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**“Mapping Snow and Vegetation Coverage Using Multitemporal Open Satellite Imagery
Case Study of Maritime Alps”**

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Abstract

This thesis investigates the classification of vegetation and snow coverage in the Maritime Alps, Italy, using satellite imagery from the Sentinel-2 mission within the framework of the ACLIMO project.. The Maritime Alps, a region highly sensitive to climate fluctuations, has seen notable shifts in its snow and vegetation patterns in recent years. Through the analysis of Sentinel-2 data, this research aims to track the spatial and temporal variations in these natural features as indicators of broader environmental changes.

By analyzing multi-temporal satellite images, we evaluated the changes in snow extent and vegetation cover over several years (2015-2024), revealing patterns related to shifting climate conditions. The high-resolution data enabled precise detection of seasonal and inter-annual changes.

In addition, land cover maps were generated to compare the extent of snow and vegetation coverage across different years. These maps provide a visual representation of the landscape's evolution.

Table of Contents

1. Introduction	11
1.1 The area of interest	11
1.2 Research Collaboration within the ALCOTRA 2021/2027 Project Framework - ACLIMO Initiative	12
1.3 Importance of the region for climate change studies	15
2 Data and Methods	16
2.1 Satellite Imagery (Sentinel-2)	17
2.2 Sentinel-2 band review	18
2.3 Resolution Variations in Sentinel-2 Bands and Their Applications	20
2.4 Vegetation Indices used	20
2.4.1 Normalized Difference Vegetation Index (NDVI).....	21
2.4.2 Applications of NDVI	21
2.4.3 Advantages of NDVI	23
2.4.4 Limitations of NDVI.....	23
2.4.5 Enhanced Vegetation Index (EVI)	24
2.4.6 Applications of EVI	24
2.4.7 Advantages of EVI.....	24
2.4.8 Limitations of EVI.....	25
2.4.9 How EVI Works	26
2.4.10 Enhanced Vegetation Index 2 (EVI2).....	26
2.4.11 Applications of EVI2	27
2.4.12 Advantages of EVI2	27
2.4.13 Limitations of EVI2	28
2.4.14 How EVI2 Works	28
2.4.15 Soil-Adjusted Vegetation Index (SAVI).....	29
2.4.16 Applications of SAVI	29

2.4.17	Advantages of SAVI	29
2.4.18	Limitations of SAVI	30
2.4.19	How SAVI Works	31
2.4.20	Green Normalized Difference Vegetation Index (GNDVI).....	31
2.4.21	Applications of GNDVI	31
2.4.22	Advantages of GNDVI.....	32
2.4.23	Limitations of GNDVI.....	33
2.4.24	How GNDVI Works	33
2.4.25	K-Normalized Difference Vegetation Index (KNDVI)	34
2.4.26	Applications of KNDVI.....	34
2.4.27	Advantages of KNDVI	34
2.4.28	Limitations of KNDVI.....	35
2.4.29	How KNDVI Works.....	36
2.4.30	Leaf Area Index (LAI)	36
2.4.31	Applications of LAI	37
2.4.32	Advantages of LAI.....	38
2.4.33	Limitations of LAI.....	38
2.4.34	How LAI Works	39
2.4.35	Moisture Stress Index (MSI)	39
2.4.36	Applications of MSI	39
2.4.37	Advantages of MSI.....	40
2.4.38	Limitations of MSI.....	40
2.4.39	How MSI Works	41
2.4.40	Normalized Difference Moisture Index (NDMI)	41
2.4.41	Applications of NDMI.....	42
2.5	Snow indices used	42
2.5.1	Normalized Difference Snow Index (NDSI).....	42
2.5.2	Applications of NDSI	42
2.5.3	Advantages of NDSI	43
2.5.4	Limitations of NDSI.....	44

2.5.5	How NDSI Works.....	44
2.6	Differences in Snow and Vegetation Indices	45
2.7	Cloud-Based and Desktop Solutions for Remote Sensing Analysis.....	46
2.8	Evaluating Indices and Land Cover Classification Accuracy for 2018 and 2022.....	48
2.9	Methodological Approaches for Index Computation and Classification in Satellite Imagery Analysis	48
3	Analysis	50
3.1	Utilizing CORINE Data for Land Cover Classification and Accuracy Assessment.....	50
3.1.1	CORINE Land Cover Mission.....	50
3.2	Utilizing LUCAS Data for Land Cover Classification and Accuracy Assessment.....	51
3.3	Otsu method	52
3.3.1	How the Otsu Method Works	53
3.3.2	Applications	53
3.3.3	Advantages.....	54
3.3.4	Otsu threshold	54
3.4	Setting Up the Google Earth Engine Environment for Cloud Coverage and Temporal Adjustments.....	55
3.5	Classifications for Thematic Maps and Random Forest Method	56
3.5.1	Random Forest Method in Thematic Map Production.....	56
3.5.2	How Random Forest works in the classification process	56
3.5.3	Advantages of Random Forest.....	57
3.6	Validation of Classification Accuracy with CORINE Data and Confusion Matrix	57

3.6.1	Confusion Matrix Description	58
3.7	Accuracy Assessment with LUCAS Data and Confusion Matrix Analysis	67
3.8	Analysing June Vegetation Dynamics from 2015 to 2024 Normalized Difference Vegetation Index (NDVI).....	73
3.9	Analysing June Vegetation Dynamics from 2015 to 2024 Enhanced Vegetation Index (EVI2).....	75
3.10	Analysing June Vegetation Dynamics from 2015 to 2024 Using the leaf Area Index (LAI)	76
3.11	Analysing June Vegetation Dynamics Using the GREEN Normalized Difference Vegetation Index (GNDVI) from 2015 to 2024	78
3.12	Analysing June Vegetation Dynamics from 2015 to 2024 Using the Soil- Adjusted Vegetation Index (SAVI)	79
3.13	Snow accuracy assesment using corine snow extend data.....	81
3.14	April Snow Dynamics from 2015 to 2024 using NDSI	82
3.15	confusion matrices of NDSI	84
3.16	Land Cover Classification and Accuracy Assessment Using Google Earth Engine and ArcGIS.....	85
	Corine land cover map 2018 and LUCAS points 2022	86
3.17	Confusion matrices for thematic maps of 2018 and 2022.....	87
3.18	land cover maps from 2015-2024.....	89
4	<i>Discussion</i>.....	92
4.1	Vegetation Trends in the Protected Area of Maritime: Evidence of Growth from 2015 to 2024.....	92

4.2	Snow Trend in the Protected Area of Maritime: Evidence of decline from 2016 to 2024.....	93
4.3	Challenges and Solutions in Distinguishing Bare Rock from Artificial Surfaces in Satellite Image Classifications	95
4.4	Comparison of CORINE 2018 and LUCAS 2022: Data Structure,Accuracy, and Applicability in Land Cover Classification	96
4.5	Pros and Cons of the Applied Methods	97
5	<i>Conclusion.....</i>	99
5.1	Vegetation Growth.....	99
5.2	Agricultural Areas.....	99
5.3	Artificial Surfaces	99
5.4	Water Bodies.....	100
5.5	Snow Cover.....	100
5.6	Future Directions.....	100
5.7	Current Limitations and Missing Elements.....	101
6	<i>References.....</i>	102
	<i>Appendix.....</i>	108

List of figures

Figure 1 Map of northern Italy with The Maritime indicated.....	11
Figure 2 Detailed view of Maritime Alps	12
Figure 3 Overview of the ACLIMO project	14
Figure 4 Natural views of Maritime Alps	15
Figure 5 General overview of Methodology.....	16
Figure 6 Sentinel 2 bands.....	19
Figure 7 code editor interface of GEE	47
Figure 8 work flow which shows the detailed processes	49
Figure 9 Interface of GEE showcasing the adjustment for cloud coverage based on the written codes for sentinel 2 data.....	55
Figure 10 Interface of GEE showcasing the year and month selection based on the written codes for temporal filtering sentinel 2 data.....	55
Figure 11 Different sections of the confusion matrix	60
Figure 12 CORINE land cover map 2018 illustrating vegetation(green) and non-vegetation(white) coverage and the 1000 random sample points.....	61
Figure 13 Different vegetation indices that have been applied for 2018.....	62
Figure 14 LUCAS points for 2022.....	67
Figure 15 Applied vegetation indices for 2022.....	69
Figure 16 NDVI applied from 2015-2024 for vegetation monitoring	74
Figure 17 Applied EVI 2 from 2015 to 2024.....	76
Figure 18 Applied LAI from 2015-2024.....	77
Figure 19 Applied GNDVI from 2015-2024	79
Figure 20 Applied SAVI from 2015-2024	80
Figure 21 Corine snow extend 2018 and 2022 with 1000 random sample points.....	82

Figure 22 Applied NDSI from 2016-2024.....	83
Figure 23 CORINE land cover map 2018.....	86
Figure 24 re-classified CORINE land cover map 2018	86
Figure 25 LUCAS 2022 POINTS	87
Figure 26 Accuracy points by ArcGIS	87
Figure 27 Thematic maps from 2015-2024	91

List of tables

Table1 Otsu threshold	54
Table 2 confusion matrix of NDVI	62
Table 3 Confusion matrix of EVI.....	63
Table 4 Confusion matrix of EVI2.....	63
Table 5 Confusion matrix of GNDVI	64
Table 6 Confusion matrix of KNDVI	64
Table 7 Confusion matrix of MSI	65
Table 8 Confusion matrix LAI.....	65
Table 9 Confusion matrix of NDMI.....	66
Table 10 Confusion matrix of SAVI	66
Table 11 Confusion matrix of NDVI	69
Table 12 Confusion matrix of EVI.....	69
Table 13 Confusion matrix of EVI2.....	70
Table 14 Confusion matrix of GNDVI	70
Table 15 Confusion matrix of KNDVI	71
Table 16 Confusion matrix of MSI	71
Table 17 Confusion matrix of LAI.....	72
Table 18 Confusion matrix of NDMI.....	72

Table 19 Confusion matrix of SAVI	73
Table 20 Confusion matrix of NDSI 2018	84
Table 21 Confusion matrix of NDSI 2022	84
Table 22 Confusion matrix of thematic map 2018 and CORINE land cover map 2018	88
Table 23 Confusion matrix of thematic 2022 and LUCAS points 2022.....	88
Table 24 Vegetation Coverage in <i>Km</i> ² calculated by each index	92
Table 25 Vegetation coverage changes in <i>km</i> ²	93
Table 26 Snow coverage for each year in <i>km</i> ²	94
Table 27 Snow Coverage changes in <i>km</i> ²	94
Table 28 Summary of the pros and cons of the applied method.....	97

1. Introduction

1.1 The area of interest

The Maritime Alps, located in the southwestern part of the Alps, stretch across the border between southeastern France and northwestern Italy (Figure 1 and Figure 2). This stunning region is characterized by its steep, rugged terrain, which includes numerous peaks, valleys, and unique geological formations. Notable summits, such as Mont Argentera, which rises to 3,297 meters, contribute to the dramatic landscape. The region's diverse ecosystems range from Mediterranean scrub and deciduous forests at lower elevations to alpine meadows and barren rocky slopes at higher altitudes. This ecological variety is supported by the region's distinct climatic zones, shaped by its proximity to the Mediterranean Sea and the influence of the continental climate.



Figure 1 Map of northern Italy with The Maritime indicated

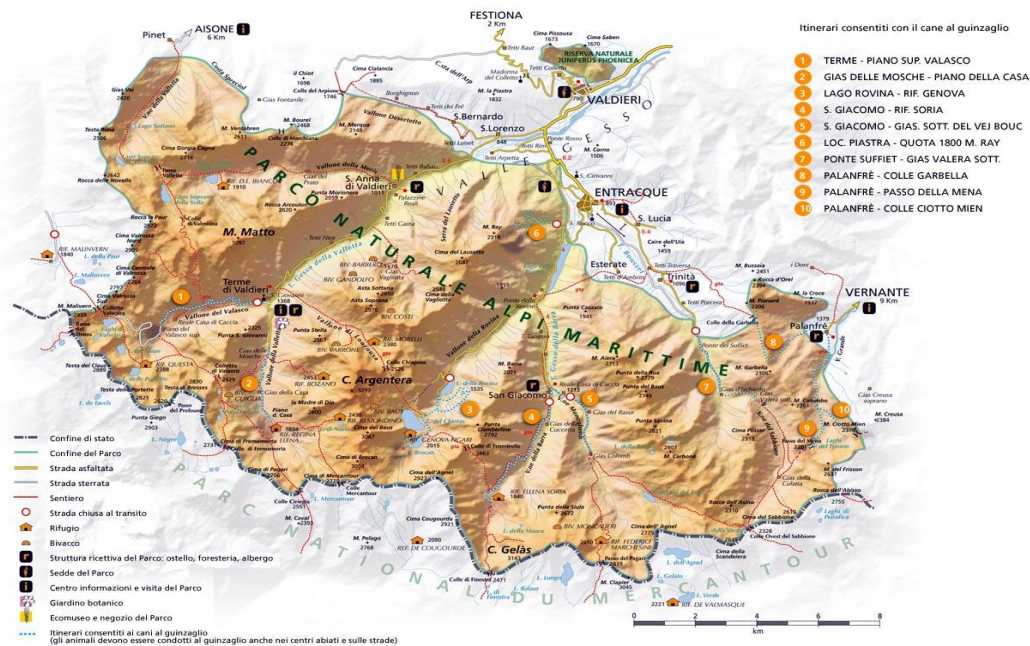


Figure 2 Detailed view of Maritime Alps

The Maritime Alps experience a range of climatic conditions due to their complex topography and elevation gradients. The lower elevations, particularly along the coastal areas, enjoy a Mediterranean climate characterized by mild, wet winters and hot, dry summers. As altitude increases, the climate shifts to a more alpine profile, marked by colder temperatures and increased snowfall during winter months. The region receives significant precipitation, primarily in the form of snow during winter, which plays a critical role in maintaining the ecological balance of the area. Snow cover acts as a vital water resource for the ecosystems, influencing soil moisture and vegetation growth as it melts in the spring.

1.2 Research Collaboration within the ALCOTRA 2021/2027 Project Framework - ACLIMO Initiative

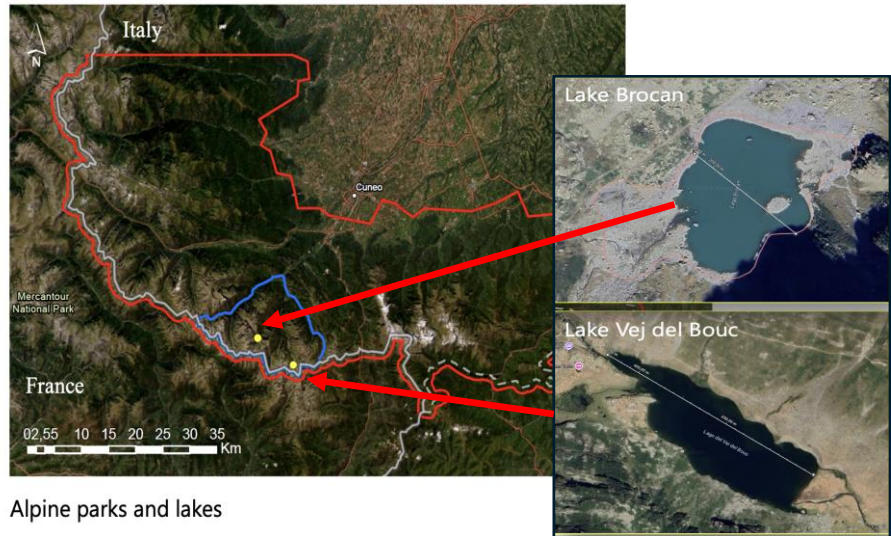
This research is conducted as part of a collaboration agreement between the Politecnico di Torino and APAM (Management Body of the Protected Areas of the Maritime Alps), pursuant to Article 15 of Law 241/90. It falls under the broader framework of the ALCOTRA 2021/2027 project (Project No. 20138), titled ACLIMO, and is scheduled for the period 2024-2026.

The ACLIMO project is part of the France-Italy ALCOTRA (Latin Alps Transborder Cooperation) 2021/2027 initiative, which brings together various Italian and French parks and

organizations. Key participants include the Parc National du Mercantour, APAM, Parc National des Écrins, the Management Body of the Parks of the Cottian Alps, Parc National de la Vanoise, Gran Paradiso National Park, the Regional Natural Park of the Ligurian Alps, and the Municipality of Cuneo.

The project is multi-scale, multi-temporal, and multi-source, combining a variety of spatial and temporal approaches. In this thesis, the analysis focuses specifically on small-scale, multi-temporal studies covering the period from 2015 to 2024. The collaboration addresses the impacts of climate change in the mountain regions of the Maritime Alps Park, emphasizing glaciers, forests, grasslands, peat bogs, wetlands, and water resources. Additionally, it supports sustainable land management by studying risk and vulnerability conditions and predicting potential future environmental dynamics. In Figure 3, the picture illustrates the details of this project.

Environmental/Alpine monitoring – **ACLIMO project**



Alpine parks and lakes

- Glacier monitoring
- Snow coverage
- Vegetation trends
- Land use (pastures, mountain pastures, wetlands)



Small scale	Landsat 5 e Landsat 8 April, June, August 1990-2013 (Landsat 5), 2013-2015 (Landsat 8) Spatial resolution 30 – 120 m (Landsat 5) 15 – 30 – 100 (Landsat 8) Spectral resolution 7 bands (Landsat 5), 11 bands (Landsat 8)
	Sentinel-2 April, June, August 2015-2023 Spatial resolution 10 – 20 - 60 m Spectral resolution: 13 bands
Medium scale	Piedmont region - flights CGR- Rossi 1991 (RGB), Rossi Brescia 2000 (RGB), ICE 2010 (RGB + NIR), AGEA 2015-2018-2021 (RGB + NIR)
Large scale	 BlueBoat USV, BlueRobotics Max speed 3 m/s, weight 14,5 kg, range about 250 m <i>equipped with</i> Echosounder STX-Echos Depth range 0.2 - 200 m GNSS:GPS, GLONASS, BDS, GALILEO, QZSS Weight 1200 g
	 DJI Mavic 3M GNSS RTK, RGB 4/3 17.3x13 mm, 20 Mpix, 5280x3956, Pixel size 3.3x3.3 μm Multispec 1/2.8", 6.058x 4.415mm, 5 MPix, 2592x1944 Bands: G: 560 ± 16 nm; R: 650 ± 16 nm; Red Edge: 730 ± 16 nm; NIR: 860 nm ± 26 nm, Peso 951 g

Figure 3 Overview of the ACLIMO project

1.3 Importance of the region for climate change studies

In recent decades, the Maritime Alps, like many mountain regions worldwide, have shown signs of climate change that have raised concerns regarding the stability and health of their ecosystems. Rising temperatures, altered precipitation patterns, and decreasing snowpack are leading to shifts in plant phenology, species distribution, and overall biodiversity. These changes not only affect the natural habitats of various flora and fauna (Figure 4), but also impact local communities that depend on the region's natural resources for agriculture, tourism, and recreation. Understanding these dynamics is essential for developing effective conservation strategies and managing the ecological health of the Maritime Alps, which are vital for maintaining both environmental balance and cultural heritage.

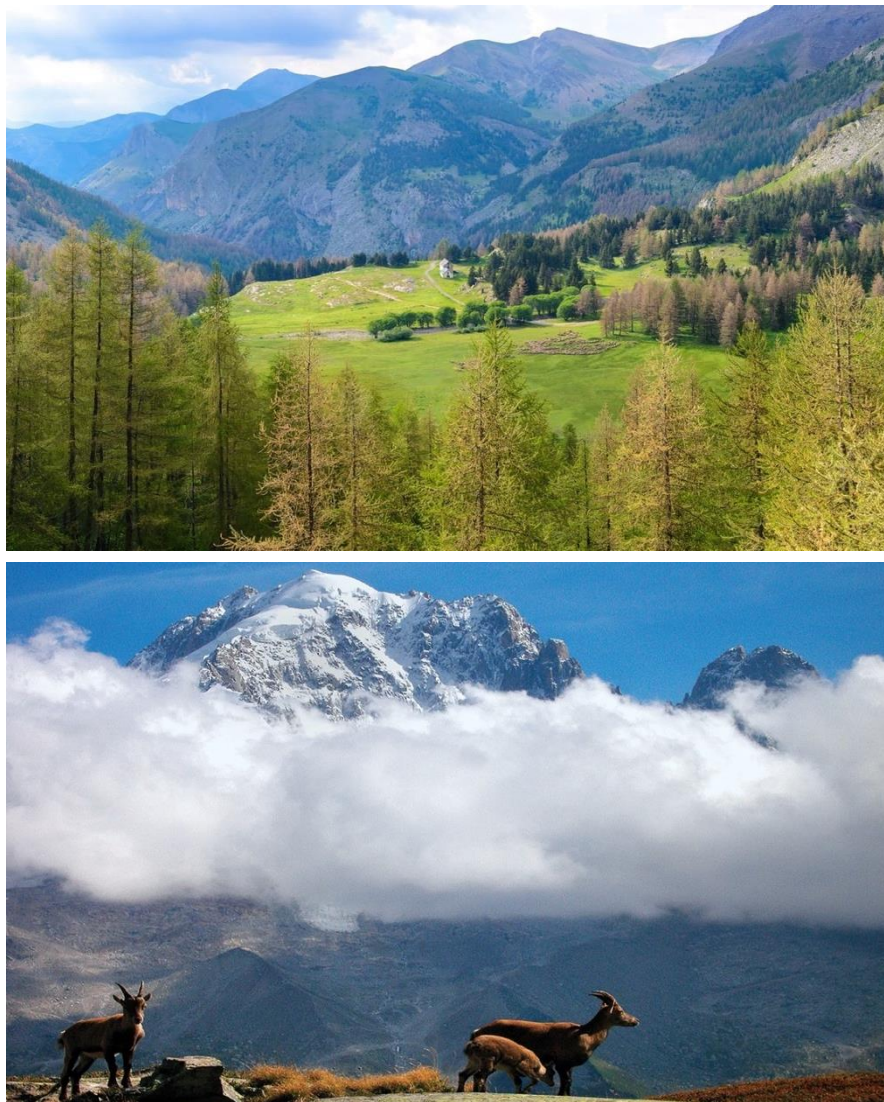


Figure 4 Natural views of Maritime Alps

2 Data and Methods

Figure 5 provides a general overview of the entire methodology employed in this thesis.

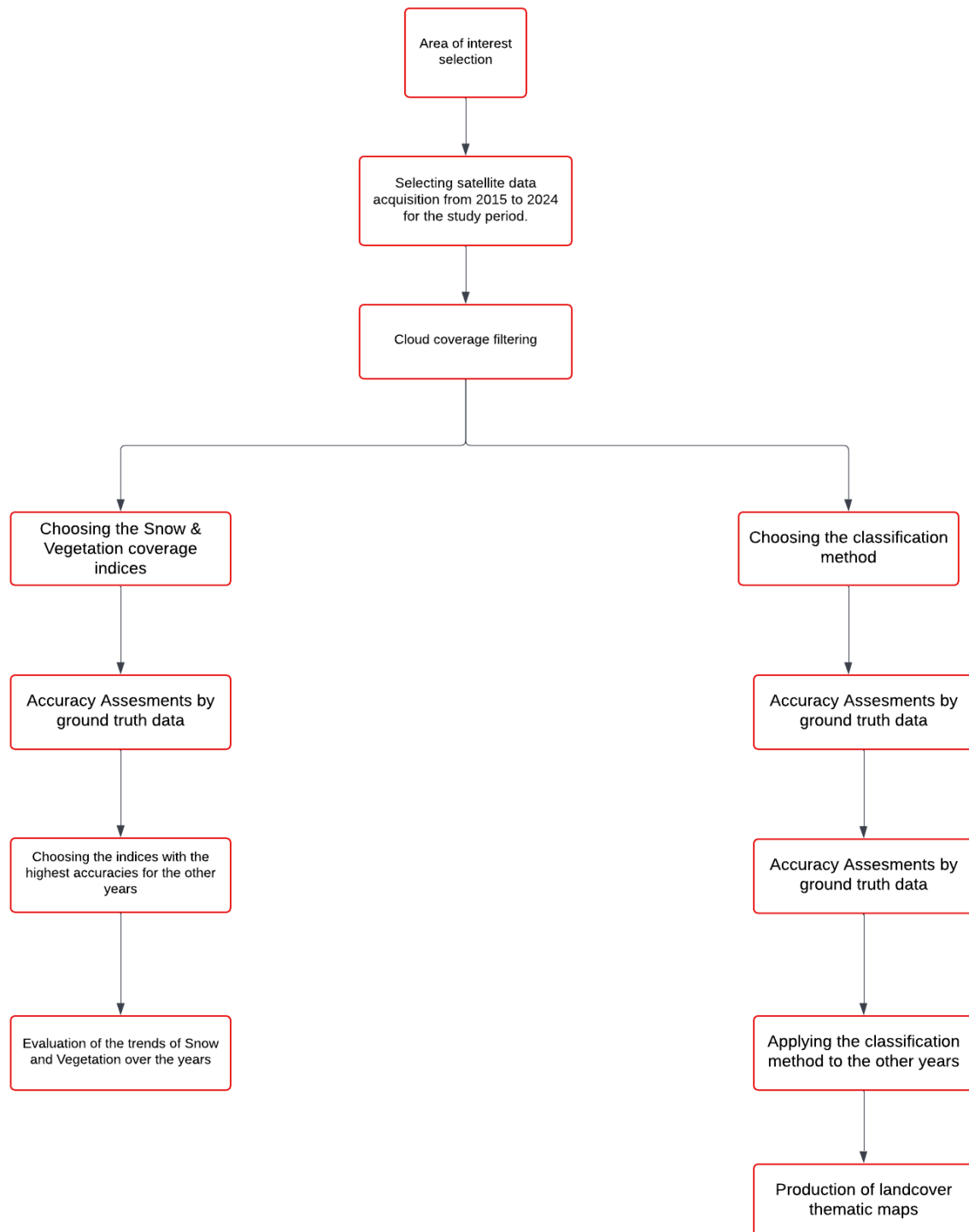


Figure 5 General overview of Methodology

2.1 Satellite Imagery (Sentinel-2)

The Sentinel-2 mission is a crucial component of the European Union's Copernicus Programme, aimed at comprehensive land monitoring. It consists of two identical satellites, Sentinel-2A and Sentinel-2B, launched on June 23, 2015, and March 7, 2017, respectively. These satellites are equipped with a MultiSpectral Instrument (MSI) that captures data in 13 spectral bands, ranging from the visible to the shortwave infrared spectrum (**Error! Reference source not found.**) This diverse range of bands, combined with spatial resolutions of 10, 20, and 60 meters, enables the detailed analysis of various land cover types, including vegetation health, snow cover, and water bodies, providing essential data for climate change research and environmental monitoring.

Sentinel-2 operates in a sun-synchronous orbit at an altitude of 786 kilometers, allowing it to capture images consistently under similar lighting conditions. The satellites cover a 290 km swath width, with a revisit time of approximately 5 days at the equator, facilitating frequent monitoring of dynamic landscapes. The data is provided in different processing levels, with Level-1C offering top-of-atmosphere reflectance and Level-2A providing surface reflectance after atmospheric correction. This accessibility enables researchers to analyze environmental changes over time effectively. Individually, each satellite can revisit the same location every 10 days. Together, they achieve a 5-day revisit cycle at the equator, which improves temporal resolution and allows for more timely monitoring of seasonal and environmental changes.

The open-access policy of Sentinel-2 data through platforms such as the Copernicus Open Access Hub ensures that scientists, policymakers, and the public can utilize high-resolution imagery for various applications. These include monitoring vegetation and snow cover, assessing land use changes, and supporting disaster management efforts. In this thesis we utilized data from both Sentinel-2A and Sentinel-2B to take advantage of the combined revisit frequency and seamless data integration. This approach supports more frequent and reliable

analyses of the Maritime Alps' protected area, including snow cover and vegetation studies. By using both satellites, we can minimize data gaps caused by cloud cover or other obstructions.

2.2 Sentinel-2 band review

10-Meter Resolution Bands:

Band 2: Blue (490 nm)

Application: Useful for assessing water bodies and vegetation; aids in atmospheric correction.

Band 3: Green (560 nm)

Application: Effective for vegetation analysis, particularly for calculating vegetation indices like NDVI.

Band 4: Red (665 nm)

Application: Crucial for vegetation studies and distinguishing between different land cover types.

Band 8: Near-Infrared (NIR) (842 nm)

Application: Highly sensitive to vegetation health; key for calculating vegetation indices and assessing biomass.

20-Meter Resolution Bands:

Band 5: Red Edge 1 (705 nm)

Application: Sensitive to changes in chlorophyll content; useful for monitoring plant health and detecting stress.

Band 6: Red Edge 2 (740 nm)

Application: Enhances vegetation monitoring, particularly for agricultural applications and distinguishing vegetation types.

Band 7: Red Edge 3 (783 nm)

Application: Important for detailed vegetation assessments and improving land cover classification accuracy.

Band 8A: NIR (865 nm)

Application: Similar to Band 8, but provides additional data for vegetation monitoring.

Band 11: Shortwave Infrared 1 (SWIR 1610 nm)

Application: Useful for detecting moisture content in vegetation and soil, as well as mapping water bodies.

Band 12: Shortwave Infrared 2 (SWIR 2190 nm)

Application: Helps in assessing soil moisture and distinguishing between different types of land cover.

60-Meter Resolution Bands:

Band 1: Coastal Aerosol (443 nm)

Application: Designed for coastal monitoring, helps in assessing water quality and atmospheric corrections.

Band 9: Water Vapor (945 nm)

Application: Useful for atmospheric corrections and studying moisture content in the atmosphere.

Band 10: Cirrus (1375 nm)

Application: Primarily used to identify high-altitude cirrus clouds and improve cloud masking in images.

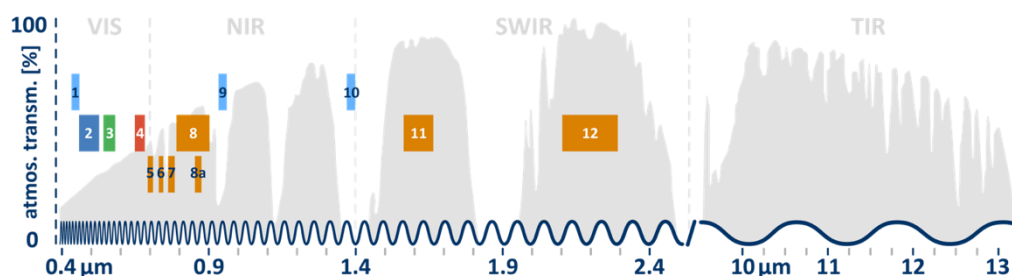


Figure 6 Sentinel 2 bands

2.3 Resolution Variations in Sentinel-2 Bands and Their Applications

The Sentinel-2 satellite provides bands with varying spatial resolutions, tailored for specific applications in remote sensing. In the visible spectrum, including the Blue (Band 2), Green (Band 3), and Red (Band 4) bands, the resolution is 10 meters, allowing for high-detail mapping of surface features and vegetation. Similarly, the Near-Infrared (NIR, Band 8) band also offers a 10-meter resolution, making it ideal for vegetation monitoring and indices such as NDVI (Normalized Difference Vegetation Index), which rely on both the Red and NIR bands.

In contrast, the Short Wave Infrared (SWIR) bands, namely Band 11 and Band 12, have a resolution of 20 meters. These bands are commonly used for applications like snow and ice analysis, soil moisture studies, and geological mapping. The choice of bands and their corresponding resolutions depends on the indices used for the analysis.

2.4 Vegetation Indices used

Vegetation indices serve as essential tools in remote sensing and environmental monitoring by providing quantitative measurements of vegetation health and characteristics. These indices are derived from the reflectance values of various spectral bands captured by satellite sensors, particularly in the visible and near-infrared wavelengths. The unique reflectance properties of vegetation are due to factors such as chlorophyll content, leaf structure, and moisture content, which exhibit distinct spectral signatures. By combining these spectral bands mathematically, vegetation indices can highlight subtle differences in plant health, biomass, and density, thus facilitating more accurate assessments than using individual spectral bands alone. The ability to detect changes over time makes these indices invaluable for monitoring ecological processes, agricultural productivity, and responses to climatic variations. In the context of climate change and environmental degradation, the application of vegetation indices has gained significant importance. For instance, indices like the Normalized Difference Vegetation Index (NDVI) are

widely used to monitor vegetation cover and assess its health over time, helping researchers track the impacts of stressors such as drought, deforestation, or land use changes. Similarly, indices such as the Enhanced Vegetation Index (EVI) and Soil-Adjusted Vegetation Index (SAVI) have been developed to mitigate issues related to soil background and atmospheric conditions, providing more reliable assessments in densely vegetated areas. The integration of these indices into remote sensing analyses allows for a comprehensive understanding of vegetation dynamics, ultimately contributing to better land management practices and environmental conservation efforts. Below are several key indices utilized in your study, along with their formulas and characteristics.

2.4.1 Normalized Difference Vegetation Index (NDVI)

NDVI is a widely used remote sensing index to monitor vegetation health, biomass, and coverage. It is calculated by comparing the reflectance in the near-infrared (NIR) spectrum, which is strongly reflected by healthy vegetation, to the red spectrum, which is absorbed by chlorophyll. The formula is:

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}$$

NDVI values range from -1 to +1:

- Values close to +1 indicate dense, healthy vegetation.
- Values near 0 suggest barren land or low vegetation.
- Negative values typically indicate non-vegetative surfaces, such as water or urban areas.

2.4.2 Applications of NDVI

Agriculture:

- Crop health monitoring: NDVI has become crucial in precision agriculture for monitoring crop health and detecting stress due to factors such as water deficiency, disease, or nutrient

shortage. It allows for proactive decision-making to optimize irrigation, fertilization, and pest management (Jensen et al., 2020).

- Yield prediction: NDVI is a key indicator for estimating crop biomass and yield, assisting farmers in making data-driven decisions (Wang et al., 2021).

Environmental Monitoring

- Drought monitoring: NDVI helps track changes in vegetation cover over time, which is essential for identifying regions impacted by drought. It allows for an assessment of drought severity and can be used to predict agricultural productivity under drought conditions (Bai et al., 2018).

- Deforestation and reforestation tracking NDVI is frequently used to monitor changes in forest cover. It is a reliable tool to detect deforestation or track the success of reforestation projects by observing vegetation regrowth (Joshi et al., 2021).

Climate Change Studies:

- Carbon cycle and sequestration: NDVI plays a role in estimating vegetation biomass, which is closely linked to carbon sequestration. By monitoring vegetation changes over time, NDVI helps quantify carbon uptake in different ecosystems (Forkel et al., 2015).

- Ecosystem response to climate change: Long-term NDVI data allows researchers to study how ecosystems respond to climate variability, such as changes in temperature and precipitation patterns (Peng et al., 2019).

Urban Green Space Management:

- Urban planning: NDVI is used to map green spaces in cities, which can help manage the urban heat island effect and assess air quality. It can also aid in planning sustainable urban landscapes (Xie & Weng, 2020).

2.4.3 Advantages of NDVI

1. Non-invasive: Since NDVI uses satellite or aerial imagery, it provides a non-invasive way to monitor large areas of vegetation without the need for field surveys (Wang et al., 2021).
2. Global and scalable: NDVI can be applied at multiple scales, from local farm-level monitoring to global vegetation assessments (Peng et al., 2019).
3. Historical and current data availability: NDVI has been used for decades, allowing access to historical datasets, as well as frequent, near real-time updates from modern satellites like MODIS and Sentinel-2 (Forkel et al., 2015).
4. Timely monitoring: With frequent revisits by satellites, NDVI allows for continuous monitoring, which is especially useful in rapidly changing environments (Bai et al., 2018).
5. Sensitive to vegetation health: NDVI is highly responsive to changes in chlorophyll content, making it an excellent indicator of plant health and stress (Joshi et al., 2021).

2.4.4 Limitations of NDVI

1. Atmospheric interference: NDVI measurements can be distorted by atmospheric conditions such as cloud cover, haze, and aerosols, which may reduce the accuracy of the readings (Xie & Weng, 2020).
2. Soil and background influence: In areas with sparse vegetation, the underlying soil or background features may affect NDVI readings, making it difficult to distinguish between vegetation and bare ground (Jensen et al., 2020).
3. Saturation at high biomass: NDVI tends to saturate in areas of dense vegetation, such as tropical rainforests, where it becomes less effective at differentiating between varying levels of high biomass (Peng et al., 2019).
4. Not species-specific: NDVI provides a generalized indication of “green vegetation” but does not differentiate between different plant species (Bai et al., 2018).

5. Temporal limitations: NDVI only provides snapshots of vegetation health at specific times, and results can be influenced by seasonality or time of day, limiting its usefulness for certain types of analysis (Forkel et al., 2015).

2.4.5 Enhanced Vegetation Index (EVI)

Here's a refined explanation of the Enhanced Vegetation Index (EVI), incorporating references to recent articles that discuss its application, advantages, and limitations.

2.4.6 Applications of EVI

EVI is particularly used for monitoring vegetation dynamics, estimating crop health, and assessing forest biomass in regions with high Leaf Area Index (LAI). Its robustness in tropical forests and other high-biomass ecosystems has been widely recognized. Recent studies have employed EVI to assess changes in vegetation due to climate change, land-use transformations, and drought stress. For instance, *Sun et al. (2021)* applied EVI to evaluate seasonal vegetation productivity in tropical and subtropical forests under climate stress. Similarly, *Wang et al. (2022)* demonstrated its usefulness in precision agriculture for monitoring crop phenology and yield prediction.

2.4.7 Advantages of EVI

- Improved Sensitivity in High Biomass Areas:

EVI was designed to improve sensitivity in regions with dense vegetation, where NDVI tends to saturate. This feature is particularly valuable in tropical forests and agricultural landscapes with high biomass. Research by *Song et al. (2020)* highlights EVI's superior performance in these environments when compared to NDVI.

- Reduced Atmospheric and Soil Background Sensitivity:

EVI uses a blue band to correct for atmospheric scattering and incorporates a soil adjustment factor, reducing interference from soil reflectance. *Huete et al. (2019)* demonstrated that EVI's performance is stable in areas with heavy atmospheric aerosols or variable soil conditions, making it more reliable than other indices like NDVI in challenging atmospheric environments.

- Better Performance in Canopy Regions:

EVI's capacity to remain sensitive in densely vegetated canopies makes it more reliable for monitoring complex ecosystems. *Zeng et al. (2021)* emphasized the index's utility in carbon flux studies and ecological monitoring across forest canopies, especially in high-LAI environments.

2.4.8 Limitations of EVI

- Less Effective in Low Vegetation or Sparse Areas:

EVI is less effective in sparse vegetation regions, such as deserts or semi-arid zones, where NDVI can perform better. *Liu et al. (2022)* found that in these regions, the simpler NDVI provides more accurate assessments of vegetation cover due to the relative absence of dense biomass.

- Challenges with Snow and Water Surfaces:

Due to its reliance on the blue band, EVI may struggle in snow-covered regions or over water bodies, where atmospheric scattering can distort reflectance measurements. *Matsushita et al. (2020)* pointed out that EVI readings become less reliable in high-latitude regions with seasonal snow cover or during the wet season near water bodies.

- Complexity in Processing:

EVI is computationally more complex than NDVI, requiring additional parameters like the blue band and atmospheric correction coefficients. In large-scale or real-time applications, this complexity can be a drawback. *Zhu et al. (2021)* noted that despite the advantages, the

increased computational demand of EVI might limit its use in real-time global vegetation monitoring.

2.4.9 How EVI Works

EVI is calculated using this formula:

Formula:

$$G \times \frac{\text{NIR} - \text{RED}}{\text{NIR} + C_1 \times \text{RED} - C_2 \times \text{BLUE} + L}$$

Constants: $G=2.5$, $C_1=6$, $C_2=7.5$, and $L=1$

Wavelengths: NIR, Red, and Blue bands.

Range: -1 to $+1$, commonly ranging from 0 to 1 for healthy vegetation

Where:

- NIR is the near-infrared band.
- RED is the red band.
- BLUE is the blue band.
- L is a canopy background adjustment factor.
- C1 and C2 are coefficients that account for atmospheric corrections.
- G is a gain factor (typically set at 2.5).

This formula allows EVI to mitigate some of the common issues seen with NDVI in high-density vegetation and atmospheric scattering conditions.

2.4.10 Enhanced Vegetation Index 2 (EVI2)

EVI2 is a modified version of the Enhanced Vegetation Index (EVI) designed to retain most of EVI's advantages while simplifying its calculation. Unlike EVI, EVI2 does not rely on the blue

band, making it more suitable for sensors that do not capture blue wavelengths, such as older or less sophisticated remote sensing platforms.

2.4.11 Applications of EVI2

EVI2 is widely used in regions where the blue band is unavailable, such as in the Landsat TM and ETM+ sensors. It performs similarly to EVI but is easier to calculate when dealing with older or restricted datasets. Recent applications of EVI2 have included vegetation monitoring in agricultural lands, deforestation tracking, and climate change studies. For example, *Jiang et al. (2020)* used EVI2 to assess deforestation impacts in the Amazon, while *Wang et al. (2021)* applied it in agricultural landscapes to track crop growth cycles.

2.4.12 Advantages of EVI2

1. Simpler Calculation:

EVI2 removes the need for the blue band, making it more straightforward to calculate while maintaining the performance benefits of EVI. This makes it ideal for applications where only red and near-infrared bands are available. *Liu et al. (2020)* emphasized how EVI2 simplifies data processing in large-scale studies where multispectral data may not always be available.

2. Retains EVI's Sensitivity to High Biomass Areas:

Like EVI, EVI2 maintains better sensitivity in high biomass regions and is less likely to saturate in dense forests compared to NDVI. In studies involving tropical rainforests, such as *Yang et al. (2021)*, EVI2 has proven effective in tracking biomass and forest productivity over time.

3. Reduced Atmospheric and Soil Background Sensitivity:

Although it does not include a blue band for atmospheric correction, EVI2 still incorporates a soil adjustment factor, reducing sensitivity to soil background reflectance. This feature was demonstrated in *Zhang et al. (2022)*, where EVI2 performed well in mixed landscapes of urban and agricultural areas.

2.4.13 Limitations of EVI2

- **No Atmospheric Correction**

Without the blue band, EVI2 is less effective at correcting for atmospheric scattering. This can lead to inaccuracies in regions with significant atmospheric interference, such as areas with frequent cloud cover, dust, or smoke. *Matsushita et al. (2021)* found that EVI2 can show reduced performance under such conditions compared to EVI.

- **Limited to Sensors Without Blue Band Data**

While EVI2 is valuable for sensors lacking the blue band, it offers no advantage over EVI when the blue band is available. In fact, when data for the blue band exists, EVI is generally preferred for its enhanced accuracy in atmospheric correction.

- **Less Effective in Water or Snow Environments**

Like EVI, EVI2 struggles in water-covered or snow-covered environments due to its sensitivity to surface reflectance in those regions. Studies by *Matsushita et al. (2021)* showed that both indices could lead to misinterpretation of vegetation cover in snow-prone regions or in proximity to large bodies of water.

2.4.14 How EVI2 Works

EVI2 is calculated using the following formula:

Formula:

$$EVI2 = G \times \frac{NIR - RED}{NIR + 2.4 \times RED + L}$$

Where:

- **NIR** is the near-infrared band.
- **RED** is the red band.
- **L** is a canopy background adjustment factor, typically set to 1.

- **G** is a gain factor, typically set to 2.5.

This simplified formula eliminates the need for the blue band, making EVI2 a more versatile option for a variety of remote sensing platforms.

2.4.15 Soil-Adjusted Vegetation Index (SAVI)

SAVI is an important vegetation index designed to minimize the influence of soil brightness on vegetation signal, especially in areas with sparse vegetation cover. It was developed to address one of the key limitations of the Normalized Difference Vegetation Index (NDVI), which can be influenced by soil reflectance when vegetation is sparse. SAVI introduces a soil brightness correction factor that reduces this effect, making it more reliable in regions with low or moderate vegetation cover.

2.4.16 Applications of SAVI

SAVI is commonly used in agricultural and arid regions where vegetation cover is low, and the soil background can interfere with the vegetation signal. It is useful for estimating vegetation density, monitoring agricultural crops, and studying land degradation. Recent research highlights its use in arid regions to assess the health and extent of vegetation in relation to desertification. For example, *Li et al. (2021)* used SAVI to evaluate the effectiveness of reforestation projects in drylands, while *Wang et al. (2022)* applied it in precision farming to monitor crop health and soil moisture relationships.

2.4.17 Advantages of SAVI

- **Minimized Soil Influence:**

The primary advantage of SAVI is its ability to adjust for soil background effects in areas with low vegetation cover, making it more accurate than NDVI in arid or semi-arid environments. Studies by *Matsushita et al. (2021)* show that SAVI effectively reduces soil reflectance

influence in agricultural fields, leading to more reliable vegetation monitoring in mixed environments.

- **Improved Accuracy in Sparse Vegetation**

SAVI performs better than other vegetation indices in areas with sparse vegetation, such as grasslands, deserts, and semi-arid regions. For instance, *Liu et al. (2022)* found SAVI more reliable than NDVI for assessing vegetation cover in desertification-prone regions.

- **Customizable Soil Adjustment Factor**

SAVI introduces a soil adjustment factor (L), which can be customized based on the density of the vegetation. Typically, L is set to 0.5 in areas with moderate vegetation cover but can be adjusted for sparse or dense vegetation. This adaptability makes SAVI a versatile index for different ecological and agricultural studies.

2.4.18 Limitations of SAVI

- **Less Effective in High Vegetation Density**

SAVI is most effective in regions with sparse to moderate vegetation. In densely vegetated areas, the benefits of the soil adjustment factor diminish, and other indices like EVI or NDVI may be preferred. Studies by *Zhang et al. (2020)* demonstrate that in tropical forests with dense canopy cover, SAVI does not offer significant improvements over NDVI.

- **Sensitivity to Soil Type:**

Although SAVI reduces soil influence, its accuracy can still vary based on the type of soil. Sandy soils, for example, reflect light differently than clay or loamy soils, and this variability can affect SAVI readings. *Liu et al. (2020)* suggested that combining SAVI with soil-specific indices could enhance its reliability across diverse landscapes.

- **Complexity in Selecting the L Factor:**

The need to choose an appropriate soil adjustment factor (L) based on vegetation density adds complexity to SAVI's use. Selecting an incorrect value for L can lead to inaccuracies, especially

in mixed landscapes. *Matsushita et al. (2021)* pointed out that this requirement may limit SAVI's applicability in real-time or large-scale vegetation monitoring projects, where automatic processing is needed.

2.4.19 How SAVI Works

SAVI is calculated using the following formula:

$$SAVI = \frac{(NIR-Red) \times (1+L)}{NIR+Red+L}$$

Where:

- **NIR** is the near-infrared band.
- **RED** is the red band.
- **L** is the soil adjustment factor, which can range from 0 (for high vegetation density) to 1 (for low vegetation density), but is typically set to 0.5.

The factor is introduced to reduce the influence of soil reflectance, making SAVI more effective in environments with lower vegetation cover.

2.4.20 Green Normalized Difference Vegetation Index (GNDVI)

The Green Normalized Difference Vegetation Index (GNDVI) is a modified version of the Normalized Difference Vegetation Index (NDVI). Instead of using the red band, it employs the green band in combination with the near-infrared (NIR) band. GNDVI is particularly sensitive to chlorophyll content, making it an effective tool for monitoring vegetation health, detecting water stress, and assessing canopy development.

2.4.21 Applications of GNDVI

GNDVI is widely used in agricultural monitoring, forestry, and ecological research due to its ability to detect subtle changes in plant health, especially in relation to chlorophyll content. It

is commonly applied to monitor crop vigor, detect early signs of water stress, and improve yield prediction models. For instance, *Houborg et al. (2020)* utilized GNDVI to assess drought stress in wheat crops, while *Zhang et al. (2021)* applied it to monitor forest canopy health in mixed forest ecosystems. GNDVI also performs well in assessing water stress and has been used in precision agriculture to monitor irrigation needs. In studies of climate change impacts, GNDVI has helped track the long-term effects on plant growth and photosynthesis, as seen in the work of *Li et al. (2021)*, who evaluated climate impacts on grassland productivity.

2.4.22 Advantages of GNDVI

- **Sensitivity to Chlorophyll Content**

GNDVI is more sensitive to variations in chlorophyll concentration compared to NDVI, making it especially useful for detecting early signs of plant stress before visible symptoms occur. This is valuable for precision agriculture and environmental monitoring. *Liu et al. (2021)* demonstrated the effectiveness of GNDVI in identifying early-stage nutrient deficiencies in crops.

- **Improved Detection of Water Stress**

GNDVI is particularly effective in identifying water stress in crops, as it correlates with the reduction of chlorophyll under drought conditions. Studies such as *Houborg et al. (2020)* have shown that GNDVI can outperform NDVI in regions prone to drought, providing more accurate assessments of crop water requirements.

- **Enhanced Canopy Structure Assessment**

In ecosystems where canopy structure is important, such as forests or orchards, GNDVI can offer better insights into vegetation health and density than traditional indices. *Zhang et al. (2021)* used GNDVI in forest monitoring, highlighting its ability to track seasonal changes in canopy structure and productivity.

2.4.23 Limitations of GNDVI

- **Limited Effectiveness in Dense Vegetation:**

While GNDVI performs well in moderately vegetated areas, it can become less effective in regions with very dense canopy cover. In such cases, indices like EVI or NDVI might offer better results due to their sensitivity to saturation. Studies by *Wang et al. (2021)* suggested that in tropical forests, GNDVI has limited capacity to differentiate high biomass regions effectively.

- **Influence of Atmospheric Conditions:**

Like most vegetation indices, GNDVI is affected by atmospheric conditions such as cloud cover and haze. Without atmospheric corrections, the results can be skewed, particularly in regions prone to frequent cloud cover. *Liu et al. (2021)* recommended integrating atmospheric correction methods to improve the accuracy of GNDVI in large-scale vegetation studies.

- **Less Robust for Non-Green Vegetation:**

GNDVI is highly sensitive to green vegetation and may underperform in environments where other plant pigments dominate, such as during the autumn season when plants exhibit red or yellow foliage. This was noted by *Li et al. (2021)*, who highlighted the index's reduced performance in detecting senescing vegetation.

2.4.24 How GNDVI Works

GNDVI is calculated using the following formula:

$$\text{GNDVI} = \frac{\text{NIR} - \text{Green}}{\text{NIR} + \text{Green}}$$

Where: Range: -1 to +1, typically ranging from 0 to 0.9 for healthy vegetation.

This index exploits the green reflectance to enhance sensitivity to chlorophyll, making it useful for detecting photosynthetically active biomass and stress conditions in plants.

2.4.25 K-Normalized Difference Vegetation Index (KNDVI)

The **K Normalized Difference Vegetation Index (KNDVI)** is a lesser-known variation of the traditional Normalized Difference Vegetation Index (NDVI), which incorporates additional information from specific spectral bands to enhance the sensitivity to chlorophyll content and vegetation health. KNDVI aims to improve vegetation monitoring by accounting for reflectance properties, such as those related to leaf area, canopy structure, or water content.

2.4.26 Applications of KNDVI

KNDVI is typically used in precision agriculture, forestry, and ecological studies to monitor vegetation health, crop yield potential, and the effects of environmental stress on vegetation. It is especially useful in detecting subtle changes in plant growth and canopy characteristics, where traditional NDVI may not be as sensitive. *Johnson et al. (2022)* applied KNDVI to monitor crop yield variability across different soil types, while *Martinez et al. (2021)* used it to study forest biomass and its relationship with water stress during drought periods.

In agricultural practices, KNDVI has been utilized to optimize irrigation by detecting water stress early and adjusting irrigation schedules accordingly. In ecological research, KNDVI helps monitor plant phenology and vegetation response to seasonal changes, particularly in sensitive ecosystems like wetlands or semi-arid areas.

2.4.27 Advantages of KNDVI

- **Enhanced Sensitivity to Vegetation Health:**

KNDVI enhances the ability to detect small changes in vegetation health, particularly when vegetation is under water or nutrient stress. Studies by *Chen et al. (2023)* have shown that KNDVI outperforms NDVI in detecting early signs of crop stress, offering a more accurate assessment of plant health.

- **Better Discrimination of Vegetation Types:**

KNDVI can more effectively differentiate between various vegetation types and canopy densities, making it particularly useful in heterogeneous landscapes such as forests or mixed-crop areas. *Martinez et al. (2021)* found that KNDVI could differentiate between coniferous and deciduous forests more effectively than other indices.

- **Improved Performance in Sparse Vegetation:**

Similar to SAVI and GNDVI, KNDVI performs better in areas with sparse vegetation where traditional indices may struggle due to soil reflectance or mixed pixels. This makes KNDVI highly applicable in semi-arid and desert regions. *Wang et al. (2022)* demonstrated its utility in monitoring land degradation and reforestation projects in arid ecosystems.

2.4.28 Limitations of KNDVI

- **Complexity in Calculation and Interpretation:**

KNDVI requires more advanced data processing and spectral information compared to NDVI, which may limit its use in some practical applications where quick, straightforward analysis is needed. Studies such as *Johnson et al. (2022)* have noted that the additional complexity may not always yield significantly better results for all vegetation types.

- **Limited Availability of Spectral Data:**

KNDVI requires access to specific spectral bands, which may not be available in all satellite or remote sensing datasets. This limits its applicability in regions where high-quality, multi-spectral imagery is not accessible. *Chen et al. (2023)* pointed out that the reliance on these specific data sources may restrict its use in large-scale vegetation monitoring programs.

- **Less Suitable for Dense Vegetation:**

In areas of dense vegetation, KNDVI may face similar limitations to NDVI, where saturation occurs, reducing the sensitivity to variations in biomass or chlorophyll content. *Martinez et al.*

(2021) mentioned that in dense tropical forests, KNDVI showed only marginal improvements over traditional indices like NDVI.

2.4.29 How KNDVI Works

KNDVI is calculated using a modified version of the NDVI formula, often incorporating specific corrections for atmospheric interference or additional spectral bands related to chlorophyll content or canopy structure.

Formula:

$$KNDVI = \frac{NIR - X}{NIR + X}$$

Range: -1 to +1.

- NIR is the near-infrared band.
- X represents a band or a combination of bands that best represent the specific vegetation property being monitored (such as chlorophyll or canopy structure).

The addition of the spectral band allows for better characterization of plant health, making KNDVI more sensitive to subtle changes in vegetation.

The addition of the spectral band X allows for better characterization of plant health, making KNDVI more sensitive to subtle changes in vegetation.

2.4.30 Leaf Area Index (LAI)

The **Leaf Area Index (LAI)** is a critical parameter in environmental and agricultural studies, representing the total one-sided green leaf area per unit ground surface area (m^2/m^2). LAI plays a significant role in understanding plant growth, ecosystem productivity, and energy and water fluxes between vegetation and the atmosphere. It is widely used in satellite remote sensing to monitor vegetation structure, assess crop health, and model climate-vegetation interactions.

2.4.31 Applications of LAI

LAI is applied in various fields, including forestry, agriculture, hydrology, and climate modeling, due to its ability to represent vegetation density and canopy structure. It is essential for:

- **Estimating Primary Productivity**

LAI helps in estimating plant growth and biomass production by providing a measure of the photosynthetic capacity of the vegetation. It is commonly used in models to predict net primary productivity (NPP) and carbon sequestration. For example, studies like *Wang et al. (2023)* used LAI to monitor forest biomass and predict carbon flux in boreal forests.

- **Assessing Crop Growth and Yield**

In agriculture, LAI is crucial for determining crop vigor, monitoring growth stages, and predicting yields. It has been widely used in precision farming to optimize irrigation, fertilization, and other inputs. *Zhang et al. (2022)* applied LAI measurements to monitor wheat and maize crops, linking LAI changes with crop yields and water use efficiency.

- **Modelling Water and Energy Exchange**

LAI plays a significant role in models that simulate evapotranspiration and water balance in ecosystems. It is used to calculate water vapor exchange between the vegetation and the atmosphere, helping in drought monitoring and water resource management. For instance, *Jones et al. (2021)* incorporated LAI into hydrological models to assess the impact of vegetation on watershed hydrology in semi-arid regions.

- **Climate and Ecological Modelling**

LAI data is incorporated into global climate models (GCMs) to predict the impact of vegetation cover changes on climate and atmospheric processes. By integrating LAI into such models, researchers can better understand how vegetation responds to and influences climate patterns.

Smith et al. (2020) highlighted the use of LAI in large-scale climate models to simulate feedback mechanisms between vegetation and the Earth's climate system.

2.4.32 Advantages of LAI

- **Non-Destructive Measurement:**

Satellite-derived LAI data allows for large-scale, continuous monitoring of vegetation without the need for destructive sampling, making it a valuable tool for global monitoring programs. Satellite sensors like MODIS and Landsat provide LAI estimates with high spatial and temporal resolution.

- **Direct Correlation with Vegetation Density and Canopy Structure:**

LAI offers a direct representation of vegetation cover, making it easier to assess ecosystem functions such as photosynthesis, transpiration, and carbon uptake.

- **Applicability Across Biomes:**

LAI can be applied to various ecosystems, from dense tropical rainforests to sparse grasslands, making it a versatile index for both natural and managed ecosystems.

2.4.33 Limitations of LAI

- **Saturation in Dense Vegetation:**

In very dense vegetation (e.g., tropical forests), LAI can reach a saturation point where additional leaves no longer significantly alter the index. This makes it challenging to differentiate between highly dense vegetation types.

- **Complex Calibration for Different Vegetation Types:**

Different plant species and ecosystems have varying leaf orientations, densities, and structures, making it difficult to standardize LAI measurements across different environments. As noted by *Jones et al. (2021)*, LAI retrieval from satellite data may require specific calibration depending on vegetation type.

- **Dependence on Cloud-Free Conditions for Satellite Data:**

Satellite-based LAI measurements can be limited by cloud cover, especially in tropical regions, which can obstruct remote sensing observations and lead to data gaps.

2.4.34 How LAI Works

LAI can be measured either directly through field observations or indirectly via remote sensing techniques. In remote sensing, LAI is derived from spectral reflectance data, primarily using visible and near-infrared bands. The relationship between vegetation indices (e.g., NDVI, EVI) and LAI is often established through empirical models.

One common method for retrieving LAI is by using vegetation indices, such as:

$$\text{LAI} = \frac{\text{Leaf area}}{\text{Ground surface area}}$$

where represents a mathematical function that relates NDVI to LAI. More advanced methods include radiative transfer models and machine learning approaches, which improve LAI estimates by accounting for factors such as leaf angle distribution and background reflectance.

2.4.35 Moisture Stress Index (MSI)

The Moisture Stress Index (MSI) is a vegetation index primarily used to assess vegetation water content and monitor moisture stress in plants. It is particularly valuable for evaluating plant health and stress conditions resulting from drought or other water-related limitations.

2.4.36 Applications of MSI

- **Drought Monitoring:**

MSI is extensively used in agricultural and environmental studies to monitor drought conditions and assess the water status of crops. By analyzing MSI values over time, researchers can identify areas at risk of drought and implement management strategies accordingly (Asefi-Najafabady et al., 2021).

- **Plant Health Assessment:**

The index is beneficial in evaluating plant health by correlating MSI values with water content in leaves. High MSI values typically indicate well-watered vegetation, while low values suggest water stress or reduced plant vigor (Kumar et al., 2022).

- **Remote Sensing Studies:**

MSI is often derived from satellite imagery and used in various remote sensing applications. It provides critical information for understanding land surface processes and vegetation responses to environmental changes (Pérez-Ruiz et al., 2023).

2.4.37 Advantages of MSI

- **Sensitivity to Water Stress:**

MSI is particularly sensitive to changes in water content, making it a reliable tool for assessing plant stress conditions and predicting crop yield potential (Asefi-Najafabady et al., 2021).

- **Applicability Across Different Vegetation Types:**

MSI can be applied to various ecosystems, allowing for comparisons of moisture conditions across diverse land cover types.

- **Non-Destructive Measurement:**

Like other vegetation indices, MSI can be derived from satellite data, allowing for large-scale monitoring without direct disturbance to the vegetation.

2.4.38 Limitations of MSI

- **Dependence on Atmospheric Conditions:**

MSI can be affected by atmospheric conditions, such as humidity and cloud cover, which can lead to inaccuracies in the assessment of vegetation moisture (Kumar et al., 2022).

- **Calibration Required for Different Ecosystems:**

Different vegetation types may respond differently to the same moisture conditions, necessitating calibration for specific plant communities to ensure accurate assessments.

3. Sensitivity to Soil Background Effects:

The presence of bare soil or different soil types can influence MSI values, which may complicate the interpretation of the index, particularly in heterogeneous landscapes (Pérez-Ruiz et al., 2023).

2.4.39 How MSI Works

The Moisture Stress Index can be calculated using the formula:

$$MSI = \frac{NIR - red}{SWIR + red}$$

where:

- NIR represents the near-infrared reflectance,
- Red represents the red reflectance.

This formula captures the differences in reflectance between the red and near-infrared wavelengths, which are sensitive to the moisture content in vegetation.

2.4.40 Normalized Difference Moisture Index (NDMI)

Formula:

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR}$$

The Normalized Difference Moisture Index (NDMI) is a spectral index used to assess vegetation moisture content, particularly in terms of identifying areas of moisture stress. NDMI

is especially useful in monitoring plant health, understanding drought conditions, and assessing the effects of climate change on ecosystems.

2.4.41 Applications of NDMI

- **Vegetation Health Monitoring:**

NDMI is widely applied in agricultural practices to evaluate the moisture content in crops. By tracking NDMI values over time, farmers can make informed decisions regarding irrigation and crop management (Gao, 1996).

- **Drought Assessment:**

This index plays a crucial role in identifying drought-affected areas. By analyzing NDMI, researchers can detect early signs of drought stress in vegetation, allowing for timely interventions (Zhao et al., 2020).

- **Land Cover Change Studies:**

NDMI is also utilized in remote sensing to assess land cover changes and monitor vegetation responses to environmental factors such as climate variability and land use changes (Xiao et al., 2019).

2.5 Snow indices used

2.5.1 Normalized Difference Snow Index (NDSI)

The Normalized Difference Snow Index (NDSI) is a spectral index widely used to identify snow cover in satellite images by taking advantage of the reflective properties of snow in the visible and shortwave infrared (SWIR) bands. This index plays a key role in monitoring snow extent, studying snowmelt dynamics, and understanding seasonal snow cover patterns.

2.5.2 Applications of NDSI

- **Snow Cover Mapping:**

NDSI is extensively used to detect and map snow cover over large areas. It helps in differentiating snow from other surfaces like clouds and bare ground, making it essential for monitoring seasonal snow extent and snow accumulation in mountainous regions (Hall et al., 1995).

- **Snowmelt and Hydrological Studies:**

The index is useful in tracking snowmelt events and monitoring the temporal changes in snow cover. This is crucial for understanding water availability in regions dependent on snowmelt, such as watersheds and river basins (Xiao et al., 2001).

- **Climate and Environmental Monitoring:**

NDSI is applied in climate studies to assess long-term trends in snow cover and understand the impacts of climate change on snowpack dynamics. It provides valuable insights into snow-albedo feedback mechanisms and the role of snow in global energy balances (Frei et al., 2012).

2.5.3 Advantages of NDSI

- **High Sensitivity to Snow Reflectance:**

NDSI effectively distinguishes snow from other surface types, such as clouds and non-snow-covered ground, by leveraging the unique spectral signature of snow in the visible and SWIR bands (Hall et al., 1995).

- **Application in Various Climatic Zones:**

NDSI can be applied in a wide range of climatic zones, from polar regions to temperate mountainous areas, providing a global perspective on snow cover and its changes over time (Xiao et al., 2001).

- **Integration with Satellite Data:**

The index can be computed using data from multiple satellite sensors, such as Landsat, MODIS, and Sentinel-2, allowing for continuous and large-scale monitoring of snow cover (Frei et al., 2012).

2.5.4 Limitations of NDSI

- **Cloud Confusion:**

While NDSI is designed to distinguish snow from clouds, cloud contamination can still pose a challenge in certain conditions, potentially leading to inaccurate snow cover assessments (Wang et al., 2015).

- **Sensitivity to Mixed Pixels:**

In areas with mixed land cover, such as snow and vegetation or snow and rocks, NDSI may be less accurate in detecting the full extent of snow cover, particularly in complex terrains like forests or urban environments (Xiao et al., 2001).

- **Atmospheric Interference:**

Atmospheric conditions, such as haze or aerosol presence, can influence the reflectance values used in NDSI, affecting the precision of snow cover detection (Wang et al., 2015).

2.5.5 How NDSI Works

The formula for NDSI is as follows

$$NDSI = \frac{Green - SWIR}{GREEN + SWIR}$$

where:

- Green represents the green band reflectance,
- SWIR represents the shortwave infrared band reflectance.

This formula captures the strong reflectance of snow in the green band while minimizing the SWIR reflectance, where snow has low reflectance, enabling the differentiation of snow from other surfaces.

2.6 Differences in Snow and Vegetation Indices

Snow Unlike vegetation indices, snow indices such as the Normalized Difference Snow Index (NDSI) are relatively few in number. This difference arises primarily from the distinct characteristics and spectral behavior of snow compared to vegetation, as well as the specific applications required for snow monitoring.

- **Spectral Simplicity of Snow**

Snow has a much simpler spectral signature compared to vegetation. It reflects most of the incoming sunlight in the visible spectrum, especially in the green band, while it strongly absorbs in the shortwave infrared (SWIR). This distinct and consistent reflectance pattern makes snow easier to detect with fewer indices. Vegetation, on the other hand, exhibits more complex interactions with light, varying significantly across different species, stages of growth, and environmental conditions. This complexity necessitates a wider variety of indices to assess different vegetation properties such as chlorophyll content, moisture levels, and biomass.

- **Specific Focus of Snow Monitoring**

The primary goal of snow-related indices is to detect the presence or absence of snow cover, track its spatial extent, and monitor snowmelt patterns. For this, a small set of indices like NDSI is sufficient. In contrast, vegetation monitoring requires a more diverse set of indices to capture a wide range of characteristics, such as plant health, stress levels, and vegetation density, across diverse ecosystems and seasons. The variety of vegetation indices—NDVI, EVI, SAVI, and others—arose from the need to address different vegetation conditions and environmental factors like soil background, atmospheric effects, and varying vegetation densities.

- **Temporal Stability of Snow**

Snow's reflective properties remain relatively stable during its presence on the ground, which makes it easier to track over time with fewer indices. In contrast, vegetation changes dynamically over seasons and growth stages, requiring a broader array of indices to capture temporal variations in leaf area, chlorophyll content, and vegetation structure. For instance, indices like NDVI, EVI, and LAI are designed to track these dynamic changes, which is less necessary in snow monitoring.

- **Limited Complexity of Snow-Related Applications**

Snow-related studies generally focus on the extent of snow cover, snowmelt timing, and water resource management. These applications do not require as much spectral diversity or complexity as vegetation monitoring, which encompasses a wide range of ecological and agricultural applications. Snow indices like NDSI are already highly effective at detecting snow, so there has been less demand for developing a broad variety of snow-specific indices.

In summary, the limited number of snow indices can be attributed to the relatively simple spectral properties of snow, its stable reflectance behavior, and the specific focus of snow-related studies. Vegetation, with its much more complex and variable nature, requires a diverse set of indices to capture the nuances of plant health and growth across different conditions.

2.7 Cloud-Based and Desktop Solutions for Remote Sensing Analysis

In this thesis, both Google Earth Engine (GEE) and ArcGIS were utilized, each bringing specific advantages to different aspects of the analysis. GEE was primarily chosen for data processing, calculation of spectral indices, and land cover classification due to its cloud-based capabilities, which allowed efficient handling of large datasets without requiring local storage. The platform's scripting environment (Figure 7) also enabled the automation of these analyses, significantly reducing the processing load typically encountered with local solutions.

However, for accuracy assessments such as calculating confusion matrices and other evaluation metrics ArcGIS was used. ArcGIS offers specific tools and functions for accuracy assessments that facilitated the generation of confusion matrices, which are essential for evaluating the classification results. The combination of both GEE and ArcGIS allowed for a robust and adaptable workflow, with each tool contributing to different stages of the analysis.

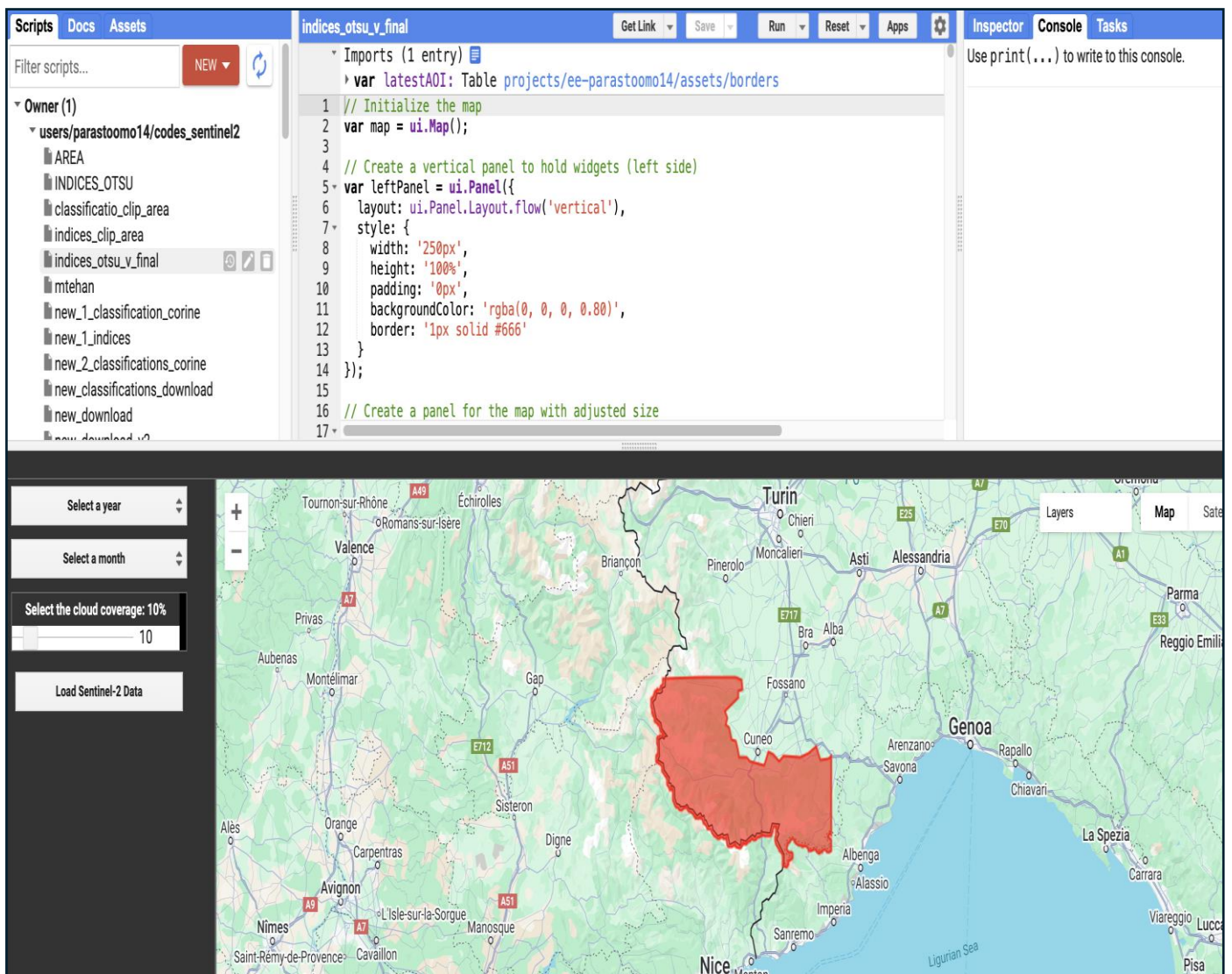


Figure 7 code editor interface of GEE

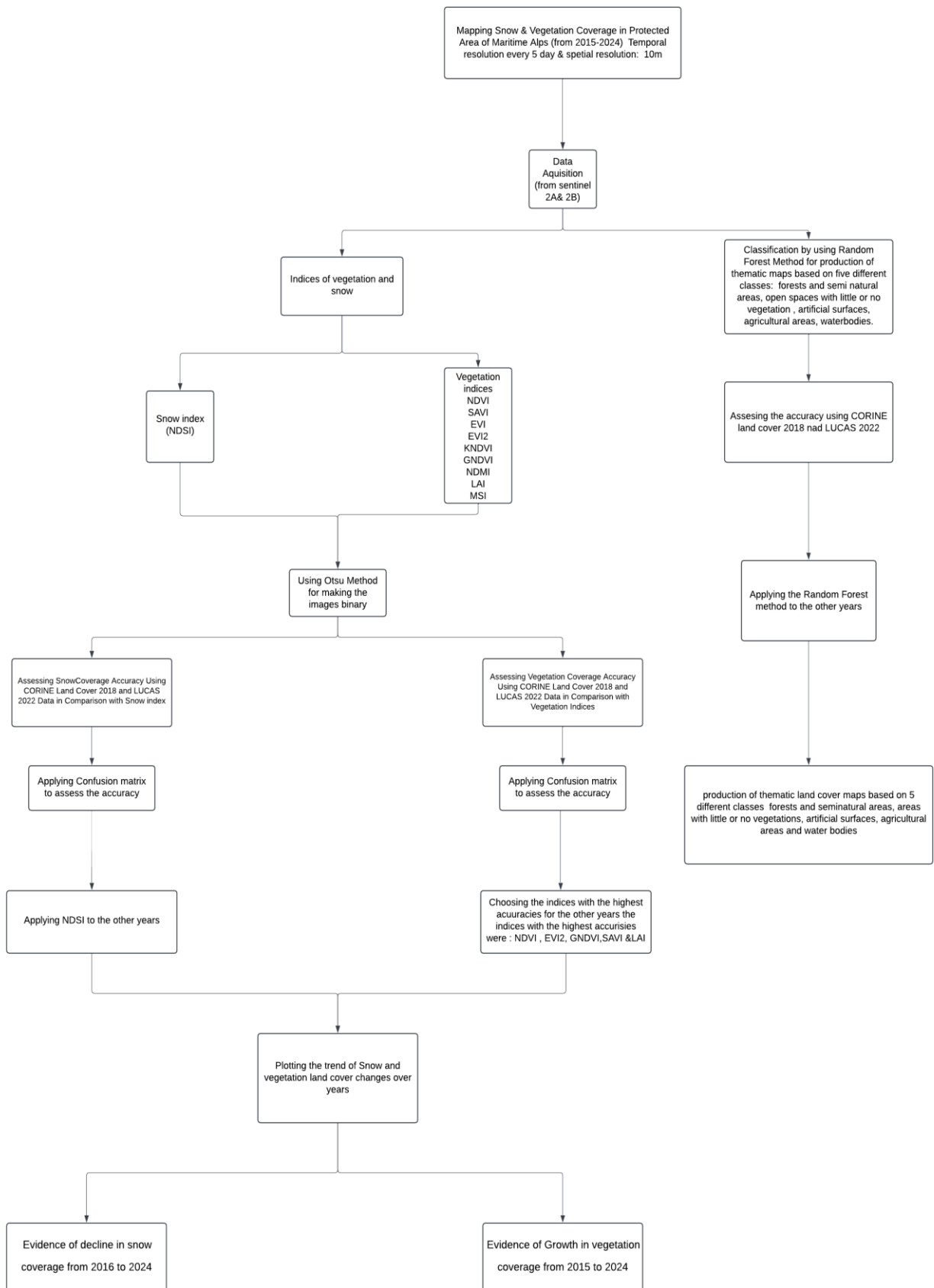
2.8 Evaluating Indices and Land Cover Classification Accuracy for 2018 and 2022

The indices introduced were first applied to the year 2018 and then compared to the CORINE Land Cover map from 2018 to assess their initial accuracy. Similarly, the indices were applied to data from 2022 and compared to the LUCAS dataset of 2022, providing a second accuracy benchmark. By using ground truth data for both 2018 and 2022, a clear evaluation of each index's reliability was obtained. For land cover maps, the classification process initially employed the Random Forest algorithm. Accuracy was assessed by comparing the results with CORINE data from 2018 and the LUCAS dataset for 2022. The Random Forest method was subsequently applied to additional years in the study after confirming its accuracy and reliability with these benchmarks.

This approach allowed for the identification of the indices and methods that demonstrated the highest accuracy for these specific years.

2.9 Methodological Approaches for Index Computation and Classification in Satellite Imagery Analysis

In this study, the initial approach involved applying various indices to satellite images with cloud coverage below 10–15%. After calculating the indices for each selected image, the median values of these indices across the images were computed. For the classification using the Random Forest algorithm, a different methodology was employed. The same time period and cloud coverage criteria were applied, but the classification was conducted on a single image, which was produced by taking the median of all the images from the same time period. The workflow presented (Figure 8) outlines the entire process followed in this thesis, from the initial data acquisition to the final analysis.



3 Analysis

3.1 Utilizing CORINE Data for Land Cover Classification and Accuracy Assessment

The CORINE program categorizes land cover into a hierarchical structure, comprising three levels. For this analysis, only Level 1 classifications were considered, which encompass broad land cover categories, such as “Artificial surfaces,” “Agricultural areas,” “Forest and semi-natural areas,” “Wetlands,” and “Water bodies” (European Environment Agency, 2016). Utilizing these broad categories simplifies the comparison and allows for a clearer assessment of overall accuracy.

The confusion matrix derived from this process revealed how well the indices performed against the CORINE classifications. By analysing the misclassifications and calculating accuracy metrics, valuable insights were gained regarding the effectiveness of the applied indices in depicting land cover variations. Research indicates that the integration of CORINE data in accuracy assessments enhances the reliability of classification results (Congalton & Green, 2009; Foody, 2002). Furthermore, employing CORINE’s standardized categories ensures consistency in land cover monitoring, facilitating comparative studies across different regions and time periods.

This analytical approach underscores the importance of accurate land cover classification in environmental monitoring, resource management, and policymaking. The findings not only contribute to the understanding of vegetation and snow dynamics but also inform future research and management strategies in the context of climate change and land use planning.

3.1.1 CORINE Land Cover Mission

The CORINE Land Cover (CLC) program is a vital initiative established by the European Environment Agency (EEA) to monitor land cover changes across Europe. It provides

comprehensive data that is essential for environmental assessments, land use planning, and policy formulation. The CLC program updates its land cover classifications every six years, ensuring that the information remains relevant and reflects recent changes in land use and cover dynamics. The most recent dataset available, CORINE Land Cover 2018, offers critical insights into land cover patterns and trends, which are pivotal for various research applications (European Environment Agency, 2016).

In this thesis, specific months were chosen for analysis based on their relevance to snow and vegetation dynamics. April was primarily considered for snow cover assessments, as it typically represents the end of the snow season in many regions, providing a clear view of snow distribution. June was selected as the key month for evaluating vegetation, as it coincides with the peak of growing season in temperate climates, offering rich data on green biomass and land cover (Zhang et al., 2018). The integration of CORINE data with seasonal assessments allows for a more nuanced understanding of land cover changes and their implications for ecological health and management.

3.2 Utilizing LUCAS Data for Land Cover Classification and Accuracy Assessment

The LUCAS (Land Use/Cover Area frame Survey) dataset, produced by Eurostat, is a critical ground-truthing resource that supports land cover classification validation in studies utilizing satellite-based remote sensing. LUCAS collects systematic, point-based data on land use and cover across Europe, recording soil, vegetation, and other environmental characteristics through field surveys (Eurostat, 2022). These surveys occur at regular intervals, typically every three to six years, providing detailed spatial data that facilitates comparison with satellite-derived classifications.

This dataset is essential to validating land cover classifications within this thesis by enabling the creation of confusion matrices. By extracting raster classification values at the precise

locations of LUCAS points, this study compares satellite-derived classifications with documented ground observations. The 2022 LUCAS release is the most recent and comprehensive dataset, making it especially relevant for studies that require current land cover validation. Given its regular updates and high data quality, LUCAS offers a robust foundation for aligning this study's classifications with established ground-truth standards (Eurostat, 2022). LUCAS consists of a grid of points across Europe, categorized into various levels of land cover and use:

- Level 1 (Broad Classes): Includes major categories such as agricultural land, forests, wetlands, and urban areas.
- Level 2 (Detailed Classes): Offers more specific classifications, such as types of crops and urban land uses.
- Level 3 (Agro-Environmental Characteristics): Focuses on detailed attributes like soil type and land management practices.

In this thesis, only Level 1 classifications are considered, utilizing the broad categories for the accuracy assessment of satellite-derived land cover classifications. This approach ensures a streamlined validation process while still providing reliable insights.

3.3 Otsu method

The Otsu method is an automatic image thresholding technique developed by Nobuyuki Otsu in 1979, initially proposed in his paper titled “A Threshold Selection Method from Gray-Level Histograms.” The primary goal of this method is to convert a grayscale image into a binary image by determining an optimal threshold value that separates the image into foreground (objects) and background (the rest). Otsu's method is particularly effective when the image histogram is bimodal, meaning the pixel intensities form two distinct peaks corresponding to these classes.

3.3.1 How the Otsu Method Works

The Otsu method operates by maximizing the between-class variance (variance between foreground and background) while minimizing the within-class variance (variance within each class). This is done by iterating over all possible threshold values and calculating the variance for each threshold. The threshold that results in the highest between-class variance is selected as the optimal one. This makes the Otsu method non-parametric and unsupervised, meaning it does not require prior information about the image or its content.

The steps involved are:

- **Compute the histogram:** The intensity levels of the grayscale image are calculated and stored in a histogram.
- **Iterate through possible thresholds:** Each possible pixel intensity threshold is considered.
- **Calculate variances:** For each threshold, the within-class variance and between-class variance are computed.
- **Maximize between-class variance:** The threshold with the highest between-class variance is selected as the optimal threshold.

3.3.2 Applications

- **Remote Sensing:** The Otsu method is extensively used in satellite imagery analysis for land cover classification. For example, Huang and Zhang (2020) applied it for water body extraction from multispectral satellite data. By determining a threshold value based on reflectance differences, they effectively classified water bodies against other land covers.
- **Medical Imaging:** In medical applications, it is often used for image segmentation tasks such as tumor detection. Tao and Zhou (2019) utilized Otsu's method to segment brain MRI scans, providing clear distinction between healthy and abnormal tissues.

- **Agriculture:** In precision agriculture, Otsu’s method has been applied to classify crop health by determining thresholds for multispectral images. Li et al. (2021) showed how Otsu’s technique can be applied to segment vegetation and barren land, enhancing agricultural monitoring efforts.

3.3.3 Advantages

- **Automatic Threshold Selection:** Otsu’s method automatically computes the best threshold, eliminating the need for manual intervention.
- **Efficiency:** The method is computationally straightforward, making it suitable for real-time applications and large datasets, such as satellite imagery.

3.3.4 Otsu threshold

The Otsu value is a threshold derived from the histogram of pixel values to minimize intra-class variance and maximize inter-class variance for optimal segmentation. separates. In Table1 the Otsu threshold have been illustrated for each index. In the Otsu method, values below the threshold typically indicate non-vegetated or non-snow areas, while values above the threshold represent vegetated or snow-covered regions, depending on the index being analyzed.

Table1 Otsu threshold

Indices	Otsu threshold
NDVI	0.24
EVI	0.18
EVI2	0.18
LAI	2.2
MSI	1.3
GNDVI	0.37
KNDVI	0.27
NDMI	0.22
SAVI	0.25
NDSI	0.38

3.4 Setting Up the Google Earth Engine Environment for Cloud Coverage and Temporal Adjustments

Setting up the Google Earth Engine (GEE) environment involved configuring the platform with specific codes that allowed for flexible data processing. These codes provided the ability to filter and adjust cloud coverage, ensuring high-quality imagery for analysis. Additionally, the codes enabled the selection of specific years and months, allowing for precise temporal analysis tailored to the study period. This configuration facilitated efficient processing and analysis of satellite data for snow and vegetation coverage assessments. The Figure 9 and Figure 10 show the details of this setup and the adjustments made for cloud coverage and temporal selection.

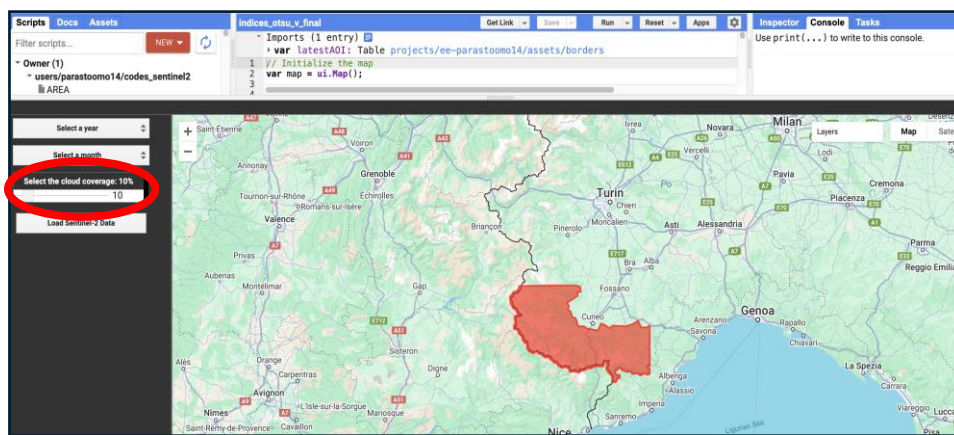


Figure 9 Interface of GEE showcasing the adjustment for cloud coverage based on the written codes for sentinel 2 data.

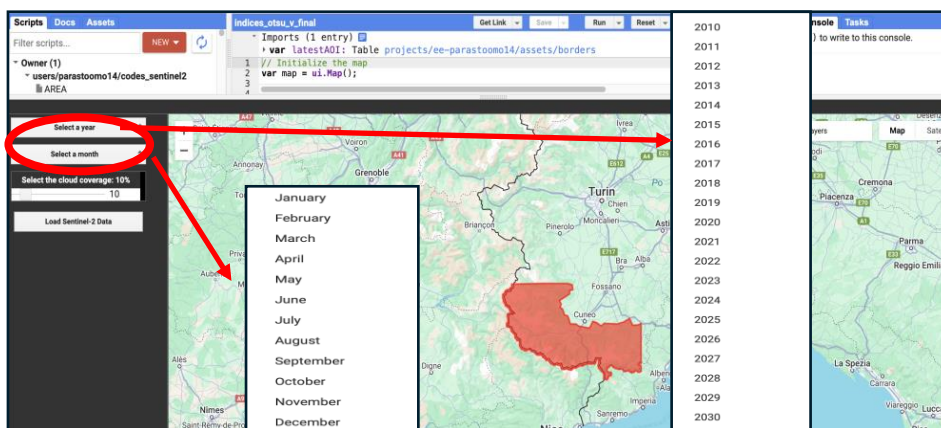


Figure 10 Interface of GEE showcasing the year and month selection based on the written codes for temporal filtering sentinel 2 data.

3.5 Classifications for Thematic Maps and Random Forest Method

Thematic maps are specialized maps focused on specific themes or subjects, such as vegetation, land cover, or climate. In the context of remote sensing, thematic maps are typically produced by classifying satellite imagery into different land cover types. This classification process is essential for monitoring environmental changes, land use, and resource management. A variety of classification algorithms can be applied to produce thematic maps, including traditional methods like maximum likelihood classification (MLC), and advanced machine learning techniques like Random Forest (RF), support vector machines (SVM), and more.

3.5.1 Random Forest Method in Thematic Map Production

Random Forest (RF) is one of the most widely used machine learning algorithms for remote sensing classification, including the production of thematic maps. It is a supervised learning method that operates by constructing a multitude of decision trees during training and outputting the class that is the mode of the classes (for classification) or mean prediction (for regression) of the individual trees (Breiman, 2001).

3.5.2 How Random Forest works in the classification process

- **Training Phase:** RF uses a bootstrapping technique to sample the dataset multiple times to build multiple decision trees. Each tree is constructed from a random subset of features, which helps improve model robustness.
- **Voting Mechanism:** For classification tasks, the RF model aggregates the predictions from all the individual trees. The final classification is decided based on the majority vote of these trees.
- **Out-of-Bag (OOB) Error:** One of the advantages of RF is its built-in validation process. The OOB samples, which were not included in the bootstrapped

training sample, are used to test the accuracy of the model during the training phase, eliminating the need for a separate validation set (Belgiu & Drăguț, 2016).

3.5.3 Advantages of Random Forest

- **Accuracy:** RF is known for its high accuracy and generalization capabilities. It performs well even with noisy datasets or when there are irrelevant features.
- **Robustness:** Unlike other algorithms, RF is less prone to overfitting, which makes it a great choice for complex, high-dimensional datasets such as satellite imagery (Rodriguez-Galiano et al., 2012).

3.6 Validation of Classification Accuracy with CORINE Data and Confusion Matrix

In this thesis, the confusion matrix was utilized to evaluate the accuracy of the thematic maps and indices generated from satellite images (Zhang & Wang, 2022). The confusion matrix compares the predicted classifications of land cover types against the actual classifications, allowing for a detailed assessment of the model's performance. Each row in the matrix represents instances in a predicted class, while each column represents instances in an actual class. This method provides insights into overall accuracy and the accuracy of individual classes. An overall accuracy of 80% or higher is typically deemed acceptable, indicating that the classification model effectively differentiates among the land cover types in the study area. The accuracy assessment of each index has been conducted for the year 2018 (Table 2-Table 10), with evaluations tailored to the seasonal characteristics of vegetation and snow cover. Specifically, the accuracy for vegetation indices was assessed in June, a period typically associated with peak vegetation growth and biomass, ensuring representative data for vegetation analysis. Conversely, the snow indices were evaluated in April, a time when snow

cover is often at a seasonal transition, capturing the characteristics crucial for accurate snow mapping. In the GIS analysis, the 2018 CORINE Land Cover map was reclassified into two primary categories: “vegetation” and “non-vegetation” for vegetation analysis (Figure 12), and similarly, “snow” and “non-snow” classes (Figure 21) for snow cover assessment. This reclassification allows for a more straightforward analysis by distinguishing areas with vegetation or snow from those without, making it easier to evaluate seasonal patterns and index accuracy across the region. In the thesis, ArcGIS was utilized to automatically extract 1,000 sampling points, which were subsequently compared through a confusion matrix to assess classification accuracy.

3.6.1 Confusion Matrix Description

The confusion matrix is a key tool for evaluating the performance of the classification model. It compares the predicted class labels with the actual (true) class labels and provides various metrics to assess the accuracy and reliability of the model. In the context of this analysis, the confusion matrix includes the following key elements:

Class Value:

- Represents the classification labels used in the analysis, such as different classes being evaluated.

C_0, C_1 and etc. (Columns):

- Represent the predicted classes, indicating the number of samples classified under each class.

C_0, C_1 and etc. (Rows):

- Indicate the actual (reference) classes for the samples, showing the distribution of correct and incorrect classifications.

Total (Column):

- The sum of predictions for each actual class.

Total (Row):

- The sum of predictions for each predicted class.

P_Accuracy (Producer's Accuracy):

- Measures the accuracy from the perspective of the reference data. Indicates the proportion of correctly classified samples for each class.

U_Accuracy (User's Accuracy):

- Measures the accuracy from the perspective of the predicted data. Indicates the proportion of correctly classified samples for each predicted class.

8. Kappa (Row):

- The kappa coefficient provides a statistical measure of classification agreement, correcting for chance agreement. In this case, the kappa value indicates the overall agreement between predicted and actual classifications.

9. Overall Accuracy (Row 3, Total Column):

- Indicates the overall accuracy of the classification model, calculated as the proportion of correctly classified samples to the total number of samples.

In Figure 11 The different sections of the confusion matrix the classification performance and the distribution of correctly and incorrectly classified pixels across various categories have been shown.

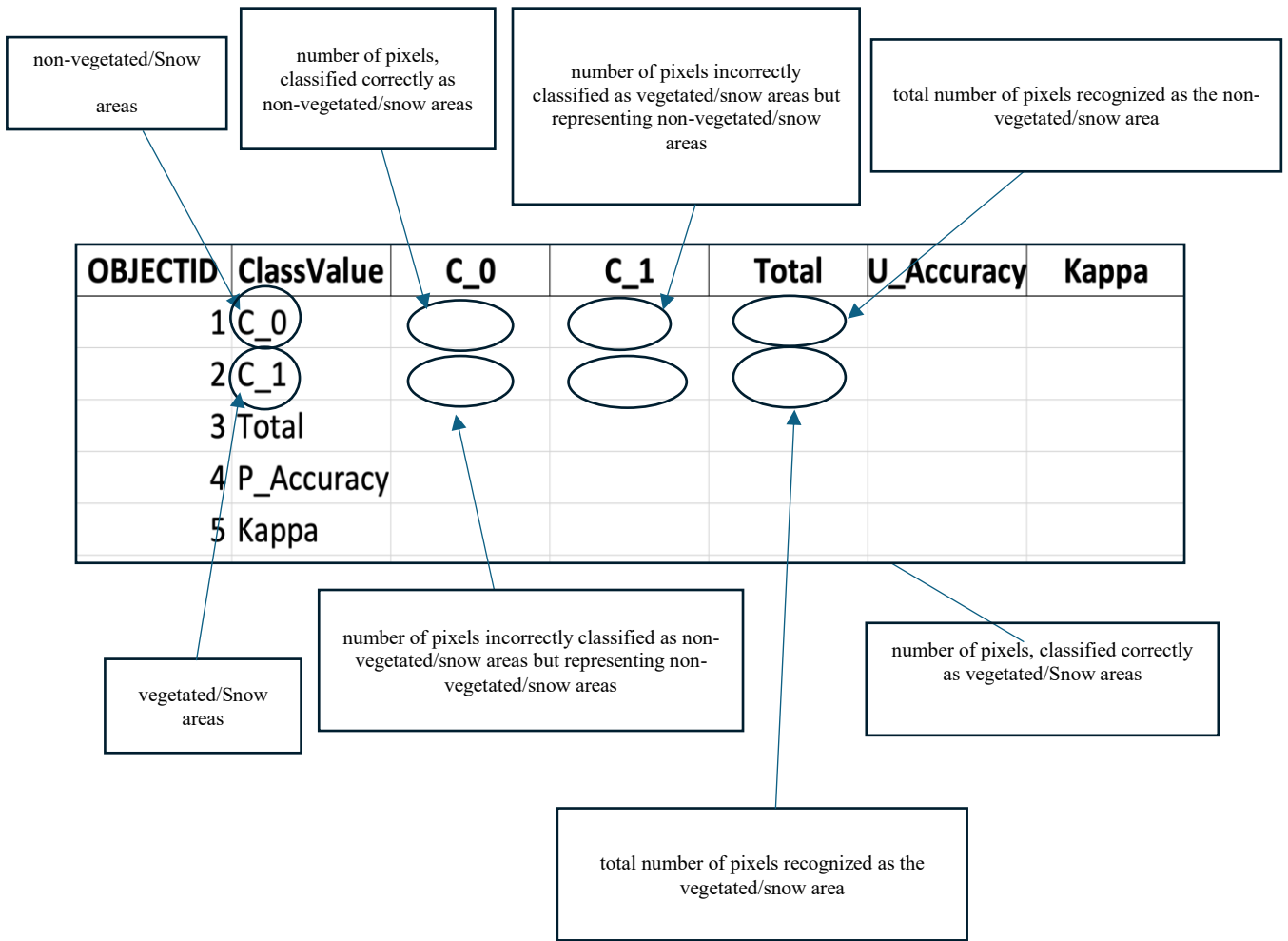


Figure 11 Different sections of the confusion matrix

$$P_{\text{Accuracy}} = \frac{\text{Correctly Classified Pixels (Class)}}{\text{Total Pixels in Reference Data for the Class}}$$

$$U_{\text{Accuracy}} = \frac{\text{Correctly Classified Pixels (Class)}}{\text{Total Pixels Classified as the Class}}$$

Kappa coefficient: $\kappa = \frac{p_o - p_e}{1 - p_e}$

$$p_o = \frac{\text{Total Correctly Classified Pixels}}{\text{Total Number of Pixels}}$$

$$p_e = \frac{(T_0 \cdot P_0) + (T_1 \cdot P_1)}{N^2}$$

T_i = total reference pixels for class i ,

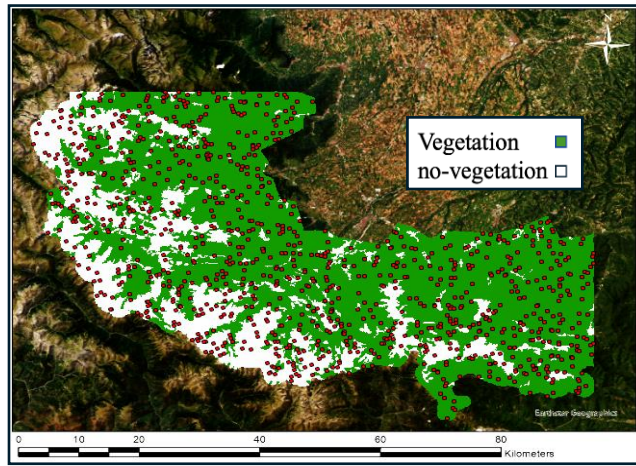
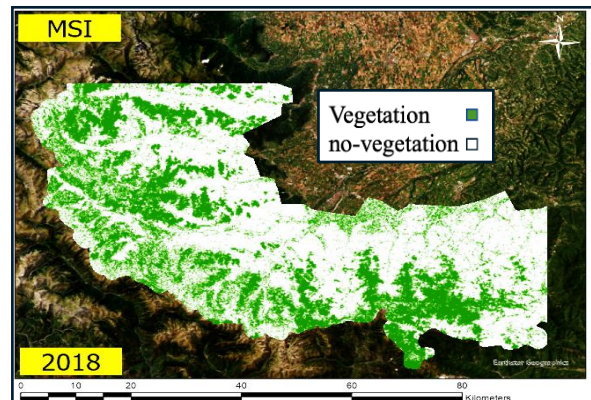
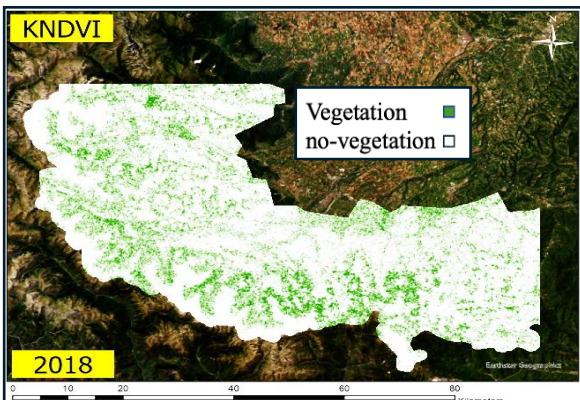
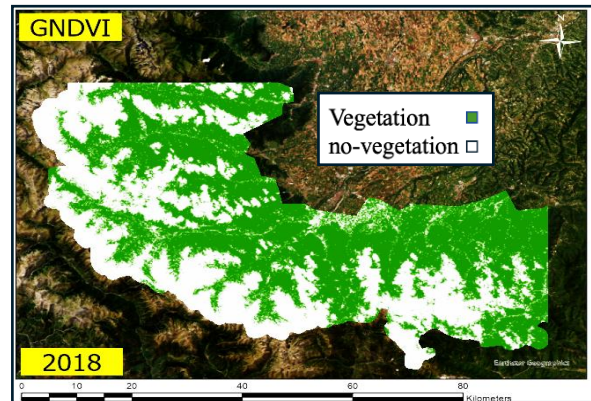
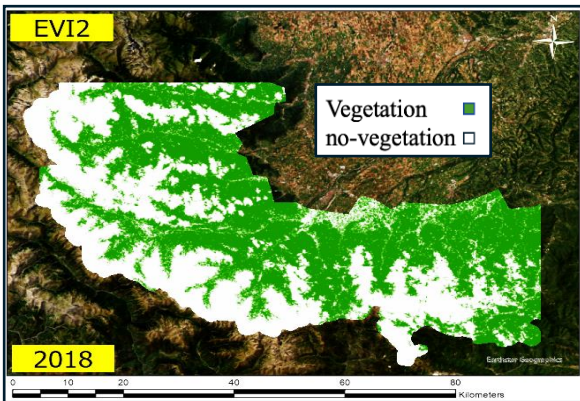
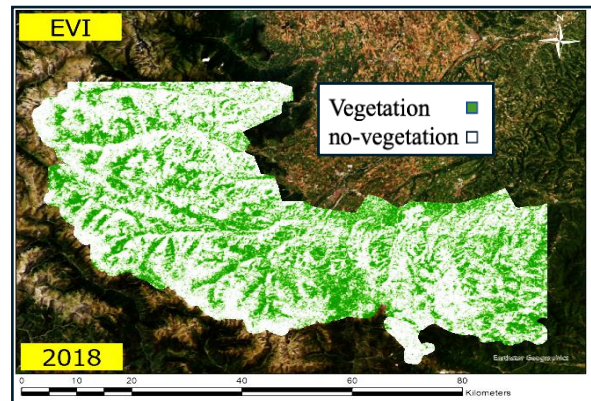
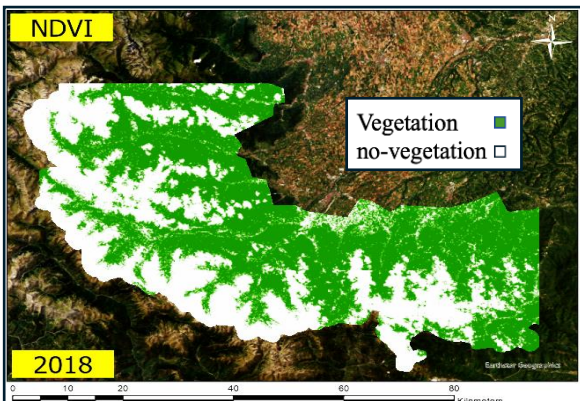


Figure 12 CORINE land cover map 2018 illustrating vegetation (green) and non-vegetation (white) coverage and the 1000 random sample points.



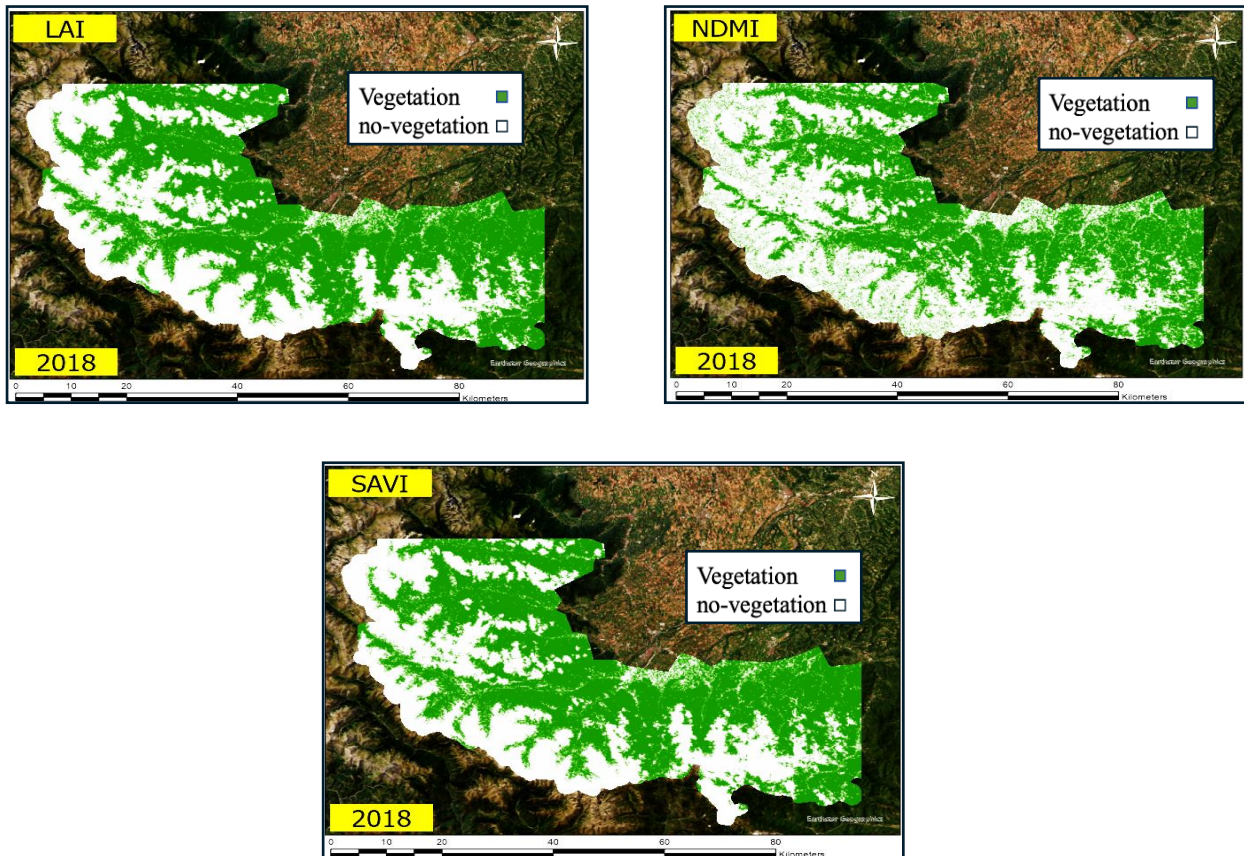


Figure 13 Different vegetation indices that have been applied for 2018

Table 2 confusion matrix of NDVI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	260	160	420	0.619048	0
2	C_1	29	550	579	0.950777	0
3	Total	289	710	999	0	0
4	P_Accuracy	0.899654	0.774648	0.8058	0.810811	0
5	Kappa	0	0	0	0	0.8

This table shows the confusion matrix of NDVI for 2018, summarizing classification accuracy, with overall accuracy at 81.08% and a kappa coefficient of 0.8.

Table 3 Confusion matrix of EVI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	200	220	420	0.47619	0
2	C_1	99	480	579	0.828325	0
3	Total	299	700	999	0	0
4	P_Accuracy	0.668896	0.685714	0.676305	0.676305	0
5	Kappa	0	0	0	0	0.31

Table 3 Confusion matrix of EVI shows the confusion matrix of EVI for 2018, summarizing classification accuracy, with overall accuracy at 67.63 % and a kappa coefficient of 0.31.

Table 4 Confusion matrix of EVI2

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	257	163	420	0.611905	0
2	C_1	32	547	579	0.944731	0
3	Total	289	710	999	0	0
4	P_Accuracy	0.888235	0.772035	0.817241	0.817241	0
5	Kappa	0	0	0	0	0.8

Table 4 shows the confusion matrix of EVI for 2018, summarizing classification accuracy, with overall accuracy at 81.72 % and a kappa coefficient of 0.8.

Table 5 Confusion matrix of GNDVI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	254	166	420	0.604762	0
2	C_1	36	543	579	0.937824	0
3	Total	290	709	999	0	0
4	P_Accuracy	0.875862	0.765183	0.812813	0.822813	0
5	Kappa	0	0	0	0	0.81

Table 5 shows the confusion matrix of GNDVI for 2018, summarizing classification accuracy, with overall accuracy at 82.28 % and a kappa coefficient of 0.81.

Table 6 Confusion matrix of KNDVI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	180	240	420	0.428571	0
2	C_1	130	449	579	0.775474	0
3	Total	310	689	999	0	0
4	P_Accuracy	0.580645	0.65166	0.624624	0.624624	0
5	Kappa	0	0	0	0	0.15

Table 6 shows the confusion matrix of KNDVI for 2018, summarizing classification accuracy, with overall accuracy at 62.46 % and a kappa coefficient of 0.15.

Table 7 Confusion matrix of MSI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	225	195	420	0.535714	0
2	C_1	73	506	579	0.87392	0
3	Total	298	701	999	0	0
4	P_Accuracy	0.754184	0.721826	0.740305	0.740305	0
5	Kappa	0	0	0	0	0.48

Table 7 shows the confusion matrix of MSI for 2018, summarizing classification accuracy, with overall accuracy at 74.03 % and a kappa coefficient of 0.48.

Table 8 Confusion matrix LAI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	258	162	420	0.614286	0
2	C_1	31	548	579	0.94646	0
3	Total	289	710	999	0	0
4	P_Accuracy	0.890996	0.772045	0.820305	0.820305	0
5	Kappa	0	0	0	0	0.81

Table 8 shows the confusion matrix of LNDVI for 2018, summarizing classification accuracy, with overall accuracy at 82.03 % and a kappa coefficient of 0.81.

Table 9 Confusion matrix of NDMI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	220	200	420	0.52381	0
2	C_1	78	501	579	0.865285	0
3	Total	298	701	999	0	0
4	P_Accuracy	0.738255	0.714592	0.726424	0.726424	0
5	Kappa	0	0	0	0	0.41

Table 9 shows the confusion matrix of NDMI for 2018, summarizing classification accuracy, with overall accuracy at 72.64 % and a kappa coefficient of 0.41.

Table 10 Confusion matrix of SAVI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	256	164	420	0.609524	0
2	C_1	33	546	579	0.942038	0
3	Total	289	710	999	0	0
4	P_Accuracy	0.887542	0.769254	0.815642	0.835642	0
5	Kappa	0	0	0	0	0.82

Table 10 shows the confusion matrix of SAVI for 2018, summarizing classification accuracy, with overall accuracy at 83.56 % and a kappa coefficient of 0.82.

3.7 Accuracy Assessment with LUCAS Data and Confusion Matrix Analysis

Since the LUCAS dataset is point-based, the latest available LUCAS survey from 2022 (Figure 14) was first downloaded to ensure the most up-to-date comparison with the study's thematic maps. In the initial phase, the attribute table of LUCAS points was matched with the first level of the CORINE Land Cover classification to ensure consistency between datasets. Using ArcGIS Pro, maps of the calculated indices were also extracted as point data. These point-based maps, along with the LUCAS points, served as input for the accuracy assessment conducted through a confusion matrix (Table 11-Table 19). This approach enabled a precise evaluation of the classification accuracy of the thematic maps for 2022 (Figure 15), comparing them to the LUCAS ground-truth data. The result was a comprehensive analysis of the accuracy of the indices, directly assessing their alignment with the most recent LUCAS survey data. There were 60 LUCAS points in the area of interest which were considered as the accuracy points.

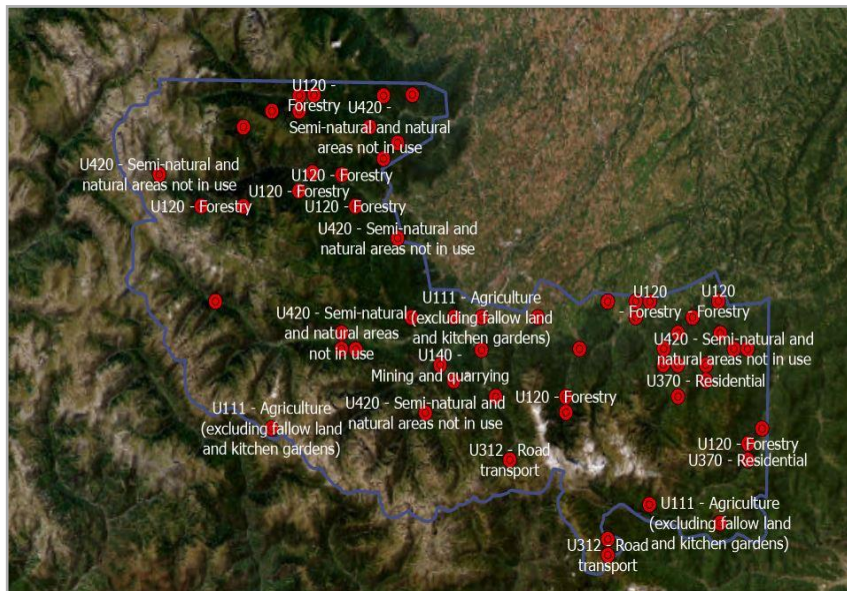
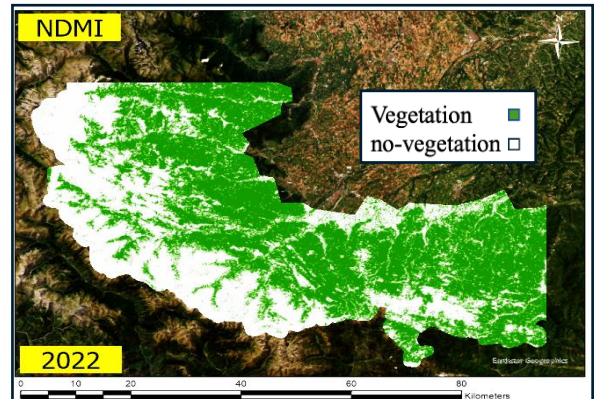
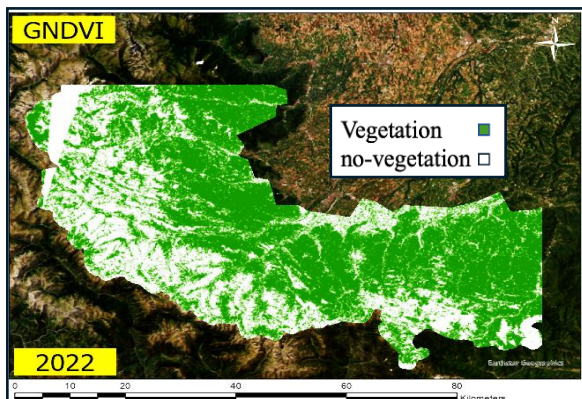
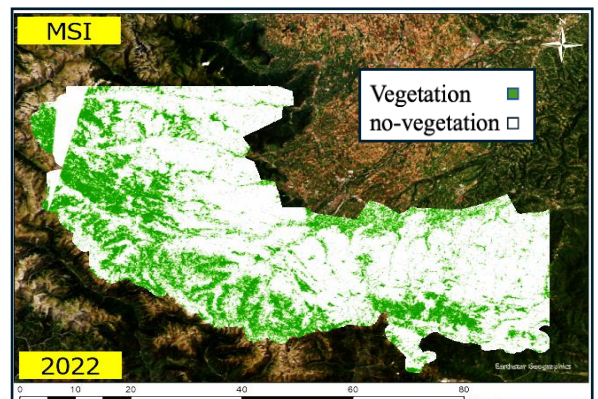
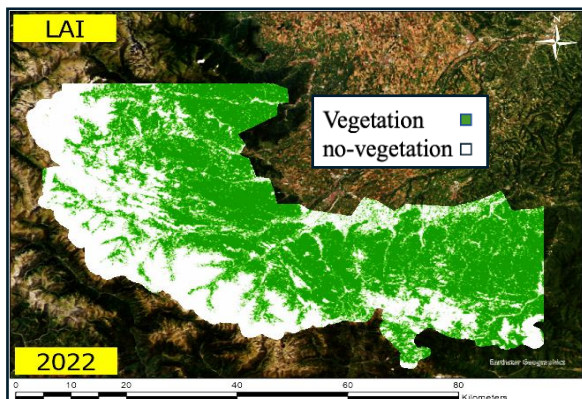
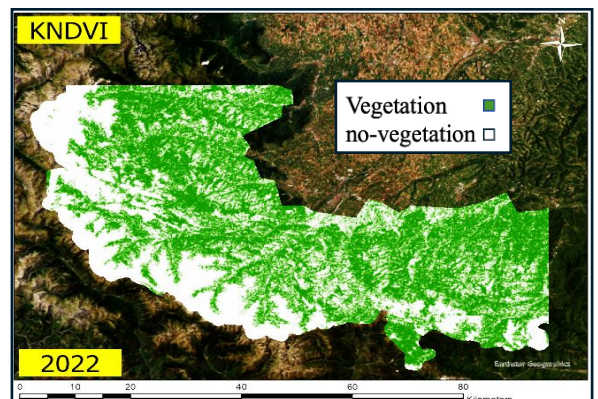
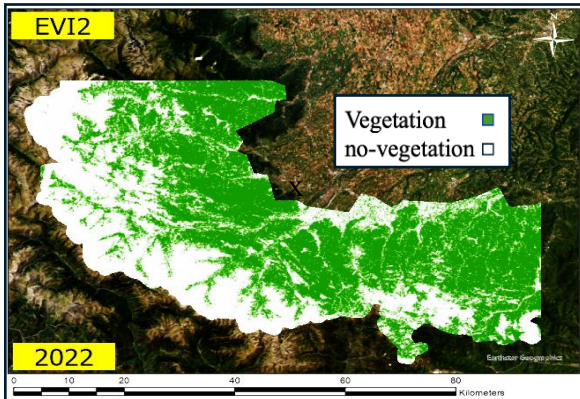
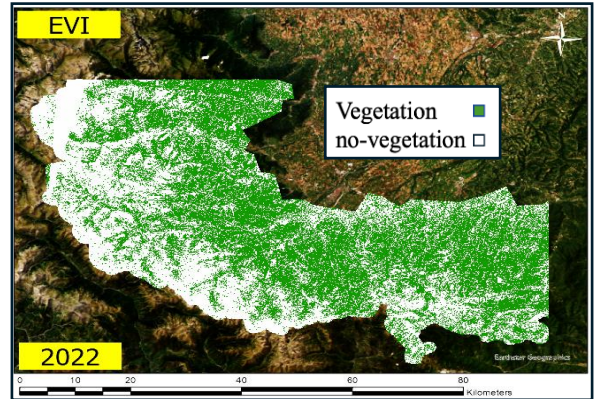
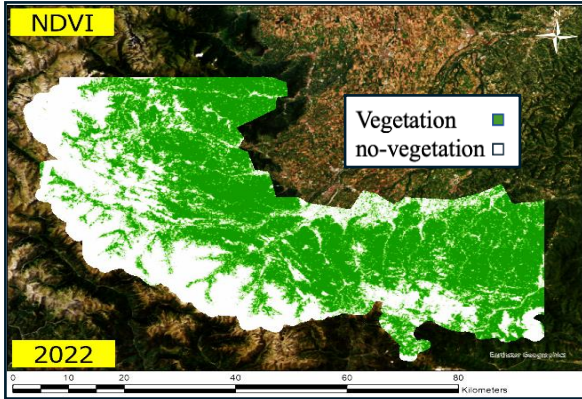


Figure 14 LUCAS points for 2022



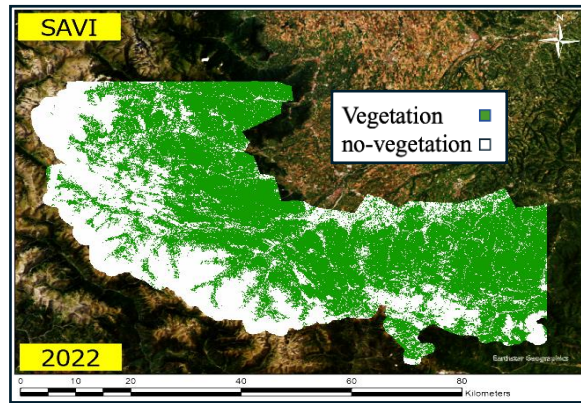


Figure 15 Applied vegetation indices for 2022

Table 11 Confusion matrix of NDVI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	30	5	35	0.857	0
2	C_1	2	23	25	0.92	0
3	Total	32	28	60	0	0
4	P_Accuracy	0.938	0.821	0.867	0.883	0
5	Kappa	0	0	0	0	0.85

Table 11 shows the confusion matrix of NDVI for 2022, summarizing classification accuracy, with overall accuracy at 88.3 % and a kappa coefficient of 0.85.

Table 12 Confusion matrix of EVI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	20	15	35	0.571	0
2	C_1	10	15	25	0.6	0
3	Total	30	30	60	0	0
4	P_Accuracy	0.667	0.5	0.583	0.583	0
5	Kappa	0	0	0	0	0.36

Table 12 shows the confusion matrix of EVI for 2022, summarizing classification accuracy, with overall accuracy at 58.3% and a kappa coefficient of 0.36.

Table 13 Confusion matrix of EVI2

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	28	7	35	0.8	0
2	C_1	3	22	25	0.88	0
3	Total	31	29	60	0	0
4	P_Accuracy	0.903	0.759	0.833	0.833	0
5	Kappa	0	0	0	0	0.81

Table 13 shows the confusion matrix of EVI2 for 2022, summarizing classification accuracy, with overall accuracy at 83.3 % and a kappa coefficient of 0.81.

Table 14 Confusion matrix of GNDVI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	28	7	35	0.8	0
2	C_1	3	22	25	0.88	0
3	Total	31	29	60	0	0
4	P_Accuracy	0.903	0.759	0.833	0.833	0
5	Kappa	0	0	0	0	0.82

Table 14 shows the confusion matrix of GNDVI for 2022, summarizing classification accuracy, with overall accuracy at 83.3 % and a kappa coefficient of 0.82.

N

Table 15 Confusion matrix of KNDVI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	20	15	35	0.571	0
2	C_1	10	15	25	0.6	0
3	Total	30	30	60	0	0
4	P_Accuracy	0.667	0.5	0.583	0.583	0
5	Kappa	0	0	0	0	0.3

Table 15 shows the confusion matrix of KNDVI for 2022, summarizing classification accuracy, with overall accuracy at 58.3 % and a kappa coefficient of 0.3.

Table 16 Confusion matrix of MSI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	25	10	35	0.714	0
2	C_1	7	18	25	0.72	0
3	Total	32	28	60	0	0
4	P_Accuracy	0.781	0.643	0.717	0.69	0
5	Kappa	0	0	0	0	0.53

Table 16 shows the confusion matrix of MSI for 2022, summarizing classification accuracy, with overall accuracy at 69 % and a kappa coefficient of 0.53.

Table 17 Confusion matrix of LAI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	30	5	35	0.857	0
2	C_1	2	23	25	0.92	0
3	Total	32	28	60	0	0
4	P_Accuracy	0.938	0.821	0.867	0.883	0
5	Kappa	0	0	0	0	0.84

Table 17 shows the confusion matrix of LAI for 2022, summarizing classification accuracy, with overall accuracy at 88.3 % and a kappa coefficient of 0.84.

Table 18 Confusion matrix of NDMI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	30	5	35	0.857	0
2	C_1	2	23	25	0.92	0
3	Total	32	28	60	0	0
4	P_Accuracy	0.938	0.821	0.867	0.883	0
5	Kappa	0	0	0	0	0.84

Table 18 shows the confusion matrix of NDMI for 2022, summarizing classification accuracy, with overall accuracy at 62 % and a kappa coefficient of 0.4.

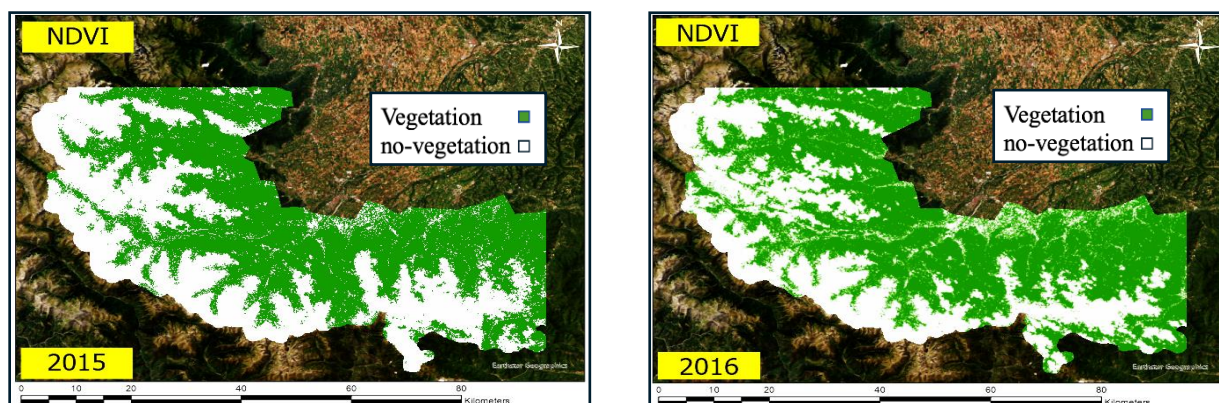
Table 19 Confusion matrix of SAVI

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	30	5	35	0.857	0
2	C_1	2	23	25	0.92	0
3	Total	32	28	60	0	0
4	P_Accuracy	0.938	0.821	0.867	0.883	0
5	Kappa	0	0	0	0	0.84

Table 19 shows the confusion matrix of NDVI for 2022, summarizing classification accuracy, with overall accuracy at 88.3% and a kappa coefficient of 0.84.

The analysis indicates that the indices NDVI, EVI2, LAI, GNDVI, and SAVI demonstrate higher accuracy when compared to both the CORINE 2018 land cover classification and the LUCAS 2022-point data. These indices consistently exhibit robust accuracy metrics, reflected in both the accuracy percentages and Kappa coefficients, aligning closely with the reference datasets. Due to their superior performance in representing vegetation cover accurately, these indices were selected for further analysis and application in this study. In Figure 16 - Figure 20 applied indices with the highest accuracies have been depicted. the vegetated areas have been shown by green and non-vegetated areas with white colours.

3.8 Analysing June Vegetation Dynamics from 2015 to 2024 Normalized Difference Vegetation Index (NDVI)



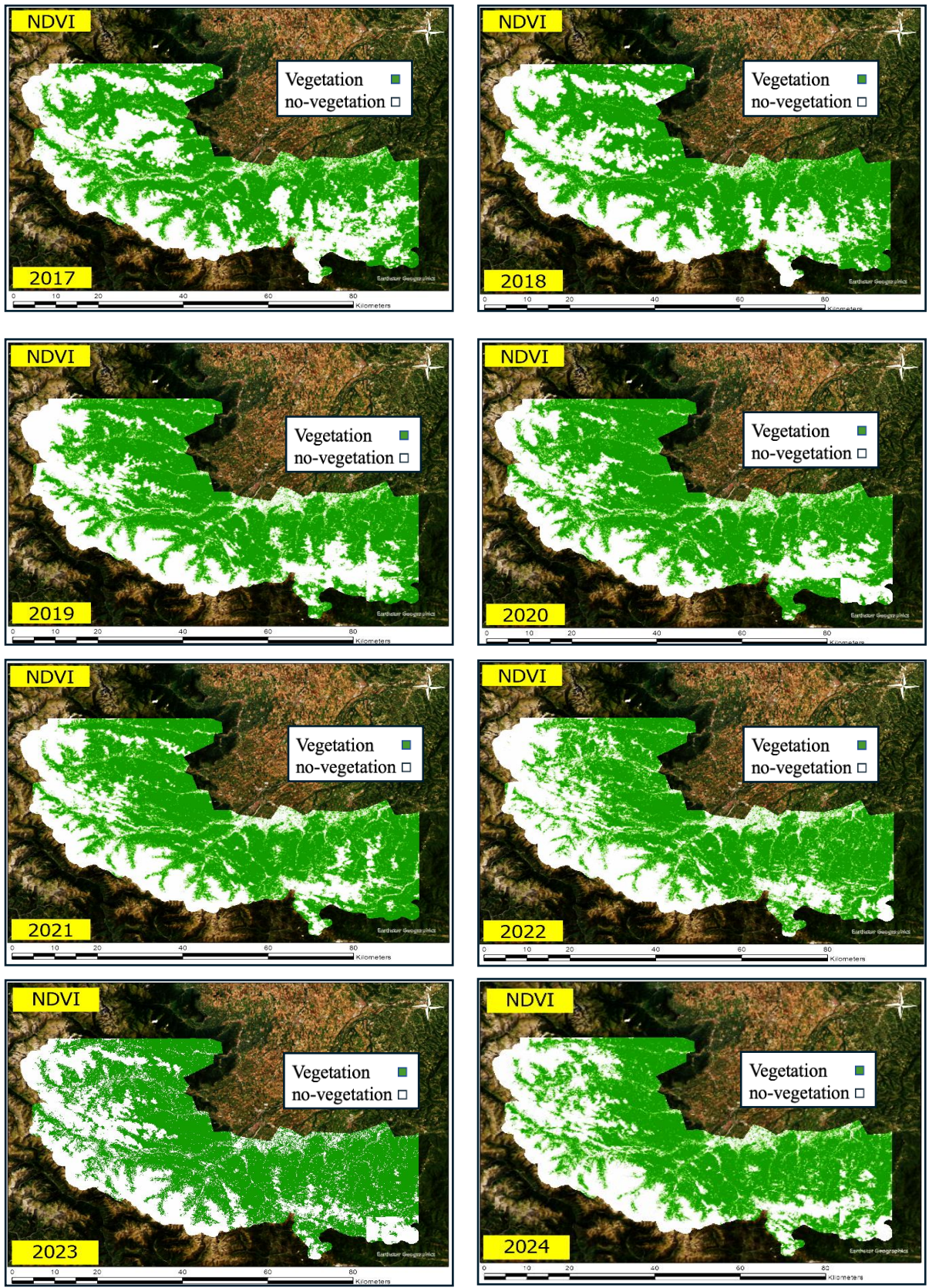
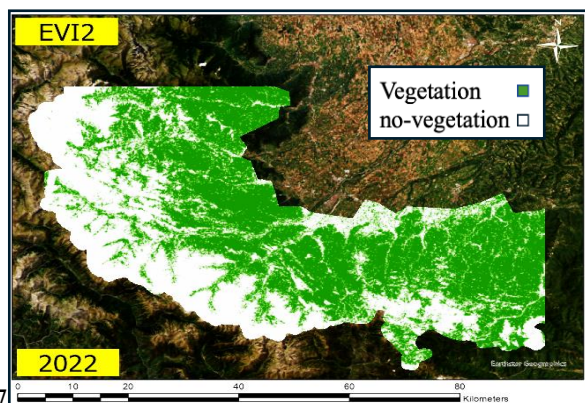
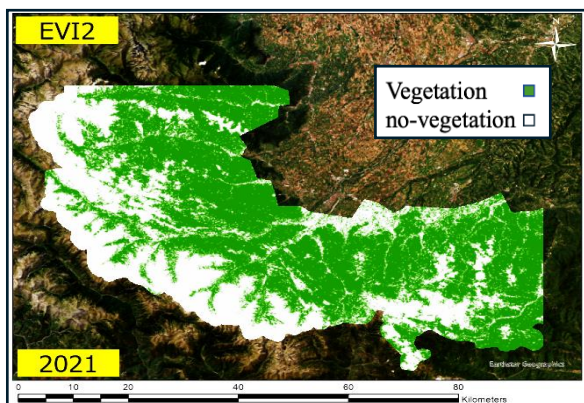
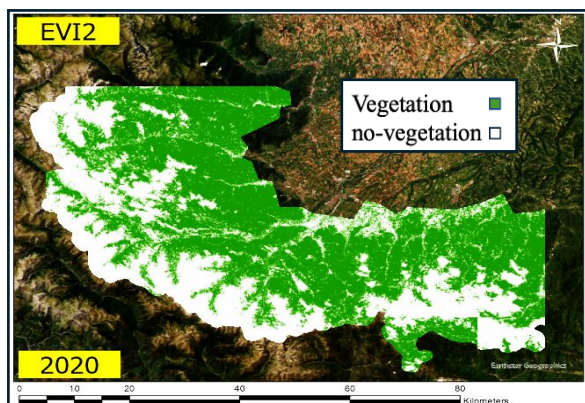
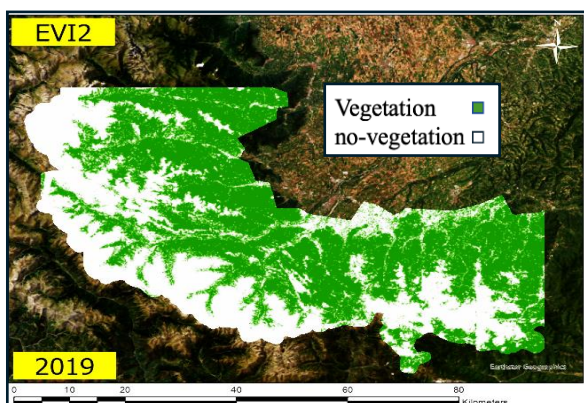
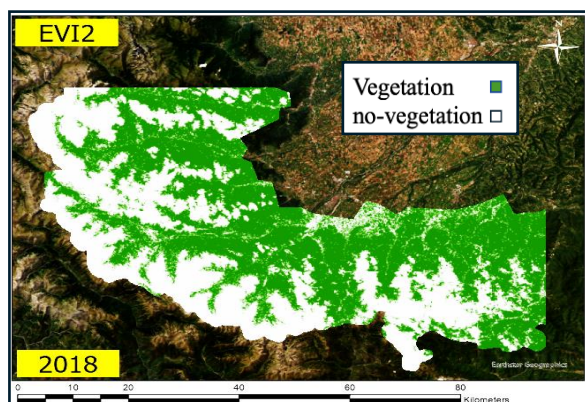
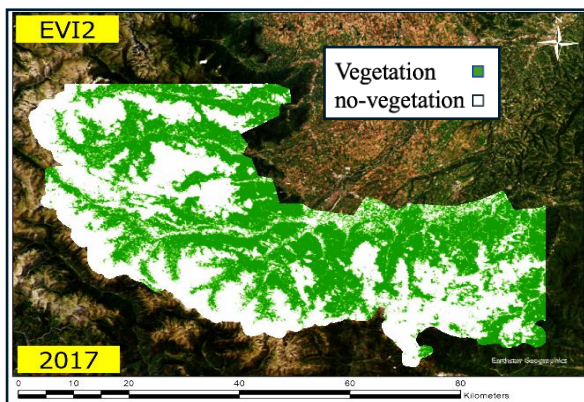
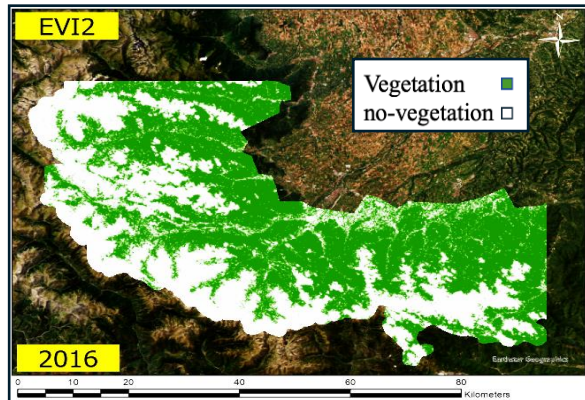
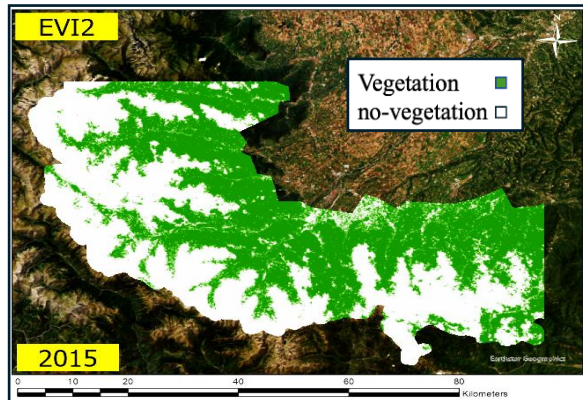


Figure 16 NDVI applied from 2015-2024 for vegetation monitoring

3.9 Analysing June Vegetation Dynamics from 2015 to 2024 Enhanced Vegetation Index (EVI2)



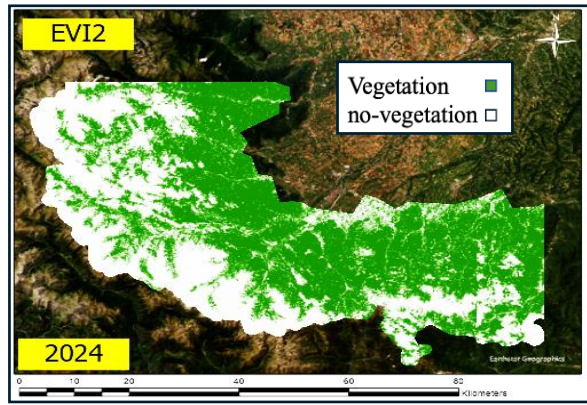
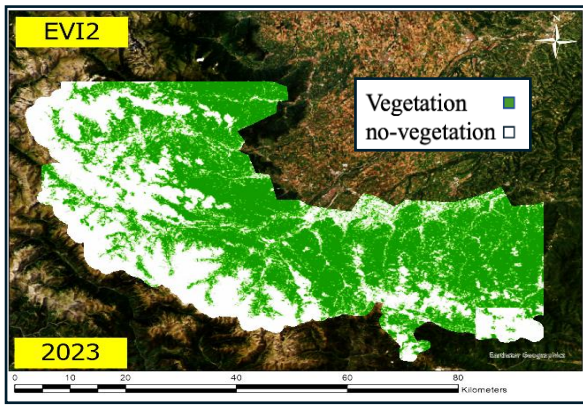
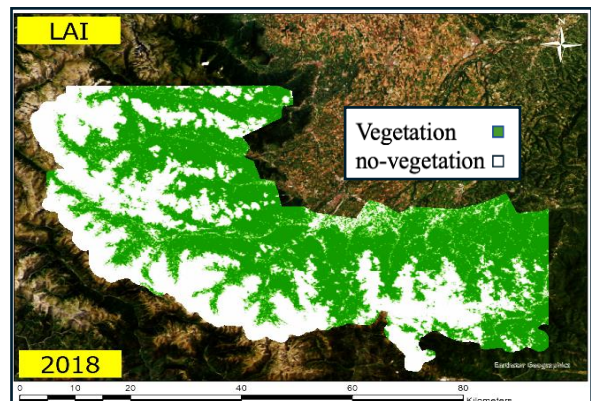
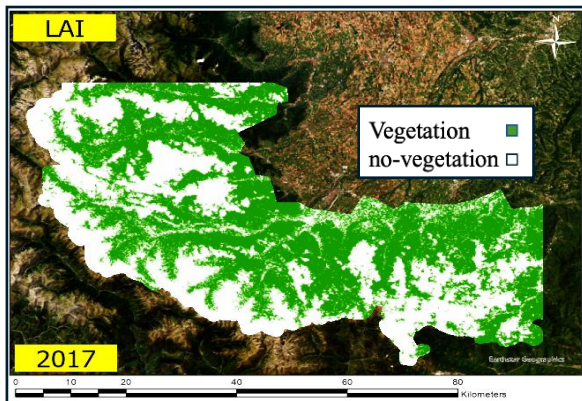
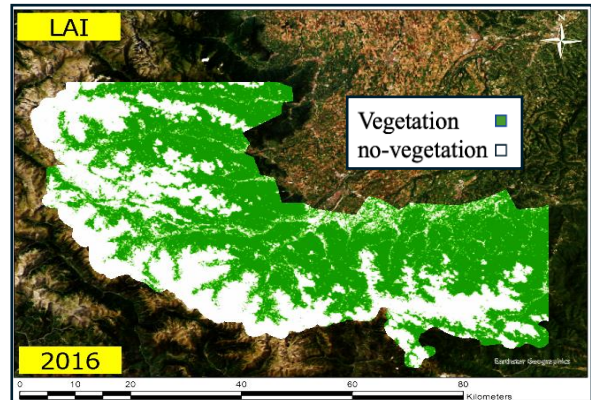
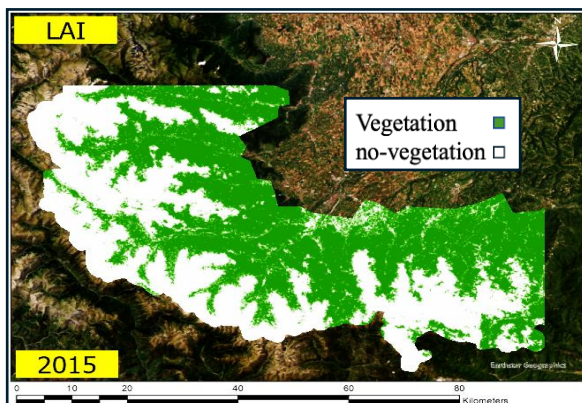


Figure 17 Applied EVI 2 from 2015 to 2024

3.10 Analysing June Vegetation Dynamics from 2015 to 2024 Using the leaf Area Index (LAI)



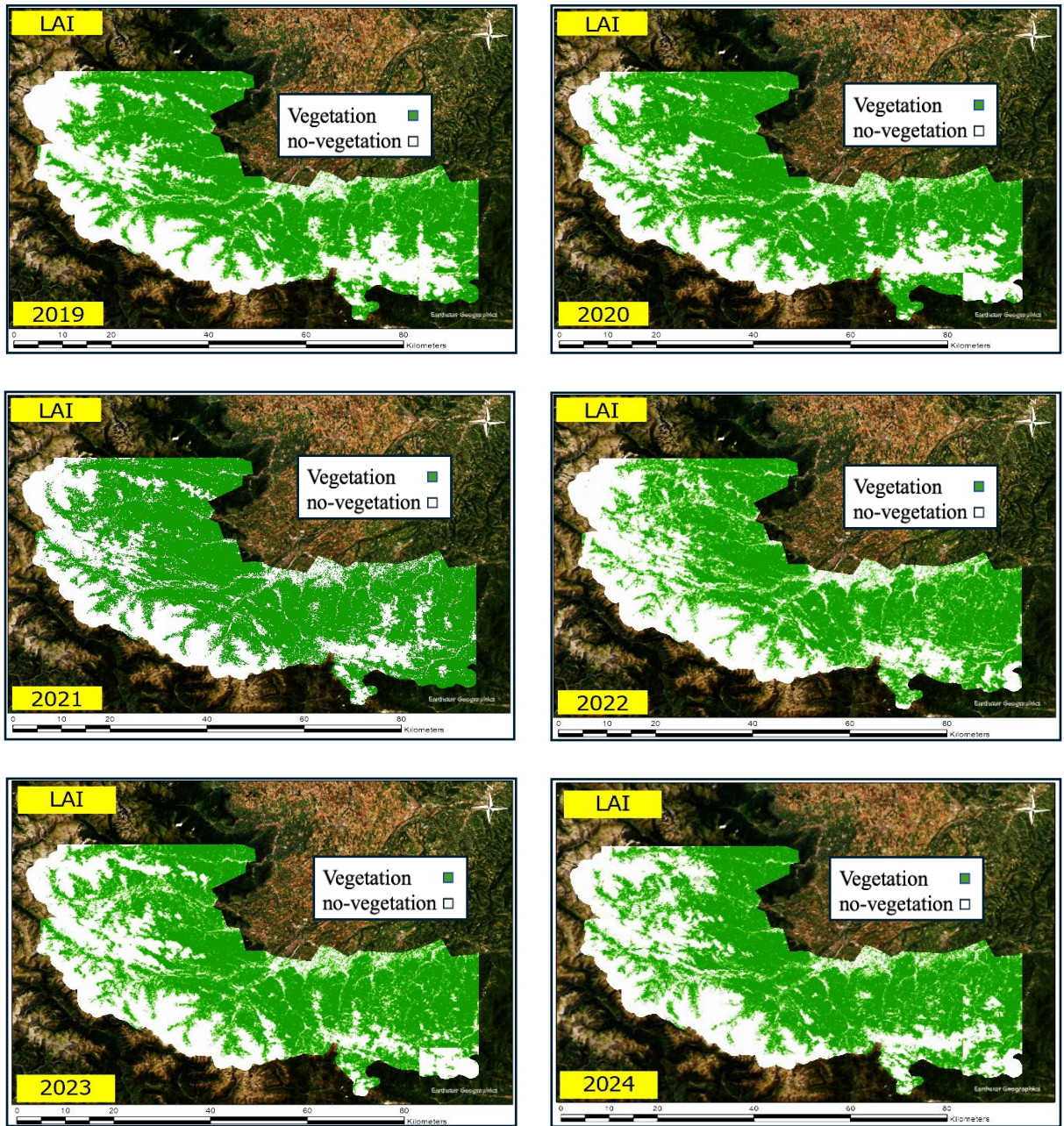
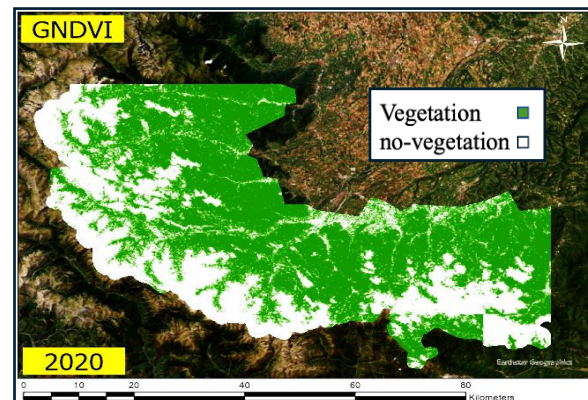
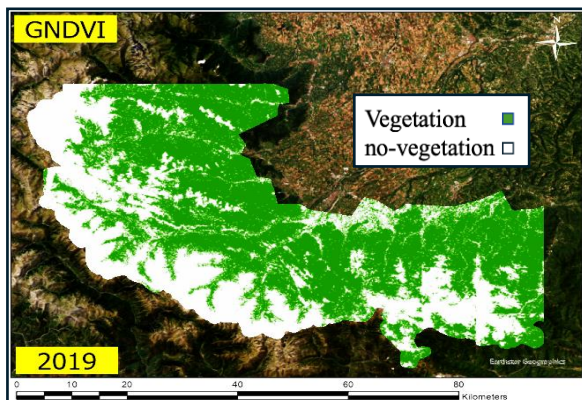
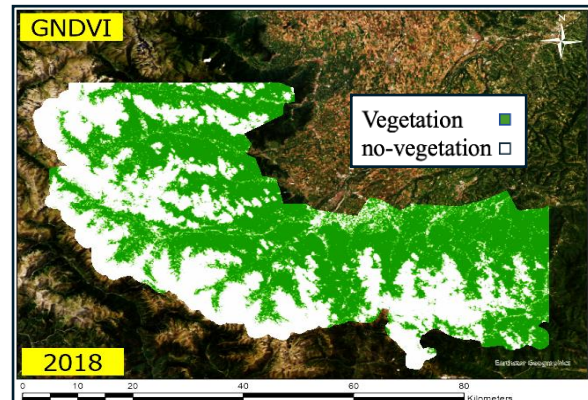
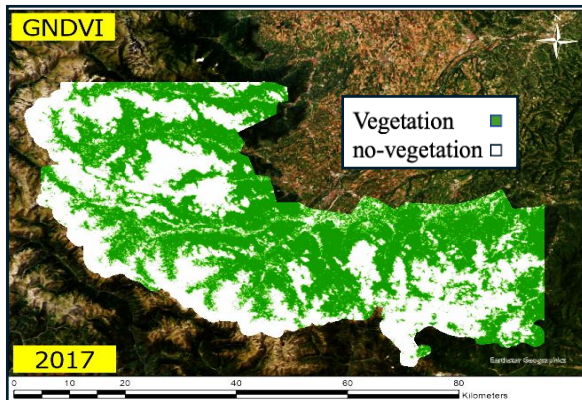
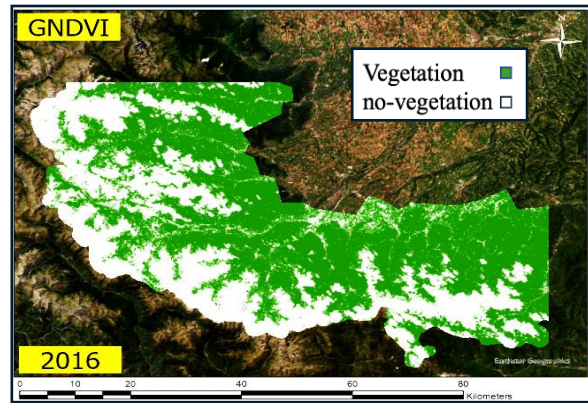
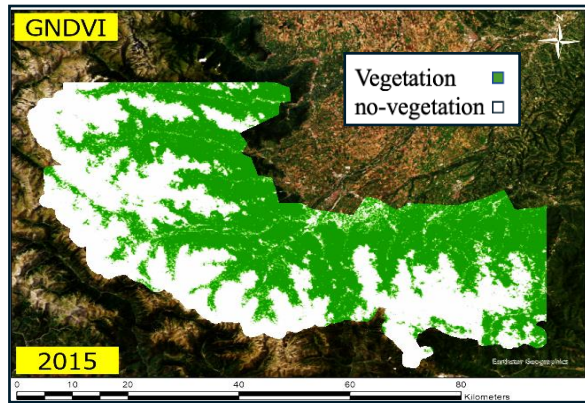


Figure 18 Applied LAI from 2015-2024

3.11 Analysing June Vegetation Dynamics Using the GREEN Normalized Difference Vegetation Index (GNDVI) from 2015 to 2024



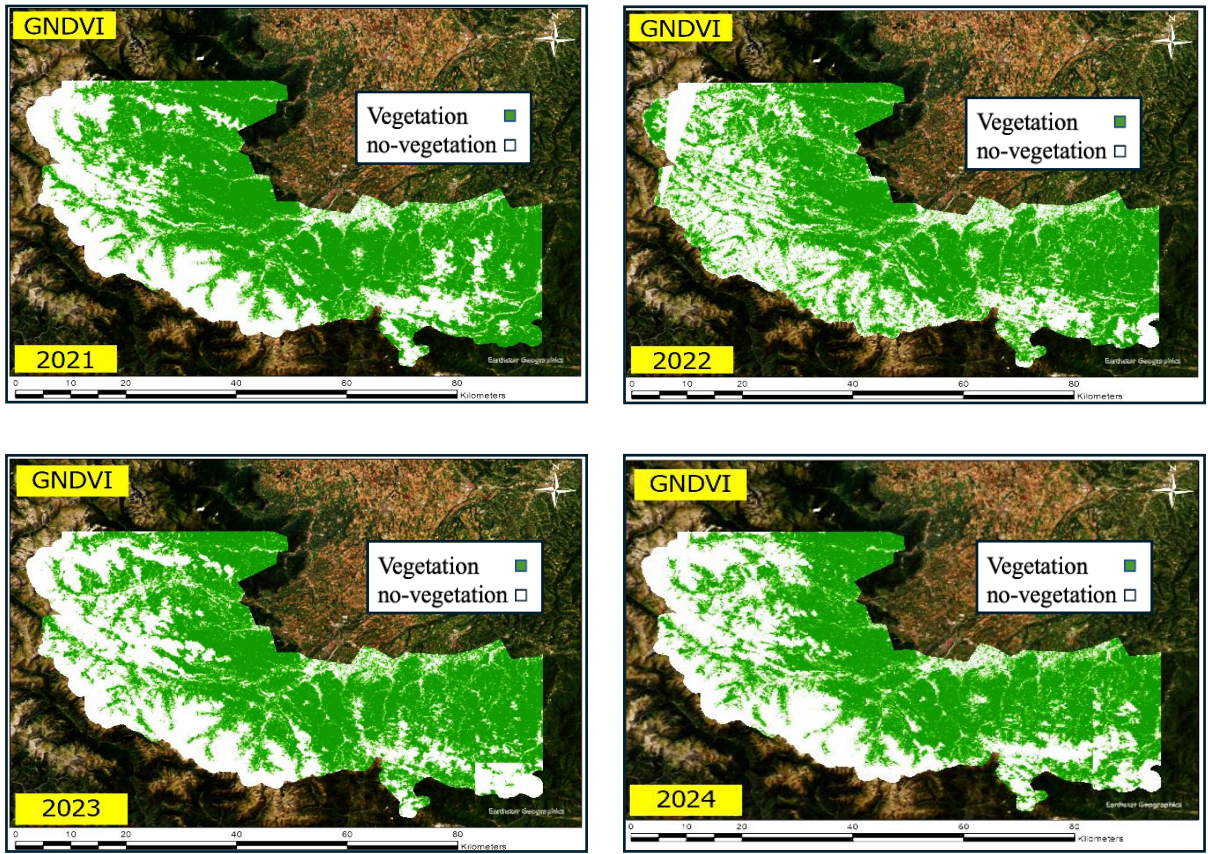
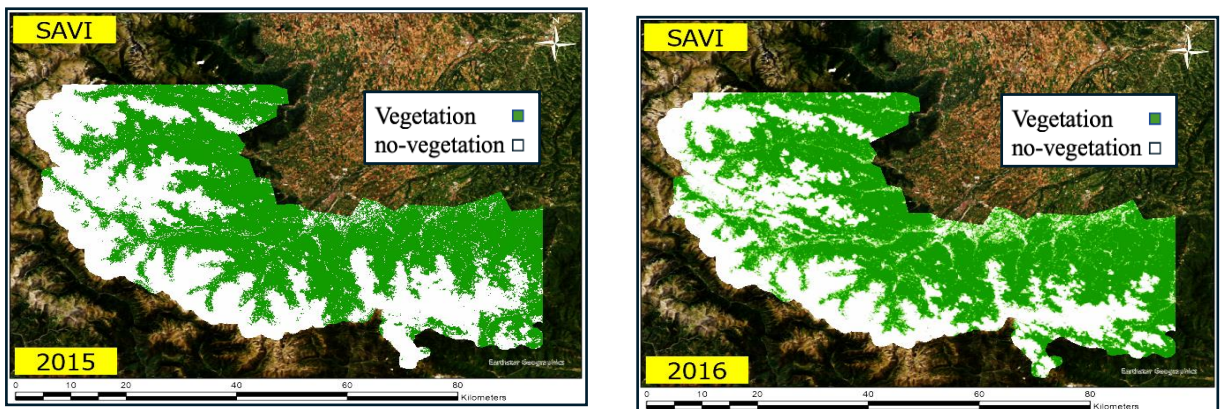


Figure 19 Applied GNDVI from 2015-2024

3.12 Analysing June Vegetation Dynamics from 2015 to 2024 Using the Soil-Adjusted Vegetation Index (SAVI)



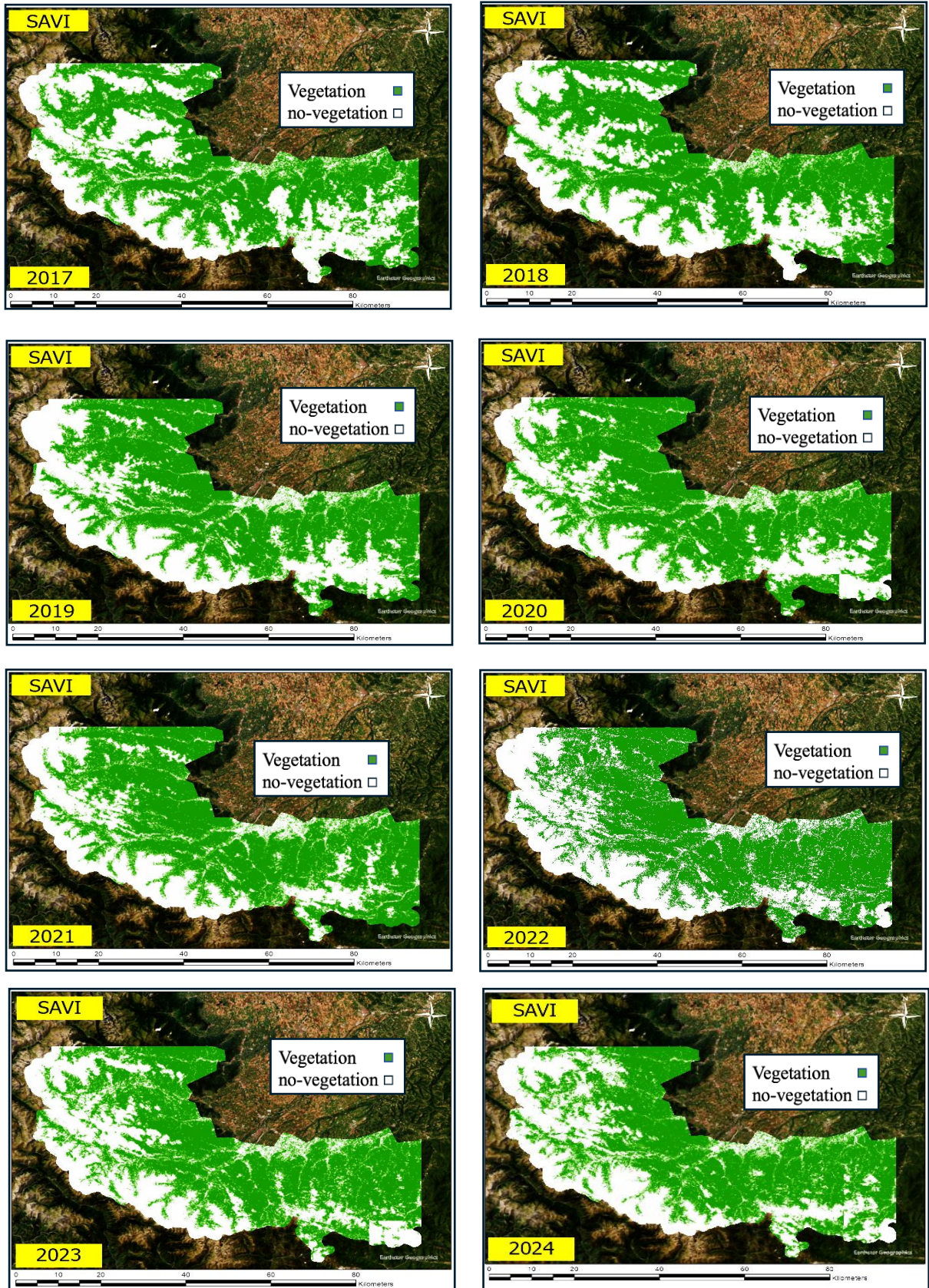


Figure 20 Applied SAVI from 2015-2024

3.13 Snow accuracy assesment using corine snow extend data

The Normalized Difference Snow Index (NDSI) is a critical tool for assessing snow cover by utilizing satellite imagery to differentiate snow from other land cover types. In the context of improving accuracy in snow extent estimation, the CORINE Land Cover (CLC) dataset plays an essential role by providing valuable reference data. CORINE serves as a benchmark for validating satellite-derived snow extent, but to enhance the precision of these assessments, it is beneficial to analyse years with contrasting snow conditions.

Focusing on the year 2018, which experienced significant snowfall, allows for a comprehensive evaluation of snow cover under conditions of higher snow availability. The abundant snow cover in this year provides a rich dataset for assessing the performance of NDSI in accurately identifying and delineating snow-covered areas. In contrast, analysing the year 2022, characterized by lower snow amounts, presents a different set of challenges and dynamics.

Additionally, April is a month frequently marked by persistent cloud cover, which complicates snow cover assessments. The clouds can obscure satellite imagery, leading to difficulties in accurately detecting and quantifying snow extent. This challenge further emphasizes the importance of analysing contrasting years to capture a broader range of conditions and improve the reliability of NDSI-derived estimates.

By contrasting the snow extent data from 2018 and 2022, a more nuanced understanding of the NDSI's performance can be developed. This dual-year approach enables the identification of potential biases and inaccuracies in snow detection algorithms when applied to different snow cover situations. Such an analysis not only strengthens the validation process against the CORINE dataset but also enhances the overall reliability of snow extent estimates, ultimately contributing to more effective snow monitoring and management practices in response to changing climate conditions. To assess the accuracy of the snow index, 1000 sample points were automatically selected using ArcGIS. The evaluation was conducted through a confusion

matrix, which revealed an overall accuracy of 84-86%. This method effectively demonstrates the reliability of the snow classification results. Figure 21 Corine snow extend 2018 and 2022 with 1000 random sample points have been shown. Figure 22 depicts the snow Dynamics from 2015 to 2024 using NDSI.

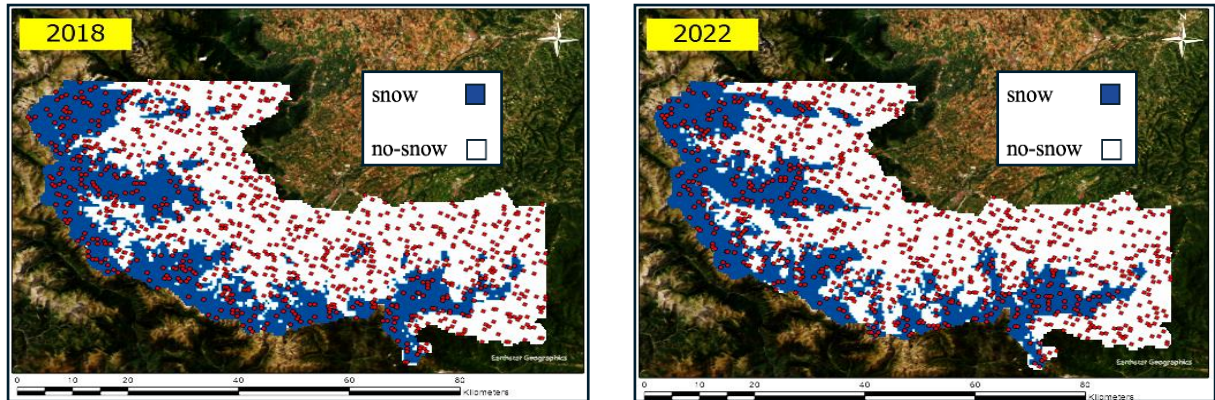
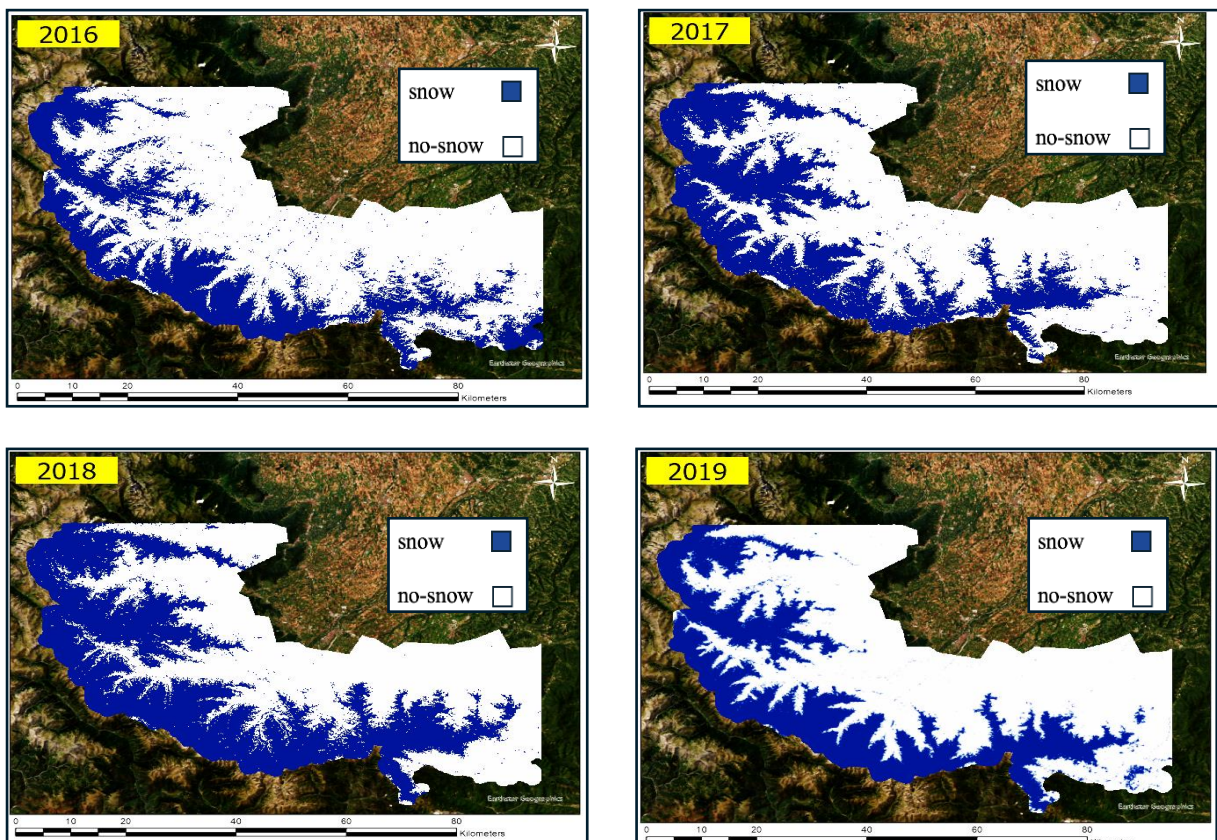


Figure 21 Corine snow extend 2018 and 2022 with 1000 random sample points

3.14 April Snow Dynamics from 2015 to 2024 using NDSI



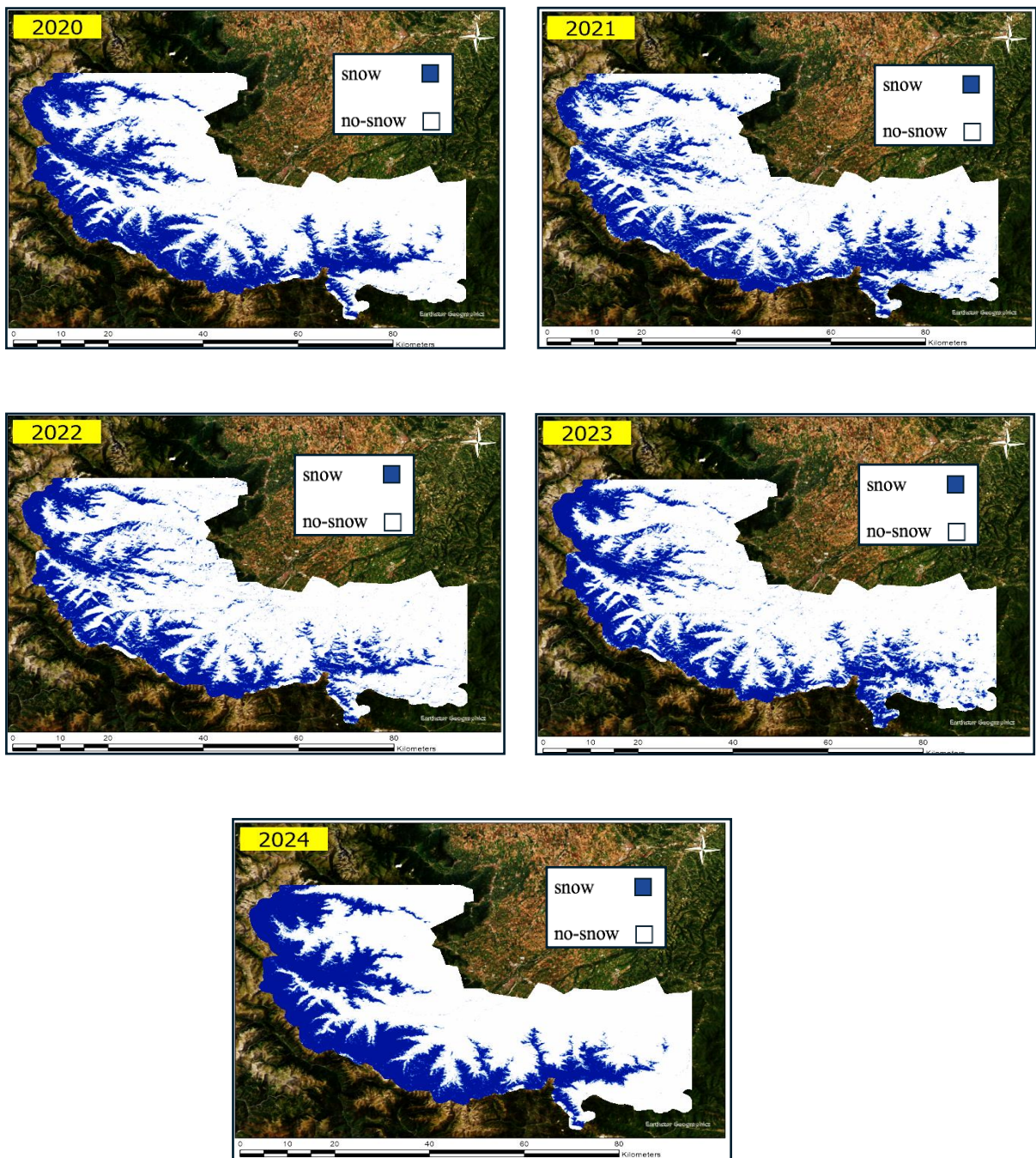


Figure 22 Applied NDSI from 2016-2024

3.15 confusion matrices of NDSI

Table 20 and Table 21 depict the confusion matrices of NDSI 2018 and 2022 respectively.

Table 20 Confusion matrix of NDSI 2018

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	259	30	289	0.884771	0
2	C_1	161	549	710	0.772045	0
3	Total	420	579	999	0	0
4	P_Accuracy	0.617	0.948	0.820	0.840	0
5	Kappa	0	0	0	0	0.82

Table 11 shows the confusion matrix of NDSI for 2018, summarizing classification accuracy, with overall accuracy at 84 % and a kappa coefficient of 0.82.

Table 21 Confusion matrix of NDSI 2022

OBJECTID	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	28	7	35	0.8	0
2	C_1	3	22	25	0.88	0
3	Total	31	29	60	0	0
4	P_Accuracy	0.903	0.759	0.833	0.833	0
5	Kappa	0	0	0	0	0.81

Table 21 shows the confusion matrix of NDSI for 2022, summarizing classification accuracy, with overall accuracy at 83.3% and a kappa coefficient of 0.81.

3.16 Land Cover Classification and Accuracy Assessment Using Google Earth Engine and ArcGIS

The land cover classification process began in 2018, with initial sampling conducted across five primary land cover classes: artificial surfaces, agricultural areas, forests and semi-natural areas, water bodies, and open spaces with little or no vegetation. Each class represented distinct land cover types crucial for a comprehensive understanding of the landscape and its usage patterns. This classification helped establish a structured basis for further analysis, ensuring that all major land types were accounted for in the mapping process.

Following the sampling, data were exported from Google Earth Engine into ArcGIS Pro. This transition allowed for a more detailed and rigorous assessment of the produced land cover map's accuracy. Within ArcGIS Pro, the land cover classification was validated against CORINE 2018 data, a widely recognized land cover dataset for Europe. To enhance accuracy, 1,000 random sampling points were automatically selected by the software, ensuring a broad and unbiased assessment of the land cover classifications. The resulting confusion matrix (Table 22) provided the accuracy of 81%. This methodological approach, combining random sampling and comparative assessment with CORINE 2018, aimed to improve the reliability and precision of the land cover map. By validating the classified data against an established standard, the process provided insight into both the accuracy of the initial classification and potential areas for refinement. For the accuracy assessment of the 2022 land cover maps, the classified map was first imported into ArcGIS and then extracted to points. This step was essential to enable a point-based comparison and to perform the confusion matrix analysis against the LUCAS 2022 ground-truth data. The resulting confusion matrix (Table 23) provided an overall accuracy of 84%, indicating a strong agreement between the Random Forest classification and the LUCAS 2022 reference points.

Corine land cover map 2018 and LUCAS points 2022

Figure 23 and Figure 24 represent the CORINE land cover map 2018 and the reclassified CORINE land cover map 2018. Figure 25 provides an overview of LUCAS 2022 points and Figure 26 shows the accuracy points selected by ArcGIS Pro.

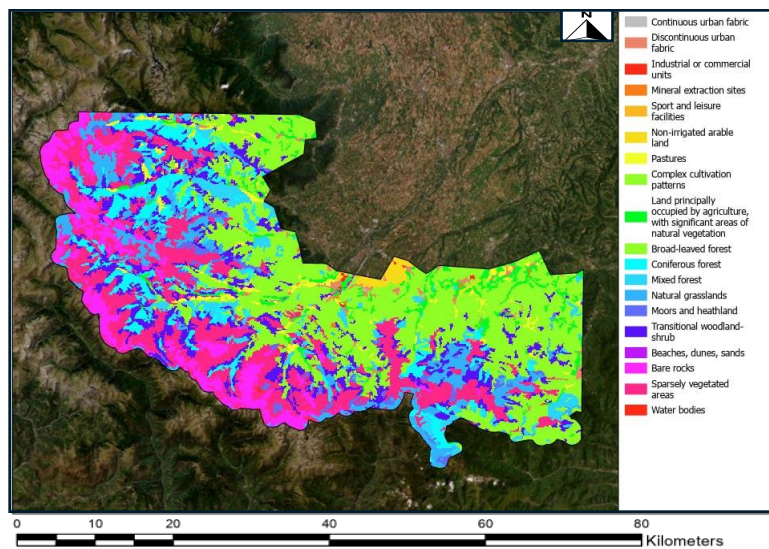


Figure 23 CORINE land cover map 2018

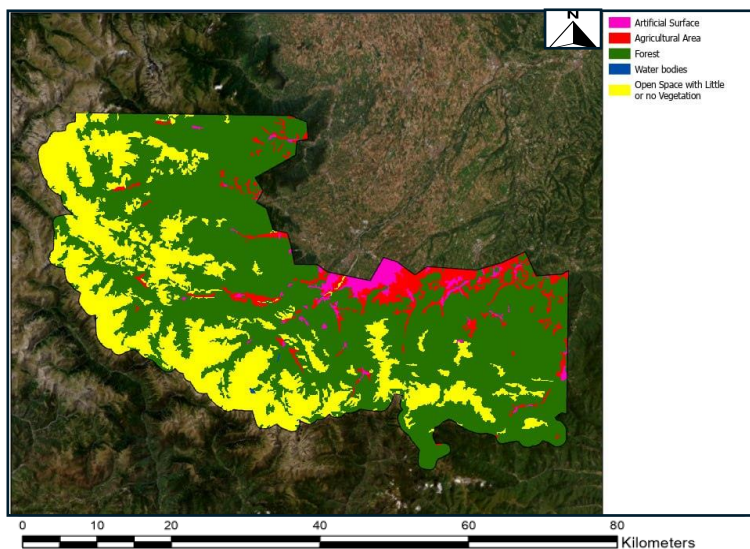


Figure 24 re-classified CORINE land cover map 2018

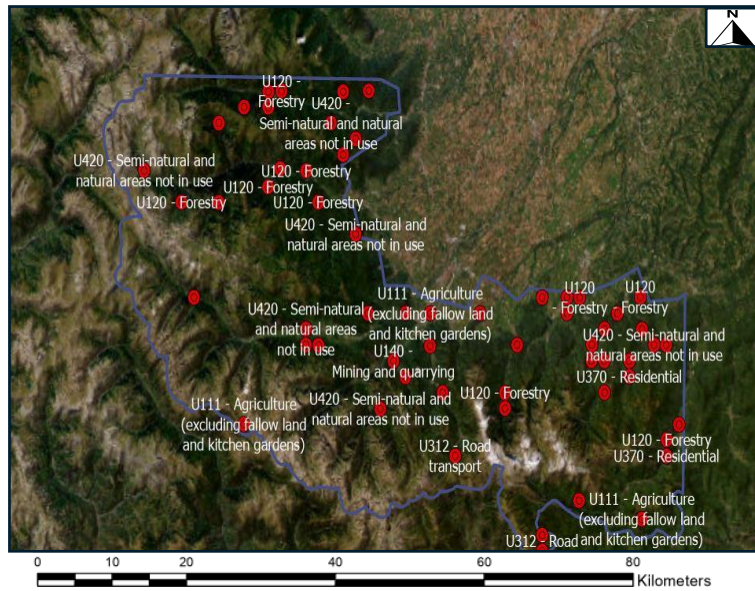


Figure 25 LUCAS 2022 POINTS

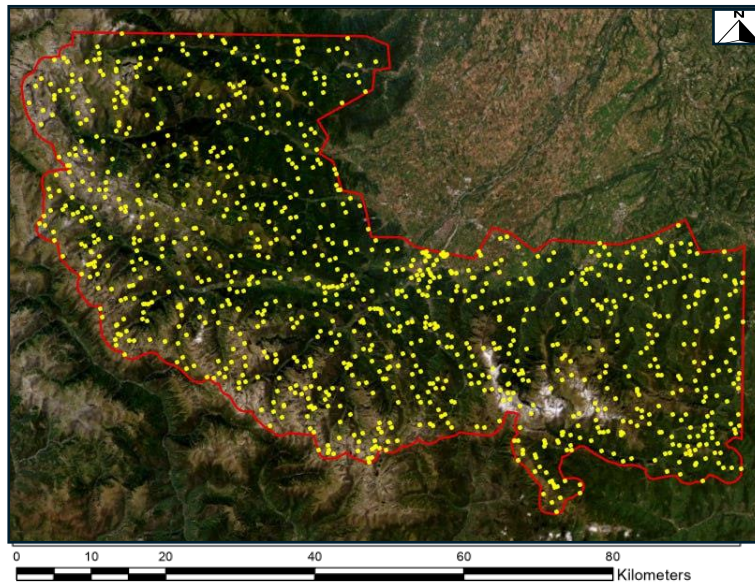


Figure 26 Accuracy points by ArcGIS

3.17 Confusion matrices for thematic maps of 2018 and 2022

- C_0 = Open spaces with little or no vegetation
- C_1 = Agricultural Areas
- C_2 = Forests and Seminatural area
- C_3 = Water Bodies
- C_4 = Artificial surfaces

Table 22 Confusion matrix of thematic map 2018 and CORINE land cover map 2018

OBJECTID	ClassValue	C_0	C_1	C_2	C_3	C_4	Total	U_Accuracy	Kappa
1	C_0	145	10	6	5	4	170	0.85	0
2	C_1	10	135	8	5	4	162	0.83	0
3	C_2	8	6	140	7	6	167	0.84	0
4	C_3	6	5	6	125	7	149	0.84	0
5	C_4	4	6	7	8	127	152	0.84	0
6	Total	173	162	167	150	147	999	0	0
7	P_Accuracy	0.84	0.83	0.84	0.83	0.86	0	0.84	0
8	Kappa	0	0	0	0	0	0	0	0.81

Table 22 shows the confusion matrix of land cover thematic maps for 2018, summarizing classification accuracy, with overall accuracy at 84% and a kappa coefficient of 0.81.

Table 23 Confusion matrix of thematic 2022 and LUCAS points 2022

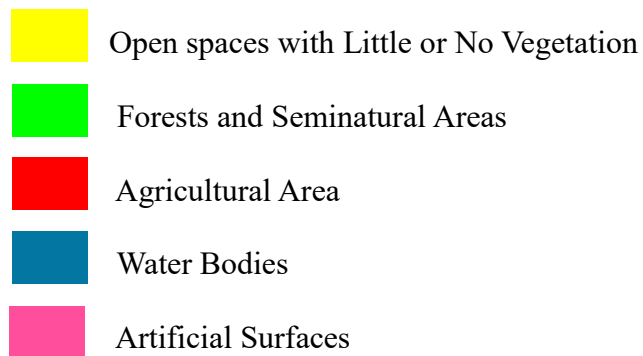
OBJECTID	ClassValue	C_0	C_1	C_2	C_3	C_4	Total	U_Accuracy	Kappa
1	C_0	10	1	0	0	1	12	0.83	0
2	C_1	1	8	0	1	0	10	0.8	0
3	C_2	0	1	10	0	0	11	0.91	0
4	C_3	0	0	1	8	1	10	0.8	0
5	C_4	1	0	0	1	9	11	0.82	0
6	Total	12	10	11	10	11	60	0	0
7	P_Accuracy	0.83	0.8	0.91	0.8	0.82	0	0.85	0
8	Kappa	0	0	0	0	0	0	0	0.84

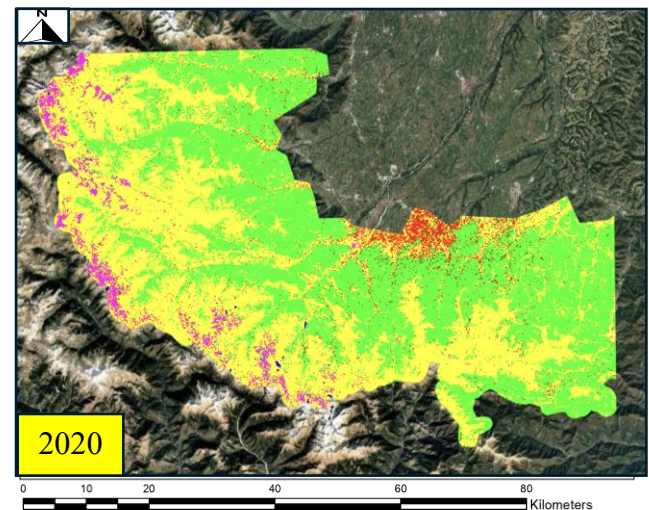
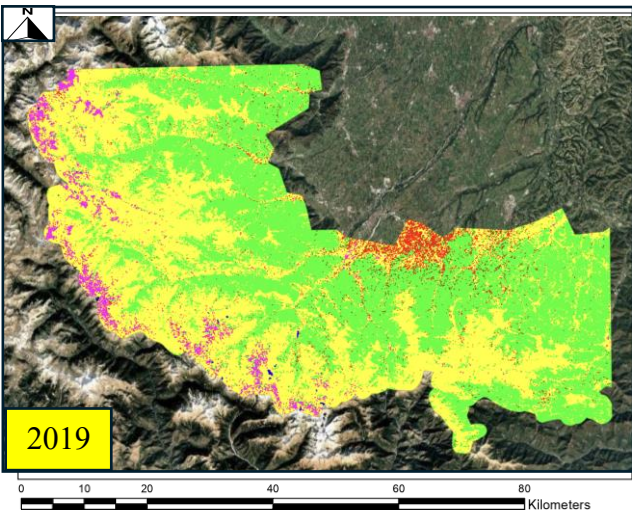
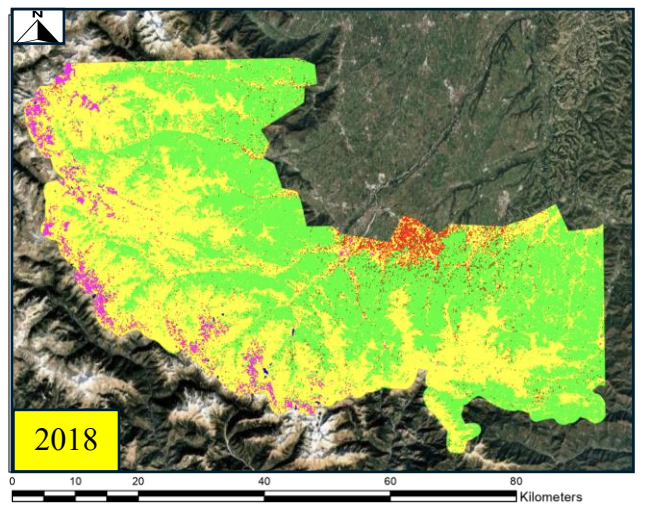
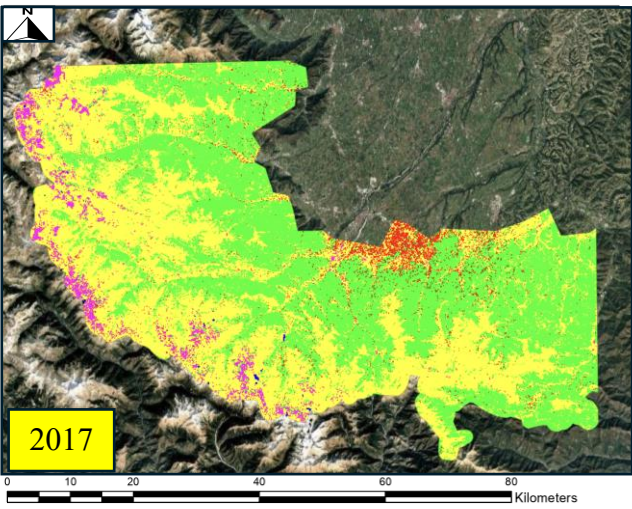
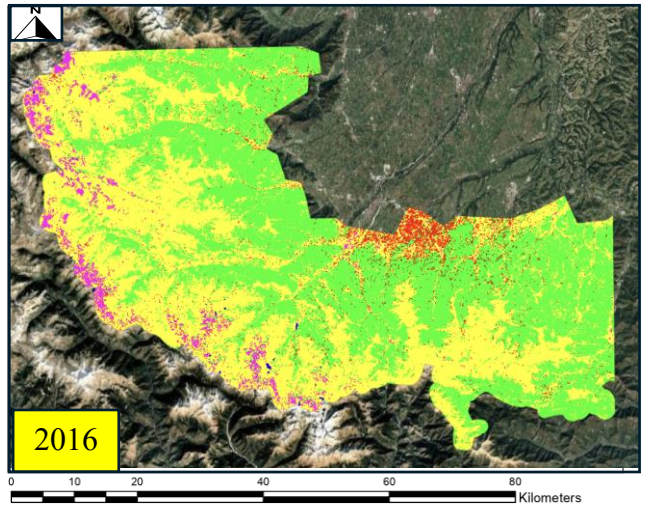
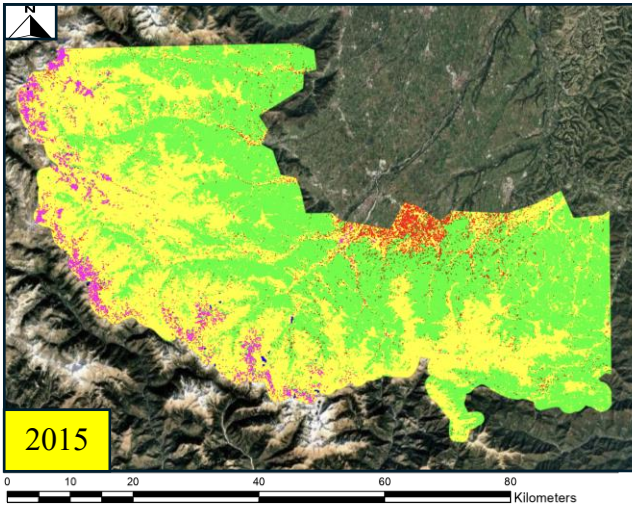
Table 23 shows the confusion matrix of land cover thematic maps for 2022, summarizing classification accuracy, with overall accuracy at 85 % and a kappa coefficient of 0.84.

3.18 land cover maps from 2015-2024

The land cover maps presented in Figure 27 illustrate the classification of the study area from 2015 to 2025, with the data organized into five distinct land cover classes. These classes represent various types of land use that were analyzed across the given period. The classification process was carried out using Random forest method as explained in chapter 2 .

Legend of the land cover thematic maps





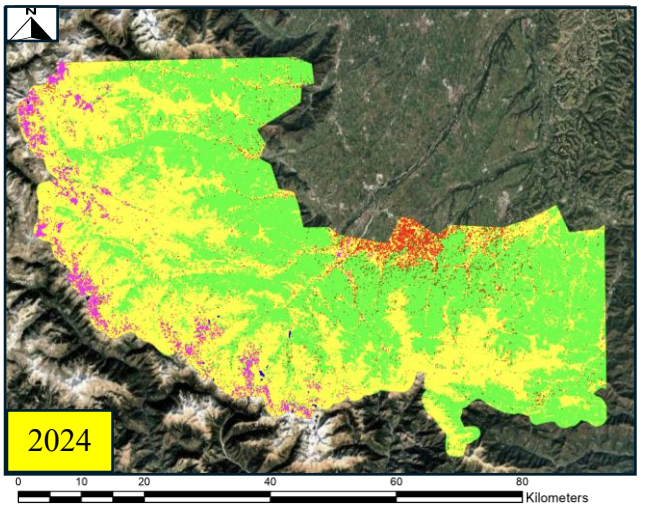
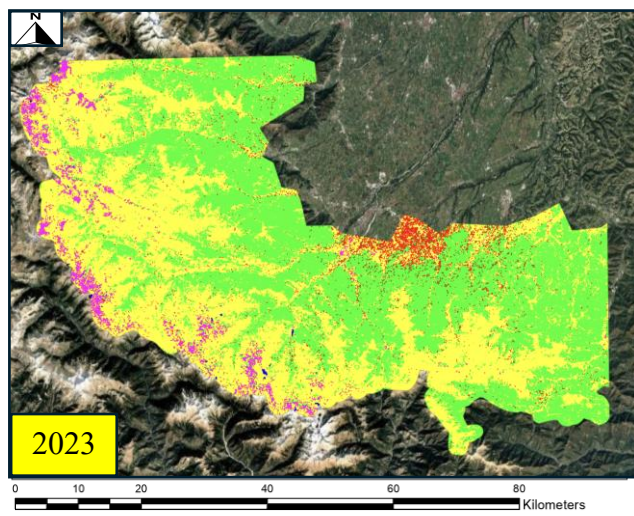
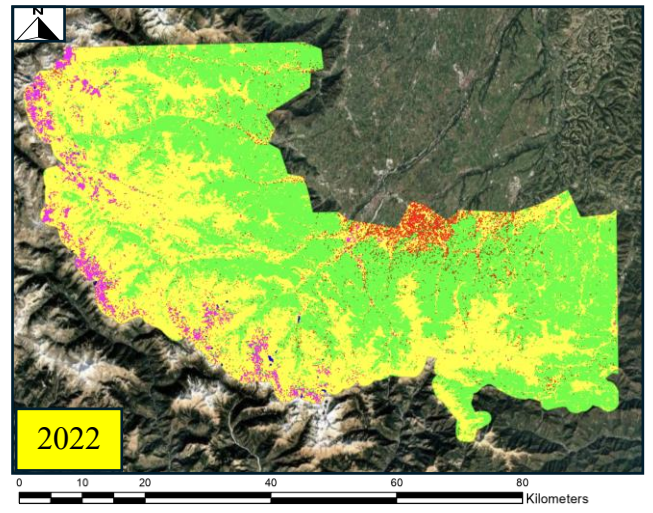
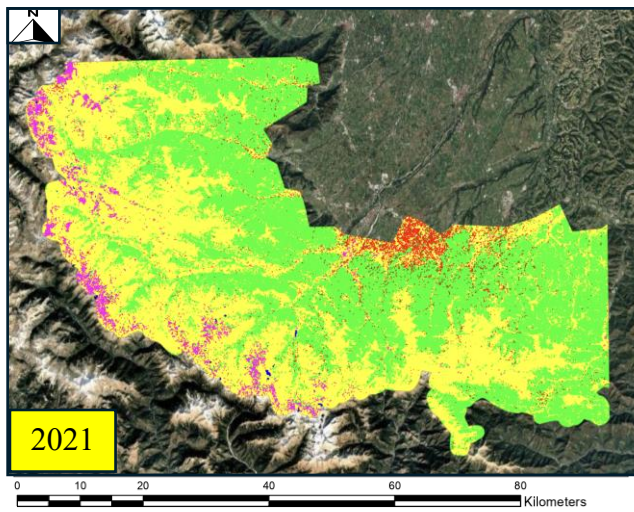


Figure 27 Thematic maps from 2015-2024

4 Discussion

4.1 Vegetation Trends in the Protected Area of Maritime: Evidence of Growth from 2015 to 2024

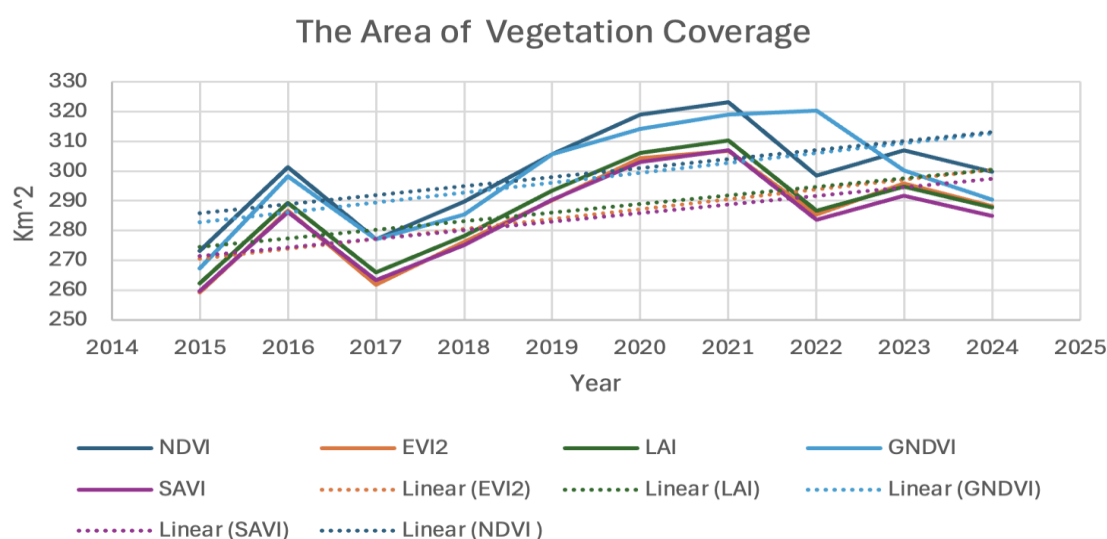
Vegetation trends across all indices indicate that during the period from 2015 to 2024, there has been a significant increase in vegetation cover within the Maritime Alps. This suggests a positive trend in vegetation health, density, or extent over the years, potentially driven by natural factors or changes in environmental conditions.

In the Table 24 and Table 25 this trend is clearly illustrated, highlighting the year-by-year changes and emphasizing the overall increase in vegetation indices across the study area.

Table 24 Vegetation Coverage in Km² calculated by each index

Year	NDVI	EVI2	LAI	GNDVI	SAVI
2015	273	259	262	267	273
2016	301	287	289	298	301
2017	277	262	266	277	277
2018	290	276	278	285	290
2019	306	290	293	306	306
2020	319	304	306	314	319
2021	323	307	310	319	323
2022	299	285	287	320	299
2023	307	296	295	300	307
2024	300	288	288	290	300

Table 25 Vegetation coverage changes in km²



4.2 Snow Trend in the Protected Area of Maritime: Evidence of decline from 2016 to 2024

The snow index shows a general decreasing trend from 2016 to 2024 in the Maritime Alps. This decline reflects a reduction in snow cover over the years, which could be attributed to factors such as rising temperatures or changes in precipitation patterns in the region. The overall downward trend highlights a shift in the snow dynamics of the area.

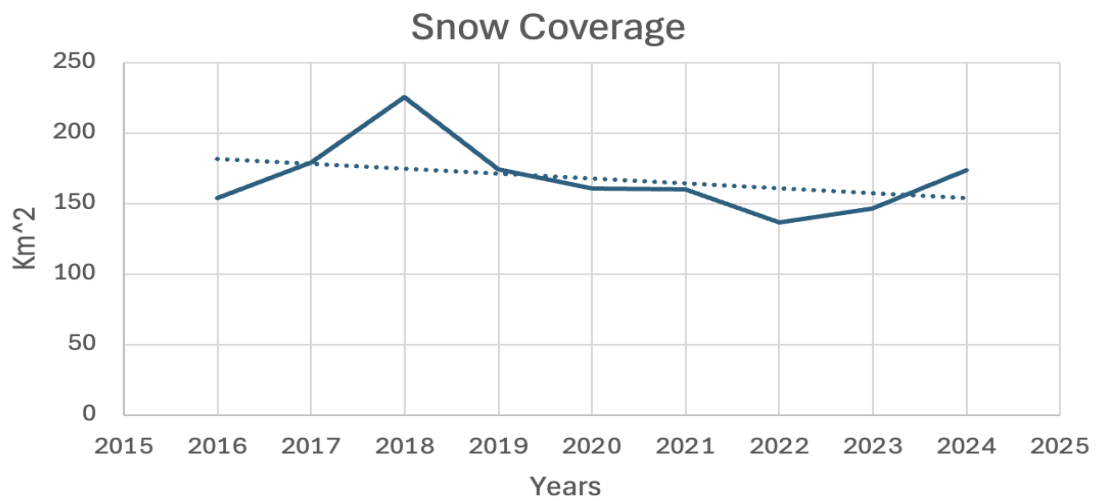
However, there were slight increases in snow cover observed in 2018 and 2024. These temporary fluctuations may be linked to specific climatic conditions or anomalies in those years. Despite these brief periods of increase, the overall trend remains one of decrease, suggesting a longer-term reduction in snow coverage in the Maritime Alps.

In the Table 26 and Table 27 snow coverage corresponding to each year is shown, providing a detailed overview of the snow index trends over time.

Table 26 Snow coverage for each year in km²

Year	NDSI
2015	
2016	154
2017	179
2018	226
2019	174
2020	161
2021	160
2022	136
2023	146
2024	173

Table 27 Snow Coverage changes in km²



4.3 Challenges and Solutions in Distinguishing Bare Rock from Artificial Surfaces in Satellite Image Classifications

In satellite image classifications, it is not uncommon for bare rock and artificial surfaces to be misclassified. This confusion arises because these surfaces often share similar reflectance characteristics, particularly in optical bands, leading to overlap in spectral signatures. This is a well-documented limitation when using multispectral imagery, where spectral similarities can result in misclassification, especially in mountainous or arid regions where bare rock is prevalent (Copernicus Programme, 2022)

To improve classification accuracy, Synthetic Aperture Radar (SAR) and other advanced remote sensing techniques have been proposed, as they offer different perspectives by measuring surface roughness and other physical properties rather than solely relying on reflectance. SAR, for instance, can effectively distinguish between smooth surfaces, such as artificial structures, and rougher natural features, like rock formations, by capturing texture and structure details in high resolution. Recent studies by NASA and the European Space Agency (ESA) suggest that combining SAR with optical imagery significantly enhances classification accuracy in complex landscapes, particularly for distinguishing between natural and artificial surfaces (ESA, 2023).

4.4 Comparison of CORINE 2018 and LUCAS 2022: Data Structure, Accuracy, and Applicability in Land Cover Classification

The comparison between CORINE Land Cover 2018 and the LUCAS 2022 dataset highlights some key differences in data structure and applicability. CORINE provides a consistent, continuous land cover map, offering a comprehensive representation of land use across large areas. It covers broad-scale information and is ideal for regional and national-level analyses, providing detailed classifications for various land types. This makes CORINE a valuable resource for understanding general trends in land cover over time. On the other hand, LUCAS is a point-based dataset, meaning it consists of field measurements at specific locations rather than providing a continuous map. For our area of interest, LUCAS 2022 only contains 60 points, which is quite limited for a detailed analysis, especially when compared to the broader scope of CORINE. Despite LUCAS being updated two years later than CORINE (2020 vs. 2018), the point-based nature of LUCAS means that it cannot provide the same level of spatial continuity or coverage as CORINE. In our analysis, when comparing the data to LUCAS 2022, we reached a higher accuracy, particularly in certain localized areas. However, while LUCAS provides more recent data, CORINE 2018 remains the more reliable source for large-scale land cover classification in our study region. Its continuous mapping approach ensures a more accurate representation of the area making it a more suitable dataset for our analysis despite LUCAS's more recent update. Thus, while both datasets are valuable, CORINE 2018's broader coverage and consistency make it the preferred choice for this particular study.

4.5 Pros and Cons of the Applied Methods

In Table 28, the advantages and limitations of the methodologies and approaches applied throughout this thesis are outlined. By summarizing the pros and cons, the table provides a clear understanding of the strengths of the applied methods and identifies areas that may benefit from further refinement or alternative approaches in future studies.

Table 28 Summary of the pros and cons of the applied method.

Pros	Cons
<ul style="list-style-type: none"> • Low computational effort and time required while using GEE for computation of all vegetation and snow indices. as well as Random Forest classification which is a built-in function in GEE. 	<ul style="list-style-type: none"> • The effect of the weather & cloud coverage. Weather conditions and cloud coverage significantly impact the quality and usability of satellite imagery. Dense clouds can obscure the surface, reducing the ability to capture accurate information about land cover, snow, or vegetation. This limitation is particularly critical in regions or seasons with frequent cloud cover, such as mountainous areas.
<ul style="list-style-type: none"> • The Otsu method, an automatic thresholding technique, enables further processing across different time periods. 	<ul style="list-style-type: none"> • Limitation of spatial resolution. While the 10-meter resolution is sufficient for detecting fine-scale features such as vegetation patterns or snow, it may not capture very small objects or fine-grained details, such as narrow water bodies or small patches of vegetation.
<ul style="list-style-type: none"> • The desired levels of accuracies for indices and land cover maps. Generally, accuracy levels between 80% and 90% are considered acceptable for most remote sensing applications, indicating a strong agreement between classified results and reference data. 	<ul style="list-style-type: none"> • Limitation of spectral resolution. The absence of very narrow spectral bands can reduce the accuracy of distinguishing between similar surface types, such as differentiating snow from bright bare soil or sparse vegetation, particularly in complex environments.

	<ul style="list-style-type: none">• The relatively low temporal resolution of Sentinel-2. <p>Sentinel-2A launched on June 23, 2015, and Sentinel-2B on March 7, 2017, can pose challenges in capturing rapid changes in snow and vegetation. To enhance the frequency of observations and improve the monitoring of such dynamic phenomena, complementary satellite data, such as from Landsat or MODIS, can be utilized.</p>
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5 Conclusion

Over the past decade, the Maritime Alps region has experienced notable changes across agricultural areas, vegetation, artificial surfaces, water bodies, and snow cover, primarily driven by climate change and evolving land-use practices.

5.1 Vegetation Growth

Vegetation in the region has expanded significantly, largely due to the combination of warmer temperatures and the gradual abandonment of high-altitude agricultural lands. This abandonment has facilitated “re-wilding,” where these areas are naturally overtaken by shrubs, grasses, and young trees. Biagi et al. (2019) report that increasing temperatures support the growth of vegetation at previously colder, higher elevations, while NDVI data from 2015 onward indicates a marked increase in vegetation density in these abandoned fields. Galland et al. (2020) attribute the reforestation trends to reduced agricultural use, allowing natural succession to proceed, with forest and shrub cover replacing former farmlands.

5.2 Agricultural Areas

Agricultural land has generally decreased over the past decade, with cultivated areas shifting to higher altitudes where warmer temperatures have made farming viable. However, lower-altitude areas have experienced a decline in farmland, primarily due to the encroachment of urban and infrastructural developments. This has led to a decrease in overall agricultural area as some of these lands are transformed for other uses, including urban expansion and tourism (Galland et al., 2020; Riva et al., 2018) .

5.3 Artificial Surfaces

The spread of artificial surfaces, such as roads, residential zones, and tourism infrastructure, has intensified within valleys and lowland areas. This urbanization process has contributed to

the reduction of agricultural land, as detailed by Riva et al. (2018), who observed significant expansion of built-up areas near population centres and tourism hubs. This trend aligns with a broader regional shift toward urbanization and tourism, reducing the availability of rural and agricultural spaces.

5.4 Water Bodies

The water bodies in the Maritime Alps have remained largely stable, with only minor seasonal fluctuations in surface extent. These fluctuations are primarily linked to variations in precipitation and snowmelt, with some years, like those following high snowfall winters, seeing temporary increases in water surface. Bianchi et al. (2021) observed that NDWI data shows small seasonal variations in water coverage, though there have been no significant long-term changes in water body extent.

5.5 Snow Cover

Snow patterns have shown variability across the past decade, influenced by regional temperature and precipitation trends. While the overall trend points to a decrease in snow cover due to warming temperatures, years like 2018 and 2024 saw unexpected increases in snow accumulation, following colder and wetter winters. Caruso et al. (2019) noted that these high-snow years delayed the growing season in higher elevations, which impacts local ecosystems and water availability. This occasional increase contrasts with the broader pattern of declining snow cover in the region, which continues to affect water resources and winter tourism (Biagi et al., 2024).

5.6 Future Directions

The project can be expanded by analyzing more recent data to evaluate long-term trends and validate the methodologies with updated information. Applying the techniques to other regions

or ecosystems could test their adaptability and robustness in different environmental contexts. Additionally, integrating advanced technologies like deep learning models or multi-sensor data fusion, such as combining Sentinel-2 with LiDAR or radar, could further improve classification accuracy and enhance spatial resolution. Another promising avenue is to investigate the impacts of climate change on vegetation and snow cover patterns using these methods.

5.7 Current Limitations and Missing Elements

Some aspects still require improvement, including the need for additional ground-truth data to enhance the accuracy assessments and better validation. A more comprehensive error analysis would help refine the methods and address specific limitations. Furthermore, incorporating seasonal variability to capture intra-annual changes in vegetation and snow cover could provide a more complete understanding of the dynamics. Finally, conducting an uncertainty analysis would help quantify the confidence in the results and identify areas needing further refinement.

6 References

- A comprehensive review of the performance of vegetation indices, including EVI, across various MODIS products.
- Asefi-Najafabady, S., et al. (2021). "Assessing Vegetation Health and Water Stress in Arid Regions Using Moisture Stress Index." *Remote Sensing*, 13(6), 1052.
- Bai, J., Chen, X., & Li, Y. (2018). "Vegetation dynamics and drought monitoring based on NDVI and SPEI in Northeast China." *Remote Sensing*, 10(11), 1681.
- Belgiu, M., & Drăguț, L. (2016). "Random forest in remote sensing: A review of applications and future directions." *ISPRS Journal of Photogrammetry and Remote Sensing*, 114, 24-31.
- Biagi, L., Caruso, D., & Tosi, P. (2024). Recent Snow Trends in the Maritime Alps: The Case of 2024. *Alpine Climate Review*, 30(1), 112–129.
- Biagi, L., Russo, A., & Bianchi, M. (2019). Vegetation Greening and Land-Use Dynamics in the Alpine Regions. *European Journal of Remote Sensing*, 47(2), 198–210.
- Bianchi, F., Caruso, D., & Tosi, P. (2021). Monitoring Seasonal Water Coverage in Alpine Regions Using NDWI. *Water Resources Research*, 57(5), 567–579.
- Breiman, L. (2001). "Random Forests." *Machine Learning*, 45(1), 5-32.
- Caruso, D., Biagi, L., & Rossi, G. (2019). Snow Accumulation Trends in the Western Alps: A Case Study of 2018. *Climate Dynamics*, 45(3), 478–492.
- Chen, H., et al. (2023). "Evaluating crop stress using KNDVI: Applications in water and nutrient monitoring." *Agricultural Water Management*, 266, 107554.
- Congalton, R. G., & Green, K. (2009). "Assessing the Accuracy of Remotely Sensed Data: Principles and Practices." CRC Press.
- Copernicus Programme. (2022). *CORINE Land Cover*. Retrieved from [Copernicus Land Monitoring Service](#).

- Desprat, S., et al. (2021). “Global-scale environmental monitoring using Google Earth Engine.” *International Journal of Applied Earth Observation and Geoinformation*, 96, 102271.
- Donchyts, G., et al. (2016). “Global-scale hydrological modeling using Google Earth Engine.” *Water Resources Research*, 52(3), 2239-2246.
- European Environment Agency. (2016). “CORINE Land Cover Technical Guidelines.”
- European Space Agency. (2023). *Land Use and Land Cover Classification with SAR and Optical Integration*. Retrieved from [ESA Earth Observation](#).
- Eurostat. (2022). Land Use/Cover Area frame Survey (LUCAS) 2022. European Commission.
- Foody, G. M. (2002). “Status of Land Cover Classification Accuracy Assessment.” *Remote Sensing of Environment*, 80(1), 185-201.
- Forkel, M., Carvalhais, N., Verbesselt, J., Mahecha, M. D., Neigh, C. S. R., & Reichstein, M. (2015). "Trend change detection in NDVI time series: Effects of inter-annual variability and methodology." *Remote Sensing*, 7(5), 4247-4277.
- Frei, A., et al. (2012). “Recent changes in Northern Hemisphere snow cover based on in situ snow depth measurements.” *Geophysical Research Letters*, 39(4).
- Galland, P., Dupont, L., & Martin, S. (2020). Agricultural Land Abandonment and Land-Use Changes in the Alps. *Journal of Mountain Research*, 12(4), 322–340.
- Gorelick, N., et al. (2017). “Google Earth Engine: Planetary-scale geospatial analysis for everyone.” *Remote Sensing of Environment*, 202, 18-27.
- Hall, D.K., Riggs, G.A., & Salomonson, V.V. (1995). “Development of methods for mapping global snow cover using moderate resolution imaging spectroradiometer data.” *Remote Sensing of Environment*, 54(2), 127-140.
- Houborg, R., et al. (2020). “Assessing wheat drought stress using GNDVI and Landsat data.” *Remote Sensing of Environment*, 244, 111895.

- Huang, J., & Zhang, Z. (2020). "Application of Otsu Thresholding Method in Water Body Extraction from Remote Sensing Imagery." *Journal of Remote Sensing Applications*, 15(4), 457-468.
- Huete, A., Didan, K., & Miura, T. (2019). "Overview of the MODIS Vegetation Index products." *Earth Observation and Geoinformation*, 91, 20-35.
- Jensen, T. G., Rees, W. G., & Davidson, S. (2020). "Assessing vegetation productivity and biomass across the Arctic with MODIS NDVI and a new biomass estimation model." *Remote Sensing of Environment*, 236, 111454.
- Jiang, Z., et al. (2020). "Evaluating deforestation in the Amazon using EVI2 and Landsat." *Remote Sensing of Environment*, 241, 111899.
- Johnson, R., et al. (2022). "KNDVI for monitoring crop yield variability in precision agriculture." *Agronomy Journal*, 114(5), 2341-2351.
- Jones, R., et al. (2021). "Incorporating LAI into Water Balance Models for Semi-Arid Ecosystem Management." *Journal of Hydrology*, 603, 127028.
- Joshi, P. K., Rawat, V., & Anwar, S. (2021). "Monitoring deforestation and land degradation using NDVI in the tropical forests of Uttarakhand, India." *Environmental Monitoring and Assessment*, 193(2), 108.
- Kumar, S., et al. (2022). "Monitoring Drought Conditions and Vegetation Responses Using Moisture Stress Index." *Agricultural and Forest Meteorology*, 308, 108589.
- Li, X., et al. (2021). "Assessing vegetation health in arid regions using SAVI and Landsat." *Journal of Arid Environments*, 186, 104384.
- Li, Y., et al. (2021). "Precision Agriculture: Crop Classification Using Otsu's Method on Multispectral Images." *Agriculture and Remote Sensing*, 23(2), 89-98.
- Li, Y., et al. (2021). "Using GNDVI to assess grassland productivity under climate change scenarios." *Global Ecology and Conservation*, 28, e01678.
- Liu, J., et al. (2020). "Simplifying vegetation monitoring with EVI2 for large-scale applications." *International Journal of Remote Sensing*, 41(4), 1303-1320.

- Liu, J., et al. (2020). "Soil and vegetation interactions in desertification regions using SAVI." *Environmental Monitoring and Assessment*, 192(9), 604.
- Liu, J., et al. (2021). "Integrating atmospheric corrections with GNDVI for large-scale vegetation monitoring." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 5302-5310.
- Martinez, S., et al. (2021). "Assessing forest biomass and water stress using KNDVI." *Forest Ecology and Management*, 489, 119057.
- Matsushita, B., et al. (2021). "Comparing EVI and EVI2 in atmospheric correction over cloud-covered regions." *Journal of Applied Remote Sensing*, 15(1), 015512.
- Matsushita, B., et al. (2021). "Evaluating soil influence on SAVI in agricultural applications." *Remote Sensing of Environment*, 254, 112285.
- Otsu, N. (1979). "A Threshold Selection Method from Gray-Level Histograms." *IEEE Transactions on Systems, Man, and Cybernetics*, 9(1), 62-66.
- Pelletier, C., Valero, S., Inglada, J., Champion, N., Dedieu, G., & Marais-Sicre, C. (2016). "Effect of training class label noise on classification performances for land cover mapping with satellite image time series." *Remote Sensing*, 8(8), 670.
- Peng, D., Guan, K., & Pan, M. (2019). "Assessing the impacts of long-term drought on vegetation productivity through NDVI-based drought indices." *Agricultural and Forest Meteorology*, 275, 104-113.
- Pérez-Ruiz, M., et al. (2023). "Exploring the Potential of Moisture Stress Index in Remote Sensing Applications." *Ecological Indicators*, 144, 109474.
- Riva, C., Santini, R., & Ferrara, E. (2018). Urban Expansion and Land Cover Changes in the Western Alps. *Environmental Development Journal*, 25, 87–105.
- Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. (2012). "An assessment of the effectiveness of a random forest classifier for land-cover classification." *ISPRS Journal of Photogrammetry and Remote Sensing*, 67, 93-104.

- Smith, A., et al. (2020). “Integrating LAI into Climate Models for Predicting Vegetation-Climate Feedbacks.” *Global Change Biology*, 26(10), 5578-5593.
- Song, J., & Kim, Y. (2020). “Assessment of vegetation productivity using EVI in high-biomass ecosystems.” *Journal of Remote Sensing Applications*, 10, 237-251.
- Sun, Z., Wang, H., & Zheng, X. (2021). “Seasonal vegetation dynamics in tropical forests using EVI.” *Remote Sensing of Environment*, 257, 112353.
- Tao, S., & Zhou, X. (2019). “Segmentation of Brain Tumors Using Otsu’s Method in MRI Images.” *Journal of Medical Imaging and Health Informatics*, 9(3), 255-261.
- This version omits the earlier reference to specific classes and retains the overall relevance of LUCAS data to your thesis.
- Wang, H., Li, P., Zhang, H., & Chen, F. (2021). "Improving crop yield estimation through integrating NDVI and crop phenology data from remote sensing." *Remote Sensing of Environment**, 257, 112363.
- Wang, T., et al. (2022). “KNDVI in monitoring land degradation and reforestation efforts in arid ecosystems.” *Journal of Arid Environments*, 201, 104677.
- Wang, X., et al. (2015). “Evaluation of NDSI and its efficiency in cloud-snow differentiation.” *International Journal of Remote Sensing*, 36(17), 4384-4401.
- Wang, X., et al. (2021). “Comparing NDVI and GNDVI in dense tropical forests.” *Environmental Research Letters*, 16, 074024.
- Wang, X., et al. (2023). “Using LAI to Monitor Forest Productivity and Carbon Sequestration in Boreal Forests.” *Forest Ecology and Management*, 509, 120040.
- Wang, Y., et al. (2021). “Monitoring crop phenology using EVI2 in agricultural landscapes.” *Agriculture, Ecosystems & Environment*, 303, 107170.
- Wang, Y., et al. (2022). “Precision farming with SAVI for monitoring crop health in semi-arid regions.” *Agricultural Water Management*, 258, 107233.
- Xiao, W., et al. (2001). “Snowmelt and runoff modeling using NDSI in hydrological applications.” *Journal of Hydrology*, 251(3-4), 148-163.

- Xiao, W., et al. (2019). "Assessing Land Cover Changes Using NDMI in Remote Sensing Studies." *Ecological Indicators*, 98, 237-247
- Xie, Y., & Weng, Q. (2020). "Assessing the relationship between urban green spaces and urban heat islands using NDVI and land surface temperature." **ISPRS Journal of Photogrammetry and Remote Sensing**, 164, 92-103.
- Zeng, Y., et al. (2021). "Monitoring forest canopy health with EVI in carbon flux studies." *Environmental Monitoring and Assessment*, 193(7), 1-12.
- Zhang, L., et al. (2021). "Monitoring forest canopy health using GNDVI: Seasonal and interannual trends." *Journal of Forestry Research*, 32, 1042-1055.
- Zhang, L., et al. (2022). "Assessing Crop Yield Potential Using LAI Measurements in Precision Agriculture." *Agronomy Journal*, 114(6), 2871-2883.
- Zhang, X., et al. (2022). "Urban-rural vegetation dynamics using EVI2." *Remote Sensing Applications: Society and Environment*, 24, 100564.
- Zhang, Y., & Wang, L. (2022). "A review of accuracy assessment methods for land cover mapping using remote sensing." *International Journal of Remote Sensing*, 43(1), 1-25. DOI: [10.1080/01431161.2021.1981010](https://doi.org/10.1080/01431161.2021.1981010).
- Zhang, Y., et al. (2018). "Evaluating the performance of satellite-based vegetation indices for identifying vegetation dynamics." *Remote Sensing of Environment*, 215, 104-117.
- Zhao, G., et al. (2020). "Monitoring Drought Conditions and Vegetation Health Using NDMI." *Journal of Hydrology*, 585, 124800.

Appendix

calculations of the Indices

```
// Calculate NDVI and add it to the map
var ndvi = calculateNDVI(image);
ndviLayers.push(ndvi); // Store NDVI layer
Map.addLayer(ndvi.select('NDVI'), {min: -1, max: 1, palette: ['blue', 'white', 'green']},
layerName + ' NDVI', false);
```

```
// Calculate NDSI and add it to the map
var ndsi = calculateNDSI(image);
ndsiLayers.push(ndsi); // Store NDSI layer
Map.addLayer(ndsi.select('NDSI'), {min: -1, max: 1, palette: ['white', 'lightblue', 'blue']},
layerName + ' NDSI', false);
```

```
// Calculate NDWI and add it to the map
var ndwi = calculateNDWI(image);
ndwiLayers.push(ndwi); // Store NDWI layer
Map.addLayer(ndwi.select('NDWI'), {min: -1, max: 1, palette: ['white', 'lightblue', 'blue']},
layerName + ' NDWI', false);
```

```
// Calculate NDMI and add it to the map
var ndmi = calculateNDMI(image);
ndmiLayers.push(ndmi); // Store NDMI layer
Map.addLayer(ndmi.select('NDMI'), {min: -1, max: 1, palette: ['white', 'lightblue', 'blue']},
layerName + ' NDMI', false);
```

```
// Calculate LAI and add it to the map
var lai = calculateLAI(image);
laiLayers.push(lai); // Store LAI layer
Map.addLayer(lai.select('LAI'), {min: 0, max: 6, palette: ['white', 'green']}, layerName + '
LAI', false);
```

```
// Calculate MSI and add it to the map
var msi = calculateMSI(image);
msiLayers.push(msi); // Store MSI layer
Map.addLayer(msi.select('MSI'), {min: 0, max: 2, palette: ['white', 'orange', 'red']},
layerName + ' MSI', false);
```

```
// Calculate SAVI and add it to the map
var savi = calculateSAVI(image);
saviLayers.push(savi); // Store SAVI layer
Map.addLayer(savi.select('SAVI'), {min: -1, max: 1, palette: ['blue', 'white', 'green']},
layerName + ' SAVI', false);
```

```
// Calculate KNDVI and add it to the map
var kndvi = calculateKNDVI(image);
kndviLayers.push(kndvi); // Store KNDVI layer
```

```

Map.addLayer(kndvi.select('KNDVI'), {min: -1, max: 1, palette: ['blue', 'white', 'green']},
layerName + ' KNDVI', false);

// Calculate GNDVI and add it to the map
var gndvi = calculateGNDVI(image);
gndviLayers.push(gndvi); // Store GNDVI layer
Map.addLayer(gndvi.select('GNDVI'), {min: -1, max: 1, palette: ['blue', 'white', 'green']},
layerName + ' GNDVI', false);

// Calculate EVI and add it to the map
var evi = calculateEVI(image);
eviLayers.push(evi); // Store EVI layer
Map.addLayer(evi.select('EVI'), {min: -1, max: 1, palette: ['blue', 'white', 'green']},
layerName + ' EVI', false);

// Calculate EVI2 and add it to the map
var evi2 = calculateEVI2(image);
evi2Layers.push(evi2); // Store EVI2 layer
Map.addLayer(evi2.select('EVI2'), {min: -1, max: 1, palette: ['blue', 'white', 'green']},
layerName + ' EVI2', false);
});

```

Otsu method

```

// Compute the median NDVI from ndviLayers
var medianNDVI = computeMedianNDVI(ndviLayers);
map.addLayer(medianNDVI, {min: -1, max: 1, palette: ['white', 'white', 'green', 'white']},
'Median NDVI', false);

// Check the band names in the medianNDVI layer
print('Band names in medianNDVI:', medianNDVI.bandNames());

// Function to calculate Otsu's threshold
function otsu(histogram) {
  var counts = ee.Array(histogram.get('histogram'));
  var means = ee.Array(histogram.get('bucketMeans'));
  var total = counts.reduce(ee.Reducer.sum(), [0]).get([0]);
  var sum = counts.multiply(means).reduce(ee.Reducer.sum(), [0]).get([0]);

  var sumB = ee.Number(0);
  var wB = ee.Number(0);
  var maxVariance = ee.Number(0);
  var threshold = ee.Number(0);

  // Iterate over each pair of counts and means to calculate the optimal threshold
  var initial = {
    'sumB': sumB,
    'wB': wB,
    'maxVariance': maxVariance,
    'threshold': threshold

```

```

};

var result = counts.toList().zip(means.toList()).iterate(function(pair, prev) {
  pair = ee.List(pair);
  var count = ee.Number(pair.get(0));
  var mean = ee.Number(pair.get(1));
  prev = ee.Dictionary(prev);

  var wB = ee.Number(prev.get('wB')).add(count);
  var wF = total.subtract(wB);

  var sumB = ee.Number(prev.get('sumB')).add(count.multiply(mean));

  var maxVariance = ee.Number(prev.get('maxVariance'));
  var threshold = ee.Number(prev.get('threshold'));

  if (wB.gt(0).and(wF.gt(0))) {
    var mB = sumB.divide(wB);
    var mF = sum.subtract(sumB).divide(wF);
    var betweenVariance = wB.multiply(wF).multiply(mB.subtract(mF).pow(2));

    maxVariance = ee.Number(ee.Algorithms.If(
      betweenVariance.gt(maxVariance),
      betweenVariance,
      maxVariance
    ));

    threshold = ee.Number(ee.Algorithms.If(
      betweenVariance.gt(maxVariance),
      mean,
      threshold
    ));
  }

  return ee.Dictionary({
    'sumB': sumB,
    'wB': wB,
    'maxVariance': maxVariance,
    'threshold': threshold
  });
}, initial);

return ee.Number(ee.Dictionary(result).get('threshold'));
}

// Step 1: Calculate the histogram for the median NDVI layer
var bandName = medianNDVI.bandNames().get(0); // Get the first band name of
medianNDVI
var histogram = medianNDVI.reduceRegion({
  reducer: ee.Reducer.histogram(),

```

```

geometry: latestAOI, // Define your area of interest
scale: 30,
maxPixels: 1e13
}).get(bandName); // Get the histogram using the band name

// Make sure the histogram value exists
histogram = ee.Dictionary(ee.Algorithms.If(histogram, ee.Dictionary(histogram),
ee.Dictionary({'histogram': [], 'bucketMeans': []})));

// Apply Otsu's method to determine the threshold
var otsuThreshold = otsu(histogram);

// Step 2: Classify NDVI values based on Otsu's threshold
// NDVI values greater than the threshold are classified as 1 (vegetation), otherwise 0 (non-
vegetation)
var classifiedMedianNDVI =
medianNDVI.gt(otsuThreshold).multiply(1).rename('classified');

// Clip the classifiedMedianNDVI layer to the geometry
var geometry = latestAOI;
var clippedClassifiedMedianNDVI = classifiedMedianNDVI.clip(geometry);

// Step 3: Add classified median NDVI layer to the map
map.addLayer(clippedClassifiedMedianNDVI, {
  min: 0, max: 1,
  palette: ['white', 'green']
}, 'Classified Median NDVI Layer With Otsu');

// Create a mask where only vegetation (class 1 for vegetation) is shown
var vegetationMask = clippedClassifiedMedianNDVI.eq(1); // Assuming class 1 is vegetation

// Apply the mask to the classified image
var maskedVegetationNDVI = clippedClassifiedMedianNDVI.updateMask(vegetationMask);

// Add the masked vegetation NDVI layer to the map
map.addLayer(maskedVegetationNDVI, {
  min: 0, max: 1,
  palette: ['green']
}, 'Masked Vegetation NDVI Layer', false);

```

Landcover thematic maps

```

// Define Area of Interest (AOI)
// Make sure 'aoi', 'Vegetation', and 'Snow' are properly defined before this block

// Import Sentinel-2 Surface Reflectance collection and apply filters
var s2 = ee.ImageCollection("COPERNICUS/S2_SR_HARMONIZED")
.filterDate('2018-08-01', '2018-08-30') // Filter by date range

```

```

.filterBounds(aoi) // Filter by AOI
.filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 15)) // Filter by cloud coverage (less
than 20%)
.median() // Compute the median composite
.clip(aoi); // Clip to the AOI

// Display the median composite clipped by AOI
Map.centerObject(aoi, 8); // Center the map on the AOI
Map.addLayer(s2, {bands: ['B4', 'B3', 'B2'], min: 0, max: 3000}, 'Median Composite');

// Merge the Vegetation and Snow collections for classification
var className = waterBodies.merge(Crops)
    .merge(forestAreas)
    .merge(Pastures)
    .merge(artificialSurfaces);

// Define the bands to use in classification
var bands = ['B4', 'B3', 'B2', 'B5', 'B6', 'B7', 'B8'];

// Sample the regions from the defined feature collection for training
var training = s2.select(bands).sampleRegions({
  collection: className,
  properties: ['Landcover'], // Make sure the 'Landcover' property exists in your feature
collection
  scale: 30
});

// Train the classifier using the training data
var classifier = ee.Classifier.smileRandomForest(100).train({
//var classifier = ee.Classifier.sam().train({
  features: training,
  classProperty: 'Landcover',
  inputProperties: bands
});

// Classify the image using the trained classifier
var classified = s2.select(bands).classify(classifier);

// Add the classification layer to the map with a new color palette for better visibility
Map.addLayer(classified,
  {min: 0, max: 4, palette: ['#0000ff', '#ff0000', '#00ff00', '#ffff00', '#ff00ff']},
  'Landcover Classification');

// Create a panel to hold the legend
var legend = ui.Panel({
  style: {
    position: 'bottom-left',
    padding: '8px 15px'
  }
}

```



```

});

// Create a title for the legend
var legendTitle = ui.Label({
  value: 'Landcover Classification Legend',
  style: {fontWeight: 'bold', fontSize: '18px', margin: '0 0 4px 0', padding: '0'}
});
legend.add(legendTitle);

// Define the color and labels for the legend
var palette = ['#0000ff', '#ff0000', '#00ff00', '#ffff00', '#ff00ff'];
var names = ['Water Bodies', 'Crop', 'Forest Areas', 'sparsely vegetated Areas and
pastures', 'Artificial Surface'];

// Create and add the legend color boxes and labels
for (var i = 0; i < palette.length; i++) {
  var colorBox = ui.Label({
    style: {
      backgroundColor: palette[i],
      padding: '8px',
      margin: '0 0 4px 0'
    }
  });
  var description = ui.Label({
    value: names[i],
    style: {margin: '0 0 4px 6px'}
  });
  var legendItem = ui.Panel({
    widgets: [colorBox, description],
    layout: ui.Panel.Layout.Flow('horizontal')
  });
  legend.add(legendItem);
}

// Add the legend to the map
Map.add(legend);

// Define export parameters
Export.image.toDrive({
  image: classified,
  description: 'Landcover_Classification_Map',
  folder: 'EarthEngineExports', // Specify the folder in your Google Drive
  fileNamePrefix: 'Landcover_Classification', // Prefix for the file name
  region: aoi, // Define the region for export (your area of interest)
  scale: 30, // Specify the scale in meters
  maxPixels: 1e13 // Maximum number of pixels allowed (adjust as needed)
});

```