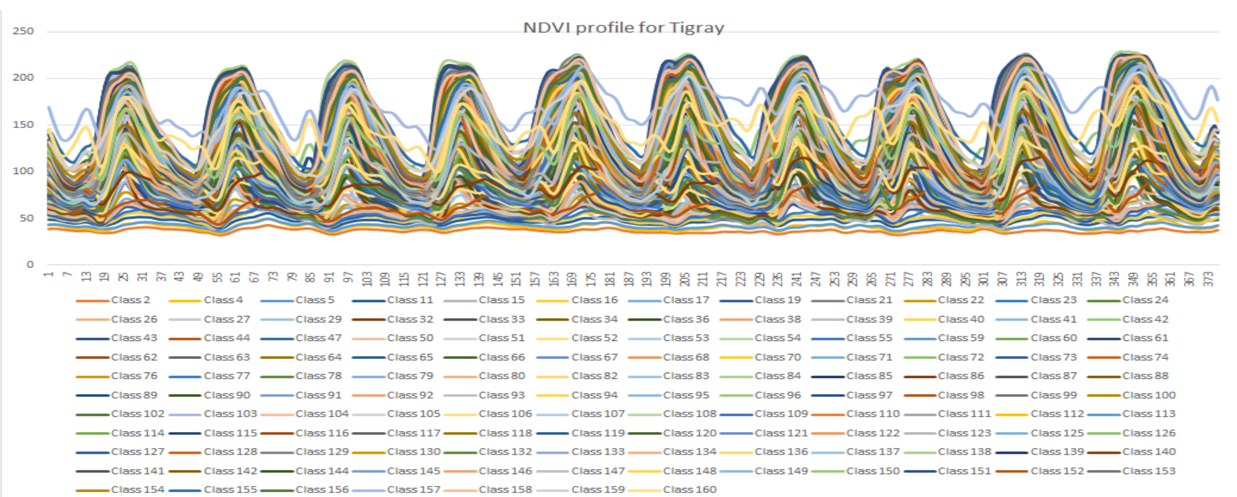


Figure 11: NDVI time series, the result of exported Isodata classification with 160 classes

In this exported signature profile, the high NDVI values during the dry season are found in the final category of the classes. The profiles that presented the six highest NDVI values were taken to identify the possible area of interest.

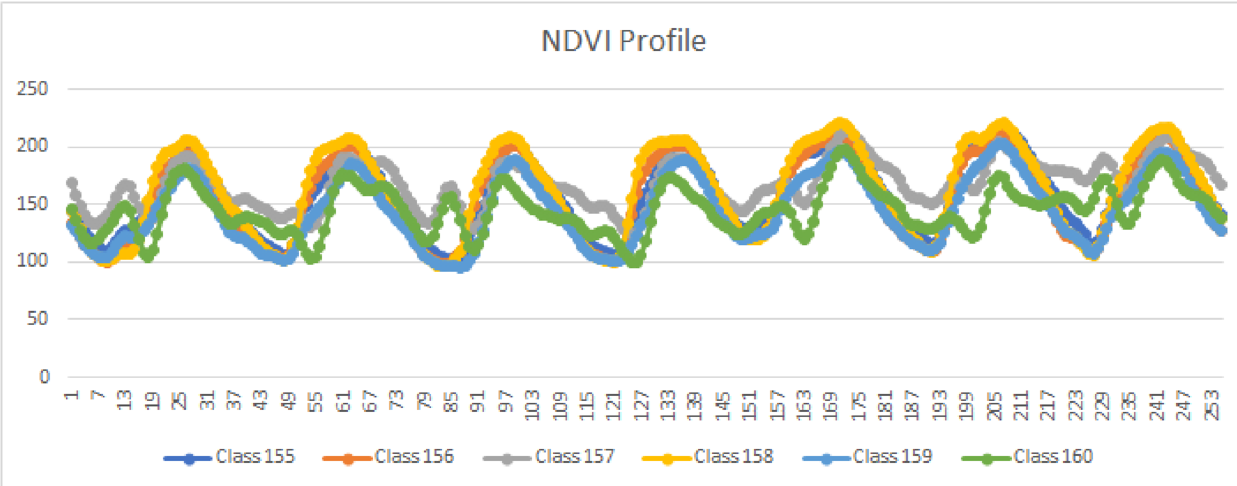


Figure 12: NDVI time series for areas that have high NDVI value during the dry season

In the end, there were some AOIs with the potential NDVI profile but that didn't correspond to the horticultural field. For instance, the land cover of **class** 155 (Figure 13) shows the lowest NDVI value of the six NDVI profiles selected. As shown on google earth, the area contains shrubland; thus, the land use is considered as shrubland. This class covers areas around Madra Gavaia, and Inda Maryam, also around areas Bil'amba, Amba Gheri and Adi Ramet, Tigray.

Figure 13: Images showing google earth image of class 155

Another example is **Class 160** (Figure 14) that has high NDVI values covering areas between Inda Aba Guna and Debrekerbe, Tigray. It also contains shrubland on a mountain but also is found along with cultivated areas with streams passing through.

Figure 14: Images showing google earth image of class 160

In these cases, shrubs and trees are responsible for the relatively high NDVI-values during the dry season, and not, as assumed before, the presence of fields that are irrigated during the dry season. Therefore, another approach must be selected to select areas where horticulture is likely to occur and create a more specific AOI. Clearly, the use of temporal NDVI-data alone could not identify the required horticultural areas as shown above.

5.2 Identifying potential AOI using DEM

5.2.1 DEM approach in AOI selection

Since the first assumption did not work a DEM analysis was carried out. The result of extracted flow accumulation pixels above 100000, the pixels with only 0-5% slopes and with a new reference surface height < 20m was generating areas relatively flat along rivers with sufficient water flow (drainage area) and that have a relatively low height (< 20m) above that river.

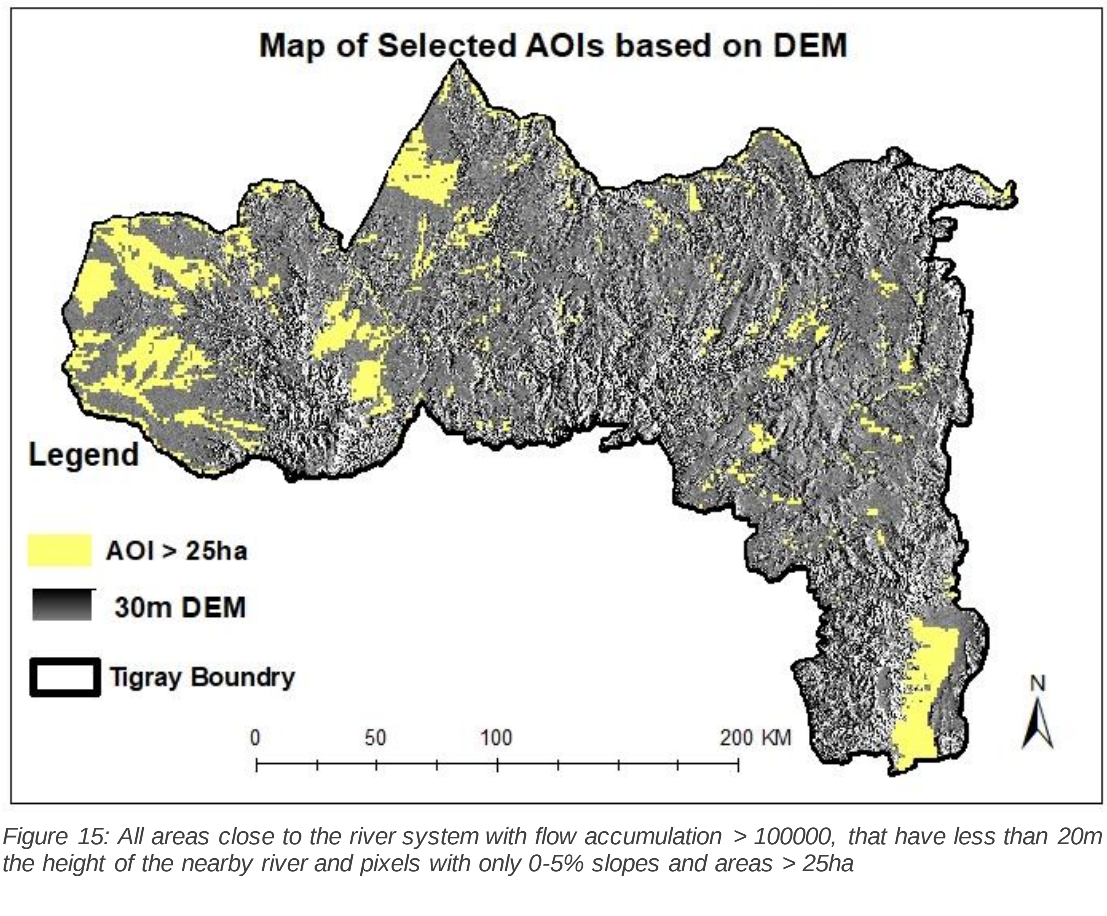


Figure 15: All areas close to the river system with flow accumulation > 100000, that have less than 20m height above the height of the nearby river and pixels with only 0-5% slopes and areas > 25ha

The AOI that possibly contains irrigated fields was selected (Figure 15). This AOI covers all major irrigated areas but is still too broad. Hence, the IMG map was converted to a Polygon map, and the hectares calculated and all that were greater than 25 hectares were selected.

These polygons were converted to a KMZ file and loaded in Google Earth to see if those polygons fit the AOI criteria and to see which areas those polygons cover (Figure 16).

Figure 16:Potential Areas of Interest displayed in Google Earth image

The above-selected areas are close to the river system with flow accumulation > 100000. They have less than 20m height above the height of the nearby river and they are the potential areas where irrigation (horticulture) is possible. This generated possible AOI will be used to re-cluster the NDVI-time series and find the AOI using only 1km NDVI-pixels that overlap the DEM AOI.

5.3 Selecting AOI using DEM + NDVI

5.3.1 Selecting AOI using DEM + NDVI for all Tigray

The potential AOIs derived from the DEM approach were classified into 50 classes using NDVI profile. The result of each class was explored with google earth and decided whether each class is a horticulture field. It should be noted that In addition to the steps taken to get the desired AOI's, signature profiles and google earth images, 'known horticultural areas' were taken as a benchmark to explore the rest of the classes. In this case Agula was taken as a benchmark and classes that show similar patterns were also considered as potential horticultural areas.

There are so many uncertainties and limitations when analyzing the classes this way and this is discussed in the uncertainties section of this research. In the below figure, the red polygon shows the AOI based on DEM and the yellow color polygon shows the AOIs based on DEM and NDVI. Both converted to KMZ files and loaded on Google earth image.

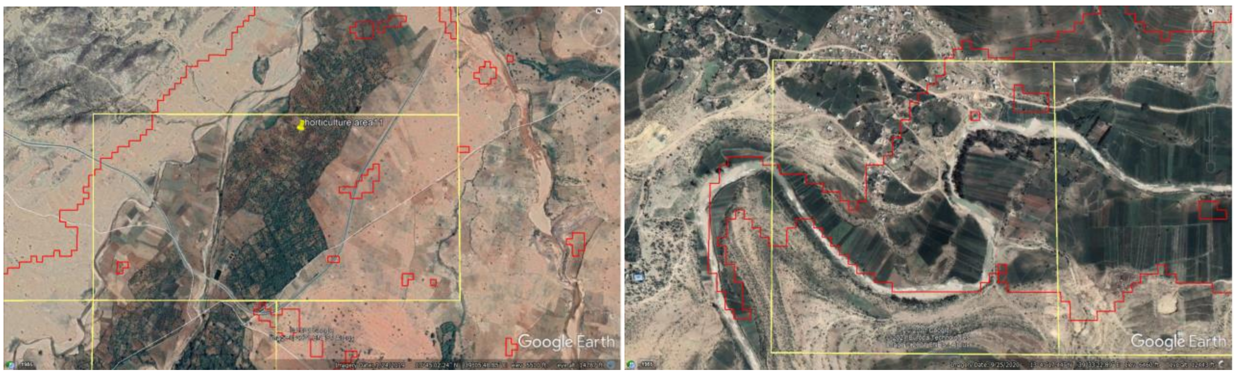


Figure 17: Showing google earth image of (class 12) Covers a lot of places in Tigray, found also around Logol Ch'ak'o, possibly a horticultural area because it shows a similar pattern with horticulture in other places.

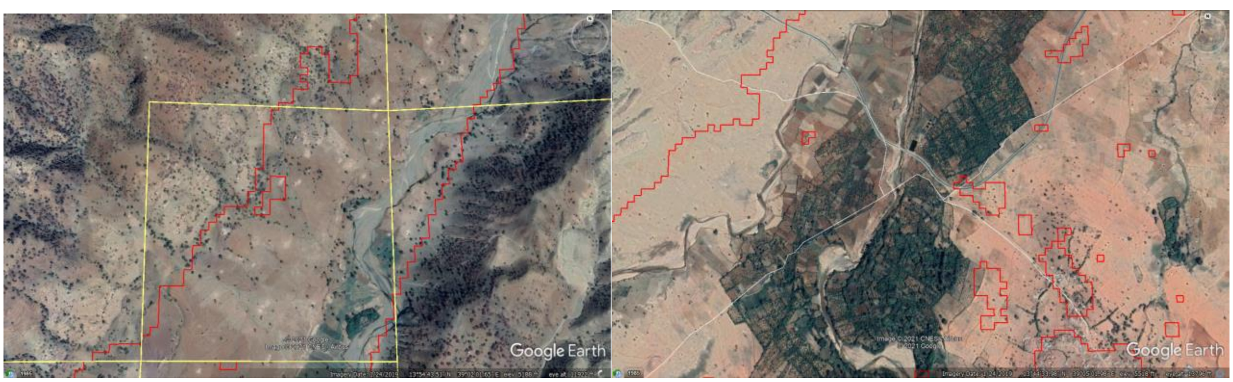


Figure 18: Showing google earth image of (class 15) Most of the areas are found toward the eastern of Tigray, around Agula, farmland area.

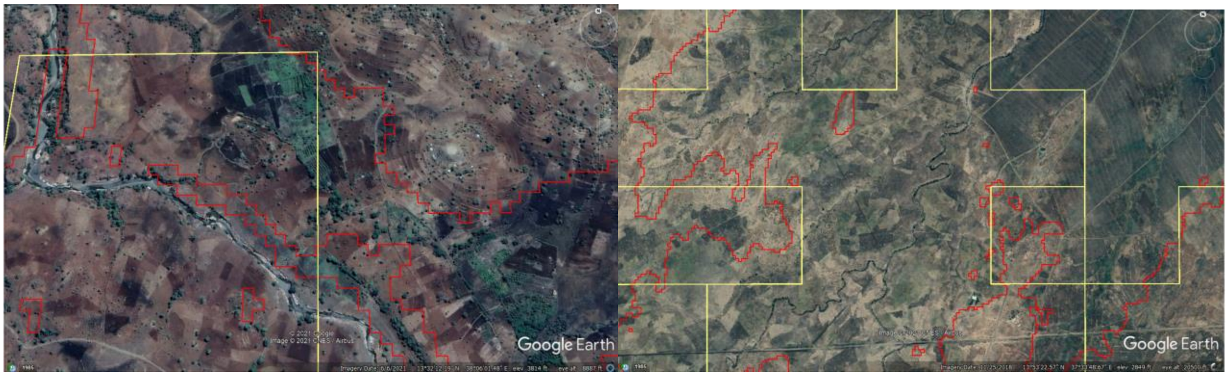


Figure 19:Showing google earth image of (class 30) covers farming area.

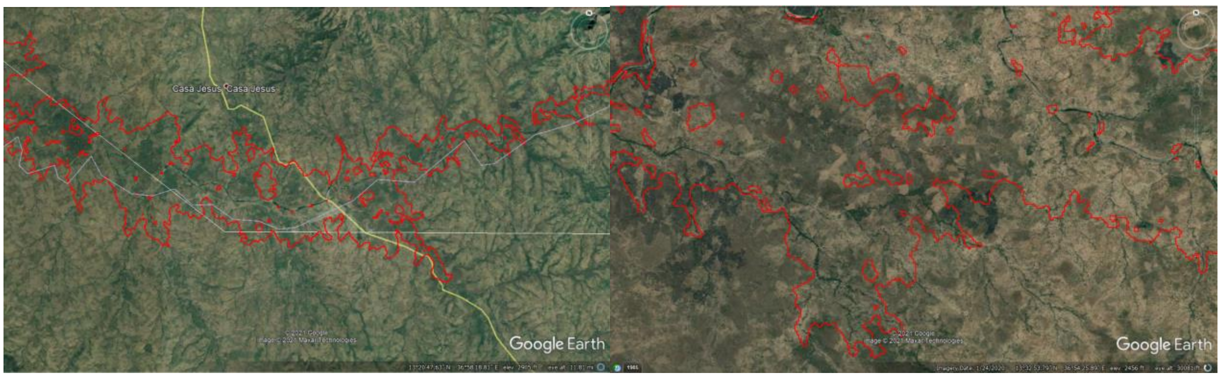


Figure 20: Showing google earth image of (class 44) covers farmland areas.

Figure 21: Showing google earth image of (class 45) covers farmland areas. Found around Mekoni, it covers farmland and possibly horticultural areas.

Figure 22:Showing google earth image of (class 50) found around Mekoni, covers farm land areas and possibly horticultural areas.

Out of the 50 classes that show farmlands are (4,5,79,10,11,12,14,1516,17,18,19,20,21, 22,23,24,25,26,27,28,30,31,32,33,35,37,39,42,44,45,47,49,50)

Out of the 50 classes (12, 14, 15, 21, 23, 26, 30, 39, 42, 44, 45, 47, 49, and 50) were selected as potential horticultural classes. To select those final classes, methods of: Google earth images, prior knowledge of the author on the study area, signature profile of the classes, and the closeness of the areas to the capital city were considered. In addition to this, near-dam areas with farmland were also considered as agricultural areas.

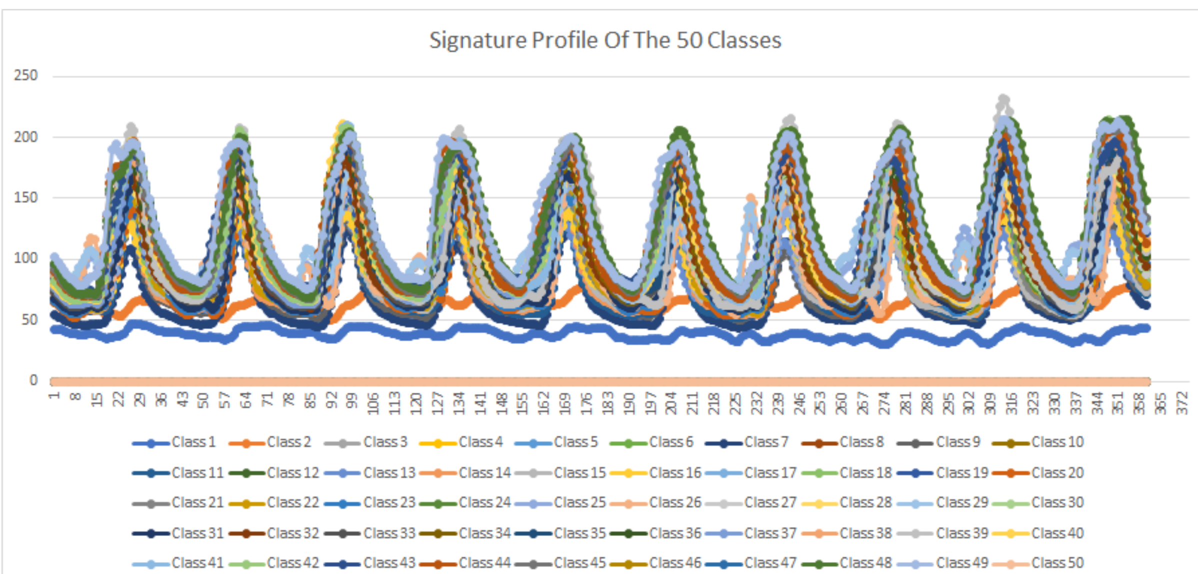


Figure 23: Graph of NDVI time series of the 50 classes.

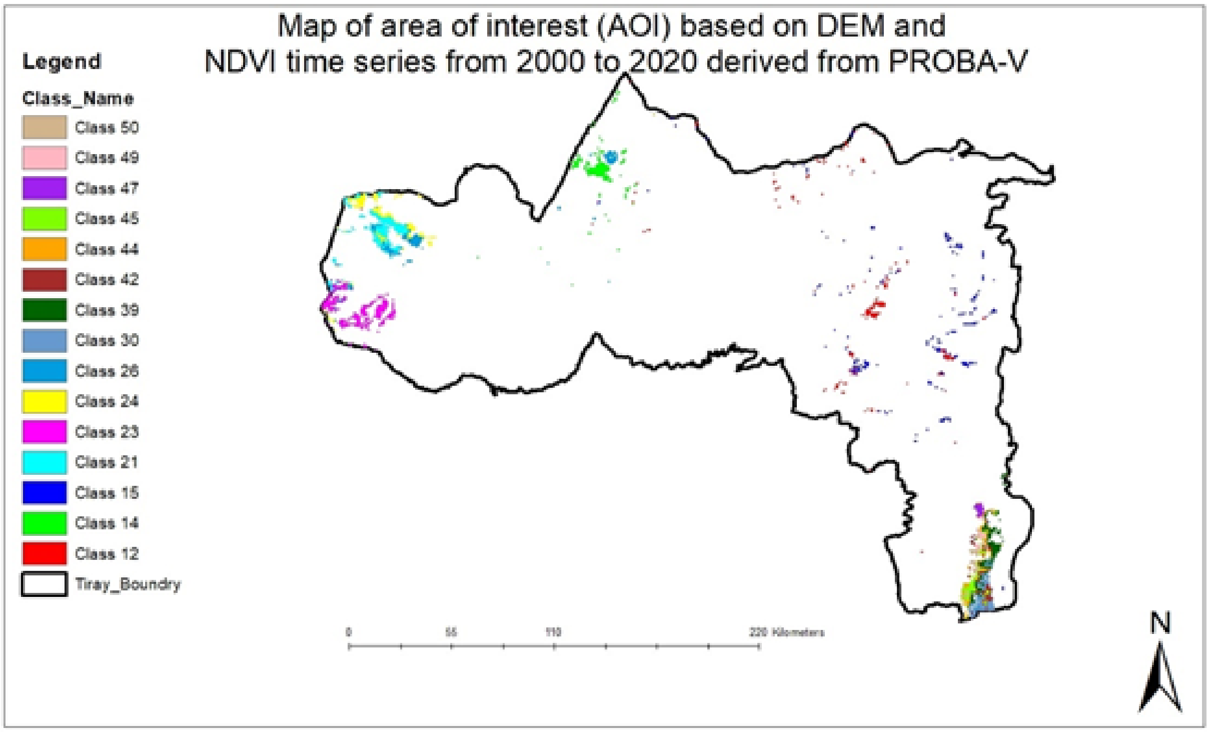


Figure 24: Map of the selected possible (AOI) from 50 classes based on NDVI and DEM time series from 2000 to 2020 derived from PROBA-V.

5.3.2 Selecting AOI using DEM + NDVI for East-Tigray

Now that it becomes clear that most of the potential areas are alongside east Tigray and that eastern Tigray is closer to the capital city, which is Mekelle, the potential area of interest is selected as East Tigray. The main market is Mekelle and most of the products produced at the rural parts of Tigray are transported to Mekelle regional Market. Once the AOI was reduced to East-Tigray, to further see the details it was classified in 25 classes and analyzed with google earth imagery.

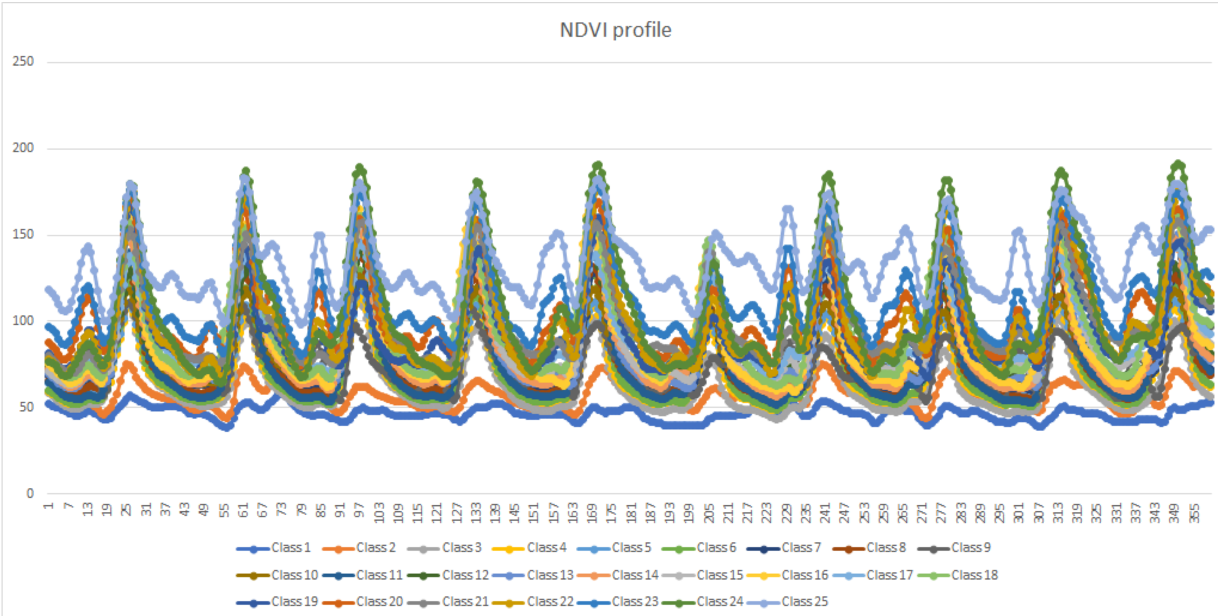


Figure 25:- NDVI profile of the classified East Tigray area.

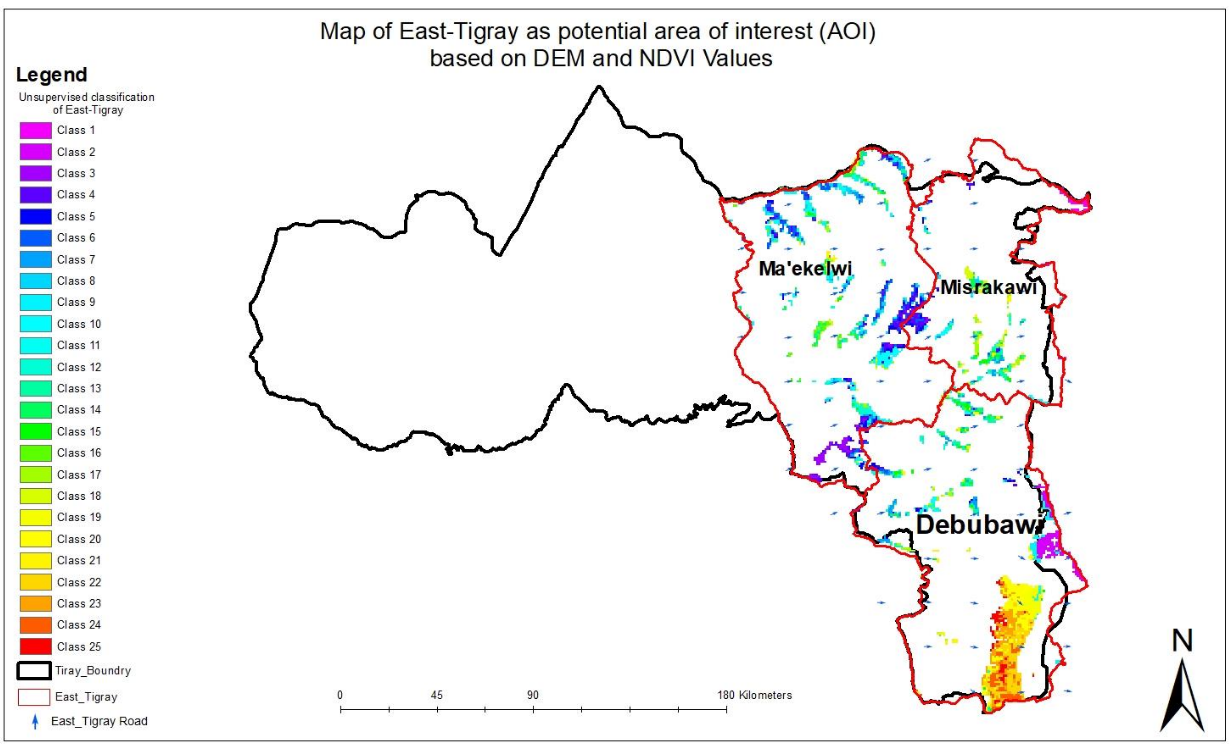


Figure 26: Map of East Tigray with the potential area of interest (AOI) based on DEM and NDVI values, with the zonal boundaries

Each class was analyzed with the NDVI signature mean plot and zooming in to google earth image. Also, the standard deviation of each class was calculated to evaluate how the representative is the mean of the entire class.

The land cover of **class 1** shows low NDVI and has no seasonal variation. The area in google earth shows no vegetation and it is assumed to be a bare Land.

- **Class 2,** Mostly found around Guangua and Uare Uaio shows no seasonal variation, and the NDVI values are low. In google earth it shows shrubland and bushes.
- **Class 3,** Shows higher NDVI values when compared to class 1 and class 2. Some of the names however it only contains bushes and shrublands
- **Class 4,** Is found around Gera'alta and shows tree shrublands.
- **Class 5,** Found around Atebei and Adi Quarario and contains shrubland.
- **Class 6,** Is found around AD Garab Sadiai and some part of it is found around Gere'alta and shows bushes and shrublands.
- **Class 7,** Is found dispersed in many areas of East-Tigray. Some of the places are Around Hiwane, Adi Hana, Agerba and around Indaselassie airport and shows bushes and shrublands. However, some other areas like Adikolen contain farmland areas, and are found around water bodies. In addition to that some areas of Agula are also covered in **class 7.** As research indicates Agula contains horticultural areas. This class also has a higher NDVI value than the last 6 classes. This means it can possibly be a horticultural area, thus it is considered as one of the areas of interest.

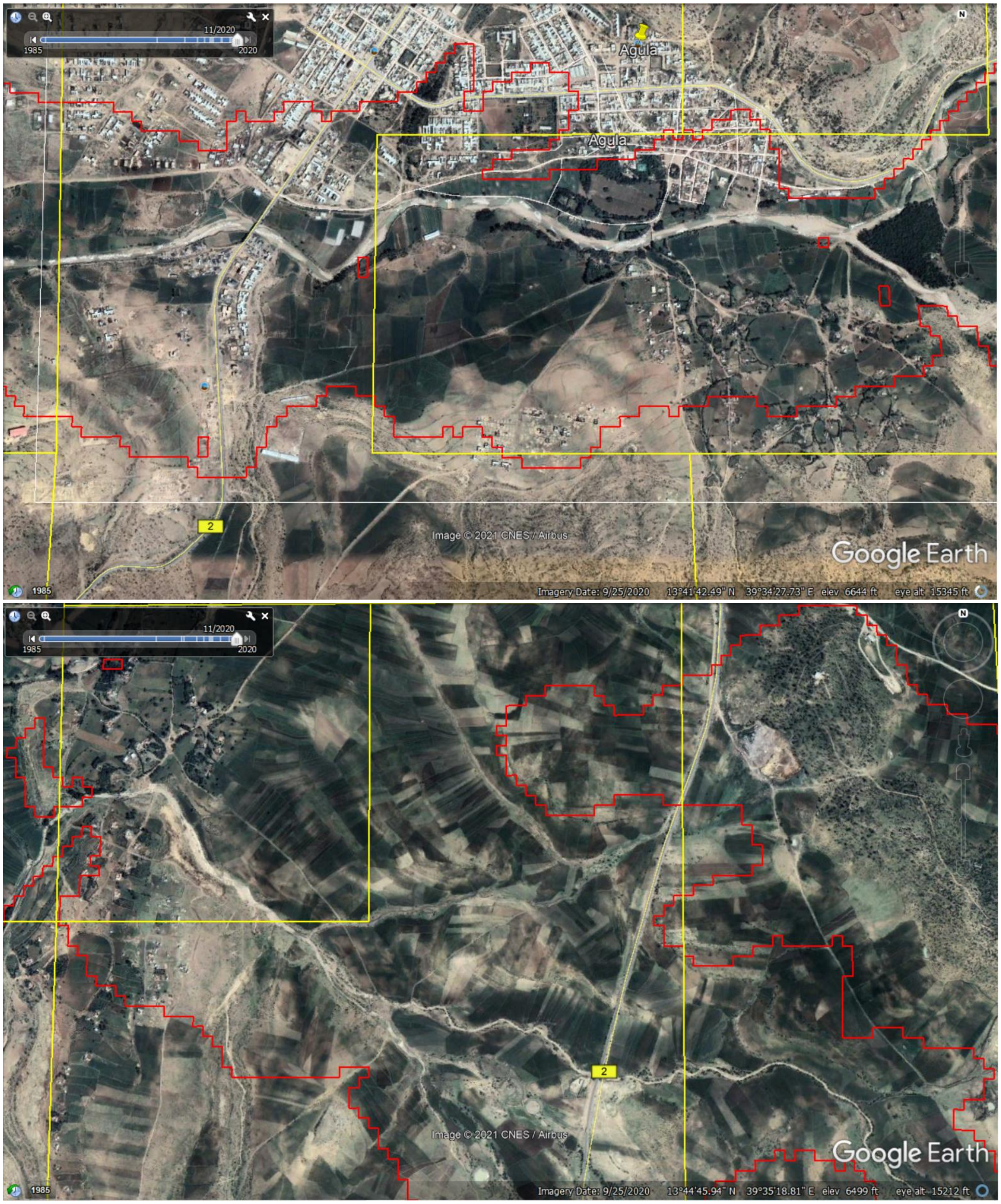
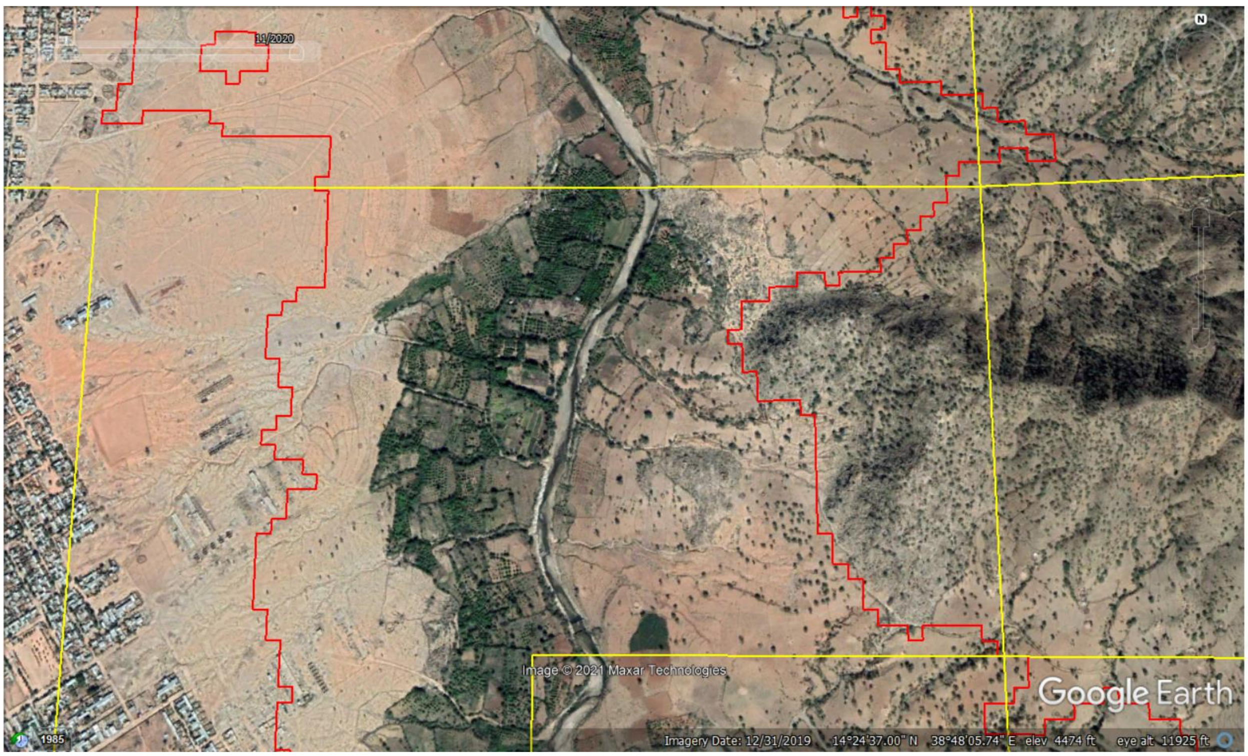


Figure 27: Both images showing googles earth image of class 7 around Agula and around Korar, Wikro.

● **Class 8:** Clearly shows forests and some bushes.

● **Class 9:** The area in google earth shows shrubland and bushes and is found around Uare Uaio.

● **Class 10,** The areas that are found around Ch'ak'o show bushes and shrubland. However, some areas that have the same class are found around **Rama** which is a horticultural area. **class 11** and **class 12**: also behave similarly. They all show shrubland in some areas but also show agricultural land which are possibly horticultural areas. Hence, they are all considered areas of interest for further analysis.



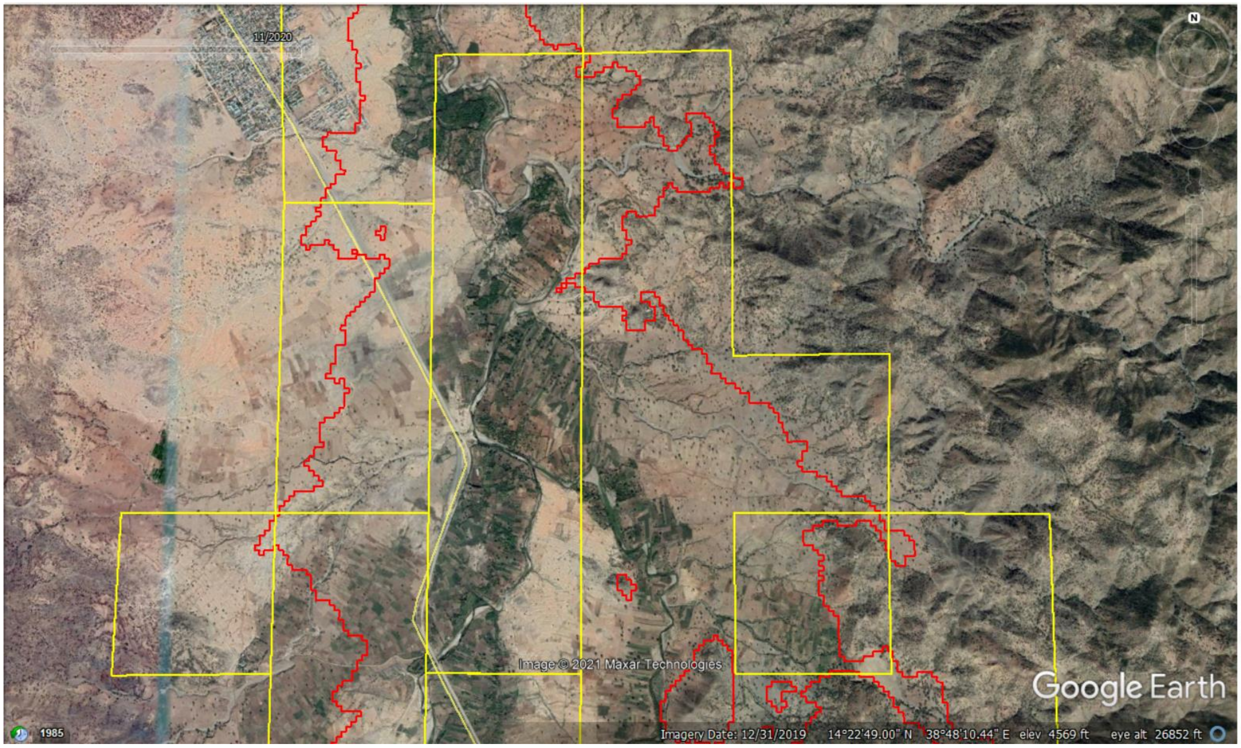


Figure 28: Both images showing googles earth images of classes 10 and 11 which are ound around Rama.

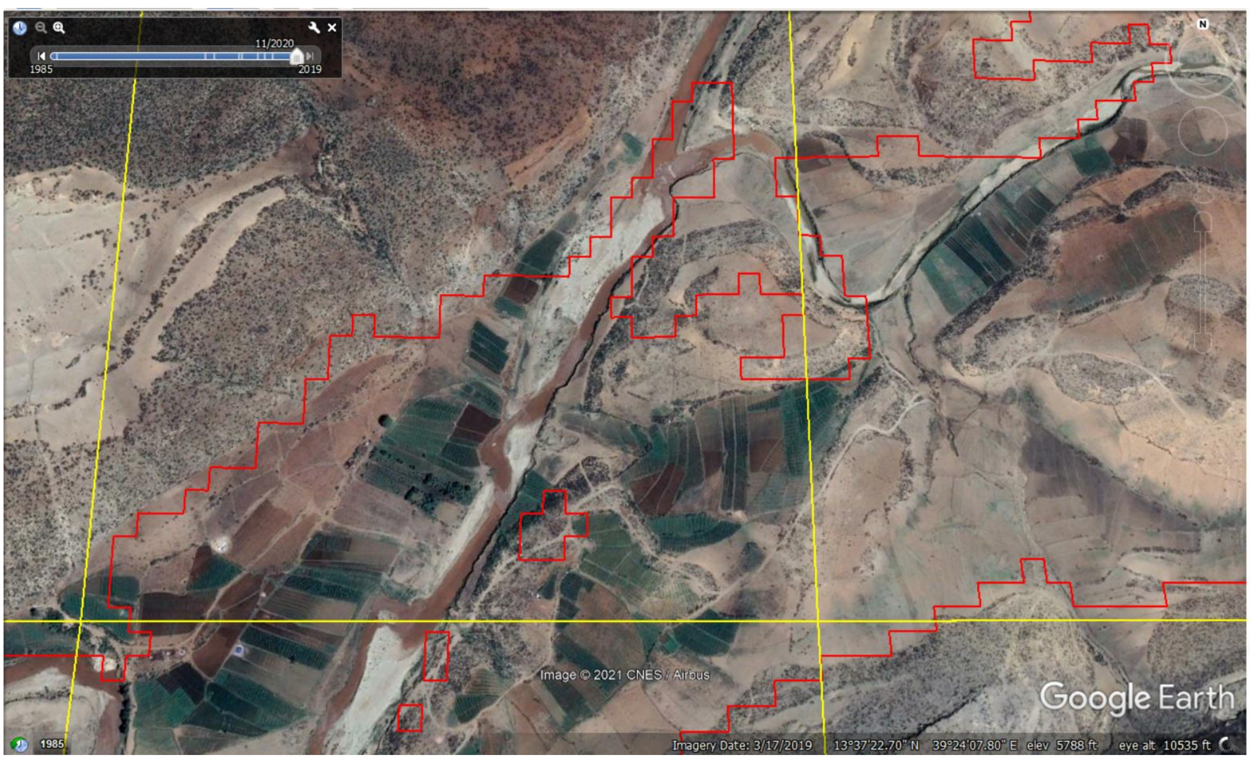


Figure 29: Showing google earth image of class 12, a place found to the right of Kuhila and Diyadin.

Class 13: is found around Hiwane and contains higher NDVI values with seasonal variation and is found around streams. Some parts of Agula also lay in this class. This class is also considered as an area of interest.

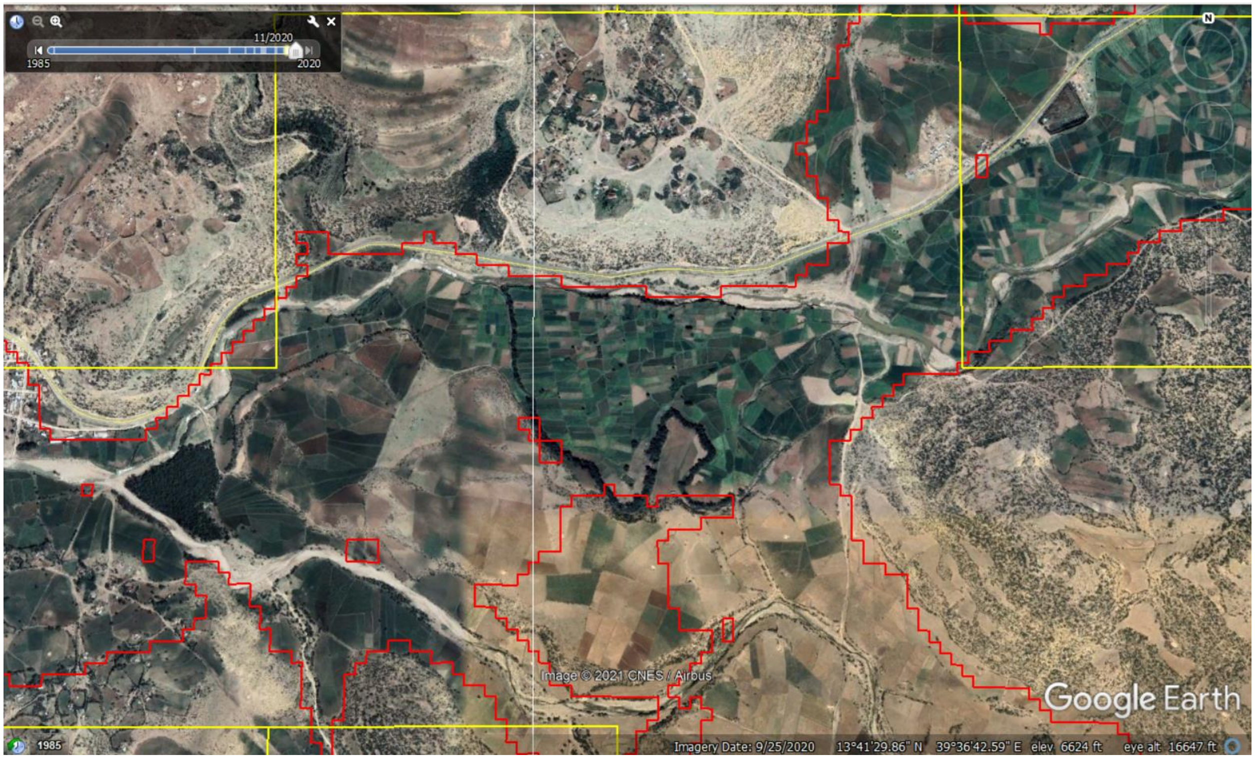


Figure 30: Showing google earth image of Class 13, around Agulae

- **Class 14:** Shows high NDVI but shows bushes and shrublands on google earth image.
- **Class 15:** Has a seasonal variation with relatively high NDVI values. Shows farmland areas on google earth image and could possibly be horticultural areas and is considered as areas of interest.

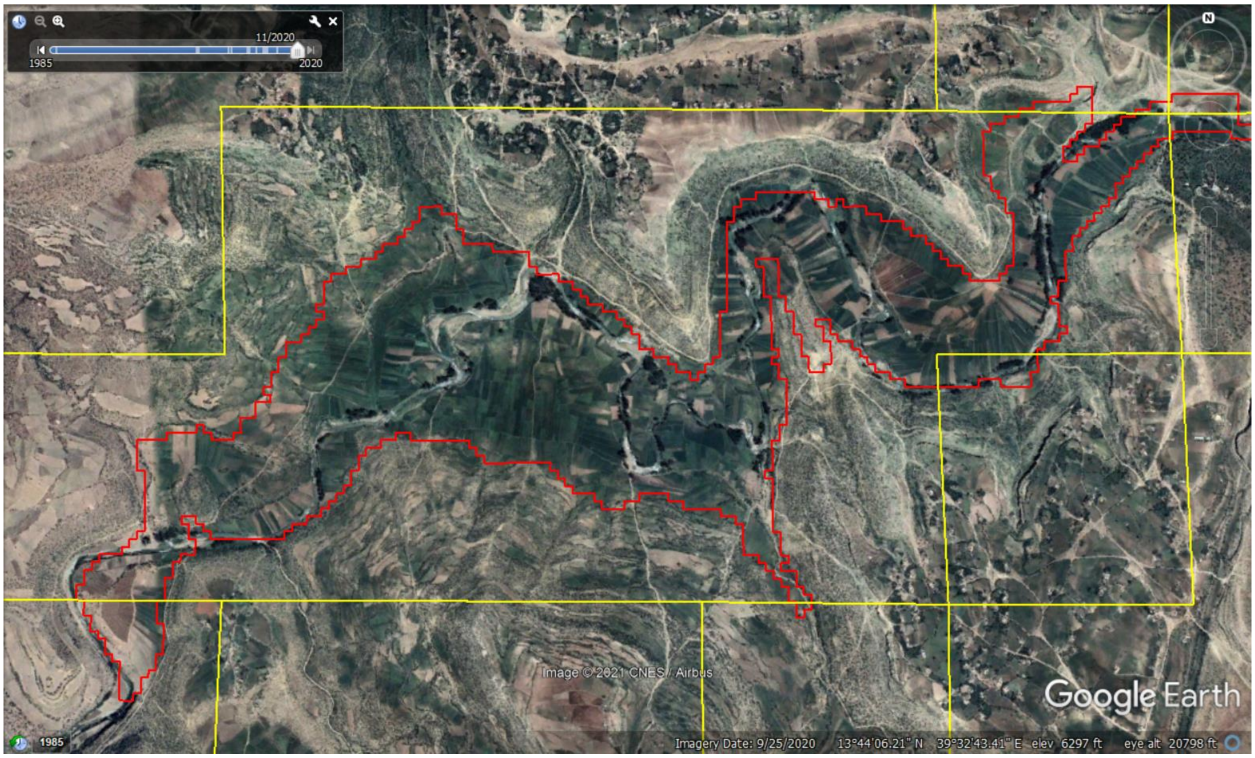


Figure 31: Both images showing googles earth image of class 15 around Wikro

● **Class 16:** In google earth this class shows shrubland trees and buses.

● **Class 17:** Has high NDVI value with seasonal variation, found in places like May Tiwa and Abraha Atsebeha. In google earth it shows bushes, trees and shrublands but also in Agula it covers areas that are possibly horticultural. Hence this class is considered as an area of interest. **Class 18** and **class19** also behave similarly and are considered as areas of interest.

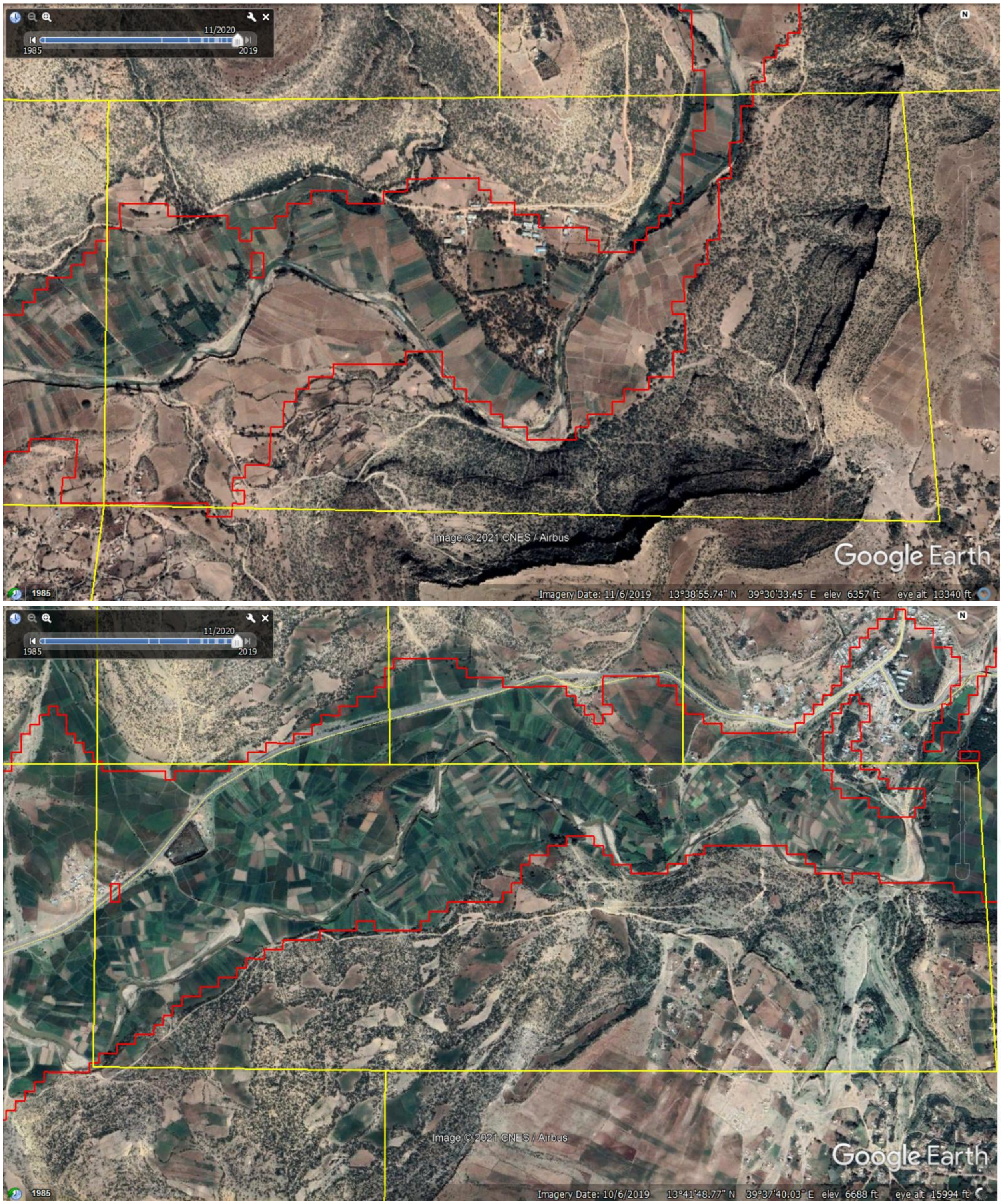


Figure 32: Showing google earth image of class 17 around Agula

● **Class 20:** Is found around Du'alga, North of Mekoni and in Waja. It shows high NDVI values, and shows farmland areas on google earth. This class is considered as an area of interest as well.

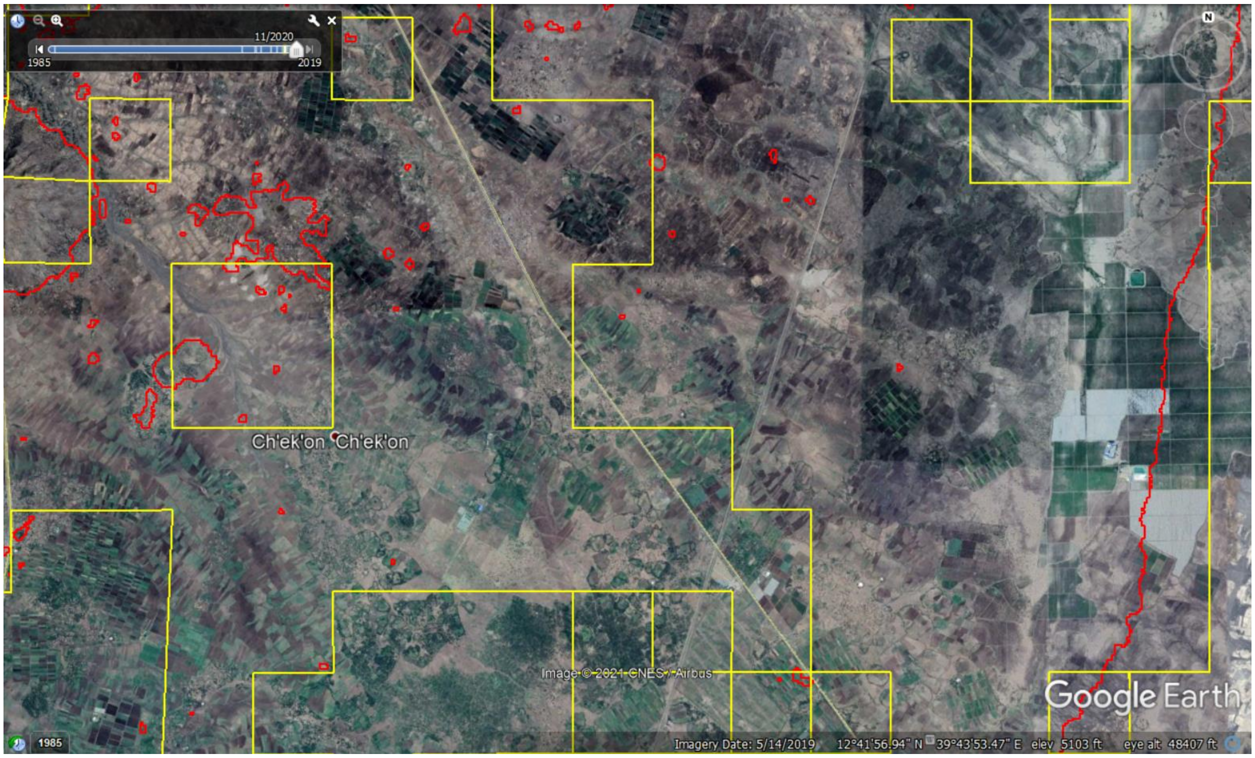


Figure 33:Showing google image of earth Class 20, around Ch'ek'on

● **Class 21**: Is found around Abna'o and around wikro. It shows a similar pattern with the areas that show horticultural areas and shows high NDVI values. This class is considered as an area of interest. Classes 22 23 24 and 25 which are mostly found in the southern part of Tigray shows high NDVI values and in google earth it shows farmlands, those areas are also considered as area of interest.

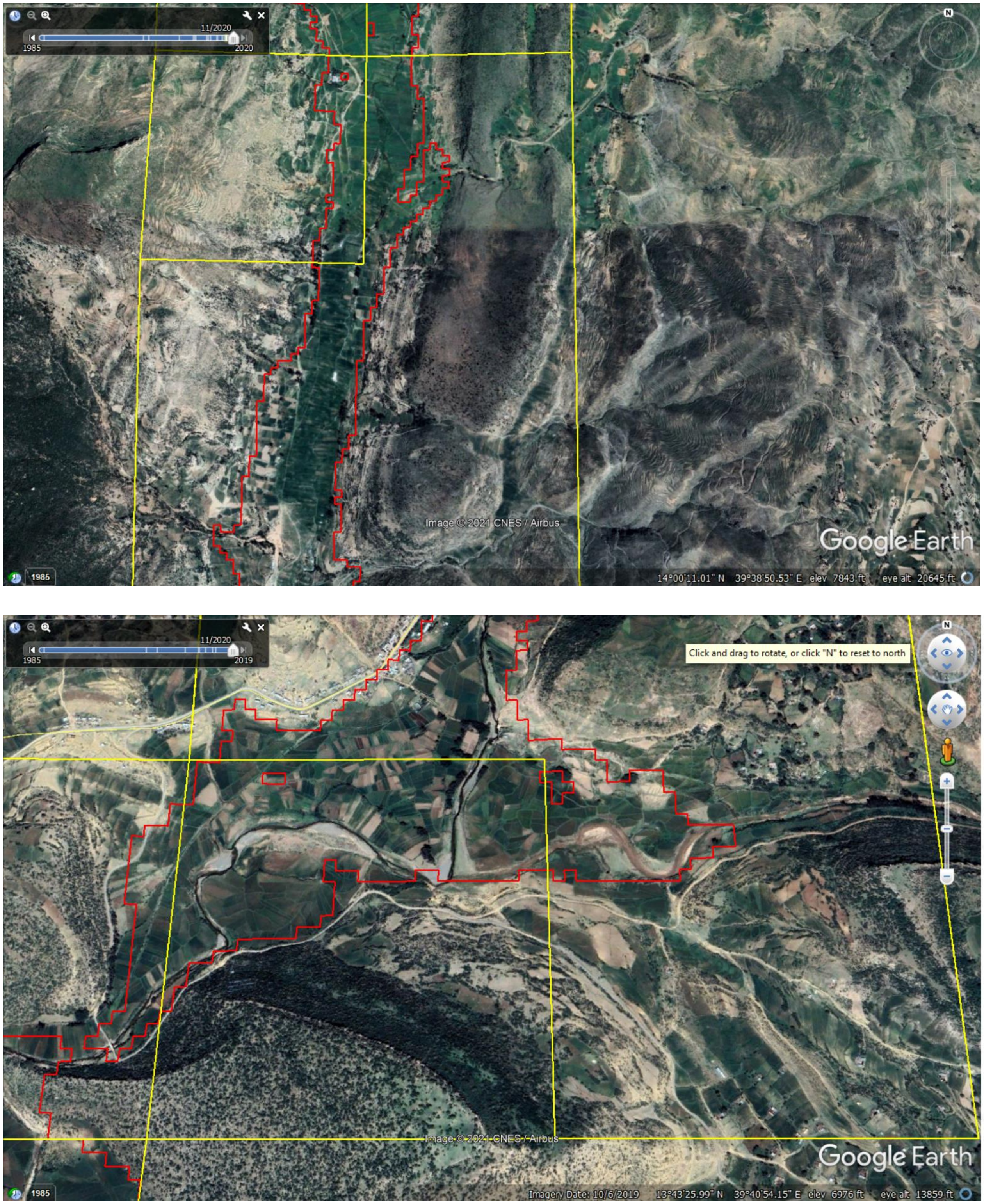


Figure 34: Showing google earth image of class 21 around Abna'o, Tigray, Adi Washo and around Agulae

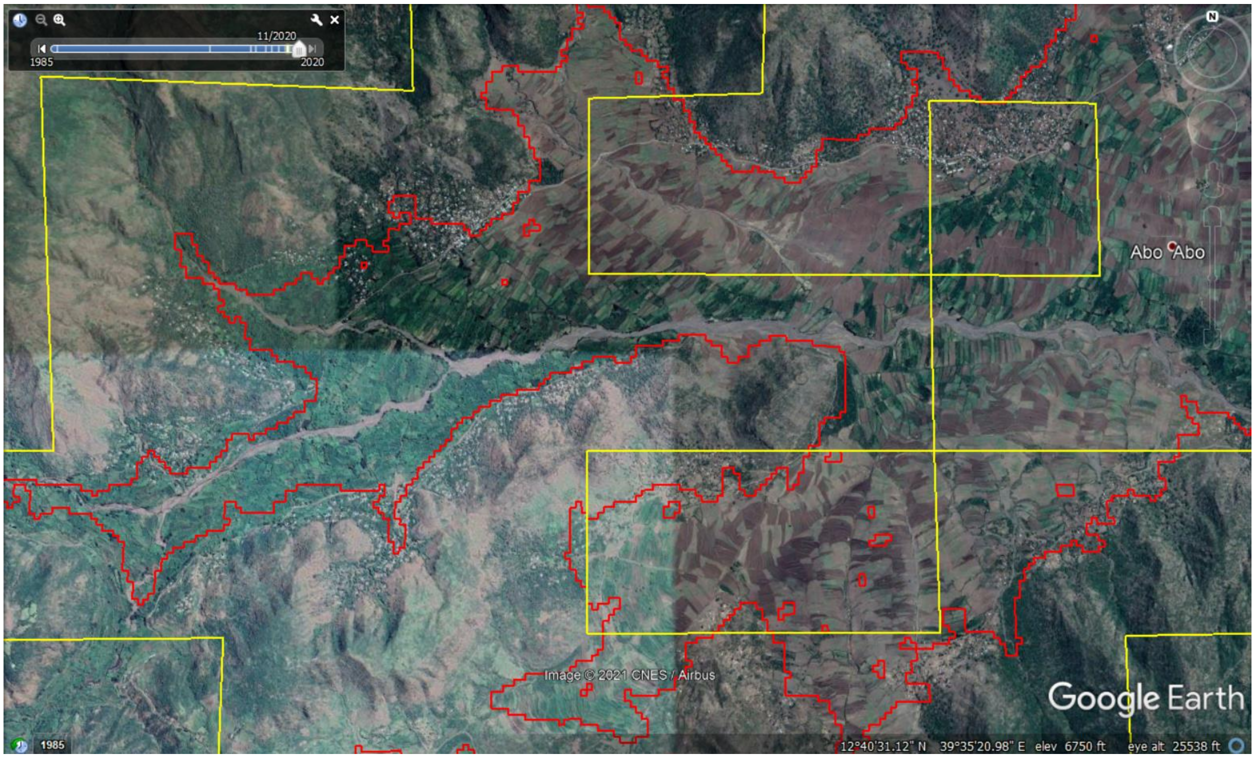


Figure 35: Showing google earth image of class 25 around Kube, and Abo

Finally, 15 classes were selected as finally areas of interest, those are class (7, 10, 11, 12, 13, 15, 17, 18, 19, 20, 21, 22, 23, 24, 25).

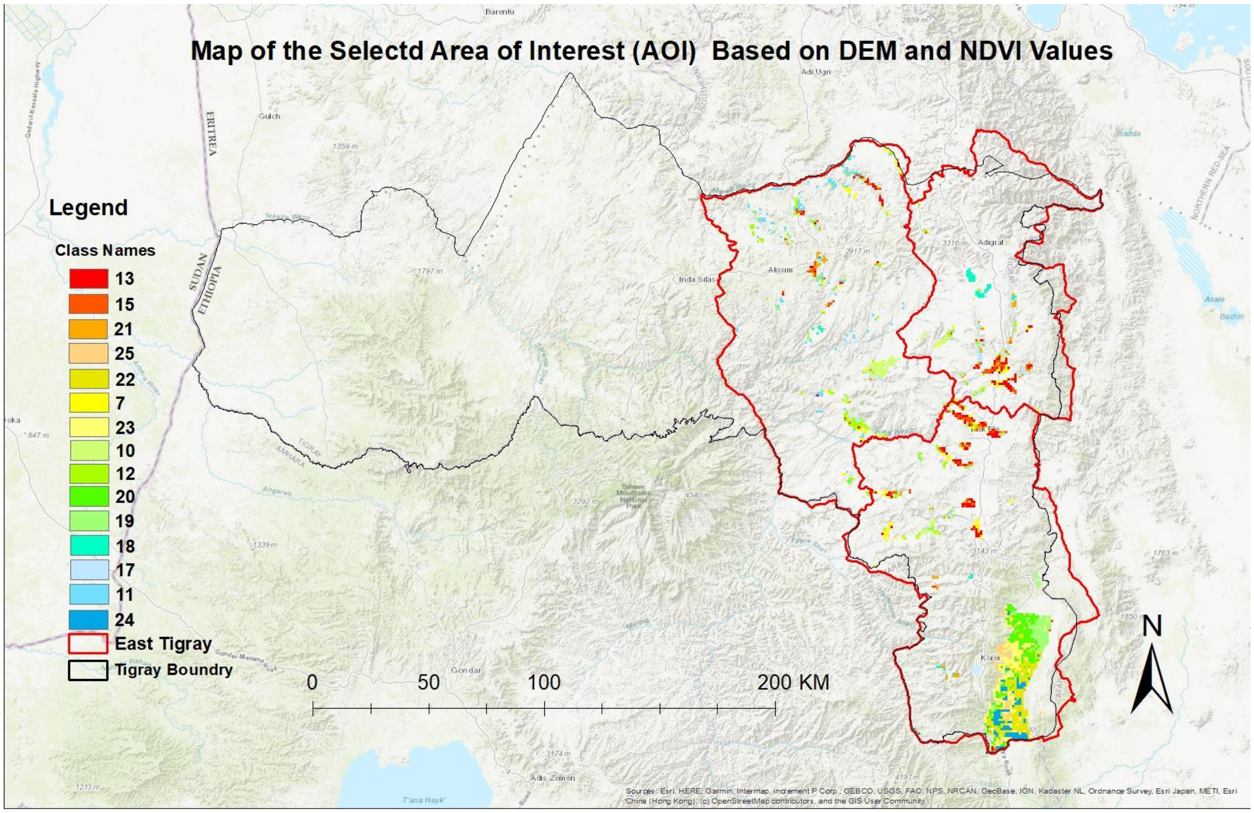


Figure 36: Showing Map of selected areas in East-Tigray as an area of interest (AOI) based on DEM and NDVI Values.

5.4 Estimating percentage of horticultural areas per pixel from NDVI value

As shown on the google earth images above many of the final selected NDVI-classes covering the AOI are not fully covered with horticulture fields. Thus, to specify the horticultural whereabouts beyond the criteria as specified through DEM-analysis. All the 11 final AOI's were studied, and the percentage fraction of that class covered by horticultural fields was estimated using Google Earth.

Table 3: Showing % fraction of each class

Classes	Total area	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Sum	Average in %
Class 7	13929.17427	0	85	80	0	10	40	70	70	20	0	375	37.5
Class 10	15806.15497	0	0	90	95	80	20	0	0	50	0	335	33.5
Class 11	13336.44388	40	0	0	0	0	50	10	0	0	5	105	10.5
Class 12	18177.08021	30	0	0	0	0	20	90	95	50	20	305	30.5
Class 13	16201.30569	90	95	90	10	90	50	95	90	100	50	760	76
Class 15	12052.19523	80	70	90	80	40	30	0	0	30	20	440	44
Class 17	14027.95927	0	0	20	50	0	0	0	90	20	0	180	18
Class 18	6322.465408	20	0	0	40	0	0	95	0	50	0	205	20.5
Class 19	12743.70937	0	50	25	30	0	75	30	0	0	0	210	21
Class 20	21239.52466	25	0	0	75	0	0	10	90	0	25	225	22.5
Class 21	8989.750289	50	50	25	80	25	90	80	5	0	50	455	45.5
Class 22	22918.95523	5	0	20	90	80	0	75	80	50	20	420	42
Class 23	20943.15997	90	50	10	0	90	90	20	0	10	0	360	36
Class 24	11459.46091	10	0	15	0	5	40	0	10	0	20	100	10
Class 25	7507.922027	90	0	80	20	90	95	50	0	0	10	435	43.5

To cross-check the estimated percentages of each class, manual sampling of 3 classes was taken, and polygons were drowned in the areas that are covered by horticulture, and areas of those polygons were measured. The numbers are not exactly the same, but it shows the approximations.

Table 4: Cross checking the gained % fraction

Classes	Area Coverd by Horticulture (ha)	Total Area of each classes	% of each class
Class 7	4109.5	13929.17427	29.5
Class 17	1643.4	14027.95927	11.7
Class 24	1639.27	11459.46091	14.3

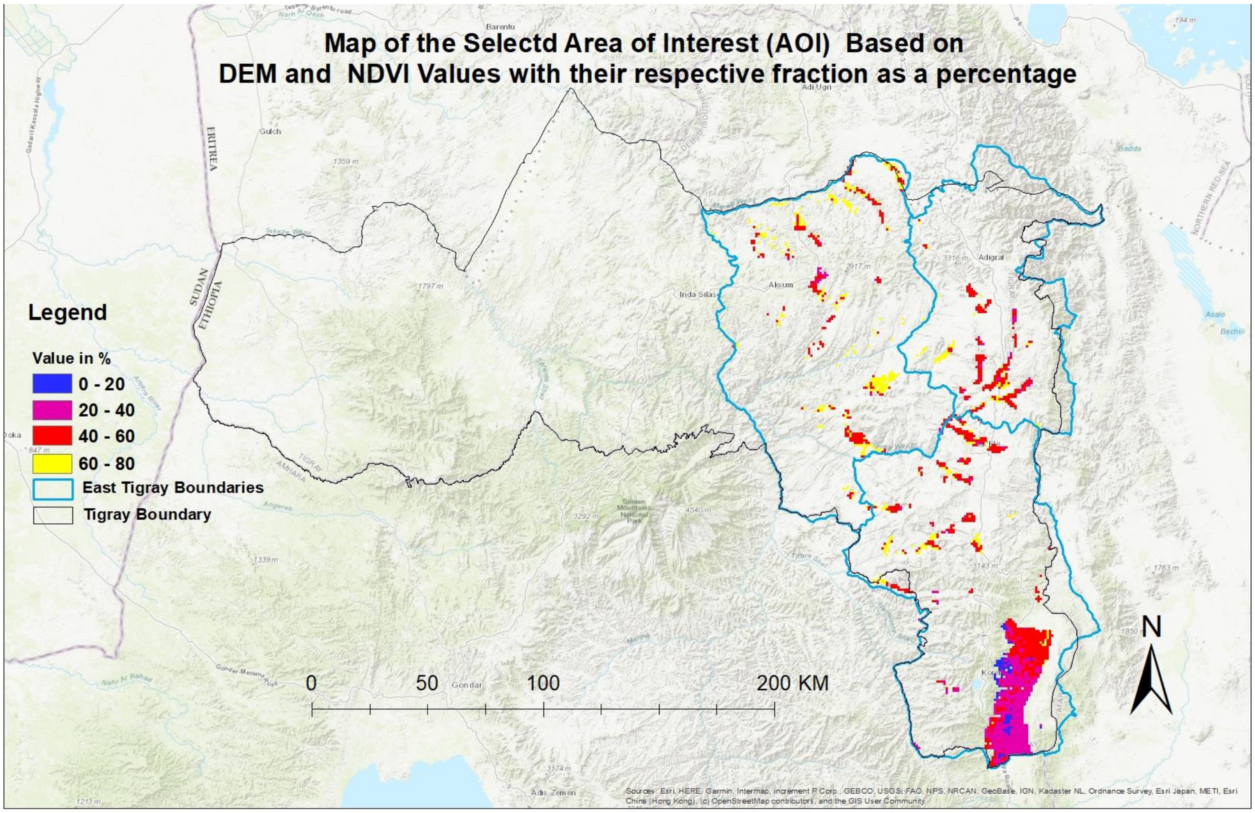


Figure 37: The selected area of interest (AOI) based on DEM and NDVI Values and the fractions of each class range as a percentage.

5.5 Spatiotemporal Analysis for Monitoring

Below is the stacked PROBA -V image that was used to extract the selected final AOI's.

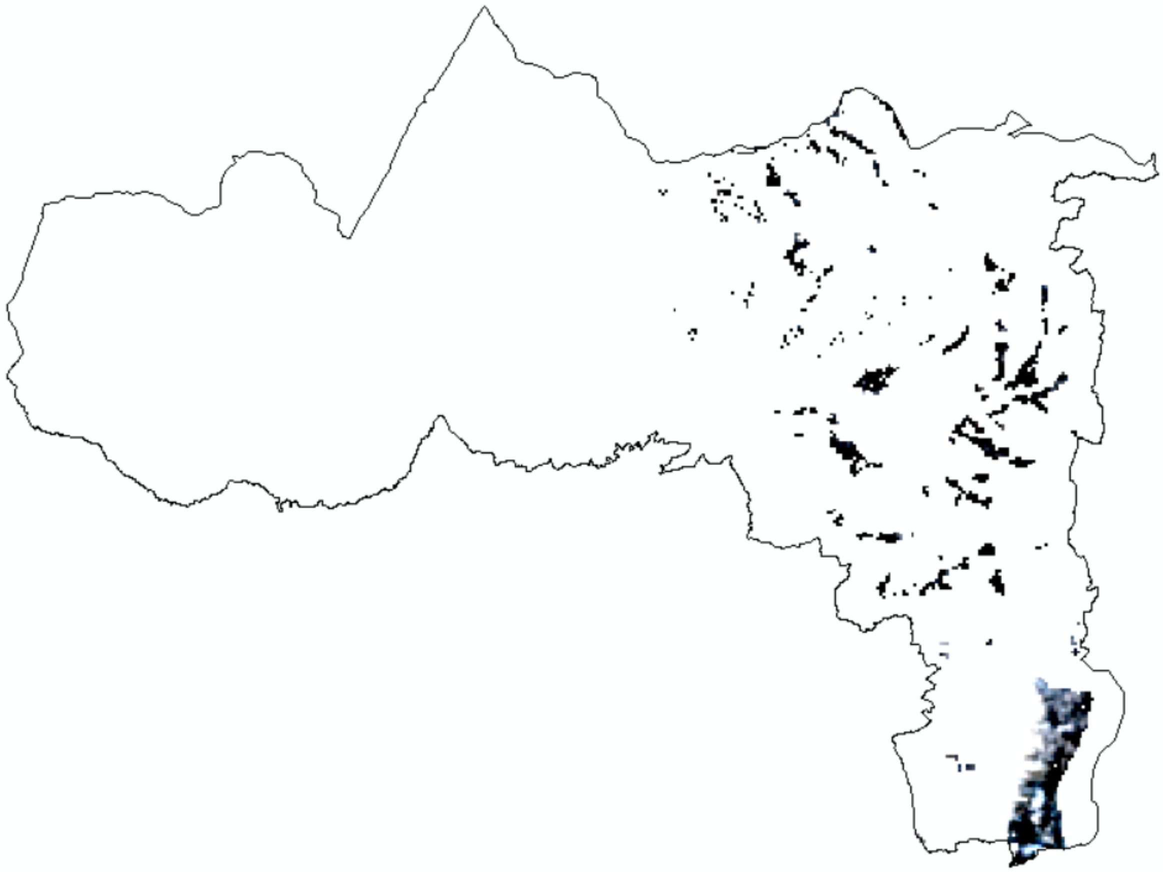


Figure 38: Stacked image of the selected area of interest (AOI)

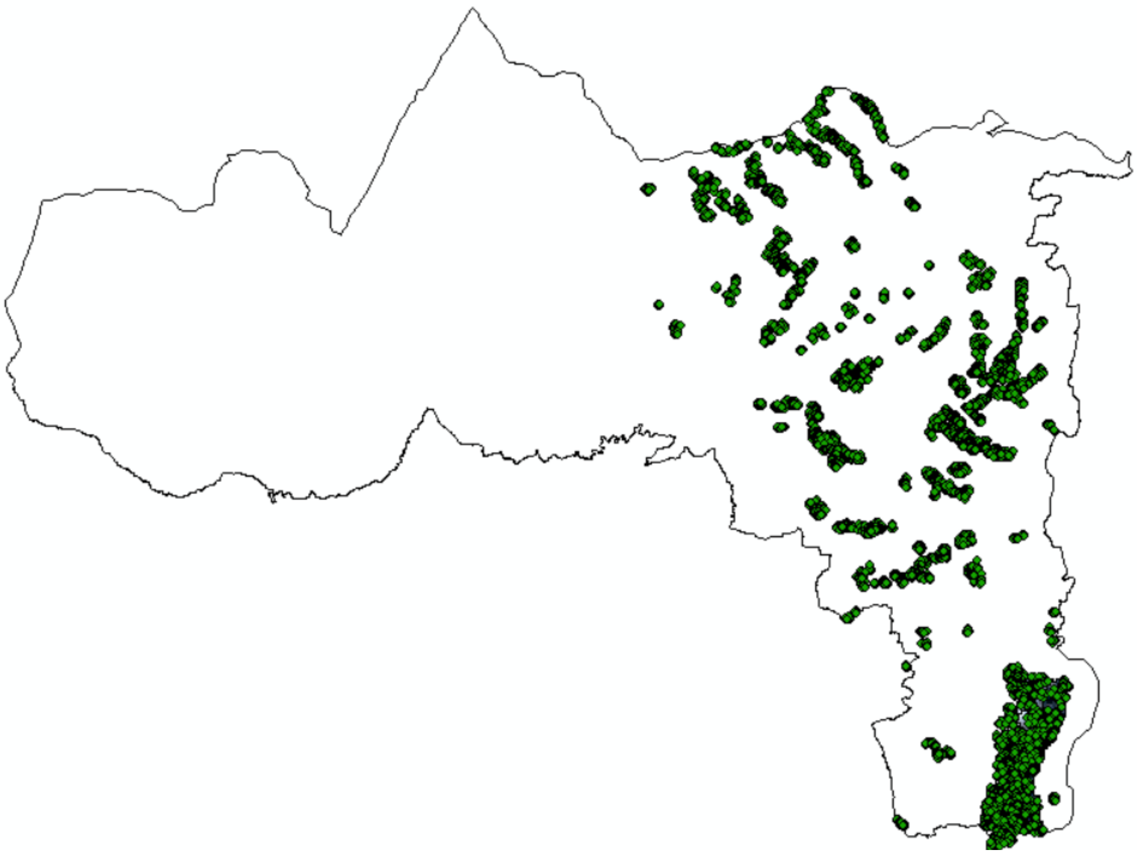


Figure 39: The stacked AOI's with the random points.

The spatiotemporal was analyzed based on the classes and the three zonal administrative polygons that are found in east Tigray, namely Debubawi, Misraqawi and Ma'eklawi.

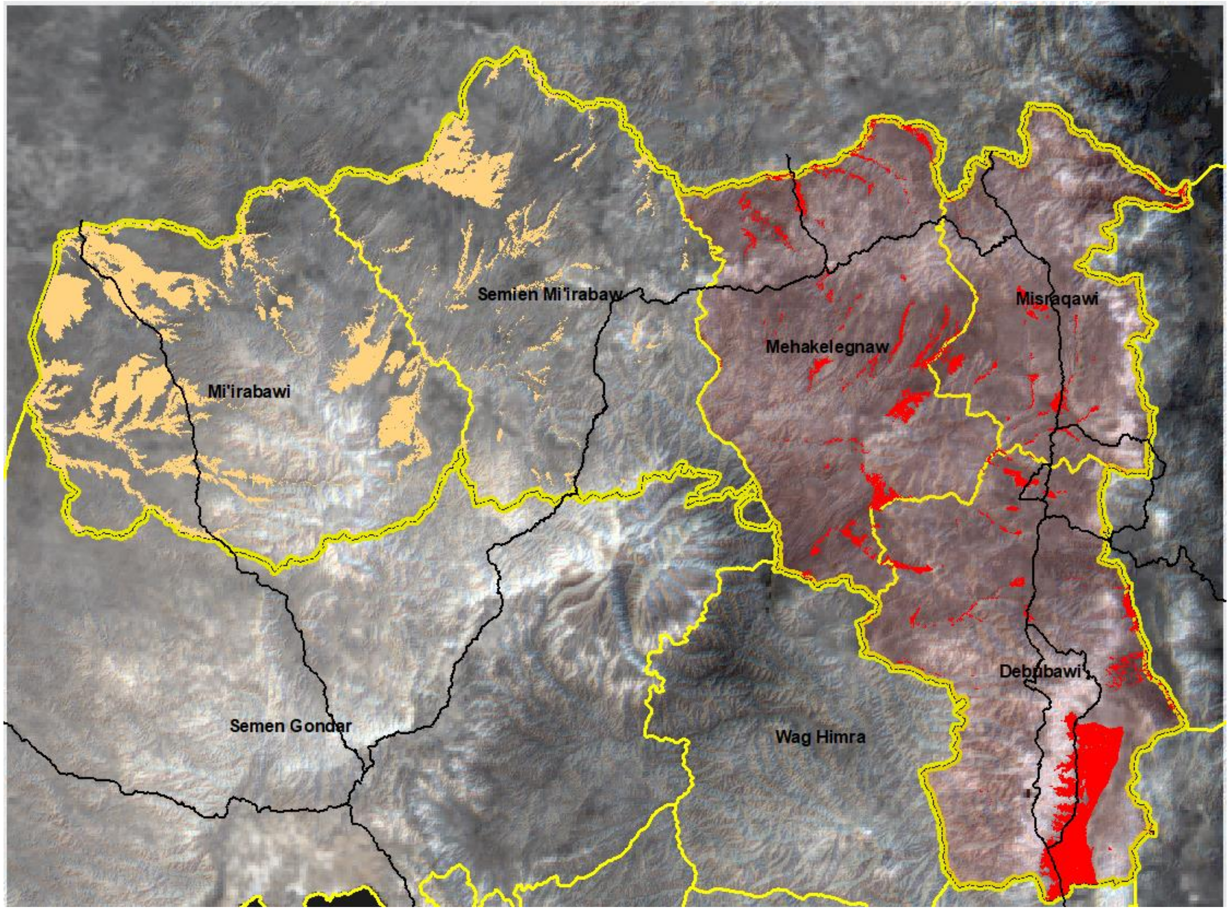


Figure 40: Map of Tigray with the zonal boundaries

Since classes that contain greater than 40% of horticultural areas were selected, class number (21, 22, 23, 24 and class 25) were the only selected for analysis. The only class that was available in all three zonal polygons is class 21, which was counted once in Meakelawi and Misraqawi and 22 times on Debubawi areas of east Tigray. Additionally, Class 24 appears in both Meakelwai and Debubawi Zonal polygons and Class 23 appears in both Misraqawi and Debubawi Zonal polygons.

Table 5:The number of classes of each zonal polygon

	Classes	Amount of class	Random points
Maekelawi			10
	Class 21	12X	10
	Class 24	1X	
Misraqawi			
	Class 21	19X	10
	Class 23	1X	10
Debubawi			
	Class 21	22X	10
	Class 22	25X	10
	Class 23	51X	10
	Class 24	22X	10
	Class 25	17X	10

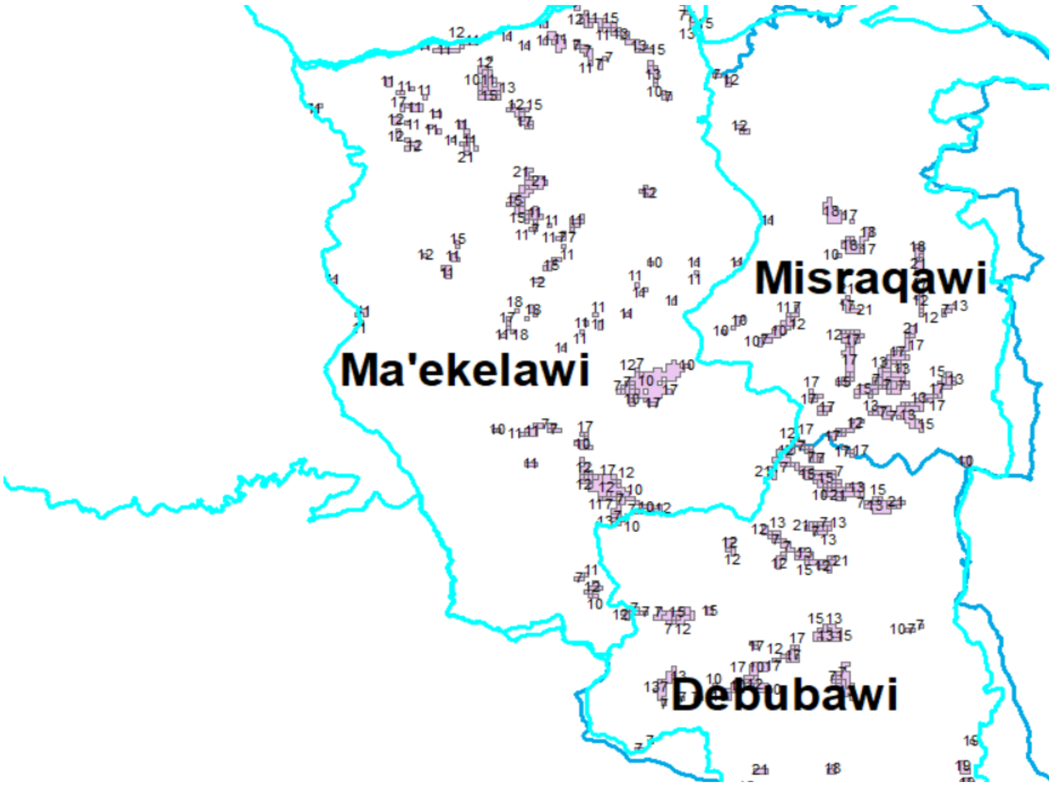
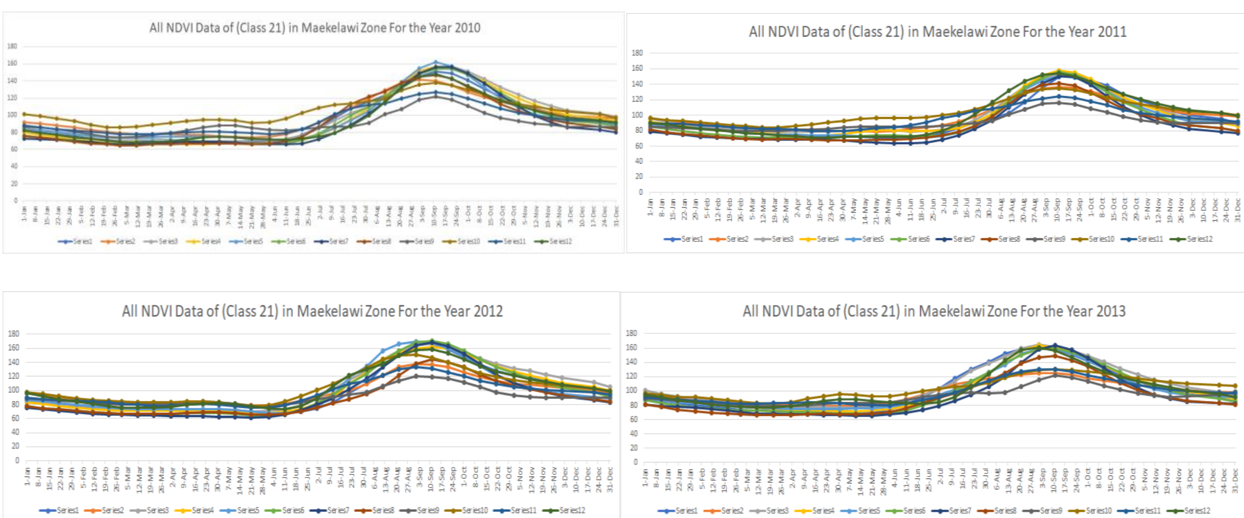


Figure 41: Labels of each class in each the zonal polygons

Furthermore, signature profile was plotted, and the result was analyzed as following:
For polygons that are found in Maekelawi zonal areas are class 21 and class 24, which cover 45.5% and 10% of horticultural areas respectively.



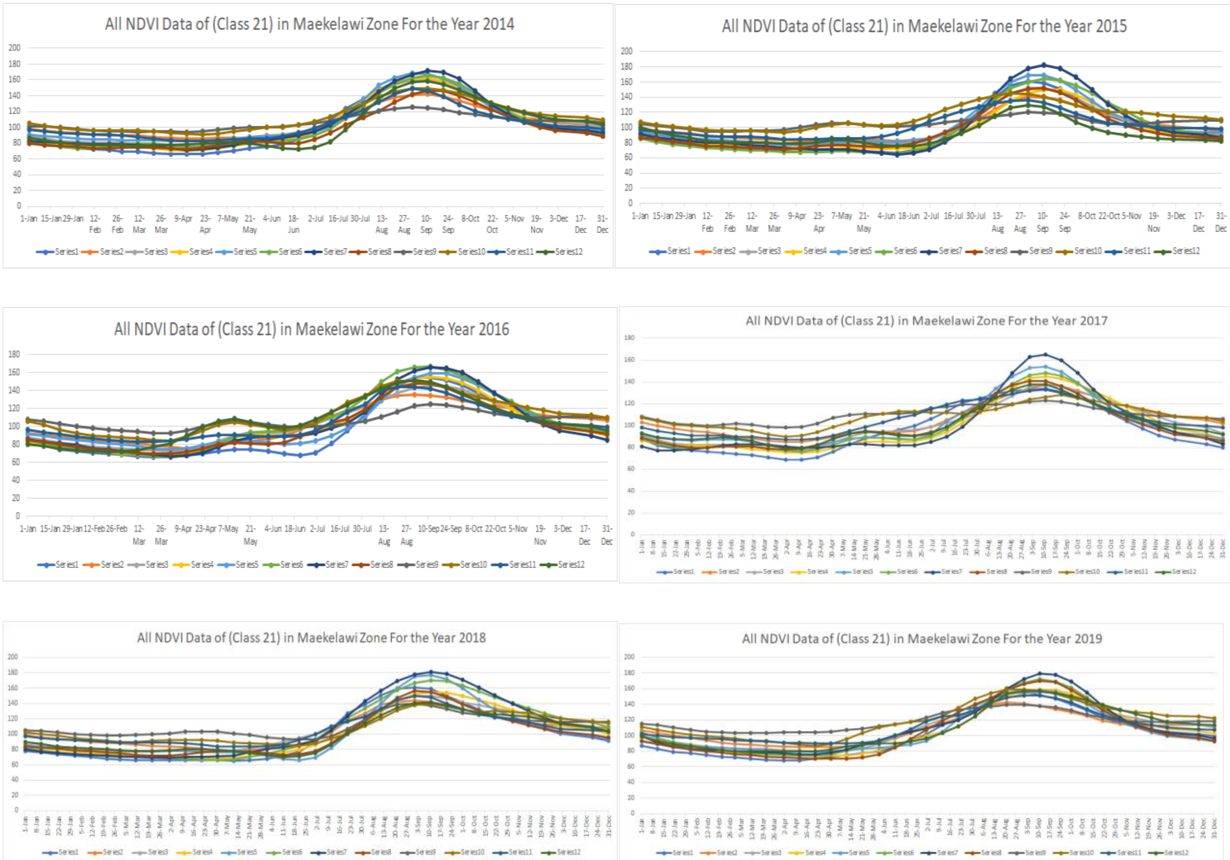
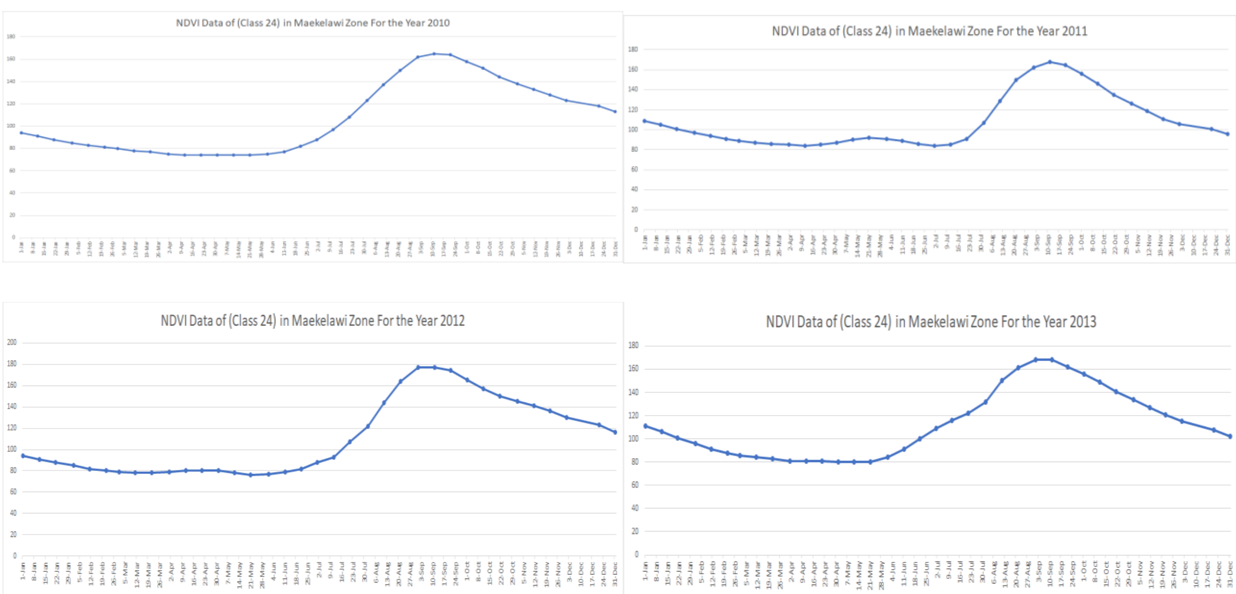


Figure 43: Showing, 10 years (2010-2019) of signature profile of the selected AOI's class 21 found at the Maekelawi Zone.



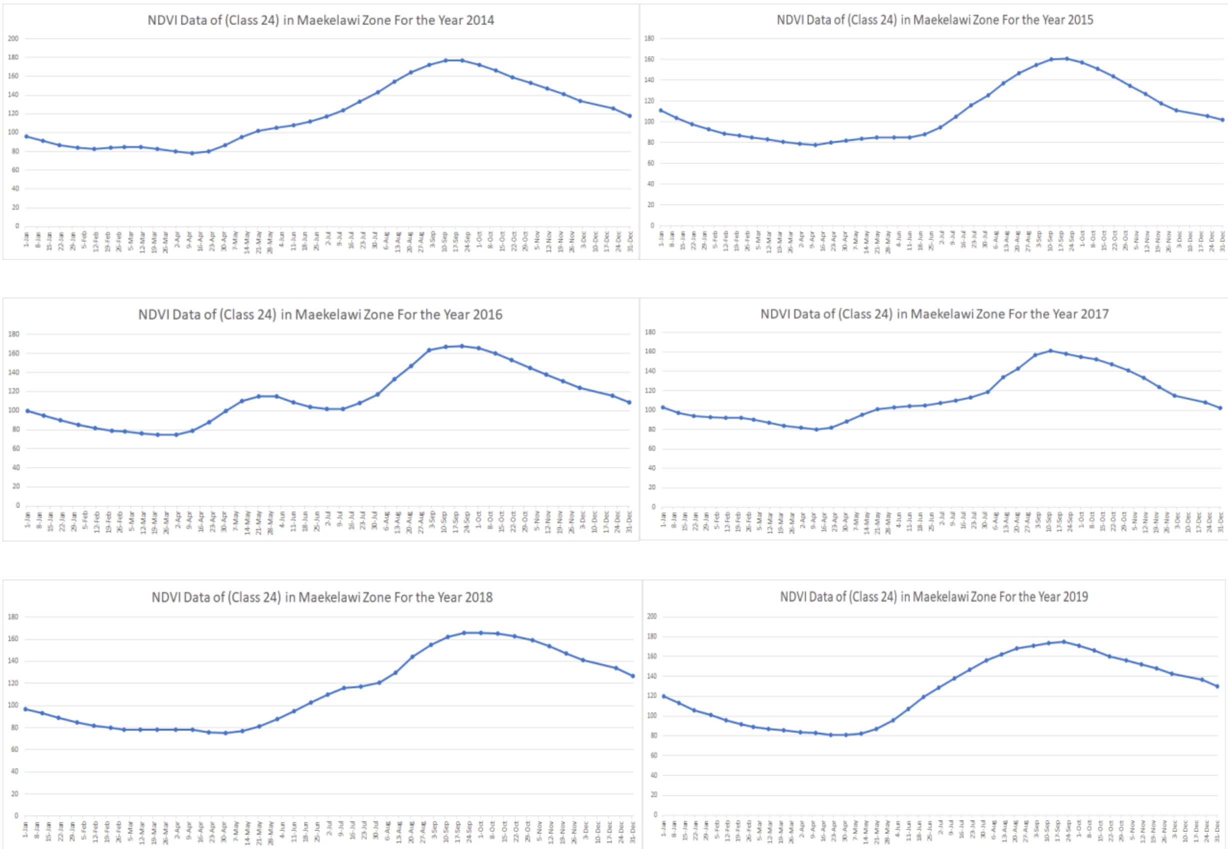


Figure 42: Showing,10 years (2010-2019) signature profile of the selected AOI's class 24 found at Maekelawi Zone.

When looking at Class 21 in Makelawi, the first 6 years (2010 and 2015) and the last 2 years (2018 and 2019) show higher greenness during summertime which is the season between from the beginning of August until the beginning of October, called Kiremt and it is the main rainy season in Tigray. The remaining two years (2016 and 2017) show some greenness during the dry seasons of the region, specifically in May which is under Azmera season. This is similar to class 21 that is found in Misraqawi zone. However, in Debubawi only the first four years (2010-2013) follow the same pattern as Meakelawi and Mibraqawi. The remaining six years (2014-2019) show higher NDVI during summer and relatively higher during Azmera. Additionally, there is one single value that shows high NDVI during Summer and Azmera but also during Hagai, which is from (January -March). This single point value is different because Hagai is the driest of all the four seasons in Tigray.

In class 24 Only one class point exists, and average is taken as the results are similar in all points. Class 24 shows higher NDVI values during Kiremt, but also a small rise during dry season in the year 201, more rise in the year 2016, and 2017.

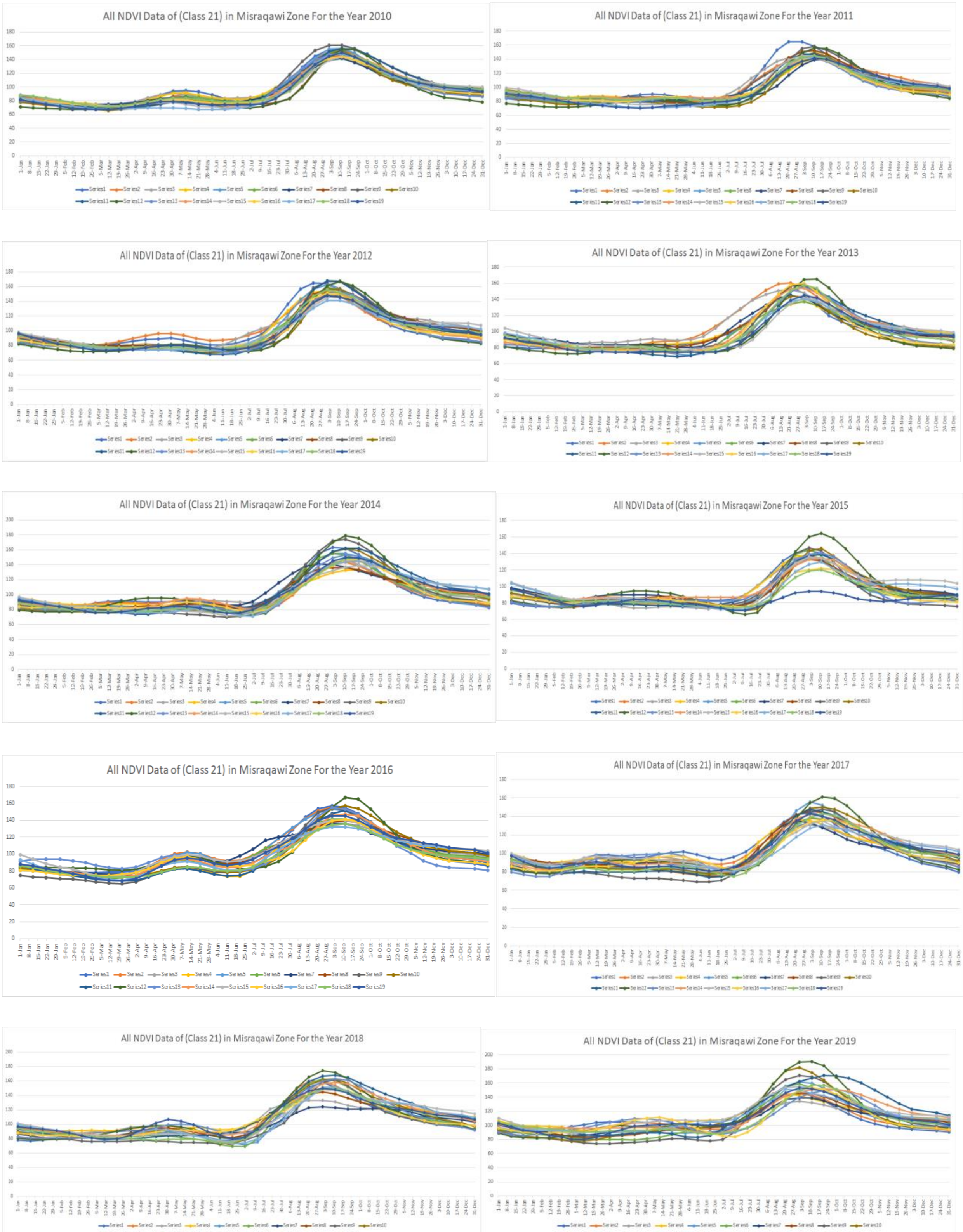
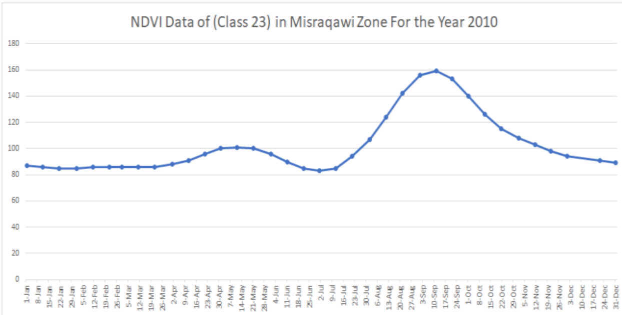
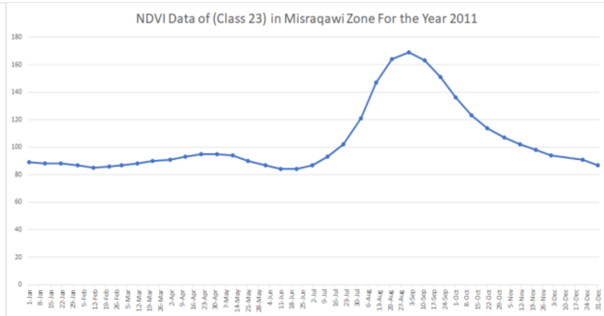
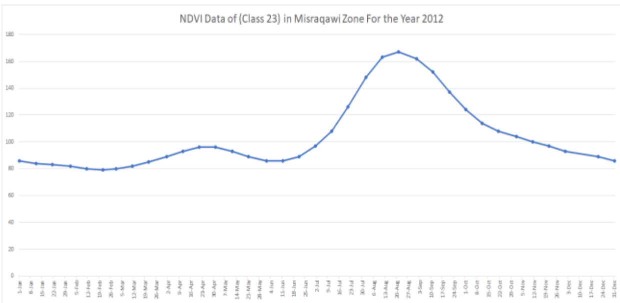
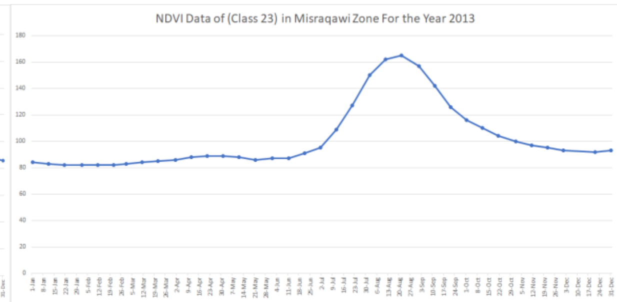
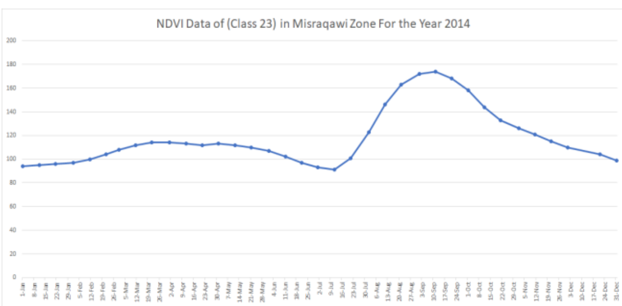
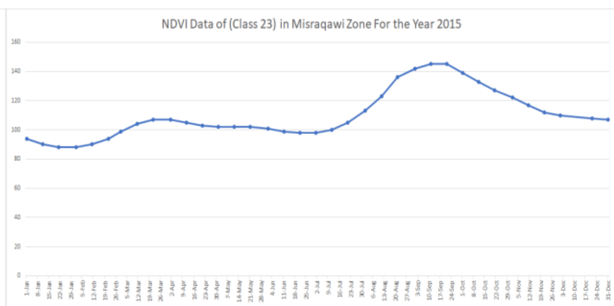
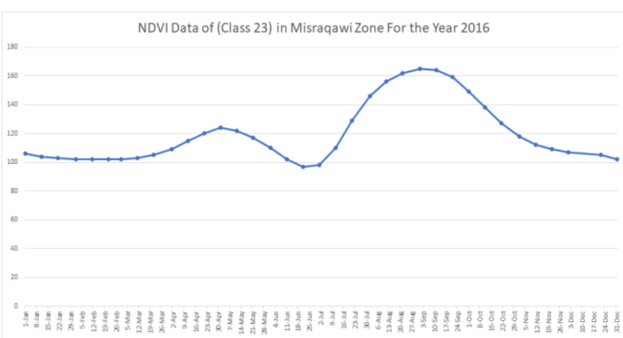
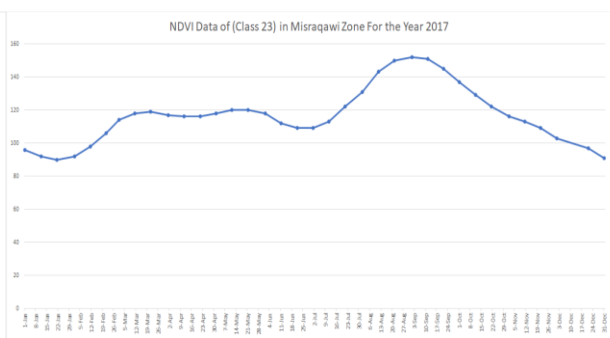


Figure 43: Showing,10 years (2010-2019) signature profile of the selected AOI's class 21 found at Misraqawi Zone


NDVI Data of (Class 23) in Misraqawi Zone For the Year 2010

NDVI Data of (Class 23) in Misraqawi Zone For the Year 2011

NDVI Data of (Class 23) in Misraqawi Zone For the Year 2012

NDVI Data of (Class 23) in Misraqawi Zone For the Year 2013

NDVI Data of (Class 23) in Misraqawi Zone For the Year 2014

NDVI Data of (Class 23) in Misraqawi Zone For the Year 2015

NDVI Data of (Class 23) in Misraqawi Zone For the Year 2016

NDVI Data of (Class 23) in Misraqawi Zone For the Year 2017

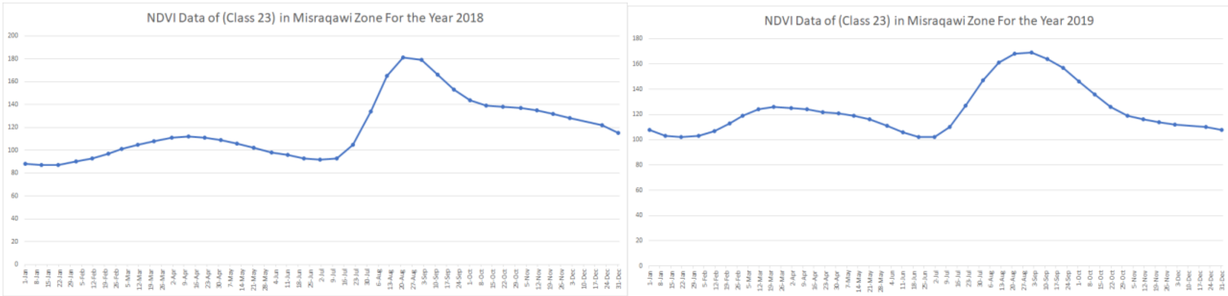
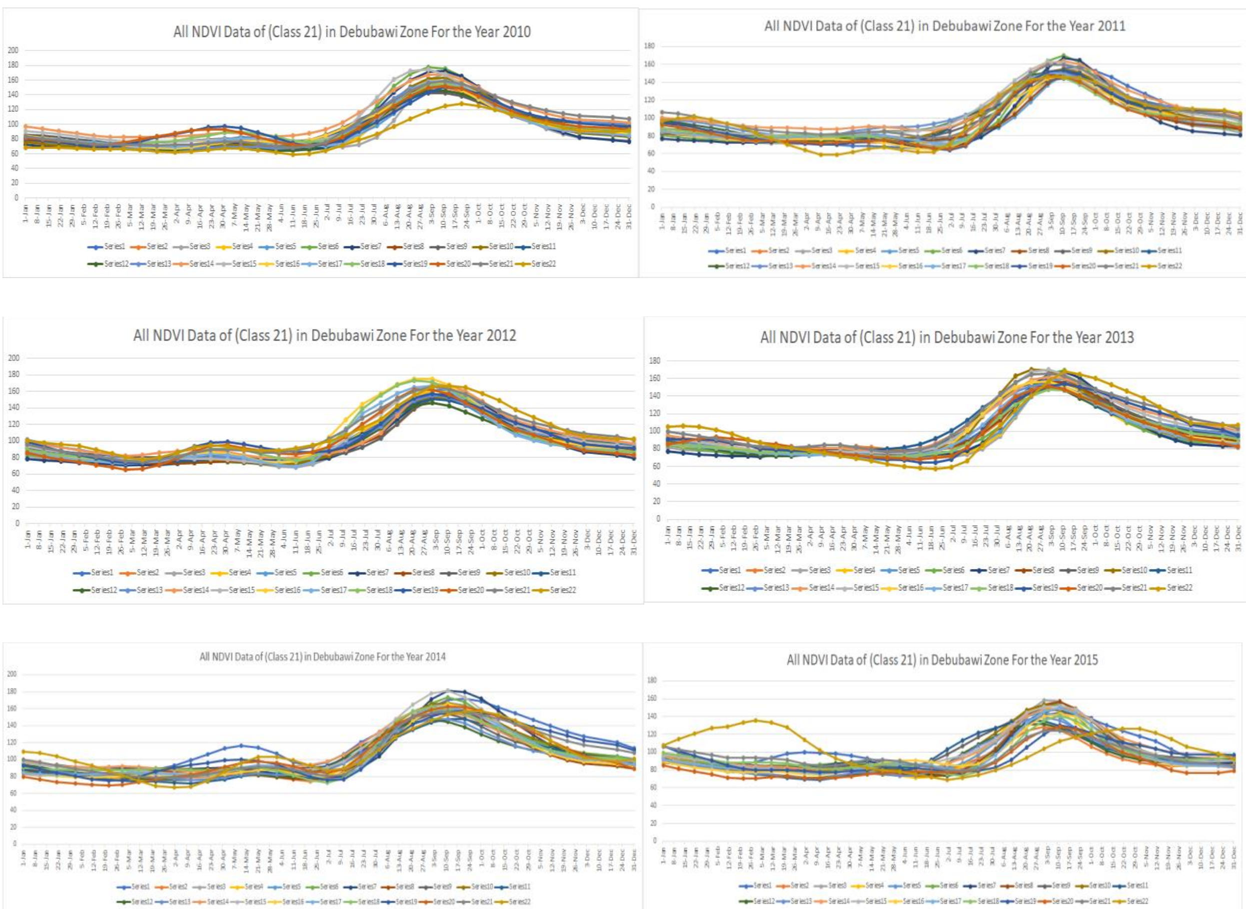


Figure 44: Showing,10 years (2010-2019) signature profile of the selected AOI's class 23 found at Misraqawi Zone

Class 23 of the polygon of the Misraqawi zone Shows similar trend throughout the 10 years, that is by having relatively higher value during the Hagay, the dry season and peak high value during Kiremti like the rest of the classes in all polygons.



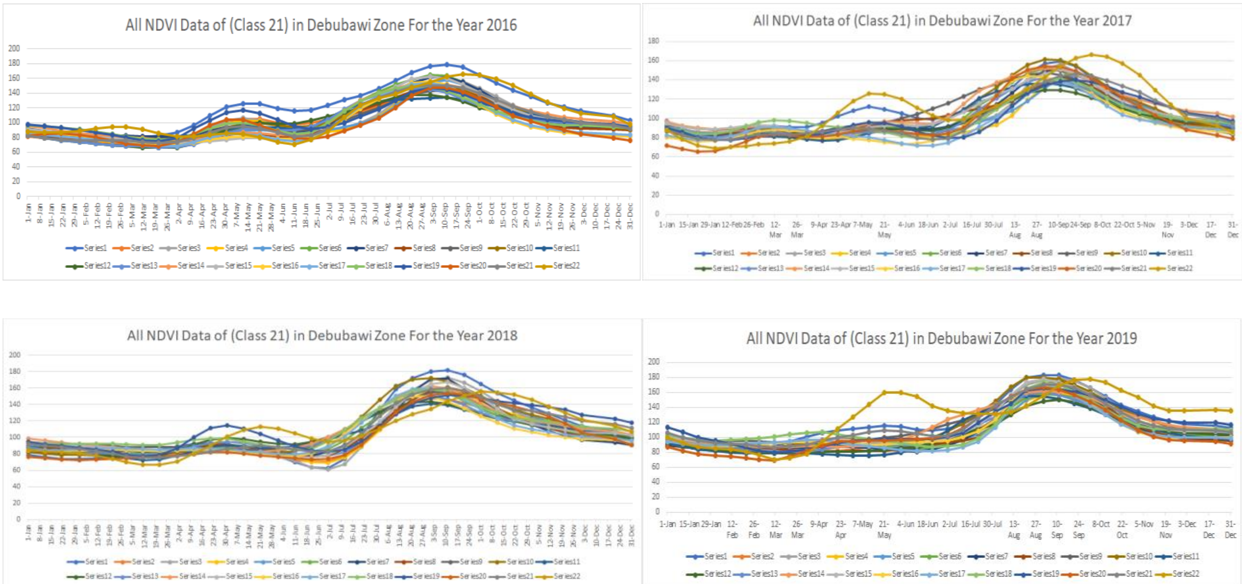
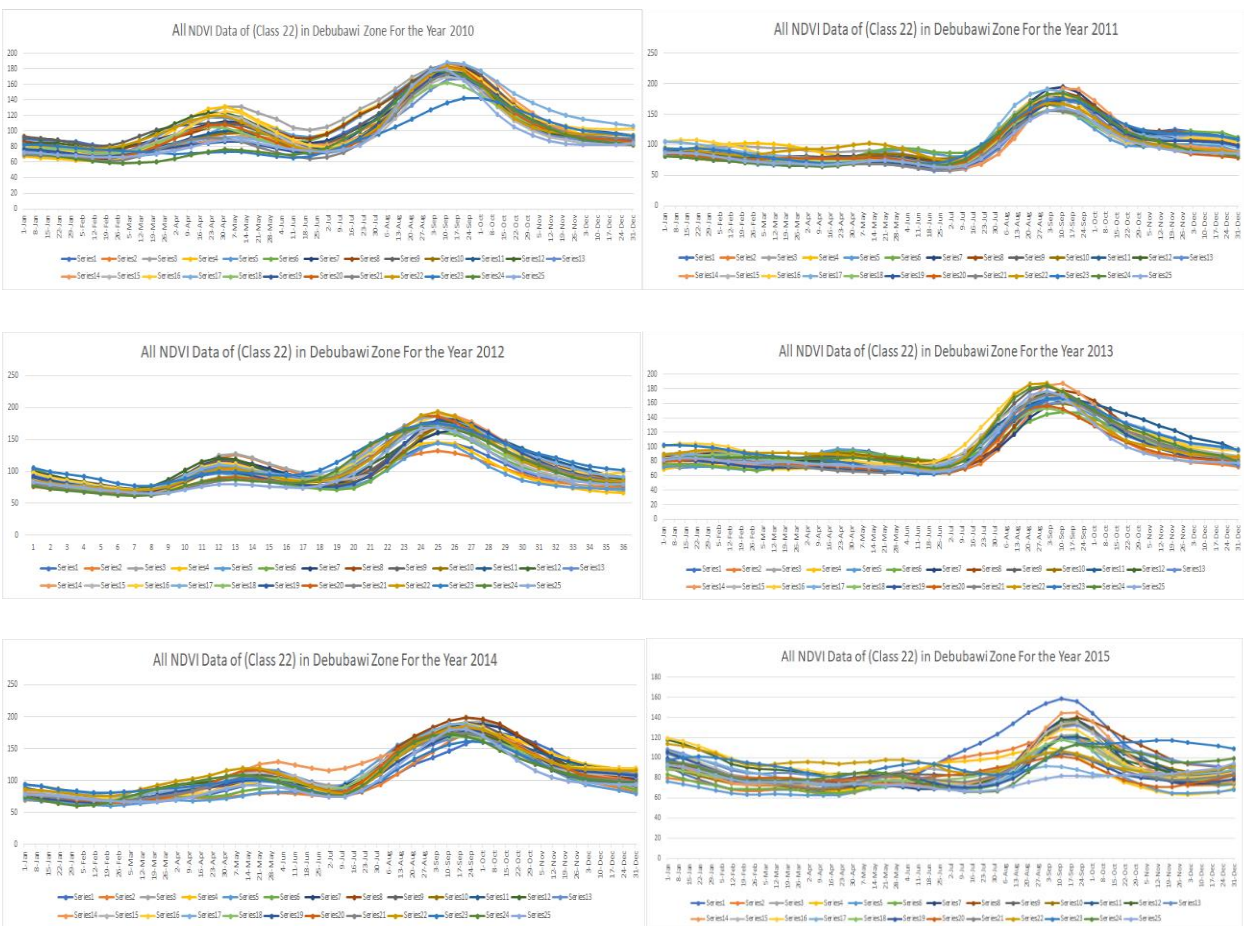


Figure 45: Showing, 10 years (2010-2019) signature profile of the selected AOI's class 21 found at Debubawi Zone



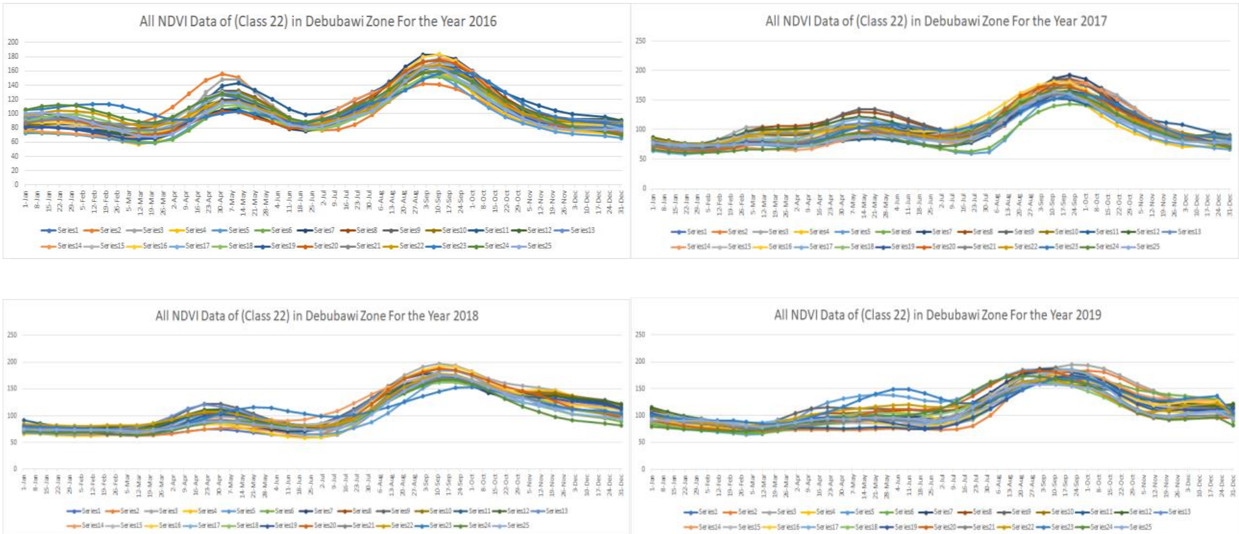
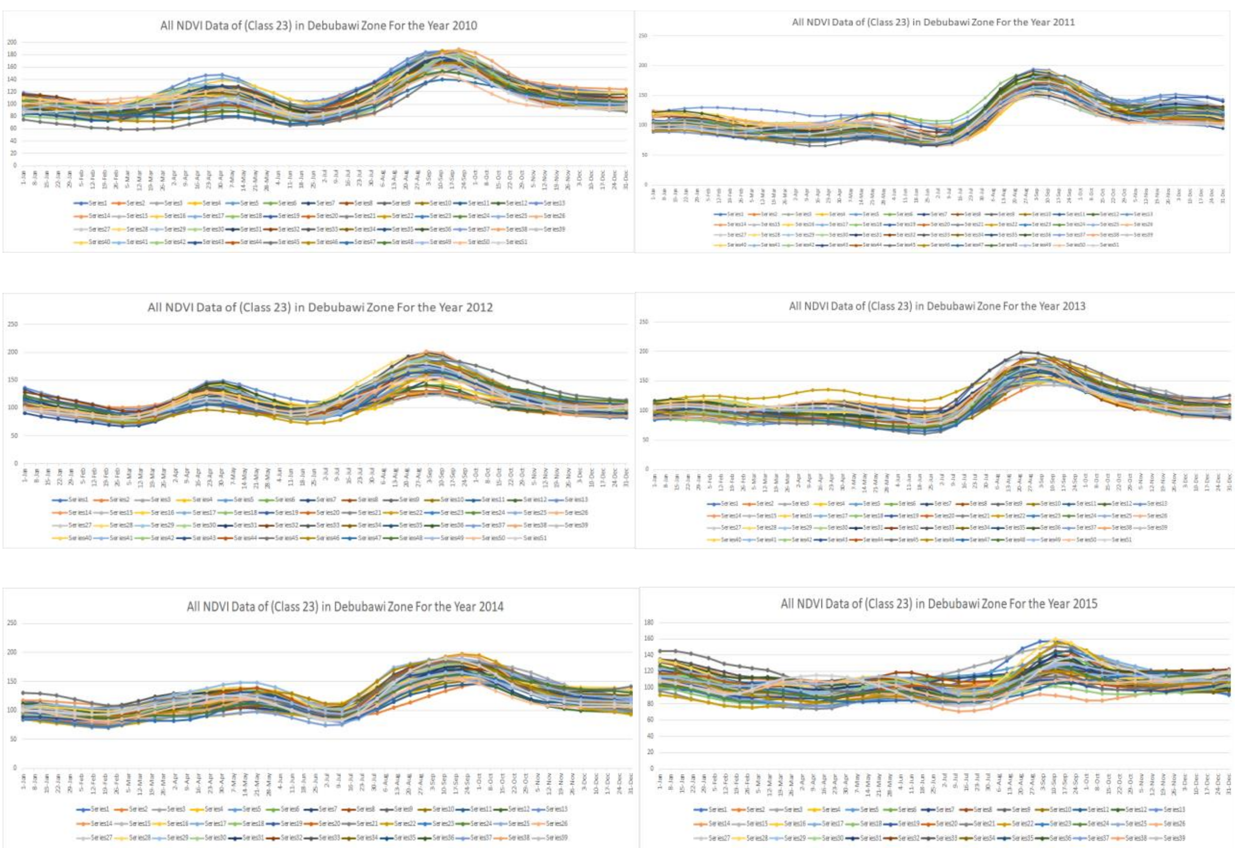


Figure 46: Showing, 10 years (2010-2019) signature profile of the selected AOI's class 22 found at Debubawi Zone

Class 22 of the polygon Debubawi zone, shows greens during Kiremt and Azmera, in all years except for the year 2011 and 2015. This is during the wet and dry season, with higher values during the Kremti season of the year.



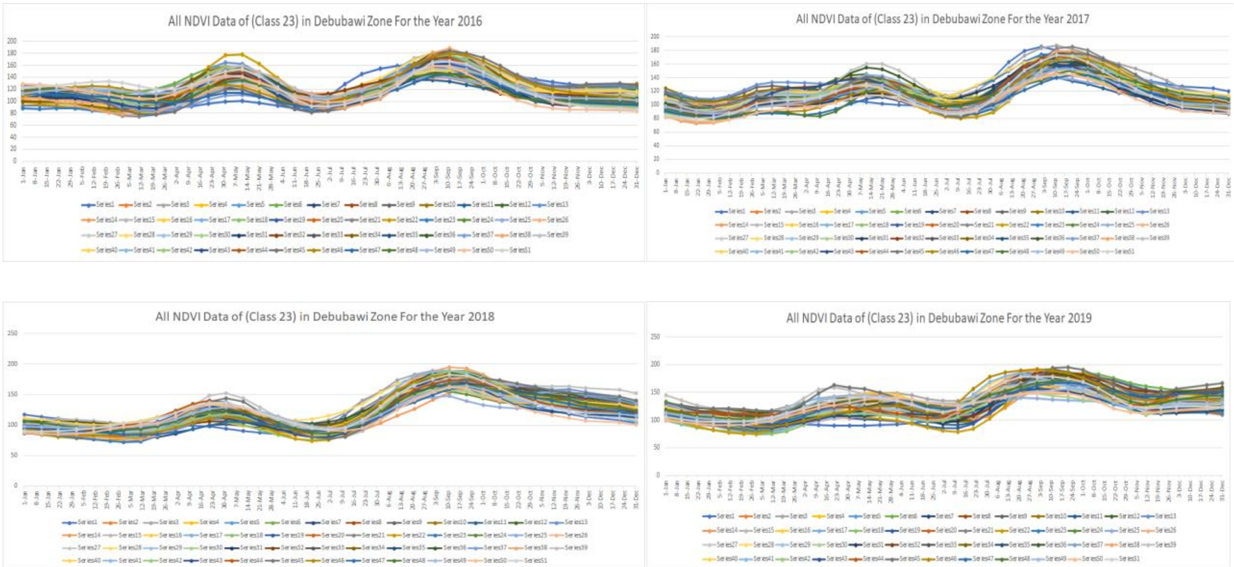
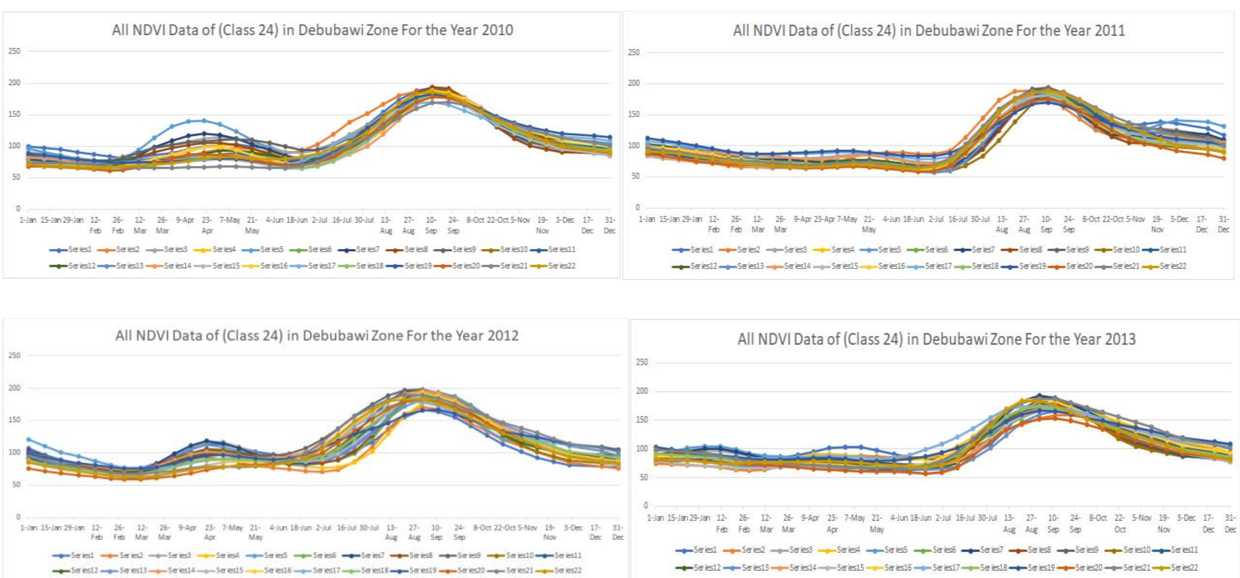


Figure 47: Showing, 10 years (2010-2019) signature profile of the selected AOI's class 23 found at Debubawi Zone

Class 23 has similar results with class 22. All the other 9 years have high NDVI values during Azmera and Kiremt, both during dry and wet seasons respectively. In the Azmera season it is relatively high but in Kiremt it shows the peak greenness. However, the year 2013 has a very small rise during the dry season but high NDVI values during Kiremt.



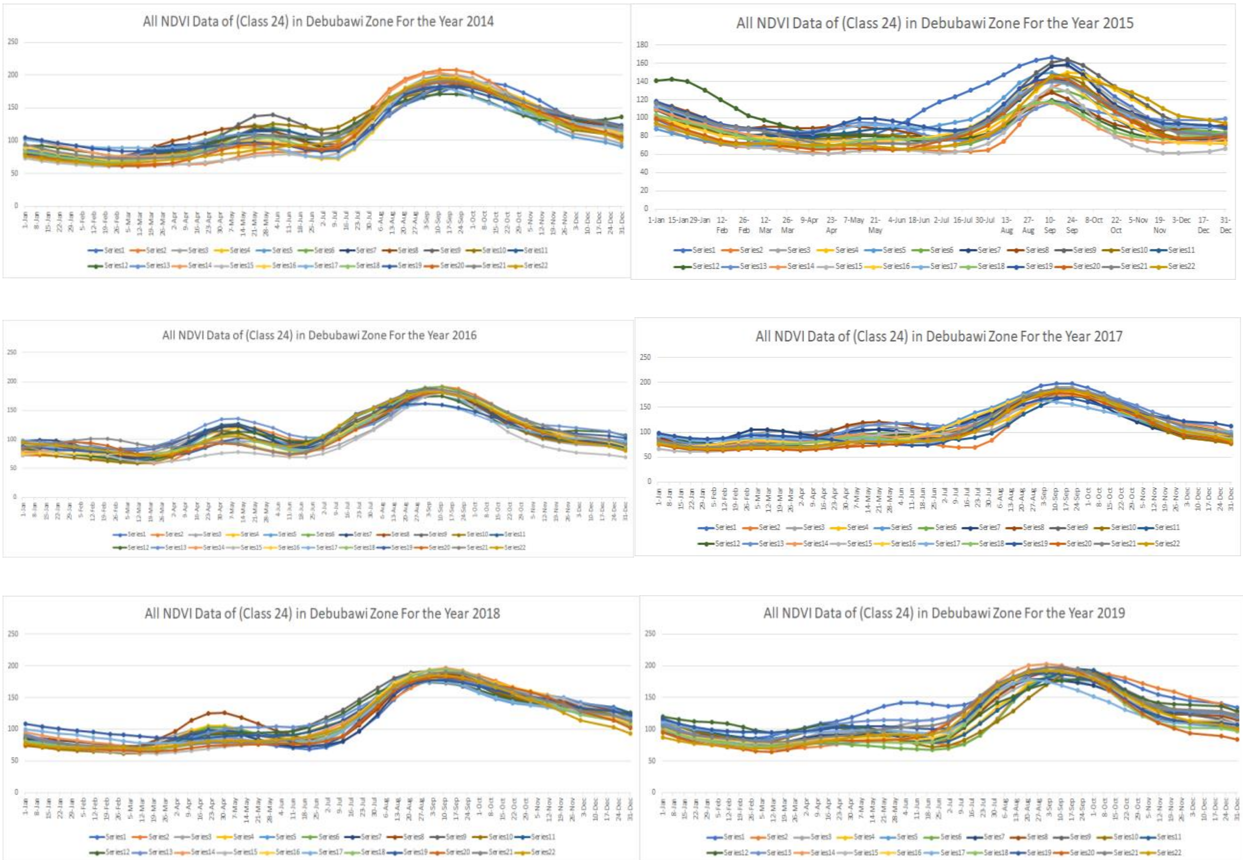
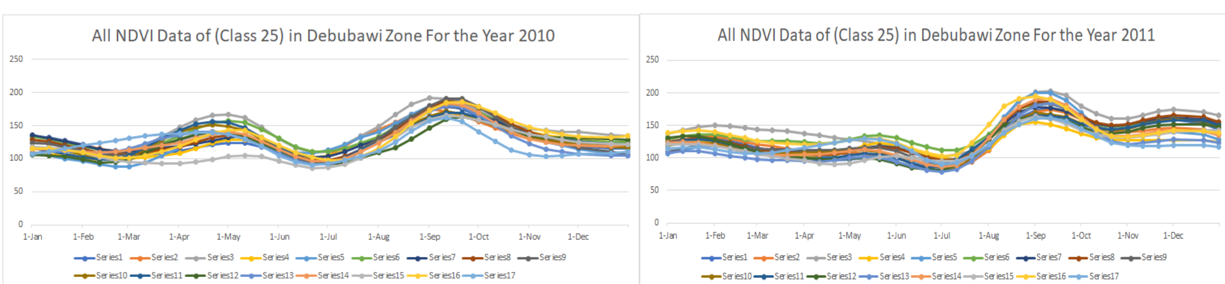


Figure 48: Showing, 10 years (2010-2019) signature profile of the selected AOI's class 24 found at Debubawi Zone.

Finally, class 24 in Debubawi Zone also shows high NDVI values during both the dry and wet season. Having high NDVI values during the Kiremt season and relatively high values during Azmera. Mainly in the year 2010, 2012, and 2016 shows higher NDVI value even during the dry season of Azmera of all the 10 years. This is similar to class 25 found in the Debubawi Zonal area of east Tigray.



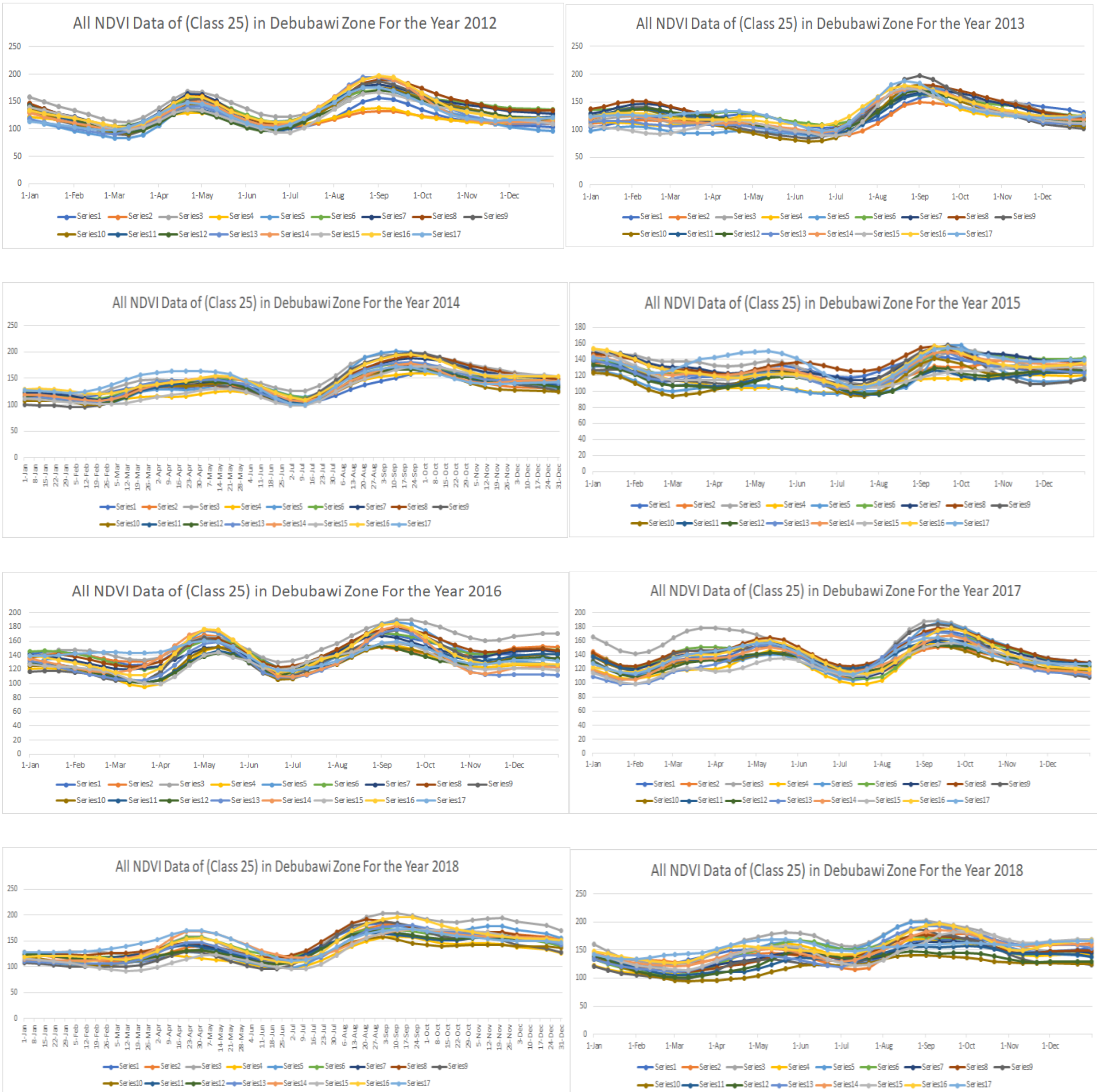


Figure 49: Showing, 10 years (2010-2019) signature profile of the selected AOI's class 25 found at Debubawi Zone.

Below is the summer of all the classes spatiotemporal variation. The color indicated the rise of the NDVI data. The color ramp indicates the intensity of the rise.

Table 6:Showing the summary of the spatiotemporal variation of the AOI's of the year (2010-2019) The color ramp indicates the intensity of the rise.

		year 2010				year 2011				year 2012				year 2013				year 2014			
	seasons	Kiremt	Hagai	Azmera	Kewua	Kiremt	Hagai	Azmera	Kewua	Kiremt	Hagai	Azmera	Kewua	Kiremt	Hagai	Azmera	Kewua	Kiremt	Hagai	Azmera	Kewua
	Classes																				
Maekelawi																					
	Class 21																				
	Class 24																				
Misraqawi																					
	Class 21																				
	Class 23																				
Debubawi																					
	Class 21																				
	Class 22																				
	Class 23																				
	Class 24																				
	Class 25																				

		year 2015				year 2016				year 2017				year 2018				year 2019			
	seasons	Kiremt	Hagai	Azmera	Kewua	Kiremt	Hagai	Azmera	Kewua	Kiremt	Hagai	Azmera	Kewua	Kiremt	Hagai	Azmera	Kewua	Kiremt	Hagai	Azmera	Kewua
	Classes																				
Maekelawi																					
	Class 21																				
	Class 24																				
Misraqawi																					
	Class 21																				
	Class 23																				
Debubawi																					
	Class 21																				
	Class 22																				
	Class 23																				
	Class 24																				
	Class 25																				

The major variation seen temporally is that most of the classes show relatively high NDVI values during dry seasons with the rise of the year but are less than the NDVI values of the wet season in all years. Most of the areas show higher NDVI values during Kirmet, the main rainy season of Tigray. Furthermore, the classes that were previously esteemed to have a high percentage (%) fraction of horticultural areas do show higher NDVI values during the dry season than the other classes; for instance, class 23 and class 24 and 25. Thus, giving additional proof that the estimation of percentage was accurate to some level. Additionally, classes that are found in Debubawi zone have higher NDVI value during the wet and dry season than Meakelawi and Mibraqawi Zones.

6. Discussion and Conclusion

6.1 Discussion

This research tries to explore how to get information on the whereabouts and variability of clusters of fields using the latest, hyper-temporal images available. In the beginning the assumption was that the required information can be easily acquired using NDVI time series from PROBA-V data, to map and monitor horticultural areas in Tigray. It was assumed that higher NDVI values during dry season could possibly represent horticultural areas. However, to the contrary, shrubs and trees were responsible for the relatively high NDVI-values during the dry season. Hence, additional parameters were required to get the desired information. Then with the use of DEM it was possible to narrow down the area of interest, to areas that have flow accumulation pixels above 100,000 areas relatively flat along rivers with sufficient water flow (drainage area) and areas that have a relatively low height (< 20m) above that river. In addition to the criteria, the distance to the central market, mainly the capital city was also considered, and the focus was on the Eastern part of Tigray. This way it was easy to target the area of interest and further refine it using the NDVI values to get the desired final AOI's. Finally, AOI's that are expected to be horticultural areas in Tigray were selected and spatiotemporal variability was assessed.

This was done using only DEM and NDVI time series from PROBA-V satellite data. However, given the complexity and variety of parameters that require a high level of accuracy, and possible noise on satellite derived data, it is important to generate and label ground-truth based data. This will also help make effective use of the bulk of data provided by remote sensing satellites. Several works (Heliyon., 2021) have demonstrated how the generation of field survey-based ground data can assist in validating or calibrating models and results that are generated with the use of satellite data.

Taking into consideration how expensive generating and labeling ground-truth data can be, unsurprisingly there is a serious lack of ground-truth data in the developing countries (Kehs, Annalyse McCloskey, Peter, 2021). This makes the use and accurate interpretation of the satellite-derived remote sensing data challenging.

Unfortunately, due to the same reason/the lack of ground-based data, this research is also pursuing the unsupervised learning approach. There is not enough ground-based data for our target classes (i.e., horticulture crops) in the areas of interest.

On the other hand, this research can serve as a starting point for identifying likely areas of horticulture when deciding to collect ground-truth data of horticulture in the target region. In general, considering how expensive collecting field-based survey data can be, this approach applies to other developing countries as well where budgets can be constrained.

6.2 Conclusion

Research Question 1 and 2; Which AOI were derived from DEM and PROBA-V?

As explained in section 4.5.1 of the research project, fields with horticulture areas in Tigray region were the main target. The first approach was to use NDVI values and select the AOI assuming that higher NDVI values during the dry season can possibly represent horticultural areas and can be used to detect the areas. However, this was not the case, as higher NDVI values can represent any types of vegetation and forests, which are not the target areas in this research. Hence, to get those areas it was necessary to add additional parameters. With the assumption that areas that are along streams with supplemental irrigation at a dry season and are easily accessible, areas with < 5% slope, fields with >=100,000 pixels of water accumulation and < 20m height above the height of the nearby river, could possibly contain horticultural areas. To get those areas DEM was used, and it was successful. Then, once the target areas are selected then NDVI values were used to further specify the whereabouts of horticultural fields beyond the criteria as specified through DEM-analysis and identify the final AOI's. Finally, since the whole Tigray is larger and most of the areas that were identified as AOI's were found in Eastern part of Tigray, the AOI's were selected from Eastern Tigray.

Research Question 2; What percentage of each AOI's is covered by horticulture?

Calculating the percentage fraction was done by pixel level, by creating random points of 1km pixels for each specific NDVI-class in ArcMap and checking how much percentage of that pixel is covered by horticulture on google earth image. This is done for 10 random points of that specific class. To minimize the risk of wrong estimation and to crosscheck, additional manual digitization and measuring was conducted. This was done by drawing polygons manually of each class and calculating their areas to get the % of each class by comparing it with the whole area (horticulture + bare) of one class. In the end 3 (class, 10, and 11) were found to contain (0-20) % fractions of horticultural areas, 7 classes (12, 13, 15, 17, 18, 19, 20) contains (20-40) % fraction of horticulture, 4 classes (21, 22, 23, 24) contains (40-60) % and one class (25) was estimated to have >60% fraction of horticultural area.

Research Question 3; Is there any temporal variability in the selected horticultural areas for the year (2010-2019)?

NDVI time series was used to assess the spatiotemporal variability of the final AOIs. All final AOIs show higher NDVI value during Kiremit, which is the rain season of the region. Also, most of the classes that have higher percentage (%) availability of horticulture appears to show relatively higher NDVI values during dry season.

7. Recommendation

Since this research was conducted using DEM and NDVI time series from PROBA-V further refinement of the research is required. Satellites, such as Sentinel-2, with higher spatial and temporal resolution can be used in combination of hyper-temporal images from PROBA-V to estimate and identify product availability in heterogeneous clusters.

There are works (Burke & Lobell, 2017) that demonstrate the sole use of uncalibrated satellite-derived data, such as high-resolution satellite imagery, can be used to make predictions which can be roughly as accurate as ground-truth based measurements.

This research methodologies can then be used as the first step to get the possible AOIs and further studies can be done using higher resolution images. This way information about small clusters of fields at a 5-day interval can be generated. Since horticultural marketing in Tigray is constrained by lack of access to market information (Amare, Yalemwork., 2019), Integrating the information of whereabouts, availability and with the ground data and making it available can help for the betterment of the supply chain.

This overall research aim was to be able to provide and contribute to the improvement of accessibility of agricultural products. Making the whereabouts of horticultural products and other agricultural products can possibly help users to easily have access to information and for farmers to sell their products easily. However, further implementation study is needed. Furthermore, to increase the market efficiency of the horticultural products, there should be local or national information access to producers through different media. And this research with further improvement can be used to give the information required.

8. Limitations

Though this research tries to present and integrate different aspects due to different factors it has obvious limitations. The fact that the research has a fixed time scale makes the research to explore only in specific aspects. But most importantly the technical knowledge of the author was limited when it came to this specific research and that has taken so much time. When estimating the percentage fraction of the classes to get the amount of horticulture they contain, expertise and experience is required but the author have limited experience and knowledge in this aspect, hence this result can be affected. However, to compensate for those potential errors an additional checking method was used, but still the limitation remains. In addition to this and most importantly the author was not able to find filed data for two main reasons. Firstly, there is not enough ground-based data for our target classes (i.e., horticulture crops) on the area of interest. Secondly, due to COVID-19 traveling and interviewing the target groups or visiting the area of interest in person was hard but even became impossible when a war broke out in that region during the time of the research. (Wikipedia, 2021). It is also fair to say that the author was not 100% well while working on the thesis as she is from the same area of the war zone.

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