Verification of forest loss in the Wider Munela Mountain Region and Polis-Valamara Region

Follow-up study on the report of 2019

A report on results for forestry monitoring

via remote sensing in Albania

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Abbreviations

AI	Artificial Intelligence
ESA	European Space Agency
GEE	Google Earth Engine
GIS	Geographical Information System
F-TEP	Forestry Thematic Exploitation Platform
GFW	Global Forest Watch
JAXA	Japan Aerospace Exploration Agency
LULC	Land Use Land Cover
NASA	National Aeronautics and Space Administration
NBR	Normalized Burn Ration
NDMI	Normalized Difference Moisture Index
NDVI	Normalized Difference Vegetation Index
NIR	Near InfraRed
PPNEA	Protection and Preservation of Natural Environment in Albania
RS	Remote Sensing
SWIR	Short Wave InfraRed
UN	United Nations
UTM	Universal Transverse Mercator

0) Executive Summary

This report presents the results of a comprehensive assessment of the Munela and Polis-Valamara regions using three distinct methodologies: Global Forest Watch (GFW) data analysis, manual NDVI (Normalized Difference Vegetation Index) assessment, and ESA (European Space Agency) landcover data analysis. The study primarily focuses on forest surface, forest loss, and forest height gain trends over various time periods, aiming to provide insights into the changing forest landscape and potential environmental factors impacting these regions.

Global Forest Watch Data Analysis:

The analysis of GFW data revealed that both regions exhibited significant forest cover changes. In Munela, approximately 43% of the area was classified as forest in 2010 (654 km^2), with only about 5.1% of forest regrowth over a 20-year period. Forest loss from 2016 onward was 2.2 km^2 per year primarily attributed to fires, resulting in a net loss of forested area. In Polis-Valamara, approximately 42% of the region was considered forested in 2010 (304 km^2), with very limited reforestation evident and consistent forest losses of about 0.32% annually (1 km^2) from 2016 onwards. Here, forest fires played little role in forest loss.

Manual NDVI Assessment:

The NDVI assessment, supported by GFW results and historical imagery verification, provided insights into forest cover changes. In both regions, NDVI images demonstrated visible gaps corresponding to forest loss areas, indicating its capability to capture deforestation trends. However, the NDVI method had limitations in accurately identifying certain types of vegetation, such as widely spaced pine trees, and its susceptibility to variations in terrain and moisture content. This method is however at the moment the only one that could provide data for 2023.

ESA Landcover Data Analysis:

ESA landcover data analysis revealed variations in forest cover estimations over different years, highlighting challenges in accurately assessing forest stability. The discrepancies between the GFW forest classification and ESA landcover data suggest complexities in defining and categorizing forests. The accuracy of this method was affected by factors such as drought and other environmental conditions.

Key Findings and Implications:

- Both regions experienced forest loss due to various factors, including logging, fires, and other disturbances.
- Reforestation was limited, and only in very few cases, regrowth was observed in areas with previous forest loss.
- Forest loss through logging was identified as a systemic issue, particularly in Polis-Valamara.
- NDVI assessments showed potential for capturing deforestation trends, but accuracy varied based on terrain and vegetation types.
- ESA landcover data exhibited challenges in accurately assessing forest stability, partially due to factors like drought.
- Deforestation was a significant concern, raising the need for sustainable forestry management practices and fire prevention strategies.

Conclusion:

The assessment of the Munela and Polis-Valamara regions using different methodologies provided valuable insights into forest cover changes, contributing to the understanding of environmental dynamics. Deforestation emerged as a major challenge, emphasizing the importance of robust conservation efforts, reforestation initiatives, and fire prevention strategies. Combining multiple assessment methods can offer a more comprehensive perspective on complex forest dynamics and guide effective land management decisions. Planned weekly radar enhanced forest cover assessments will make the analysis close to ‘real time’.

1) Introduction

In 2019 PPNEA investigated the possibilities for monitoring of forest resources via free for usage Remote Sensing data. In that report 3 methodologies were reviewed with the limited available resources at that time. In the last 4 years, new methodologies have become available and due to Google Earth Engine (GEE) and AI developments in remote sensing, many contributors to free and open-source remote sensing change detection are now much faster in updating their annual results.

The two methods that were delivering the best results in 2019 were manual NDVI (Normalized Difference Vegetation Index) comparisons between images of individual years, and analysis by F-TEB (Forestry-TEB) which is now a paid service. The results were limited to the years 2016-17 and 2017-18. Although both these methods are still valuable, it is important to also look at new tools that have become available, or older ones that now are able to provide much faster updates of their annual results.

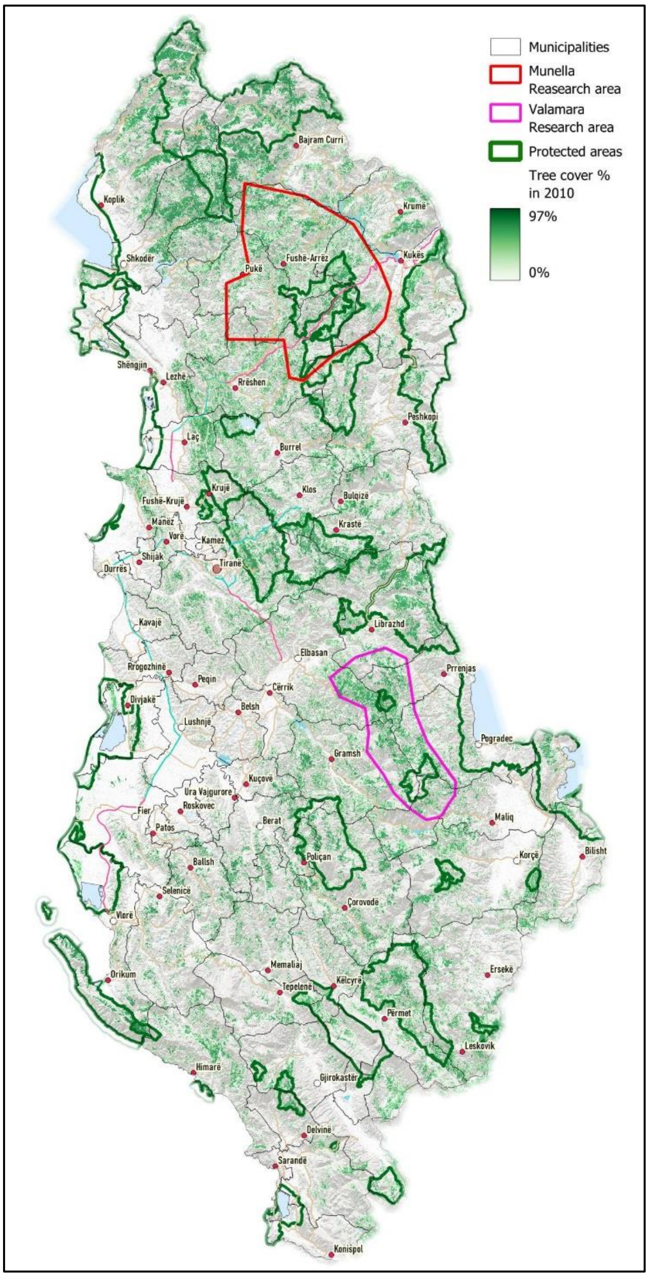

Figure 1: Forests in 2010 in Albania (GFW)

In this report an assessment of the different options for forest monitoring in the temperate regions is done so that the results for at least 3 methods can be verified and compared. One website with different tools, is the Global Forest Watch website, that with the support of the university of Maryland (USA) has been monitoring forest decline and gain for the last 23 years (since 2000). In 2018 this website was also available and was used but the frequency of updating information and analysis of different tools, was not as it is available now.

Presently the deforestation data is available till 2022, and we now can verify annually the forest loss in the monitoring area. Not only for monitoring but also a useful tool for pressuring the government to do more on protection of the forest and nature in general in the country.

The government of Albania issued a logging ban in 2016 in an attempt to stop further uncontrolled deforestation. PPNEA committed to verify the results in the Munela Region and the Polis-Valamara Region and check the impact of this logging ban with regards to legal and illegal logging. Due to the constant improvements of research methodologies and making these available, in this report I can show the difference between forest loss due to fire or from logging. This is one of the new data layers (created 2022) found which can help understanding the effect of the logging ban in Albania.

2) Methodology development

The process of verification of methodologies for forest analysis started with the verification of the tools that were introduced in the report of 2019. Of the 2 tools that were proposed to be combined, the F-TEB website has become a paid service and no longer free for usage and thus now disregarded. The manual NDVI process requires images of the target area that are very similar in exposure and circumstances (drought/humidity/time of the day/sun angle) between the years, and thus this needs verification and analysis of many images. To support the identification of forests, the PPNEA team has gathered information in the target region according to the forest monitoring protocol, to support the understanding and identification of forests on the NDVI imagery.

The search for other systems on forest cover/change verification requires checking websites for services provided by the major space agencies (NASA, ESA, JAXA) and major (international) organisations like UN and universities.

A good source of information related to the natural world is www.UNBIODIVERSITYLAB.org, that have gathered many different research results for review on a single website. Many of the results on this website have been created by PhD students and researchers via Google Earth Engine protocols. Google Earth Engine is a cloud computing platform for processing satellite imagery and other geospatial and observation data. It provides access to a large database of satellite imagery and the computational power needed to analyse those images. Google Earth Engine allows observation of dynamic changes in agriculture, natural resources, and climate using geospatial data.

Google Earth Engine has become a platform that makes Landsat and Sentinel-2 data easily accessible to researchers in collaboration with the Google Cloud Storage. Google Earth Engine provides a data catalogue along with computers for analysis; this allows scientists to collaborate using data, algorithms, and visualizations. In 2013, researchers from University of Maryland produced the first high-resolution global forest cover and loss maps using Earth Engine, reporting an overall loss in global forest cover[1].

In recent years AI has come in as a tool for faster analysis and learning/understanding the enormously large amounts of data. Land cover classification is the 2nd-most-developed domain area using GEE and AI[2], and thus is used in identifying all aspects of remote sensing analysis including forest losses.

The research area for Munela is approximately 152143 Ha or 1521 Km^2. For the Polis-Valamara region it is 72005 Ha or 720 Km^2, resulting in forests on 654 and 305 Km^2 respectively (GFW 2010[3]).

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[1] Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. 2013. "High-Resolution Global Maps of 21st-Century Forest Cover Change." Science 342 (15 November): 850–53

[2] Yang, L.; Driscol, J.; Sarigai, S.; Wu, Q.; Chen, H.; Lippitt, C.D. Google Earth Engine and Artificial Intelligence (AI): A Comprehensive Review. *Remote Sens.* **2022**, *14*, 3253. https://doi.org/10.3390/rs14143253

[3] Hansen/UMD/Google/USGS/NASA, accessed through Global Forest Watch

3) Technical assessment of methodologies

3.1. Global Forest Watch methodology

GFW has been working on verification of forests via remote sensing, with the first global results since 2013. Now the products provided are:

- Tree cover loss 2000 – 2022
- Tree cover 2010
- Tree cover loss due to fire 2001 - 2022
- Forest height gain 2000 to 2020

<u>Tree cover loss 2001 – 2022:</u>

This data set, a collaboration between the GLAD (Global Land Analysis & Discovery) lab at the University of Maryland, Google, USGS, and NASA, measures areas of tree cover loss across all global land (except Antarctica and other Arctic islands) at approximately 30 × 30 meter resolution. The data were generated using multispectral satellite imagery from the Landsat 5 thematic mapper (TM), the Landsat 7 thematic mapper plus (ETM+), and the Landsat 8 Operational Land Imager (OLI) sensors. Over 1 million satellite images were processed and analysed, including over 600.000 Landsat 7 images for the 2000-2012 interval, and more than 400.000 Landsat 5, 7, and 8 images for updates for the 2011-2022 interval. The clear land surface observations in the satellite images were assembled and a supervised learning algorithm was applied to identify per pixel tree cover loss.

In this data set, “tree cover” is defined as all vegetation greater than 5 meters in height and may take the form of natural forests or plantations across a range of canopy densities. Tree cover loss is defined as “stand replacement disturbance,” or the complete removal of tree cover canopy at the Landsat pixel scale. Tree cover loss may be the result of human activities, including forestry practices such as timber harvesting or deforestation (the conversion of natural forest to other land uses), as well as natural causes such as disease or storm damage. Fire is another widespread cause of tree cover loss and can be either natural or human-induced.

This data set has been updated five times since its creation, and now includes loss up to 2022 (Version 1.10). The analysis method has been modified in numerous ways, including new data for the target year, re-processed data for previous years (2011 and 2012 for the Version 1.1 update, 2012 and 2013 for the Version 1.2 update, and 2014 for the Version 1.3 update), and improved modelling and calibration. These modifications improve change detection for 2011-2022, including better detection of boreal loss due to fire, smallholder rotation agriculture in tropical forests, selective losing, and short cycle plantations. Eventually, a future “Version 2.0” will include reprocessing for 2000-2010 data, but in the meantime integrated use of the original data and Version 1.10 should be performed with caution. Read more about the Version 1.10 update here.

When zoomed out (< zoom level 13), pixels of loss are shaded according to the density of loss at the 30 x 30 meter scale. Pixels with darker shading represent areas with a higher concentration of tree cover loss, whereas pixels with lighter shading indicate a lower concentration of tree cover loss. There is no variation in pixel shading when the data is at full resolution (≥ zoom level 13).

<u>Tree cover 2010:</u>

This data set, a collaboration between the GLAD (Global Land Analysis & Discovery) lab at the University of Maryland, Google, USGS, and NASA, displays tree cover over all global land (except for

Antarctica and a number of Arctic islands) for the years 2000 and 2010 at 30 × 30 meter resolution. "Percent tree cover" is defined as the density of tree canopy coverage of the land surface.

Data in this layer were generated using multispectral satellite imagery from the Landsat 7 thematic mapper plus (ETM+) sensor. The clear surface observations from over 600.000 images were analysed using Google Earth Engine, a cloud platform for earth observation and data analysis, to determine per pixel tree cover using a supervised learning algorithm.

Tree cover loss due to fire:

This data is produced by the Global Land Analysis & Discovery (GLAD) lab at the University of Maryland and measures areas of tree cover loss due to fires compared to all other drivers across all global land (except Antarctica and other Arctic islands) at approximately 30 × 30-meter resolution. The data were generated using global Landsat-based annual change detection metrics for 2001-2020 as input data to a set of regionally calibrated classification tree ensemble models. The result of the mapping process can be viewed as a set of binary maps (tree cover loss due to fire vs. tree cover loss due to all other drivers).

In this dataset, tree cover is defined as all vegetation greater than 5 meters in height and may take the form of natural forests or plantations across a range of canopy densities. Tree cover loss is defined as any stand replacing disturbances (i.e., the complete removal of tree cover canopy at the scale of a 30 m pixel) and may not necessarily equate to deforestation. Tree cover loss may be the result of human activities, including forestry practices such as timber harvesting or deforestation (the conversion of natural forest to other land uses), as well as natural causes such as disease or storm damage. Tree cover loss due to fires may be caused by natural or human-induced fire activity.

The analysis method for the base tree cover loss map on GFW that is used as input for this dataset has been modified in numerous ways to improve detection of boreal loss due to fires, smallholder rotation agriculture in tropical forests, selective logging, and short cycle plantations for data covering the 2011-2022 period. Due to these changes, comparing trends across the 2000-2010 and 2011-2022 periods should be performed with caution. You can read more about the updates to the modelling process here.

When zoomed out (< zoom level 13), pixels of loss are shaded according to the density of loss at the 30 x 30 meter scale. Pixels with darker shading represent areas with a higher concentration of tree cover loss, whereas pixels with lighter shading indicate a lower concentration of tree cover loss. There is no variation in pixel shading when the data is at full resolution (≥ zoom level 13).

Tree cover gain (forest height gain):

This data set from the GLAD (Global Land Analysis & Discovery) lab at the University of Maryland measures areas of tree cover gain from the year 2000 to 2020 across the globe at 30 × 30 meter resolution, displayed as a 20-year cumulative layer. Tree cover gain was determined using tree height information from the years 2000 and 2020. Tree height was modelled by the integration of the Global Ecosystem Dynamics Investigation (GEDI) lidar forest structure measurements and Landsat analysis-ready data time-series. The NASA GEDI is a spaceborne lidar instrument operating onboard the International Space Station since April 2019. It provides point-based measurements of vegetation structure, including forest canopy height at latitudes between 52°N and 52°S globally. Gain was identified where pixels had tree height ≥5 m in 2020 and tree height <5 m in 2000.

Tree cover gain may indicate a number of potential activities, including natural forest growth, the tree crop rotation cycle, or tree plantation management.

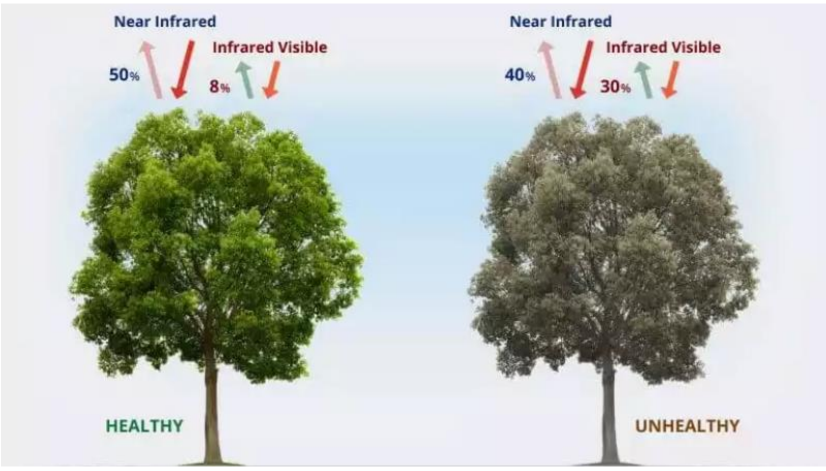
When zoomed out (< zoom level 12), pixels of gain are shaded according to the density of gain at the 30 x 30 meter scale. Pixels with darker shading represent areas with a higher concentration of tree cover gain, whereas pixels with lighter shading indicate a lower concentration of tree cover gain. There is no variation in pixel shading when the data is at full resolution (≥ zoom level 12).

3.2. NDVI method

To be able to assess logging in the research area, the process of finding anomalies in Remote Sensing Data has to deal with the fact that many areas have had human interventions over time. This has resulted in a mixed landscape from fertile valleys to rugged mountain tops with a varied land cover strongly affected by fire, logging, hunting, livestock rearing and farming. A second issue are all the natural systems, like climate, the seasons and water availability, geography and geology making certain areas more suitable for certain types of plants and trees, which are all captured by remote sensing in a different manner, and therefore difficult to interpret.

A way of finding forested areas is done via the NDVI (Normalized Difference Vegetation Index). With the Sentinel 2 imagery this means (B8-B4)/B8+B4) whereby B8 is the near-infrared band and B4 is the red band. This well-known way of verifying vegetation conditions is based on the heat radiation of vegetation. The principle is that humid vegetation (trees with leaves) will release much less infrared (heat) than any other land cover, except for water.

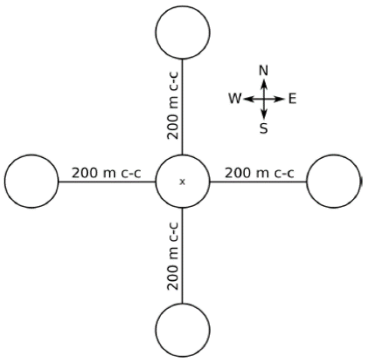
Figure 2: Vegetation radiation and NDVI



One of the issues with the NDVI methodology is the recognition of forests. There are great height differences, species mixed differently, and the orientation of the slope (thus impact & drying effect of the sun) greatly vary on top of the logging and fire impact on forests, shrubs, and pastures. To verify where the 'cut-off' is between forests or wooded areas and shrubby grasslands is thus quite difficult and must be adapted from image to image.

To verify more closely the area with forests in the region, and rectify influences of climate, drought or inclination with respect of the sun and satellite a field verification is required. To have good baseline information, PPNEA team members have adopted a forest monitoring protocol by which they assess the vegetation and forest type while on the trail for other activities in the same area. The protocol requires that from a centre point a photo is made, including forest type noted.

Figure 3: Forest monitoring protocol distance from centre point



Next, in the 4 wind directions at 200-meter distance from the centre point vegetation and forest type is noted and a photo of the typical habitat (figure 3).

In most cases the centre point was a camera trapping location, which will thus give a much clearer impression of the habitat around these points. Elaboration of linkages between location, habitats and species observed might thus be done over time. At every location, the following attributes were checked: forest/non-forest, forest type, forest cover and maturity. The results can be found in annex 2.

These ‘ground proofed’ forest assessment data will support the NDVI assessment in recognizing the difference between forests and other land use types, but also it is useful to assess the accuracy of the other tools with the actual data from the field.

Once the ‘cut-off’ for the NDVI is verified for each annual image selected, based on the review of the field data and the photos thereof, the calculations on forest cover are done and the differences can be calculated for the assessment of deforestation per year. The data can then also be compared with the results from the other tools.

The photos and forest assessment are also used in the verification of the accuracy of the other methods, as this is the only field data basis for the assessment of their accuracy.

3.3. Land Cover / Land Use Changes

The land cover/land use changes are verified at an even greater detail, as an indication of the changing planet and the impact humans have on it. For this most make use of the Sentinel satellites that have up to 10 meter resolution. For this region I have selected the Planetary Computer[4]. The Planetary Computer puts global-scale environmental monitoring capabilities in the hands of scientists, developers, and policy makers, enabling data-driven decision making.

Thes layers display a global map of land use/land cover (LULC) derived from ESA Sentinel-2 imagery at 10m resolution. Each year is generated with Impact Observatory’s deep learning AI land classification model, trained using billions of human-labelled image pixels from the National Geographic Society. The global maps are produced by applying this model to the Sentinel-2 Level-2A image collection on Microsoft’s Planetary Computer, processing over 400.000 Earth observations per year.

The algorithm generates LULC predictions for nine classes, described in detail below.

The year 2017 has a land cover class assigned for every pixel, but its class is based upon fewer images than the other years. The years 2018-2022 are based upon a more complete set of imagery. For this reason, the year 2017 may have less accurate land cover class assignments than the years 2018-2022.

- Variable mapped: Land use/land cover in 2017, 2018, 2019, 2020, 2021, 2022
- Source Data Coordinate System: Universal Transverse Mercator (UTM) WGS84
- Service Coordinate System: Web Mercator Auxiliary Sphere WGS84 (EPSG:3857)
- Extent: Global
- Source imagery: Sentinel-2 L2A
- Cell Size: 10-meters
- Type: Thematic
- Attribution: Esri, Impact Observatory, and Microsoft

[4] Karra, Kontgis, et al. “Global land use/land cover with Sentinel-2 and deep learning.” IGARSS 2021-2021 IEEE International Geoscience and Remote Sensing Symposium. IEEE, 2021.

Class definitions

1 Water; Areas where water was predominantly present throughout the year; may not cover areas with sporadic or ephemeral water; contains little to no sparse vegetation, no rock outcrop nor built up features like docks; examples: rivers, ponds, lakes, oceans, flooded salt plains.

2 Trees; Any significant clustering of tall (~15 feet or higher) dense vegetation, typically with a closed or dense canopy; examples: wooded vegetation, clusters of dense tall vegetation within savannas, plantations, swamp or mangroves (dense/tall vegetation with ephemeral water or canopy too thick to detect water underneath).

4 Flooded vegetation; Areas of any type of vegetation with obvious intermixing of water throughout a majority of the year; seasonally flooded area that is a mix of grass/shrub/trees/bare ground; examples: flooded mangroves, emergent vegetation, rice paddies and other heavily irrigated and inundated agriculture.

5 Crops; Human planted/plotted cereals, grasses, and crops not at tree height; examples: corn, wheat, soy, fallow plots of structured land.

7 Built Area; Human made structures; major road and rail networks; large homogenous impervious surfaces including parking structures, office buildings and residential housing; examples: houses, dense villages / towns / cities, paved roads, asphalt.

8 Bare ground; Areas of rock or soil with very sparse to no vegetation for the entire year; large areas of sand and deserts with no to little vegetation; examples: exposed rock or soil, desert and sand dunes, dry salt flats/pans, dried lake beds, mines.

9 Snow/Ice; Large homogenous areas of permanent snow or ice, typically only in mountain areas or highest latitudes; examples: glaciers, permanent snowpack, snow fields.

10 Clouds; No land cover information due to persistent cloud cover.

11 Rangeland; Open areas covered in homogenous grasses with little to no taller vegetation; wild cereals and grasses with no obvious human plotting (i.e., not a plotted field); examples: natural meadows and fields with sparse to no tree cover, open savanna with few to no trees, parks/golf courses/lawns, pastures. Mix of small clusters of plants or single plants dispersed on a landscape that shows exposed soil or rock; scrub-filled clearings within dense forests that are clearly not taller than trees; examples: moderate to sparse cover of bushes, shrubs and tufts of grass, savannas with very sparse grasses, trees or other plants.

Classification Process

These maps include Version 003 of the global Sentinel-2 land use/land cover data product. It is produced by a deep learning model trained using over five billion hand-labelled Sentinel-2 pixels, sampled from over 20.000 sites distributed across all major biomes of the world.

The underlying deep learning model uses 6-bands of Sentinel-2 L2A surface reflectance data: visible blue, green, red, near infrared, and two shortwave infrared bands. To create the final map, the model is run on multiple dates of imagery throughout the year, and the outputs are composited into a final representative map for each year.

3.4. Appropriate technology

After the application of all 3 tools for both Munela and Polis-Valamara regions a comparison of the different tools will show the appropriate manner in which to keep on following up the condition of the forests in Albania.

4) Results in Munela region

The results for Munela region are divided into 4 parts, 3 different tools. The first tool is from Global Forest Watch, the second is the manual NDVI and the third is ESA landcover data.

A. Results with Global Forest Watch data

First are the results of Global Forest Watch (GFW) on 3 different issues:

- the forests surface in the research area for 2010
- The forest loss per year from 2000 till 2022
- The forest height gain from 2000 till 2020

In figure 4 you can see all areas that are called forest according to the international validated system, whereby forests are classified as such when higher than 5 meters and have more than 10% tree cover per 0.5 Ha. In table 1 is shown the different forests as it is used in the Albanian Forestry; open, dense and very dense forests.

Before that, the differences were only based on the tree cover which is shown in the second part of table 1.

Figure 4: Forests areas (above 10% forest cover per 0.5 ha) with open, dense, and very dense forests in 2010 (Hansen et al 2013)

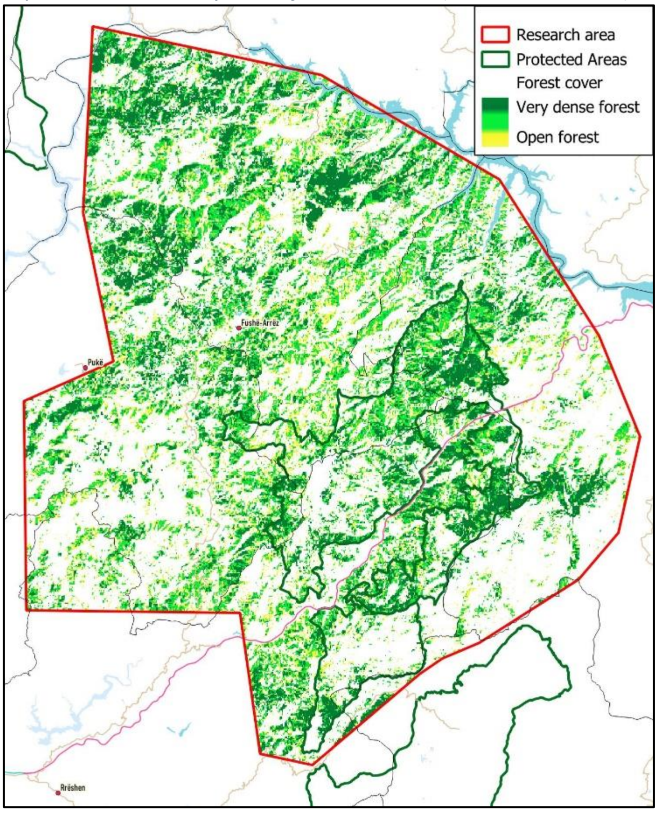


Table 1: Global Forest Watch: Forest Cover 2010

Value	Area (m²)	%
0-9% = No forest	867.425.771	57%
10-39% = Open forest	177.388.101	12%
40-69% = Moderate dense forest	275.565.698	18%
70-100% = Very dense forest	201.053.189	13%

The old value system:		
Value	**Area (m²)**	**%**
< 30% = No Forest	992.348.639	65%
30 – 59% = Open Forest	257.719.802	17%
60 – 90% = Closed Forest	271.364.318	18%

The figures from table 1 indicate that some 57 % of the area was not forest and the remaining 43% was classified as forest in 2010, corresponding to some 654 Km^2. This seems quite a high percentage and is caused due to the inclusion of all open forests.

GFW is also providing data with regards to forest loss and forest gain. The following figures 5 and 6 show the respective results. Forest loss is all areas that have lost forests due to different reasons like logging but also forest fires and diseases. Forest gain is based on the increase of the height of the trees, between the year 2000 and 2020. The surface of land that has an increase of height shows a change from low or non-existent forests to a growing/mature forest. Forests that have had no negative impact from either logging, fire or other natural disasters will not show an increase in height.

Figure 5: GFW - Forest Loss between 2001 and 2022 (Hansen et al 2013)

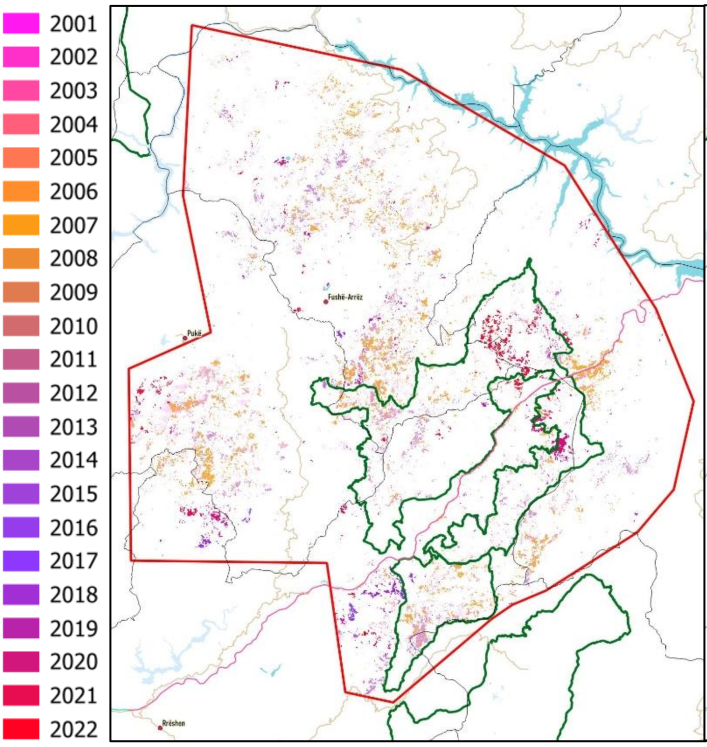


Figure 6: GFW - Forest height gain 2000 – 2020 in meters (Potapov et al 2022)

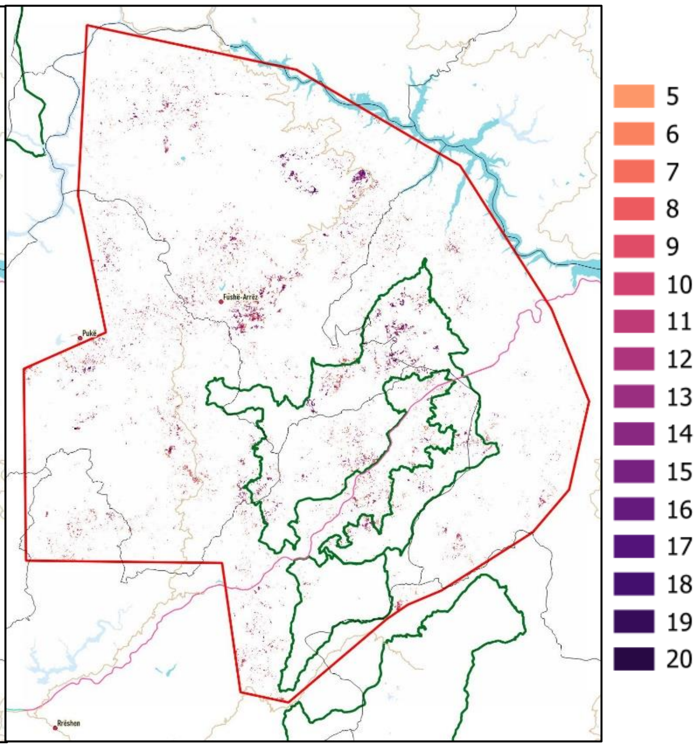


Table 2: GFW - Forest loss per year 2001 - 2022

Value	Year	Area (m²)	% of total forest area
1	2001	10.395.195	1,59%
2	2002	584.407	0,09%
3	2003	539.903	0,08%
4	2004	5.079.896	0,78%
5	2005	1.239.084	0,19%
6	2006	1.143.049	0,17%
7	2007	19.518.514	2,98%
8	2008	10.995.999	1,68%
9	2009	1.158.860	0,18%
10	2010	321.482	0,05%
11	2011	534.633	0,08%
12	2012	17.572.635	2,69%
13	2013	5.417.189	0,83%
14	2014	1.153.004	0,18%
15	2015	77.881	0,01%
16	2016	510.624	0,08%
17	2017	1.099.717	0,17%
18	2018	1.776.646	0,27%
19	2019	1.425.884	0,22%
20	2020	3.250.548	0,50%
21	2021	1.852.771	0,28%
22	2022	5.335.794	0,82%
Average 2016 - 22		2.178.852	0,33%

Table 3: Forest height gain between 2000 and 2020

Value (meter height)	Area (m²)	% of total forest area
1 - 4	189.531	0,03%
5	5.754.853	0,88%
6	3.676.903	0,56%
7	3.594.198	0,55%
8	3.502.305	0,54%
9	3.232.941	0,49%
10	3.027.328	0,46%
11	2.755.667	0,42%
12	2.295.049	0,35%
13	1.809.734	0,28%
14	1.302.595	0,20%
15	956.270	0,15%
16	625.452	0,10%
17	401.461	0,06%
18	209.058	0,03%
19	87.299	0,01%
>20	104.529	0,02%
Total 5 - >20	33.335.642	5,10%

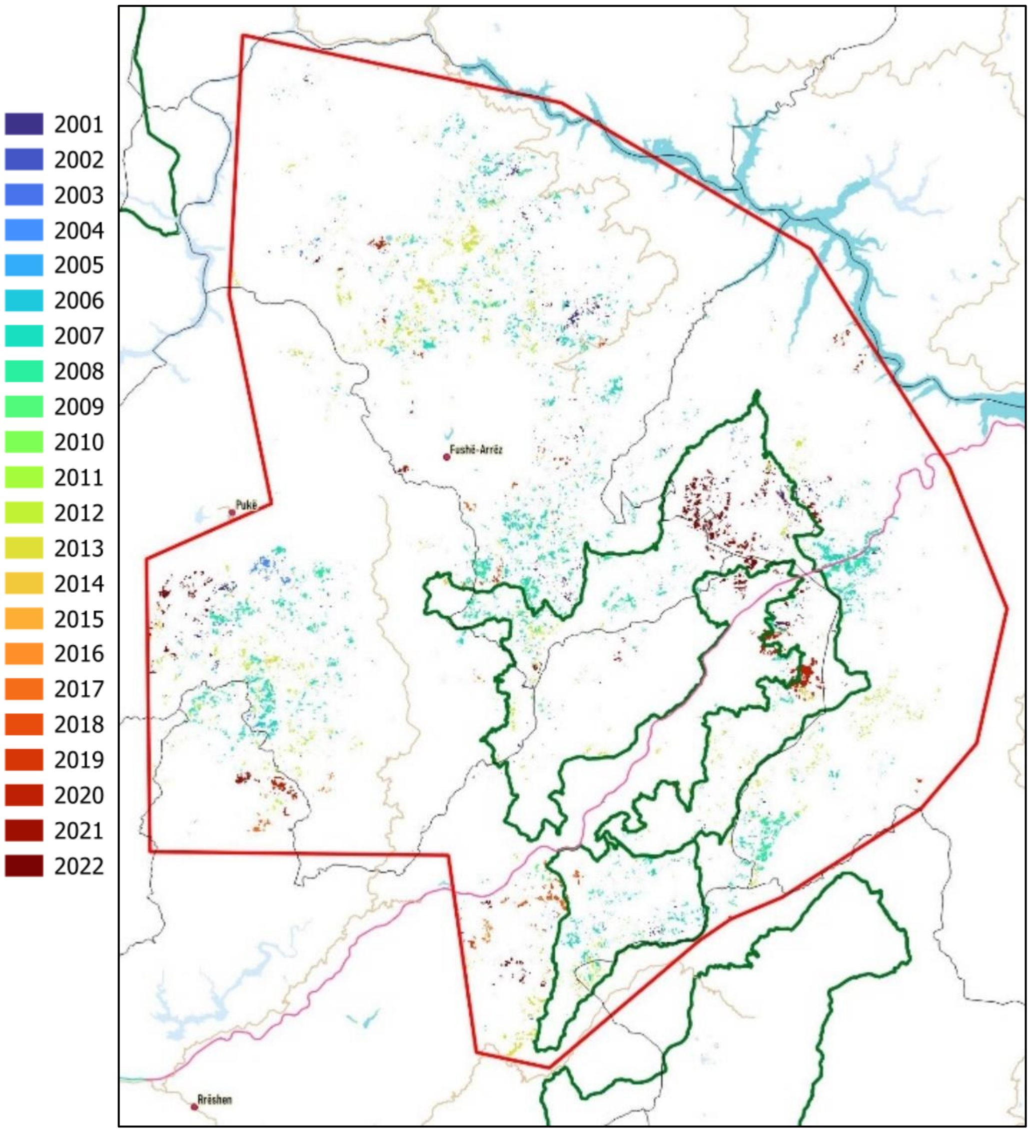
Some of the forest gain from 2001 to 2020 should logically be in the areas that were forest losses have occurred. A verification showed that only an area of 0,9 Km^2 has an overlap between forest height increase above 5 meters and forest loss from 2001 onwards. This means that there has been very little regrowth of forests where these were lost due to fire or logging.

Some forests have re-grown as is shown in the tables above. It is over a period of 20 years, and this comes down to approximately 5,1% of the forest surface or 33,5 Km^2. When comparing the existing forests of 2010 with the areas of growth some 19,3 Km^2 overlaps with forests existing in 2010 and 13,6 Km^2 is in places where no forest was established in 2010 (= lower than 5 m within 0,5 ha).

Looking at the forest loss from 2010 till present, it is clear that in some years the felling and forest fires have had a great impact, certainly the value for 2012 (logging and burning season August 2011 - April 2012) saw significant decrease of forests, just like 2013 and 2022. Only for these last 12 years it is a loss of 6,2% of the total forest surface in the research area, or 40,3 Km^2. When comparing the forest losses with the forest height gain, there is a net loss. There is too little growth to compensate for the losses and sustainable forestry activities.

For a better understanding of the reasons for forest loss, a comparison must be made between the forest loss and forest fire loss assessments.

Figure 7: Forest loss due to fire 2001-2022 (Tyukavina et al 2020)



Year	Area (m²)
2001	2.318.892
2002	103.062
2003	194.412
2004	1.061.654
2005	199.097
2006	134.098
2007	13.943.218
2008	7.934.008
2009	226.033
2010	21.666
2011	112.431
2012	6.807.354
2013	3.275.142
2014	348.419
2015	8.198
2016	218.421
2017	559.813
2018	785.261
2019	714.992
2020	2.674.339
2021	1.012.466
2022	4.220.852

To review the result from forest loss with the forest fire loss one can just put the tables next to each other. To verify that the forest losses from fire are fully within the areas of forest loss an overlap was created which confirms that the losses due to fire were only in areas recognized as forest loss.

Table 4: Forest loss % due to fire

Value	Year	Forest loss Area (m²)	Forest fire loss Area (m²)	% Forest loss due to Fire per year
1	2001	10.395.195	2.318.892	22,31%
2	2002	584.407	103.062	17,64%
3	2003	539.903	194.412	36,01%
4	2004	5.079.896	1.061.654	20,90%
5	2005	1.239.084	199.097	16,07%
6	2006	1.143.049	134.098	11,73%
7	2007	19.518.514	13.943.218	71,44%
8	2008	10.995.999	7.934.008	72,15%
9	2009	1.158.860	226.033	19,50%
10	2010	321.482	21.666	6,74%
11	2011	534.633	112.431	21,03%
12	2012	17.572.635	6.807.354	38,74%
13	2013	5.417.189	3.275.142	60,46%
14	2014	1.153.004	348.419	30,22%
15	2015	77.881	8.198	10,53%
16	2016	510.624	218.421	42,78%
17	2017	1.099.717	559.813	50,91%
18	2018	1.776.646	785.261	44,20%
19	2019	1.425.884	714.992	50,14%
20	2020	3.250.548	2.674.339	82,27%
21	2021	1.852.771	1.012.466	54,65%
22	2022	5.335.794	4.220.852	79,10%

The table 4 shows that the big forest fires of 2006 - 07 and 2013 result in a high percentage of forest losses by fire, but from 2016 onward every year the percentages were high. This seems to show that the logging ban has raised the risk for fire in the Munela region, and even in years with little forest losses, there is still some 50 – 60% lost due to fire.

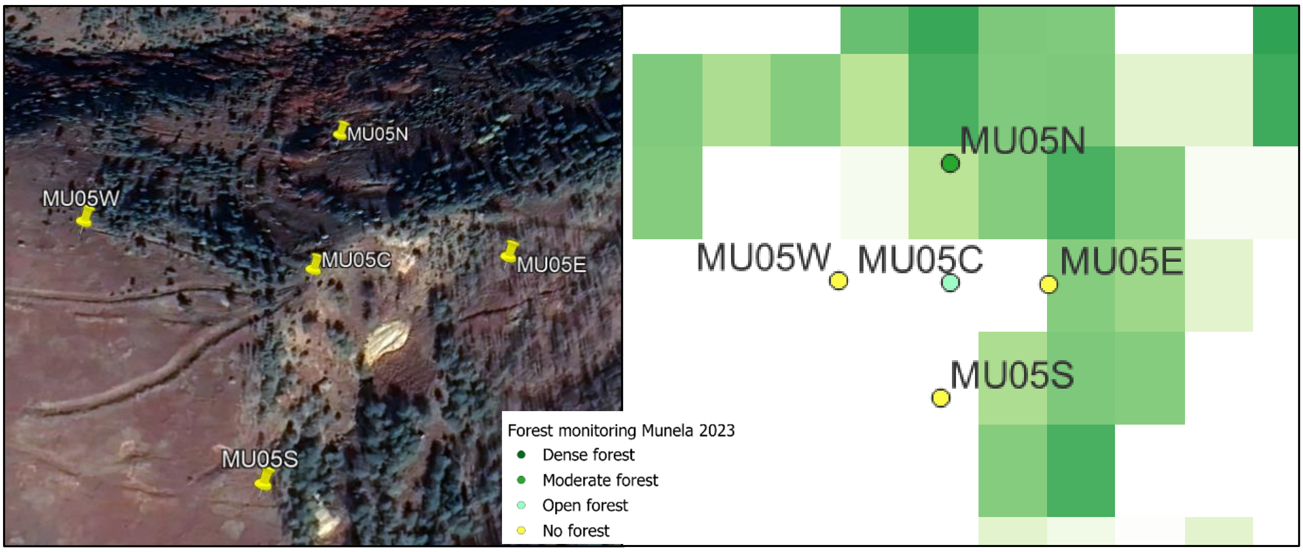
B. Results with manual NDVI data

Before using the field forest monitoring data for the calibration of the NDVI ‘cut-off’ for forest and non-forest, the accuracy of the results has to be verified.

<u>Accuracy of the field forest monitoring data</u>

To ascertain if the gathered field monitoring data of the forest was in line with what can be ‘seen’ via satellites, a verification of the data was done via Google Earth, with historical data to see how certain locations were transformed over time.

Figure 8: Verification of forest monitoring data with Google Earth historical imagery compared with GFW data



The results of the comparison of the forest monitoring, the google earth imagery of different dates and the GFW forest cover 2010 / forest loss / gain, provides strong evidence that the field data and other data sources do correspond at a high level (see figure 8). In comparison with the Land Use Land Cover data the results are less convincing. In some areas (like is the case for MU05 in Figure 8) the land cover only recognises rangeland in this area for 2022.

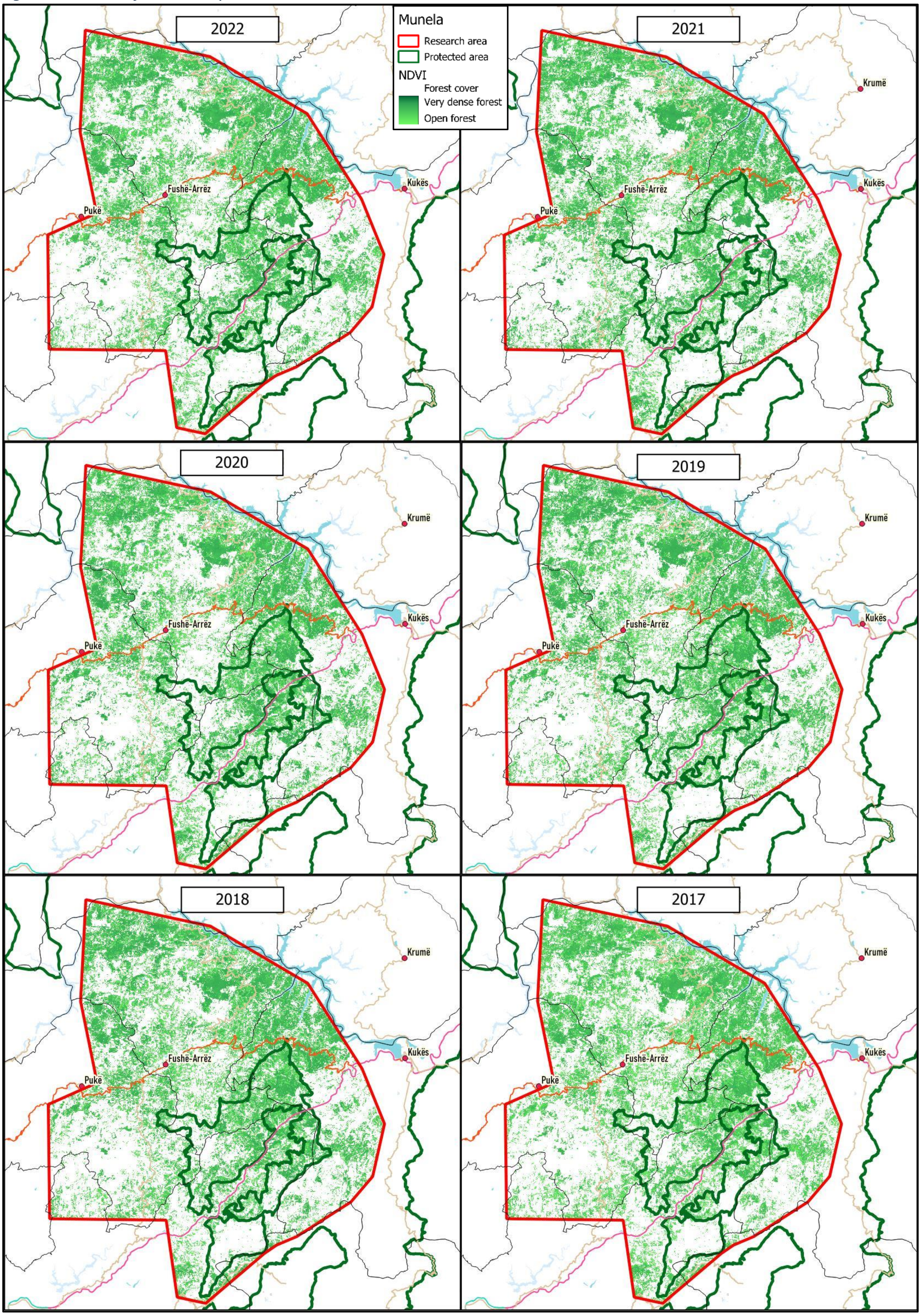
The imagery used in the NDVI assessment are from the end of the summer: 19/09/2017, 20/08/2018, 20/08/2019, 13/09/2020, 13/09/2021, 08/09/2022. For each of these dates the results were downloaded from the sentinel browser hub (https://apps.sentinel-hub.com/eo-browser) for the bands 2, 3, 4, 8, 11 and true colour. The resolution of the images is 21 x 21 meters.

Table 5: NDVI cut-off value & resulting forest surface

Year	NDVI Cut-off	Surface (Km2)
2017	0,746	635,40
2018	0,729	636,21
2019	0,7745	635,38
2020	0,7525	632,66
2021	0,7435	631,08
2022	0,762	627,06

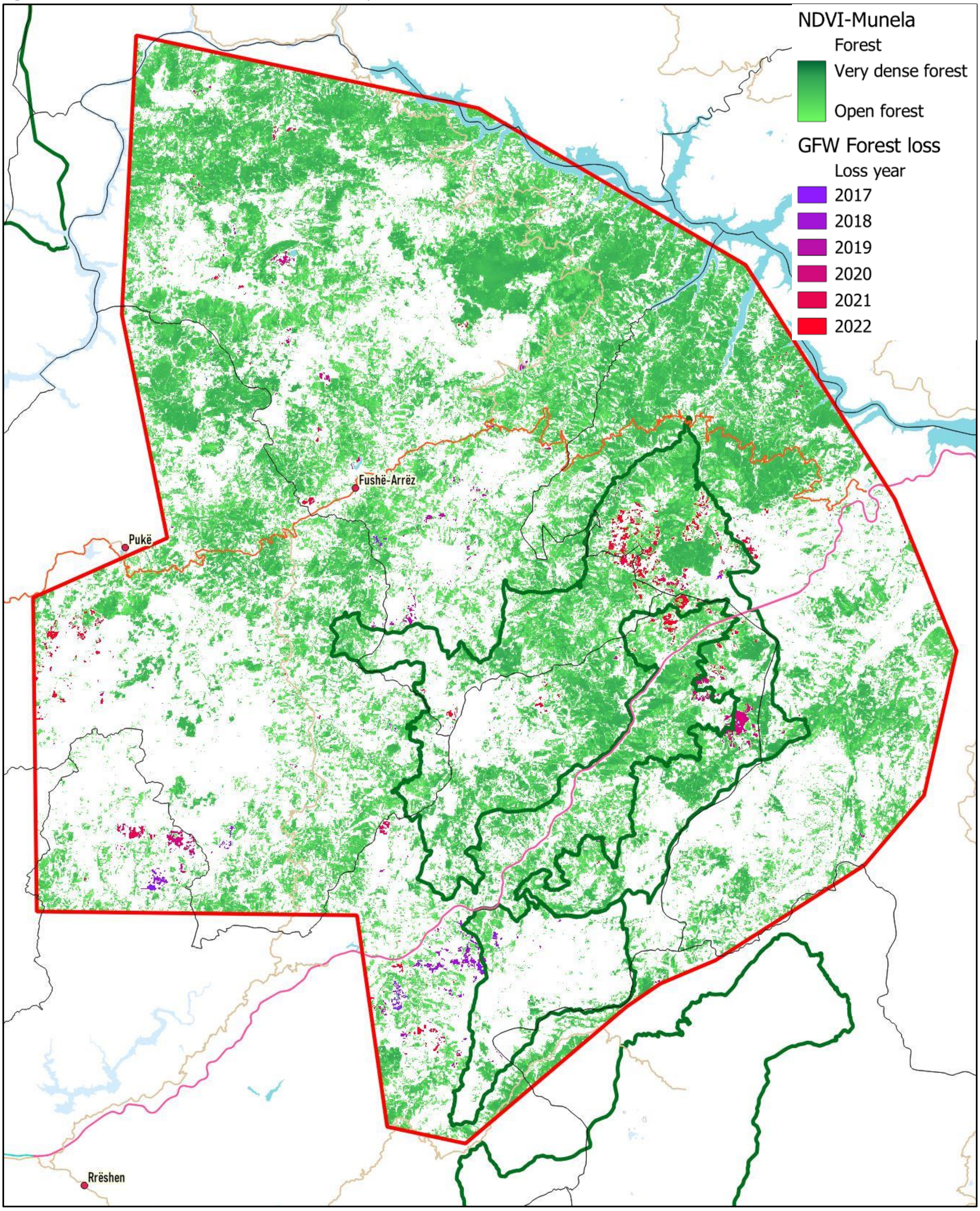
The results are in line with the findings of the GFW results: the deforestation and changes in the landscape due to fires. In Figure 9 the results are shown, but at this scale the results are difficult to interpret.

Figure 9: Results of NDVI analysis 2017 - 2022



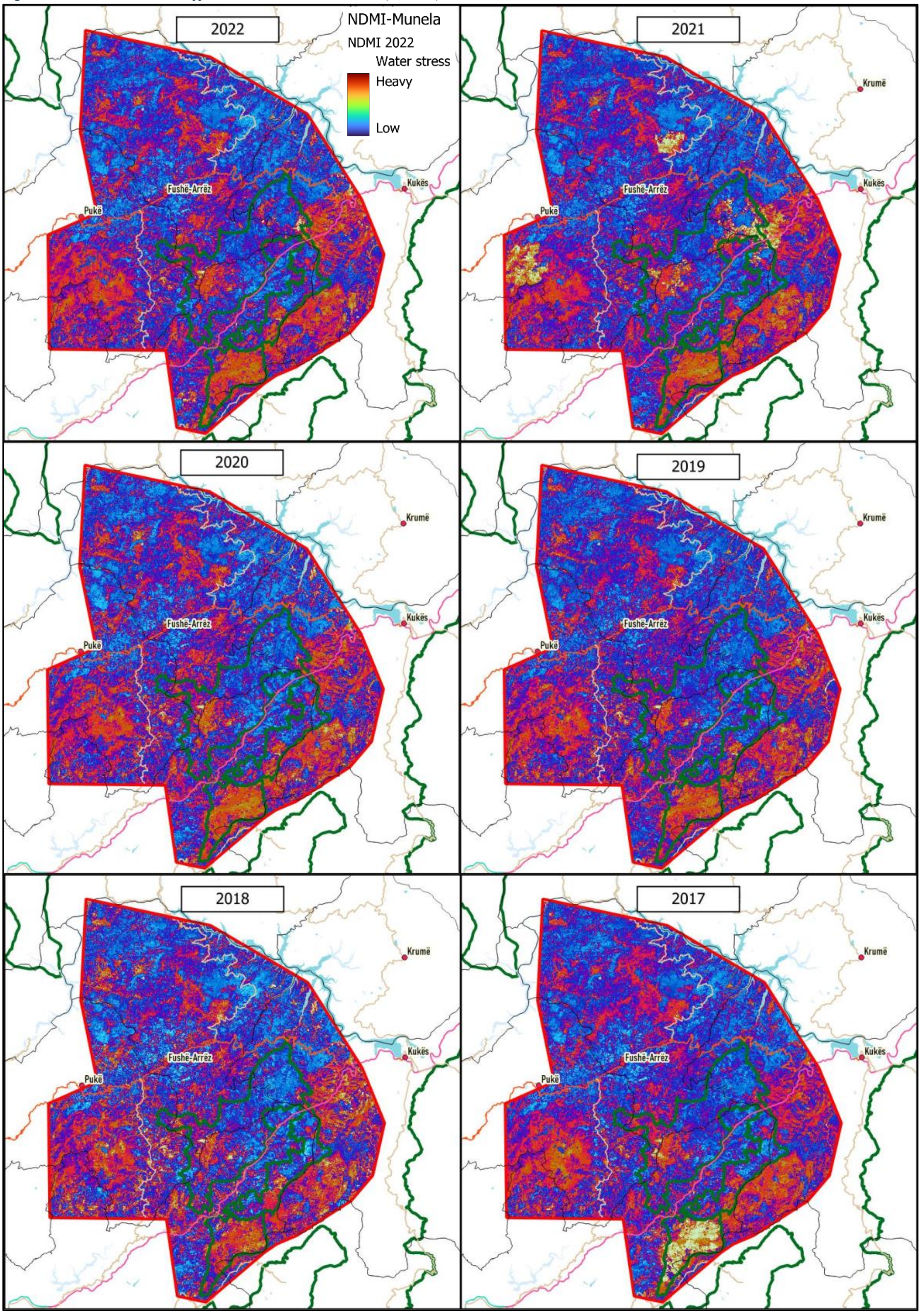
Some of the problems with the NDVI methodology is that it does not recognize wildly spaced pine trees very well, and areas angled towards North or North-East are quickly found to be more humid and thus more easily recognized as forested. However, the results are very much corresponding to the GFW results. In figure 10 the NDVI is overlaid with the Forest losses from 2017 – 2022. These fall clearly in the gaps left by the NDVI.

Figure 10: Forest loss 2017-22 and NDVI overlap



A second assessment assesses if there was water stress during the time the images were taken via the Normalized Difference Moisture Index (NDMI). It is used to determine vegetation water content and monitor droughts. The calculation with the Sentinel-2 imagery is:
NDMI = **(B08 - B11) / (B08 + B11)**

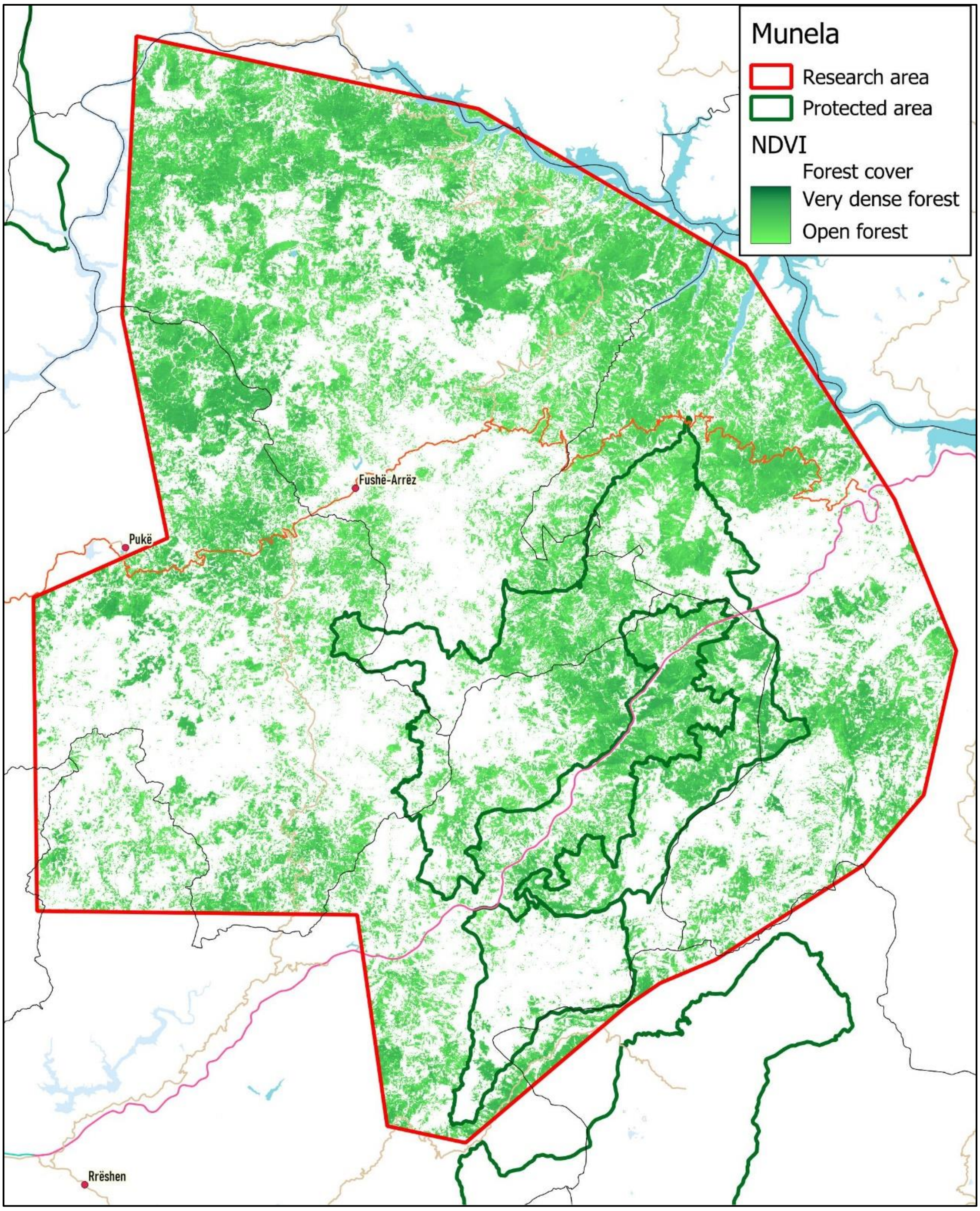
Figure 11: Normalized Difference Moisture Index (NDMI) 2017 - 2022



The red areas show the lack of moisture for the plants to grow. It is visible that the land under trees and vegetation clearly have more moisture. In 2017 and 2020 the lighter areas indicate some moisture on the non-forested areas but without as much water stress as in the other years. All images show there is some form of water stress (the lighter blue areas) where the forests are showing problems with the lack of water at the end of the summer. The darkest areas are in the valleys that get the least impact from the sun.

In 2023 there have been plenty rains in the summer making it difficult to recognize via NDVI which areas are forested and which are non-forest. The result with an NDVI cut-off at 0.723 a surface of 626.03 Km^2 and is shown below.

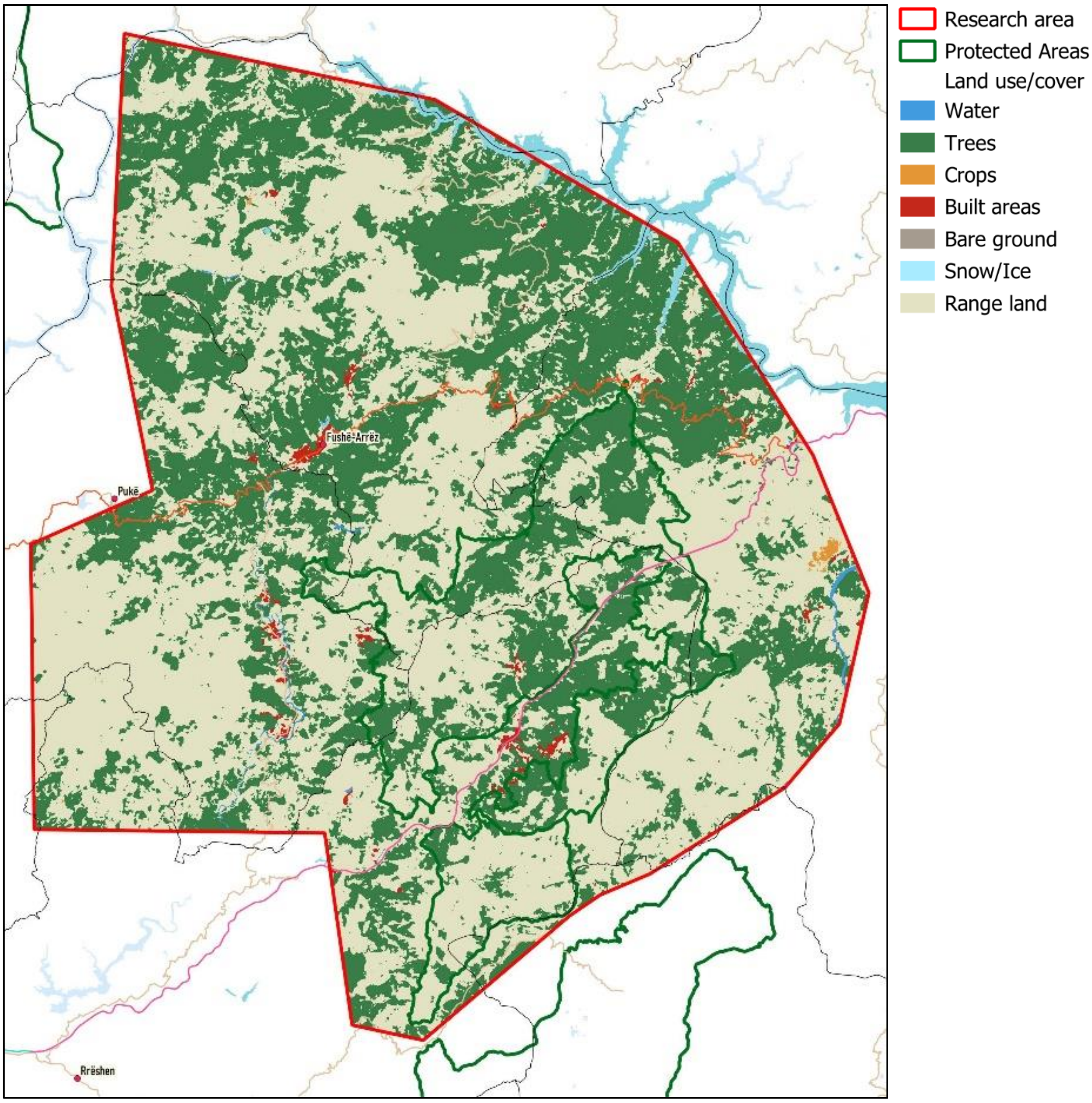
Figure 12: NDVI of Munela in 2023



C. Results with ESA landcover data

The land cover data are as shown before, depending on the images available during that year and have been improving due to the usage of AI assessments. For Munela region the result looks like figure 13 which shows the large expanse of rangeland and trees.

Figure 13: Land Use Land Cover for 2022



Over the years quite some differences are visible in the sizes of the areas under the different forms of land cover, see table 6 and annex 1.

Table 6: Land Use / Cover over the years in m² for Munela region

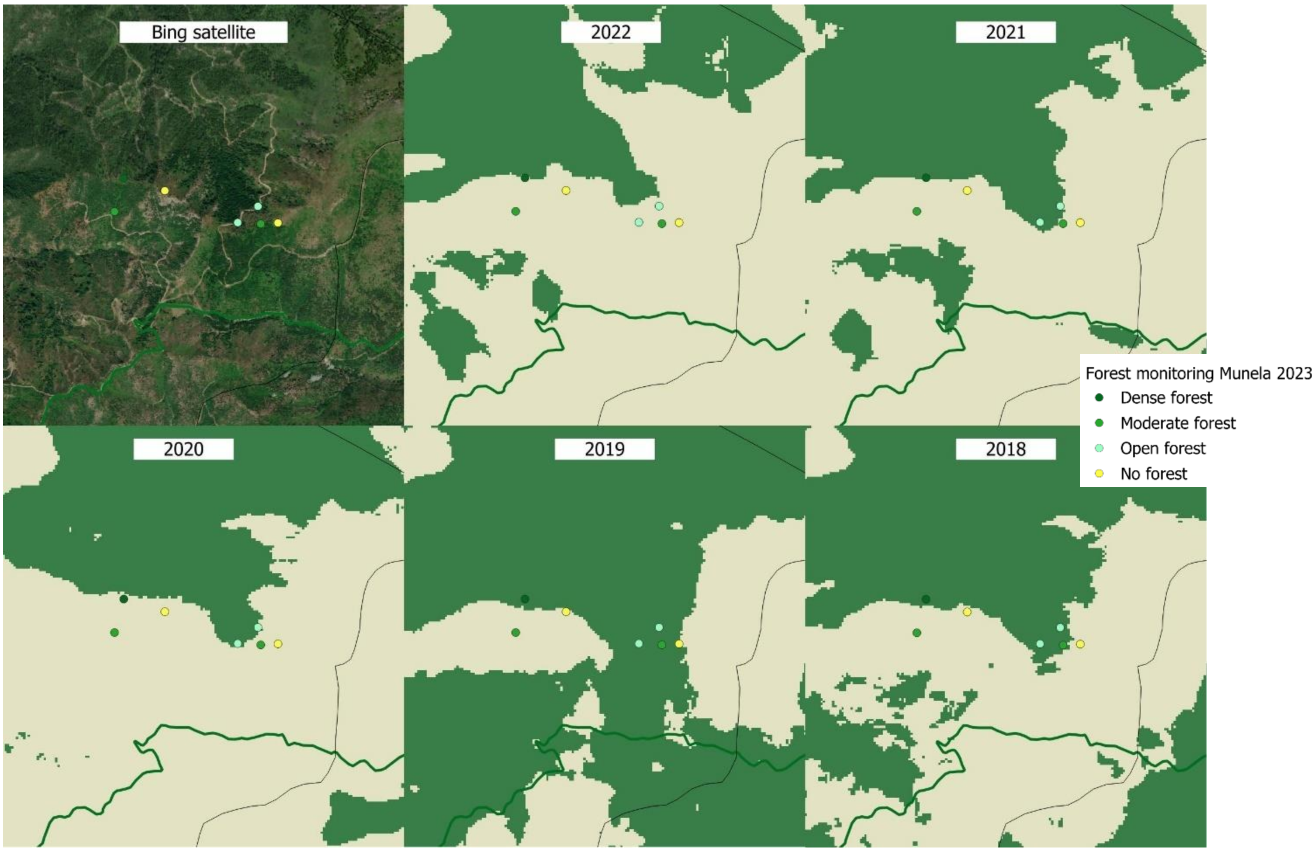
Value	Land cover/use	2017	2018	2019	2020	2021	2022
1	Water	10.860.760	12.996.593	11.629.668	11.081.077	12.615.690	11.774.344
2	Trees	638.248.483	671.244.682	680.071.063	481.761.093	644.931.528	631.949.443
5	Crops	853.653	801.525	2.456.103	1.478.184	1.725.815	1.309.094
7	Built area	5.573.056	5.744.547	6.294.838	6.642.823	6.642.823	10.006.407
8	Bare ground	3.122.756	1.888.001	1.831.671	1.526.610	1.266.972	1.295.987
9	Snow/Ice	18.410	1.201	15.208	4.903	68.636	9.605
11	Range land	863.709.953	829.710.522	820.088.519	1.019.892.381	855.135.605	866.042.190

From these figures it seems exceedingly difficult to assess if the forests are stable or not. The decreasing trend from 2010 when 654 Km^2 were classified as Forest by Global Forest Watch does seem to correspond with the 624,70 Km^2 on average over the 6 years for the land cover of trees.

The results of 2020 on the total area under trees and under rangeland shows that many areas (some 143 Km^2) which in other years is indicated as covered with trees, is in actual fact very sparsely covered (with pine?) or with 'bush' / re-growth that has dried out. To verify that the assessment is the same whether for forests (> 5 m high per 0,5 ha) or for land use under trees, a transformation of the pixels to 0,5 ha was done. The total area under trees and under forests are very much the same.

Why the category trees in 2020 was so low might possibly have to do with the average accuracy of 85% as described in the methodology. Due to these big differences between the years, it seems to provide too little accuracy for a proper assessment of the changes in the forest cover of the area. However, when putting the resulting images of each year next to each other, the locations with changes in land use can clearly be seen. Figure 14 is a typical example of an area with many small

Figure 3: Land use / land cover changes over time with field data and RS data



forest areas that has seen a chance over time. One of the indicators for land use change are the many (logging) roads that can be seen in the Bing satellite image.

Even though the changes per year are too big to reliably give conclusions on the issues related to deforestation with this method, over the years the changes do indicate that the land use and land cover of the area is changing into more rangeland, which is an indication that the forests are diminishing.

5) Results Polis-Valamara region

The assessment for the Polis-Valamara region will follow the same 3 methods. The first tool is from Global Forest Watch. The second is the manual NDVI and the third is ESA landcover data.

A. Results with Global Forest Watch data

First are the results of Global Forest Watch (GFW) on 3 different issues:

- the forests surface in the research area for 2010
- The forest loss per year from 2000 till 2022
- The forest height gain from 2000 till 2020

In figure 15 you can see all areas that are called forest according to the international validated system, whereby forests are classified as such when higher than 5 meters and have more than 10% tree cover per 0,5 Ha. In table 7 is shown the different forests as it is used in the Albanian Forestry; open, dense and very dense forests.

Before that, the differences were only based on the tree cover which is shown in the second part of table 7.

The figures from table 7 show that 58% of the area was not forest and the remaining 42% or 305 Km^2 was classified as forest in 2010. This seems quite a high percentage and is caused due to the inclusion of all open forests.

Figure 15: Forests areas (above 10% forest cover per 0.5 ha) with open, dense, and very dense forests in 2010 (Hansen et al 2013)

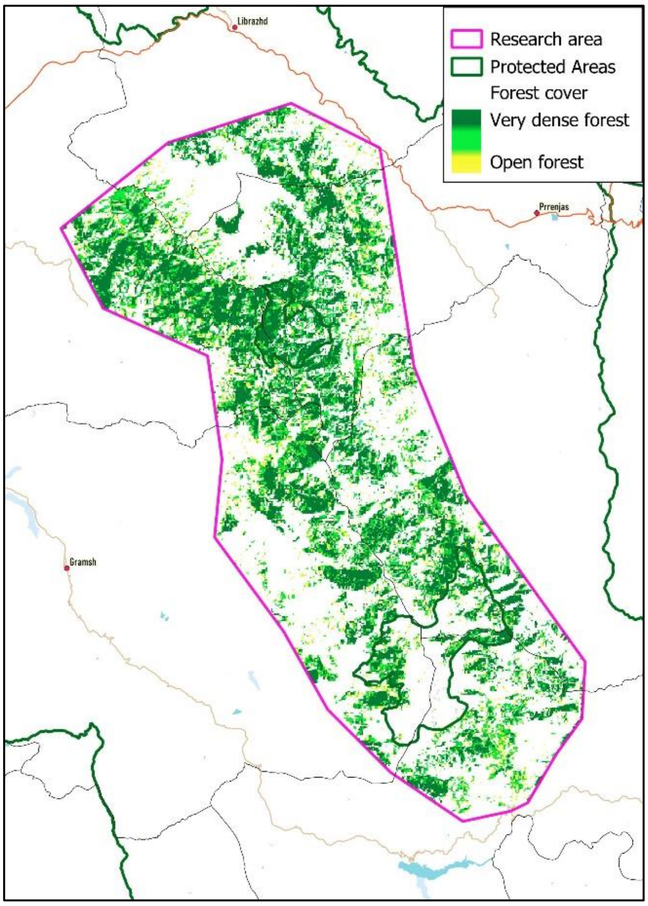


Table 7: Global Forest Watch: Forest Cover 2010 Polis-Valamara region

Value	Area (m²)	%
0-9% = No forest	415.105.016	58%
10-39% = Open forest	47.771.747	7%
40-69% = Moderate dense forest	108.984.765	15%
70-100% = Very dense forest	148.188.889	21%

The old value system:		
Value	**Area (m²)**	**%**
< 30% = No Forest	448.895.643	62%
30 – 59% = Open Forest	79.552.930	11%
60 – 90% = Closed Forest	191.601.845	27%

GFW is also providing data with regards to forest loss and forest gain. The following figures 16 and 17 show the respective results. Forest loss is all areas that have lost forests due to different reasons like logging but also forest fires and diseases. Forest gain is based on the increase of the height of the trees, between the year 2000 and 2020. The surface of land that has an increase of height indicates a change from low or non-existent forests to a growing/mature forest. Mature forests that have had no negative impact from either logging, fire or other natural disasters will not show an

Figure 16: GFW - Forest Loss between 2001 and 2022 (Hansen et al 2013)

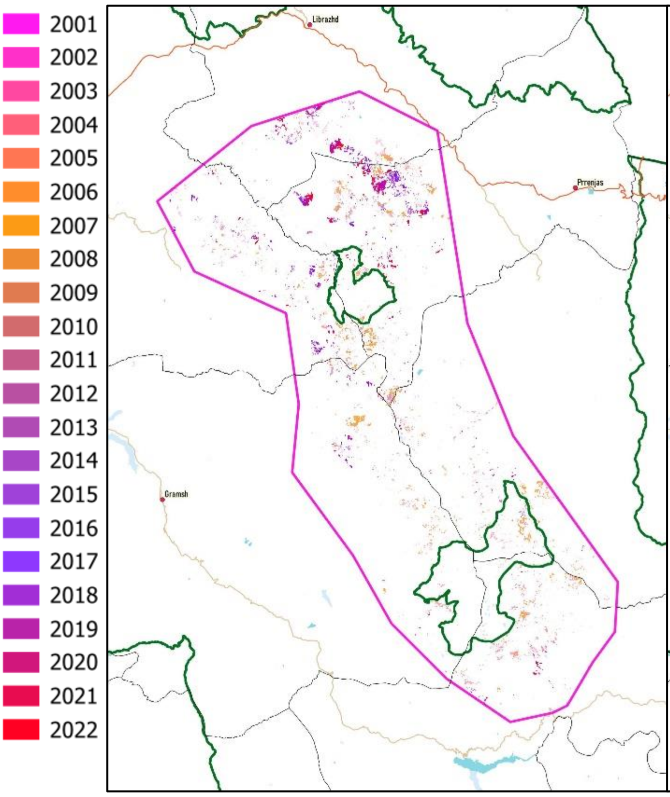
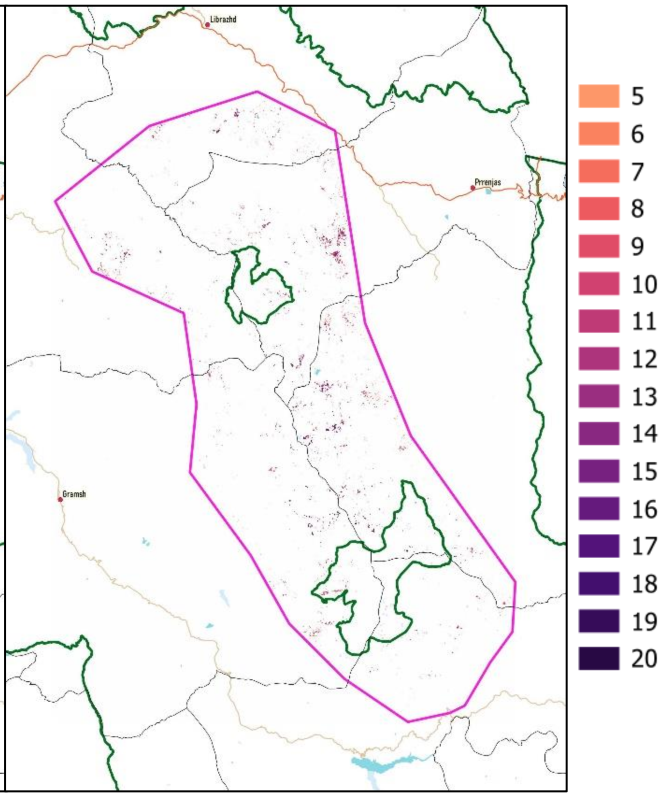


Figure 17: GFW - Forest height gain 2000 – 2020 in meters (Potapov et al 2022)



increase in height.

Table 8: GFW - Forest loss per year 2001 - 2022

Value	Year	Area (m²)	% of total forest area
1	2001	846,125	0,28%
2	2002	1,137,872	0,37%
3	2003	60,607	0,02%
4	2004	2,371,409	0,78%
5	2005	403,454	0,13%
6	2006	1,245,420	0,41%
7	2007	1,270,971	0,42%
8	2008	3,859,258	1,27%
9	2009	1,422,489	0,47%
10	2010	715,998	0,23%
11	2011	412,367	0,14%
12	2012	1,672,048	0,55%
13	2013	411,179	0,13%
14	2014	985,760	0,32%
15	2015	316,703	0,10%
16	2016	767,692	0,25%
17	2017	612,609	0,20%
18	2018	1,181,248	0,39%
19	2019	1,035,672	0,34%
20	2020	1,119,452	0,37%
21	2021	1,139,061	0,37%
22	2022	967,934	0,32%
Average 2016-22		974,810	0,32%

Table 9: Forest height gain between 2000 and 2020

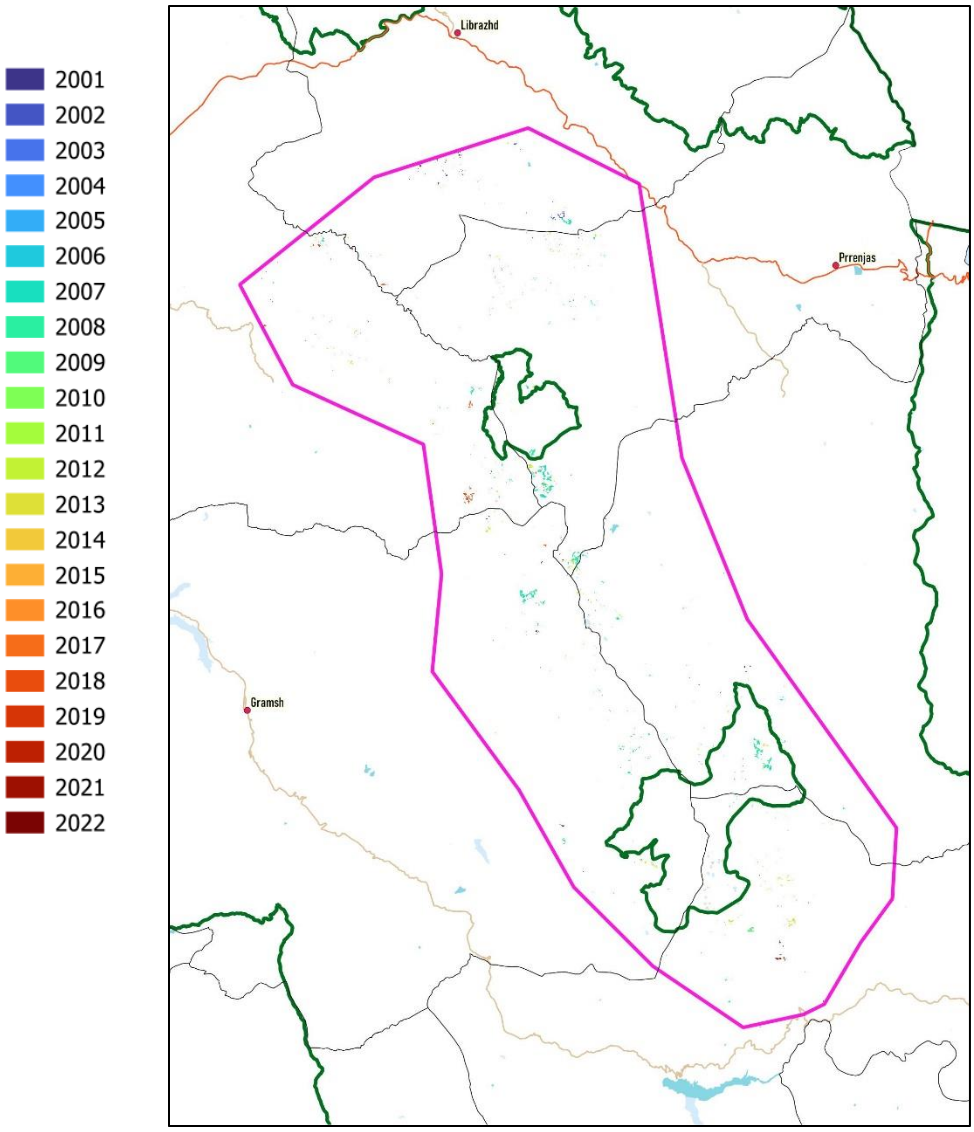
Value (meter height)	Area (m²)	% of total forest area
1 - 4	33,275	0,01%
5	777,794	0,26%
6	631,029	0,21%
7	626,275	0,21%
8	781,953	0,26%
9	809,286	0,27%
10	737,983	0,24%
11	685,100	0,22%
12	513,379	0,17%
13	336,905	0,11%
14	284,617	0,09%
15	188,358	0,06%
16	151,518	0,05%
17	97,447	0,03%
18	58,825	0,02%
19	42,782	0,01%
>20	93,288	0,03%
Total 5 - >20	6,816,539	2,24%

Looking at the forest loss till present, it is clear that in some years the felling and forest fires have had an impact, certainly the value for and 2008 (logging and burning season August 2007 - April 2008) saw significant decrease of forests. Also 2004 and 2012 were bad. It seems that from 2012 onwards the forest loss has been at a similar level. From 2016 till now the loss is on average about 0.32% annually of the total forest surface in the research area, or 6.8 Km^2 of forests.

Some forests have re-grown as is shown in table 9. It is over a period of 20 years, and this comes down to approximately 2.24 % of the forest surface or 6.8 Km^2. Of this some 3.7 Km^2 came as new growth in previously barren areas and 2.8 km^2 from areas already having forests. The re-growth after forest loss is minimal, only 45.752 m^2 (0.04 km^2). All this together is too little growth to compensate for the losses and sustainable forestry activities.

For a better understanding of the reasons for forest loss, a comparison must be made between the forest loss and forest fire loss assessments.

Figure 18: Forest loss due to fire 2001-2022 (Tyukavina et al 2020)



Year	Area (m^2)
2001	36.840
2002	161.619
2004	29.709
2005	12.478
2006	19.608
2007	306.007
2008	1.073.700
2009	91.505
2010	20.202
2011	16.043
2012	456.337
2013	86.157
2014	17.231
2015	1.783
2016	2.377
2017	34.463
2018	169.938
2019	13.072
2020	23.173
2021	51.694
2022	25.550

To review the result from forest loss with the forest fire loss one can just put the tables next to each other. To verify that the forest losses from fire are fully within the areas of forest loss an overlap was created which confirms that the losses due to fire were only in areas recognized as forest loss.

Table 10 shows that the big forest fires of 2007 – 08, 2012 - 13 and 2018 give a high percentage of forest losses by fire. For the rest, these losses are minimal which suggests that the forest losses in the Polis-Valamara region are mainly due to logging. From 2016 onwards it is approximately 1 Km^2 per year that is logged. It thus seems to be systematic.

Table 10: Forest loss % due to fire

Year	Forest loss Area (m^2)	Forest fire loss Area (m^2)	% forest loss due to fire per year
2001	846.125	36.840	4,35%
2002	1.137.872	161.619	14,20%
2003	60.607	-	0,00%
2004	2.371.409	29.709	1,25%
2005	403.454	12.478	3,09%
2006	1.245.420	19.608	1,57%
2007	1.270.971	306.007	24,08%
2008	3.859.258	1.073.700	27,82%
2009	1.422.489	91.505	6,43%
2010	715.998	20.202	2,82%
2011	412.367	16.043	3,89%
2012	1.672.048	456.337	27,29%
2013	411.179	86.157	20,95%
2014	985.760	17.231	1,75%
2015	316.703	1.783	0,56%
2016	767.692	2.377	0,31%
2017	612.609	34.463	5,63%
2018	1.181.248	169.938	14,39%
2019	1.035.672	13.072	1,26%
2020	1.119.452	23.173	2,07%
2021	1.139.061	51.694	4,54%
2022	967.934	25.550	2,64%

B. Results with manual NDVI data

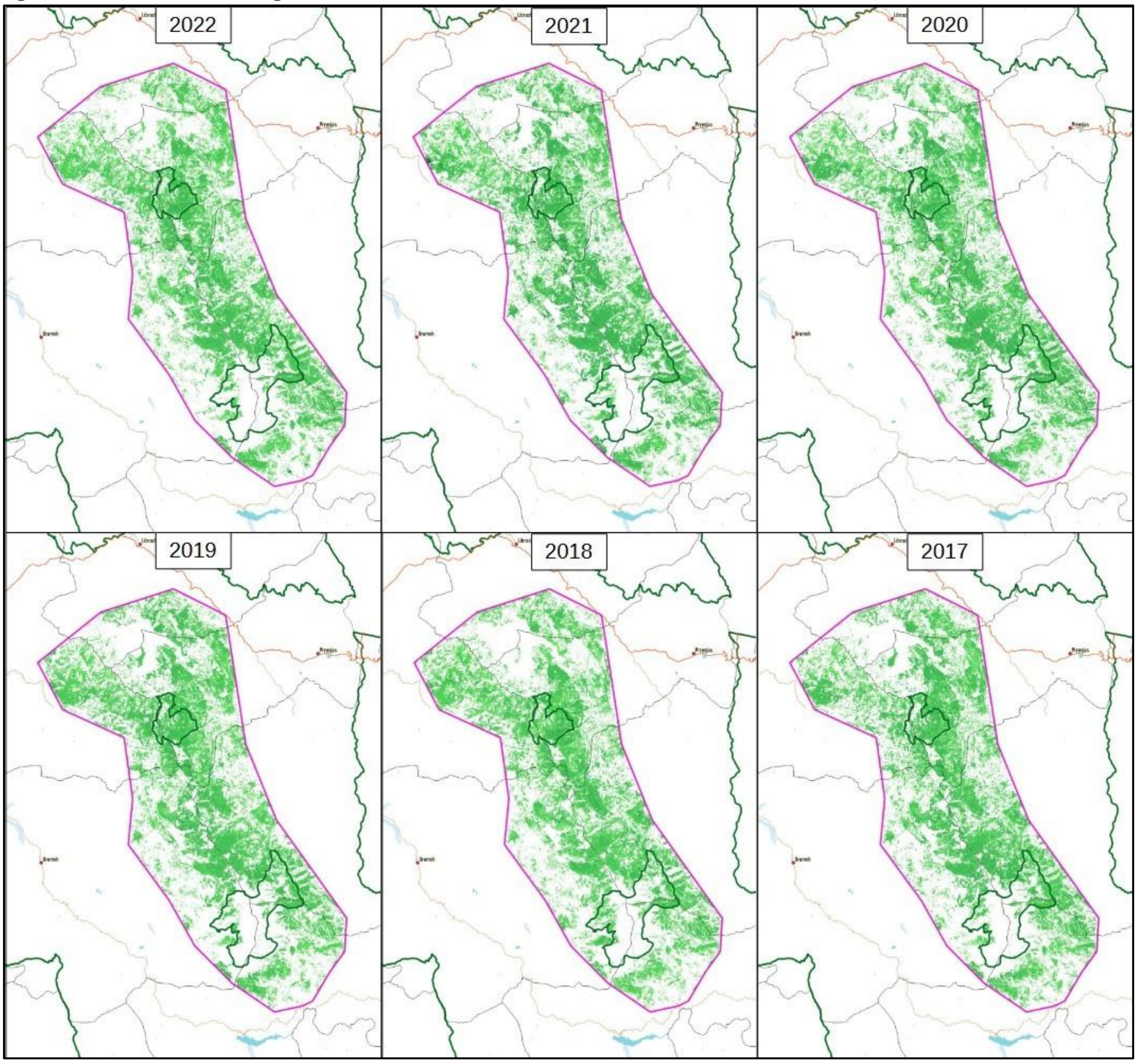
The results in the Polis-Valamara region does not have field level forest monitoring data, and thus the adaptation of the NDVI imagery has to happen based on the figures from the GWF results and the verification with historical google earth imagery.

The imagery used in the NDVI assessment are from the end of the summer: 19/09/2017, 20/08/2018, 20/08/2019, 13/09/2020, 13/09/2021, 08/09/2022. For each of these dates the results were downloaded from the sentinel browser hub (https://apps.sentinel-hub.com/eo-browser) for the bands 2, 3, 4, 8, 11 and true colour. The resolution of the images is 21 x 21 meters.

Table 11: NDVI cut-off value & resulting forest surface

Year	NDVI Cut-off	Surface (Km2)
2017	0,774	301,71
2018	0,799	300,55
2019	0,835	299,97
2020	0,808	299,93
2021	0,809	298,79
2022	0,835	297,75

Figure 49: Polis-Valamara region NDVI results



The results correspond with the indicated forest losses from the GFW results presented above, where specifically in the northern parts of the region forest losses are visible.

The sequence of images clearly shows the forests of 2010, the forest losses for 2010-2022 and the NDVI of 2022. The resulting image shows how the gaps visible in the NDVI image are created by the forest losses.

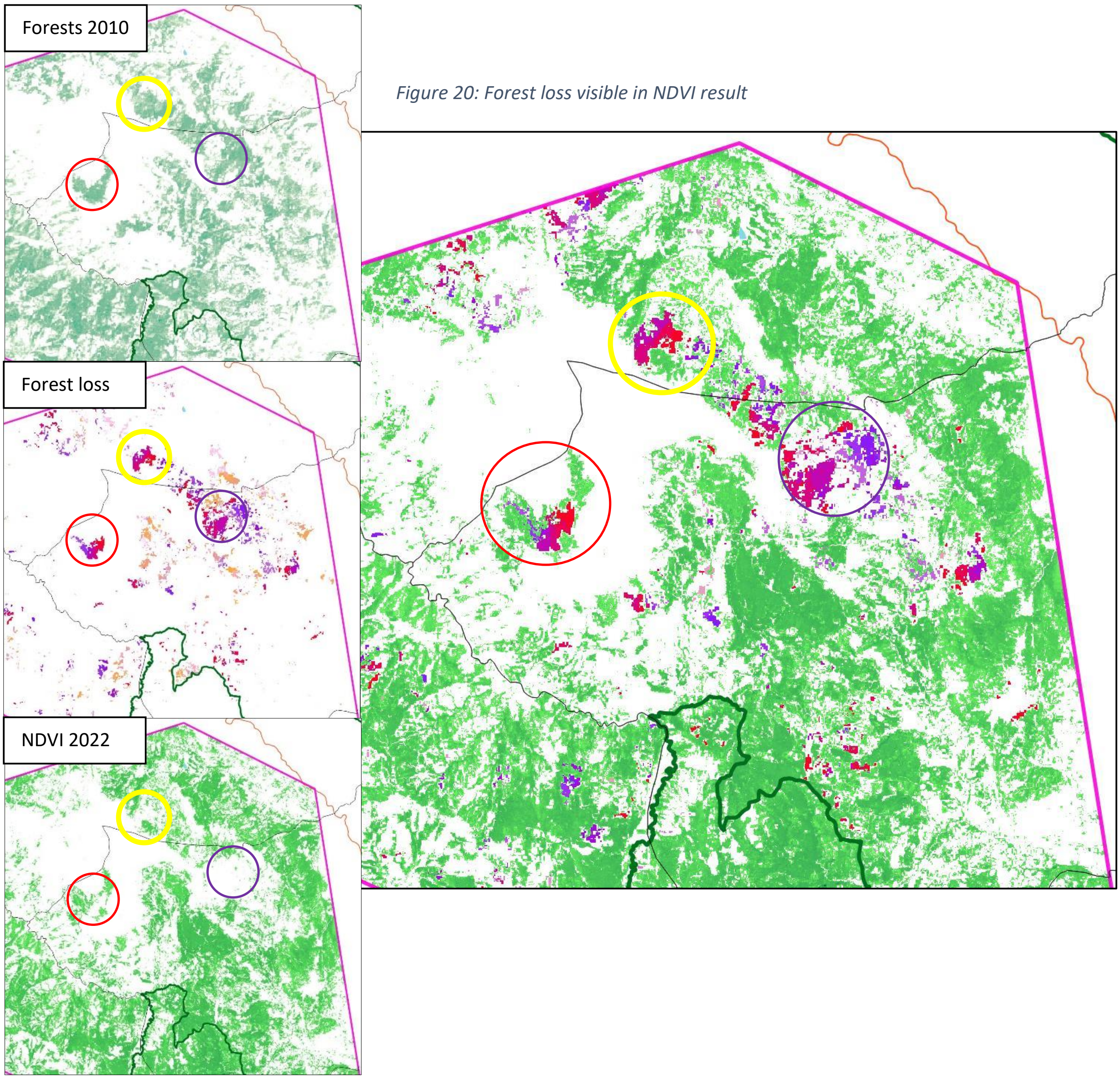
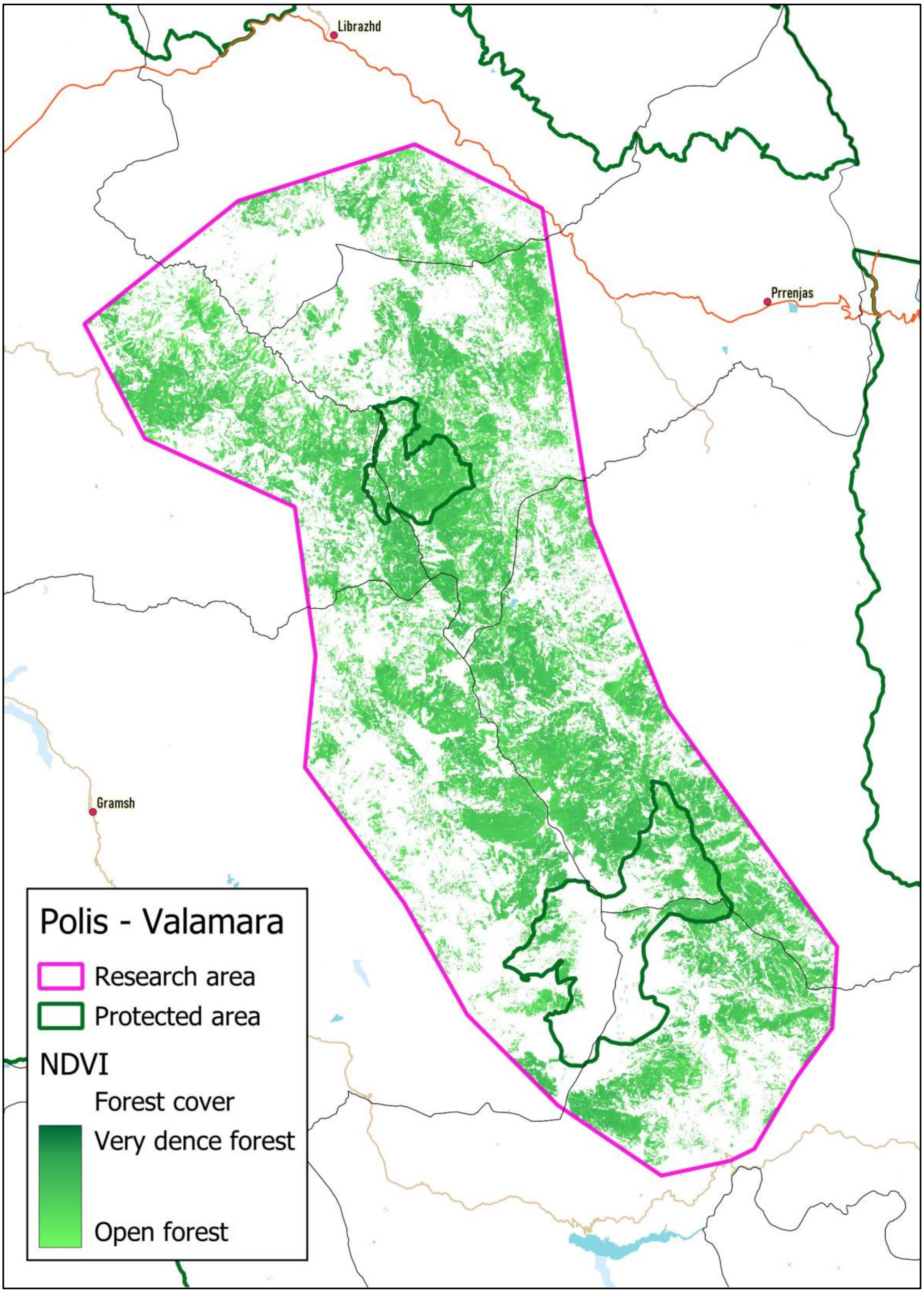


Figure 20: Forest loss visible in NDVI result

For the year 2023 the image of 13 September 2023 was the clearest. Due to the amount of rain and regular rains during the summer of 2023 the differences between forests and non-forest is much more difficult to see with the NDVI method than in other years.

The result with an NDVI cut-off at 0.837 a surface of 296,57 Km^2 and is shown below.

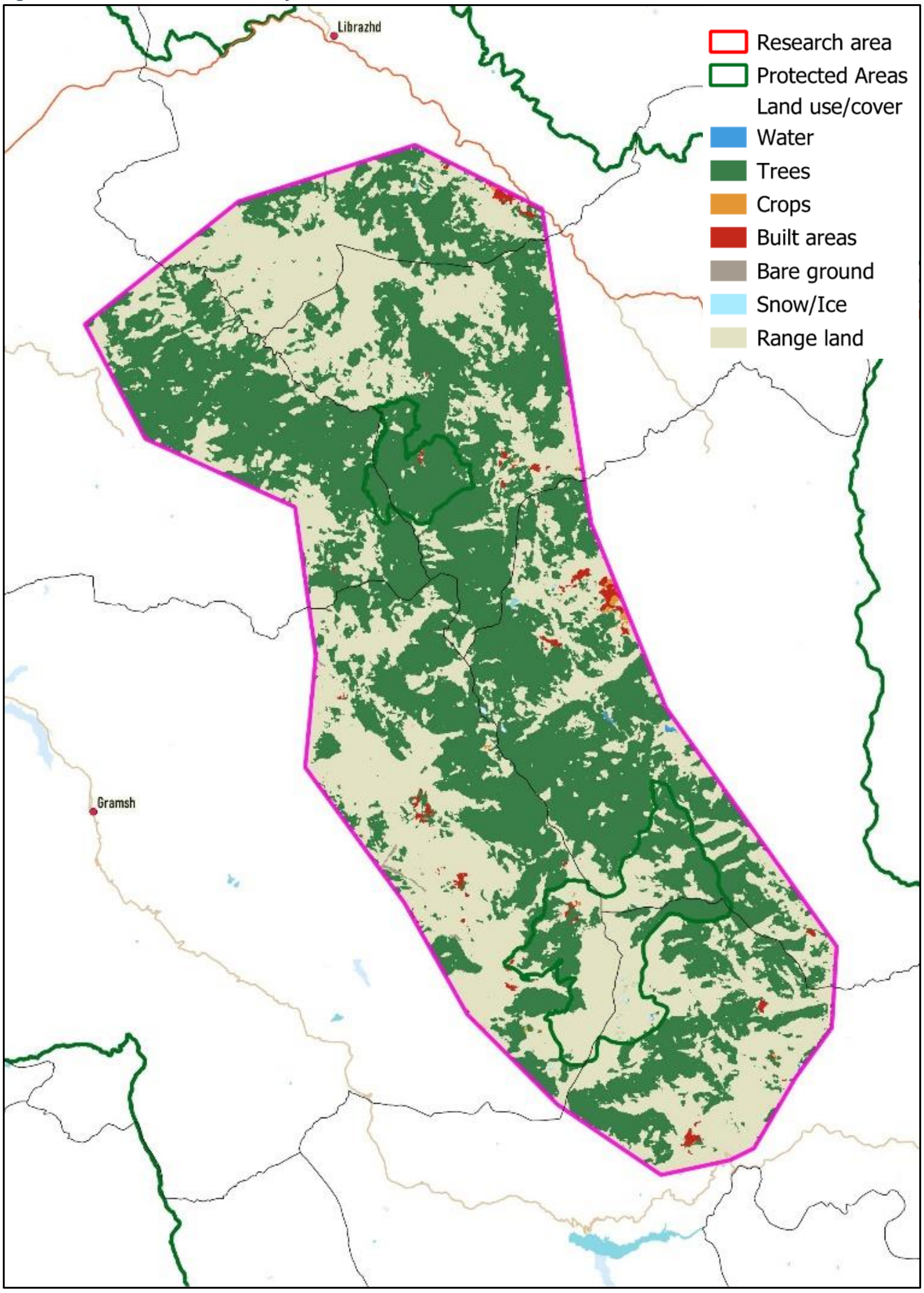
Figure 21: NDVI results for forests in 2023



C. Results with ESA landcover data

The land cover data are as shown before depending on the images available during that year and have been improving due to the usage of AI assessments. For the Polis-Valamara region the result looks like figure 22 which shows the large expanse of trees in the central part of the region.

Figure 22: Land Use Land Cover for 2022



Over the years quite some differences are visible in the sizes of the areas under the different forms of land cover, see table 12 and annex 1.

For the Polis-Valamara region the results are as follows:

Table 12: Land Use / Cover over the years in m^2 for Polis-Valamara region

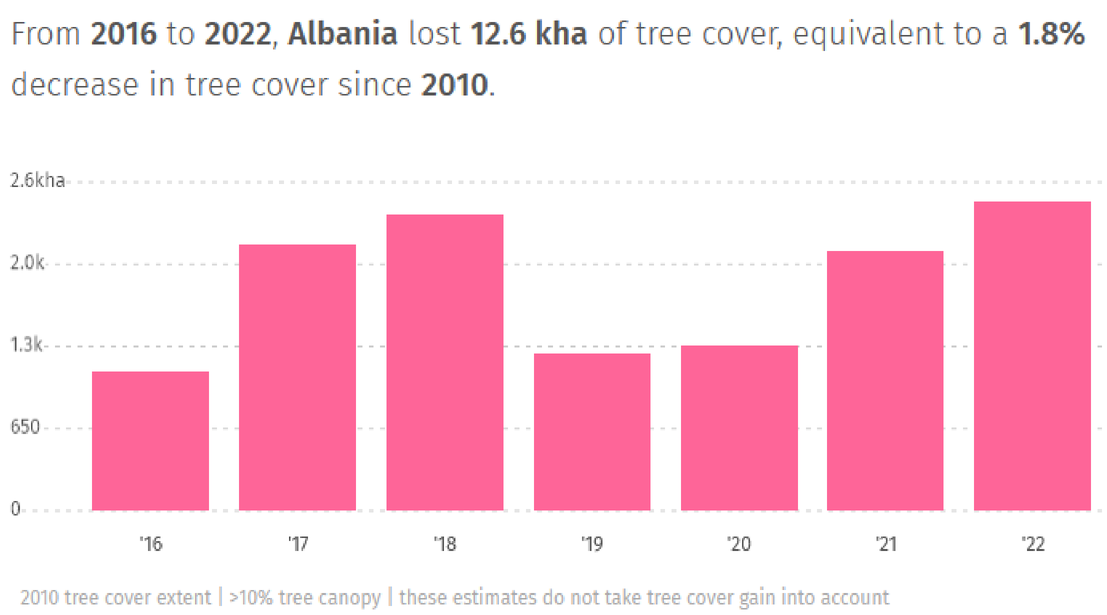
Value		2017	2018	2019	2020	2021	2022
1	Water	511.333	708.461	598.690	602.192	717.667	682.144
2	Trees	400.585.981	395.247.806	418.592.604	251.114.476	408.672.846	379.869.395
5	Crops	1.229.600	740.882	1.043.479	1.013.360	596.388	973.434
7	Built area	4.160.108	3.705.112	3.809.780	4.112.677	3.993.400	4.567.473
8	Bare ground	1.147.147	808.226	725.672	671.437	587.583	539.551
9	Snow/Ice	-	801	100	-	2.802	-
11	Range land	312.415.182	318.838.064	295.279.027	462.535.210	305.478.667	333.417.355

From these figures it seems very difficult to assess if the forests are stable or not. Also, the decreasing trend from 2010 when some 305 Km^2 were classified as Forest by Global Forest Watch does not seem to correspond with the average 375.68 Km^2 of trees on average over the 6 years for the land cover for trees seems a little too high.

Like in the Munela region, why the category trees in 2020 was so low is unknown and might have something to do with the drought. The accuracy of 85% seems here to provide too little information for a proper assessment of the changes in the forest cover of the area.

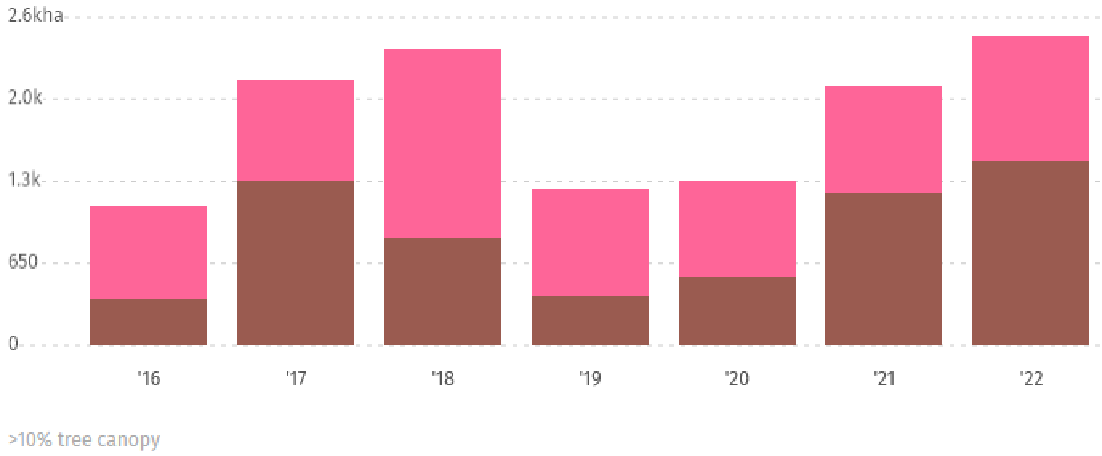
6) General country wide observations by Global Forest Watch

Global Forest Watch also has some analysis available country wide which have a consistent monitoring system since 2015. Some of the results are:



Specifically, fires have been analysed and the following results have been found since 2016.

From **2016** to **2022**, **Albania** lost **6.12 kha** of tree cover from fires and **6.50 kha** from all other drivers of loss. The year with the most tree cover loss due to fires during this period was **2022** with **1.46 kha** lost to fires — **60%** of all tree cover loss for that year.



Per region the forest losses are measured as indicated in table 13.

Figure 13: Forest loss per region and year

	Tree cover loss year							
	2016	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Total Ha**
Berat	105.1	576.6	378.0	66.3	101.2	141.6	196.7	**1565.5**
Diber	64.2	119.6	283.0	105.4	102.3	81.5	36.4	**792.4**
Durres	24.0	44.5	44.9	24.3	20.2	38.3	99.9	**296.2**
Elbasan	152.4	144.9	210.6	126.7	135.5	152.0	145.2	**1067.3**
Fier	58.2	70.0	61.7	36.5	58.6	131.8	42.1	**458.8**
Gjirolaster	51.9	121.6	58.9	38.5	39.9	93.1	58.5	**462.4**
Korce	102.1	149.8	142.9	59.2	75.2	99.1	69.1	**697.4**
Kukes	29.6	13.3	16.1	12.1	68.5	44.7	247.1	**431.4**
Lezhe	68.4	198.7	438.4	195.0	276.3	361.4	548.5	**2086.7**
Shkoder	57.9	162.6	164.9	254.7	155.3	205.2	508.3	**1508.9**
Tirane	51.8	158.7	164.9	130.1	43.5	59.2	80.6	**688.9**
Vlore	342.6	350.8	381.0	197.8	235.0	650.4	409.2	**2566.7**

On forest gain data, the only available data is from between the years 2000 to 2020 with a total gain to 16.5 kha.

Table 14: GFW data for Albania

Country	**Stable forest**	**Forest loss**	**Forest gain**	**Disturbed forest**	**Net result**	**Change in %**	**Total Ha (2000)**
ALB	814,631.9	40,701.8	16,472.2	41,219.9	-24,229.6	-2.70	2,873,542.7

From this data it is clear that fires are a main component of the forest loss in Albania, and that the forest gain is very limited and not enough to replace the forests lost by fire and logging.

7) Appropriate methodology

From both the example of Munela region and Polis-Valamara region it is clear that a methodology that is focussed on forests recognition and monitoring (GFW) is the easiest and probably most reliable way of monitoring the development of forests in Albania via remote sensing. This said, a verification of the situation on the ground via forest monitoring protocols helps to get a better understanding of the environment and the habitats which are important for an understanding of the impact from forest degradation due to logging and fire.

It is still important to verify and understand better the quality of the results from Global Forest Watch by having field data on forest/non forest including forest types, as this clearly is important to monitor. One disadvantage is the lack of updates during the year. Only at the end of a year new updates of the state of the forests is provided.

In those areas where forest fires are the main concern, the specialized satellites which detect forest fires at a 4 hour interval can provide more detailed information during the year.

8) Conclusion

This investigation and assessment of various methodologies for monitoring forest resources using remote sensing data underscores the importance of selecting an appropriate methodology for forest monitoring, favouring those that are focused on forests and verified by ground-based observations.

The first study was conducted by PPNEA in 2019, but the Remote Sensing landscape has evolved since then due to advancements in technology, such as Google Earth Engine and AI applications. The two methodologies that yielded promising results in 2019 were manual NDVI comparisons between images and analysis by the Forestry-TEB (F-TEB) service, which is now a paid service. However, with the emergence of new tools and improved capabilities, the need to explore newer options for more efficient and exact forest monitoring is emphasized.

The methodologies used this time include Global Forest Watch (GFW), manual NDVI assessments, and land cover/land use changes analysis. GFW offers valuable data on forest cover, forest loss (at annual interval), and forest height gain, while NDVI analysis uses normalized difference vegetation index to recognize forests. The land cover/land use changes analysis, employing Sentinel satellites and AI, provides detailed insights into changes on the Earth's surface, but rather at a lesser accuracy. Improved methods are now combining satellite imagery with radar detection (height of tree cover) that soon will become available as tools for bi-weekly verification of activities inside forests, even in bad weather.

GFW data reveals forest loss due to several factors, including logging and fire, while NDVI assessments demonstrate similar trends. However, NDVI has limitations in recognizing specific forest types and its accuracy can only be verified through field data and comparison with other sources.

The case study of the Munela and Polis-Valamara regions in Albania shows the differences in management of the area. The results obtained using the different methodologies, highlights the differences in fire and logging as causes for deforestation.

In Munela region the average deforestation rate from 2016 – 2022 is at 0.33% (or 2.2Km^2) per year with on average 57% by fire. The forest gain over a period of 20 years is 5.10% (or 33.5 Km^2), but only 14.5 Km^2 in new/reforested.

In Polis-Valamara, the deforestation from 2016 - 2022 is on average 0.32% (or 1 km^2) of which on average only 4% by fire. The forest gain over 20 years is 2.24% (or 6.8 Km^2), but only 3.7 Km^2 on new/reforested areas.

For both areas, the deforestation rate is higher than the re-growth. The ban on logging of 2016 has not seen an increase of forestry activities that increase the total volume of forests, rather the opposite has occurred whereby the forest losses due to fires in Munela are worrying.

The combination of remote sensing data and field monitoring can provide a comprehensive understanding of forest dynamics, aiding in effective forest management and conservation efforts in Albania. Unfortunately, the deforestation seems to be ongoing, and the logging ban does not seem to have positive impact on the state of the forests. In fact, there seems to be very little done in form of re- or afforestation during the logging ban till this time in the 2 areas under review.

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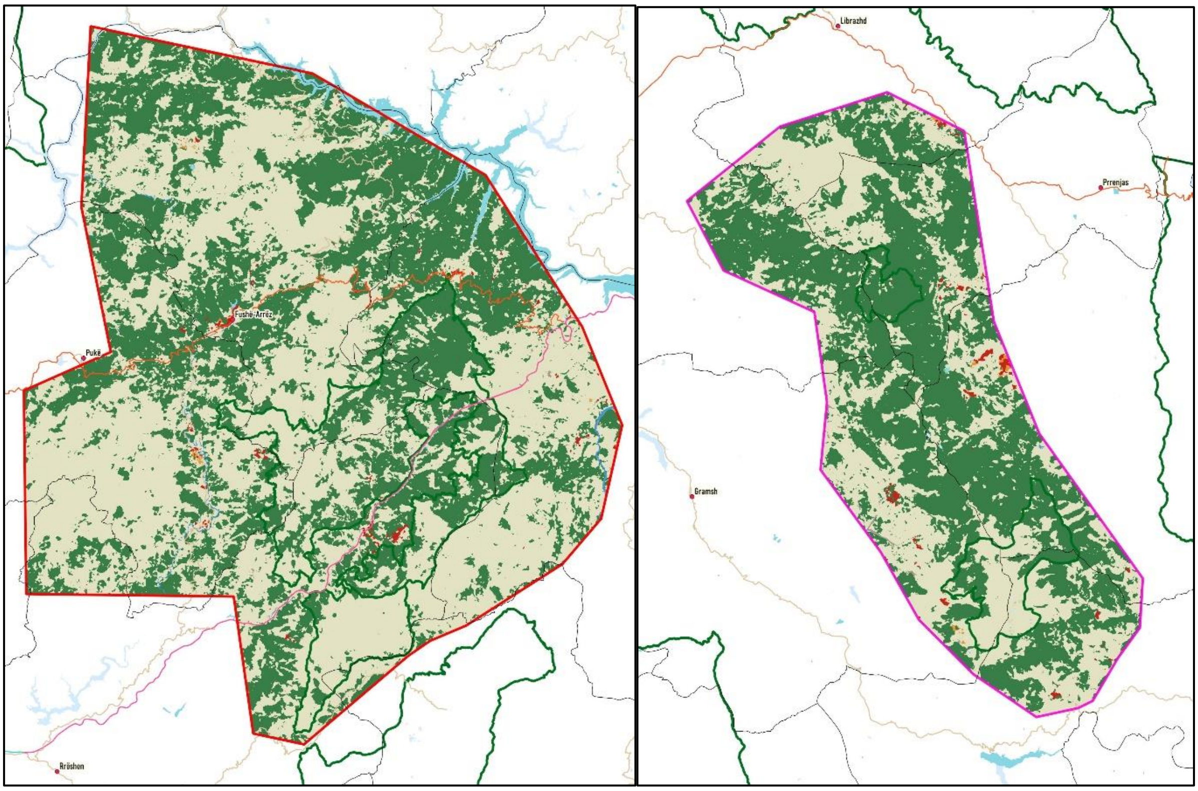
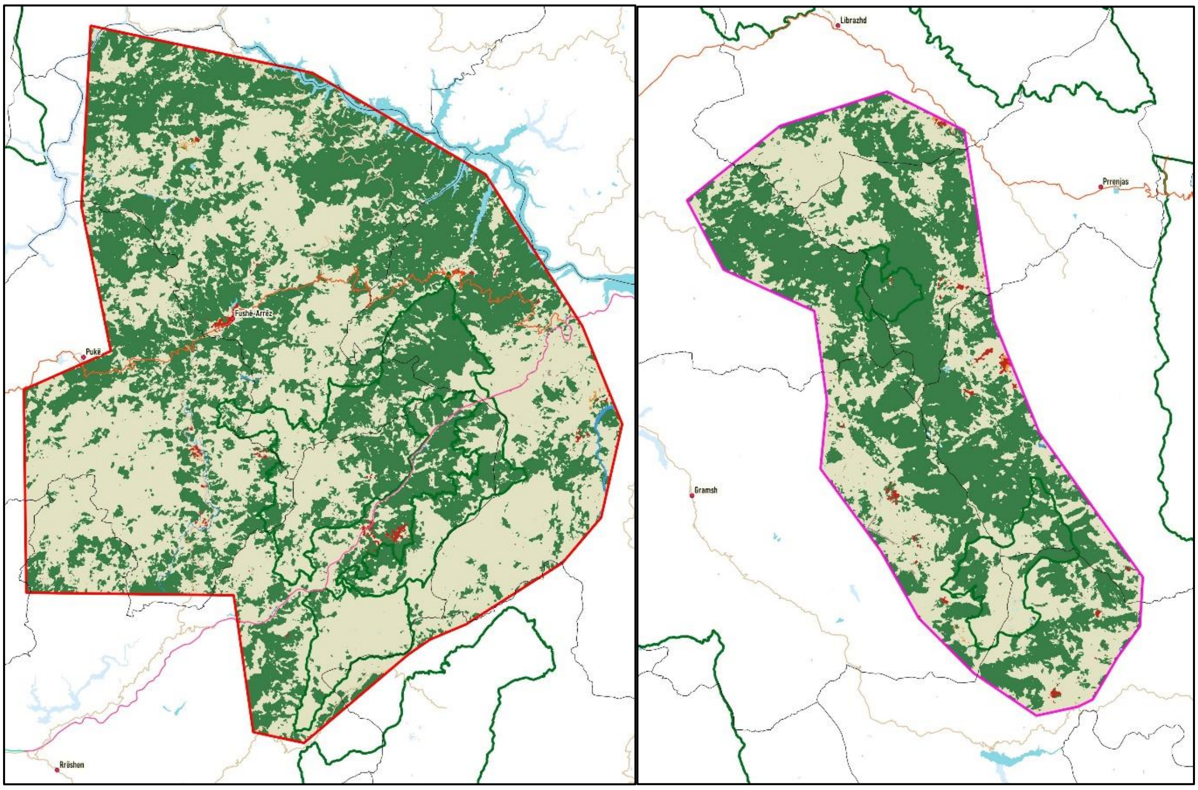
Annex 1: Maps of Land Use Land Cover for Munela region and Polis-Valamara region

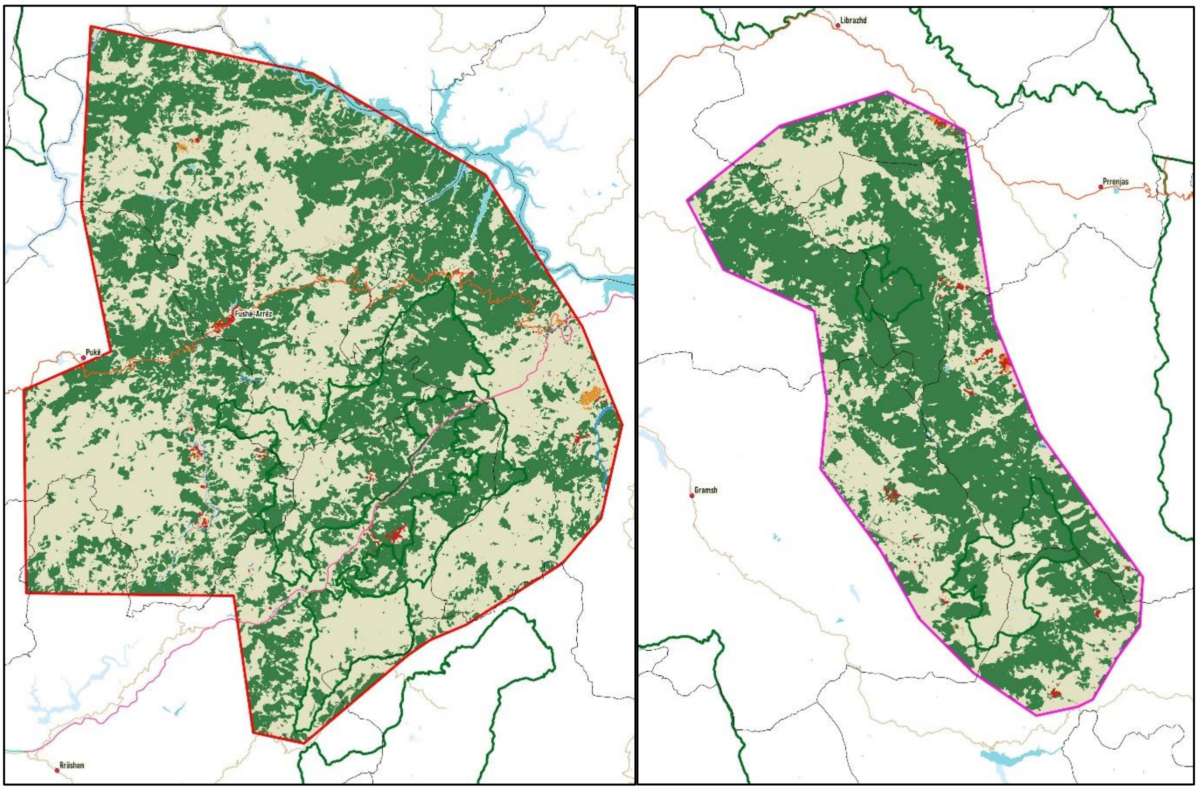
2017 Land Use Land Cover Munela region & Polis-Valamara region



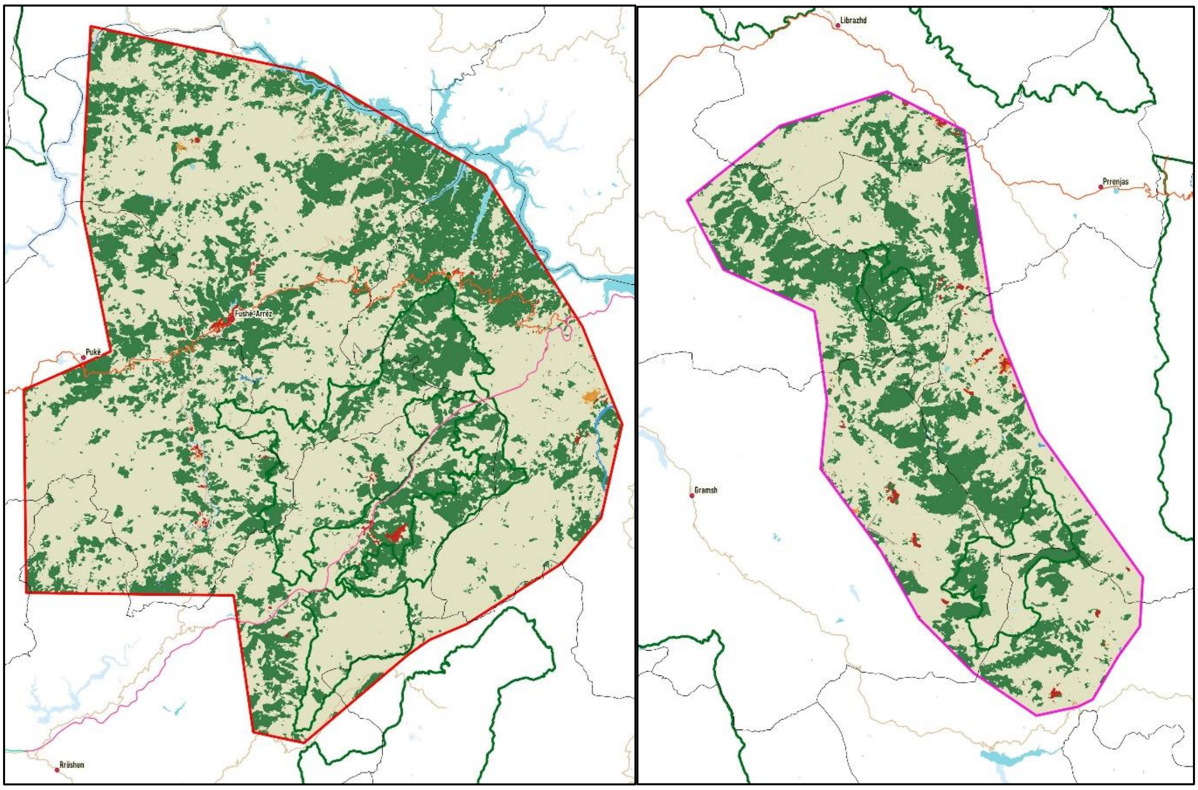
2018 Land Use Land Cover Munela region & Polis-Valamara region



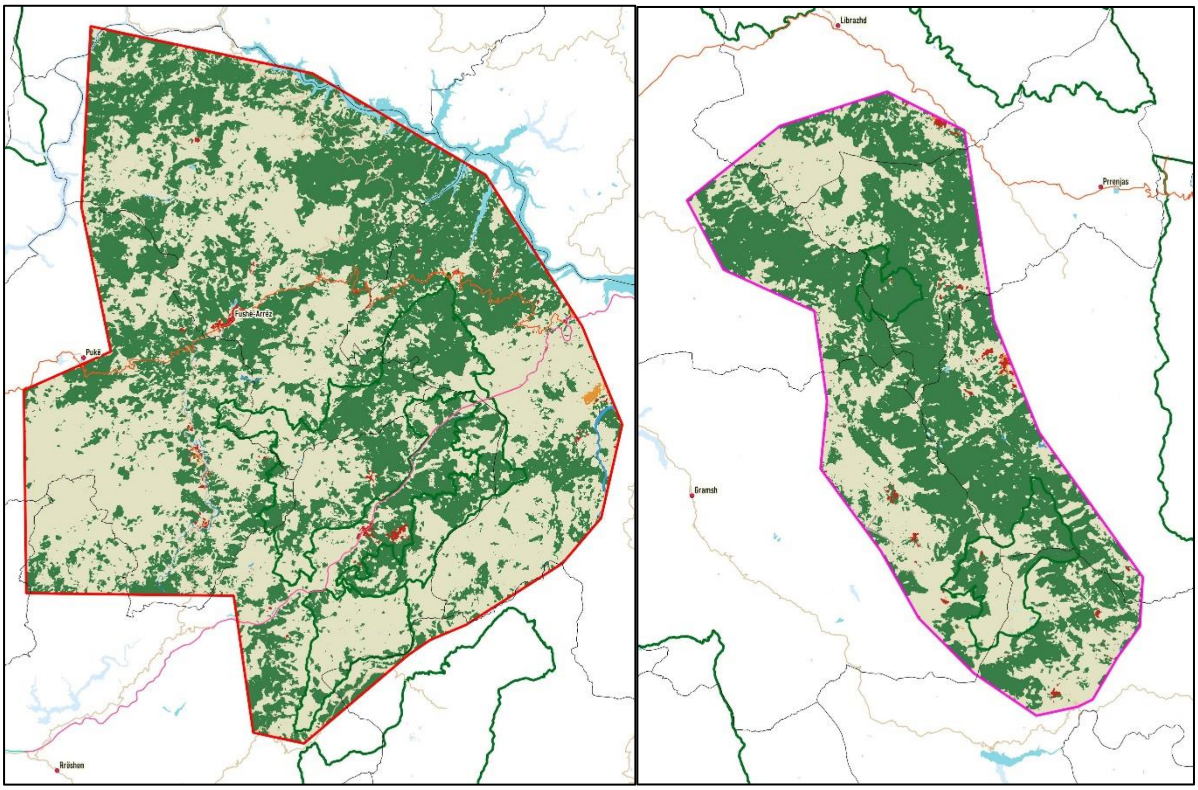
2019 Land Use Land Cover Munela region & Polis-Valamara region



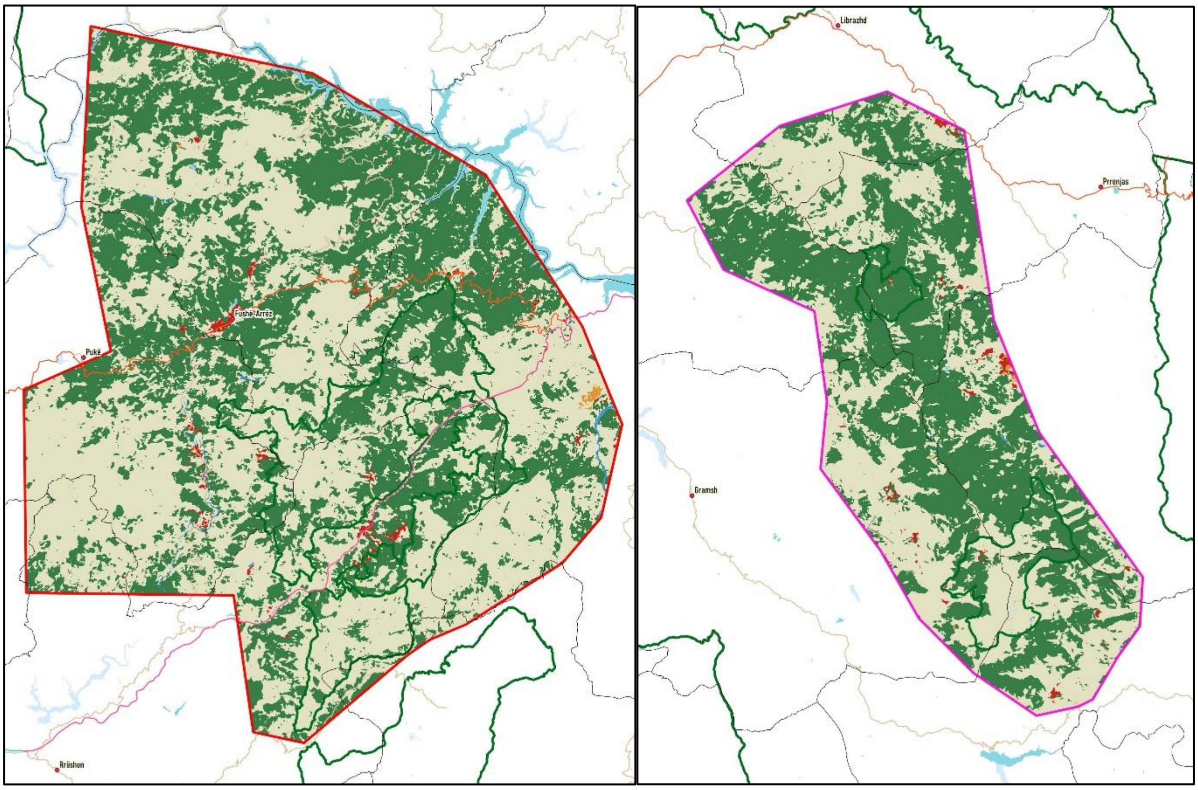
2020 Land Use Land Cover Munela region & Polis-Valamara region



2021 Land Use Land Cover Munela region & Polis-Valamara region



2022 Land Use Land Cover Munela region & Polis-Valamara region



Annex 2 Attributes for the forest monitoring in Munela region

Name	Foto nr	Forest-YN	Forest-type	F-Cover	Maturity
MU06N	20230228_113438919	Y	Forest, mixed dominated by deciduous (Beech and Fir)	C	
MU06C	20230228_113834840	Y	Forest, mixed dominated by deciduous (Beech and Fir)	C	
MU06S	20230228_114126104	Y	Forest, mixed dominated by deciduous (Beech and Fir)	C	
MU07C	20230228_122733716	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU07N	20230228_123017787	Y	Forest, Deciduous (Beech)	C	
MU07S	20230228_123826611	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU28C	20230313_122446034	Y	Forest, Deciduous (Oak)	M	
MU28S	20230313_123054130	Y	Forest, mixed dominated by deciduous (Oak and Juniper)	M	
MU28W	20230313_123946781	Y	Forest, Deciduous (Oak)	C	
MU29C	20230313_170401201	Y	Forest, mixed dominated by deciduous (Oak and Pine)	C	
MU29S	20230313_170840591	Y	Forest, mixed dominated by deciduous (Oak and Pine)	M	
MU04C	20230327_130151206	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU04N	20230327_130411338	N	Non forest	-	
MU04E	20230327_130835280	Y	Forest, Coniferous (Pine)	O	
MU30E	20230327_133843500	Y	Forest, mixed dominated by conifers (Pine and Beech)	O	
MU30C	20230327_134059517	Y	Forest, mixed dominated by deciduous (Pine and Beech)	C	
MU30N	20230327_134234552	Y	Forest, mixed dominated by deciduous (Beech and Pine)	O	
MU30S	20230327_134517569	Y	Forest, mixed dominated by deciduous (Beech and Pine)	M	
MU30W	20230327_134754951	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU07E	20230328_104425638	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU07W	20230328_104915749	Y	Forest, mixed dominated by deciduous (Beech and Pine)	O	
MU31C	20230328_112204985	Y	Forest, mixed dominated by deciduous (Beech and Fir)	C	
MU31E	20230328_112442980	Y	Forest, mixed dominated by deciduous (Beech and Fir)	C	
MU31N	20230328_112752237	Y	Forest, mixed dominated by deciduous (Beech and Fir)	C	
MU31W	20230328_113202336	Y	Forest, mixed dominated by deciduous (Beech and Fir)	C	
MU31S	20230328_113452492	Y	Forest, mixed dominated by deciduous (Beech and Fir)	C	
MU09C	20230328_141956833	Y	Forest, Deciduous (Beech)	C	
MU09E	20230328_142144682	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU09N	20230328_142326915	Y	Forest, Deciduous (Beech)	M	
MU09W	20230328_142738668	Y	Forest, Deciduous (Beech)	C	
MU32N	20230328_145619644	Y	Forest, Deciduous (Beech)	C	Fully grown
MU32C	20230328_145808449	Y	Forest, Deciduous (Beech)	C	Fully grown
MU32S	20230328_15001020	Y	Forest, mixed dominated by deciduous (Beech and Pine)	M	Fully grown

	3				
MU08C	20230328_153941095	Y	Forest, Deciduous (Beech)	C	
MU08N	20230328_154132206	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU08E	20230328_154432609	Y	Forest, mixed dominated by deciduous (Beech and Pine)	M	
MU08S	20230328_155002135	Y	Forest, Deciduous (Beech)	C	
MU08W	20230328_155702700	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU10C	20230329_112855146	Y	Forest, Deciduous (Beech)	C	
MU10N	20230329_113248583	Y	Forest, Deciduous (Beech)	C	
MU10E	20230329_113641836	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU10W	20230329_114106455	N	Non forest	-	
MU10S	20230329_115856719	N	Non forest	-	
MU27C	20230329_124126986	Y	Forest, Deciduous (Beech)	O	
MU27W	20230329_124255739	N	Non forest	-	
MU27S	20230329_124529043	N	Non forest	-	
MU27E	20230329_124834275	N	Non forest	-	
MU27N	20230329_125113703	N	Non forest	-	
MU11C	20230329_141109958	Y	Forest, mixed dominated by deciduous (Oak and Pine)	C	
MU11W	20230329_141338183	Y	Forest, mixed dominated by deciduous (Oak and Pine)	O	
MU11E	20230329_141756232	Y	Forest, mixed dominated by conifers (Pine and Oak)	M	
MU11S	20230329_142355523	Y	Forest, Deciduous (Oak)	C	
MU18C	20230329_155254686	Y	Forest, mixed dominated by conifers (Pine and Oak)	M	
MU18S	20230329_155609322	Y	Forest, mixed dominated by deciduous (Oak and Pine)	C	
MU18E	20230329_160136990	Y	Forest, mixed dominated by deciduous (Oak and Pine)	C	
MU18N	20230329_160454890	Y	Forest, mixed dominated by conifers (Pine and Oak)	M	
MU17C	20230330_105057409	N	Non forest	-	
MU17S	20230330_105233439	N	Non forest	-	
MU17N	20230330_105506528	N	Non forest	-	
MU17W	20230330_105754082	N	Non forest	-	
MU25C	20230330_124244787	Y	Forest, mixed dominated by conifers (Pine and Beech)	C	
MU25E	20230330_124546757	N	Non forest	-	
MU25S	20230330_124854929	Y	Forest, Coniferous (Pine)	C	
MU25W	20230330_125201318	N	Non forest	-	
MU25N	20230330_125836441	Y	Forest, Deciduous (Beech)	O	
MU26C	20230330_140212399	N	Non forest	-	
MU26N	20230330_140446585	N	Non forest	-	

MU26E	20230330_140941196	Y	Forest, Coniferous (Pine)	O	
MU26S	20230330_141430770	Y	Forest, Deciduous (Beech)	O	
MU26W	20230330_141818089	Y	Forest, Deciduous (Beech)	O	
MU05C	20230330_162024830	Y	Forest, Coniferous (Pine)	O	
MU05E	20230330_163203082	N	Non forest	-	
MU05W	20230330_163558745	N	Non forest	-	
MU05S	20230330_163900330	N	Non forest	-	
MU05N	20230330_164626618	Y	Forest, mixed dominated by conifers (Pine and Beech)	M	
MU16C	20230331_114826077	Y	Forest, Deciduous (Beech)	M	
MU16S	20230331_115107368	Y	Forest, Deciduous (Beech)	O	
MU16N	20230331_11555233	Y	Forest, Deciduous (Beech)	O	
MU16E	20230331_120229243	N	Non forest	-	
MU03C	20230331_143133669	Y	Forest, Coniferous (Pine)	C	
MU03W	20230331_143404219	Y	Forest, Coniferous (Pine)	M	
MU03E	20230331_144018818	Y	Forest, Coniferous (Pine)	C	
MU03S	20230331_144912782	Y	Forest, Coniferous (Pine)	C	
MU13C	20230403_105343698	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU13N	20230403_105702517	N	Non forest	-	
MU13E	20230403_110040406	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU13S	20230403_110828658	Y	Forest, mixed dominated by deciduous (Beech and Pine)	M	
MU21C	20230403_121651403	N	Non forest	-	
MU21E	20230403_121947270	Y	Forest, mixed dominated by deciduous (Beech and Pine)	O	
MU21S	20230403_122245685	N	Non forest	-	
MU21W	20230403_122755230	N	Non forest	-	
MU21N	20230403_123448932	N	Non forest	-	
MU14C	20230403_133912765	Y	Forest, Deciduous (Oak)	M	
MU14E	20230403_134111417	N	Non forest	-	
MU12C	20230403_161836522	Y	Forest, mixed dominated by conifers (Pine and Beech)	C	Fully grown
MU12W	20230403_162323804	Y	Forest, mixed dominated by conifers (Pine and Beech)	O	
MU12S	20230403_162633633	Y	Forest, mixed dominated by conifers (Pine and Beech)	C	Fully grown
MU12N	20230403_163109621	Y	Forest, mixed dominated by conifers (Pine and Beech)	C	Fully grown
MU12E	20230403_163741051	Y	Forest, mixed dominated by conifers (Pine and Beech)	C	Fully grown
MU20C	20230404_105710205	Y	Forest, mixed dominated by deciduous (Oak and Pine)	C	
MU20W	20230404_110001292	Y	Forest, mixed dominated by deciduous (Oak and Pine)	C	Fully grown
MU20E	20230404_110701672	Y	Forest, mixed dominated by deciduous (Oak and Pine)	C	Fully grown

MU19C	20230404_123700136	Y	Forest, mixed dominated by deciduous (Oak and Pine)	O	Fully grown
MU19W	20230404_124556901	Y	Forest, Deciduous (Oak)	C	Fully grown
MU19E	20230404_135838776	Y	Forest, Deciduous (Oak)	C	Fully grown
MU33C	20230330_093711305	Y	Forest, Coniferous (Pine)	M	
MU33N	20230330_094137924	Y	Forest, Coniferous (Pine)	M	
MU33S	20230330_113710473	Y	Forest, Coniferous (Pine)	C	
MU33E	20230330_112950334	Y	Forest, Coniferous (Pine)	M	
MU33W	20230330_112610151	Y	Forest, Coniferous (Pine)	O	
MU34C	20230331_130409620	Y	Forest, mixed dominated by deciduous (Beech and Pine)	M	
MU34N	20230331_130534707	Y	Forest, mixed dominated by conifers (Pine and Beech)	M	
MU34W	20230331_130200745	N	Non forest	-	
MU01C	20230424_092627237	Y	Forest, Coniferous (Pine)	C	
MU01E	20230424_092948832	Y	Forest, Coniferous (Pine)	C	
MU01W	20230424_093345866	Y	Forest, Coniferous (Pine)	M	
MU02C	20230424_105739601	Y	Forest, Deciduous (Beech)	C	Fully grown
MU02N	20230424_110045712	Y	Forest, Deciduous (Beech)	C	Fully grown
MU02S	20230424_111124167	Y	Forest, mixed dominated by deciduous (Beech and Pine)	M	
MU04S	20230424_122706354	N	Non forest	-	
MU09S	20230425_131005260	N	Non forest	-	
MU36S	20230426_121435084	N	Non forest	-	
MU36C	20230426_121814359	N	Non forest	-	
MU36N	20230426_122038513	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU37N	20230427_111104379	N	Non forest	-	
MU37C	20230427_111247125	Y	Forest, Coniferous (Pine)	O	
MU36S	20230427_111442549	N	Non forest	-	
MU38W	20230427_122848070	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU38C	20230427_122656257	Y	Forest, mixed dominated by deciduous (Beech and Pine)	M	
MU38S	20230427_122517421	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU39S	20230427_144920656	Y	Forest, mixed dominated by conifers (Pine and Beech)	C	
MU39C	20230427_145121619	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU39N	20230427_145321869	Y	Forest, mixed dominated by conifers (Pine and Alder)	M	
MU40N	20230427_172315108	Y	Forest, mixed dominated by conifers (Pine and Beech)	M	
MU40C	20230427_172529040	Y	Forest, Coniferous (Pine)	O	
MU40S	20230427_172732102	Y	Forest, Coniferous (Pine)	M	
MU16W	20230428_12354237	N	Non forest	-	

	6				
MU14W	20230502_140054460	Y	Forest, mixed dominated by deciduous (Beech and Pine)	O	
MU14N	20230502_140239841	Y	Forest, mixed dominated by conifers (Pine and Oak)	O	
MU29E	20230502_141250948	N	Non forest	-	
MU22C	20230502_160830252	Y	Forest, mixed dominated by conifers (Pine and Oak)	C	
MU22E	20230502_161259260	Y	Forest, mixed dominated by deciduous (Oak and Pine)	C	
MU22W	20230502_161723578	Y	Forest, mixed dominated by deciduous (Oak and Pine)	C	
MU24C	20230503_105835968	Y	Forest, mixed dominated by deciduous (Beech and Pine)	C	
MU24S	20230503_110008285	Y	Forest, mixed dominated by deciduous (Beech and Pine)	M	
MU24N	20230503_110233154	Y	Forest, Deciduous (Beech)	C	
MU15C	20230503_125148629	N	Non-Forest	-	
MU15S	20230503_125321846	Y	Forest, mixed dominated by conifers (Pine and Hazel)	O	
MU15N	20230503_125537393	N	Non-Forest	-	
MU23C	20230503_145344723	Y	Forest, Deciduous (Beech)	M	
MU23E	20230503_145536685	Y	Forest, Deciduous (Beech)	O	
MU23S	20230503_145833989	Y	Forest, Deciduous (Beech)	C	
MU23W	20230503_150011473	Y	Forest, Deciduous (Beech)	C	
MU24E	20230503_151714423	Y	Forest, Coniferous (Pine)	M	
MU42C	20230503_151836589	Y	Forest, Coniferous (Pine)	O	
MU42W	20230503_152019486	Y	Forest, mixed dominated by conifers (Pine and Hazel)	M	
MU42S	20230503_152255389	Y	Forest, Coniferous (Pine)	O	
MU42N	20230503_152540863	Y	Forest, Coniferous	M	
MU43W	20230503_154033446	Y	Forest, Coniferous (Pine)	C	
MU43C	20230503_154210248	Y	Forest, mixed dominated by coniferous (Pine and Beech)	C	
MU43E	20230503_154341339	Y	Forest, mixed dominated by coniferous (Pine and Beech)	C	