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Effects of Skid Trails on Soil Moisture and
Vegetation Indices: A Multi-Season Satellite Analysis

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Abstract

Forests play a crucial role in maintaining global ecological balance, supporting biodiversity, and regulating carbon and water cycles. However, human activities such as logging and the construction of forest roads have introduced significant disturbances, including skid trails. These infrastructures, used for timber transportation, cause lasting ecological impacts such as soil compaction, hydrological alterations, and vegetation degradation. Previous studies have demonstrated that soil compaction along skid trails reduces porosity and water infiltration, negatively affecting vegetation recovery. Despite these insights, the localized effects of skid trails on remote sensing-derived vegetation indices remain underexplored.

This study aims to bridge this knowledge gap by using environmental indices such as NDVI, SAVI, NDMI, NDWI, and MNDWI, derived from Sentinel-2 satellite data, to assess the impact of skid trails on vegetation and soil moisture dynamics. The study spans four years (2021–2024) and includes a detailed spatial and temporal analysis of variations in these indices within and outside areas impacted by skid trails. Additionally, the research investigates correlations between these indices and climatic factors, such as precipitation and temperature, to better understand the interactions between anthropogenic disturbances and environmental conditions.

The results reveal significant differences across the study areas, with a clear reduction in vegetation indices in skid trail-impacted zones, indicating negative effects on vegetation health. Moisture indices also exhibit patterns consistent with hydrological changes induced by soil compaction. Correlation analyses show that seasonal and interannual variations in the indices are strongly influenced by precipitation, while temperature plays a complementary role in modulating vegetation responses.

This research provides a meaningful contribution to the existing literature, offering new insights into the localized effects of skid trails and demonstrating the efficacy of remote sensing in analysing forest disturbances. The findings can inform sustainable forest management strategies aimed at minimizing the adverse effects of human activities and promoting the ecological recovery of degraded areas.

Riassunto

Le foreste svolgono un ruolo cruciale nell'equilibrio ecologico globale, supportando la biodiversità e regolando i cicli del carbonio e dell'acqua. Tuttavia, le attività umane, come l'abbattimento di alberi e la costruzione di strade forestali, hanno introdotto disturbi significativi, tra cui le piste forestali (skid trails). Queste infrastrutture, utilizzate per il trasporto del legname, causano impatti ecologici duraturi, come la compattazione del suolo, alterazioni idrologiche e la degradazione della vegetazione. Studi precedenti hanno dimostrato che la compattazione del suolo lungo le piste forestali può ridurre la porosità e l'infiltrazione idrica, influenzando negativamente il recupero della vegetazione. Tuttavia, gli effetti localizzati di queste infrastrutture su indici di vegetazione derivati da telerilevamento non sono ancora stati esplorati a fondo.

Questo studio mira a colmare tale lacuna, utilizzando indici di vegetazione e umidità come NDVI, SAVI, NDMI, NDWI e MNDWI, derivati dai dati satellitari Sentinel-2, per valutare l'impatto delle piste forestali sulle dinamiche della vegetazione e dell'umidità del suolo. Il periodo di studio comprende quattro anni (2021–2024), e include un'analisi spaziale e temporale dettagliata delle variazioni di tali indici all'interno e all'esterno delle aree occupate dalle piste forestali. Inoltre, sono state studiate le correlazioni tra questi indici e fattori climatici, come precipitazioni e temperature, per comprendere meglio le interazioni tra i disturbi antropogenici e le condizioni ambientali.

I risultati hanno evidenziato significative differenze tra le aree di studio, con una chiara riduzione degli indici di vegetazione nelle aree influenzate dalle piste forestali, suggerendo un impatto negativo sulla salute della vegetazione. Inoltre, gli indici di umidità hanno mostrato alterazioni coerenti con le modifiche idrologiche associate alla compattazione del suolo. Le analisi di correlazione hanno indicato che le variazioni stagionali e interannuali degli indici sono fortemente influenzate dalle precipitazioni, sebbene la temperatura giochi un ruolo complementare nel modulare le risposte della vegetazione.

Questa ricerca rappresenta un contributo significativo alla letteratura esistente, fornendo nuove conoscenze sugli effetti delle piste forestali a scala locale e dimostrando l'efficacia del telerilevamento nell'analisi dei disturbi forestali. I risultati possono guidare strategie di gestione sostenibile delle foreste, con l'obiettivo di minimizzare gli impatti negativi delle attività antropiche e promuovere il recupero ecologico delle aree degradate.

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1. Introduction

Forests play a pivotal role in maintaining ecological balance, supporting biodiversity, and regulating global carbon and water cycles. However, human interventions such as logging, road construction, and skid trail establishment have introduced significant disturbances to forest ecosystems (Froehlich et al. 1985; Williamson and Neilsen 2000; Heninger et al. 2002; J. Wang 2007; Jourgholami et al. 2018; Naghdi et al. 2018; Dearmond et al. 2021). Many studies have shown that the compaction caused by machinery on skid trails can significantly reduce soil porosity and infiltration rates, leading to long-term impacts on forest hydrology and vegetation recovery. Understanding the impact of these disturbances is essential for sustainable forest management and conservation efforts (Picchio et al. 2012; Cambi et al. 2015, 2016, 2017; D'Acqui et al. 2020).

Remote sensing has revolutionized forest monitoring by providing tools to quantify vegetation health and moisture dynamics over large spatial and temporal scales (e.g., Pettorelli et al. 2014). Vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), Normalized Difference Moisture Index (NDMI), and water indices like the Normalized Difference Water Index (NDWI) and Modified NDWI (MNDWI) have been extensively used to study forest disturbances and recovery dynamics. These indices are particularly suited for studying forest disturbances because they provide quantitative measures of vegetation cover, health, and soil moisture—key factors influenced by human activities and environmental changes. For instance, NDVI and SAVI are sensitive to changes in leaf chlorophyll and canopy structure, making them ideal for assessing vegetation health, while NDWI and MNDWI are effective in detecting moisture variations that are critical in understanding hydrological impacts caused by disturbances like skid trails. These indices capture critical information about vegetation cover, health, and soil moisture, which are directly or indirectly influenced by human activities.

Studies have shown that vegetation indices like NDVI and SAVI are reliable indicators of vegetation health, responding to variations in plant biomass, leaf chlorophyll content, and canopy structure (Tucker 1979; Huete 1988a, 2012; Gamon et al. 1995; Pettorelli et al. 2005; Zou and Möttus 2017). Similarly, NDWI and MNDWI are widely used to monitor surface water and soil moisture dynamics, reflecting the hydrological responses of ecosystems to environmental conditions and anthropogenic activities (McFeeters 1996a; Xu 2006a; Khalifeh Soltanian et al. 2019). NDMI has also been employed to track vegetation moisture content, particularly in drought-prone and disturbed areas (Berca and Horoiş n.d.; Zargar et al. 2011).

Research on forest disturbances has highlighted the significant role of logging and road construction in altering vegetation and soil properties (Günther et al., 2012; Zipperer et al., 2020).

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These studies emphasize that soil compaction caused by heavy machinery, especially along skid trails, can lead to reduced water infiltration, increased erosion, and impaired root growth, ultimately affecting vegetation recovery (Wilpert and Schffer 2006; Cambi et al. 2015; Venanzi et al. 2016, 2020; Mohieddinne et al. 2019; Picchio et al. 2020). Despite these insights, there is limited literature focusing explicitly on the influence of skid trails on vegetation and moisture indices derived from remote sensing data.

While vegetation indices have been extensively applied to monitor forest dynamics, their application to assess the specific impacts of skid trails remains underexplored. Most existing studies address forest disturbances at a broader scale, without isolating the localized effects of skid trails. Furthermore, the temporal dynamics of vegetation recovery and hydrological changes along skid trails are not well-documented. The interaction between skid trail-induced soil compaction and its manifestation in vegetation indices like NDVI, NDWI, and SAVI has yet to be systematically studied. Understanding this interaction has the potential to inform sustainable forest management practices by elucidating how soil disturbances translate into measurable changes in vegetation health and hydrological balance at localized scales.

Another notable gap is the lack of integration between remote sensing data and on-ground observations. Studies often focus solely on satellite-derived indices, which may miss nuanced changes in soil properties, microclimatic conditions, and species composition. Addressing these gaps is crucial for developing effective forest management practices that mitigate the long-term ecological impacts of skid trails.

1.1. Objectives

The primary aim of this study is to evaluate the impact of skid trails on vegetation and moisture dynamics using remote sensing-based vegetation indices. The specific objectives include:

- Evaluating changes in NDVI, SAVI, NDMI, NDWI, and MNDWI within and outside skid trail areas over a four-year period (2021–2024).
- Analysing seasonal and interannual trends in environmental indices in response to environmental conditions and anthropogenic disturbances.
- Investigating the correlation between vegetation indices and climatic factors such as precipitation and temperature to understand their combined influence on forest dynamics.
- Identifying spatial patterns of vegetation degradation and moisture stress associated with skid trails, with implications for forest restoration strategies.

Introduction

This study seeks to fill a critical gap in the literature, providing insights into the localized impacts of skid trails on forest ecosystems and contributing to the development of sustainable forestry practices.

2. Materials and methods

2.1. Study Areas

This study focuses primarily on two areas: Passo Lavazé (Lavazejoch) and Piana di Marcesina (also known as Merck-wisen or Marcesina Plateau), both located in the Autonomous Province of Trento, within the Trentino-Alto Adige/South Tyrol region of northeastern Italy (Figure 1). Both areas are situated within the Italian Alps, characterized by mountainous terrain with distinct ecological features.

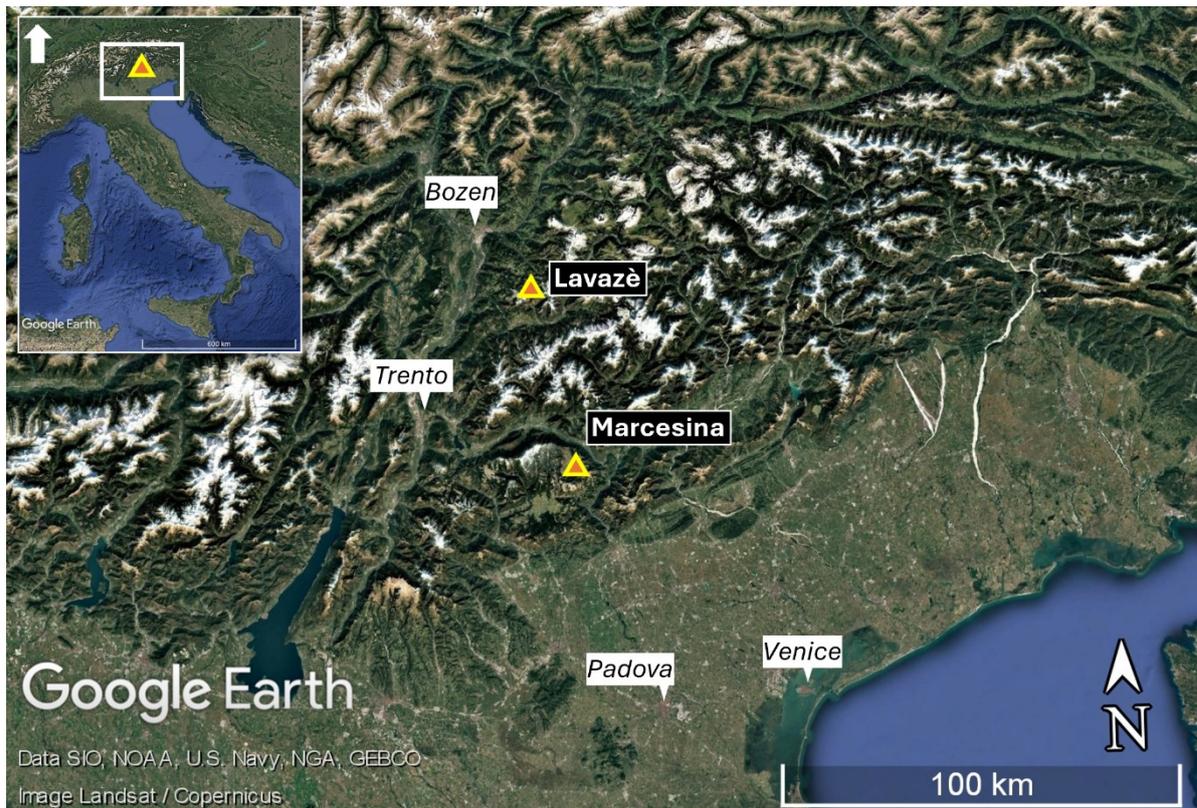


Figure 1: Satellite image showing the location of the two study areas: Passo Lavazé and Piana di Marcesina.

Passo Lavazé

The Lavazé Pass, situated at an elevation of 1.808 m a.s.l., serves as a mountain pass between Val d'Ega in South Tyrol and Val di Fiemme in Trentino. This pass is marked by a plateau of dolomite origin, surrounded by notable massifs such as Latemar, Catinaccio, Corno Bianco, and Corno Nero. The region's topography includes a mosaic of meadows, coniferous forests, and dolomite rock formations, fostering a rich Alpine ecosystem with high biodiversity. The pass also functions as a watershed dividing the Adige and Avisio river basins, which has a significant impact on the local microclimate and vegetation distribution (Ingegnoli and Giglio 2008). For the purposes of this

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study, the Lavazé Pass area is divided into two sub-areas, each corresponding to a logging site: Lavazé 1 (40,5 ha) and Lavazé 2 (68,4 ha), both facing northeast (Figure 2).

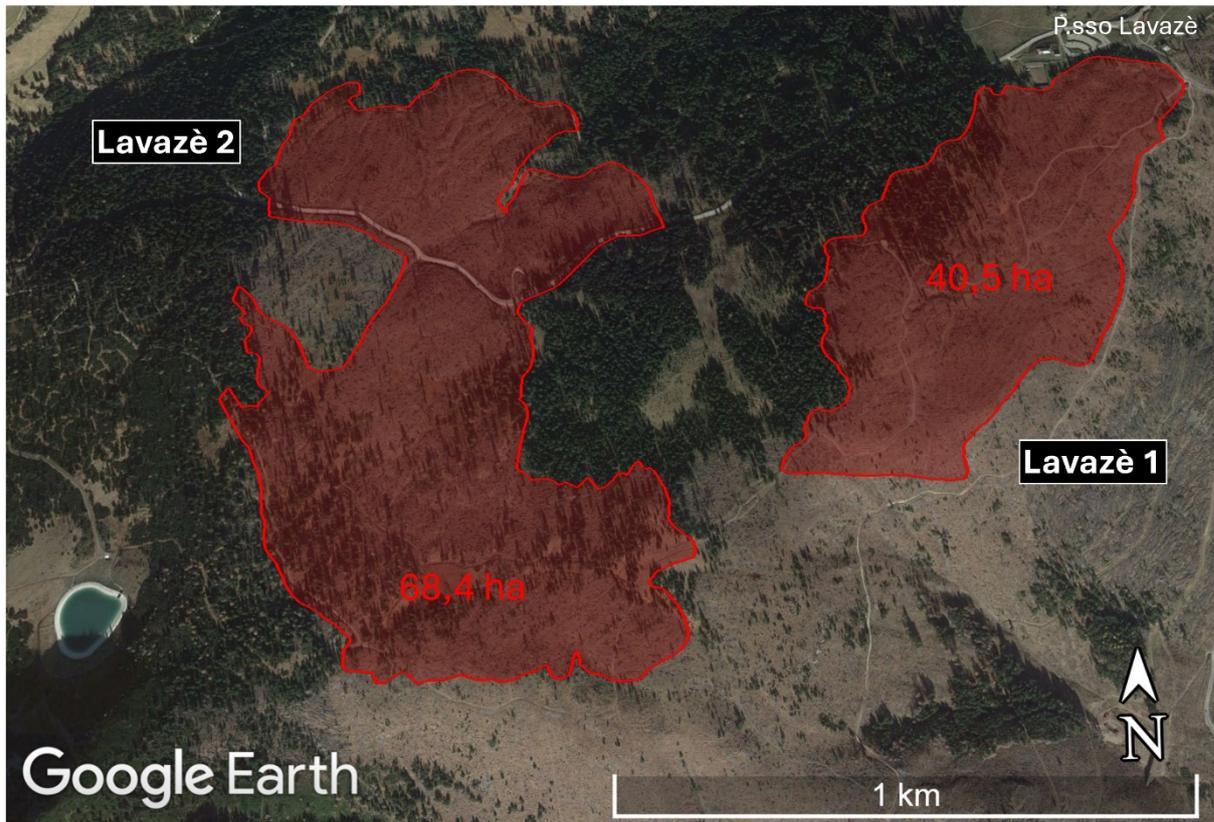


Figure 2: Sub-areas and logging sites in the Passo Lavazé area: Lavazé 1 and Lavazé 2. We also report their extension in hectares. Satellite Image from Google Earth Pro.

Piana di Marcesina

The Piana di Marcesina, located at an average altitude of 1,400 m a.s.l. in the Altopiano dei Sette Comuni, straddles the border between Veneto and Trentino-Alto Adige. This karst plateau is known for its harsh climate, particularly extreme cold due to the stagnation of cold air in the region (Giovagnoli and Tasinazzo 2014). It is notable for peat bogs such as Palù di San Lorenzo and Palù di Sotto, which are part of the Natura 2000 Network due to their biodiversity. These areas host rare species, including glacial relics like *Andromeda polifolia* and *Drosera rotundifolia* (GBIF n.d.; Da Ronch et al. 2005; Buffa et al. 2010). The area acts as a watershed between the Brenta and Piave river basins, contributing to the region's hydrological dynamics. The areas of interest for this study are three logging sites specifically in the “Barricata” area in the Trentino portion of the Marcesina plain (Figure 3): Marcesina 1 (with a western aspect), Marcesina 2 (with a southeastern exposure), and Marcesina 3 (with an eastern aspect).

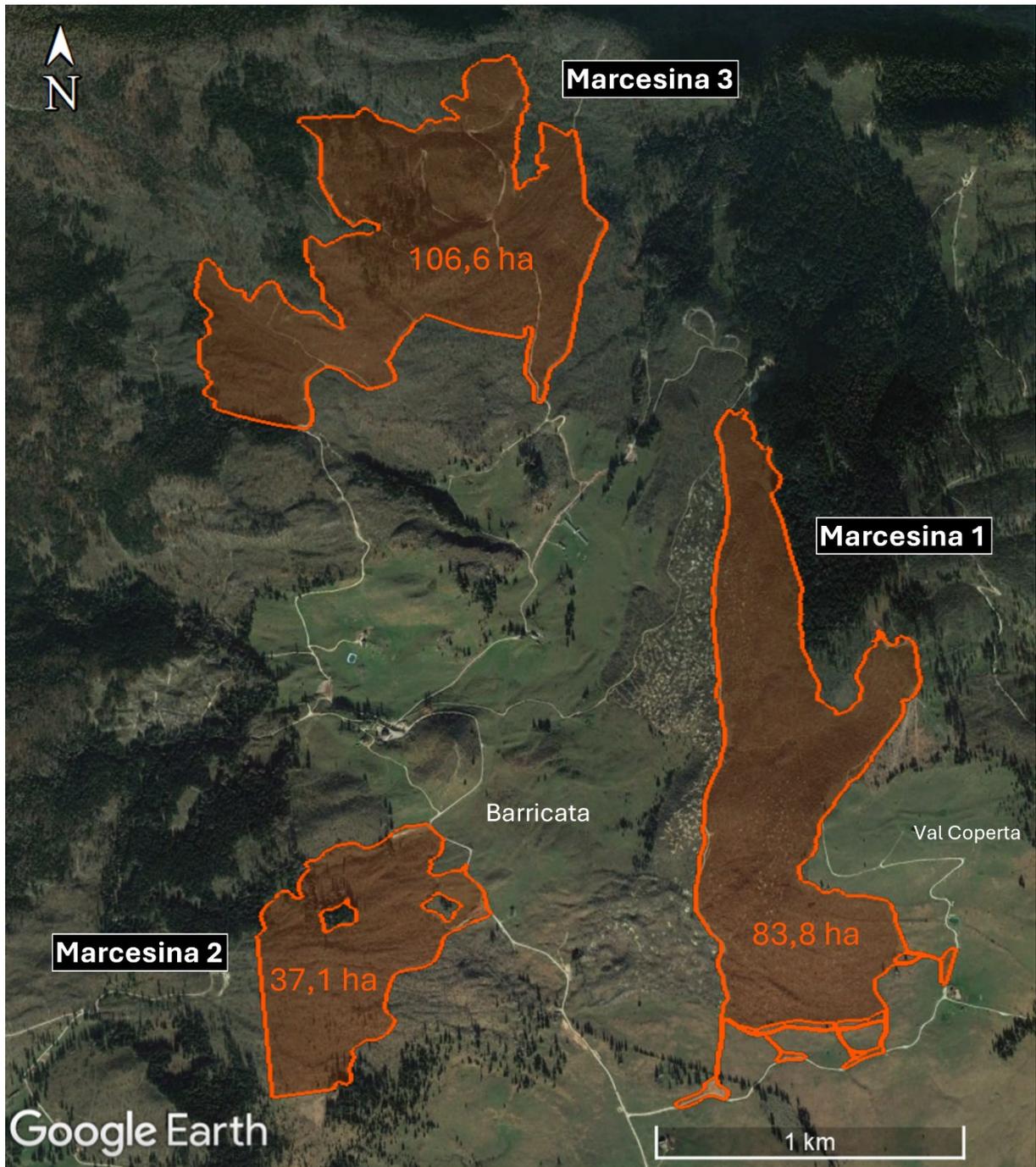


Figure 3: Sub-areas and logging sites in the “Barricata” area of Marcesina: Marcesina 1, Marcesina 2, Marcesina 3. We also report their extension in hectares. Satellite Image from Google Earth Pro.

2.2. Software

In this thesis work, I used a combination of advanced software tools that provide powerful functionalities for geographic information systems (GIS), remote sensing and data manipulation to process geospatial data. The primary tools used in this research—Google Earth Engine (GEE), QGIS, and Microsoft Excel—each played a crucial role in different stages of data retrieval and analysis.

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2.2.1. Google Earth Engine (GEE)

Google Earth Engine (GEE) is a cloud-based platform widely used for processing, analysing and visualising geospatial data. It provides access to a vast archive of remote sensing imagery and other geospatial datasets, such as that obtained through the Copernicus Sentinel programme. In this study, GEE was used for the processing of large-scale data, including the analysis of satellite images, the computation of environmental indices and the detection of temporal changes. The platform's ability to handle huge datasets with parallel computing capabilities made it particularly suitable for the analysis of time-series satellite data, enabling efficient processing and retrieval of results. The use of GEE's extensive library of pre-processed data and its powerful JavaScript-based API facilitates the development of customised analysis scripts, optimising workflows and enabling reproducible results.

2.2.2. QGIS

Quantum GIS (QGIS) is an open-source geographic information system that offers a robust suite of tools for spatial data management, analysis, and visualization. It supports a wide range of vector and raster data formats, making it an ideal tool for handling various types of geospatial datasets. In this research, QGIS 2024, v. 3.34.12, was employed for tasks such as data visualization, map creation, and spatial analysis. Key functionalities included the application of spatial overlays, buffering, and geostatistical operations. QGIS also enabled the integration of remote sensing data obtained from Google Earth Engine with other local datasets, allowing for more comprehensive spatial analyses. Additionally, its user-friendly interface and the extensive availability of plugins made it a versatile tool for the manipulation and presentation of the results of various analyses.

2.2.3. Microsoft Excel

Microsoft Excel is a widely used spreadsheet application that provides basic to advanced data management and analysis tools. In this study, Excel was primarily used for organizing, processing, and performing statistical analyses on the data generated from the geospatial tools. It served as an essential tool for tabular data management, allowing for easy manipulation and visualization of results such as summarizing datasets, creating pivot tables, and generating graphs. Excel's ability to handle large datasets, along with its formula-based approach to analysis, made it a valuable resource for secondary analysis, particularly in calculating descriptive statistics and processing non-spatial data that complemented the geospatial findings. Additionally, the integration of Excel with other software tools facilitated seamless data export and further analysis.

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2.3. Data and sources

This study utilized various datasets from different sources for spatial and environmental analysis. The data were obtained through shapefiles, raster, satellite imagery, and meteorological data, all selected for their relevance and quality for the analysis conducted.

2.3.1. Local Datasets of Shapefiles and Rasters

From the local datasets, shapefiles representing the forest operation areas and the complete dataset of the digitalized skid trails over the study sites were derived, as well as the rasters containing detailed spatial information such as a digital terrain model (DTM), and the derived slope and aspect, the density of skid trails obtained through a Kernel Density Estimation (KDE). This data was obtained from previous or parallel works conducted by the research group of Prof. Stefano Grigolato at the University of Padova. These data served as the basis for spatial analyses and perform spatial overlays required for the study.

2.3.2. Sentinel Satellite Data

Satellite data from the Sentinel missions, specifically Sentinel-1 and Sentinel-2, were used to calculate various environmental indices, including NDVI, NDWI, MNDWI, NDMI, SAVI, NDSI (see the following paragraphs for an explanation of acronyms), as well as evapotranspiration and soil moisture index. These datasets were sourced exclusively from GEE, which provided access to pre-processed and ready-to-use imagery.

Sentinel-2 provides multispectral imagery at a spatial resolution of 10, 20, and 60 meters, depending on the band, with a temporal resolution of 5 days at the equator. This high spatial and temporal resolution made Sentinel-2 data particularly useful for monitoring vegetation health (via NDVI and SAVI), land cover changes, and moisture content (via NDWI and MNDWI). The 13 spectral bands cover a wide range of wavelengths, from the visible to the shortwave infrared, enabling detailed analysis of vegetation, water bodies, and soil conditions. Sentinel-2's 5-day revisit time allowed for frequent monitoring, which was essential for capturing seasonal variations and short-term environmental changes.

Using GEE, I applied these satellite data to calculate environmental indices and assess the dynamics of vegetation, water and humidity on the ground over time, covering the time interval from 1.1.2021 to 31.12.2024. The indices derived from these datasets were essential to the environmental analysis, such as monitoring vegetation health, assessing soil moisture, and tracking water behaviour. Further details on the methods for calculating and extracting these indices are explained in subsequent sections.

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2.3.3. Meteorological data

Meteorological data for precipitation and temperature were obtained both from the meteotrentino.it network of weather stations and from Sentinel Data. These data supported the analysis of climatic conditions in the study areas and the calculation of key environmental parameters, such as evapotranspiration and soil moisture. The meteorological data contextualized the satellite data by considering climatic changes and atmospheric variables, thus supporting the analysis of environmental dynamics in the forested areas.

2.4. Environmental indices and their meaning

I calculated various environmental indices using satellite data provided by GEE and developed specific scripts for each index. This approach allowed for the extraction of data as time series and as quarterly averages over the period 2021–2024. Below, I describe the calculation methods for each index, their ecological and environmental significance, and the general structure of the script development process. The complete scripts, ensuring transparency and reproducibility, are included in full in the Appendix.

2.4.1. NDVI (Normalized Difference Vegetation Index)

The NDVI is a widely used index for assessing the health and vigour of vegetation by comparing the reflectance of light in the near-infrared (NIR) and red bands. Healthy vegetation reflects strongly in the NIR and absorbs red light, which makes it an excellent indicator of vegetation density and health (e.g., Rouse et al. 1974; Weier and Herring 2000).

The formula for NDVI is:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \quad (1)$$

Value range is 1 to -1. Bands Used: NIR (B8) and RED (B4)

This index is particularly useful for assessing vegetation density, health, and the extent of green cover. Positive values, close to +1, indicate healthy, dense vegetation, while values close to 0 or negative suggest either sparse vegetation or surfaces like bare soil, water, or snow. However, in regions with sparse vegetation, it can be influenced by underlying soil, leading to inaccurate readings. Similarly, in areas with dense vegetation, the index can become saturated, limiting its ability to distinguish between different types of healthy vegetation. Atmospheric conditions like cloud cover also tend to affect the reflectance values.

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2.4.2. NDWI (Normalized Difference Water Index)

The NDWI is used to detect water bodies and monitor moisture content in vegetation, which makes it useful in detecting changes in water availability. There are two versions of NDWI, each based on different band combinations, which helps tailor its application to specific needs. For the purpose of this study, we used the McFeeters' formula (McFeeters 1996b):

$$NDWI = \frac{(GREEN - NIR)}{(GREEN + NIR)} \quad (2)$$

Value range is 1 to -1. Bands Used: GREEN (B3) and NIR (B8).

Values lower than 0,3 indicate possible water bodies or areas with high moisture, while values lower than 0 typically represent non-water surfaces such as soil or vegetation. This index is effective in identifying surface water bodies, a crucial factor in water resource management, flood monitoring, and vegetation analysis. It also helps track water stress in vegetation. On the other hand, dense vegetation or soil moisture can influence the readings, sometimes leading to misclassification of areas with limited water bodies. Additionally, NDWI may be less accurate in regions affected by cloud cover or atmospheric disturbances.

2.4.3. MNDWI (Modified Normalized Difference Water Index)

The MNDWI modifies the traditional NDWI by replacing the NIR band with the SWIR (Shortwave Infrared) band, which enhances its ability to distinguish water from urban surfaces and dry soils (Xu 2006b).

$$MNDWI = \frac{(GREEN - SWIR)}{(GREEN + SWIR)} \quad (3)$$

Value range is 1 to -1. Bands Used: GREEN (B3) and SWIR (B11).

Values greater than 0,5 suggest the presence of pure water, while values between 0 and 0,5 represent humid surfaces or vegetation, and values lower than 0 suggest dry ground (or buildings). MNDWI excels in detecting water bodies in urban or peri-urban regions, where traditional indices may confuse water with artificial surfaces. It also provides improved contrast between water and dry areas. However, it can be less effective in turbid waters or places with high levels of suspended particles, and it may struggle with detecting shallow water bodies or low-reflectance waters, such as muddy rivers, which anyway are beyond the scope of this work.

2.4.4. NDMI (Normalized Difference Moisture Index)

The NDMI uses NIR and SWIR bands to assess moisture content in vegetation, helping to identify areas under water stress or with limited water availability. This is particularly valuable for monitoring vegetation during drought conditions.

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$$NDMI = \frac{(NIR - SWIR)}{(NIR + SWIR)} \quad (4)$$

Value range is 1 to -1. Bands Used: NIR (B8) and SWIR (B11).

Positive values of NDMI indicate vegetation with a high-water content, which is typical of healthy, hydrated plants. Negative values suggest water stress, drought, or even bare soil. However, soil moisture levels can affect its accuracy, especially in areas with sparse vegetation. It may also provide misleading results in places where soil moisture or a combination of wet soil and vegetation influence the readings.

2.4.5. SAVI (Soil-Adjusted Vegetation Index)

The SAVI is designed to reduce the influence of soil reflectance in areas with sparse or low vegetation. By adjusting for soil contributions, it provides a more accurate picture of vegetation health in arid or semi-arid environments, where NDVI might be less reliable (Huete 1988b).

$$SAVI = \frac{(NIR - RED)}{(NIR + RED + L)} \times (1 + L) \quad (5)$$

Value range is 1 to -1. Bands Used: NIR (B8) and RED (B4). L (Adjustment Factor): Typically set to 0.5 for areas with intermediate vegetation cover.

Values between 0,2 to and 1 suggest moderate to dense vegetation, and values lower than 0,2 represent exposed soil or scarce vegetation. SAVI is especially useful in sparse vegetation areas, such as deserts or agricultural lands, where soil reflectance can distort readings in traditional vegetation indices. However, its performance is contingent on the appropriate choice of L value (soil adjustment factor), which must be calibrated for local environmental conditions. Misapplication of this factor can lead to reduced accuracy.

2.4.6. NDSI (Normalized Difference Snow Index)

The NDSI is designed to detect snow and ice by exploiting the unique spectral characteristics of snow. Snow reflects strongly in the green band and weakly in the SWIR band, making it an ideal index for distinguishing snow from other land surfaces (Salomonson and Appel 2006; Hall and Riggs 2010).

$$NDSI = \frac{(GREEN - SWIR)}{(GREEN + SWIR)} \quad (6)$$

Value range is 1 to -1. Bands Used: GREEN (B3) and SWIR (B11).

Values higher than 0,4 indicate snow or ice, while lower ones refer to non-snow surfaces (such as vegetation, water, or soil). NDSI is highly effective in detecting snow cover, and it is widely used in environmental studies, hydrology, and climate monitoring. However, it can face challenges when

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snow is mixed with other materials, such as dirt or minerals, reducing its ability to distinguish snow from other surfaces. Additionally, vegetation beneath snow can also influence the results.

The NDSI values were calculated as part of this analysis; however, they were used solely as a reference. The primary indices analysed in this study are NDVI, NDWI, MNDWI, NDMI, and SAVI.

2.5. Script implementation

To develop the programming scripts, it was essential to account for the spectral characteristics and resolution of each satellite, as discussed in the "Sentinel" section. Sentinel-2, for example, operates at a maximum spatial resolution of 10 m and includes bands that are sensitive to atmospheric conditions, such as cloud cover and snow.

Pre-Processing Steps

The implementation began with pre-processing steps to reduce atmospheric influences, particularly the impact of clouds. Sentinel-2 images were filtered based on their spatial coverage and temporal range, focusing on the study area and the 2015–2024 period. To improve data quality, a two-step cloud masking process was applied. First, images with cloud coverage above 30% (`CLOUDY_PIXEL_PERCENTAGE > 30`) were excluded, ensuring the selection of images with minimal cloud interference:

```
var filteredS2 = s2
  .filter(ee.Filter.date('2015-01-01', '2024-01-01'))
  .filter(ee.Filter.bounds(geometry))
  .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 30));
```

Cloud Masking with Cloud Score+

In addition to this basic filtering, we applied the "Cloud Score+" method (Pasquarella et al. 2023) for more reliable cloud detection. This method computes a cloud score for each pixel based on a combination of spectral bands, including the blue, green, red, and near-infrared bands. The cloud score is used to identify cloud pixels more effectively, especially in complex conditions where clouds may overlap with vegetation or water. The Cloud Score+ dataset was linked to the Sentinel-2 collection using the `linkCollection()` function:

```
var csPlus = ee.ImageCollection('GOOGLE/CLOUD_SCORE_PLUS/V1/S2_HARMONIZED');
var csPlusBands = csPlus.first().bandNames();
var filteredS2WithCs = filteredS2.linkCollection(csPlus, csPlusBands);
```

To refine the cloud masking, a pixel-level quality threshold was applied using the 'cs' band from the Cloud Score+ dataset. Only pixels with a cloud score of 55% or higher were retained, effectively masking low-quality pixels:

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```
function maskLowQA(image) {
  var qaBand = 'cs';
  var clearThreshold = 0.55;
  var mask = image.select(qaBand).gte(clearThreshold);
  return image.updateMask(mask);
}

var filteredMasked = filteredS2WithCs.map(maskLowQA);
```

This two-step approach ensured both image-level and pixel-level quality assurance. By combining a cloud percentage threshold (30%) with the advanced "Cloud Score+" method, the dataset was optimized for subsequent analysis, even in areas with complex terrain or high cloud coverage.

Area of Interest (AOI) and Buffers

The analysis was performed on specific areas of interest (AOIs) corresponding to the areas of our study. For each AOI, internal and external buffers of 5 meters were calculated. These buffers were designed to minimize edge effects and provide a detailed analysis of the target areas. However, buffer calculations were not always successful due to geometric inconsistencies, which were addressed on a case-by-case basis.

```
var bufferIn = aoi.geometry().buffer(-5); // 5-meter internal buffer
var bufferOut = aoi.geometry().buffer(5); // 5-meter external buffer
```

Calculation of Indices

Once the pre-processed images were prepared, various spectral indices were calculated for each AOI.

Example code for Indices calculation:

```
function addNDVI(image) {
  var ndvi = image.normalizedDifference(['B8', 'B4']).rename('ndvi');
  return image.addBands(ndvi);
}

function addNDWI(image) {
  var ndwi = image.normalizedDifference(['B3', 'B8']).rename('ndwi');
  return image.addBands(ndwi);
}

function addMNDWI(image) {
  var mndwi = image.normalizedDifference(['B3', 'B11']).rename('mndwi');
  return image.addBands(mndwi);
}

function addNDMI(image) {
  var ndmi = image.normalizedDifference(['B8', 'B11']).rename('ndmi');
```

Materials and methods

```
return image.addBands(ndmi);
}
function addSAVI(image) {
var savi = image.expression(
  '1.5 * ((NIR - RED) / (NIR + RED + 0.5))', {
    'NIR': image.select('B8').multiply(0.0001),
    'RED': image.select('B4').multiply(0.0001)
  }).rename('savi');
}
function addNDSI(image) {
var ndsi = image.normalizedDifference(['B3', 'B11']).rename('ndsi');
return image.addBands(ndsi);
}
```

The calculated indices were added as new bands to the original images, enabling further analysis.

Temporal Aggregation and Composites

To analyse temporal patterns, the scripts filtered the image collections to the study period (January 2021 to December 2024). Aggregations were performed to compute daily, monthly, and quarterly averages. For quarterly composites, the images within each quarter were averaged, creating a representative image for that period:

```
function quarterlyComposite(startDate, endDate) {
  var collection = ee.ImageCollection('COPERNICUS/S2')
    .filterDate(startDate, endDate)
    .filterBounds(aoi)
    .map(maskClouds)
    .map(calculateNDVI);
  return collection.mean().set('system:time_start',
    ee.Date(startDate).millis());
}
```

The resulting quarterly composites were labelled (e.g., Q1, Q2) and exported as GeoTIFF files for further analysis.

Time-Series Analysis

The scripts also generated time-series graphs for each index. These graphs highlighted temporal trends in vegetation health, water availability, and soil moisture. The data was averaged over daily, monthly, and quarterly intervals, and the time-series outputs were visualized using Google Earth Engine's charting tools.

2.6. Statistical Analyses

Statistical analyses were conducted to investigate spatial and temporal variations in vegetation and water-related indices (NDVI, NDWI, MNDWI, NDMI, SAVI) across the study areas (Lavazé 1, Lavazé 2, Marcesina 1, Marcesina 2, and Marcesina 3) over the study period (2021–2024). A One-Way Analysis of Variance (ANOVA) was performed for each index to assess significant differences between the areas, with a significance threshold of $\alpha = 0.05$. This analysis aimed to detect whether specific indices exhibited spatial variability across the study regions.

To assess the impact of skid trail proximity, two-sample t-tests were used to compare indices calculated within 5 m buffer zones around skid trails and those outside these buffer zones. The analyses focused on Lavazé 1, Lavazé 2, and Marcesina 2. Prior to conducting the t-tests, variance homogeneity was evaluated and confirmed, as all variances were close to 1.

Finally, Pearson correlation analyses were conducted to explore relationships between indices within and across study areas, as well as their associations with climatic variables such as precipitation and mean temperature. These correlations provided insights into vegetation responses and water-related dynamics across spatial and temporal scales, highlighting interactions between indices and environmental conditions.

3. Results

3.1. Indices Trends and Environmental Changes (2021–2024)

The trends of environmental indices across the Lavazé and Marcesina study areas from 2021 to 2024 highlight significant seasonal variations. The following graphs (Figure 4) show the trends in precipitation (monthly cumulative) and average monthly temperatures for the Lavazé and Marcesina areas over the time interval 2021 to December 2024.

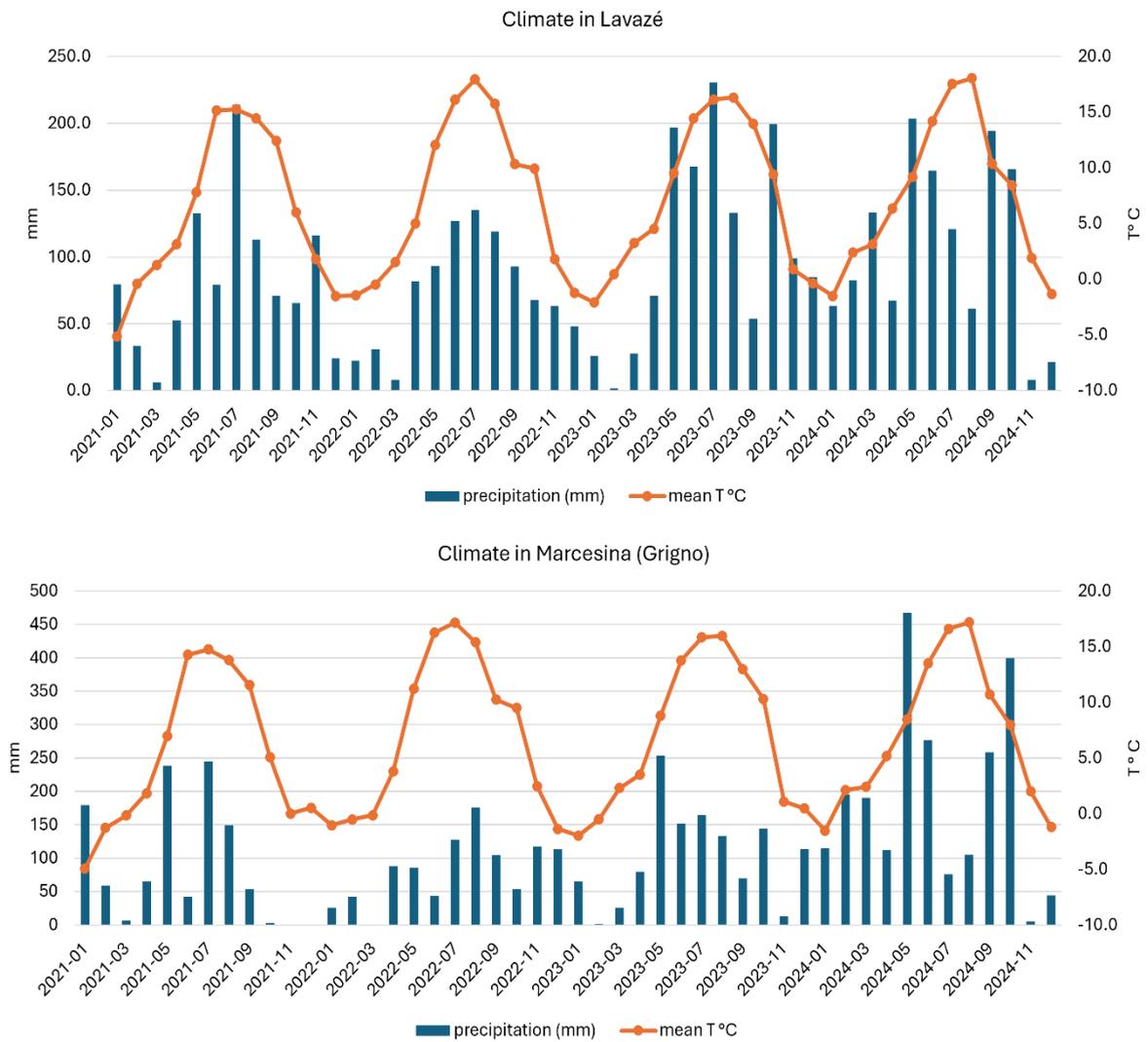


Figure 4: Graphs of monthly average precipitation and temperatures for the Lavazé and Marcesina areas.

Results

In Figure 5 and Figure 6 we compare the evolution of each index in the different areas.

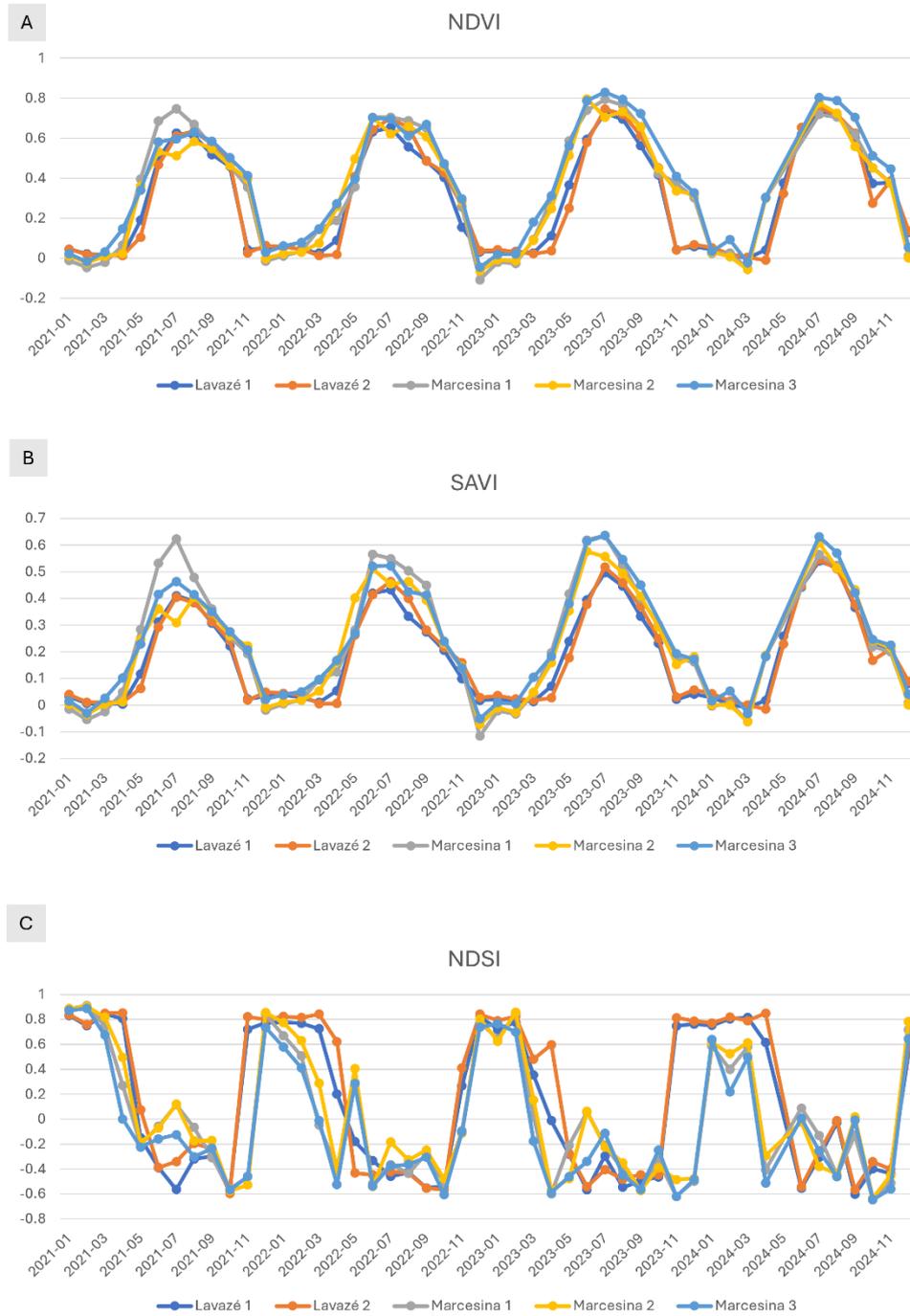


Figure 5: Graphs comparing the NDVI, SAVI and NDSI indices. (A, B, C) for each study area.

Results

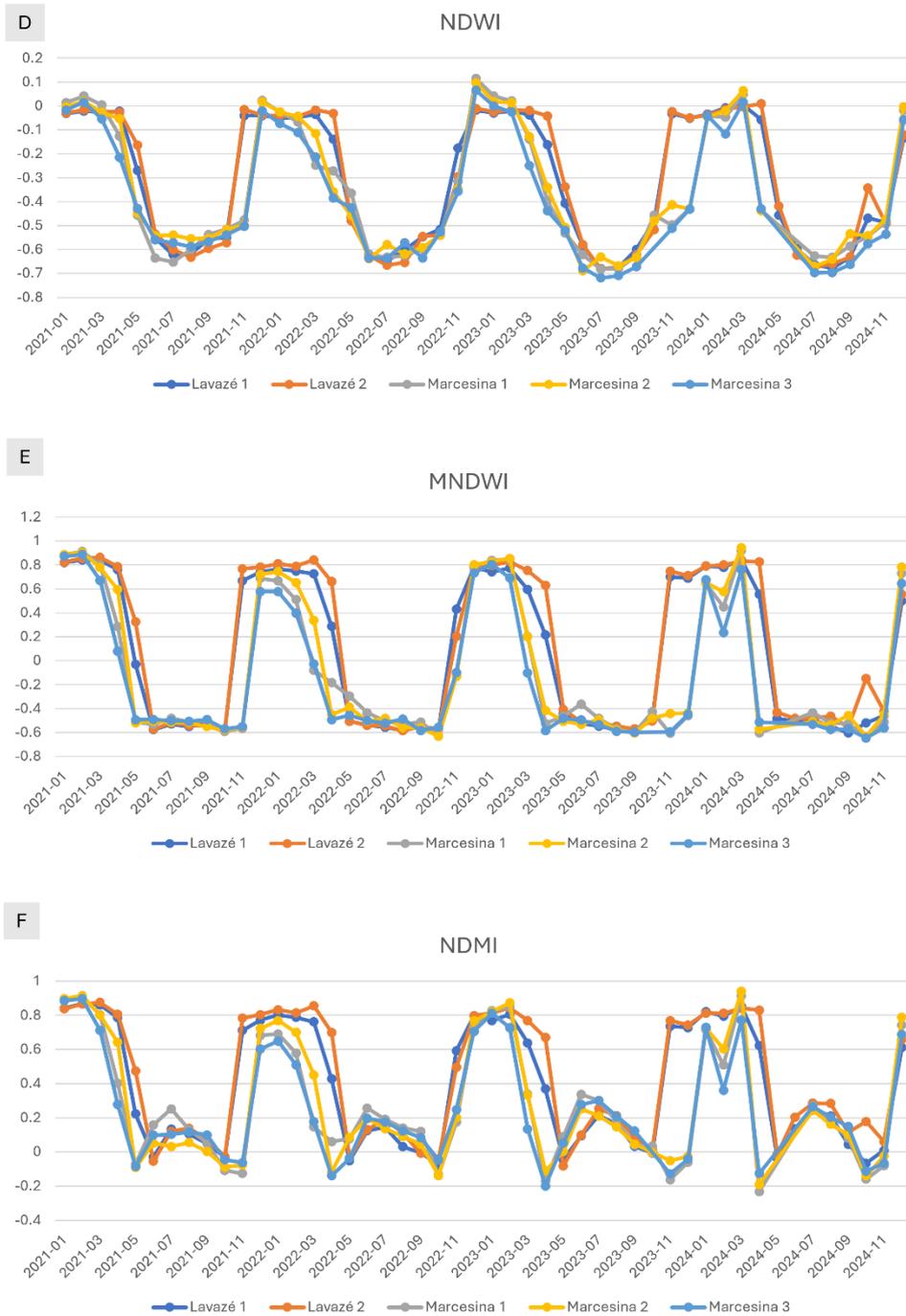


Figure 6: Graphs comparing of NDWI, MNDWI, NDMI indices (D, E, F) for each study area.

The following subsections summarize the trends for each area. In the Appendix are reported the raw data.

Lavazé 1

In Lavazé 1, environmental indices displayed substantial seasonal variation between 2021 and 2024. The NDVI started relatively low in January 2021 at 0.0502, reflecting dormant vegetation. As the year progressed, it steadily increased, reaching a peak of 0.6337 in July, signalling the expansion of vegetation during the growing season. Following this peak, NDVI began to decline

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during the colder months, aligning with the typical seasonal cycle. Similar trends were observed across subsequent years, with slight interannual differences.

The NDWI remained predominantly negative, particularly during the summer months, when moisture content was lowest. For instance, NDWI in June 2021 reached -0.3523, indicative of dry conditions. The MNDWI followed a similar pattern, with negative values during the drier periods and values closer to zero during wetter months. NDMI, which indicates moisture levels, mirrored the NDVI trend, increasing during the growing season and declining as vegetation senesced.

SAVI, which accounts for soil influences on vegetation, peaked in the summer, reaching 0.5224 in July 2021, reflecting healthy vegetation. The index proved useful for monitoring vegetation dynamics, particularly in semi-arid areas where soil effects are significant. Across years, SAVI values remained consistent, peaking during summer and declining in winter.

Environmental factors like precipitation and temperature significantly influenced vegetation dynamics in Lavazé 1. Precipitation was highest in May 2021 at 183.9 mm, coinciding with the increased vegetation activity observed during this period. Temperature followed typical seasonal patterns, with the coldest month in January 2021 at -4.2°C and the warmest in July 2022 at 16.5°C.

Lavazé 2

Lavazé 2 exhibited similar trends in environmental indices but showed slight differences in magnitude and timing. The NDVI started at 0.0435 in January 2021, indicating dormant vegetation, and rose to a peak of 0.5842 in July, reflecting the summer vegetation peak. Afterward, NDVI values decreased during autumn and winter, a pattern consistent across subsequent years.

The NDWI remained negative throughout the summer months, with the lowest value recorded in June 2021 (-0.4105), indicating dry conditions. MNDWI values showed a stronger response during wet months, such as April 2024, when it peaked at 0.4927, reflecting increased water content in vegetation. NDMI showed similar seasonal trends, with higher values during the growing season.

SAVI reached a maximum of 0.4601 in July 2021, reflecting the summer vegetation peak. This index effectively captured vegetation health while accounting for soil effects. Seasonal changes in SAVI were similar across years, with peaks during summer and declines in winter.

Precipitation and temperature patterns in Lavazé 2 mirrored those in Lavazé 1. The highest rainfall occurred in May 2021 (178.2 mm), and the temperature ranged from -3.8°C in January 2021 to 18.4°C in July 2022. These factors were closely linked to the seasonal and interannual variations in vegetation indices.

Results

Marcesina 1

In Marcesina 1, we observed a general variation in indices over time, consistent with seasonal trends. The NDVI ranged from negative values in the winter months to higher values during the warmer months. For example, NDVI in January 2021 was -0.01217, but by June, it increased significantly to 0.68467, reflecting vegetation growth during spring and summer. The NDVI peaked at 0.74625 in July 2021 and followed similar trends across subsequent years, declining during the colder months.

The NDWI was predominantly negative, especially in the summer months, indicating dry conditions. In June 2021, NDWI was -0.635917, a pattern consistent across years. MNDWI followed a similar seasonal trend, with high negative values during the dry season and values approaching zero during wetter months. NDMI showed strong seasonal variation, increasing alongside vegetation growth and declining in winter.

SAVI reflected the seasonal vegetation dynamics, peaking at 0.62375 in July 2021. The index provided a reliable measure of vegetation health, accounting for soil influences. Seasonal peaks in SAVI were consistent across years, corresponding to the growing season.

Precipitation and temperature patterns in Marcesina 1 influenced these indices. Rainfall peaked in May 2021 (238.6 mm), while the temperature ranged from -5°C in January 2021 to 17.2°C in July 2022. These climatic factors closely aligned with the observed seasonal and interannual vegetation trends.

Marcesina 2

Marcesina 2 exhibited similar seasonal trends in vegetation and moisture indices, with slight differences in timing and magnitude. The NDVI began near zero in January 2021 (0.011333) and gradually increased, reaching its peak in July 2021 at 0.5105. NDVI trends across years followed a similar pattern, with peaks in summer and declines in winter.

NDWI remained mostly negative, reflecting dry conditions, with the lowest values recorded during the summer months, such as June 2021 (-0.542). MNDWI values peaked during wetter months, such as April 2024 (0.944), indicating higher water content in vegetation. NDMI followed the seasonal vegetation growth, peaking during the growing season.

SAVI dynamics mirrored those of NDVI, with a peak of 0.405083333 in August 2021. Precipitation in Marcesina 2 was highest in May 2021 (238.6 mm), and temperatures ranged from -5°C in January 2021 to 17.2°C in July 2022, consistent with vegetation dynamics.

Results

Marcesina 3

In Marcesina 3, environmental indices exhibited a seasonal variation similar to that of Marcesina 1 and 2, with a clear annual trend. NDVI started with low values in January 2021 (0.021) and gradually increased during the growing season, peaking at 0.80305 in July 2024. As in the other sites, NDVI decreased in the winter months, reaching 0.0525625 in December 2024, indicating reduced vegetation due to low temperatures.

NDWI was predominantly negative, reflecting dry conditions during the summer months, with the lowest value recorded at -0.71825 in July 2023. However, values approached zero during wetter months, such as January 2024 (-0.04185). MNDWI followed a similar pattern, with negative values during the dry season and positive values during wetter periods. A notable peak was observed in April 2021 (0.8725), and the lowest value occurred in June 2023 (-0.536), reflecting fluctuations in soil moisture.

NDMI followed the same seasonal pattern, increasing during the growing season and decreasing in winter. The peak was observed in July 2023 (0.29975), and in December 2024, it dropped to 0.68784375. SAVI followed a similar trend to NDVI, with a summer peak in July 2023 (0.63525) and a decline in winter, reaching 0.04084375 in December 2024.

Precipitation in Marcesina 3 was higher during the summer months, with a significant peak in October 2024 (399.2 mm). Temperatures were generally low in winter, with values of -5°C in January 2021 and -1.5°C in January 2024, increasing during the summer months, reaching around 16-17°C in July and August 2023.

3.2. Composite maps of indices

The composite maps presented in Figure 7 to Figure 16 represent quarterly composites of NDVI, NDWI, MNDWI, NDMI, and SAVI indices for the Lavazé and Marcesina areas during the 2021–2024 period. Each row corresponds to a quarter (Q1: January–March, Q2: April–June, Q3: July–September, Q4: October–December), and each column represents a year within the study period. These maps provide a spatial and temporal representation of the indices, highlighting seasonal variations and multi-year trends in vegetation conditions, soil moisture, and surface water presence, with a specific focus on areas impacted by forest skid trails.

For each index (NDVI, NDWI, MNDWI, NDMI, SAVI) and each macro-study area (Lavazé and Marcesina, including their sub-areas), detailed maps were generated to highlight significant temporal and spatial variations linked to environmental conditions and anthropogenic activities. In the Appendix are also available maps showing the skid trails overlay the density kernel for easier comparison with the composite maps.

Results

3.2.1. Lavazé Area

NDVI

The analysis of the Normalized Difference Vegetation Index (NDVI) shows a stable trend for Q1, likely influenced by snow (Figure 7). In Q2, a progressive increase in vegetation cover is observed until 2023, with a slight decline in 2024. During Q3, a sharp increase in the index is noted, with lower values in areas with forest skid trails and roads. Finally, Q4 highlights a reduction in bare soil areas, with an improvement in vegetation cover in 2022.

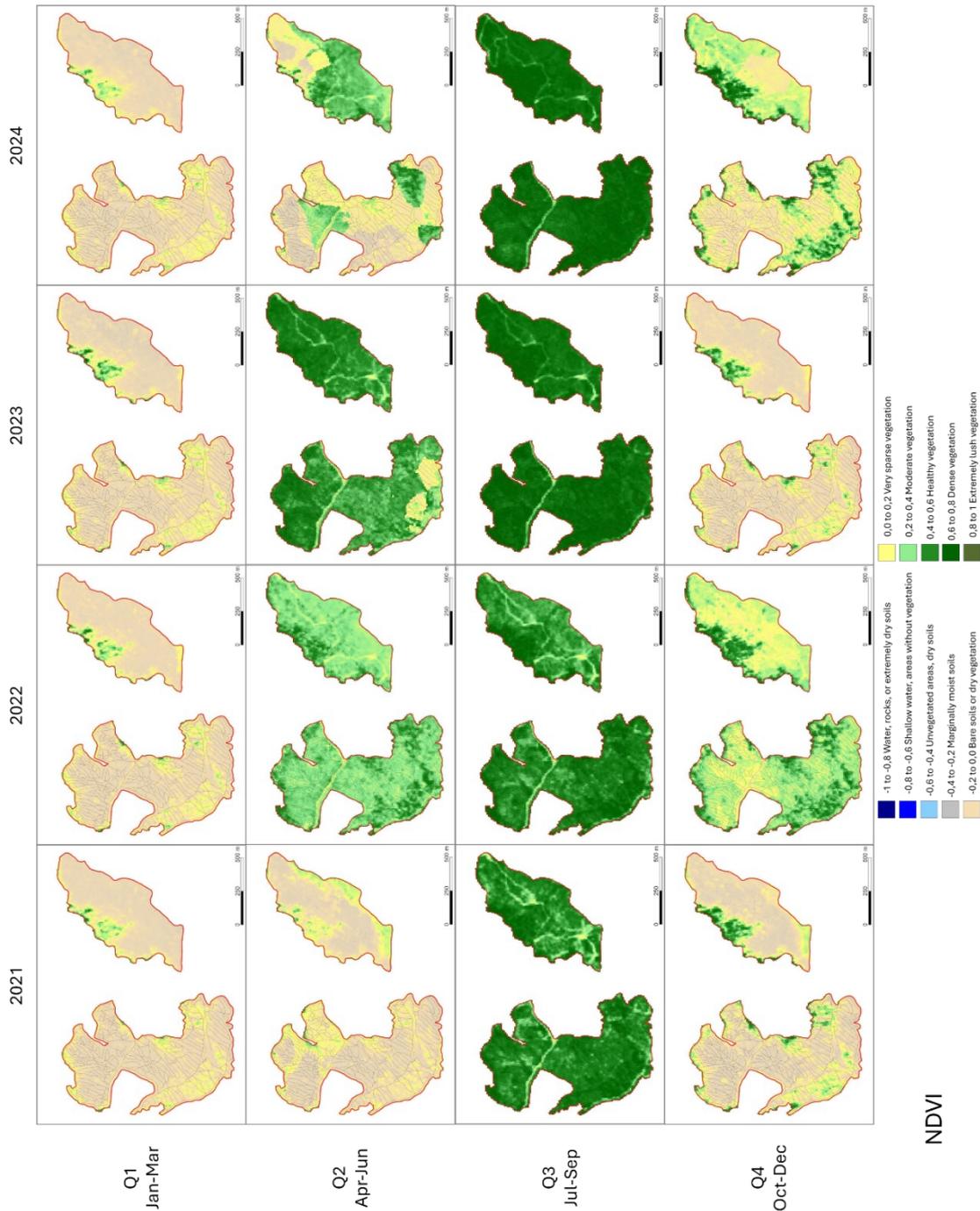


Figure 7: NDVI composite map for Lavazé area (2021-2024).

Results

NDWI

The Normalized Difference Water Index (NDWI) for Lavazé (Figure 8) confirms traces of soil moisture during Q1 across the period considered, with some marginally drier areas north of Lavazé 1. In Q2, a trend toward greater dryness is noted, followed by an increase in soil moisture in 2024. During Q3, the areas are generally dry, with more humid values localized along forest skid trails. In Q4, 2024 shows a slight increase in moisture compared to previous years.

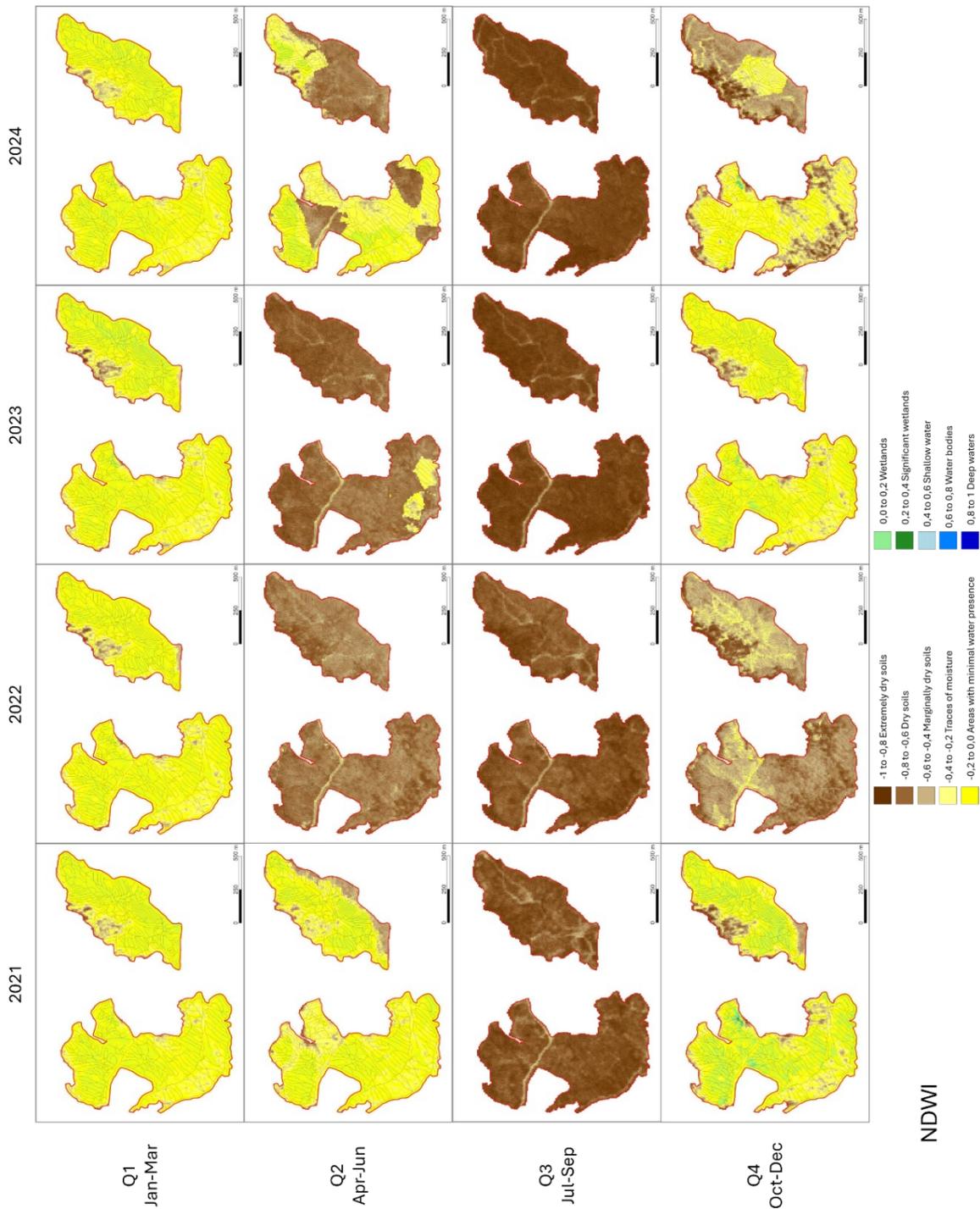


Figure 8: NDWI composite map for Lavazé area (2021-2024).

Results

MNDWI

The analysis of the Modified Normalized Difference Water Index (MNDWI) for Lavazé highlights significant changes in water content and soil moisture (Figure 9). During Q1, a gradual reduction of wet areas is observed from 2021 to 2024. In Q2, the situation evolves from marked water presence in 2021 to drier soils in 2022 and 2023, with a significant increase in moisture in 2024. This increase is more evident in Lavazé 1, where forest skid trails seem to favour greater soil dryness in the affected areas. During Q3, a progressive increase in moisture is noted, especially near forest skid trails and roads. In Q4, the data shows contrasting situations: 2021 and 2023 are characterized by higher surface water presence and moisture near the trails, while 2024 marks a reduction in moisture, with some exceptions in Lavazé 2.

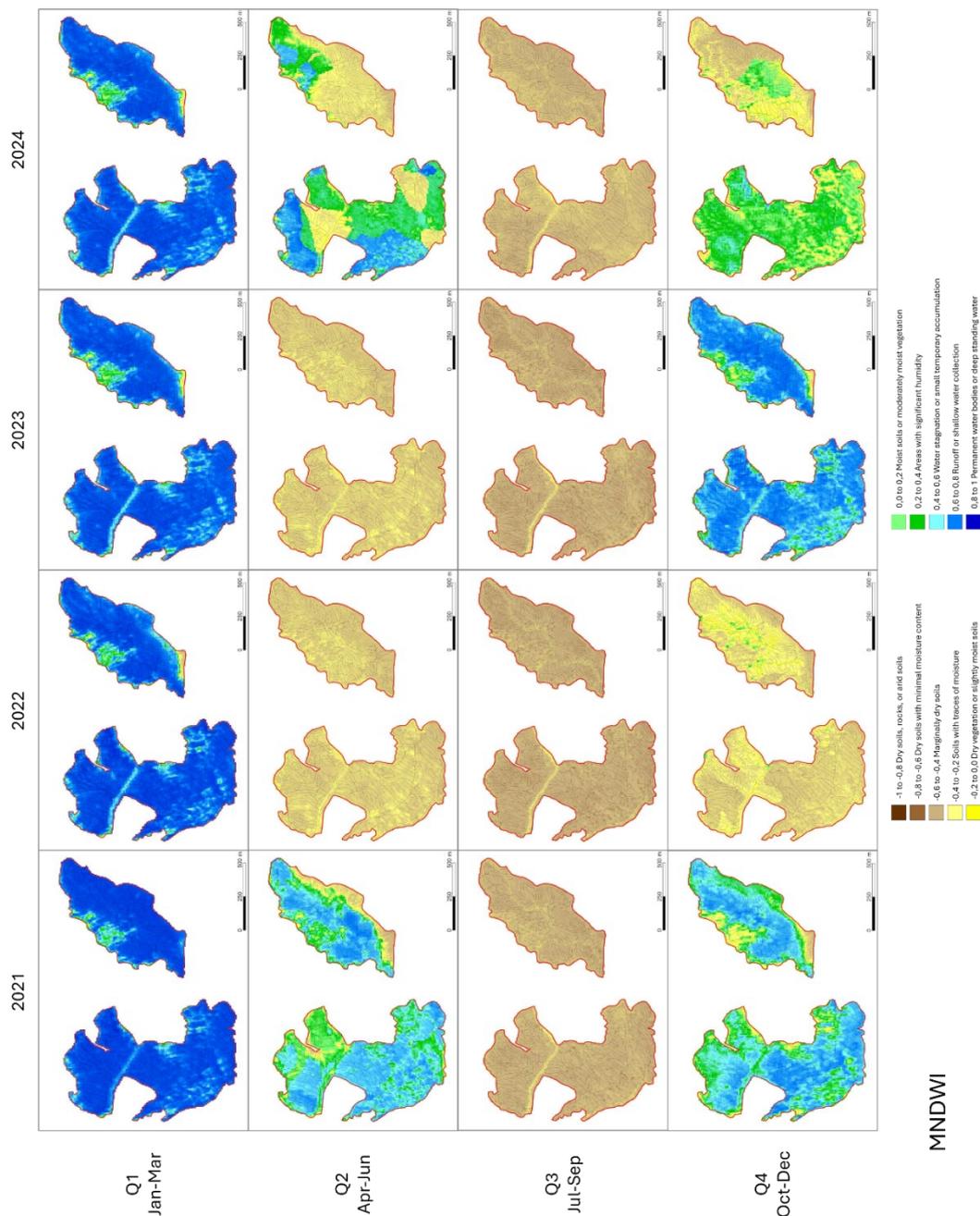


Figure 9: MNDWI composite map for Lavazé area (2021-2024).

Results

NDMI

The Normalized Difference Moisture Index (NDMI) for Lavazé reveals interesting trends (Figure 10). During Q1, the areas are generally wet throughout the 2021–2024 period, with a progressive decrease in favour of moist vegetation in 2023 and 2024. In Q2, a gradual decline in water content is observed, with some areas of stagnation more evident in 2024. During Q3, drier areas are found near forest skid trails, while in Q4, there is a progressive decrease in wet areas, except for 2023, characterized by particularly moist vegetation.

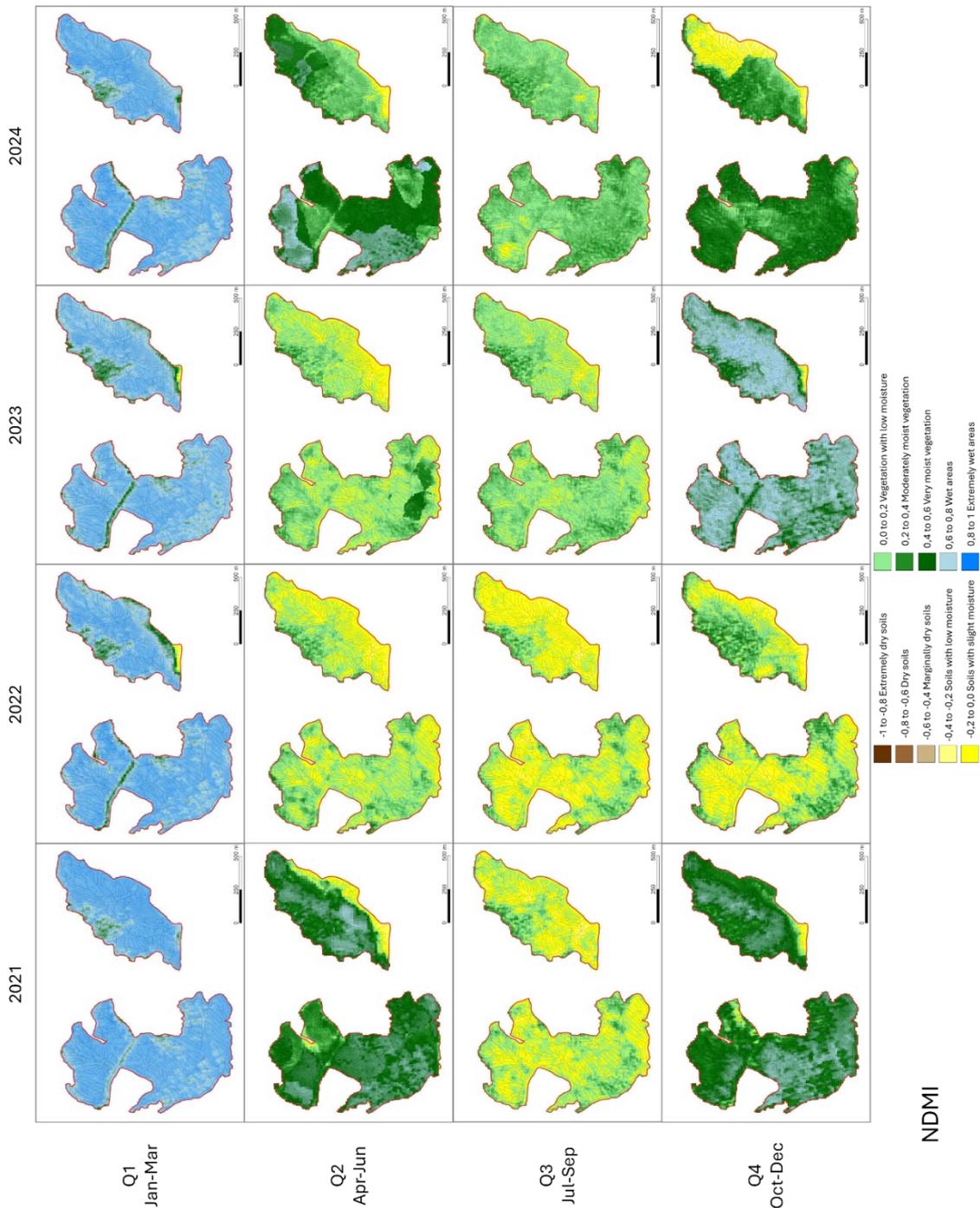


Figure 10: NDMI composite map for Lavazé area (2021-2024).

Results

SAVI

The SAVI (Figure 11) shows a relatively stable situation in Q1. In Q2, a transition from stressed vegetation in 2021 to healthier conditions in 2023 is evident, followed by increased vegetative stress in 2024, particularly in Lavazé 2. During Q3, vegetation improves significantly from 2021 to 2024, while Q4 shows a gradual recovery of healthy vegetation with some areas of evident regeneration.

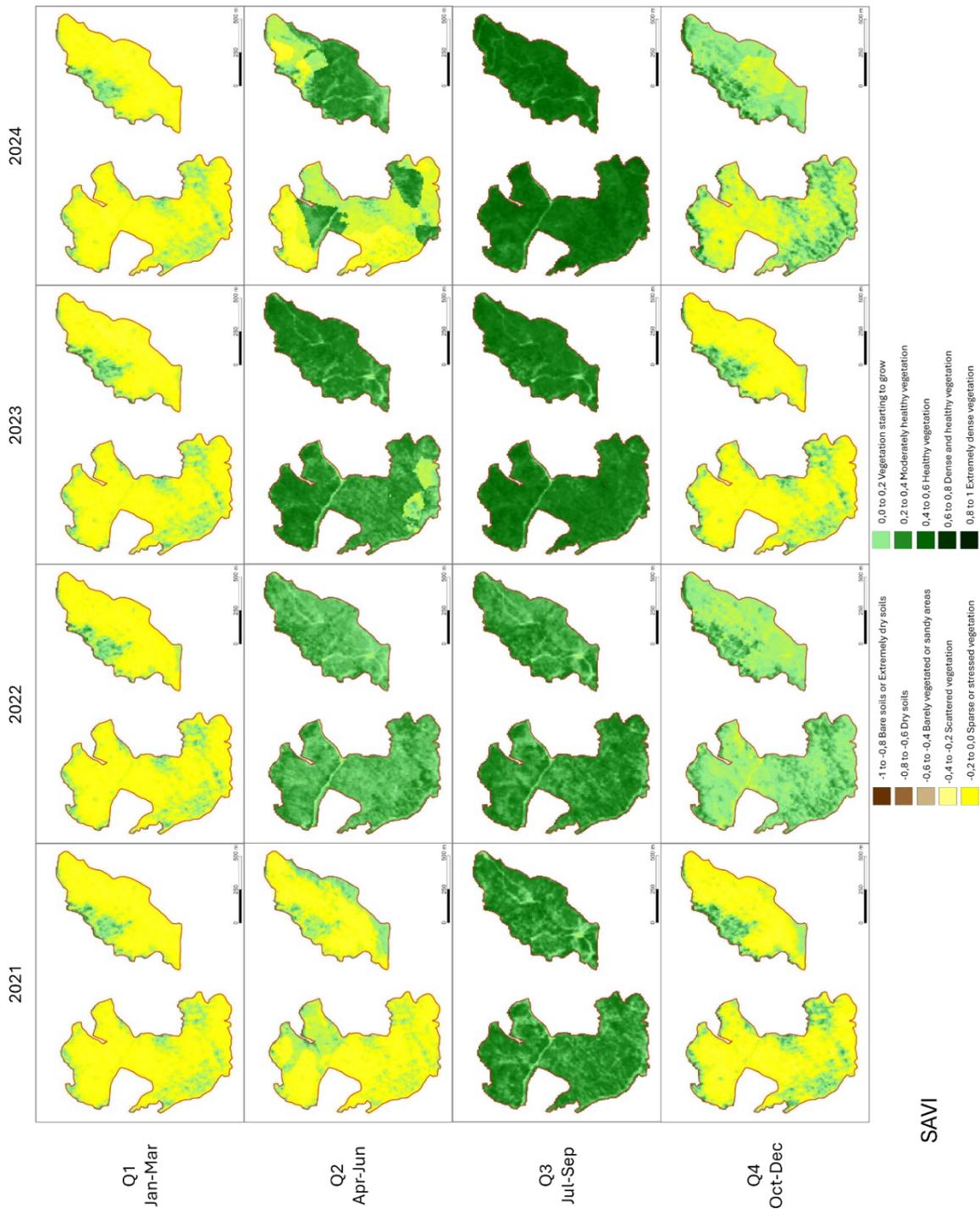


Figure 11: SAVI composite map for Lavazé area (2021-2024).

Results

3.2.2. Marcesina Area

NDVI

In Q1, NDVI indicates sparse vegetation cover, except for 2022. During Q2, a progressive decline in vegetation is observed until 2024, with moderate values. In Q3, the index increases significantly, indicating very dense vegetation in 2024, while Q4 shows a reduction in vegetation cover in road and trail areas (Figure 12).

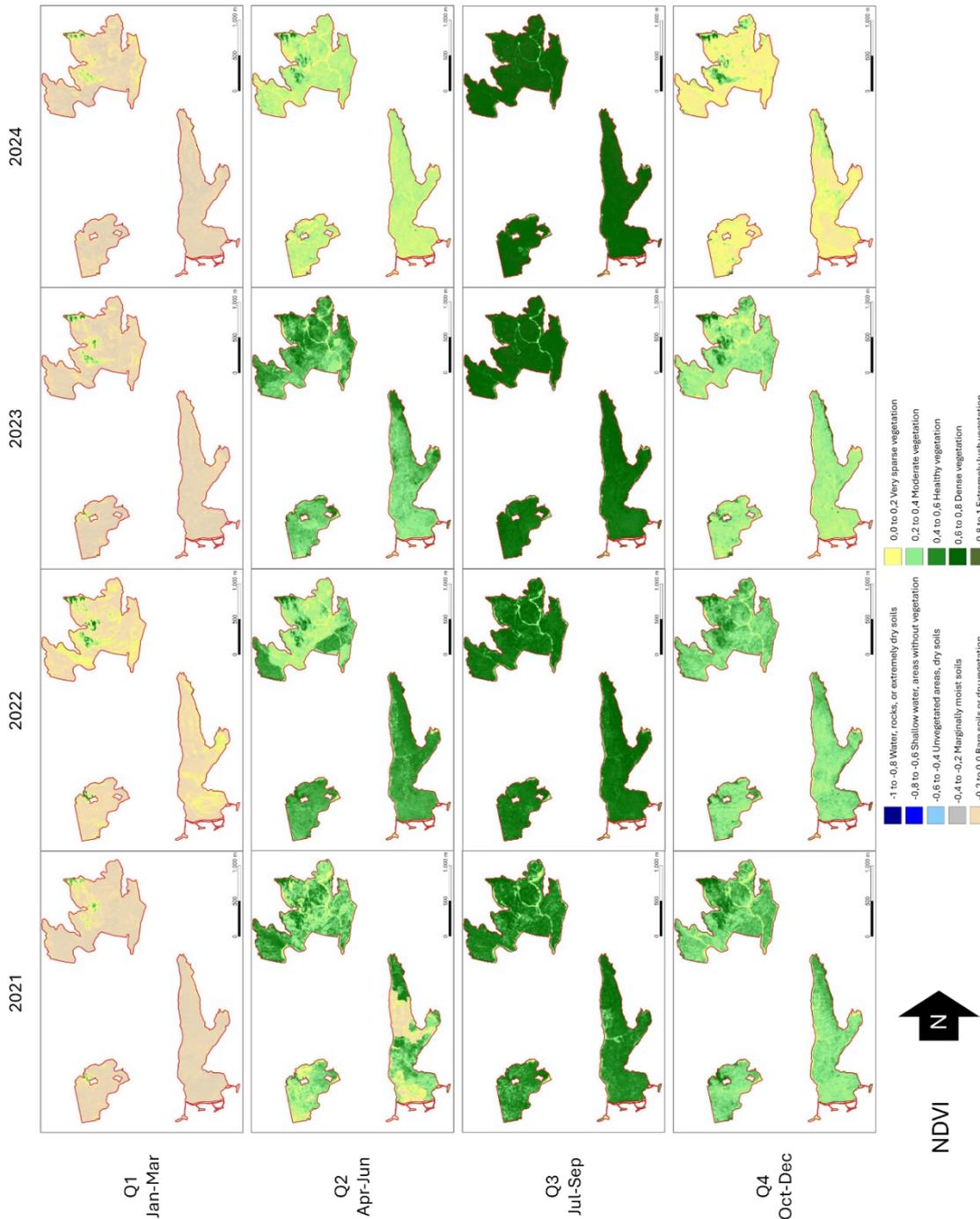


Figure 12 NDVI composite map for Marcesina area (2021-2024).

Results

NDWI

In Q1, a general increase in moisture is noted, with some areas becoming true wet zones by 2024 (Figure 13). During Q2, moisture progressively decreases until 2023, with a slight increase in 2024. Q3 maps show a progressive reduction in soil moisture, while in Q4, a significant increase in moisture is observed in areas near forest skid trails.

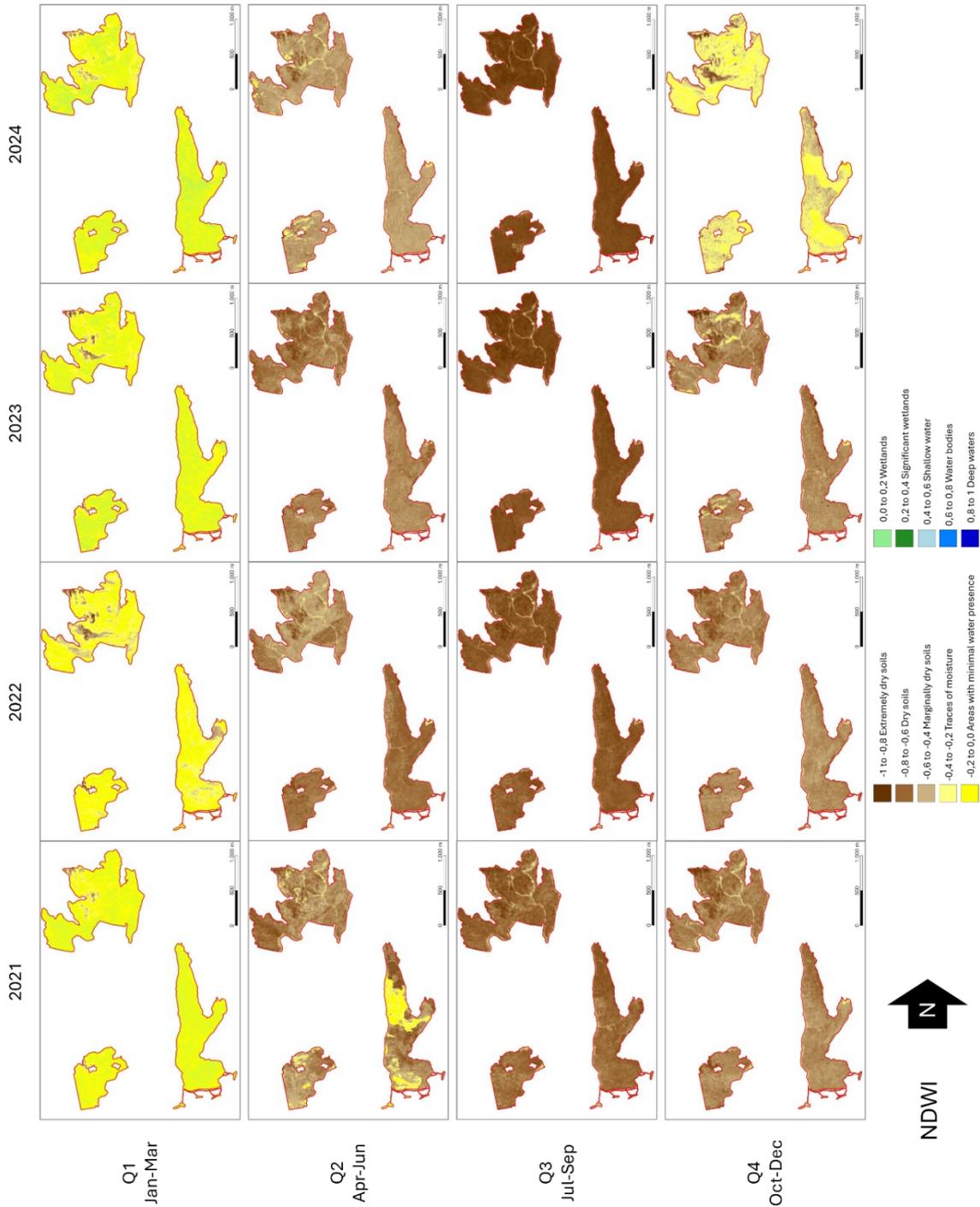


Figure 13 NDWI composite map for Marcesina area (2021-2024).

Results

MNDWI

In Marcesina, Q1 highlights surface water stagnation that progressively decreases toward 2024 (Figure 14). In Q2, the area shifts from wet zones in 2021 to drier soils in 2024, with greater moisture near forest skid trails. During Q3, the areas become drier, while in Q4, an increase in moisture is recorded, especially along trails and roads.

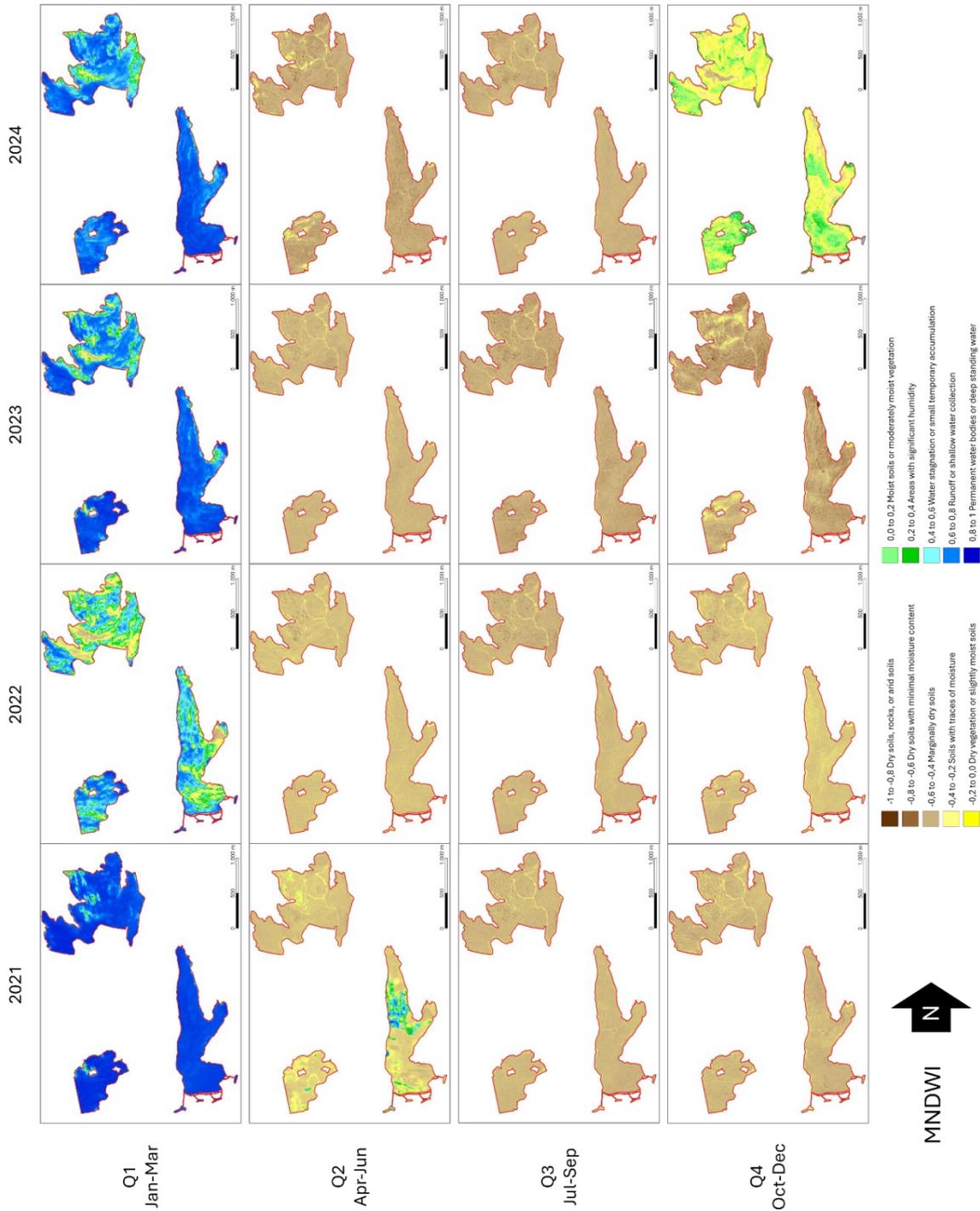


Figure 14: MNDWI composite map for Marcesina area (2021-2024).

Results

NDMI

For Q1, NDMI shows wet soils with moist vegetation, while Q2 highlights a transition from wet to marginally dry soils by 2024. During Q3, wetter areas are found away from roads, while Q4 shows a sharp increase in moisture in trail areas (Figure 15).

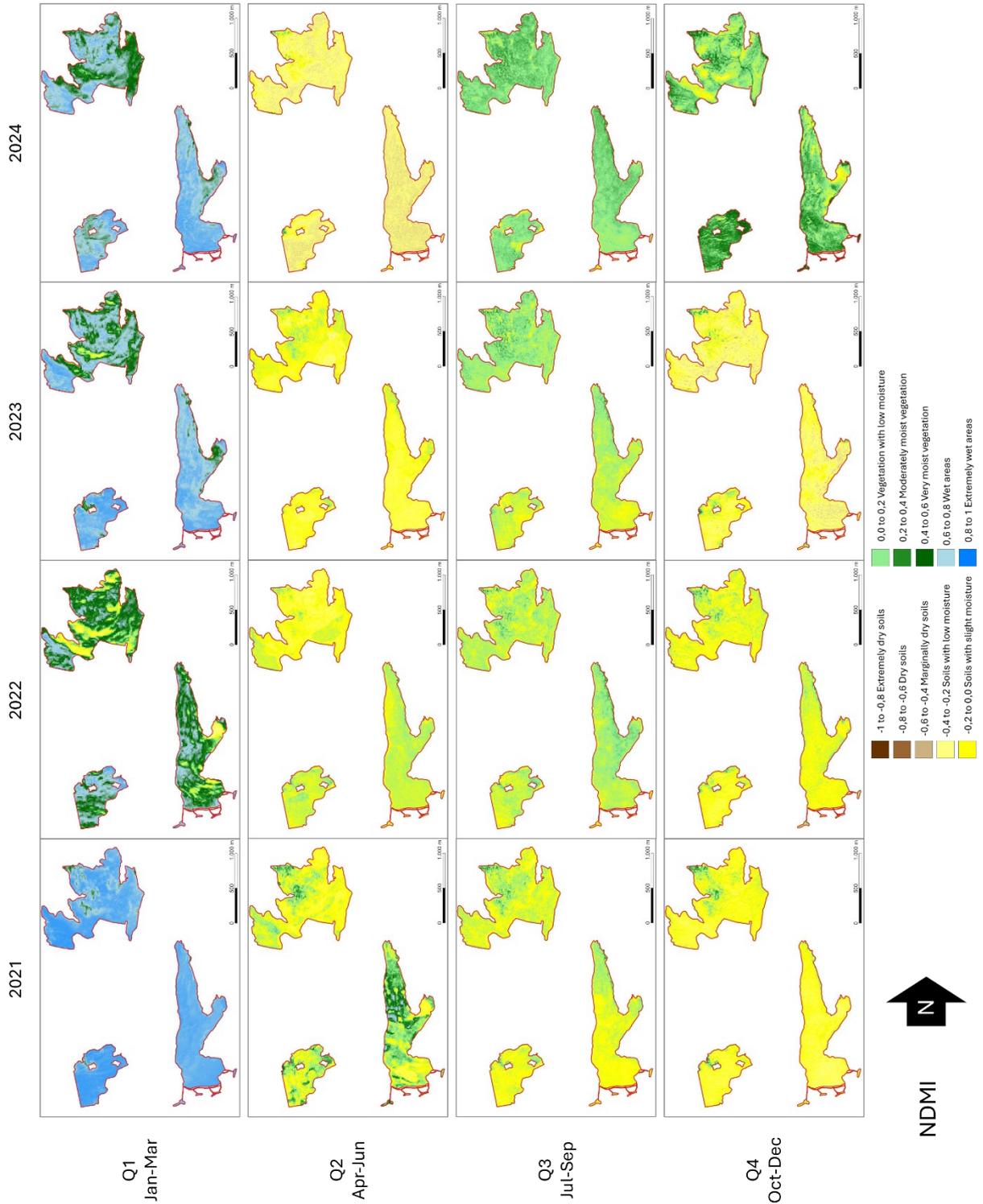


Figure 15 NDMI composite map for Marcesina area (2021-2024).

Results

SAVI

The SAVI for Q1 shows a consistent trend, while Q2 highlights a reduction in vegetation from 2021 to 2024. During Q3, vegetation improves, with lower values along roads. In Q4, there is a transition towards healthier vegetation cover, though areas near roads and skid trails show lower values (Figure 16).

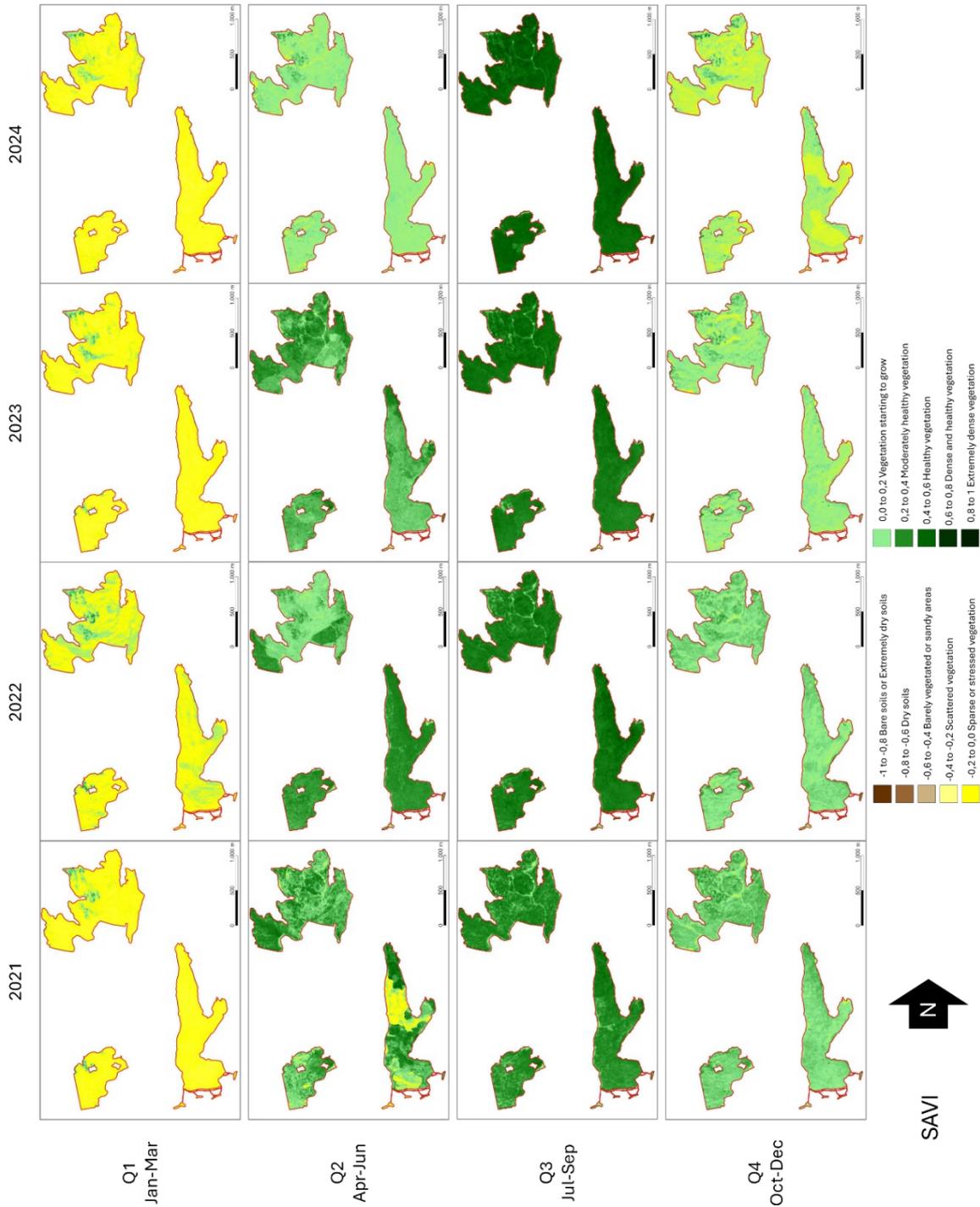


Figure 16 SAVI composite map for Marcesina area (2021-2024).

Results

3.3. Integrated Statistical Analyses

Statistical analyses highlighted spatial and temporal variations in vegetation and water-related indices across the study areas (Lavazé 1, Lavazé 2, Marcesina 1, Marcesina 2, and Marcesina 3) over the period 2021–2024. The ANOVA results indicated that NDMI was the only index exhibiting a statistically significant difference ($p < 0.05$), primarily driven by disparities between Lavazé 1 and Lavazé 2. While other indices also displayed distinct trends between the Lavazé and Marcesina areas, these differences were not statistically significant at the selected confidence level.

For buffer zone analyses, the results from the t-Test revealed no statistically significant differences across all areas and indices. Although some variation in means was observed between the two zones, the t-statistic remained consistently near 0, within a range of -1 to 1 across all indices, and never exceeded the critical t-value. This confirms the lack of significant differences between buffer and non-buffer zones.

Pearson correlation analyses provided additional insights into relationships within and across sub-areas, as well as the influence of climatic variables. Strong correlations were observed within sub-areas. NDVI in Lavazé 1 and Lavazé 2 was highly correlated with SAVI ($r = 0.99$) and mean temperature ($r = 0.93$). Negative correlations were identified with NDWI ($r = -0.99$), MNDWI ($r = -0.94$), and NDMI ($r = -0.84$). Precipitation showed moderate positive correlations with NDVI ($r = 0.59$) and SAVI ($r = 0.60$), but weak negative correlations with other indices (approximately $r = -0.58$).

In the Marcesina sub-areas, correlation patterns mirrored those in Lavazé, though with reduced intensity. In Marcesina 1, NDVI remained strongly correlated with SAVI ($r = 0.98$) and mean temperature ($r = 0.94$). Negative correlations with NDWI ($r = -0.97$), MNDWI ($r = -0.86$), and NDMI ($r = -0.64$) were observed but were less pronounced compared to Lavazé. Precipitation correlations were minimal, with maximum positive values of $r = 0.31$ (NDVI) and negative values of $r = -0.28$ (NDWI).

Marcesina 2 and 3 exhibited trends similar to Marcesina 1. NDVI was positively correlated with SAVI ($r = 0.99$) and mean temperature ($r = 0.93$), while negative correlations with NDWI, MNDWI, and NDMI persisted, ranging from $r = -0.98$ to $r = -0.61$. Weak precipitation correlations were consistent, with maximum values of $r = 0.27$ for NDVI and SAVI, and slightly negative correlations for the other indices.

These results emphasize that vegetation and water-related indices respond differently to climatic and spatial factors across the study areas. The correlation analyses, despite no significant differences were observed between buffer and non-buffer zones, highlighted consistent trends

Results

within sub-areas and variability across larger spatial scales. NDMI and MNDWI, in particular, exhibited weaker cross-area correlations, further suggesting distinct environmental influences.

4. Discussion

The analysis of the temporal and spatial trends in vegetation and moisture-related indices across the study areas revealed substantial seasonal variation and spatial differences that can be attributed to environmental factors, notably precipitation and temperature, as well as the presence of forest skid trails. In this section, we discuss the implications of these findings in relation to existing literature, with a focus on how these indices relate to forest management practices and land cover dynamics.

4.1. Indices Trends and Environmental Changes (2021–2024)

The following sections summarize the seasonal and multi-year trends of vegetation and moisture indices, precipitation, and temperature across the study areas in the considered time range. These trends offer insight into the temporal variations in vegetation and moisture levels, considering the effects of environmental factors such as precipitation and temperature.

As expected, the indices followed typical seasonal patterns, with higher NDVI values during the growing season (spring and summer) and lower values during the colder months. These trends are consistent with previous studies that have highlighted the strong seasonality of vegetation dynamics in temperate forests (e.g., Tucker 1979; Gamon et al. 1995; Carlson and Ripley 1997; Pettorelli et al. 2005; Klisch and Atzberger 2016). The NDVI values in Lavazé and Marcesina were comparable to those found in other Mediterranean and Alpine areas, where vegetation dynamics are strongly influenced by temperature and precipitation patterns (Pettorelli et al. 2005). The consistently low NDVI values observed during the winter months (January–March) across both study areas also align with findings in other high-latitude regions (Myneni et al. 1997; Kato et al. 2021).

The NDVI trends reflect the typical seasonal variation expected in temperate forest ecosystems, with clear peaks during the summer months each year. These trends provide a baseline for understanding vegetation dynamics in the presence of skid trails:

Lavazé 1 and 2 (Figure 17): NDVI peaks remained stable during summer (June–July), indicating steady vegetation growth. However, 2023 saw a slight reduction in NDVI peaks, possibly due to reduced rainfall and disturbances from skid trails, particularly in areas with higher trail density. These disturbances may limit vegetation recovery, even during wetter years.

Marcesina 1, 2, 3 (Figure 18): Similar trends were observed across the sites, with peaks in summer and some interannual variations. Areas with higher skid trail density, such as in Marcesina 2, exhibited reduced NDVI peaks, likely influenced by the increased disturbance.

Discussion

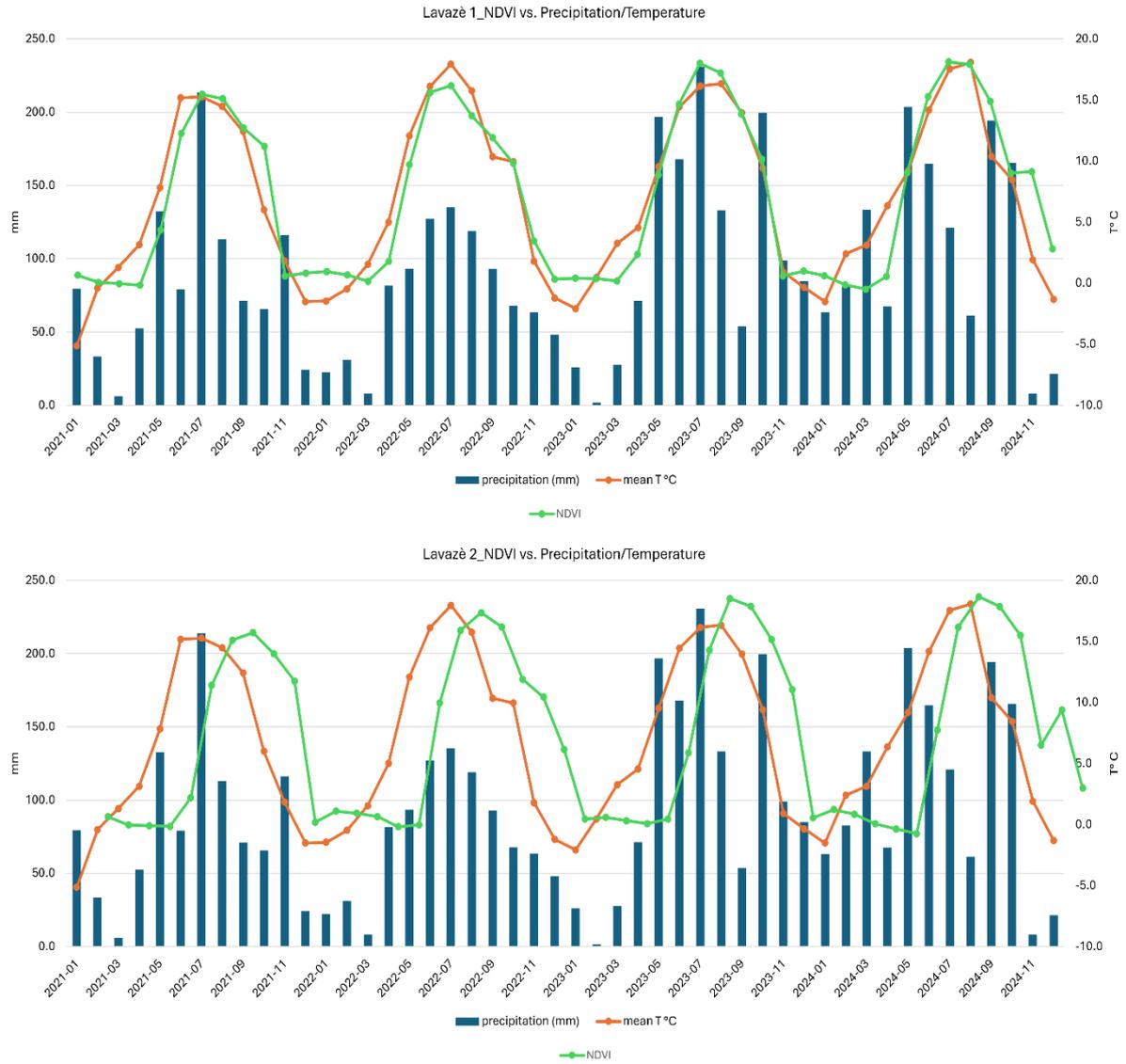


Figure 17: Comparison of NDVI index with respect to average monthly precipitation and temperature in Lavazé 1 (high) and Lavazé 2 (low)

Discussion

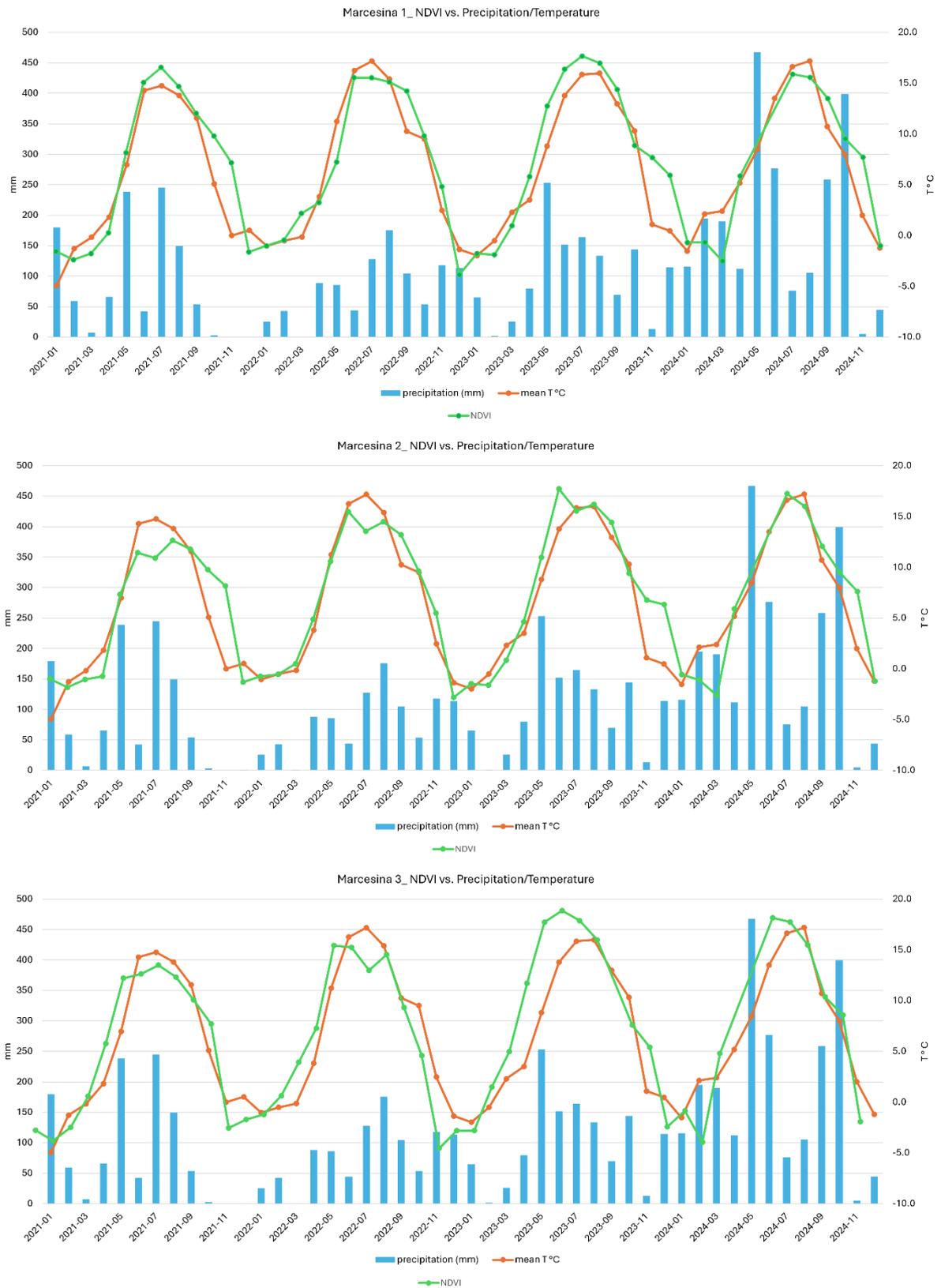


Figure 18: Comparison of NDVI index with respect to average monthly precipitation and temperature in Marcesina 1 (high), Marcesina 2 (middle), and Marcesina 3 (low).

Discussion

Both NDWI and MNDWI exhibited seasonal responses to moisture availability, with distinct changes depending on the amount of precipitation each year:

Lavazé 1 and 2 (Figure 19): Negative moisture values during summer reflected dry conditions. However, the wetter year of 2024 showed improved moisture indices, especially in regions with lower skid trail density, indicating better moisture retention. In contrast, areas with more intensive skid trail impacts saw more pronounced declines in moisture indices, suggesting increased runoff and reduced water retention.

Marcesina 1, 2, 3 (Figure 20): Moisture availability showed typical seasonal responses, but areas with dense skid trails in Marcesina 1 and 3 exhibited lower moisture retention, particularly during the drier months. This suggests that these trails, through soil compaction and altered surface properties, may exacerbate moisture loss.

The moisture indices (NDWI, MNDWI) displayed a similar seasonal pattern, with lower moisture content in the summer months, reflecting the drier conditions of the growing season. The negative values observed in the NDWI during the summer, particularly in Lavazé 1 and Marcesina 1, are consistent with findings by McFeeters (1996), who noted that NDWI is a useful indicator of water stress during dry seasons. Conversely, higher values of MNDWI during wetter months, such as April and May, corroborate research that links the MNDWI to wetland and floodplain monitoring, where moisture levels fluctuate in relation to precipitation. (Xu 2006a; Khalifeh Soltanian et al. 2019)

Discussion



Figure 19: Comparison of NDWI, MNDWI indices with respect to average monthly precipitation in Lavazé 1 (high) and Lavazé 2 (low).

Discussion



Figure 20: Comparison of NDWI, MNDWI indices with respect to average monthly precipitation in Marcesina 1 (high), Marcesina 2 (middle), and Marcesina 3 (low).

Discussion

The NDSI and NDWI indices showed consistent seasonal patterns, with moisture stress becoming more pronounced during summer:

Lavazé 1 and 2 (Figure 21): Both indices showed declines during summer, indicating reduced moisture availability. However, the 2024 wetter year helped sustain moisture levels in non-disturbed areas. In regions with higher skid trail density, moisture loss was more pronounced, as seen by the sharper decline in these indices.

Marcesina 1, 2, 3 (Figure 22): Similar patterns were observed, with moisture stress being more severe in areas with skid trails, especially in drier years. These patterns suggest that skid trails accelerate moisture depletion, especially in areas with limited vegetation recovery.



Figure 21: Comparison of NDSI vs. NDWI in Lavazé 1 (high) and Lavazé 2 (low).

Discussion

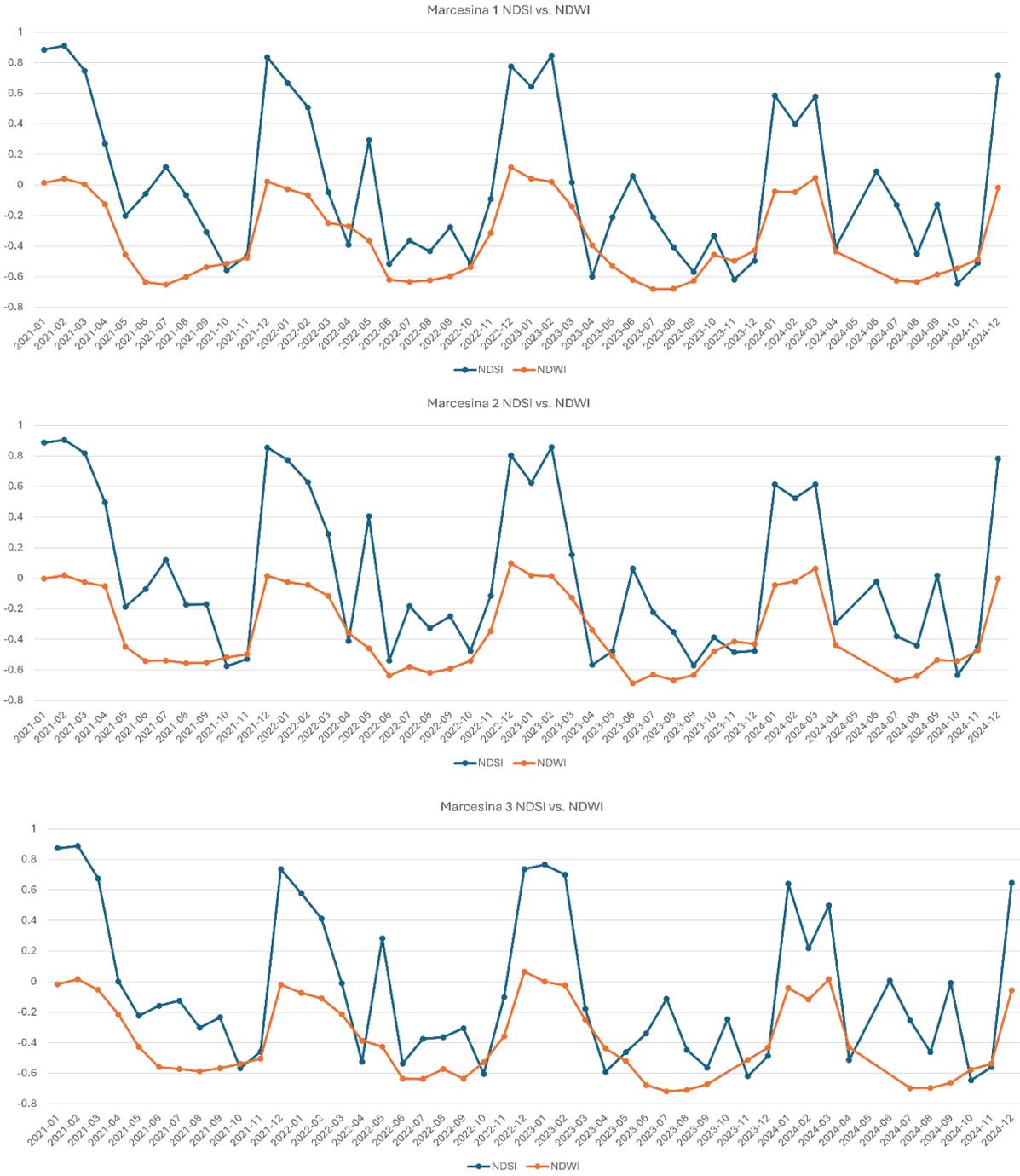


Figure 22: Comparison of NDSI vs. NDWI in Marcesina 1 (high), Marcesina 2 (middle), and Marcesina 3 (low).

Discussion

The NDVI and SAVI indices showed strong correlations, with both peaking during the summer:

Lavazé 1 and 2 (Figure 23): NDVI and SAVI peaked during the summer, although 2023 showed slight reductions, likely linked to both drier conditions and disturbances from skid trails. In areas with more intense skid trail presence, these reductions in vegetation vigour were more pronounced.

Marcesina 1, 2, 3 (Figure 24): Similar seasonal patterns were observed in Marcesina, with higher NDVI and SAVI values in wetter years. However, areas with more skid trail impact showed lower vegetation indices, confirming the role of disturbance in reducing vegetation health.

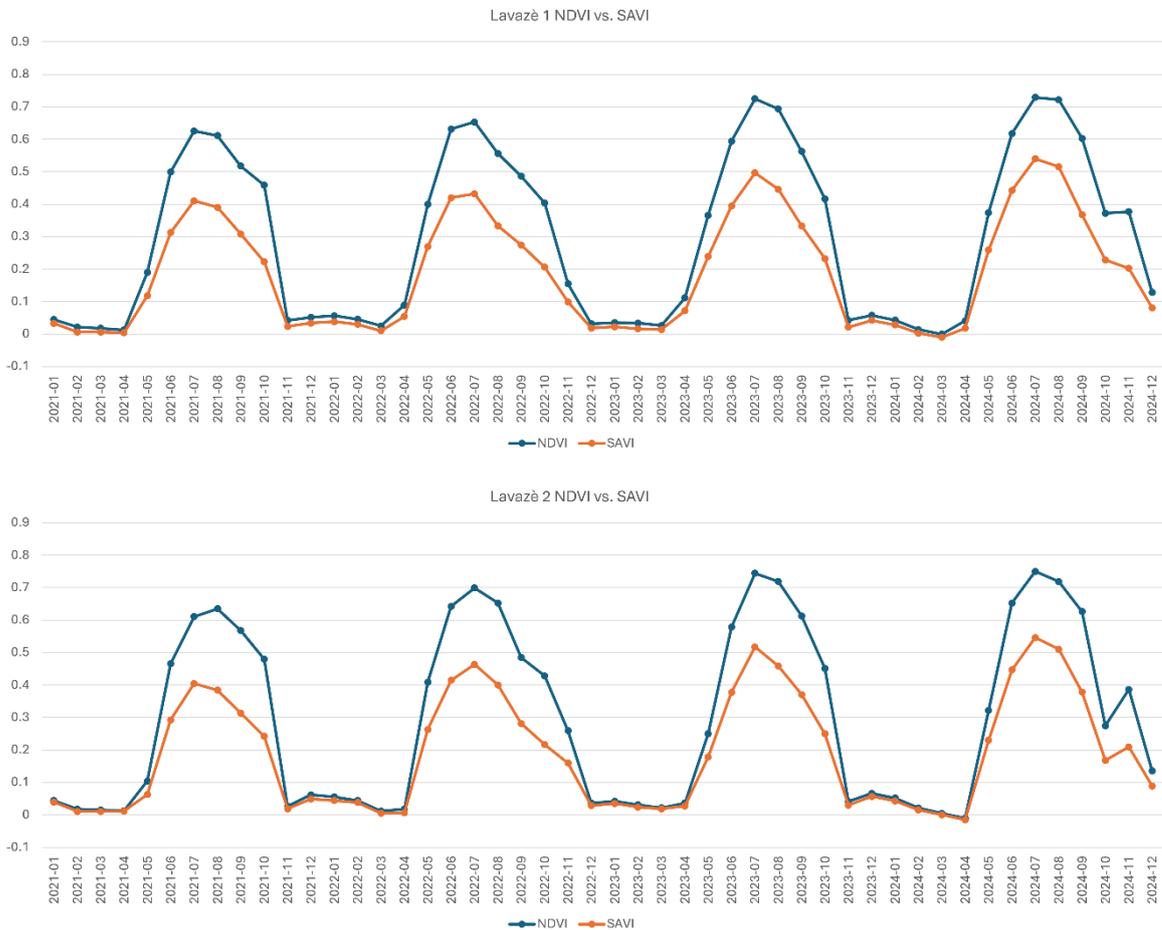


Figure 23: Comparison of NDVI vs. SAVI in Lavazé 1 (high) and Lavazé 2 (low).

Discussion

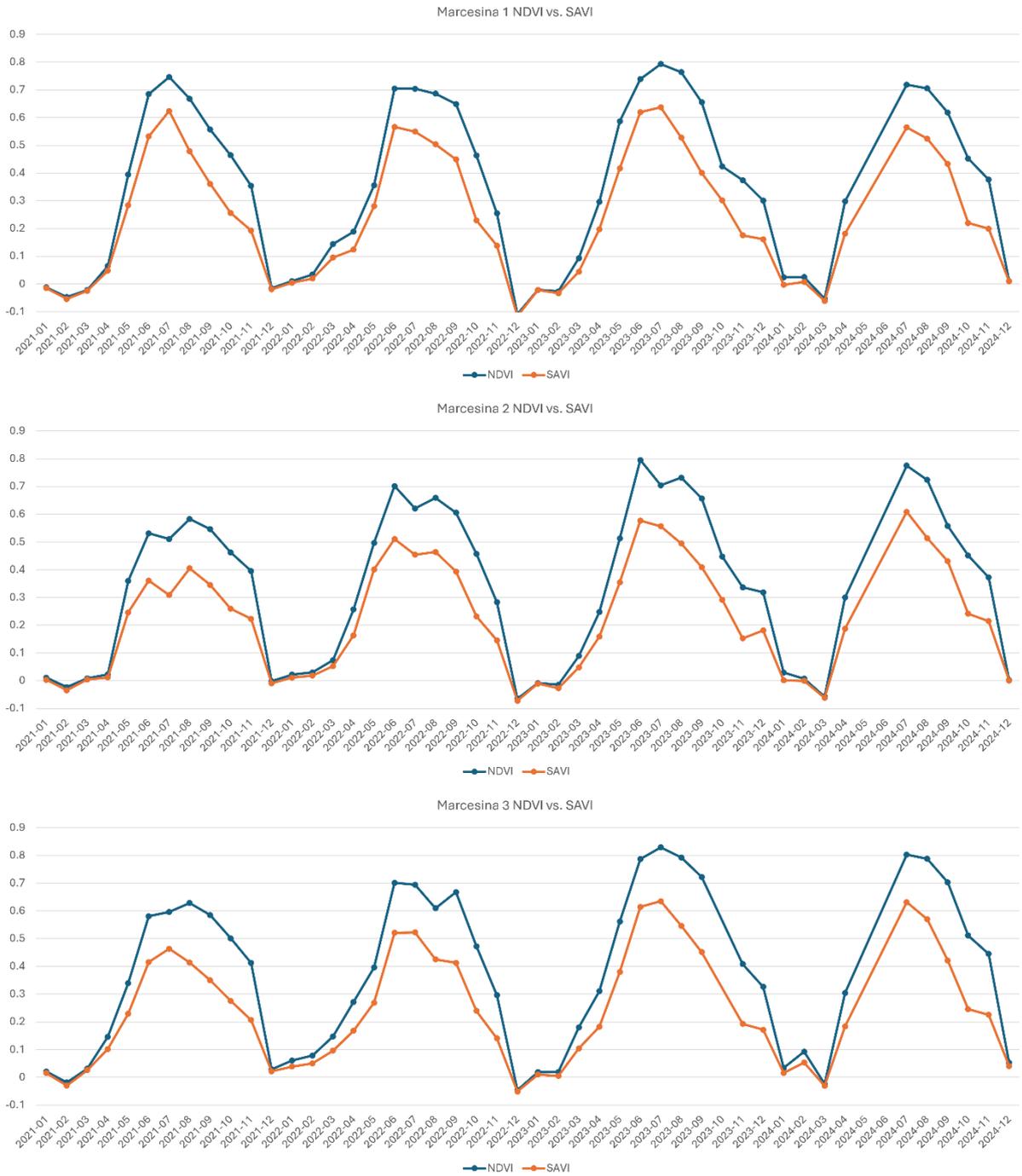


Figure 24: Comparison of NDVI vs. SAVI in Marcesina 1 (high), Marcesina 2 (middle), and Marcesina 3 (low).

4.2. Use of Maps for Monitoring Land Cover and Vegetation Dynamics

The composite maps generated from the indices provide important insights into vegetation dynamics and soil moisture conditions throughout the 2021–2024 period, with notable variations across different quarters. These trends reflect the impact of seasonal changes as well as the effects of human interventions, such as the construction of skid trails in the Lavazé and Marcesina areas.

4.2.1. Lavazé Area

In the Lavazé area, the analysis of MNDWI indicates a clear pattern of moisture fluctuations over time, with notable dryness in areas impacted by forest skid trails, especially in 2024. During Q1, the moisture content decreased gradually from 2021 to 2024, with drier conditions becoming more prominent. In Q2, marked dryness in 2022 and 2023 contrasts with a wetter period in 2024. The NDWI analysis further confirms a trend of increasing dryness in Q2, with some areas showing recovery in 2024. However, areas near the skid trails often displayed more pronounced soil moisture fluctuations. NDMI, in turn, shows a decreasing trend in water content across the four years, particularly in Q2, where vegetation moisture stress is more apparent. This was observed especially near the skid trails, which could alter soil moisture retention due to disturbed ground cover.

NDVI trends highlight a consistent level of vegetation coverage in Q1, likely due to snow, with vegetation growth peaking in Q2 and showing a slight decline in Q4. In areas impacted by the skid trails, however, lower vegetation values were recorded, indicating potential stress or degradation from the trails' presence. Similarly, SAVI revealed a stable trend in Q1, with a noticeable improvement in vegetation health by 2023, followed by a decline in 2024, particularly in Lavazé 2, which could be linked to increasing stress.

4.2.2. Marcesina Area

The Marcesina area, particularly in Q1, showed clear evidence of moisture stagnation, which decreased towards 2024. This reduction in moisture was more pronounced near the skid trails, indicating that these areas may experience altered moisture retention. In Q2, soil moisture generally decreased, with noticeable recovery in 2024. Similarly, NDWI trends reflected a progression toward drier conditions in Q2, with a slight recovery in Q4, especially in regions near the trails. NDMI revealed a trend from wet to dry soils in Q2, suggesting that moisture levels were influenced by both seasonal conditions and human activities.

NDVI trends in Marcesina showed a decline in vegetation over the four years, with areas near the skid trails showing more significant reductions in vegetation cover, particularly in Q3. The SAVI

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index highlighted a gradual decline in vegetation health, with a notable recovery towards the end of the study period, albeit with lower values near forest roads and skid trails.

Overall, the composite maps of environmental indices provided a valuable tool for understanding the temporal and spatial dynamics of the study areas. These maps effectively highlighted both the natural seasonal changes and the potential long-term effects of forest management practices, particularly the presence of skid trails. While no direct, significant impact of the skid trails on vegetation indices was observed, the surrounding areas exhibited altered hydrological dynamics, which could affect vegetation recovery in the long term.

4.3. Impact of Skid Trails on Vegetation and Moisture Indices

The primary aim of this study was to assess the influence of skid trails on environmental indices within the buffer zones surrounding the trails. However, as revealed by the statistical tests, no significant differences were observed in the indices when comparing values inside and outside the 5-meter buffer zones around the skid trails. These findings suggest that, in this specific case, the presence of the skid trails did not exert a substantial or immediate impact on vegetation health as measured by NDVI and SAVI, nor on moisture levels as measured by NDWI and MNDWI.

This result may be explained by the fact that the skid trails are relatively small in scale and their impact on soil compaction, vegetation regeneration, and moisture availability might be more localized or temporary. Other studies have found that forest disturbances, including skid trails, can cause short-term vegetation degradation, but the effects tend to diminish over time as vegetation recovers (Zenner et al. 2007; Seidl et al. 2014; Venanzi et al. 2020). This may explain the absence of significant differences in indices during the four-year study period, as vegetation likely recovered after the disturbances caused by trail construction.

Additionally, the relatively small buffer zones used in the analysis (5 meters) may not have fully captured any potential ecological changes caused by the trails. In some cases, larger buffer zones (e.g., 10–20 meters) have been shown to better reflect the impact of forest disturbance (Characterizing land disturbance in Atewa Range Forest Reserve and Buffer Zone - ScienceDirect n.d.; Willson and Dorcas 2003; Kintz et al. 2006; Kuglerová et al. 2014; Kusimi 2015). Future research may consider expanding the buffer zones or examining more sensitive indices, such as soil moisture or species-specific vegetation health metrics, which could provide a more accurate assessment of the trails' long-term effects.

4.4. Correlation with Climatic Factors

The Pearson correlation analysis revealed significant relationships between precipitation and vegetation indices, particularly NDVI and SAVI, which exhibited moderate positive correlations

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with precipitation. This suggests that vegetation growth, as reflected by NDVI and SAVI, is strongly influenced by climatic variables such as rainfall and temperature, aligning with previous studies (Tucker 1979; Chuvieco et al. 2010). Additionally, the strong negative correlation between NDWI and NDVI is expected, as these indices are inversely related—NDWI reflects moisture content, while NDVI represents vegetation growth (Jensen and Lulla 1987).

The analysis also showed that temperature had a moderate effect on vegetation indices, with higher temperatures positively influencing NDVI and SAVI values, which is consistent with findings in temperate forest ecosystems (Solomon et al. 2013; Yu et al. 2013; Zhu and Ruth 2013; Zhu et al. 2022). However, temperature alone does not seem to explain all variations in the indices, highlighting the complex interactions between climatic and environmental factors in determining vegetation and moisture levels.

5. Overview, Implications, and Future Perspectives

5.1. Summary of Key Findings

This study analysed the impact of skid trails on vegetation dynamics and moisture content using remote sensing indices (NDVI, NDWI, MNDWI, NDMI, and SAVI) over the period 2021–2024 in two selected study areas, Lavazè and Marcesina, in Northeastern Italy. The results indicate that vegetation indices generally followed expected seasonal patterns, with higher values during the growing season (spring and summer) and lower values in winter. NDVI and SAVI showed a moderate correlation with climatic factors, particularly precipitation, confirming the strong influence of rainfall on vegetation growth. However, the presence of skid trails was found to have complex effects on vegetation and moisture dynamics.

The analysis of moisture-related indices, such as NDWI and MNDWI, revealed significant temporal variations, with drier conditions observed during the summer months and wetter conditions in the spring and autumn. The presence of skid trails appeared to influence the moisture dynamics in affected areas, contributing to increased soil dryness in certain seasons. Specifically, forested areas with higher trail densities were more susceptible to reduced moisture retention, especially during drier years like 2023.

Additionally, while skid trails did not show a direct and consistent impact on vegetation health, their indirect influence on hydrological dynamics, such as soil compaction and water runoff, likely contributed to variations in vegetation recovery and moisture stress over time. The use of quarterly composite maps revealed spatial and temporal patterns of vegetation and moisture changes, helping to identify regions that are more susceptible to degradation due to both climatic and anthropogenic factors.

5.2. Implications of the Study

The findings of this study have several implications for forest management, particularly in the context of sustainable forestry practices and the monitoring of forest ecosystems. The results suggest that while skid trails do not directly cause major changes in vegetation indices, they may still have significant long-term effects on vegetation recovery due to altered soil moisture dynamics and hydrological conditions. Therefore, careful planning and management of skid trails, including their spatial distribution and construction techniques, are crucial for mitigating potential negative impacts on forest ecosystems.

Furthermore, the study underscores the importance of monitoring vegetation and moisture dynamics using remote sensing technologies. Satellite-based indices such as NDVI, NDWI, and

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SAVI provide valuable insights into the health of vegetation and the moisture content of soils over large spatial scales, which is essential for tracking changes in response to both natural and anthropogenic factors. These indices can serve as important tools for forest managers to assess the effectiveness of forest management interventions and to predict the potential impacts of future disturbances.

The correlation between vegetation indices and climatic factors such as precipitation and temperature highlight the sensitivity of forest ecosystems to changing climatic conditions. As climate change continues to affect weather patterns, it is essential to integrate climate variables into forest management strategies to ensure the resilience of forest ecosystems. The results also suggest that forested areas in regions with higher trail densities may be more vulnerable to climate-related stressors, emphasizing the need for adaptive management practices that account for both environmental and anthropogenic pressures.

5.3. Limitations and Future Directions

While this study has provided valuable insights into the impact of skid trails on vegetation and moisture indices, it is important to acknowledge its limitations and identify areas for future research. First, the temporal resolution of the satellite data used in the study (Sentinel-2) provides a snapshot of vegetation and moisture dynamics at a monthly scale, which might not be sufficient to detect more subtle changes in vegetation health or moisture content that occur on shorter timescales. For example, the response of vegetation to rainfall events, trail construction, or other disturbances may require more frequent temporal data collection, such as weekly or bi-weekly intervals. This would improve the detection of immediate impacts of disturbances like skid trails on forest dynamics.

Moreover, the study's reliance on a 5-meter buffer zone around the skid trails may have constrained the ability to capture the full extent of the trails' impact on vegetation and soil moisture. While the buffer zone was selected to capture localized effects, larger-scale impacts, such as deeper soil compaction, erosion, and hydrological alterations, might extend beyond the 5-meter radius. Future studies could expand this buffer zone or investigate the impacts of trails on a landscape scale, considering broader effects such as changes in surrounding vegetation communities and long-term ecological processes.

The study also lacked detailed field data on soil conditions, vegetation species composition, and microclimatic variations, which are essential for understanding the complex interactions between skid trails and environmental factors. Soil compaction, for example, is known to alter water retention and nutrient cycling, but these changes may not be fully captured by remote sensing indices alone. Future research could benefit from integrating field-based measurements with

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satellite-derived data to create a more holistic understanding of forest disturbance dynamics. Collecting data on vegetation species composition would also provide valuable information on how specific plant species respond to disturbances and climatic conditions.

Additionally, the study focused on the direct effects of skid trails, but future research could explore the combined effects of multiple anthropogenic activities, such as logging, road construction, and land use changes, on forest dynamics. Understanding the cumulative effects of these activities, in addition to skid trails, would offer a more comprehensive view of the environmental impacts of human interventions in forest ecosystems.

Finally, as climate change continues to impact weather patterns, it is important to consider how changing climatic conditions, such as increased frequency and intensity of droughts, may interact with anthropogenic disturbances to affect vegetation and moisture dynamics. Future research should consider the potential synergistic effects of climate change and human activity on forest ecosystems, as well as the role of adaptive forest management strategies in mitigating these impacts.

6. Conclusions

This study provides a comprehensive analysis of the effects of skid trails on vegetation and moisture dynamics in temperate forest ecosystems. By utilizing remote sensing indices such as NDVI, NDWI, MNDWI, NDMI, and SAVI, the study effectively captured the temporal and spatial variations in vegetation health and soil moisture over a four-year period (2021–2024). The analysis revealed that while skid trails did not cause significant direct changes in the vegetation indices, they did influence moisture retention and soil dynamics, which in turn affected long-term vegetation recovery.

The study's findings highlight the need for careful planning and management of skid trails to minimize their impact on forest ecosystems. Monitoring environmental indices using satellite-based remote sensing provides a valuable tool for assessing the health of forest ecosystems and detecting changes in response to human activities and environmental factors. Additionally, the study stresses the importance of integrating climatic variables into forest management practices to account for the increasing sensitivity of forests to changing climatic conditions.

While the study provides important insights, it also highlights the limitations of current remote sensing technologies and the need for more frequent temporal data and detailed field measurements to capture the full extent of the impact of human activities on forest ecosystems. Future research should expand on these findings by integrating field data, considering larger-scale impacts, and exploring the combined effects of multiple anthropogenic disturbances. In light of ongoing climate change, adaptive forest management strategies will be critical to ensuring the resilience of forest ecosystems and their ability to cope with both environmental and human-induced stressors.

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Appendix

Maps

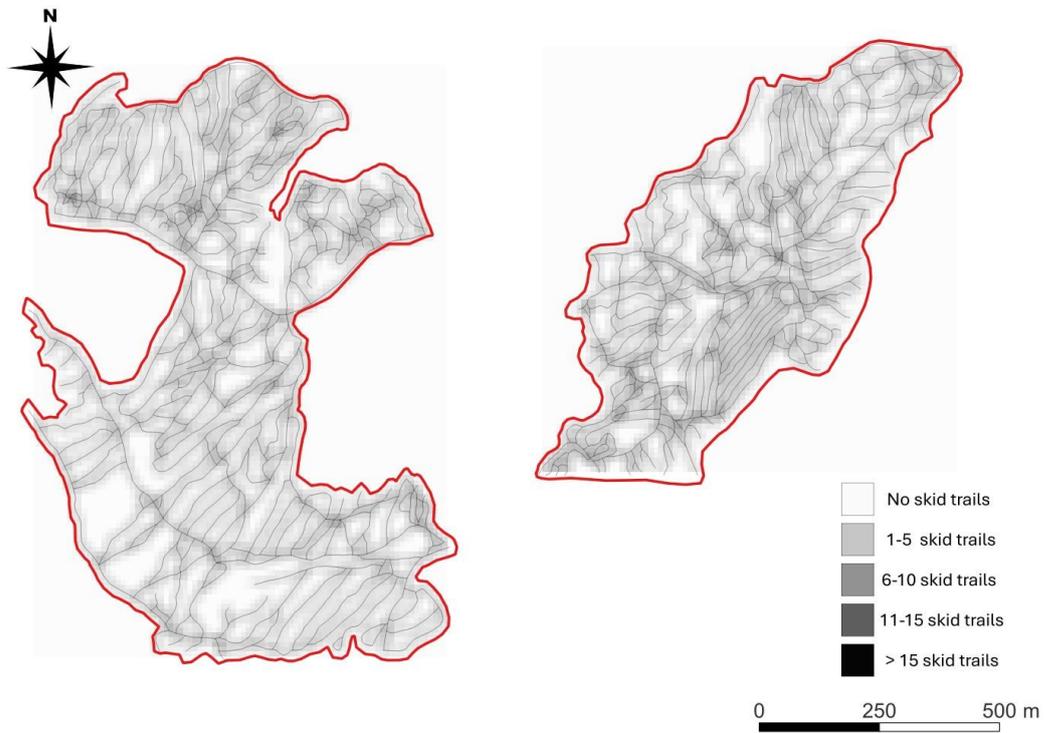


Figure 25: Map showing the Lavazé study area (Lavazé 1 on the right, and Lavazé 2 on the left). Also shown are the skid trails superimposed on the kernel density of the trails themselves.

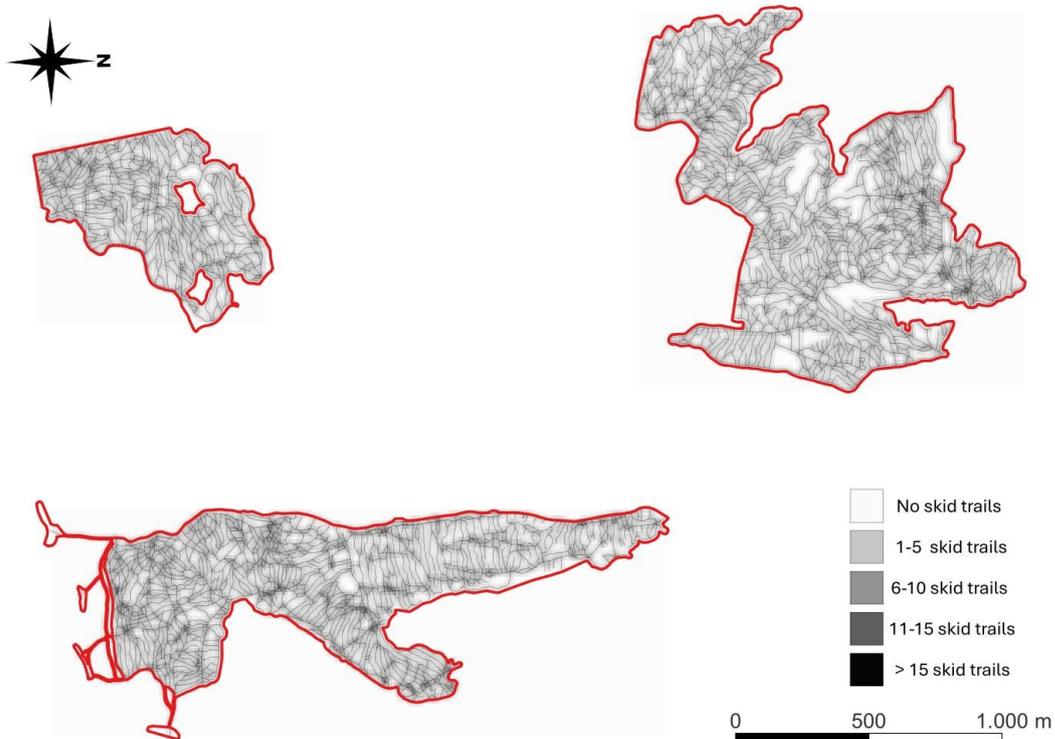


Figure 26: Map showing the Marcesina study area (Marcesina 1 on the bottom; Marcesina 2 on the top left; Marcesina 3 on the top right). Also shown are the skid trails superimposed on the kernel density of the trails themselves.

Appendix

Data on indices for all areas

Table 1: NDVI raw data

DATE	NDVI				
	Lavazé 1	Lavazé 2	Marcesina 1	Marcesina 2	Marcesina 3
2021-01	0.0446	0.0441	-0.0122	0.0113	0.0210
2021-02	0.0216	0.0176	-0.0469	-0.0233	-0.0183
2021-03	0.0178	0.0152	-0.0216	0.0087	0.0313
2021-04	0.0124	0.0131	0.0644	0.0223	0.1460
2021-05	0.1897	0.1048	0.3946	0.3600	0.3396
2021-06	0.4993	0.4658	0.6847	0.5315	0.5806
2021-07	0.6253	0.6108	0.7463	0.5105	0.5963
2021-08	0.6110	0.6350	0.6679	0.5828	0.6286
2021-09	0.5173	0.5676	0.5569	0.5465	0.5850
2021-10	0.4583	0.4798	0.4639	0.4622	0.5014
2021-11	0.0418	0.0263	0.3537	0.3953	0.4124
2021-12	0.0516	0.0620	-0.0151	-0.0020	0.0291
2022-01	0.0563	0.0553	0.0105	0.0219	0.0604
2022-02	0.0457	0.0443	0.0343	0.0300	0.0786
2022-03	0.0250	0.0119	0.1440	0.0741	0.1476
2022-04	0.0891	0.0179	0.1887	0.2571	0.2714
2022-05	0.3994	0.4091	0.3558	0.4968	0.3960
2022-06	0.6315	0.6422	0.7043	0.7020	0.7012
2022-07	0.6531	0.6991	0.7039	0.6206	0.6943
2022-08	0.5560	0.6529	0.6864	0.6593	0.6098
2022-09	0.4863	0.4850	0.6490	0.6059	0.6677
2022-10	0.4039	0.4279	0.4634	0.4573	0.4725
2022-11	0.1547	0.2595	0.2550	0.2827	0.2961
2022-12	0.0318	0.0365	-0.1089	-0.0650	-0.0458
2023-01	0.0349	0.0420	-0.0213	-0.0085	0.0189
2023-02	0.0338	0.0313	-0.0264	-0.0145	0.0194
2023-03	0.0260	0.0217	0.0932	0.0889	0.1805
2023-04	0.1115	0.0364	0.2960	0.2475	0.3108
2023-05	0.3660	0.2500	0.5868	0.5130	0.5619
2023-06	0.5943	0.5788	0.7389	0.7955	0.7869
2023-07	0.7246	0.7443	0.7933	0.7044	0.8295
2023-08	0.6936	0.7193	0.7639	0.7319	0.7929
2023-09	0.5625	0.6130	0.6554	0.6569	0.7221
2023-10	0.4162	0.4516	0.4241	0.4475	
2023-11	0.0423	0.0410	0.3741	0.3365	0.4081
2023-12	0.0578	0.0666	0.3011	0.3183	0.3265
2024-01	0.0429	0.0520	0.0244	0.0294	0.0340
2024-02	0.0136	0.0212	0.0247	0.0071	0.0923
2024-03	-0.0003	0.0047	-0.0528	-0.0575	-0.0238
2024-04	0.0408	-0.0102	0.2985	0.3005	0.3043
2024-05	0.3740	0.3220			
2024-06	0.6174	0.6527			
2024-07	0.7291	0.7501	0.7184	0.7754	0.8031
2024-08	0.7216	0.7187	0.7052	0.7238	0.7880
2024-09	0.6030	0.6263	0.6181	0.5580	0.7033
2024-10	0.3723	0.2743	0.4523	0.4513	0.5115
2024-11	0.3768	0.3864	0.3764	0.3724	0.4451
2024-12	0.1285	0.1358	0.0106	0.0019	0.0526

Appendix

Table 2: NDWI raw data

DATE	NDWI				
	Lavazé 1	Lavazé 2	Marcesina 1	Marcesina 2	Marcesina 3
2021-01	-0.0314	-0.0291	0.0141	-0.0027	-0.0172
2021-02	-0.0212	-0.0160	0.0415	0.0198	0.0158
2021-03	-0.0262	-0.0222	0.0041	-0.0271	-0.0546
2021-04	-0.0220	-0.0263	-0.1260	-0.0528	-0.2148
2021-05	-0.2691	-0.1631	-0.4563	-0.4473	-0.4276
2021-06	-0.5523	-0.5352	-0.6359	-0.5420	-0.5599
2021-07	-0.6221	-0.6012	-0.6523	-0.5390	-0.5718
2021-08	-0.6175	-0.6320	-0.6002	-0.5552	-0.5878
2021-09	-0.5563	-0.5956	-0.5371	-0.5525	-0.5664
2021-10	-0.5498	-0.5713	-0.5152	-0.5171	-0.5383
2021-11	-0.0405	-0.0155	-0.4770	-0.4982	-0.5030
2021-12	-0.0400	-0.0380	0.0229	0.0163	-0.0197
2022-01	-0.0512	-0.0411	-0.0265	-0.0251	-0.0739
2022-02	-0.0476	-0.0440	-0.0665	-0.0439	-0.1100
2022-03	-0.0352	-0.0172	-0.2482	-0.1160	-0.2142
2022-04	-0.1390	-0.0309	-0.2704	-0.3587	-0.3854
2022-05	-0.4646	-0.4790	-0.3641	-0.4585	-0.4258
2022-06	-0.6202	-0.6257	-0.6211	-0.6383	-0.6352
2022-07	-0.6484	-0.6658	-0.6327	-0.5793	-0.6366
2022-08	-0.6007	-0.6539	-0.6247	-0.6189	-0.5724
2022-09	-0.5468	-0.5444	-0.5971	-0.5914	-0.6353
2022-10	-0.5156	-0.5401	-0.5383	-0.5403	-0.5271
2022-11	-0.1763	-0.2965	-0.3141	-0.3453	-0.3571
2022-12	-0.0180	-0.0103	0.1148	0.0970	0.0658
2023-01	-0.0296	-0.0249	0.0418	0.0185	-0.0004
2023-02	-0.0206	-0.0163	0.0211	0.0133	-0.0252
2023-03	-0.0370	-0.0195	-0.1391	-0.1278	-0.2496
2023-04	-0.1615	-0.0420	-0.3950	-0.3399	-0.4371
2023-05	-0.4070	-0.3380	-0.5309	-0.5071	-0.5205
2023-06	-0.5843	-0.5800	-0.6220	-0.6890	-0.6770
2023-07	-0.6793	-0.6804	-0.6815	-0.6310	-0.7183
2023-08	-0.6757	-0.6794	-0.6796	-0.6680	-0.7091
2023-09	-0.5992	-0.6222	-0.6273	-0.6335	-0.6715
2023-10	-0.4797	-0.5178	-0.4571	-0.4798	
2023-11	-0.0324	-0.0241	-0.4973	-0.4132	-0.5111
2023-12	-0.0514	-0.0501	-0.4293	-0.4303	-0.4314
2024-01	-0.0349	-0.0384	-0.0425	-0.0456	-0.0419
2024-02	-0.0072	-0.0136	-0.0465	-0.0200	-0.1172
2024-03	0.0033	-0.0030	0.0475	0.0638	0.0155
2024-04	-0.0574	0.0086	-0.4351	-0.4374	-0.4305
2024-05	-0.4560	-0.4190			
2024-06	-0.5962	-0.6237			
2024-07	-0.6631	-0.6740	-0.6267	-0.6703	-0.6967
2024-08	-0.6788	-0.6603	-0.6326	-0.6405	-0.6962
2024-09	-0.6310	-0.6318	-0.5854	-0.5341	-0.6623
2024-10	-0.4688	-0.3423	-0.5445	-0.5428	-0.5758
2024-11	-0.4868	-0.4919	-0.4853	-0.4733	-0.5364
2024-12	-0.1346	-0.1211	-0.0174	-0.0027	-0.0576

Appendix

Table 3: MNDWI raw data

DATE	MNDWI				
	Lavazé 1	Lavazé 2	Marcesina 1	Marcesina 2	Marcesina 3
2021-01	0.8209	0.8237	0.8870	0.8868	0.8725
2021-02	0.8410	0.8542	0.9121	0.9055	0.8883
2021-03	0.8356	0.8622	0.8013	0.7791	0.6707
2021-04	0.7611	0.7864	0.2844	0.5949	0.0793
2021-05	-0.0303	0.3261	-0.5123	-0.5177	-0.4932
2021-06	-0.5757	-0.5734	-0.5325	-0.5063	-0.4906
2021-07	-0.5296	-0.5185	-0.4803	-0.5170	-0.5008
2021-08	-0.5509	-0.5405	-0.5110	-0.5176	-0.5059
2021-09	-0.5209	-0.5466	-0.5000	-0.5515	-0.4923
2021-10	-0.5741	-0.5908	-0.5899	-0.5794	-0.5703
2021-11	0.6680	0.7687	-0.5656	-0.5537	-0.5495
2021-12	0.7410	0.7815	0.6883	0.7219	0.5773
2022-01	0.7661	0.8103	0.6664	0.7443	0.5783
2022-02	0.7484	0.7892	0.5104	0.6527	0.3973
2022-03	0.7258	0.8419	-0.0801	0.3385	-0.0259
2022-04	0.2877	0.6597	-0.1835	-0.4503	-0.4941
2022-05	-0.5054	-0.5053	-0.2963	-0.3888	-0.4558
2022-06	-0.5390	-0.5402	-0.4343	-0.5064	-0.5018
2022-07	-0.5561	-0.5451	-0.5048	-0.4831	-0.5215
2022-08	-0.5829	-0.5854	-0.5322	-0.5598	-0.4870
2022-09	-0.5508	-0.5502	-0.5121	-0.5608	-0.5830
2022-10	-0.5716	-0.5723	-0.6260	-0.6318	-0.5559
2022-11	0.4303	0.2040	-0.1307	-0.1310	-0.0984
2022-12	0.7808	0.7885	0.7846	0.8013	0.7328
2023-01	0.7409	0.7960	0.8393	0.8268	0.8053
2023-02	0.7736	0.8266	0.8466	0.8552	0.6915
2023-03	0.5953	0.7532	0.2045	0.2014	-0.1008
2023-04	0.2148	0.6312	-0.5243	-0.4163	-0.5843
2023-05	-0.4440	-0.4075	-0.4639	-0.5059	-0.4820
2023-06	-0.5235	-0.5126	-0.3626	-0.5303	-0.4946
2023-07	-0.5471	-0.5168	-0.4825	-0.4941	-0.5360
2023-08	-0.5763	-0.5469	-0.5718	-0.5784	-0.5896
2023-09	-0.5772	-0.5698	-0.6021	-0.6036	-0.5984
2023-10	-0.4805	-0.5042	-0.4261	-0.4805	
2023-11	0.7005	0.7485	-0.6079	-0.4423	-0.5954
2023-12	0.6891	0.7109	-0.4594	-0.4382	-0.4491
2024-01	0.7914	0.7915	0.6453	0.6543	0.6780
2024-02	0.7796	0.8008	0.4498	0.5757	0.2361
2024-03	0.8427	0.8323	0.9183	0.9440	0.7623
2024-04	0.5560	0.8262	-0.6039	-0.5724	-0.5132
2024-05	-0.4840	-0.4320			
2024-06	-0.5064	-0.4827			
2024-07	-0.4965	-0.4843	-0.4351	-0.5114	-0.5313
2024-08	-0.5448	-0.4630	-0.5198	-0.5376	-0.5760
2024-09	-0.6033	-0.5568	-0.5253	-0.4569	-0.5700
2024-10	-0.5195	-0.1487	-0.6470	-0.6338	-0.6455
2024-11	-0.4575	-0.4220	-0.5142	-0.4512	-0.5628
2024-12	0.4979	0.5539	0.7293	0.7835	0.6463

Appendix

Table 4: NDMI raw data

DATE	NDMI				
	Lavazé 1	Lavazé 2	Marcesina 1	Marcesina 2	Marcesina 3
2021-01	0.8413	0.8378	0.8859	0.8875	0.8723
2021-02	0.8668	0.7602	0.9118	0.9060	0.8883
2021-03	0.8602	0.8493	0.7477	0.8186	0.6746
2021-04	0.7853	0.8523	0.2703	0.4955	0.0008
2021-05	0.2226	0.0764	-0.2021	-0.1868	-0.2236
2021-06	-0.0297	-0.3868	-0.0579	-0.0712	-0.1572
2021-07	0.1341	-0.3413	0.1163	0.1195	-0.1246
2021-08	0.1051	-0.1931	-0.0663	-0.1734	-0.3020
2021-09	0.0504	-0.2392	-0.3078	-0.1712	-0.2344
2021-10	-0.0304	-0.5964	-0.5582	-0.5754	-0.5668
2021-11	0.7108	0.8210	-0.4624	-0.5285	-0.4591
2021-12	0.7709	0.8008	0.8375	0.8560	0.7360
2022-01	0.8029	0.8239	0.6691	0.7728	0.5783
2022-02	0.7873	0.8151	0.5088	0.6289	0.4129
2022-03	0.7613	0.8419	-0.0478	0.2896	-0.0100
2022-04	0.4274	0.6224	-0.3916	-0.4113	-0.5246
2022-05	-0.0510	-0.4320	0.2930	0.4060	0.2840
2022-06	0.1247	-0.4454	-0.5171	-0.5393	-0.5355
2022-07	0.1460	-0.4218	-0.3642	-0.1828	-0.3749
2022-08	0.0303	-0.4339	-0.4337	-0.3276	-0.3635
2022-09	-0.0038	-0.5533	-0.2768	-0.2484	-0.3052
2022-10	-0.0746	-0.5650	-0.5148	-0.4769	-0.6042
2022-11	0.5927	0.4120	-0.0929	-0.1147	-0.1026
2022-12	0.7968	0.8427	0.7770	0.8040	0.7370
2023-01	0.7681	0.7893	0.6450	0.6250	0.7658
2023-02	0.8053	0.8240	0.8492	0.8586	0.6993
2023-03	0.6373	0.4805	0.0180	0.1535	-0.1773
2023-04	0.3690	0.5987	-0.5993	-0.5677	-0.5900
2023-05	-0.0450	-0.2750	-0.2100	-0.4770	-0.4615
2023-06	0.0944	-0.5420	0.0584	0.0631	-0.3393
2023-07	0.2138	-0.4048	-0.2098	-0.2229	-0.1124
2023-08	0.1640	-0.4823	-0.4069	-0.3496	-0.4478
2023-09	0.0332	-0.4450	-0.5690	-0.5717	-0.5634
2023-10	-0.0047	-0.4473	-0.3330	-0.3880	-0.2470
2023-11	0.7360	0.8130	-0.6193	-0.4848	-0.6189
2023-12	0.7274	0.7874	-0.4963	-0.4758	-0.4867
2024-01	0.8196	0.7727	0.5861	0.6134	0.6401
2024-02	0.7954	0.8180	0.3992	0.5240	0.2183
2024-03	0.8527	0.7895	0.5810	0.6135	0.4978
2024-04	0.6224	0.8490	-0.4071	-0.2919	-0.5128
2024-05	-0.0330				
2024-06	0.1360	-0.5420	0.0890	-0.0230	0.0070
2024-07	0.2528	-0.2638	-0.1315	-0.3805	-0.2541
2024-08	0.2110	-0.0108	-0.4505	-0.4401	-0.4617
2024-09	0.0453	-0.5650	-0.1274	0.0181	-0.0091
2024-10	-0.0658	-0.3425	-0.6470	-0.6338	-0.6455
2024-11	0.0100	-0.4003	-0.5110	-0.4483	-0.5596
2024-12	0.6111	0.5866	0.7173	0.7834	0.6459

Appendix

Table 5: SAVI raw data

DATE	SAVI				
	Lavazé 1	Lavazé 2	Marcesina 1	Marcesina 2	Marcesina 3
2021-01	0.0330	0.0396	-0.0146	0.0034	0.0153
2021-02	0.0058	0.0108	-0.0541	-0.0347	-0.0299
2021-03	0.0058	0.0110	-0.0244	0.0043	0.0259
2021-04	0.0040	0.0117	0.0483	0.0116	0.1021
2021-05	0.1177	0.0630	0.2841	0.2463	0.2295
2021-06	0.3127	0.2930	0.5319	0.3605	0.4157
2021-07	0.4101	0.4045	0.6238	0.3085	0.4634
2021-08	0.3904	0.3842	0.4788	0.4051	0.4140
2021-09	0.3078	0.3136	0.3610	0.3450	0.3501
2021-10	0.2223	0.2419	0.2560	0.2595	0.2757
2021-11	0.0232	0.0187	0.1929	0.2228	0.2065
2021-12	0.0336	0.0490	-0.0189	-0.0096	0.0218
2022-01	0.0379	0.0443	0.0045	0.0112	0.0387
2022-02	0.0299	0.0381	0.0199	0.0183	0.0503
2022-03	0.0101	0.0053	0.0955	0.0523	0.0965
2022-04	0.0543	0.0063	0.1238	0.1633	0.1679
2022-05	0.2699	0.2631	0.2808	0.4013	0.2688
2022-06	0.4200	0.4147	0.5663	0.5105	0.5211
2022-07	0.4319	0.4639	0.5495	0.4543	0.5227
2022-08	0.3329	0.4005	0.5039	0.4640	0.4255
2022-09	0.2743	0.2816	0.4494	0.3933	0.4128
2022-10	0.2060	0.2169	0.2293	0.2316	0.2394
2022-11	0.0990	0.1598	0.1380	0.1457	0.1403
2022-12	0.0183	0.0288	-0.1159	-0.0725	-0.0513
2023-01	0.0224	0.0353	-0.0215	-0.0103	0.0103
2023-02	0.0158	0.0236	-0.0334	-0.0272	0.0052
2023-03	0.0140	0.0188	0.0442	0.0481	0.1045
2023-04	0.0715	0.0272	0.1978	0.1588	0.1825
2023-05	0.2390	0.1780	0.4170	0.3546	0.3800
2023-06	0.3949	0.3779	0.6194	0.5768	0.6143
2023-07	0.4966	0.5174	0.6370	0.5567	0.6353
2023-08	0.4460	0.4587	0.5278	0.4946	0.5463
2023-09	0.3332	0.3706	0.4003	0.4088	0.4511
2023-10	0.2327	0.2498	0.3015	0.2918	
2023-11	0.0213	0.0299	0.1755	0.1529	0.1927
2023-12	0.0420	0.0570	0.1614	0.1813	0.1719
2024-01	0.0281	0.0430	-0.0028	0.0012	0.0161
2024-02	0.0024	0.0154	0.0078	-0.0004	0.0533
2024-03	-0.0100	0.0003	-0.0608	-0.0618	-0.0308
2024-04	0.0178	-0.0150	0.1821	0.1876	0.1836
2024-05	0.2590	0.2300			
2024-06	0.4426	0.4467			
2024-07	0.5399	0.5462	0.5649	0.6088	0.6318
2024-08	0.5154	0.5103	0.5241	0.5141	0.5701
2024-09	0.3673	0.3783	0.4331	0.4308	0.4213
2024-10	0.2283	0.1680	0.2198	0.2415	0.2455
2024-11	0.2026	0.2096	0.1993	0.2147	0.2254
2024-12	0.0808	0.0889	0.0094	0.0009	0.0408

Appendix

Table 6: NDSI raw data

DATE	NDSI				
	Lavazé 1	Lavazé 2	Marcesina 1	Marcesina 2	Marcesina 3
2021-01	0.8325	0.8378	0.8859	0.8875	0.8723
2021-02	0.7498	0.7602	0.9118	0.9060	0.8883
2021-03	0.8440	0.8493	0.7477	0.8186	0.6746
2021-04	0.8067	0.8523	0.2703	0.4955	0.0008
2021-05	-0.1498	0.0764	-0.2021	-0.1868	-0.2236
2021-06	-0.3882	-0.3868	-0.0579	-0.0712	-0.1572
2021-07	-0.5645	-0.3413	0.1163	0.1195	-0.1246
2021-08	-0.3206	-0.1931	-0.0663	-0.1734	-0.3020
2021-09	-0.2985	-0.2392	-0.3078	-0.1712	-0.2344
2021-10	-0.5771	-0.5964	-0.5582	-0.5754	-0.5668
2021-11	0.7218	0.8210	-0.4624	-0.5285	-0.4591
2021-12	0.7718	0.8008	0.8375	0.8560	0.7360
2022-01	0.7798	0.8239	0.6691	0.7728	0.5783
2022-02	0.7680	0.8151	0.5088	0.6289	0.4129
2022-03	0.7258	0.8419	-0.0478	0.2896	-0.0100
2022-04	0.2020	0.6224	-0.3916	-0.4113	-0.5246
2022-05	-0.1780	-0.4320	0.2930	0.4060	0.2840
2022-06	-0.3316	-0.4454	-0.5171	-0.5393	-0.5355
2022-07	-0.4595	-0.4218	-0.3642	-0.1828	-0.3749
2022-08	-0.4257	-0.4339	-0.4337	-0.3276	-0.3635
2022-09	-0.5510	-0.5533	-0.2768	-0.2484	-0.3052
2022-10	-0.5403	-0.5650	-0.5148	-0.4769	-0.6042
2022-11	0.2665	0.4120	-0.0929	-0.1147	-0.1026
2022-12	0.8227	0.8427	0.7770	0.8040	0.7370
2023-01	0.7200	0.7893	0.6450	0.6250	0.7658
2023-02	0.7783	0.8240	0.8492	0.8586	0.6993
2023-03	0.3530	0.4805	0.0180	0.1535	-0.1773
2023-04	-0.0127	0.5987	-0.5993	-0.5677	-0.5900
2023-05	-0.2810	-0.2750	-0.2100	-0.4770	-0.4615
2023-06	-0.5670	-0.5420	0.0584	0.0631	-0.3393
2023-07	-0.2958	-0.4048	-0.2098	-0.2229	-0.1124
2023-08	-0.5460	-0.4823	-0.4069	-0.3496	-0.4478
2023-09	-0.4953	-0.4450	-0.5690	-0.5717	-0.5634
2023-10	-0.4635	-0.4473	-0.3330	-0.3880	-0.2470
2023-11	0.7488	0.8130	-0.6193	-0.4848	-0.6189
2023-12	0.7628	0.7874	-0.4963	-0.4758	-0.4867
2024-01	0.7522	0.7727	0.5861	0.6134	0.6401
2024-02	0.8040	0.8180	0.3992	0.5240	0.2183
2024-03	0.8155	0.7895	0.5810	0.6135	0.4978
2024-04	0.6150	0.8490	-0.4071	-0.2919	-0.5128
2024-05					
2024-06	-0.5530	-0.5420	0.0890	-0.0230	0.0070
2024-07	-0.3062	-0.2638	-0.1315	-0.3805	-0.2541
2024-08	-0.0264	-0.0108	-0.4505	-0.4401	-0.4617
2024-09	-0.6030	-0.5650	-0.1274	0.0181	-0.0091
2024-10	-0.3980	-0.3425	-0.6470	-0.6338	-0.6455
2024-11	-0.4371	-0.4003	-0.5110	-0.4483	-0.5596
2024-12	0.5321	0.5866	0.7173	0.7834	0.6459

Appendix

Pearson correlation among areas by Index

Table 7: Comprehensive table showing Pearson's correlation data for each index in relation to each area.

NDSI	<i>Lavazé 1</i>	<i>Lavazé 2</i>	<i>Marcesina 1</i>	<i>Marcesina 2</i>	<i>Marcesina 3</i>
<i>Lavazé 1</i>	1				
<i>Lavazé 2</i>	0.977	1			
<i>Marcesina 1</i>	0.634	0.562	1		
<i>Marcesina 2</i>	0.670	0.599	0.980	1	
<i>Marcesina 3</i>	0.640	0.562	0.976	0.965	1
NDMI	<i>Lavazé 1</i>	<i>Lavazé 2</i>	<i>Marcesina 1</i>	<i>Marcesina 2</i>	<i>Marcesina 3</i>
<i>Lavazé 1</i>	1				
<i>Lavazé 2</i>	0.975	1			
<i>Marcesina 1</i>	0.648	0.549	1		
<i>Marcesina 2</i>	0.741	0.648	0.970	1	
<i>Marcesina 3</i>	0.637	0.528	0.977	0.961	1
SAVI	<i>Lavazé 1</i>	<i>Lavazé 2</i>	<i>Marcesina 1</i>	<i>Marcesina 2</i>	<i>Marcesina 3</i>
<i>Lavazé 1</i>	1				
<i>Lavazé 2</i>	0.989	1			
<i>Marcesina 1</i>	0.935	0.910	1		
<i>Marcesina 2</i>	0.935	0.912	0.964	1	
<i>Marcesina 3</i>	0.951	0.929	0.983	0.981	1
NDVI	<i>Lavazé 1</i>	<i>Lavazé 2</i>	<i>Marcesina 1</i>	<i>Marcesina 2</i>	<i>Marcesina 3</i>
<i>Lavazé 1</i>	1				
<i>Lavazé 2</i>	0.989	1			
<i>Marcesina 1</i>	0.927	0.899	1		
<i>Marcesina 2</i>	0.922	0.898	0.980	1	
<i>Marcesina 3</i>	0.929	0.903	0.987	0.988	1
NDWI	<i>Lavazé 1</i>	<i>Lavazé 2</i>	<i>Marcesina 1</i>	<i>Marcesina 2</i>	<i>Marcesina 3</i>
<i>Lavazé 1</i>	1				
<i>Lavazé 2</i>	0.988	1			
<i>Marcesina 1</i>	0.864	0.831	1		
<i>Marcesina 2</i>	0.871	0.840	0.985	1	
<i>Marcesina 3</i>	0.865	0.832	0.988	0.986	1
MNDWI	<i>Lavazé 1</i>	<i>Lavazé 2</i>	<i>Marcesina 1</i>	<i>Marcesina 2</i>	<i>Marcesina 3</i>
<i>Lavazé 1</i>	1				
<i>Lavazé 2</i>	0.983	1			
<i>Marcesina 1</i>	0.779	0.722	1		
<i>Marcesina 2</i>	0.815	0.759	0.985	1	
<i>Marcesina 3</i>	0.777	0.713	0.988	0.980	1

Pearson correlation among indices by Area

Table 8: Comprehensive table showing Pearson's correlation data for each index in relation to index and meteorological parameter in each study area.

LAVAZÉ 1	<i>NDVI</i>	<i>NDWI</i>	<i>MNDWI</i>	<i>NDMI</i>	<i>SAVI</i>	<i>Rain</i>	<i>T °C</i>
<i>NDVI</i>	1						
<i>NDWI</i>	-0.988	1					
<i>MNDWI</i>	-0.939	0.978	1				
<i>NDMI</i>	-0.841	0.909	0.976	1			
<i>SAVI</i>	0.991	-0.965	-0.903	-1	1.000		

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Rain	0.591	-0.586	-0.599	-0.571	0.603	1	
T °C	0.926	-0.915	-0.886	-0.803	0.928	0.610	1
<hr/>							
LAVAZÉ 2	<i>NDVI</i>	<i>NDWI</i>	<i>MNDWI</i>	<i>NDMI</i>	<i>SAVI</i>	<i>Rain</i>	<i>T °C</i>
<i>NDVI</i>	1						
<i>NDWI</i>	-0.987	1					
<i>MNDWI</i>	-0.937	0.978	1				
<i>NDMI</i>	-0.834	0.906	0.974	1			
<i>SAVI</i>	0.991	-0.964	-0.903	-1	1.000		
<i>Rain</i>	0.540	-0.547	-0.579	-0.568	0.559	1	
<i>T °C</i>	0.901	-0.894	-0.871	-0.790	0.904	0.610	1
<hr/>							
MARCESINA 1	<i>NDVI</i>	<i>NDWI</i>	<i>MNDWI</i>	<i>NDMI</i>	<i>SAVI</i>	<i>Rain</i>	<i>T °C</i>
<i>NDVI</i>	1						
<i>NDWI</i>	-0.974	1					
<i>MNDWI</i>	-0.863	0.951	1				
<i>NDMI</i>	-0.636	0.786	0.938	1			
<i>SAVI</i>	0.983	-0.929	-0.789	-1	1.000		
<i>Rain</i>	0.305	-0.275	-0.230	-0.147	0.307	1	
<i>T °C</i>	0.936	-0.875	-0.746	-0.499	0.948	0.309	1
<hr/>							
MARCESINA 2	<i>NDVI</i>	<i>NDWI</i>	<i>MNDWI</i>	<i>NDMI</i>	<i>SAVI</i>	<i>Rain</i>	<i>T °C</i>
<i>NDVI</i>	1						
<i>NDWI</i>	-0.977	1					
<i>MNDWI</i>	-0.892	0.963	1				
<i>NDMI</i>	-0.735	0.852	0.961	1			
<i>SAVI</i>	0.987	-0.941	-0.838	-1	1.000		
<i>Rain</i>	0.268	-0.266	-0.256	-0.222	0.269	1	
<i>T °C</i>	0.931	-0.881	-0.781	-0.609	0.939	0.309	1
<hr/>							
MARCESINA 3	<i>NDVI</i>	<i>NDWI</i>	<i>MNDWI</i>	<i>NDMI</i>	<i>SAVI</i>	<i>Rain</i>	<i>T °C</i>
<i>NDVI</i>	1						
<i>NDWI</i>	-0.976	1					
<i>MNDWI</i>	-0.862	0.947	1				
<i>NDMI</i>	-0.612	0.761	0.928	1			
<i>SAVI</i>	0.979	-0.926	-0.786	-1	1.000		
<i>Rain</i>	0.274	-0.254	-0.217	-0.144	0.267	1	
<i>T °C</i>	0.926	-0.872	-0.753	-0.497	0.947	0.305	1

Data Descriptive Statistics

Table 9: Descriptive statistic data for each index in Lavazé 1.

LAVAZÉ 1		INDEX	LAVAZÉ 1		
DATE	NDSI		DATE	NDVI	
mx	q	mx	q	mx	q
Coeff. Ang.	Inters.	Coeff. Ang.	Inters.	Coeff. Ang.	Inters.
-0.0064	0.2690	0.0035	0.2112	-0.0034	-0.2325
mean	0.1150	mean	0.2980	mean	-0.3163
dev.st.	0.5722	dev.st.	0.2627	dev.st.	0.2671
max	0.8440	max	0.7291	max	0.0033
min	-0.6030	min	-0.0003	min	-0.6793
DATE	MNDWI	DATE	NDMI	DATE	SAVI
mx	q	mx	q	mx	q
Coeff. Ang.	Inters.	Coeff. Ang.	Inters.	Coeff. Ang.	Inters.

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-0.0082	0.2579	-0.0044	0.4912	0.0026	0.1241
mean	0.0571	mean	0.3830	mean	0.1886
dev.st.	0.6180	dev.st.	0.3537	dev.st.	0.1750
max	0.8427	max	0.8668	max	0.5399
min	-0.6033	min	-0.0746	min	-0.0100

Table 10: Descriptive statistic data for each index in Lavazé 2.

DATE		LAVAZÉ 2		INDEX	DATE	
NDSI	q	DATE	NDVI		DATE	NDWI
mx	q	mx	q		mx	q
Coeff. Ang.	Inters.	Coeff. Ang.	Inters.		Coeff. Ang.	Inters.
-0.0068	0.3364	0.0035	0.2124		-0.0032	-0.2289
mean	0.1731	mean	0.2982		mean	-0.3083
dev.st.	0.5953	dev.st.	0.2763		dev.st.	0.2781
max	0.8523	max	0.7501		max	0.0086
min	-0.5964	min	-0.0102		min	-0.6804
DATE		DATE			DATE	
MNDWI	q	DATE	NDMI		DATE	SAVI
mx	q	mx	q		mx	q
Coeff. Ang.	Inters.	Coeff. Ang.	Inters.		Coeff. Ang.	Inters.
-0.0075	0.2965	-0.0037	0.5227		0.0026	0.1265
mean	0.1136	mean	0.4331		mean	0.1902
dev.st.	0.6383	dev.st.	0.3571		dev.st.	0.1783
max	0.8622	max	0.8742		max	0.5462
min	-0.5908	min	-0.0810		min	-0.0150

Table 11: Descriptive statistic data for each index in Marcesina 1.

DATE		MARCESINA 1		INDEX	DATE	
NDSI	q	DATE	NDVI		DATE	NDWI
mx	q	mx	q		mx	q
Coeff. Ang.	Inters.	Coeff. Ang.	Inters.		Coeff. Ang.	Inters.
-0.0096	0.2293	0.0029	0.2815		-0.0032	-0.2827
mean	-0.0011	mean	0.3495		mean	-0.3581
dev.st.	0.4975	dev.st.	0.2944		dev.st.	0.2657
max	0.9118	max	0.7933		max	0.1148
min	-0.6470	min	-0.1089		min	-0.6815
DATE		DATE			DATE	
MNDWI	q	DATE	NDMI		DATE	SAVI
mx	q	mx	q		mx	q
Coeff. Ang.	Inters.	Coeff. Ang.	Inters.		Coeff. Ang.	Inters.
-0.0076	0.0794	-0.0046	0.3811		0.0015	0.2051
mean	-0.0993	mean	0.2728		mean	0.2394
dev.st.	0.5717	dev.st.	0.3444		dev.st.	0.2286
max	0.9183	max	0.9123		max	0.6370
min	-0.6470	min	-0.2315		min	-0.1159

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Table 12: Descriptive statistic data for each index in Marcesina 2.

		MARCESINA 2				
DATE	NDSI	DATE	NDVI	INDEX	DATE	NDWI
mx	q	mx	q		mx	q
Coeff. Ang.	Inters.	Coeff. Ang.	Inters.		Coeff. Ang.	Inters.
-0.0105	0.2833	0.0036	0.2539		-0.0034	-0.2701
mean	0.0314	mean	0.3376		mean	-0.3501
dev.st.	0.5152	dev.st.	0.2769		dev.st.	0.2619
max	0.9060	max	0.7955		max	0.0970
min	-0.6338	min	-0.0650		min	-0.6890
DATE	MNDWI	DATE	NDMI		DATE	SAVI
mx	q	mx	q		mx	q
Coeff. Ang.	Inters.	Coeff. Ang.	Inters.		Coeff. Ang.	Inters.
-0.0078	0.1000	-0.0042	0.3751		0.0025	0.1625
mean	-0.0835	mean	0.2771		mean	0.2222
dev.st.	0.5978	dev.st.	0.3642		dev.st.	0.2021
max	0.9440	max	0.9408		max	0.6088
min	-0.6338	min	-0.1901		min	-0.0725

Table 13: Descriptive statistic data for each index in Marcesina 3.

		MARCESINA 3				
DATE	NDSI	DATE	NDVI	INDEX	DATE	NDWI
mx	q	mx	q		mx	q
Coeff. Ang.	Inters.	Coeff. Ang.	Inters.		Coeff. Ang.	Inters.
-0.0086	0.1476	0.0044	0.2728		-0.0041	-0.2905
mean	-0.0578	mean	0.3749		mean	-0.3845
dev.st.	0.4885	dev.st.	0.2834		dev.st.	0.2569
max	0.8883	max	0.8295		max	0.0658
min	-0.6455	min	-0.0458		min	-0.7183
DATE	MNDWI	DATE	NDMI		DATE	SAVI
mx	q	mx	q		mx	q
Coeff. Ang.	Inters.	Coeff. Ang.	Inters.		Coeff. Ang.	Inters.
-0.0077	0.0327	-0.0033	0.3284		0.0026	0.1834
mean	-0.1453	mean	0.2527		mean	0.2439
dev.st.	0.5457	dev.st.	0.3194		dev.st.	0.2061
max	0.8883	max	0.8969		max	0.6353
min	-0.6455	min	-0.1989		min	-0.0513

Appendix

ANOVA: One Way Analysis of Variance

Table 14: ANOVA table for NDVI.

NDVI						
Analysis of variance: one-factor						
OVERVIEW						
Groups	Counts	Sum	Mean	Variance		
Lavazé 1	48	14.30615952	0.29804499	0.06902304		
Lavazé 2	48	14.31356468	0.298199264	0.076367853		
Marcesina 1	46	16.07771111	0.349515459	0.086683567		
Marcesina 2	46	15.52789861	0.337563013	0.0766708		
Marcesina 3	45	16.86998611	0.37488858	0.080324536		
VARIANCE ANALYSIS						
Origine della variazione	Sum of squares	degree of freedom	MQ	F	Significance value P	F crit
Among Groups	0.20819944	4	0.05204986	0.669769022	0.6135782	2.411239087
Within Groups	17.71859805	228	0.077713149			
Tot	17.92679749	232				

Table 15: ANOVA table for NDWI.

NDWI						
Analysis of variance: one-factor						
OVERVIEW						
Groups	Counts	Sum	Mean	Variance		
Lavazé 1	48	15.18075278	0.316265683	0.071350809		
Lavazé 2	48	14.79952659	0.308323471	0.07733712		
Marcesina 1	46	16.47079583	0.358060779	0.070603068		
Marcesina 2	46	16.10663681	0.350144278	0.06858303		
Marcesina 3	45	17.30242222	0.384498272	0.066021579		
VARIANCE ANALYSIS						
Origine della variazione	Sum of squares	degree of freedom	MQ	F	Significance value P	F crit
Among Groups	0.18228674	4	0.045571685	0.643099899	0.632292231	2.411239087
Within Groups	16.15665652	228	0.070862529			
Tot	16.33894326	232				

Table 16: ANOVA table for NDMWI:

MNDWI				
Analysis of variance: one-factor				
OVERVIEW				
Groups	Counts	Sum	Mean	Variance
Lavazé 1	48	2.740738889	0.057098727	0.381902822
Lavazé 2	48	5.452139683	0.113586243	0.407464531

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Marcesina 1	46	4.569990972	-0.09934763	0.326848798
Marcesina 2	46	3.841774306	0.083516833	0.357367718
Marcesina 3	45	6.539047917	0.145312176	0.297835063

VARIANCE ANALYSIS

<i>Origine della variazione</i>	<i>Sum of squares</i>	<i>degree of freedom</i>	<i>MQ</i>	<i>F</i>	<i>Significance value P</i>	<i>F crit</i>
Among Groups	2.304847429	4	0.576211857	1.622034772	0.169547325	2.411239087
Within Groups	80.9947516	228	0.355240139			
Tot	83.29959902	232				

Table 17: ANOVA table for NDMI.

NDMI						
Analysis of variance: one-factor						
OVERVIEW						
<i>Groups</i>	<i>Counts</i>	<i>Sum</i>	<i>Mean</i>	<i>Variance</i>		
Lavazé 1	48	18.38375278	0.38299485	0.125090238		
Lavazé 2	48	20.78683889	0.433059144	0.127536692		
Marcesina 1	46	12.54672292	0.272754846	0.118600153		
Marcesina 2	46	12.74759167	0.277121558	0.132635487		
Marcesina 3	45	11.36959792	0.252657731	0.102025464		
VARIANCE ANALYSIS						
<i>Origine della variazione</i>	<i>Sum of squares</i>	<i>degree of freedom</i>	<i>MQ</i>	<i>F</i>	<i>Significance value P</i>	<i>F crit</i>
Among Groups	1.18838786	4	0.297096965	2.448230553	0.047138379	2.411239087
Within Groups	27.66818996	228	0.12135171			
Tot	28.85657782	232				

Table 18: ANOVA table for SAVI.

SAVI						
Analysis of variance: one-factor						
OVERVIEW						
<i>Groups</i>	<i>Counts</i>	<i>Sum</i>	<i>Mean</i>	<i>Variance</i>		
Lavazé 1	48	9.054189286	0.188628943	0.030616549		
Lavazé 2	48	9.130094048	0.190210293	0.031807802		
Marcesina 1	46	11.01312917	0.239415851	0.052235556		
Marcesina 2	46	10.22013056	0.222176751	0.04085144		
Marcesina 3	45	10.97357569	0.243857238	0.042487477		
VARIANCE ANALYSIS						
<i>Origine della variazione</i>	<i>Sum of squares</i>	<i>degree of freedom</i>	<i>MQ</i>	<i>F</i>	<i>Significance value P</i>	<i>F crit</i>
Among Groups	0.129766577	4	0.032441644	0.822557975	0.511948778	2.411239087

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Within Groups	8.992308298	228	0.039439949
Tot	9.122074875	232	

Table 19: ANOVA table for NDSI.

NDSI						
Analysis of variance: one-factor						
OVERVIEW						
Groups	Counts	Sum	Mean	Variance		
Lavazé 1	48	18.38375278	0.38299485	0.125090238		
Lavazé 2	48	20.78683889	0.433059144	0.127536692		
Marcesina 1	46	12.54672292	0.272754846	0.118600153		
Marcesina 2	46	12.74759167	0.277121558	0.132635487		
Marcesina 3	45	11.36959792	0.252657731	0.102025464		
VARIANCE ANALYSIS						
Origine della variazione	Sum of squares	degree of freedom	MQ	F	Significance value P	F crit
Among Groups	1.18838786	4	0.297096965	2.448230553	0.047138379	2.411239087
Within Groups	27.66818996	228	0.12135171			
Tot	28.85657782	232				