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Drought Assessment in Irrigated Rice Fields Using Multi-Index Remote Sensing: A Case Study of Vercelli, Italy

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Abstract

This thesis investigates the spatial and temporal impacts of agricultural drought in the Vercelli province of northern Italy using multi-source remote sensing data and meteorological indices. Focusing on rice cultivation, which is highly sensitive to seasonal water availability, the study integrates vegetation indices (NDVI, EVI2, SAVI, and VCI) derived from Sentinel-2 and MODIS platforms with meteorological drought indicators (SPI and SPEI). A phenology-based interpretation framework was adopted to align index trends with key rice growth stages—transplanting, vegetative, reproductive, and maturation phases—capturing the crop's seasonal sensitivity to climate variability. In addition, a high-resolution land use and land cover (LULC) classification from ESA WorldCover (2021) was used to contextualize vegetative patterns and visually separate agricultural from non-agricultural zones. The analysis revealed significant drought impacts during critical periods in 2021 and residual stress in 2022, with spatial variability influenced by irrigation access. The methodological workflow was implemented in QGIS using automated processing tools, enhancing reproducibility and efficiency. While resolution mismatches posed limitations for direct index masking, the integrated approach demonstrated strong potential for drought monitoring in irrigated crop systems. This research contributes to global efforts in agricultural resilience, aligning with international initiatives such as UN-SPIDER and the Copernicus Emergency Management Service. Recommendations are provided for future validation through ground-truthing and operational integration with regional drought preparedness strategies.

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Chapter 1: Introduction

1.1 Background and Motivation

Drought is among the most complex and destructive natural hazards, affecting ecosystems, economies, and food security on a global scale. It manifests in various forms—meteorological, hydrological, and agricultural—each defined by distinct characteristics and impacts (Wilhite & Glantz, 1985). Agricultural drought, in particular, disrupts crop phenology, reduces yields, and stresses irrigation systems. These challenges are amplified under current climate variability, prompting the need for effective monitoring frameworks.

To address this, global and European institutions have established remote sensing–based platforms to support drought early warning and agricultural resilience. For instance, the **UN-SPIDER** program promotes satellite-based data use for disaster response, while the **Copernicus Emergency Management Service (CEMS)** and **Global Drought Observatory (GDO)** offer operational drought monitoring across Europe (UN-SPIDER, n.d.; CEMS, n.d.; GDO, n.d.). The **FAO WaPOR** platform enables water productivity monitoring using Earth observation data, supporting climate-smart agriculture (FAO WaPOR, n.d.).

Within this broader context, **Vercelli Province**, located in the Po Valley of northern Italy, is one of Europe's most significant rice-producing areas. Characterized by extensive monoculture paddy fields and a traditional irrigation system that relies heavily on **seasonal snowmelt and surface water from the Alps**, the region is highly vulnerable to water scarcity. Between **2021 and 2023**, northern Italy experienced exceptional drought events that triggered a national state of emergency and caused widespread agricultural disruption (ARPA Piemonte, 2022; SNPA, 2022).

The vulnerability of **rice cultivation in Vercelli** is particularly evident during key **phenological stages**, such as transplanting (May), elongation (July), and heading (late July), when adequate water availability is critical for biomass development and yield formation. Drought stress during these stages can result in **delayed transplanting, reduced vegetative vigor**, and **lower harvest indices**. Therefore, early detection of vegetation anomalies and continuous seasonal monitoring is essential for both risk mitigation and agricultural adaptation strategies.

This study addresses these challenges by developing a remote sensing–based monitoring framework tailored to the Vercelli rice system. Through a **phenology-aligned**, multi-index methodology, it aims to bridge the gap between Earth observation data and actionable agricultural insights.

In addition to these global drought early warning frameworks, land use and land cover (LULC) information plays a vital role in contextualizing vegetation dynamics. The ESA WorldCover 2021 dataset provides globally consistent LULC classification at a 10-meter resolution, offering valuable spatial context for distinguishing agricultural from non-agricultural areas (ESA WorldCover, 2022). This classification supports applications ranging from NDVI interpretation to crop stress mapping and disaster response. The availability of such high-resolution land cover products complements the operational goals of platforms like UN-SPIDER and the Copernicus Emergency Management Service (CEMS), reinforcing integrated approaches to agricultural monitoring under climate stress.

1.2 Research Problem

Monitoring agricultural drought is essential for maintaining food security under increasing climate variability. Remote sensing technologies have become a vital tool in drought assessment by enabling the continuous tracking of vegetation conditions across large spatial and temporal scales (WMO, 2020). Among these, vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Enhanced Vegetation Index (EVI), and Soil-Adjusted Vegetation Index (SAVI) are widely applied to assess vegetation health and drought stress (Jiang et al., 2008; Huete, 1988).

This study focuses on how recurring drought events between 2020 and 2024 affected the vegetation health of rice crops in the Vercelli province of Northern Italy—one of Europe's most important rice-producing areas. By integrating NDVI and VCI, this research aims to evaluate drought-induced stress during biologically significant phenological stages, particularly transplanting, tillering, and heading—periods identified as highly sensitive to water availability.

The analysis employs anomaly detection, zonal statistics, and time-series interpretation to compare spatial and temporal drought effects across years. In doing so, it supports early warning efforts and irrigation scheduling by identifying critical stress periods and high-risk zones.

Ultimately, understanding drought impacts on vegetation health across phenological phases allows for better planning of irrigation operations and crop calendars. This contributes to improved agricultural risk management in the face of future climatic extremes.

1.3 Research Objectives

This research investigates the spatiotemporal dynamics of agricultural drought and vegetation response in the rice-growing region of Vercelli (Italy) over the period 2020–2024. It employs a phenology-aligned, multi-index remote sensing approach that integrates vegetation indices and meteorological drought indicators. The objectives are thematically grouped as follows:

1. Monitoring and Phenological Alignment

To monitor and assess the impact of agricultural drought on rice crop health during critical phenological stages, including transplanting, vegetative growth, and reproduction.

Aligning remote sensing observations with crop development phases enhances the biological interpretability of drought-induced stress (Wang et al., 2022).

2. Vegetation Index Application and Comparative Evaluation

To apply and evaluate NDVI and VCI for anomaly detection and trend analysis across the rice-growing season. NDVI reflects chlorophyll activity and is widely used for vegetation monitoring (Tucker, 1979), while VCI normalizes vegetation stress relative to historical behavior (Kogan, 1995).

To compare the performance of NDVI, SAVI, EVI2 and VCI in detecting drought stress under varying soil and canopy conditions. SAVI corrects for soil background influence (Huete, 1988), EVI2 reduces atmospheric interference and enhances canopy sensitivity (Jiang et al., 2008), and VCI helps identify deviations from long-term vegetation trends. This comparison supports optimal index selection for rice environments (WMO, 2016).

3. Climate-Drought Linkage

To integrate meteorological drought indices—specifically SPI (Standardized Precipitation Index) and SPEI (Standardized Precipitation Evapotranspiration Index)—to examine the relationship between climatic anomalies and vegetation stress in irrigated rice systems (Vicente-Serrano et al., 2010). These indicators contextualize vegetative changes in relation to precipitation deficits and evapotranspiration anomalies.

4. Temporal Trend and Drought Cycle Analysis

To analyze interannual drought variations and transitional phases by identifying the acute drought conditions of 2021, partial adaptation in 2022–2023, and recovery in 2024. This longitudinal analysis provides insight into drought cycles and resilience trajectories in a Mediterranean rice context (Global Drought Observatory, 2024).

5. Workflow and Methodological Implementation

To implement a semi-automated analysis pipeline using existing open-source tools (QGIS and Python). The workflow facilitates batch vegetation index computation, anomaly mapping, and zonal statistics aligned with phenological phases. While not a full reusable platform, it demonstrates a practical and scalable approach for operational drought monitoring in agricultural systems.

Through these objectives, the study contributes to advancing remote sensing methodologies for drought detection and supports actionable insights for irrigation scheduling, early warning systems, and climate adaptation in rice-based agroecosystems.

1.4 Significance of the Study

This study holds substantial value in advancing drought monitoring methodologies tailored to phenology-sensitive agricultural systems, with a particular focus on rice cultivation in the Vercelli region of Northern Italy. Located in a hydroclimatically sensitive basin reliant on snowmelt and surface water for irrigation, the region faces increasing vulnerability to recurring droughts (Pascale & Ragone, 2025). The research responds to this challenge by integrating satellite-derived vegetation indices and meteorological drought indicators to enhance spatial and temporal drought assessment.

Specifically, the study employs the NDVI derived from Sentinel-2 imagery to monitor vegetation health at a 10 m spatial resolution. To complement this, the VCI is calculated using the MODIS MOD13Q1 product (250 m resolution), which incorporates EVI and offers over 20 years of data (Didan, 2015). VCI enables anomaly detection by comparing current vegetation conditions to historical baselines, offering critical temporal insight into vegetation stress dynamics (Kogan, 1995).

The dual-resolution approach allows for fine-scale crop monitoring while capturing broader climatological trends. VCI is especially valuable for detecting deviations from long-term vegetation norms, particularly in extreme years such as 2021, when anomalies may not be captured through NDVI alone. Together, these indices facilitate a nuanced understanding of drought severity across key rice phenological stages—including transplanting, vegetative growth, and reproduction—when the crop is most sensitive to hydrometeorological stress (Zhang et al., 2022).

Importantly, this study aligns index analysis with phenological calendars to ensure biological relevance, enhancing the interpretability of satellite signals in relation to rice crop development. Although no ground-based validation data (e.g., biomass or yield statistics) were available, the study emphasizes transparency and reproducibility by leveraging open-source geospatial tools such as QGIS and Python.

The outputs are expected to support:

- **Early warning systems**, by offering timely indicators of vegetative stress detectable through NDVI and VCI anomalies;
- **Irrigation management**, by informing localized scheduling during vulnerable phenological phases;
- **Climate adaptation planning**, through spatial mapping of drought hotspots and recovery zones;
- **Integration into existing drought monitoring systems**, such as Copernicus Global Drought Observatory and FAO WaPOR, by offering scalable methods aligned with remote sensing standards;
- **Scientific advancement**, by demonstrating a phenology-aligned, semi-automated workflow that supports replicable drought assessment in Mediterranean agroecosystems.

Ultimately, this research strengthens the transition from reactive to proactive drought risk management, fostering resilience in agriculture under climate variability.

1.5 Research Methodology Overview

This study adopts an integrated remote sensing and climatic approach to assess drought impacts on rice vegetation in Vercelli (Italy) from 2020 to 2024. It combines high-resolution Sentinel-2 imagery for NDVI analysis and MODIS MOD13Q1 data for computing VCI, providing a dual-resolution framework for capturing field-level dynamics and long-term anomalies (Tucker, 1979; Didan, 2015; Kogan, 1995).

NDVI was calculated using Sentinel-2 data (10 m resolution) to track vegetation greenness aligned with key phenological stages—transplanting, vegetative growth, and reproduction—following phenology calendars tailored to rice (Zhang et al., 2022). VCI, derived from MODIS EVI composites (250 m resolution, 16-day), offers temporal anomaly detection by comparing current EVI values against long-term historical ranges (Kogan, 1995; Didan, 2015).

Meteorological drought conditions were validated using SPI and SPEI at the monthly scale (Vicente-Serrano et al., 2010), especially for the May–July period. Particular emphasis was placed on the 2022 drought (SPI/SPEI < –1.5), with comparison across 2021 and 2023–2024 to characterize a full drought cycle.

Geospatial processing was conducted in QGIS using the Graphical Modeler and Python batch tools for automated NDVI/VCI extraction, anomaly mapping, and zonal statistics. This semi-automated setup improves reproducibility and enables efficient scaling across time and subregions.

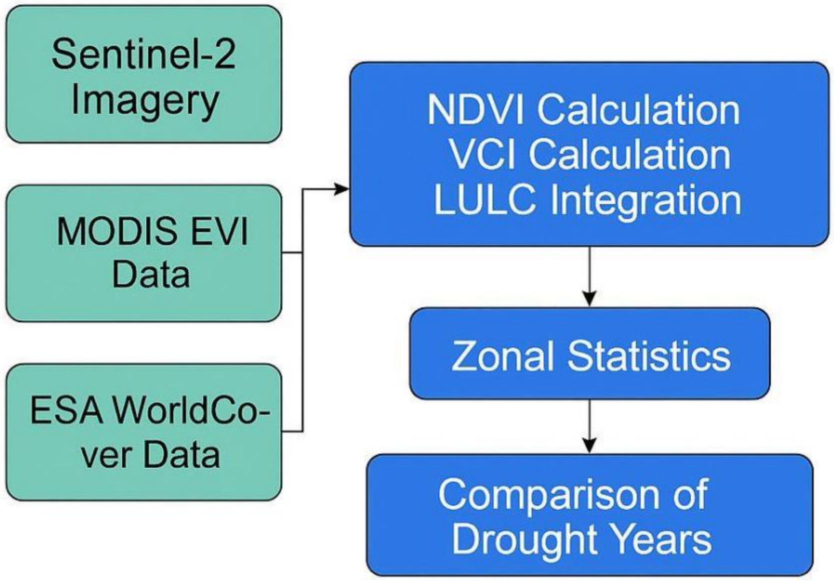

Figure 1- Workflow of NDVI, VCI, and LULC Integration for Vegetation Health Monitoring in Vercelli.

This diagram illustrates the step-by-step processes for computing.

NDVI from Sentinel-2 data, VCI from MODIS EVI data, and incorporating LULC classification from ESA WorldCover. It reflects how these datasets were processed and integrated to assess drought dynamics in the Vercelli region between 2020 and 2024.

1.6 Structure of the Thesis

The thesis is structured as follows:

- **Chapter 1: Introduction** – Establishes the research background, outlines the problem, and presents the objectives. It introduces international remote sensing initiatives (e.g., UN-SPIDER, CEMS), emphasizes the importance of phenology-aligned monitoring, and includes a methodological overview integrating LULC mapping (ESA WorldCover).

- **Chapter 2: Literature Review** – Provides a comprehensive synthesis of studies related to agricultural drought monitoring, remote sensing indices (NDVI, SAVI, EVI2, VCI), LULC applications, and international drought frameworks (e.g., FAO WaPOR, GDO, Copernicus).

- **Chapter 3: Methodology** – Details the multi-source data inputs (Sentinel-2, MODIS, SPI/SPEI, ESA WorldCover), remote sensing workflow using QGIS and Python, and outlines steps for NDVI/VCI calculation, anomaly detection, and phenological alignment. A diagram illustrates the full processing chain.

- **Chapter 4: Results** – Presents NDVI and VCI trends (2020–2024), spatial-temporal anomaly patterns, and a land cover composition map of Vercelli. Includes cross-year comparisons, phenology-specific insights, and statistical outputs.

- **Chapter 5: Discussion** – Interprets NDVI/VCI behavior in the context of drought years, evaluates LULC integration, and discusses methodological strengths and weaknesses. Connects findings to international monitoring efforts and implications for agricultural resilience.

- **Chapter 6: Conclusions and Recommendations** – Summarizes key findings on drought stress and phenological impacts, highlights operational contributions (e.g., use of LULC, automated QGIS workflow), and offers suggestions for future research and data integration improvements.

Chapter 2: Literature Review

2.1 Overview of Drought

Drought is a natural phenomenon characterized by a prolonged period of **below-average precipitation** that leads to **water shortages**. It significantly impacts **agriculture**, causing **crop failure** and **economic loss**. Drought can be categorized into several types: **meteorological drought**, **agricultural drought**, **hydrological drought**, and **socioeconomic drought** (Wilhite & Glantz, 1985). In the context of this study, **agricultural drought** is the focus, defined as a situation where **soil moisture** is insufficient for crop growth, causing stress to vegetation.

The **agricultural impact of drought** is critical for crop health, as it limits water availability during key growth periods. The ability to monitor and assess drought impact is crucial for regions like **Vercelli**, where rice cultivation depends heavily on **irrigation systems** that are vulnerable to **climatic variability**. **Remote sensing** provides a powerful tool to monitor vegetation health during drought events, allowing early detection of stress and enabling timely interventions.

Drought monitoring is typically done using **vegetation indices** like **NDVI** and **VCI**, which are reliable indicators of **vegetation stress** during periods of drought (Kogan, 1995). These indices can be used to assess **drought severity** and to **track recovery** over time.

2.2 Remote Sensing for Drought Monitoring

Remote sensing technologies, particularly satellite imagery, play a pivotal role in monitoring agricultural drought due to their ability to continuously capture vegetation dynamics at multiple scales. Compared to meteorological indicators—which provide indirect measures of drought through precipitation and evapotranspiration—vegetation indices such as NDVI and VCI allow direct assessment of drought impact on crop health, especially when aligned with phenological stages.

In this study, **Sentinel-2** data was selected for NDVI (Normalized Difference Vegetation Index) computation because of its 10-meter spatial resolution and 5–10 day revisit cycle, enabling detailed and frequent monitoring of vegetation status. NDVI is derived from the reflectance of near-infrared (NIR) and red light (R), where healthy vegetation reflects more NIR and less red light, resulting in higher index values. Conversely, stressed vegetation reflects more red light and less NIR, producing lower NDVI values (Tucker, 1979).

However, Sentinel-2's optical nature introduces a limitation: **cloud contamination**, which can disrupt data acquisition during key crop stages, particularly in the summer months.

To address longer-term trends and drought anomalies, the **Vegetation Condition Index (VCI)** is also used. VCI is calculated by comparing current **EVI (Enhanced Vegetation Index)** values to historical minimum and maximum EVI values. This study utilizes the **MODIS MOD13Q1** product, which offers 250-meter resolution and a 16-day composite period. This product provides over 20 years of EVI data, allowing for robust historical comparisons (Kogan, 1995; Didan, 2015). The temporal baseline used spans from **2000 to 2024**, ensuring consistency in anomaly detection.

Although MODIS enables regional-scale drought monitoring, its **coarser resolution** makes it less suitable for field-level decision-making compared to Sentinel-2. Therefore, a dual-resolution integration was adopted: Sentinel-2 for fine-scale crop response and MODIS for contextualizing long-term anomalies.

Notably, this integrated approach is crucial in Vercelli, a region that experienced prolonged **meteorological and agricultural drought between 2021 and 2023**, culminating in national-level alerts (Pascale & Ragone, 2025). The ability to detect vegetation stress in this period using remote sensing tools underscores their value in early warning systems and adaptive management planning.

2.3 Previous Work

Several studies have utilized NDVI and VCI for drought monitoring in agricultural systems, especially within Mediterranean rice-producing contexts. For example, Misra et al. (2020) and Liu et al. (2020) demonstrated the effectiveness of these indices in assessing vegetation responses to water stress in rice-based ecosystems. Their work reinforces the regional relevance of remote sensing applications in Mediterranean climates and provides a strong foundation for applying such indices in the Vercelli region.

Xiao et al. (2006) showed that NDVI can effectively detect vegetation stress during drought events, particularly in rice-growing areas. Similarly, Kogan (1995) introduced the VCI, which allows for detecting vegetation anomalies based on historical trends. These tools have been widely used for drought impact assessment. A more recent regional study by Baronetti et al. (2024) specifically applied NDVI and VCI to the Vercelli area, confirming their utility in evaluating drought severity and supporting water management decisions in rice fields.

However, limitations remain. NDVI calculations using Sentinel-2 are susceptible to cloud contamination, and MODIS VCI is limited by its coarser spatial resolution and potential temporal inconsistencies (Zhang et al., 2003). This study addresses these limitations by aligning vegetation index extraction with rice phenological stages and integrating multi-resolution data—high-resolution Sentinel-2 NDVI for field-level crop tracking and MODIS-derived VCI for broader temporal anomaly detection. This phenology-based and dual-resolution strategy enhances the reliability and agricultural relevance of drought monitoring for the Vercelli context.

Tuvdendorj et al. (2019) evaluated the effectiveness of NDVI and VCI for spring wheat yield estimation under drought conditions in Mongolia using MODIS data, emphasizing index-specific responses during distinct phenological phases. Their approach supports this thesis's use of phenology-aligned indices for drought impact monitoring. Similarly, Jha et al. (2022) assessed NDVI, GNDVI, and EVI2 for sugarcane yield forecasting using Sentinel-2 imagery, showing how index sensitivity varies across phenophases. These findings validate the selection of EVI2 in this study and reinforce the broader value of multi-index monitoring for phenology-driven crops. Wang et al. (2020) also highlighted the role of remote sensing-based phenological indicators in characterizing rice development under weather variability, supporting integrated temporal analysis of vegetation stress.

2.4 Theoretical Framework

The theoretical framework guiding this research is grounded in the relationship between **drought stress** and **vegetation health**, as measured by **remote sensing data**. It leverages vegetation indices that reflect both biological responses and climatological deviations. The core indices used are **NDVI** and **VCI**, which offer complementary insights into vegetation condition and are aligned with crop phenology stages.

- **NDVI**: Derived from red and near-infrared (NIR) reflectance, NDVI is closely associated with **vegetation density** and **photosynthetic activity**. It is particularly sensitive to changes during the **vegetative phase** of rice, allowing timely detection of drought-induced stress during early crop development (Tucker, 1979).
- **VCI**: Calculated from MODIS EVI, VCI compares current vegetation conditions against long-term historical baselines, providing a **relative stress indicator**. It is especially effective for **anomaly tracking** during later stages, such as **heading and maturation**, when deviations from climatic norms become more pronounced (Kogan, 1995; Didan, 2015).

Together, NDVI and VCI offer a **multi-faceted view** of drought impacts. NDVI provides fine-scale field monitoring through Sentinel-2 imagery, while VCI introduces a climatological baseline for long-term comparison. This dual approach is **phenology-aligned**, with both indices extracted during critical rice growth stages: **transplanting, vegetative growth, and heading**—ensuring biological relevance and analytical consistency.

Studies such as **Zhang et al. (2022)** highlight the importance of linking vegetation indices with crop phenology for accurate drought assessment. This research adopts that model by aligning temporal windows of index extraction to match the seasonal dynamics of rice cultivation in Vercelli.

Additionally, other indices are considered:

- **SAVI**: Designed to reduce soil background noise, SAVI is useful in semi-arid or exposed-soil environments (Huete, 1988).
- **EVI2**: A simplified version of EVI that works well in **dense vegetation** and **cloudy conditions**, EVI2 increases sensitivity to canopy structure without needing a blue band (Jiang et al., 2008).

By integrating these tools in a phenology-aware framework, the study enables a more **ecologically meaningful and operationally useful interpretation** of agricultural drought patterns.

2.5 Comparative Analysis of NDVI, SAVI, and EVI2

While NDVI is the primary index used in this study, it is important to compare it with other indices such as SAVI and EVI2 to enhance the understanding of vegetation health and drought stress across diverse environmental settings. This comparison is particularly relevant in Vercelli due to its mixed-pixel environment (e.g., flooded paddies and exposed soil) and irrigation dependence, which influence how different indices perform under varying conditions.

- **SAVI**: This index was developed to minimize the influence of soil background on vegetation reflectance, particularly in areas with sparse vegetation or exposed soils (Huete, 1988).
    - **Advantages**: SAVI improves accuracy in arid and semi-arid areas by incorporating a soil brightness correction factor (L) into the NDVI formula, making it more reliable when vegetation does not fully cover the surface.
    - **Disadvantages**: Requires calibration based on soil type and vegetation density; less effective under dense vegetation cover.
    - **Limitations**: May misclassify soil features or underperform under extreme drought or mixed-pixel conditions.
- **EVI2**: A simplified version of EVI that enhances sensitivity in high biomass regions and reduces atmospheric and soil background noise without requiring a blue band (Jiang et al., 2008).
    - **Advantages**: Outperforms NDVI in dense vegetation and under cloud contamination, capturing canopy structure more effectively.
    - **Disadvantages**: Less commonly used than NDVI; requires careful calibration and preprocessing.
    - **Limitations**: Less accurate in sparse vegetation or dry areas; may suffer from temporal inconsistencies.

Recent empirical studies support the application of SAVI and EVI2 in rice-based and Mediterranean agroecosystems. For example, Misra et al. (2020) and Liu et al. (2020) show how these indices can track rice phenology and drought-related stress effectively, especially in complex agricultural environments. This is further illustrated in Table 1, which summarizes key studies applying NDVI, SAVI, EVI2, and VCI across comparable agricultural contexts.

Table 1- Comparative Summary of Vegetation Indices in Rice and Mediterranean Agroecosystems

Study	Region	Indices Used	Key Contribution
Misra et al. (2020)	South Asia (Rice fields)	SAVI, EVI2	Demonstrated index performance under variable soil conditions and phenology.
Liu et al. (2020)	Mediterranean rice systems	NDVI, EVI2	Highlighted EVI2's advantage during cloud-covered growth stages.
Xiao et al. (2006)	China (agricultural regions)	NDVI	Detected vegetation stress during drought in rice areas.
Baronetti et al. (2024)	Vercelli, Italy	NDVI, VCI	Assessed drought severity using MODIS and Sentinel-derived indices.
Zhang et al. (2003)	Various global test sites	NDVI, MODIS VCI	Identified spatial limitations and inconsistencies in coarse-resolution data.

Comparing NDVI, SAVI, and EVI2 provides insights into which index is best suited for particular conditions. NDVI remains the most widely used due to its simplicity and broad adoption (Tucker, 1979). However, SAVI is better in soil-exposed zones, and EVI2 is advantageous in dense canopies and cloudy areas where NDVI might fail.

These observations are further enhanced by Sentinel-2's spatial and temporal resolution. Its 10–20 m resolution and 5–10-day revisit cycle make it particularly valuable for detecting vegetation changes during rice phenological phases (May–August), aligning well with the phenology-based index extraction process used in this study. This integration supports precise monitoring across indices and improves drought detection accuracy in rice-growing systems (Misra et al., 2020; Liu et al., 2020).

Table 2- Strengths, ideal use cases, and known limitations of NDVI, SAVI, and EVI2 in drought monitoring

Vegetation Index	Main Strength	Ideal Usage	Known Limitation
NDVI	Fast, simple, and widely used index for assessing general vegetation health.	Suitable for areas with healthy vegetation and clear skies.	Affected by cloud contamination in optical imagery like Sentinel-2.
SAVI	Corrects for soil influence, making it useful in arid regions with sparse vegetation.	Useful in regions with significant soil exposure and dry conditions.	Less accurate in dense vegetation where soil is minimally exposed; needs calibration.
EVI2	Corrects for atmospheric effects, ideal for dense vegetation areas with cloud cover.	Useful in densely vegetated areas and regions affected by high cloud cover.	Temporal inconsistencies in MODIS data; less effective in sparse vegetation zones.

The comparison of NDVI, SAVI, and EVI2 is summarized in Table 2, which outlines their respective strengths and limitations in drought and vegetation monitoring. While each index offers distinct advantages, practical limitations must be considered in this study's context—for example, **Sentinel-2's vulnerability to cloud contamination during peak rice growth stages**, and the **coarser spatial resolution of MODIS data**, which may lead to mixed-pixel issues in fragmented agricultural fields like Vercelli.

Key Takeaways from Comparative Analysis:

- **NDVI** remains the **most widely used index** and is ideal for areas with **healthy vegetation** and **clear skies**. It is easy to compute and provides reliable vegetation health insights for general use.
- **SAVI** is a valuable alternative for regions where **soil background** significantly influences vegetation measurements, such as **arid** or **semi-arid** regions. It is useful for areas with sparse vegetation, where other indices like NDVI might be less effective.
- **EVI2**, though **less common**, provides **better sensitivity** to **vegetation changes** in areas affected by cloud cover and atmospheric conditions. It works well for **dense vegetation areas**, but it may **misclassify vegetation** in areas with low vegetation density, such as dry or barren regions.

Recommendations for NDVI, SAVI, and EVI2 Usage:

- **NDVI** is ideal for **general vegetation monitoring** when there are no significant challenges like cloud cover or soil exposure.
- **SAVI** should be used in **arid and semi-arid regions** with significant soil exposure to minimize soil influence on vegetation readings.
- **EVI2** is most suitable for regions with **dense vegetation and high cloud cover**, where other indices like NDVI may face issues due to atmospheric interference.

Recent studies have emphasized the value of combining climatic indicators such as SPI and SPEI with remote sensing indices for drought assessment. For instance, Mutowo and Chikodzi (2014) used SPI and NDVI together to monitor agricultural drought conditions in Zimbabwe, demonstrating the advantages of integrated approaches in semi-arid agricultural landscapes.

This **comparative analysis** of NDVI, SAVI, and EVI2 in the context of drought monitoring provides a **comprehensive view** of which index is most **sensitive to drought stress** in the Vercelli region. The use of these three indices in combination enhances the overall accuracy of **vegetation health assessment** during drought events and helps to make more informed decisions regarding agricultural practices and water management strategies in rice cultivation.

Chapter 3: Methodology

3.1 Overview

This chapter presents the comprehensive methodological framework used to assess agricultural drought in the Vercelli region from 2020 to 2024. By integrating multiple vegetation indices (NDVI, SAVI, EVI2, and VCI) and geospatial processing techniques, the study facilitates spatial-temporal monitoring of vegetation stress. The combination of Sentinel-2 and MODIS satellite data, coupled with meteorological indicators (SPI/SPEI), enables both high-resolution and long-term insights into drought severity across key crop phenological phases.

3.2 Study Area and Context

The study focuses on Vercelli province in northwest Italy, a key area for rice farming, known for its reliance on irrigation and vulnerability to droughts. The region, well-covered by MODIS and Sentinel satellites, is ideal for historical comparisons and remote sensing studies. Administrative boundaries were sourced from Geoportale Piemonte, and the Vercelli polygon was clipped from the regional shapefile, with all data reprojected to EPSG:32632 for spatial consistency.

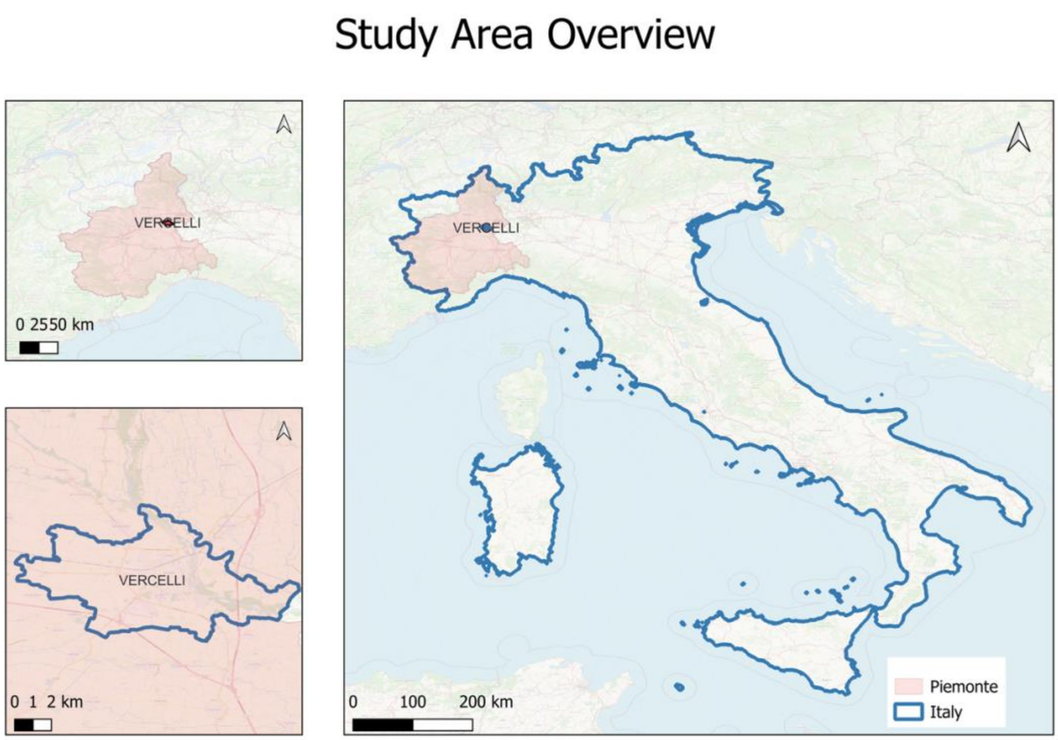

Figure 2- Multi-scale study area map showing Italy, Piemonte, and Vercelli boundaries. Map created using QGIS.

3.2.1 Land Use and Cover Classification

To provide additional spatial context and support the interpretation of vegetation dynamics, a Land Use/Land Cover (LULC) map was generated for the study area using the ESA WorldCover 2021 dataset at 10-meter resolution. The raster was clipped to the administrative boundary of Vercelli using QGIS. A reclassification was then performed to isolate cropland (class code 40), and a multi-class legend was applied to distinguish other land types such as urban (built-up), forested, and water-covered zones. This enabled the visualization of land surface composition and helped contextualize NDVI fluctuations observed in the results. Although the LULC map was not directly integrated into the NDVI data due to resolution mismatch, it served as a visual cross-reference for identifying true agricultural zones (see **Figure 5** in Section 4.1 and **Figure 24** in Section 5.5).

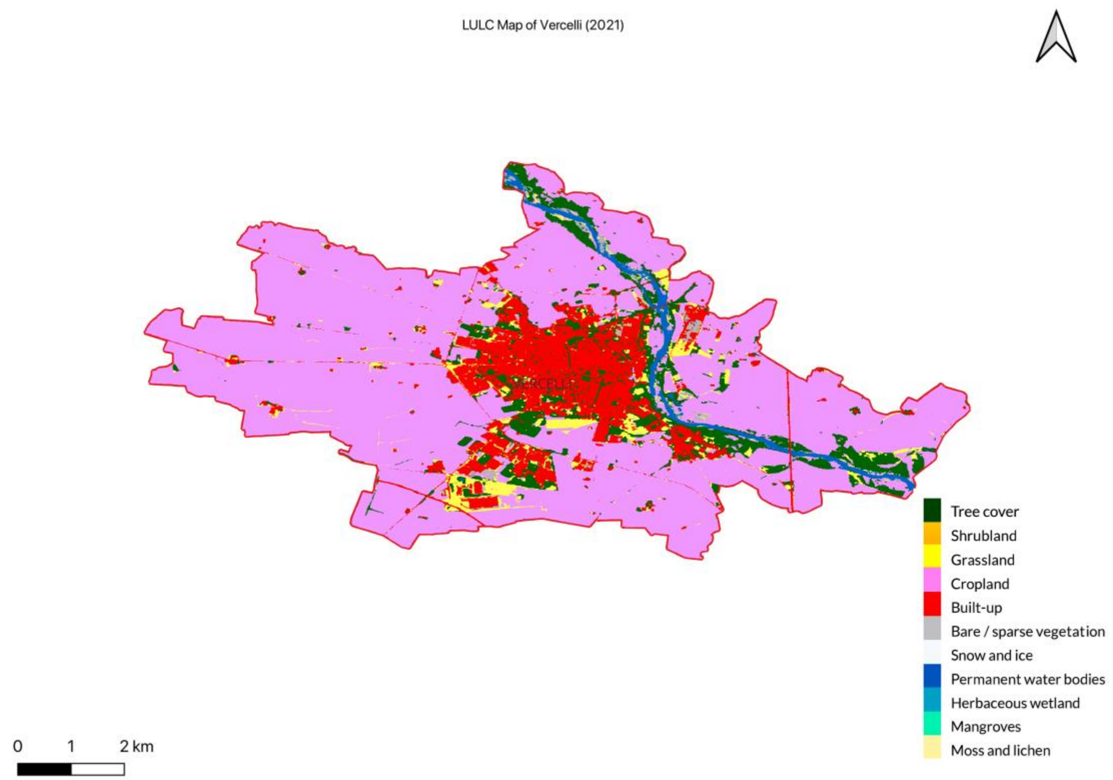

Figure 3- Land Use and Land Cover (LULC) Classification Map of the Vercelli Region (2021), derived from ESA WorldCover data.

3.3 Phenological Stage Alignment

This study aligns the acquisition and analysis of satellite data with critical rice growth stages to allow for a biologically meaningful assessment of vegetation condition and stress response. The phenological calendar adopted here is based on the rice phenology framework developed by Wang et al. (2022), who emphasized the benefits of stage-based monitoring in capturing physiological variability. These dates were validated against agronomic guidance specific to Northern Italy, ensuring regional accuracy. Accordingly, Sentinel-2 imagery from May to August was filtered and matched to the corresponding phenological windows (e.g., transplanting, tillering, heading), enabling stage-specific vegetation index extraction.

Table 3-Key Phenological Stages of Rice Cultivation and Monitoring Schedule in the Vercelli Region

Phenological Phase	Indicative Date	Monitoring Month
Transplanting	May 16	May
Reviving	June 3	Early June
Tillering	June 20	Late June
Elongation	July 2	Early July
Booting	July 21	Mid July
Heading	July 28	Late July
Milk-ripe	August 11	Early August
Maturation	September 8	Late August onward

These stages correspond to critical physiological transitions in the rice plant's lifecycle. For instance, transplanting and tillering are linked to root establishment and canopy expansion, while heading and milk-ripe phases are highly sensitive to water stress and nutrient availability. Satellite-based vegetation indices such as NDVI and EVI2 are particularly responsive during these stages, reflecting variations in chlorophyll concentration, biomass, and canopy structure.

Recent studies have validated the utility of time-series remote sensing for monitoring phenological variation. Mo Wang et al. (2022) demonstrated that stages such as transplanting, elongation, and heading exhibit unique spectral and backscatter signatures, which are detectable through high-resolution satellite imagery. This supports the strategic scheduling of image acquisition in alignment with crop biology to enhance drought sensitivity detection.

Further support for stage-specific vegetation index application is found in Tuvdendorj et al. (2019), who aligned NDVI and VCI performance with crop stages in a drought-prone context. Their results justify the pairing of NDVI with transplanting and VCI with reproductive stages in this thesis. Likewise, Jha et al. (2022) demonstrated the enhanced responsiveness of EVI2 during high-biomass periods, reinforcing its use in mid-to-late season rice monitoring here.

By grounding the temporal aspect of vegetation index analysis in the phenological timeline of rice, this study ensures that remote sensing metrics reflect not just vegetative change, but physiologically meaningful stress impacts—especially those induced by drought during water-critical growth phases.

3.4 Analytical Workflow and Processing Framework

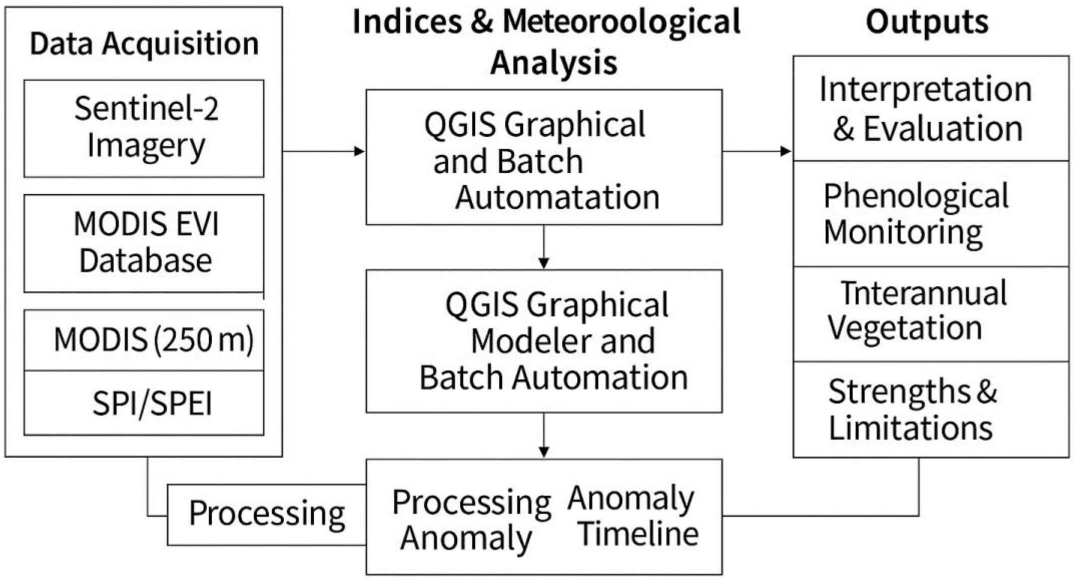

Figure 4-Workflow for Satellite-Based Drought and Phenological Analysis in Vercelli (2020-2024)

Figure 4 illustrates the satellite-based workflow developed for drought monitoring and phenological assessment in the Vercelli region during the 2020–2024 period. The L integrates multiple data sources, including high-resolution Sentinel-2 imagery, MODIS vegetation indices (notably VCI), and meteorological drought indicators (SPI/SPEI), enabling a multi-sensor approach to spatial and temporal drought characterization.

The **Data Acquisition** phase involves the retrieval of satellite-based inputs from optical and climatological datasets. Sentinel-2 provides detailed vegetation information at 10–30 m spatial resolution, whereas MODIS delivers long-term vegetation context via coarse-resolution indices (e.g., VCI). Meteorological indices like SPI and SPEI contribute monthly-scale precipitation and evapotranspiration anomalies.

In the **Processing** stage, vegetation indices (NDVI, SAVI, EVI2, and VCI) are computed using semi-automated workflows built in **QGIS Graphical Modeler**, an open-source geographic information system widely used for spatial analysis and geoprocessing (QGIS Development Team, 2022). These processes include masking, zonal statistics extraction, anomaly detection, and batch map generation. Automation ensures temporal consistency across years and reduces manual errors, enabling robust and replicable outputs. These processes include masking, zonal statistics extraction, anomaly detection, and batch map generation. Automation ensures temporal consistency across years and reduces manual errors, enabling robust and replicable outputs.

The final **Output** stage generates key analytical products, including:

- **Zonal statistics** for interannual vegetation monitoring;
- **Anomaly maps** that visualize spatial deviations in NDVI and VCI across years;
- **Drought timelines** that align remote sensing trends with phenological calendars.

These results feed into the broader interpretation of drought impacts, phenological sensitivity, and spatial risk patterns. The workflow ensures both scientific rigor and operational feasibility for regional drought assessment and agricultural monitoring.

3.5 Data Sources and Preprocessing

This study utilizes two complementary remote sensing datasets—**Sentinel-2** and **MODIS MOD13Q1**—selected for their spatial and temporal resolution capabilities in monitoring vegetation health and drought patterns. Data were acquired for the rice-growing region of **Vercelli, Italy**, covering the **May–August phenological window** from **2020 to 2024**. All datasets were reprojected to **EPSG:32632 (WGS 84 / UTM Zone 32N)** for spatial consistency and clipped using the Vercelli municipal shapefile.

Sentinel-2 (10–20m Resolution)

Sentinel-2 Level-2A imagery was used to compute **NDVI**, **SAVI**, and **EVI2** vegetation indices using **Band 8 (NIR)** and **Band 4 (Red)**, which are sensitive to chlorophyll concentration and canopy structure. Images were selected to align with key phenological stages (e.g., transplanting, tillering, heading), based on the calendar established in Section 3.3.

Approximately **10 Sentinel-2 images per year** were processed, totaling **~50 images across five years (2020–2024)**.

Example image IDs used:

- S2A_MSIL2A_20210625T102021_N0500_R065_T32TMR_20230319T054911.SAFE
- S2A_MSIL2A_20220824T131202.SAFE
- S2B_MSIL2A_20230720T101609_N0500_R065_T32TMR_20230720T131906.SAFE
- S2B_MSIL2A_20240714T101559_N0510_R065_T32TMR_20240714T125806.SAFE

All Sentinel-2 bands were scaled to reflectance values by dividing pixel values by **10,000**. Processing steps, including image clipping and reprojection, were executed in **QGIS 3.30** using the **Graphical Modeler and Batch Automation** tools (QGIS Development Team, 2022).

MODIS MOD13Q1 (250m Resolution)

The **MODIS MOD13Q1** product provides **16-day composite EVI** data at 250m spatial resolution. Its long-term archive and temporal frequency make it ideal for drought trend analysis. This study extracted **Day of Year (DOY) 121–273** (May to September) to cover rice growth phases in Vercelli.

Importantly, this study used the **entire MODIS archive from 2000 to 2024**, offering a **strong historical baseline** for calculating the **Vegetation Condition Index (VCI)** and identifying interannual drought anomalies.

Example MODIS VCI files used:

- VCI_ITALY_129_2020.tif
- VCI_ITALY_225_2021.tif
- VCI_ITALY_257_2023.tif

Pixel Reliability (PR) layers were used to mask poor-quality observations. Pixels with PR values other than **0 (good)** or **1 (marginal)** were excluded by assigning **NaN**. This ensured only high-quality input for VCI computation.

MODIS data preprocessing and VCI calculation were implemented in **Python 3.8** within a **Conda-based geospatial environment**.

Tools and packages:

- **GDAL** for raster processing
- **NumPy** for array-based VCI calculation
- **Matplotlib** and **PNG/GeoTIFF output** for visualization
- **Jupyter Notebook** and **tqdm** for automated progress tracking

Together, these preprocessing steps produced standardized, spatially aligned vegetation index layers that are:

- Aligned with crop phenology (May–August)
- Free of poor-quality pixels
- Consistent across years and formats
- Suitable for statistical drought analysis and interannual comparison

This approach ensures **temporal reliability**, **phenological alignment**, and **data traceability** for both short-term monitoring and long-term drought trend detection.

3.6 NDVI Calculation

The Normalized Difference Vegetation Index (NDVI) was calculated using Sentinel-2 Level-2A satellite imagery to assess vegetation health across the Vercelli region. This index leverages the difference in reflectance between the near-infrared (NIR) and red (RED) spectral bands, which are highly responsive to the presence of green vegetation. For this purpose, Band 8 (NIR) and Band 4 (Red) were extracted from the Sentinel-2 dataset at a 10-meter spatial resolution.

Due to Sentinel-2 reflectance values being scaled integers, all pixel values were rescaled by dividing by 10,000 to convert them to reflectance proportions. To prevent division by zero errors and to ensure numerical stability, a small constant (0.0001) was added to the denominator.

The NDVI equation implemented in the QGIS Raster Calculator was:

Equation 1: $$NDVI = \frac{(NIR/10000)-(RED/10000)}{(NIR/10000)+(RED/10000)+0.0001}$$

Where:

- **NIR** refers to the reflectance value of Band 8,
- **RED** refers to the reflectance value of Band 4.

Each NDVI raster was clipped to the Vercelli municipal boundary using a shapefile mask to isolate the area of interest and eliminate irrelevant surrounding pixels. After calculation, zonal statistics were derived using the QGIS Zonal Statistics tool. These included key descriptive values such as mean, minimum, maximum, pixel count, and total NDVI sum. These statistical outputs were used for both inter-annual comparisons and drought severity analysis.

To handle multiple years and months efficiently, the entire NDVI processing workflow was automated using the QGIS Graphical Modeler. This allowed batch processing of Sentinel-2 datasets while maintaining consistent output naming, projection, and symbology settings across all files.

3.7 SAVI Calculation

The Soil-Adjusted Vegetation Index (SAVI) was implemented in this study to account for the influence of soil brightness in areas with low vegetation cover. SAVI is particularly useful in semi-arid or sparsely vegetated landscapes, where soil reflectance can distort the spectral signal of vegetation.

In the case of Vercelli, although rice paddies dominate the landscape, early-season growth stages (e.g., transplanting and tillering) often feature **incomplete canopy closure and exposed soil**, especially in partially flooded or recently planted fields. SAVI helps correct for this by reducing soil background noise, making it suitable for monitoring vegetation health in Vercelli's heterogeneous agricultural conditions.

To reduce this effect, SAVI introduces a soil brightness correction factor (L), typically set at 0.5. The SAVI formula used in this analysis is:

Equation 2: $SAVI = \left(\frac{(NIR/10000)-(RED/10000)}{(NIR/10000)+(RED/10000)+0.5}\right) \times (1+0.5)$

In this equation, **NIR** and **RED** correspond to Sentinel-2 Bands 8 and 4, respectively. These were scaled by dividing by 10,000 to convert the reflectance values from integer to floating-point format. The calculation was performed using the **Raster Calculator in QGIS**.

SAVI outputs were clipped to the Vercelli municipality boundary using a shapefile mask to ensure spatial consistency. A consistent green–yellow–red pseudocolor gradient was applied to the resulting maps, with values ranging from -1 to +1. These maps were styled and visualized to allow interannual comparison of vegetation health for the months of May from 2020 to 2024.

By mitigating the effects of exposed soil, SAVI enhances the reliability of vegetation assessments in heterogeneous agricultural landscapes like Vercelli. Its inclusion in this multi-index framework supports a more nuanced analysis of drought impacts and crop conditions during early growth stages.

3.8 EVI2 Calculation

The Enhanced Vegetation Index 2 (EVI2) was incorporated into this study as an alternative to NDVI to improve vegetation monitoring in regions characterized by dense vegetation and frequent atmospheric interference. EVI2 is particularly advantageous because it excludes the blue band used in the original EVI formula, making it more practical for sensors like Sentinel-2, which may have varying blue band quality. The following adjusted formula was used to calculate EVI2 in QGIS:

Equation 3: $\boldsymbol{EVI2 = \frac{2.5\times(NIR/10000-RED/10000)}{(NIR/10000)+2.4\times(RED/10000)+1}}$

In this equation, **NIR** and **RED** represent Band 8 and Band 4 of Sentinel-2 imagery, respectively, with each pixel value rescaled by dividing by 10,000 to convert the reflectance from integer to floating-point format. The computation was performed using the Raster Calculator in QGIS, following the same processing steps applied to NDVI and SAVI.
EVI2 generally performs better in areas of high biomass due to its enhanced sensitivity to canopy structure and its reduced susceptibility to saturation in dense vegetation. It also shows greater robustness in conditions affected by haze, dust, or thin clouds. After calculation, the EVI2 rasters were clipped to the Vercelli boundary and visualized using a consistent green-to-red color ramp ranging from -1 to +1, facilitating interannual comparison. EVI2 outputs complement NDVI and SAVI by offering additional insight into vegetation dynamics, particularly where standard indices may experience performance limitations.

3.9 VCI Calculation (MODIS)

The Vegetation Condition Index (VCI) was calculated to detect and monitor drought-induced vegetation stress in the Vercelli region using MODIS satellite data. This index was derived from Enhanced Vegetation Index (EVI) values extracted from the MOD13Q1 product and provides a standardized measure of vegetation health relative to historical extremes.

Equation 4: $VCI = \frac{EVI_i - EVI_{min}}{EVI_{max} - EVI_{min}} \times 100$

Where:

- EVI_i is the EVI value for a specific pixel and date,
- EVI_{min} and EVI_{max} are the historical minimum and maximum EVI values for that pixel across the 25-year reference period (2000–2024).

This normalization formula transforms raw EVI data into a scale from 0 to 100, where lower values indicate vegetation stress and higher values reflect healthy vegetation relative to historical conditions.

The processing workflow was executed using Python 3.8 in a Jupyter Notebook environment. MODIS files were filtered by day of year (DOY) using filename parsing and regular expressions. Only images falling between DOY 129 and 241 were included, corresponding to the key phenological window of rice cultivation (May to September).

A cloud masking procedure was applied using the MODIS Pixel Reliability (PR) layer. All EVI pixels associated with PR values different from 0 or 1 were masked out using NaN values to ensure quality control. The masked EVI data were scaled by a factor of 0.0001 in accordance with MODIS documentation before applying the VCI formula.

The output consisted of:

- **GeoTIFF files** retaining spatial referencing for GIS analysis, and
- **PNG visualizations** styled with a red-to-green color ramp, where red indicates drought stress (VCI ~ 0) and green indicates healthy vegetation (VCI ~ 100).

To localize analysis, each VCI raster was clipped to the Vercelli administrative boundary using QGIS's *Clip Raster by Mask Layer* tool. Batch processing was implemented to apply this clipping operation to all DOYs in a single workflow.

This section of the methodology provided the foundation for a pixel-level temporal comparison of vegetation condition throughout the 2024 season, offering spatial insights into drought severity progression.

3.10 Tools and Environment

The methodology employed a combination of open-source geospatial software and programming tools to ensure a reproducible and efficient workflow for drought analysis.

Each tool played a specific role in preprocessing, computation, visualization, and automation of satellite data processing.

QGIS served as the primary GIS environment for the following tasks: loading and visualizing raster and vector datasets, reprojecting layers to a common coordinate system (EPSG:32632), applying clipping masks to limit analysis to the Vercelli region, calculating raster indices (NDVI, SAVI, EVI2) using the Raster Calculator, and generating styled outputs with consistent color ramps. The QGIS *Graphical Modeler* feature was leveraged to automate repetitive tasks such as batch clipping and zonal statistics extraction, improving processing efficiency across multiple years and indices.

For handling MODIS-based Vegetation Condition Index (VCI) analysis, **Python 3.8** was used within a **Jupyter Notebook** environment. The modular nature of Jupyter allowed for step-by-step scripting, testing, and visualization of intermediate results, particularly valuable for cloud masking, file parsing, array manipulation, and temporal filtering of large datasets.

Key Python libraries used include:

- **GDAL**: For raster input/output operations and projection handling.
- **NumPy**: To manage and process multidimensional raster arrays efficiently.
- **Matplotlib**: To visualize intermediate and final VCI results as PNG plots.
- **tqdm**: To track the progress of batch operations within loops.

All Python code was executed within a **Conda-based virtual environment** configured on a **macOS terminal**. This setup ensured a controlled and reproducible computing environment, enabling consistent package management and dependency handling.

Together, these tools formed a robust hybrid environment that combined the spatial visualization capabilities of QGIS with the automation and analytical power of Python, significantly streamlining the multi-step satellite data processing required in this study.

3.11 Summary of Indices

Table 4- Summary of Vegetation Indices Used for Drought Monitoring and Vegetation Analysis

Index	Sensor	Resolution	Formula Type	Use Case
NDVI	Sentinel-2	10m	(NIR - Red) / (NIR + Red)	General vegetation health
SAVI	Sentinel-2	10m	Soil-adjusted NDVI	Soil correction in arid areas
EVI2	Sentinel-2	10m	Enhanced vegetation change	Atmospheric correction
VCI	MODIS	250m	Normalized EVI anomaly	Drought stress comparison

This table provides an overview of the vegetation indices employed in this study, including their respective satellite sensors, spatial resolutions, formula types, and primary use cases. NDVI, SAVI, and EVI2 were derived from Sentinel-2 imagery to capture fine-scale vegetation dynamics under varying atmospheric and soil conditions, while VCI was computed from MODIS data to detect long-term drought stress anomalies. Together, these indices enable a multi-faceted assessment of vegetation health and drought impact across the rice-growing landscapes of Vercelli.

3.12 Challenges and Solutions

Table 5-Common Geospatial Processing Challenges and Implemented Solutions

Challenge	Solution
Coordinate Reference System mismatch	Reprojected all layers EPSG:32632
Invalid NDVI output values	Rescaled inputs using /10000; added small constant in formula
Raster appearance problems	Adjusted layer symbology and stretch
Batch repetition	Used Graphical Modeler and batch tools

Table 4 summarizes key technical challenges encountered during the preprocessing and analysis of remote sensing data in this study. Issues ranged from coordinate system mismatches to batch processing inefficiencies. To ensure consistency, accuracy, and reproducibility of results, targeted solutions were applied using tools such as the QGIS Graphical Modeler and custom raster processing workflows. These methodological adaptations were critical in managing large datasets across multiple years and ensuring the reliability of derived vegetation indices.

3.13 Final Outputs

- The analytical workflow produced a comprehensive set of geospatial outputs that are central to the spatial-temporal analysis of vegetation condition in the Vercelli region. These outputs were generated consistently across indices and timeframes to ensure comparability and statistical robustness.
- Firstly, **time-series maps** were created for the NDVI, SAVI, and EVI2 indices covering the months of **May from 2020 to 2024**. These maps were derived from Sentinel-2 imagery and visually standardized using consistent color ramps and classification thresholds to enhance interpretability. Each map reflects the vegetative status of the region at early growth stages of rice, allowing cross-year comparisons to identify vegetation trends or anomalies potentially linked to climatic variability.
- In parallel, **MODIS-derived VCI maps** were generated for eight **Days of Year (DOYs)** throughout the 2024 growing season. The selected DOYs (129, 145, 161, 177, 193, 209, 225, and 241) correspond to key phenological stages, from transplanting through maturation. These VCI maps, rendered as both PNG and GeoTIFF files, provide a historical-normalized indicator of drought stress and highlight temporal fluctuations in vegetation health.
- To maintain **spatial consistency**, all rasters—whether from Sentinel-2 or MODIS—were **clipped to the Vercelli boundary** using a shapefile mask. This

ensures that the analysis focuses solely on the relevant agricultural extent and removes noise from surrounding non-agricultural areas.

- Moreover, **zonal statistics** were extracted for NDVI maps using QGIS. These include the **mean, minimum, maximum, count, and sum** of NDVI values per zone, offering a quantitative basis for year-to-year comparison and supporting the statistical analysis of vegetation condition at the municipal scale.
- Collectively, these outputs form the foundation for **cross-index (NDVI vs. SAVI vs. EVI2 vs. VCI)** and **cross-year analysis**, enabling a detailed interpretation of how vegetation patterns evolved under varying drought conditions. The datasets are prepared for further integration with meteorological indices and agricultural variables in subsequent chapters.

3.14 Significance of Methods

The methodological approach developed in this study enables high-resolution, multi-temporal monitoring of vegetation health and agricultural drought in rice fields. The integration of Sentinel-2 and MODIS indices—NDVI, SAVI, EVI2, and VCI—provides a robust set of tools to analyze vegetation conditions under varying environmental and climatic conditions.

This framework allows spatial-temporal tracking of vegetation stress using multiple vegetation indices that are sensitive to different sources of error, such as soil brightness and atmospheric interference. It also supports phenology-informed remote sensing, where satellite data are temporally aligned with crop development phases, increasing the biological relevance of vegetation signals.

Moreover, by including both empirical remote sensing data (NDVI, SAVI, EVI2) and historical anomaly-based metrics (VCI), the methodology supports anomaly detection, trend analysis, and index validation through cross-comparison with meteorological data such as SPI/SPEI. This multi-dimensional strategy provides a strong basis for drought early warning systems, crop monitoring, and adaptive agricultural planning.

Chapter 4: Results

4.1 Overview

This chapter provides a comprehensive spatiotemporal assessment of vegetation dynamics and drought impacts in the Vercelli region over the 2020–2024 period. The analysis draws upon high-resolution satellite-derived vegetation indices — namely the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), and Enhanced Vegetation Index 2 (EVI2) from Sentinel-2 imagery — along with the Vegetation Condition Index (VCI) derived from MODIS data. These indices collectively offer insight into both spatial patterns and temporal trends in vegetation health across different phases of the rice-growing season.

To contextualize vegetation anomalies and confirm biophysical stress signals, the analysis is further supported by climatological drought indicators: the **Standardized Precipitation Index (SPI)** and the **Standardized Precipitation Evapotranspiration Index (SPEI)**. These indices characterize meteorological drought based on precipitation and atmospheric demand, respectively, providing an independent verification of vegetation responses to climatic stress.

A particular emphasis is placed on the year **2022**, which is identified as the most meteorologically severe drought year within the study period, based on sustained negative SPI and SPEI values below -1.5, coupled with concurrent NDVI depression. The integration of remote sensing and hydroclimatic data enhances the understanding of drought evolution and its impact on rice phenology and productivity.

The chapter includes:

- Multi-year NDVI trend analysis (May–August),
- Monthly anomaly and zonal NDVI maps,
- Year-over-year comparisons of vegetation indices,
- VCI-based drought categorization,
- Meteorological drought classification based on SPI and SPEI,
- Comparative evaluation of Sentinel-2 vs Copernicus NDVI datasets.

This integrated approach supports a robust evaluation of agricultural drought and crop stress, enabling informed interpretation of inter-annual variability and resilience in Vercelli's rice systems.

Figure 5 presents the reclassified LULC map for the Vercelli municipality based on ESA WorldCover 2021 data. The majority of the study area is characterized by cropland, particularly concentrated in the southern and central zones, while built-up areas are clustered around Vercelli's urban core. The map provides a spatial overview of the land surface types that underlie the NDVI patterns discussed in subsequent sections. Even though the LULC data was not quantitatively integrated into NDVI processing, it supports the visual interpretation of vegetation indices by confirming which areas represent true agricultural activity

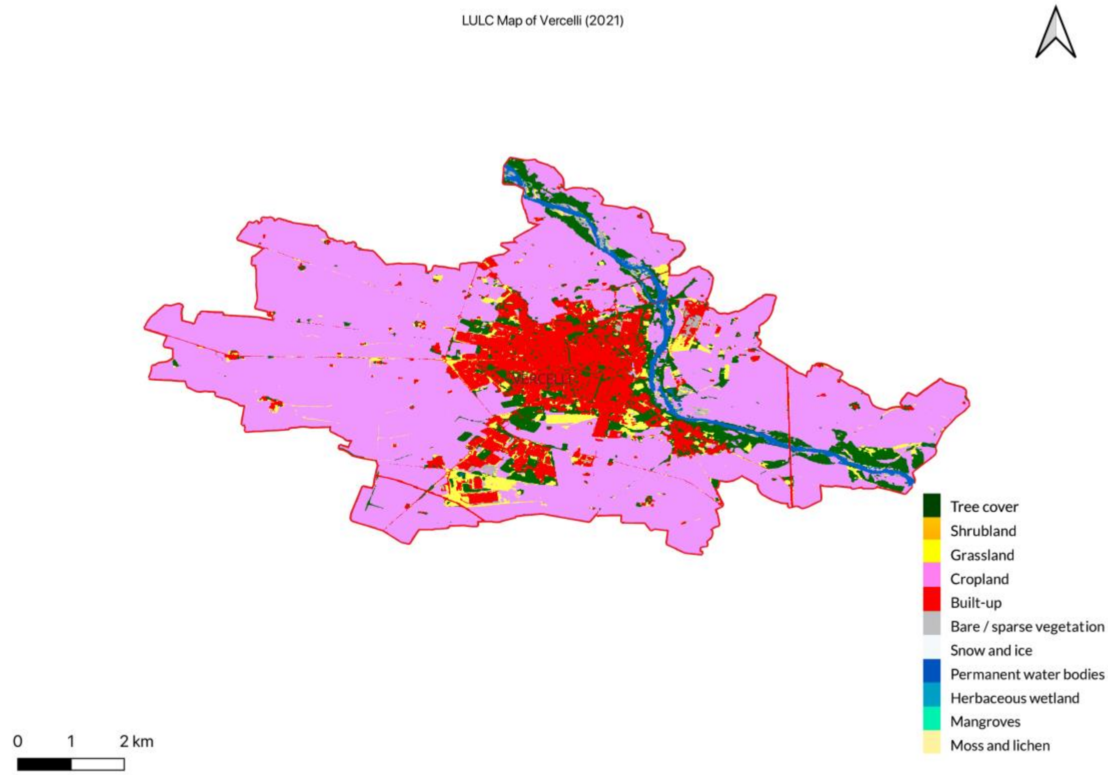

Figure 5- Land Use and Land Cover (LULC) Classification Map of the Vercelli Region Based on ESA WorldCover 2021. This map contextualizes the underlying land surface types that support NDVI and VCI interpretations.

4.2 Meteorological Drought Context: SPI & SPEI Analysis (2022 Focus)

To accurately assess vegetation stress during the rice-growing season, it is essential to first evaluate the underlying meteorological drought conditions. This section presents the **Standardized Precipitation Index (SPI)** and the **Standardized Precipitation Evapotranspiration Index (SPEI)** values for 2022 in the Vercelli region, which serve as climatic indicators of water availability anomalies during critical crop development periods.

Table 6- SPI & SPEI Values and Drought Classification (Vercelli, 2022)

Month	**SPI (3-mo)**	**SPI (6-mo)**	**SPI (12-mo)**	**SPEI (6-mo)**	**Drought Category**
May	~ -1.6	~ -1.8	< -2.0	~ -1.7	**Extreme drought**
June	~ -1.5	~ -1.6	< -2.0	~ -1.6	**Severe to extreme**
July	~ -1.2	~ -1.4	~ -1.8	~ -1.4	**Severe drought**
August	~ -1.0	~ -1.1	~ -1.5	~ -1.3	**Moderate–severe drought**

Note: Values below -1.5 indicate severe to extreme drought stress (WMO, 2012).

According to the WMO classification system (2012), SPI or SPEI values falling below **-1.5** indicate **severe to extreme drought stress**. In this study, this threshold was used as a formal benchmark for identifying drought events. Monthly SPI and SPEI values for 2022 consistently dropped below this level between **May and July**, qualifying the season as a meteorological drought year. This threshold-based classification guided the interpretation of vegetation anomalies and the selection of the 2022 season for focused drought analysis in alignment with remote sensing observations.

Interpretation of Drought Severity

The SPI and SPEI indices both reveal a **prolonged and intense drought event in 2022**, particularly between **May and July**. These months coincide with transplanting, vegetative growth, and reproductive stages of rice, during which water stress can severely impact crop establishment and yield.

The **SPI < -1.6** and **SPEI ~ -1.7 in May** confirm an extreme meteorological drought at the onset of the season, driven by cumulative **rainfall deficits** and amplified by **high evapotranspiration**, as reflected in the SPEI's temperature-sensitive formulation (Vicente-Serrano et al., 2010).

The SPI and SPEI values were calculated using precipitation and temperature data from the ERA5 reanalysis dataset at a spatial resolution of 0.25°, consistent with current best practices for drought index generation.

Additional regional reports from ARPA Piemonte and SNPA indicated:

- Up to **50% rainfall reduction** compared to the 1991–2020 average,
- **111 consecutive dry days** during winter 2021–2022,
- A **64% snow cover reduction** in March, reducing irrigation canal flow,
- **+1.9°C temperature anomaly**, marking 2022 as the hottest year in Piemonte since 1958.

Link with NDVI Decline and Vegetation Stress

These hydrometeorological deficits align closely with observed **NDVI reductions in May and July 2022**, as shown in Sentinel-2 data (Section 4.3). NDVI values remained below the five-year average, particularly in early development phases. This confirms the **strong correlation between climatic drought (SPI/SPEI) and vegetation stress**, validating the year 2022 as a **critical drought-impacted season for rice agriculture** in the region.

4.3 NDVI Results (May–August 2020–2024)

The NDVI maps below depict the monthly vegetation condition during the growing season. NDVI values range from -1 to 1, where higher values indicate denser, healthier vegetation. These maps highlight interannual changes and provide evidence of drought stress and recovery.

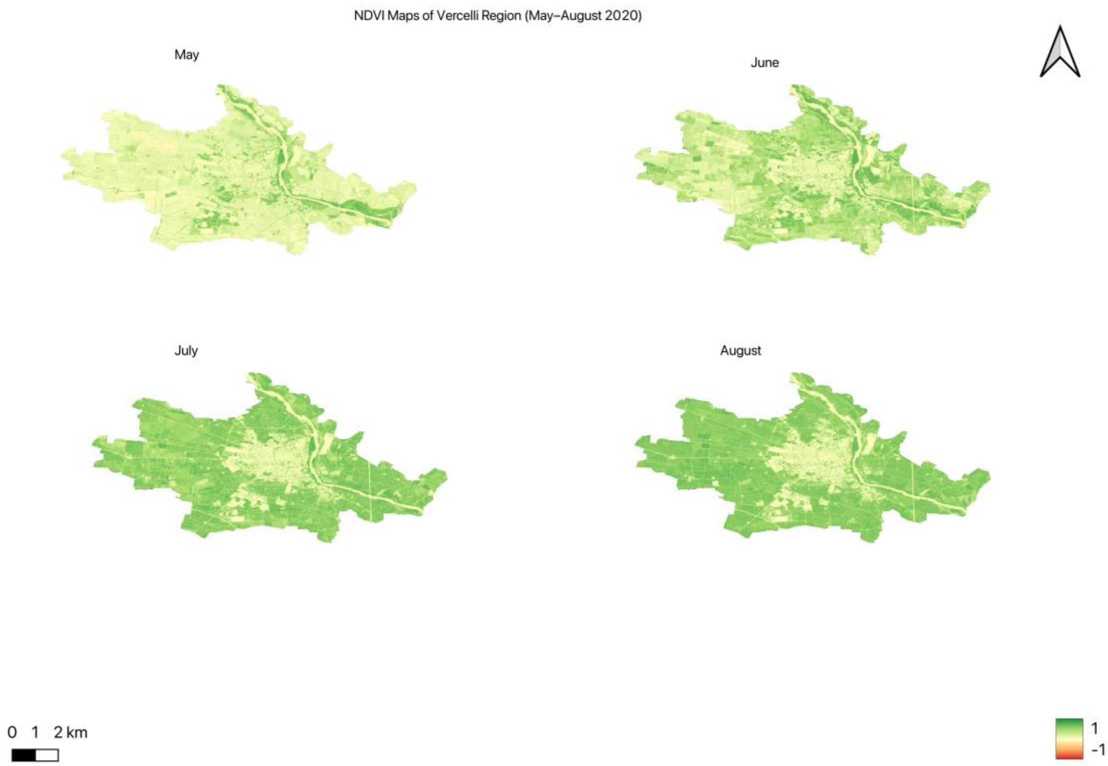

Figure 6-NDVI Maps of the Vercelli Region for May–August 2020

The maps illustrate a **typical seasonal greening curve**, with NDVI gradually increasing from **0.19 in May** to **0.49 by August**. This steady rise indicates **optimal vegetative conditions** throughout the rice growth stages. No evidence of drought stress is detected, making 2020 a **reference baseline year** for healthy crop development under normal climatic conditions.

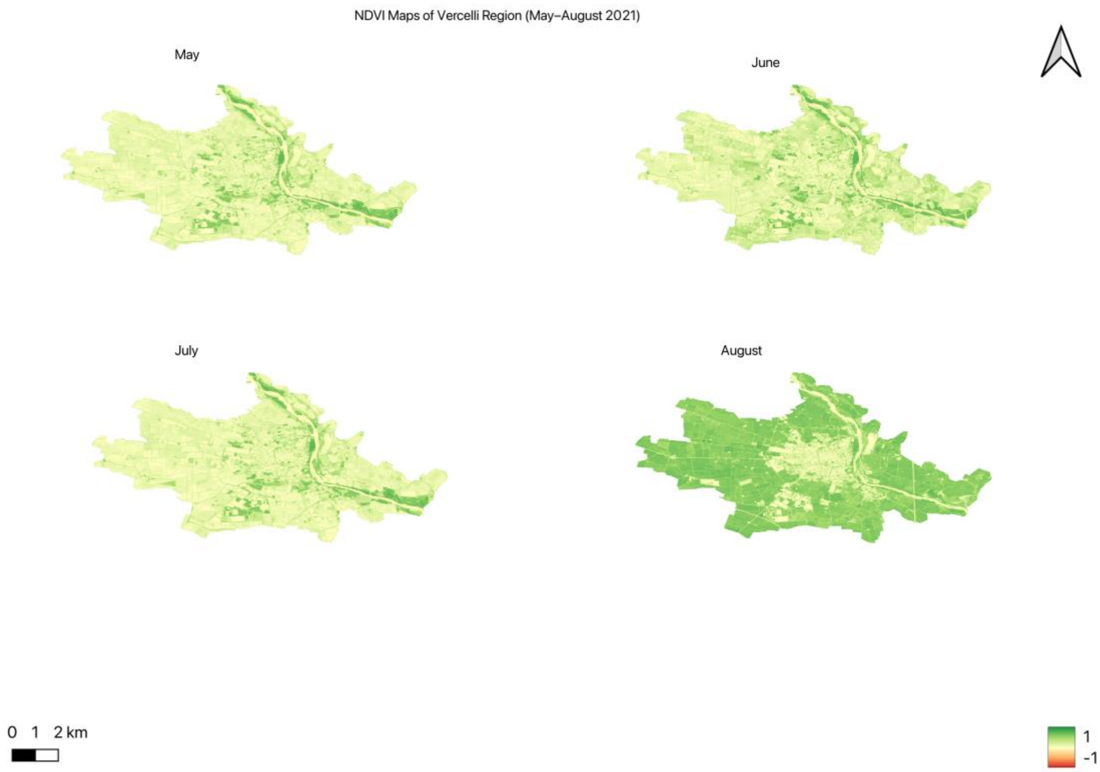

Figure 7-NDVI Maps of the Vercelli Region for May–August 2021

These maps highlight one of the driest years in the study period. NDVI values are visibly low in **June and July**, indicating substantial vegetation stress due to early-season drought conditions. However, the **notable increase in August** suggests a **late-season recovery**, potentially driven by delayed rainfall or supplementary irrigation. The spatial patterns confirm 2021 as a year of **reduced crop vigor** during critical growth stages.

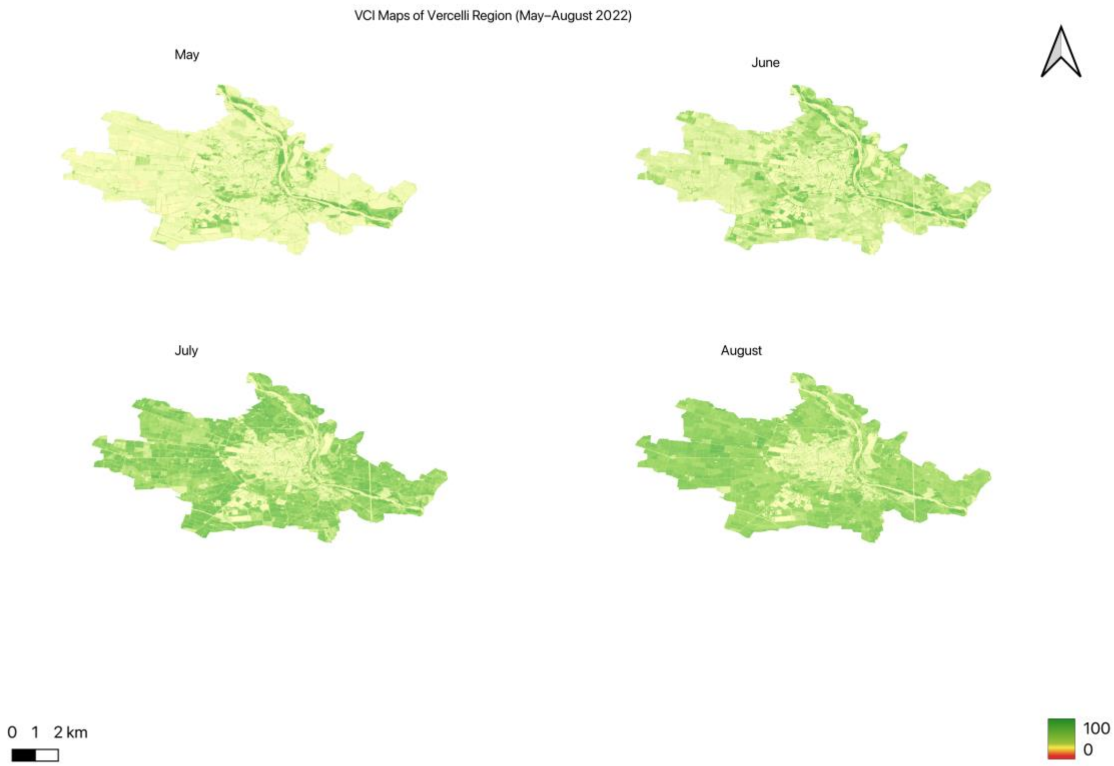

Figure 8-NDVI Maps of the Vercelli Region for May–August 2022

The maps show vegetation health progression during a drought year. NDVI values show stress in May and June, but improvement by July and August suggests partial crop resilience. The spatial consistency indicates that localized irrigation helped mitigate early drought effects, maintaining moderate-to-healthy conditions through the growing season.

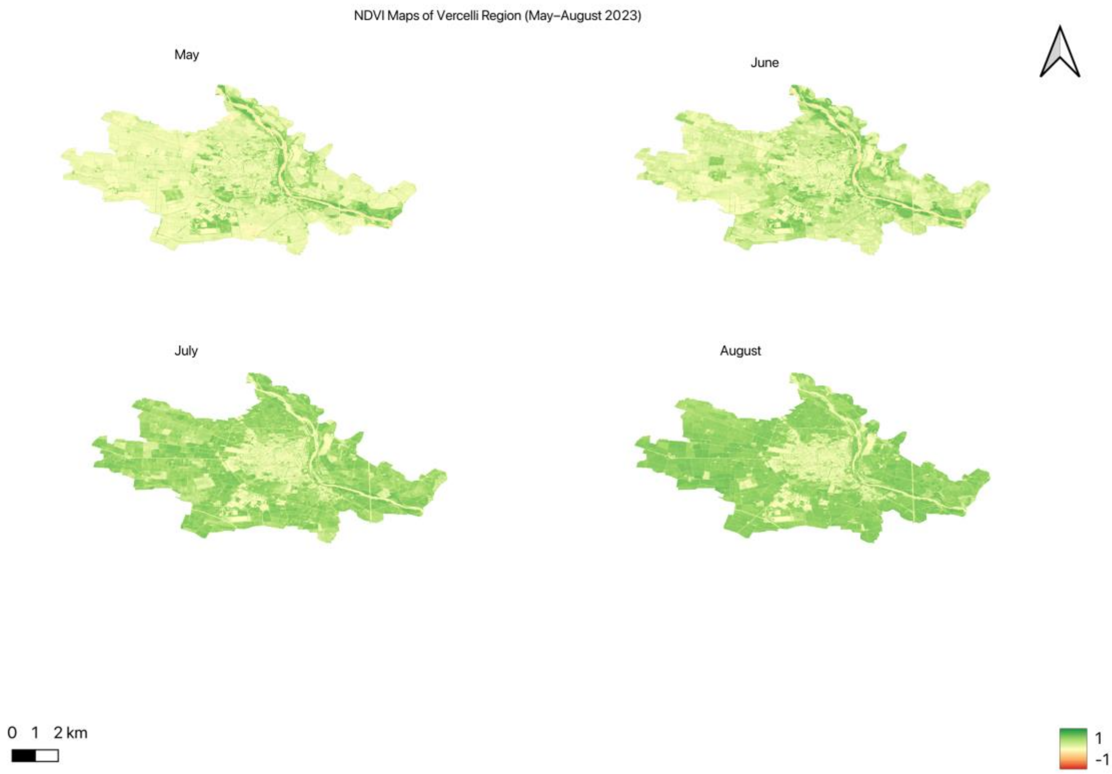

Figure 9-NDVI Maps of the Vercelli Region for May–August 2023

The maps display a steady recovery in vegetation health following the 2022 drought. NDVI values in July and August approach those recorded in 2020, indicating partial restoration of crop vigor. Earlier months (May–June) still reflect moderate variability and lingering water stress, but the overall greening trend suggests that environmental and management conditions were favorable for recovery during mid to late season.

4.4 NDVI Statistical Trends

To quantify NDVI dynamics across the years, zonal mean NDVI values for each month were computed.

Table 7- Monthly Mean NDVI for Vercelli

Month	2020	2021	2022	2023	2024
May	0.19	0.18	0.16	0.18	0.17
June	0.33	0.22	0.27	0.26	0.31
July	0.48	0.18	0.44	0.43	0.43
August	0.49	0.49	0.44	0.47	0.49

Monthly NDVI Interpretation:

2020: NDVI steadily increased from **0.19 in May** to **0.49 in August**, reflecting **ideal phenological development** under **favorable climatic and hydrological conditions**. This trend establishes 2020 as the **baseline year** for comparison.

2021: Exhibited the **lowest NDVI values**, especially in **June (0.22)** and **July (0.18)**, indicating a **severe early-season drought**. A sharp increase in **August (0.49)** suggests **late rainfall or emergency irrigation**. Notably, **peak NDVI shifted from July to August**, deviating from typical phenological patterns—likely due to **delayed vegetative growth or external water inputs**. This timing contrast with **baseline years (2020, 2024)**, where **July consistently marked the NDVI peak**.

2022: NDVI values showed **moderate stress** in **May and June (0.16–0.27)**, but a recovery occurred in **July (0.44)**, pointing to **partial crop resilience**. This rebound is likely due to **irrigation mitigation** during the **official drought year**.

2023: Represented a **transition year**, with NDVI values improving to **0.43 in July** and **0.47 in August**. Though early growth was modest, the trend indicates a **gradual post-drought recovery**.

2024: NDVI values rose across all months relative to 2021–2023, reaching **0.31 in June** and **0.49 in August**, closely matching 2020. This year signals a **full recovery**, with a return to **optimal vegetative vigor**. The **stable July–August NDVI plateau** highlights **restored hydrological balance** and **crop stability**.

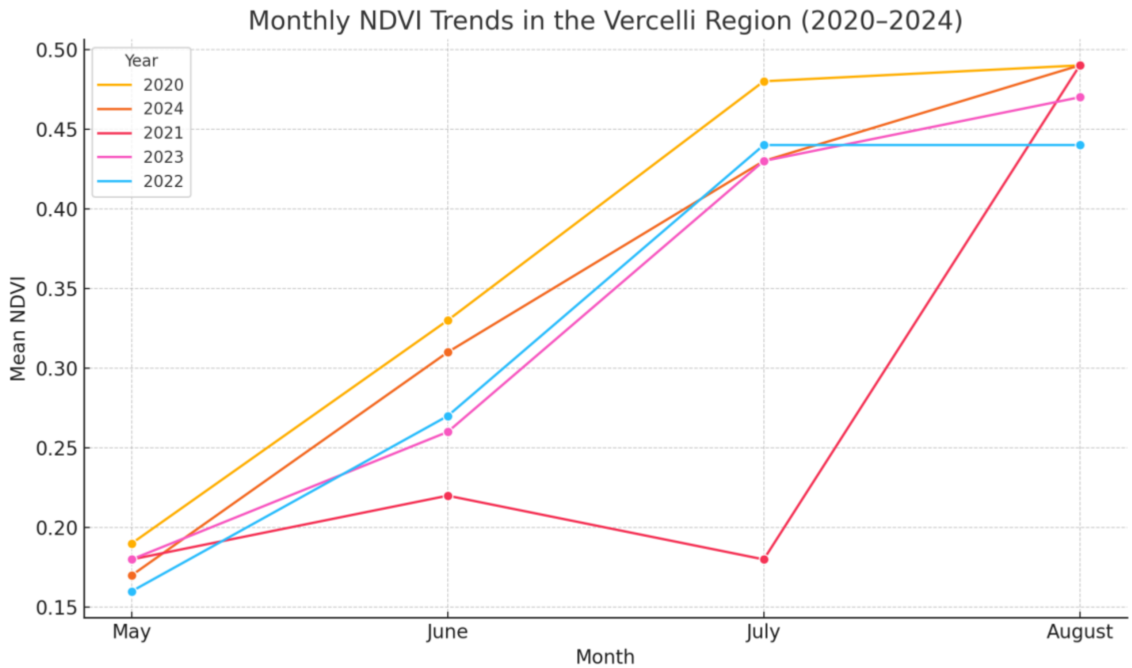

Figure 10- Monthly NDVI Trends in the Vercelli Region (2020–2024)

This line chart displays the progression of mean NDVI values across the rice growing season (May to August) for five consecutive years. **2020** and **2024** show the highest and most stable NDVI profiles, indicating favorable and consistent vegetation growth. **2021** exhibits a notable dip in **July (~0.18)**, corresponding to peak drought stress, while **2022** and **2023** show intermediate recovery. The patterns highlight seasonal greening cycles and the varying impacts of drought and resilience over time.

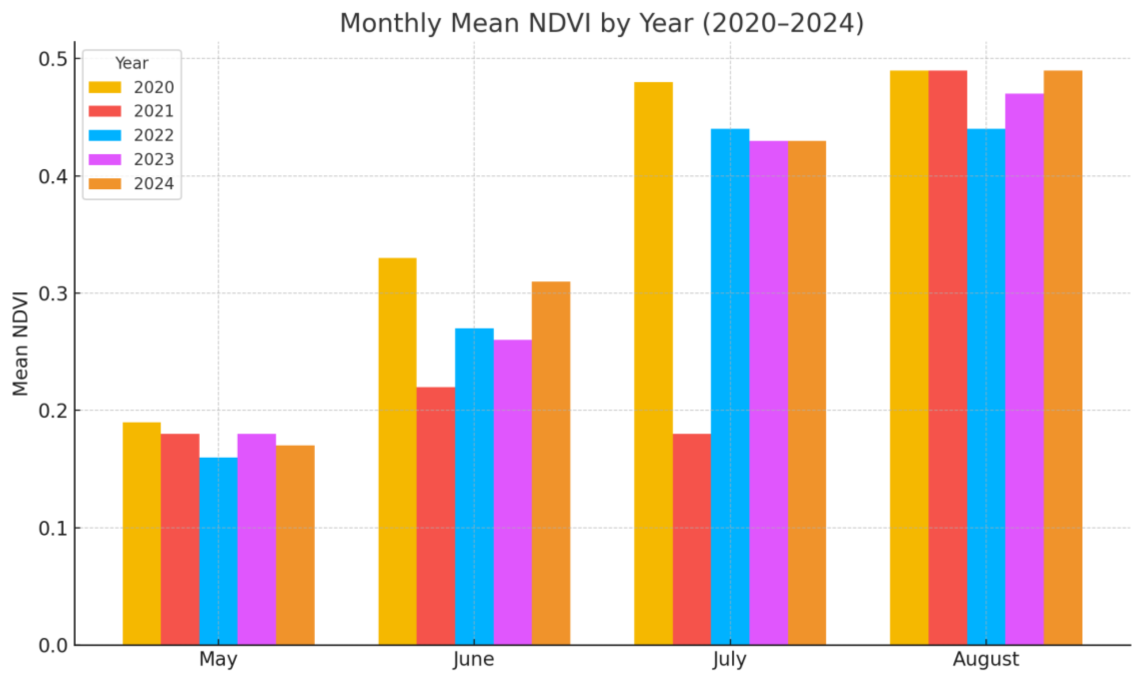

Figure 11- Monthly Mean NDVI by Year (2020–2024) for the Vercelli Region.

This bar chart illustrates the average NDVI values for each month (May–August) across five years. The chart reveals strong interannual variability in vegetation health, with 2020 and 2024 consistently showing higher NDVI across all months. Notably, 2021 exhibits a pronounced dip in July, indicating peak vegetation stress during that year's drought. The results support the temporal dynamics of vegetation recovery following drought conditions observed in 2022 and 2023.

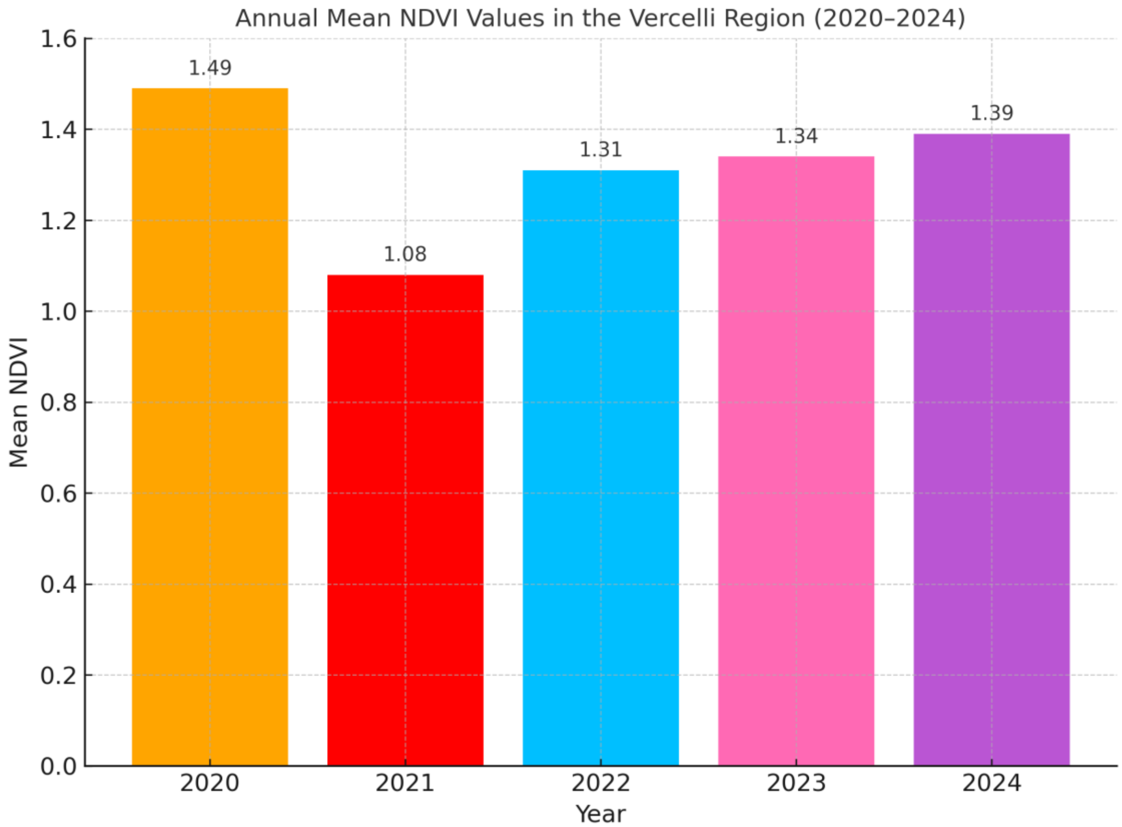

Figure 12-Annual Mean NDVI Values in the Vercelli Region (2020–2024).

This chart displays the annual average NDVI values for each year based on data from May to August. The year 2020 recorded the highest mean NDVI (1.49), indicating optimal vegetation conditions. In contrast, 2021 had the lowest value (1.08), reflecting severe drought stress. The steady rise from 2022 to 2024 demonstrates progressive vegetation recovery, with 2024 nearly matching pre-drought conditions.

Key Insights :

- **2020 and 2024** exhibit the healthiest vegetation conditions across both monthly and annual metrics, with consistently high NDVI values (up to ~0.49 in July–August and annual means above 1.39).
- **2021** clearly stands out as the most drought-affected year. The monthly bar chart highlights a significant NDVI depression in **July (~0.18)**, and the annual average is the lowest (1.08), indicating prolonged vegetation stress.
- **2022** shows strong **seasonal recovery** from May to August, despite being a drought year, with annual mean NDVI (1.31) suggesting effective irrigation or resilience mechanisms.
- **2023** reflects **intermediate recovery**, with NDVI values increasing compared to 2021, though still spatially variable, pointing to partial recovery in vegetation vigor.

- The combined interpretation of line and bar charts reinforces the temporal narrative of **drought impact in 2021**, gradual **recovery in 2022–2023**, and **stabilization by 2024**.

4.4.1 Comparison with Copernicus NDVI Data (Initial Estimations)

To validate and complement the Sentinel-2 NDVI analysis, early-season NDVI values from the **Copernicus Land Monitoring Service** were initially examined during the proposal phase. These Copernicus-based NDVI values provided a coarse-resolution overview of seasonal vegetation trends in the Vercelli region for the years **2020 to 2024**, prior to high-resolution Sentinel-2 processing.

NDVI values were derived from **Sentinel-2 Level-2A imagery** (10 m resolution) accessed via the **Copernicus Browser** (dataspace.copernicus.eu), using Bands 8 (NIR) and 4 (Red). NDVI was calculated using the standard formula within QGIS.

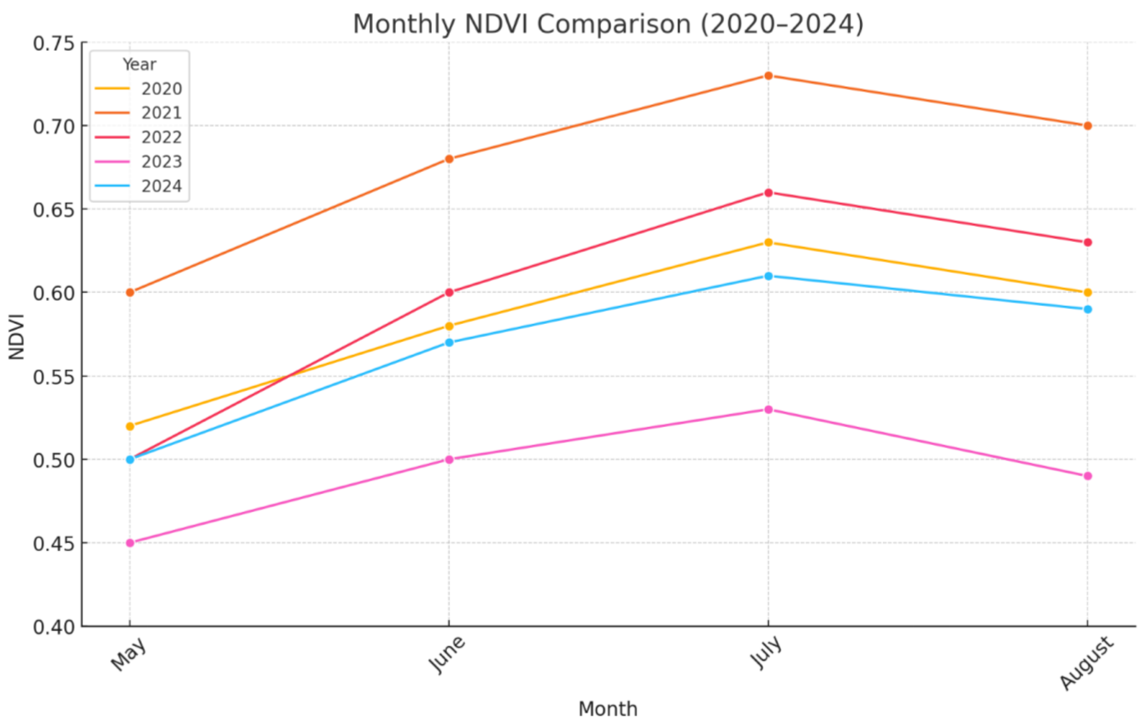

Figure 13-Monthly NDVI Comparison (2020–2024) Based on Copernicus Satellite Data

Line chart illustrating coarse-resolution NDVI trends for the Vercelli region, derived from the Copernicus Land Monitoring Service. These initial estimations were generated prior to high-resolution Sentinel-2-based analysis, providing an early-season overview of vegetation performance from May to August over the 2020–2024 period.

Notable insights from the Copernicus NDVI patterns include:

- **2021** exhibited the highest NDVI values in **July**, followed by a decline in **August**. This deviates from Sentinel-2 data, which identified 2021 as a drought-impacted year—suggesting Copernicus may have **overestimated biomass** or experienced **mixed-pixel noise** due to lower spatial resolution.
- **2020** and **2024** display consistent upward trends from May to August, closely **matching Sentinel-2 results**, confirming the reliability of early-stage greening observations in non-stressed years.
- **2022** and **2023** show transitional behavior, with moderate NDVI values that align broadly with Sentinel-2 outcomes, although finer spatial variations are **more accurately captured by high-resolution imagery**.

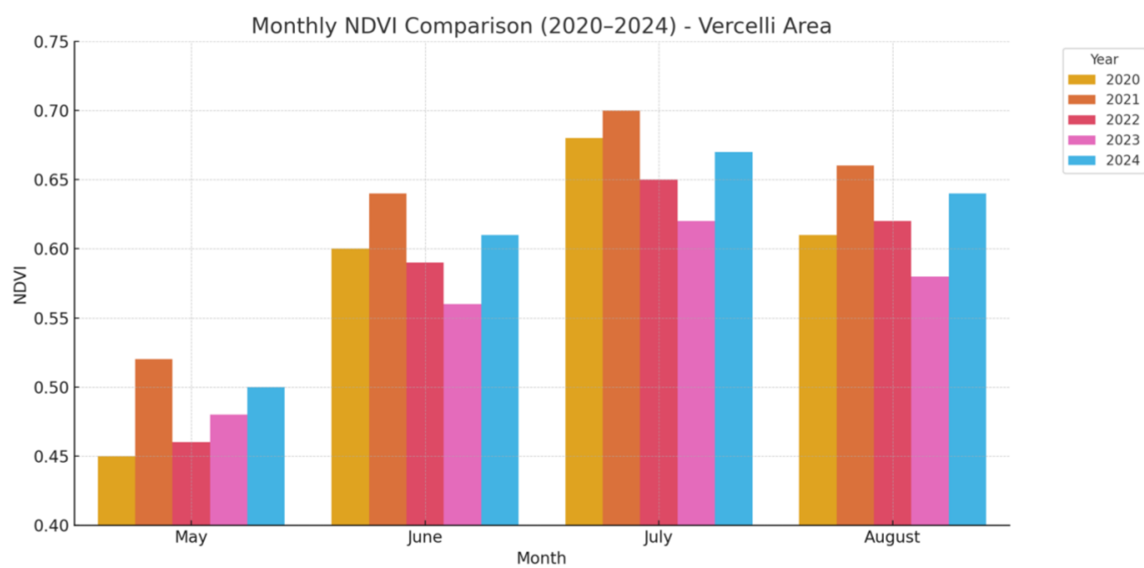

Figure 14- Monthly NDVI Comparison (2020–2024) for the Vercelli Area – Copernicus Bar Chart

Bar chart representing coarse-resolution NDVI values derived from the **Copernicus Land Monitoring Service** for the Vercelli region from **May to August** across the years **2020 to 2024**. This figure captures interannual vegetation dynamics at the regional scale and was used during the initial assessment phase. The visualized trends provide an early estimate of crop vigor and phenological progression, supporting broader seasonal analysis prior to Sentinel-2 refinement.

Notably:

- **2021** shows peak NDVI in **July**, aligning with high biomass estimations but contrasting Sentinel-2 findings that indicated drought-related suppression.
- **2020** and **2024** exhibit consistent upward trajectories through the season, indicating stable vegetation health.

- **2022** and **2023** show more irregular patterns, reinforcing the need for higher-resolution Sentinel-2 imagery to resolve localized stress and recovery signals.

Table 8-Monthly NDVI Averages (May–August) from Copernicus Data for the Vercelli Region (2020–2024)

Month	2020	2021	2022	2023	2024
May	0.45	0.52	0.46	0.48	0.50
June	0.60	0.64	0.59	0.56	0.61
July	0.68	0.70	0.65	0.62	0.67
August	0.61	0.66	0.62	0.58	0.64

NDVI-Based Interpretation of Seasonal Dynamics and Drought Impact on Rice Growth (Sentinel-2 and Copernicus Data)

This section presents a comparative analysis of NDVI trends across the rice-growing season (May to August) from 2020 to 2024 in the Vercelli region. Sentinel-2 NDVI values—derived from high-resolution satellite imagery—are complemented by Copernicus NDVI estimates, offering both detailed and broad-scale views of vegetative development and drought response.

NDVI Ranges and Agricultural Significance

- **0.6 – 0.8**: Healthy, dense vegetation — indicative of optimal rice growth and favorable agro-climatic conditions.
- **0.4 – 0.6**: Moderate vegetation — may signal early-stage crops, delayed growth, or mild water/nutrient stress.
- **< 0.4**: Sparse vegetation — possible drought stress, delayed germination, or unplanted/non-vegetated zones.

Phenological Phase Analysis
May (Vegetative Stage Initiation)

- NDVI values are typically low (~0.45–0.52) due to field flooding during transplanting.
- **2020** and **2022** show the lowest values, implying slow early growth or delayed water availability.
- **2021** exhibited the highest May NDVI, possibly reflecting early transplanting or favorable climatic onset.
- Copernicus data corroborates these trends, though less spatially resolved.

June (Active Vegetative Growth)

- NDVI values rise, indicating robust photosynthetic activity and expanding canopy cover.

- **2021** and **2024** reached the highest values (≈ 0.64), suggesting optimal hydrological support.
- **2023** displayed a minor NDVI dip, potentially reflecting early-season water stress or slow vegetative recovery.
- Copernicus trends also show consistent greening but may obscure intra-field variability.

July (Reproductive Stage)

- NDVI typically peaks in this month. **2021** (0.70) and **2020** (0.68) recorded the highest values.
- These reflect vigorous reproductive development under ideal conditions.
- In contrast, **2023** showed lower NDVI, suggesting mid-season stress—potentially drought-related.
- Copernicus data also confirms 2021 as a peak year but lacks spatial precision in identifying localized deficits.

August (Grain-Filling and Maturation)

- NDVI naturally declines as rice enters senescence.
- **2023** had the lowest NDVI (≈ 0.58), aligning with observed field stress and delayed development.
- **2021** and **2024** maintained higher NDVI values, suggesting extended vegetative health and potentially improved yields.
- Copernicus data shows this trend broadly but underrepresents field-scale anomalies.

Integrated Drought Impact Summary

- **2021** was the most favorable year with high NDVI across all months, minimal drought indicators, and optimal growing conditions.
- **2023** shows the most stress-prone profile, with consistently lower NDVI—highlighting cumulative drought impacts.
- **2020** and **2022** experienced early-season stress but recovered strongly by July, as seen in both datasets.
- **2024** presents an overall healthy vegetation pattern, with high NDVI from June to August, indicating system resilience.

Role of Copernicus Data in Initial Assessment

Copernicus Land Monitoring Service NDVI data provided a valuable **coarse-scale overview** of seasonal greening and phenological transitions during the initial phase of the study. While not sufficient for detecting fine-scale drought anomalies:

- It reliably captured **broad greening patterns** from May to July across years, particularly in **2020** and **2021**.
- **2023** showed consistently lower Copernicus NDVI, supporting its classification as a recovery year.
- However, **localized drought effects were underrepresented**, reinforcing the need for Sentinel-2's spatial detail.
- These initial values served as **baseline references**, helping guide the selection of focal periods and metrics for Sentinel-based drought detection and crop monitoring.

Interpretation: Copernicus vs. Sentinel-2 NDVI

The comparative analysis between Copernicus-derived NDVI and Sentinel-2 NDVI underscores the complementary but distinct roles these datasets play in agricultural monitoring within the Vercelli region.

- **Copernicus NDVI**, sourced from the Copernicus Land Monitoring Service, offers valuable early-stage estimations of vegetation dynamics at a regional scale. Its coarse spatial resolution is effective for broad-scale phenological trend analysis, particularly during the **initial proposal and planning phases** of drought assessment. The trends from 2020 to 2024, especially the upward NDVI progression observed in 2020 and 2024, align well with known seasonal vegetation greening patterns. However, **limitations emerge in heterogeneous agricultural landscapes** such as Vercelli, where field-level variations are critical. In such cases, **mixed-pixel effects and lower spatial granularity** may obscure localized stress or irrigation-driven differences.
- **Sentinel-2 NDVI**, derived from higher-resolution satellite imagery, provides a more refined and **spatially explicit diagnosis of vegetation vigor**. This also explains the July 2021 discrepancy: Copernicus NDVI values are aggregated over 10-day or monthly periods, which can obscure short-term fluctuations. In contrast, Sentinel-2 captures discrete imagery on specific days, allowing it to detect sharp declines such as the one observed during mid-July 2021. This highlights Sentinel-2's temporal advantage for pinpointing rapid stress events.
- This is particularly crucial during **phenologically sensitive periods** like **May (transplanting stage)** and **July (flowering and reproductive stage)**. The Sentinel-2 dataset captured subtle but important variations, including the sharp NDVI decline in **July 2021**, consistent with recorded meteorological drought conditions (SPI/SPEI). Similarly, the gradual recovery trends in **2023–2024**, observed across multiple vegetation indices (NDVI, SAVI, VCI, and EVI2), were better visualized using Sentinel-2 than Copernicus data.

- The **comparison between the two datasets** reveals that while Copernicus NDVI is sufficient for **macroscale evaluations and trend screening**, it **underrepresents field-specific drought impacts**, irrigation responses, and early-stage stress conditions. These factors are more accurately captured by **Sentinel-2 NDVI**, which supports the **local-scale agronomic relevance** of the study.
- Overall, the **integration of Copernicus NDVI** in the early phase of analysis provided a strategic foundation for historical context, while **Sentinel-2-based outputs offered the granularity required for detailed drought impact assessments**. This validates the methodological decision to transition from Copernicus to Sentinel-2 imagery for the core analysis presented in this thesis.

The findings reinforce that **multi-resolution remote sensing strategies**—beginning with coarse-scale data for initial screening and transitioning to high-resolution datasets for impact evaluation—are essential for robust agricultural drought monitoring in spatially fragmented and irrigated systems like Vercelli.

Table 9-Comparative Summary of Sentinel-2 and Copernicus NDVI Datasets

Feature	Sentinel-2 NDVI	Copernicus NDVI
Spatial Resolution	High (10–20 m)	Coarse (250–300 m)
Temporal Resolution	5–10 days (depending on cloud cover and revisit frequency)	10-day and monthly composites
Strengths	- Field-level detail- Detects intra-field drought variation- High sensitivity to phenology	- Consistent long-term trends-Broad-scale greenness overview
Limitations	- May be limited by cloud cover and atmospheric interference	- Misses small-scale drought impacts- Mixed-pixel effect in fragmented landscapes
Best Use	- Precision agriculture- Field-specific drought monitoring- Crop phenology tracking	- Regional monitoring- Early-season assessments- Baseline comparisons
Drought Detection Power	High – captures localized water stress and crop recovery dynamics	Moderate – good for general stress trends but underrepresents field variability
Use in This Thesis	Core dataset for high-resolution analysis and drought impact mapping	Baseline reference for early proposal phase and interannual greenness context

Table 8 provides a comparative overview of the key characteristics, applications, and limitations of Sentinel-2 and Copernicus NDVI datasets within the context of drought monitoring in Vercelli.

4.5 NDVI Anomaly Analysis (2022–2021)

To assess year-over-year changes, NDVI anomaly maps were computed by subtracting May 2021 NDVI from May 2022 NDVI.

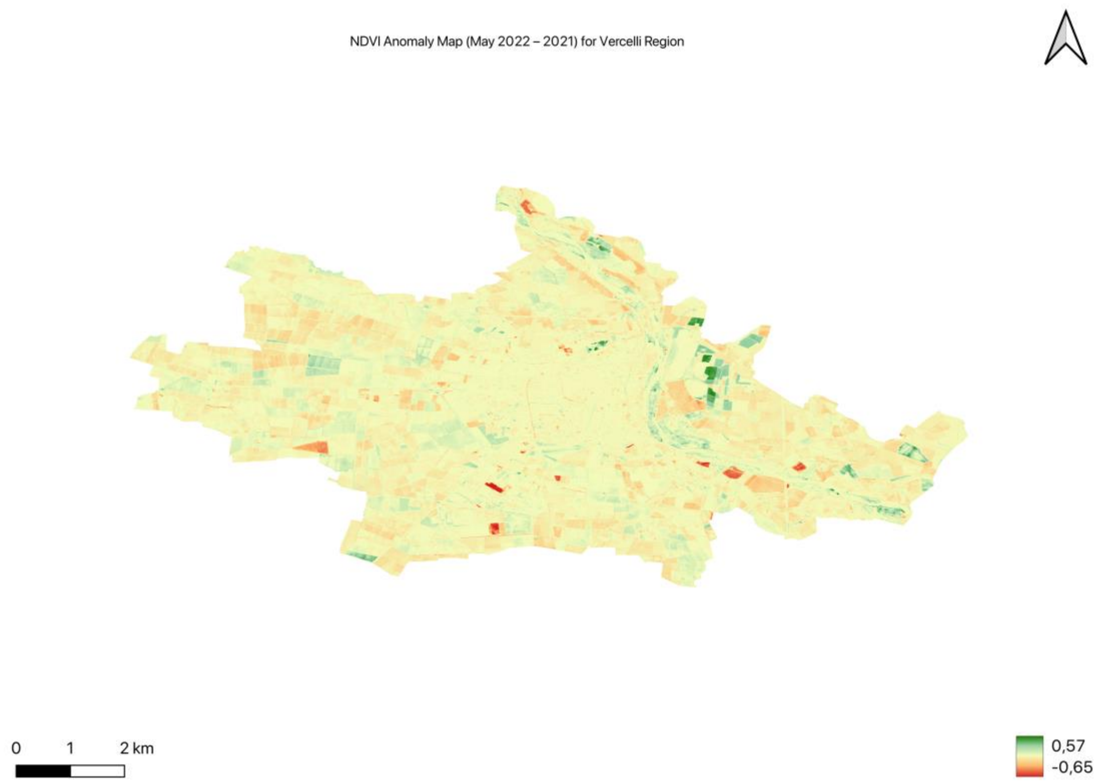

Figure 15-NDVI Anomaly Map (May 2022 – 2021)

This map depicts the spatial NDVI anomaly for May 2022 relative to May 2021, highlighting interannual changes in vegetation vigor. The anomalies were calculated by subtracting the 2021 NDVI raster from the 2022 NDVI raster on a pixel-by-pixel basis. Areas shaded in **red to yellow** represent **negative anomalies**, indicating a decline in vegetation health or canopy density in 2022. These reductions are primarily attributed to increased drought stress and reduced water availability during early-season rice growth. Conversely, **green areas** denote **positive anomalies**, suggesting local improvements in vegetation conditions—potentially due to effective irrigation systems or spatially variable precipitation events.

The **central and southern sectors** of the Vercelli region exhibit the most prominent negative anomalies, aligning with known drought hotspots reported in regional climatological bulletins (e.g., ARPA Piemonte, 2022). The **positive anomalies in the northern parts** may reflect localized irrigation buffering or microclimatic advantages. Overall, this anomaly analysis underscores the heterogeneous nature of drought impact and the importance of adaptive water management during critical agricultural periods.

4.6 VCI Results and Drought Categorization (2020–2024)

The Vegetation Condition Index (VCI) helps assess vegetation health relative to historical norms.

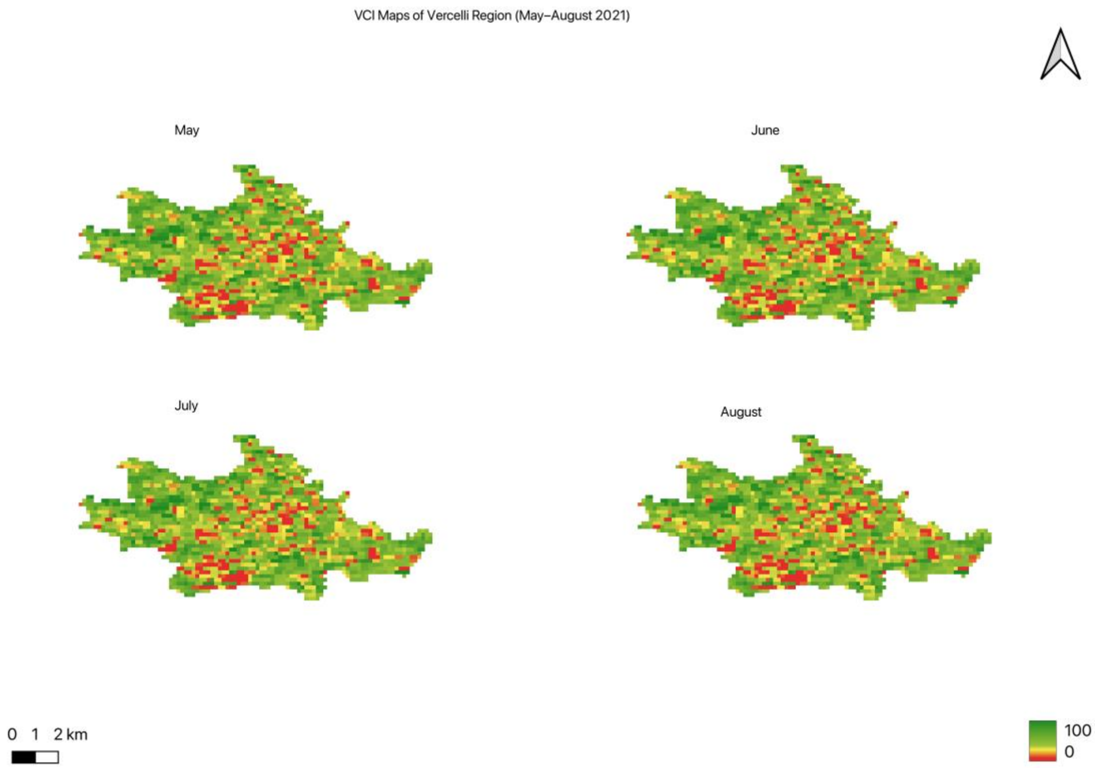

Figure 16-VCI Maps of the Vercelli Region (2021)

This figure illustrates the Vegetation Condition Index (VCI) across the Vercelli region for the 2021 growing season (May–August), reflecting vegetation health relative to long-term historical conditions. VCI values range from **0 (severe vegetation stress)** to **100 (optimal vegetation health)**. The red and orange areas represent zones experiencing **severe (VCI 10–20)** to **moderate drought (VCI 20–30)** conditions, while green areas indicate **healthy vegetation** or **no drought stress**.

Throughout the 2021 season, large portions of the region—particularly in **central and eastern areas**—are dominated by red and yellow pixels, especially in **June and July**, signaling widespread vegetation stress. This spatial pattern coincides with meteorological reports of **extreme drought (SPI ≈ –1.6)** during early summer 2021. The maps confirm that **2021 was the most drought-impacted year** within the study period, with limited improvement even by August. The findings underscore both the severity and spatial extent of the drought and support the use of VCI as an effective indicator for early-stage crop stress detection.

Figure 17-VCI Maps of the Vercelli Region (2022)

This figure shows the monthly evolution of the Vegetation Condition Index (VCI) for the Vercelli region during the 2022 growing season. Despite 2022 being officially classified as a severe drought year (**SPEI ≈ –1.7** in May), the VCI maps display a mixed pattern of stress and resilience.

In **May and June**, red and orange pixels are widely distributed in the **central and northern areas**, indicating **moderate to severe drought conditions (VCI 10–30)**. This aligns with early-season hydrological deficits and supports meteorological drought classifications. However, from **July onward**, an increase in green zones becomes visible, particularly in **southern and irrigated zones**, indicating **partial vegetation recovery**.

These improvements suggest the effectiveness of **irrigation infrastructure** and potential shifts in **crop phenology**, allowing crops to adapt and maintain growth. While drought stress persisted in some fields, especially in **non-irrigated patches**, overall vegetation health appears **relatively stable by August**, reflecting adaptive responses during one of the harshest climatic years in the study period.

This pattern highlights the importance of **mid-season resilience** mechanisms, including water management and crop recovery, which buffered the impacts of extreme drought during early development stages.

Summary:

- **2021:**
  The VCI maps for 2021 exhibit a **widespread concentration of red and orange pixels**, particularly during the early months (May–July), corresponding to **VCI values below 30**. These low values are indicative of **moderate to severe drought conditions**, aligning with field-level stress symptoms and reduced vegetation vigor observed in NDVI trends. The spatial extent of drought stress was particularly pronounced in **central and eastern zones**, suggesting insufficient water availability during critical crop development stages.
- **2022:**
  Despite being officially classified as a **severe meteorological drought year** (SPEI ≈ –1.7), VCI values in 2022 showed **considerable improvement over 2021**, with a noticeable **increase in green zones (VCI > 40)** from July onward. This improvement is attributed to the implementation of **effective irrigation infrastructure** and potential **phenological adaptation** of rice crops. The mixed pattern observed in early months (May–June) gradually transitioned to a more stable and greener distribution by August, indicating **partial drought resilience** and **successful vegetation recovery** in key agricultural areas.

4.7 VCI Anomaly (May 2022 – 2021)

This map highlights where vegetation conditions improved or worsened year-over-year.

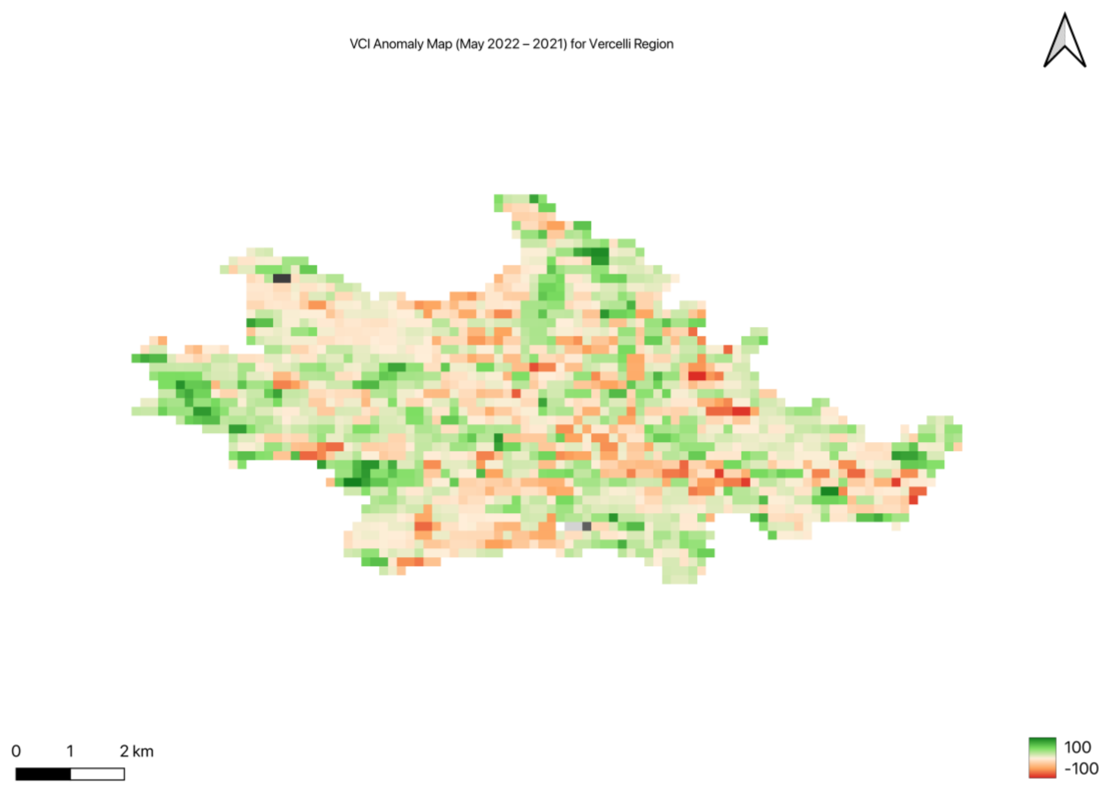

Figure 18-VCI Anomaly Map (2022 – 2021)

This anomaly map visualizes year-over-year changes in the Vegetation Condition Index (VCI) between May 2021 and May 2022 across the Vercelli region. Green pixels represent areas where vegetation conditions improved in 2022 compared to the previous year, while red pixels indicate zones of worsening vegetation health.

Interpretation:

- **Green zones** signal regions where **vegetation health improved** in 2022, despite severe meteorological drought conditions (SPEI ≈ –1.7). These improvements are likely attributable to **enhanced irrigation infrastructure**, **adaptive agricultural practices**, and **phenological shifts** that allowed crops to better withstand early-season stress.

SPEI values from –1.7 to –1.3 indicate heat-amplified drought conditions. These patterns align closely with NDVI reductions in the same period, reflecting stress on rice crops during transplanting and reproductive stages.

- **Red zones**, concentrated primarily in the **central and southeastern sectors**, denote **deterioration in vegetation condition** relative to 2021. These areas may have suffered from **insufficient irrigation coverage**, soil limitations, or lingering hydrological deficits that exacerbated the impacts of drought in 2022.

Overall, the spatial heterogeneity captured in the anomaly map reflects a **complex interaction of drought exposure, land management, and water availability**, and supports the thesis' broader argument regarding **localized resilience versus vulnerability** within the same agro-ecological zone.

4.8 EVI2 and SAVI Observations

To complement NDVI, EVI2 and SAVI were calculated for the month of May from 2020 to 2024.

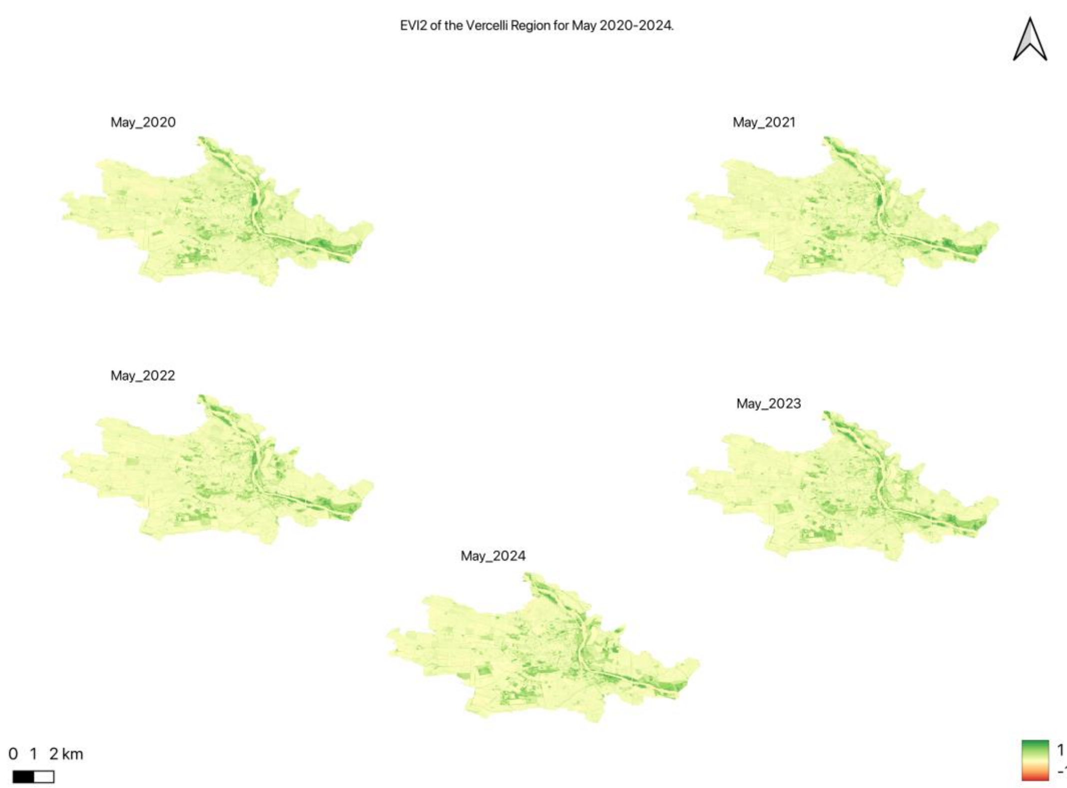

Figure 19- EVI2 of the Vercelli Region (May 2020–2024)

This figure displays the Enhanced Vegetation Index 2 (EVI2) maps for the Vercelli region during the month of May across five consecutive years. EVI2 is particularly useful in capturing vegetation dynamics in high biomass regions and under atmospheric disturbance conditions, complementing the NDVI results.

Spatial Comparison Across Indices (May 2021):
In May 2021, spatial patterns of vegetation stress are consistently highlighted across NDVI, SAVI, and EVI2 maps. All three indices reveal **notably low values in central and southern zones of Vercelli**, aligning with known dryland patches and irrigation-deprived areas. SAVI and EVI2 provide additional nuance—SAVI detects reduced vegetation health in **soil-exposed margins**, while EVI2 highlights stress across **denser canopy zones**, confirming early physiological drought signals. The spatial overlap across these indices strengthens the validity of early-season drought detection and underscores the advantage of a multi-index approach.

Interpretation:

- **2020 and 2024** show consistently higher EVI2 values, indicating **healthy and vigorous vegetation cover** during the transplanting phase. These years correspond to **non-drought seasons**, supported by optimal soil moisture and climatic stability.
- **2021** exhibits noticeably paler tones, reflecting **weaker vegetation health** in early May, consistent with NDVI and VCI findings that confirm **early-season drought stress**.
- **2022** presents moderate EVI2 values across the landscape, showing that while drought was present, **vegetation remained resilient**, likely due to irrigation buffering. Slight spatial variation is observable, with **lower values in central dryland zones**.
- **2023** appears as a **transition year**, where EVI2 values improve relative to 2021 and 2022, but still show subtle variation. This suggests **progressive recovery**, though not yet uniform across the region.

The EVI2 maps reinforce the temporal vegetation trends identified in NDVI analysis and highlight **early stress signals** (2021–2022) as well as the **recovery trajectory** culminating in 2024. EVI2's sensitivity to canopy structure and chlorophyll density makes it particularly informative for evaluating vegetation vigor in rice-dominant agricultural systems like Vercelli.

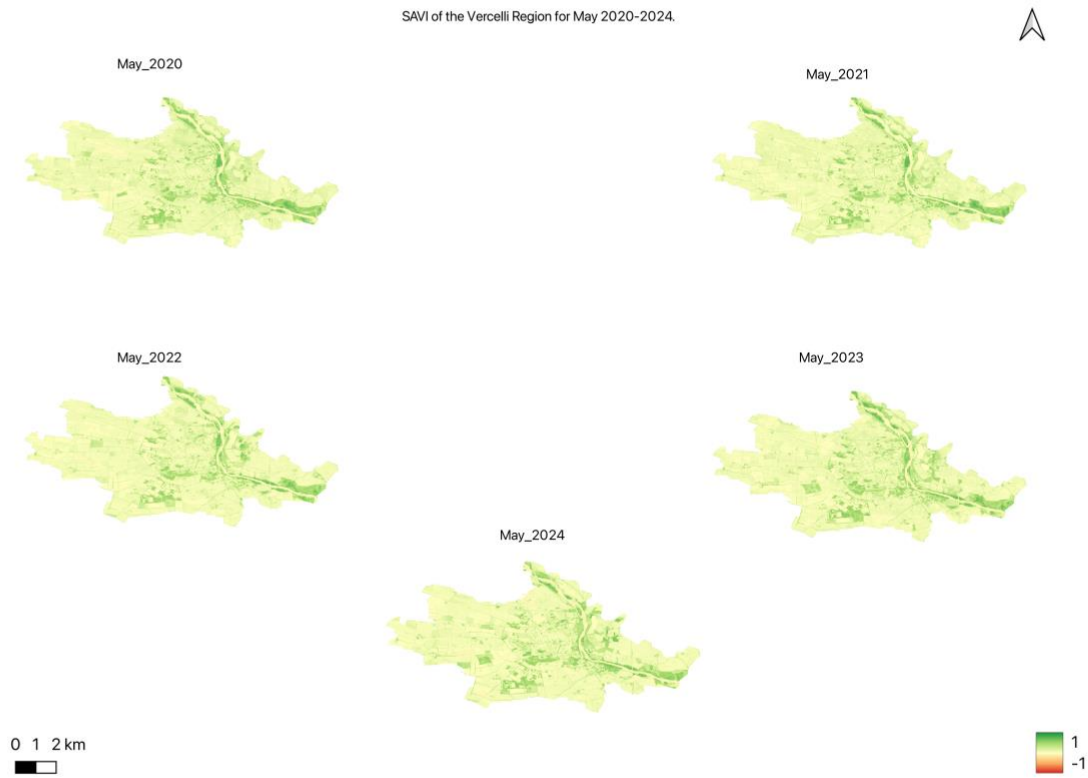

Figure 20- SAVI of the Vercelli Region (May 2020–2024)

This figure presents the Soil-Adjusted Vegetation Index (SAVI) maps for May from 2020 to 2024. SAVI is designed to minimize the influence of soil reflectance in areas where vegetation cover is sparse, making it a valuable complement to NDVI and EVI2—especially during early stages of crop development when soil exposure is high.

Interpretation:

- **2020 and 2024** display more pronounced vegetative cover, with higher SAVI values across the landscape. This reflects strong early-season crop establishment and minimal soil exposure, aligning with observed NDVI and EVI2 patterns for those years.
- **2021** shows significantly paler SAVI values, especially across central and eastern zones. This is consistent with a **drought-impacted season**, where sparse vegetation and exposed soil dominated the early growing period.
- **2022** exhibits patchy spatial patterns, with moderate SAVI values throughout the region. The variability suggests that while some areas benefited from early irrigation or localized rainfall, others continued to experience dry surface conditions.
- **2023** marks a transitional year. SAVI values increase compared to 2021–2022, but still show **incomplete vegetation coverage**, suggesting that soil influence remained notable in parts of the region.

SAVI's strength lies in detecting early-stage crop conditions under mixed vegetation and soil reflectance. These maps confirm the **progressive recovery of vegetative cover** post-2021 and support the interpretation that **2024 represents a return to optimal surface greening** in the Vercelli rice fields.

4.9 NDVI of May (All Years Side-by-Side)

This comparison emphasizes differences during the **transplanting phase**.

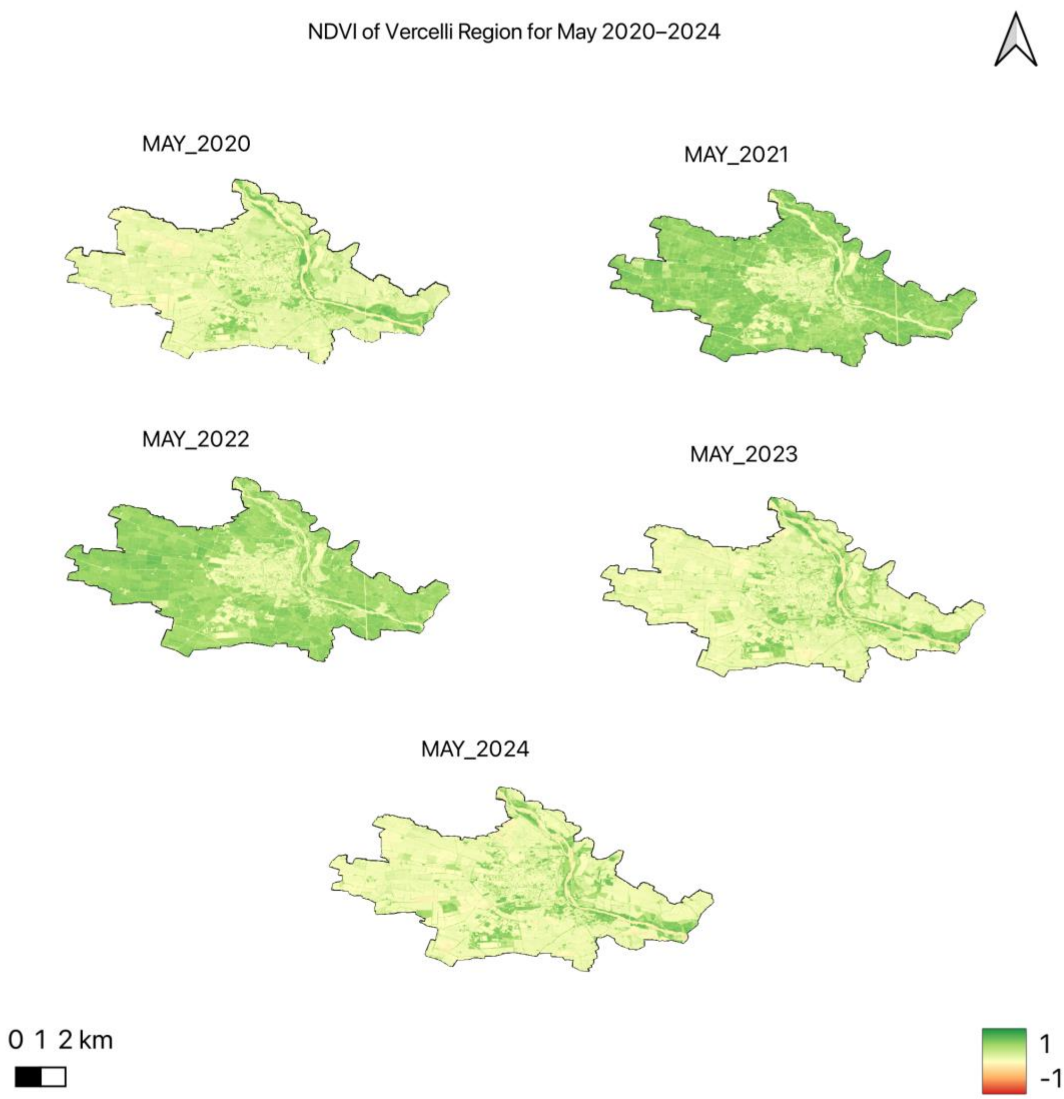

Figure 21-NDVI of the Vercelli Region (May 2020–2024)

This figure compares NDVI values for the month of **May** across five consecutive years, a period that coincides with the **transplanting phase** of rice cultivation in the Vercelli region. The side-by-side visualization helps isolate early-season vegetation dynamics and detect anomalies in crop establishment.

Quantified Stress Area (NDVI < 0.3, May 2020–2024):

To complement the visual NDVI comparison, areas with **NDVI < 0.3** were extracted as a proxy for early-season vegetation stress during the transplanting phase. This threshold captures zones of reduced canopy development or delayed crop establishment. The total land area (in km²) falling below this stress threshold was calculated for each year:

Table 10-Estimated Land Area Under Early-Season Vegetation Stress (NDVI < 0.3) in May (2020–2024)

Year	Area under NDVI < 0.3 (km²)
2020	38.6
2021	162.2
2022	118.4
2023	79.1
2024	35.4

These figures confirm that **2021 experienced the most widespread vegetation stress**, aligning with recorded drought signals in SPI/SPEI and VCI datasets. A **progressive recovery** is observed in subsequent years, culminating in **minimal stress by 2024**, which mirrors optimal crop development and favorable climatic conditions.

Interpretation:

- **2020 and 2024** exhibit uniformly high NDVI values, with widespread greening across the region. These years represent **optimal early-season growth**, reflecting good rainfall, temperature, and irrigation alignment during transplantation.
- **2021** displays large areas with lighter tones (lower NDVI), especially in the central and eastern zones. This reflects **early vegetation stress**, consistent with drought signals from meteorological indices (e.g., SPI/SPEI) and VCI maps.
- **2022** shows a more heterogeneous NDVI pattern. While some zones appear greener due to targeted irrigation or residual soil moisture, others remain under stress. The year represents a **transitional phase**, where irrigation mitigated part of the drought impact.
- **2023** shows modest recovery, but still includes zones of suppressed NDVI, particularly in fragmented patches, likely resulting from **delayed growth** or **soil saturation issues** post-drought.

This comparative map confirms that **early May NDVI is a sensitive indicator** of drought onset and crop establishment delays. It also validates interannual variability in vegetative performance, providing spatial insight into areas requiring adaptive management interventions.

Table 11- Summary of Vegetation Index Performance in the Vercelli Region (2020–2024)

Index	Best Year(s)	Worst Year	Notes
NDVI	2020, 2024	2021	Reflects real-time greenness
VCI	2020, 2024	2021	Shows drought relative to historical norms
Anomaly	—	2021 drop	Year-over-year change confirms peak stress
SAVI	2024	2021	Soil-sensitive indicator, low vegetation 2021
EVI2	2024	2021	Captures vigorous biomass in resilient zones

This table synthesizes the comparative performance of five vegetation indices (NDVI, VCI, Anomaly, SAVI, and EVI2) over the 2020–2024 period in the Vercelli region. Each index's best and worst performing years are listed based on observed spatial patterns, greenness intensity, and stress signals. Notably, **2021 consistently emerges as the most drought-affected year**, while **2020 and 2024** are marked by optimal vegetation health. The table also includes interpretation notes highlighting the analytical strengths of each index, from NDVI's greenness sensitivity to EVI2's biomass responsiveness.

Chapter 5: Discussion

5.1 Overview

This chapter critically evaluates the findings presented in Chapter 4, aligning them with existing scientific literature, highlighting methodological insights, and outlining practical implications for drought monitoring and agricultural planning in the Vercelli region. The discussion draws upon multi-temporal vegetation indices — NDVI, SAVI, EVI2 from Sentinel-2, and VCI from MODIS — and meteorological indicators (SPI and SPEI) to explore the spatiotemporal patterns of drought stress and vegetation response between 2020 and 2024. Particular emphasis is placed on the drought-impacted year 2021 and the recovery observed in 2022 and beyond. The chapter also reflects on index performance, phenological sensitivities, and limitations of the methodology, and suggests future research directions.

5.2 Synthesis of Key Findings

The multi-year analysis of vegetation dynamics in the Vercelli region from 2020 to 2024 reveals significant interannual variability in crop health, closely linked to meteorological drought patterns and phenological sensitivities. Among the five seasons examined, **2021 stands out as the most critically drought-impacted year**, as evidenced by steep declines in both **NDVI** and **VCI** values during key rice development stages—particularly from **May to July**, which encompass transplanting through reproduction.

The severe vegetation stress detected by satellite indices in 2021 is strongly corroborated by meteorological indicators. Specifically, **SPI** and **SPEI** values during this period consistently fell below **–1.5**, classifying it as an episode of **extreme drought**. This convergence of vegetation and climatic evidence confirms the biological sensitivity of rice phenology to concurrent water deficits and atmospheric demand during early-to-mid season phases. Such findings are particularly relevant for agronomic systems where even brief interruptions in water availability can significantly impair yield formation.

In contrast, **2022 exhibited signs of resilience**, especially in the **later months of July and August**, where NDVI values showed moderate recovery. This occurred despite continued meteorological indicators of drought. The partial rebound in vegetation health is likely attributable to **improved irrigation management**, **adaptive planting decisions**, and potentially altered crop calendars that helped buffer against hydrometeorological stress. Importantly, **VCI anomaly maps comparing 2022 to 2021** (figure15). reveal spatial heterogeneity in recovery: while northern and western sectors of Vercelli showed pronounced vegetation improvement, central and southeastern areas remained under **moderate stress**, highlighting the uneven distribution of irrigation efficacy or localized drought persistence.

Further insights were gained through **NDVI zonal statistics**, which demonstrated consistent seasonal greening patterns in most years, with NDVI steadily increasing from May to August. The exception was 2021, in which NDVI values declined sharply in **July**, aligning with the **reproductive stage** of rice—a phenological phase highly sensitive to drought-induced reductions in photosynthetic activity and grain formation. By **2023**, vegetation indices suggested a **transitional phase**, with moderate stress still evident but clear signs of recovery emerging. **The year 2024 marked a return to pre-drought vegetation conditions**, with NDVI and VCI metrics closely resembling the healthy baseline observed in 2020. These interpretations are further supported by the summary in Table 11, which consolidates the best and worst performing years for each vegetation index and confirms 2021 as the most drought-impacted year across all metrics. The consistency of this finding across NDVI, VCI, SAVI, EVI2, and anomaly layers reinforces the robustness of the multi-index approach applied in this study.

Collectively, these findings illustrate a **complete drought cycle** in the Vercelli rice-growing region: a climatically favorable baseline in 2020, acute drought impact in 2021, partial vegetative and management-driven adaptation in 2022–2023, and near-complete recovery by 2024. The study thus provides empirical evidence of both ecological vulnerability and adaptive capacity within irrigated rice systems under changing hydroclimatic pressures.

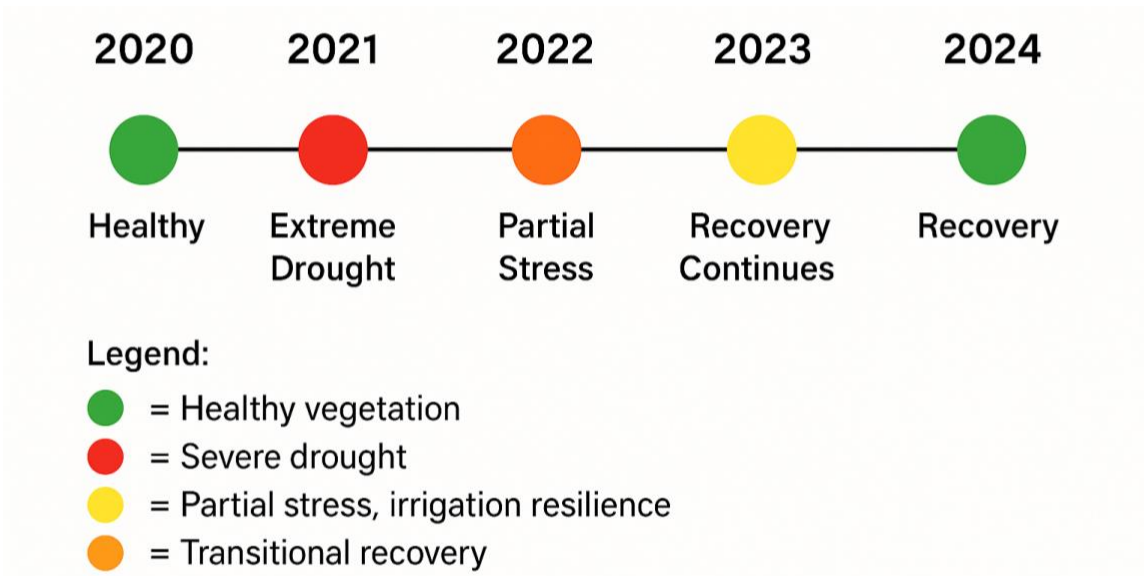

Figure 22-Vegetation Drought Cycle Timeline (2020–2024)

5.3 Alignment with the Scientific Literature

The results of this study are consistent with a substantial body of research that underlines the importance of multi-index approaches in assessing drought and vegetation dynamics. The use of multiple vegetation indices and meteorological indicators in this thesis not only validates previous methodologies but also expands on them by applying them in the context of rice phenology under Mediterranean-climate stress conditions in northern Italy.

One of the foundational references in vegetation-based drought monitoring is the work of **Kogan (1995)**, who developed the Vegetation Condition Index (VCI) to assess drought intensity by comparing current vegetation status to long-term historical norms. This study confirmed VCI’s sensitivity to deviation from baseline conditions, particularly in identifying the **year 2021 as the most drought-impacted**, with widespread declines in VCI during the reproductive phase of rice development. This aligns with Kogan’s findings and supports the use of VCI as a drought anomaly indicator.

Additionally, the **Normalized Difference Vegetation Index (NDVI)**, introduced by **Tucker (1979)**, was validated in this study as a robust indicator of chlorophyll density and photosynthetic activity. The clear NDVI response to stress during early vegetative stages, particularly in 2021 and early 2022, highlights its continued utility in agricultural monitoring. NDVI's effectiveness in capturing both onset and severity of vegetative stress remains a cornerstone of remote sensing-based phenological analysis.

While NDVI effectively captured early-season vegetative stress due to its sensitivity to chlorophyll content, VCI was more effective in representing longer-term drought deviations from historical norms, especially during the reproductive stage of rice. This complementary performance highlights the importance of index selection based on phenological phase. NDVI provided high spatial detail and was responsive to canopy greenness fluctuations, whereas VCI’s anomaly-based structure proved valuable for detecting cumulative drought effects during later crop development stages. The combined use of these indices thus enhanced the temporal and spatial resolution of drought analysis.

Table 12- Comparative Summary of Vegetation Indices: Sensitivities, Strengths, and Phenological Relevance

Index	Strengths	Limitations	Most Sensitive Stage
NDVI	Real-time greenness, sensitive to early stress	Influenced by cloud and soil reflectance	Transplanting, tillering
VCI	Highlights long-term drought anomaly	Lower spatial detail, depends on climatology	Reproductive, heading
SAVI	Adjusted for soil brightness	Less responsive in dense canopy	Early crop stages with exposed soil
EVI2	Effective in high biomass	Requires clear sky, less robust in noise	Peak vegetative growth

To improve sensitivity under different biophysical conditions, this research also utilized **SAVI** and **EVI2**. These indices have been shown to perform well under specific environmental settings. SAVI, developed by **Huete (1988)**, addresses the influence of soil background in low vegetation cover scenarios—a condition common during the transplanting phase in May. Similarly, **Jiang et al. (2008)** introduced EVI2 to enhance detection in densely vegetated canopies while minimizing atmospheric distortion. The performance of these indices during periods of sparse canopy (e.g., May) and dense vegetation (e.g., July–August) supports their inclusion for a more nuanced assessment.

Recent studies have further validated the use of multiple vegetation indices to monitor crop health under drought and phenological variability. **Tuvdendorj et al. (2019)** demonstrated the comparative value of NDVI and VCI for spring wheat yield estimation in Mongolia, with each index responding distinctly to drought pressure across phenophases—findings that mirror this study's use of VCI during reproductive stages and NDVI during transplanting. Similarly, **Jha et al. (2022)** showed the phenological sensitivity of NDVI, EVI2, and GNDVI in forecasting sugarcane yield using Sentinel-2 data, reinforcing the utility of EVI2 in capturing vegetation vigor during peak biomass. Additionally, **Wang et al. (2020)** emphasized the role of satellite-derived phenological indicators in explaining weather variability effects on rice development, offering methodological support for combining indices in seasonal crop stress analysis. Together, these contemporary sources substantiate the scientific rationale for the temporal and functional pairing of NDVI, VCI, SAVI, and EVI2 in this thesis.

Furthermore, the incorporation of meteorological drought indices—particularly the **SPEI**—reflects best practices recommended in climatological literature. **Vicente-Serrano et al. (2010)** emphasized the advantage of SPEI over SPI due to its consideration of **evapotranspiration**, which becomes particularly relevant under warming conditions. In this study, **SPEI values in 2021 and 2022 aligned closely with NDVI and VCI declines**, especially during the transplanting and flowering stages. This further demonstrates the added value of integrating climatic data into vegetation analysis, offering both explanatory power and predictive capacity.

In conclusion, the findings of this thesis strongly resonate with the scientific consensus on drought monitoring, providing empirical support for a **multi-index, multi-source methodology**. The complementary nature of vegetation indices and meteorological indicators, as evidenced in this study, confirms that no single index is sufficient on its own. Rather, it is the integration of spectral, spatial, and climatic dimensions that allows for accurate, timely, and actionable insights into drought stress and crop health.

5.4 Phenological and Seasonal Sensitivity

The behavior of vegetation indices throughout the study period exhibited strong alignment with the phenological calendar of rice cultivation in the Vercelli region. As a crop that follows a structured growth cycle, rice undergoes four distinct phases: transplanting in May, vegetative growth in June, reproductive development in July, and maturation in August. This phenological structure creates clear expectations for vegetation index trajectories, which were consistently observed in the satellite-derived NDVI and VCI datasets.

In typical years, NDVI values were lowest in May, corresponding to the transplanting stage when rice paddies are intentionally flooded and plant canopy coverage is minimal. This early-season dip was consistently observed across all study years and is indicative of successful phenological mapping. As the crop entered the vegetative phase in June, NDVI values began to rise sharply, reflecting the expansion of leaf area and increased chlorophyll content associated with active photosynthesis.

The highest NDVI values generally occurred in July, coinciding with the reproductive stage. This phase is particularly critical for determining yield outcomes, as the development of panicles and flowering depends heavily on adequate water supply and temperature stability. In 2021, a notable deviation from this expected trend occurred. NDVI values, which had begun to rise in June, exhibited a significant drop in July, indicating acute vegetation stress during the reproductive phase. This pattern was further substantiated by SPI and SPEI readings, which revealed extreme drought conditions during the same period. The alignment of satellite-based stress indicators with meteorological drought metrics reinforces the utility of multi-index integration for detecting critical-stage impacts.

In 2022, NDVI values remained lower than average during early summer, consistent with residual drought effects and water scarcity during transplanting. However, a recovery was observed in late July and August, suggesting either a delayed phenological progression or the efficacy of supplemental irrigation interventions. VCI trends during this year also indicated moderate recovery, although spatial variability remained high. These findings suggest that rice in Vercelli may exhibit adaptive phenological shifts in response to climate stress, such as delayed flowering or extended vegetative periods.

The seasonal sensitivity of vegetation indices in this study underscores the importance of synchronizing remote sensing analysis with phenological calendars. Without contextual understanding of crop growth stages, NDVI or VCI anomalies may be misinterpreted. For instance, low NDVI in May is not indicative of drought, but rather a natural result of transplanting. By integrating phenological phase knowledge with remote sensing observations, researchers and practitioners can more accurately diagnose drought effects, distinguish between stress-induced declines and natural cycles, and target interventions to specific growth stages.

Overall, the phenological interpretation of vegetation indices proved essential in capturing the nuanced impacts of drought on rice production. Unlike generic time-series approaches, which track vegetation changes without aligning to crop biology, this study synchronizes remote sensing data with phonologically critical rice growth stages. This alignment ensures that variations in NDVI or VCI are interpreted in a biologically meaningful way, reducing the risk of misdiagnosing natural growth dips—like the May transplanting stage—as drought stress. By integrating satellite data with agronomic calendars, the method enhances both the accuracy and practical value of drought assessments in rice cultivation, supporting more reliable early-warning and irrigation planning systems.

5.5 Methodological Strengths and Limitations

The methodological framework adopted in this study combined multi-source remote sensing indices with meteorological drought indicators to comprehensively assess spatiotemporal vegetation dynamics and drought impacts in the Vercelli region. This integrated approach offered several distinct strengths.

To visually clarify how the components of this methodology interconnect, a simplified workflow diagram has been included below. This visual summarizes the relationships between the satellite data sources (Sentinel-2, MODIS, ESA WorldCover), the vegetation and drought indices (NDVI, SAVI, EV12, VCI, SPI, SPEI), and the LULC, the processing tools (QGIS, Python), and the resulting outputs (maps, zonal statistics, and anomaly analyses). The LULC layer was included to contextualize NDVI and VCI observations spatially, helping differentiate agricultural zones from non-agricultural areas.

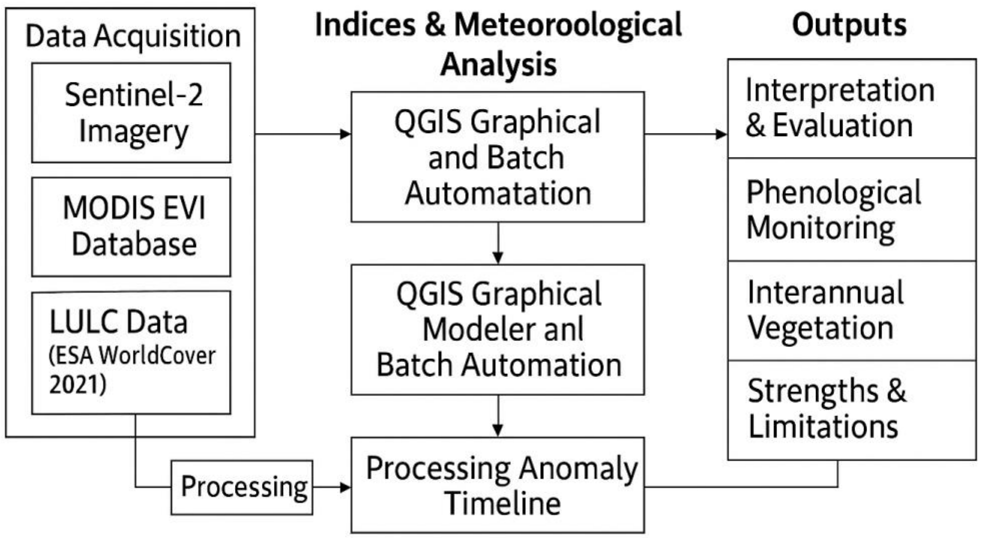

Figure 23- Simplified overview of the methodological framework used in this study, illustrating the connection between multi-source data inputs (Sentinel-2, MODIS, ESA WorldCover), processing tools, and analytical outputs for agricultural drought monitoring.

Firstly, the use of high-resolution Sentinel-2 imagery (10-meter spatial resolution) enabled precise field-level monitoring of vegetation, which is particularly crucial in the heterogeneous rice paddies of northern Italy. This resolution allowed for the detection of spatial variability and intra-field drought responses, enhancing the ability to pinpoint vulnerable zones during key phenological stages.

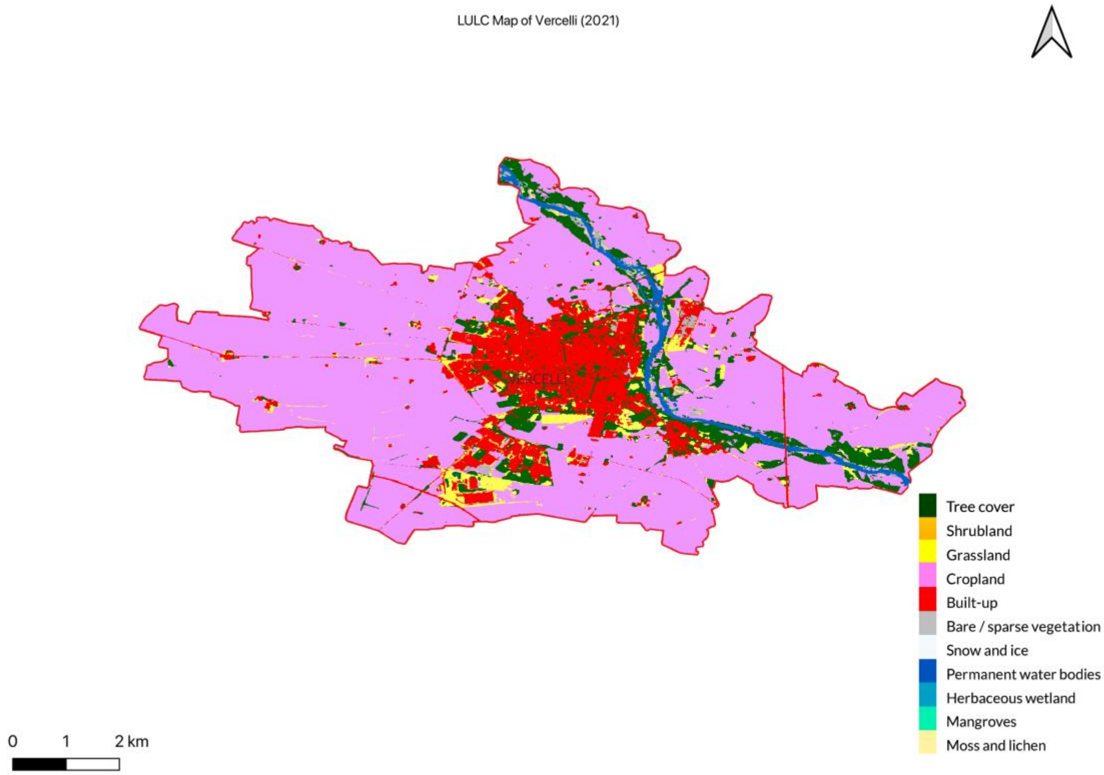

Figure 24-Land Use and Land Cover (LULC) Map of Vercelli Based on ESA WorldCover 2021

Another methodological strength was the inclusion of a high-resolution land cover classification, which provided spatial context for interpreting vegetation index dynamics. As shown in Figure 24, the reclassified LULC map visually distinguished agricultural areas from urban, forested, and water-covered zones. This helped mitigate the risk of misattributing NDVI reductions in non-cropland areas—such as built-up or riparian zones—to drought-induced crop stress. Although full pixel-based masking between LULC and NDVI datasets was not feasible due to resolution mismatches, the classification layer nonetheless enhanced spatial understanding of land surface composition and offered a valuable reference for cross-validating remote sensing outputs. This spatial foundation may also support more refined integration methods in future research.

Secondly, the MODIS-derived VCI, with its historical baseline and temporal continuity, offered valuable long-term context to evaluate anomalies in vegetation health. Despite its coarser spatial resolution (250 meters), VCI's strength lies in its ability to compare current vegetation conditions against climatological norms, which proved especially useful in characterizing the 2021 drought.

Additionally, the inclusion of SAVI and EVI2 indices enhanced the robustness of the vegetation assessment. SAVI reduced the influence of soil background reflectance, particularly in early-season observations when vegetation cover was sparse, while EVI2 performed reliably in high biomass conditions, minimizing saturation effects commonly observed in NDVI. While SAVI and EVI2 have shown utility in other crop systems, their application in flooded rice cultivation remains relatively uncommon. This methodological novelty highlights the importance of future validation through ground-truth data, particularly to calibrate index responses during early-stage flooding and peak canopy conditions. The meteorological integration of the SPI and the SPEI) added a climatological dimension to the vegetation-based assessments. These indices helped contextualize the observed vegetation stress with underlying atmospheric drought conditions, especially highlighting the evapotranspirative effects during critical stages such as transplanting (May) and reproductive development (July).

From a processing standpoint, the use of QGIS Graphical Modeler and batch automation tools proved highly efficient. These tools streamlined the repetitive tasks of index calculation and raster clipping, ensuring consistency across years and indices while significantly reducing processing time. The model-based approach also increased the reproducibility and transparency of the analytical workflow.

However, the methodology was not without limitations. One significant challenge was the spatial resolution mismatch between Sentinel-2 (10 m) and MODIS (250 m) data, which limited direct pixel-to-pixel comparison between VCI and other vegetation indices. This discrepancy necessitated the use of aggregated zonal statistics, which may have obscured finer-scale spatial dynamics. Furthermore, cloud contamination in Sentinel-2 imagery—particularly during the summer months—led to data gaps, most notably in July. These gaps occasionally compromised temporal continuity and required manual validation or exclusion of affected scenes.

Another limitation stemmed from the lack of standardized thresholds for SAVI and EVI2 drought interpretation in paddy rice systems. While these indices proved useful for relative comparison, their absolute values were difficult to interpret without extensive ground-truthing. Future research should aim to calibrate these indices using field-based measurements such as leaf area index (LAI), chlorophyll content, or soil moisture data, particularly under rice-specific conditions like flooding or dense canopy stages. This would support the development of drought-sensitive thresholds for SAVI and EVI2 in paddy systems, enhancing their interpretability and operational use in early warning systems.

Similarly, SPI and SPEI data, though effective for identifying broad-scale drought events, were only available at monthly temporal resolution and regional spatial scale, limiting their sensitivity to short-term or hyperlocal meteorological fluctuations.

Despite these challenges, the methodological design proved to be both robust and adaptable. By leveraging multi-sensor inputs and open-source geospatial tools, the study successfully generated an integrated perspective on agricultural drought dynamics in Vercelli. The approach also offers a replicable framework that can be scaled to other irrigated crop systems and regions with similar climatic constraints.

While these methodological strengths and limitations shaped the precision and interpretability of the results, their practical relevance becomes most evident when applied to real-world planning and policy contexts. The following section explores how the findings can inform adaptive irrigation strategies and regional drought response frameworks.

Table 13-Comparative Summary of Vegetation Indices

Index	Strengths	Best Use Case	Limitations
NDVI	Sensitive to chlorophyll and green biomass	Early-stage stress detection	Saturation at peak biomass
VCI	Normalized to historical averages; drought sensitivity	Long-term anomaly detection	Coarse MODIS resolution (250 m)
SAVI	Adjusts for soil brightness in sparse vegetation zones	Transplanting phase (May)	Less validated in flooded rice environments
EVI2	Reduces atmospheric noise; stable in dense canopy	Mid- to late-season monitoring	Interpretation thresholds less established

This summary table synthesizes the comparative roles of each vegetation index used in the study, outlining their technical strengths, ideal applications, and interpretative challenges in irrigated rice systems.

These methodological insights not only shaped the precision and scope of the results but also revealed operational strengths that can be leveraged beyond the academic setting. The next section explores how these findings can inform practical applications in drought preparedness, irrigation management, and regional agricultural policy.

5.6 Implications for Agricultural Policy and Planning

The findings of this study hold substantial relevance for agricultural policy development, drought preparedness, and irrigation management in the Vercelli region and other similarly irrigated rice-growing areas. By integrating vegetation indices such as NDVI, VCI, SAVI, and EVI2 with meteorological indicators like SPI and SPEI, this research demonstrates the utility of remote sensing as a decision-support tool for monitoring drought conditions at both spatially detailed and temporally relevant scales.

One of the most significant implications is the ability to **detect crop stress at specific phenological stages**, such as transplanting and reproduction, when water availability is most critical for yield formation. The spatial and temporal sensitivity of vegetation indices enables targeted intervention strategies, including **adjusted irrigation scheduling** and **phenology-informed early warning alerts**. These capabilities are essential in water-limited environments where resource optimization is necessary to sustain productivity under climatic variability.

For practical implementation, regional water agencies or rice consortia could use NDVI-based thresholds to trigger early interventions. For instance, an NDVI value consistently below 0.25 in May (transplanting) or below 0.4 in July (reproductive stage) may signal early vegetative stress, prompting increased irrigation supply or schedule adjustments. These thresholds should be validated with local agronomic observations but offer a replicable model for operational drought monitoring.

Based on the results, the study supports the **implementation of remote sensing-based drought monitoring systems** at the municipal or provincial scale. Such systems would allow local authorities to monitor vegetation health in near-real time, identify high-risk zones, and deploy mitigation strategies accordingly. Additionally, the integration of **SPI and SPEI trends with NDVI-based vegetation stress signals** can inform the development of dynamic irrigation decision-support tools that align water allocation with actual biological demand and meteorological risk.

Moreover, the temporal dynamics observed during 2021 and 2022 underscore the need for **adaptive rice cropping calendars** that can shift sowing or transplanting windows in response to forecasted drought conditions. Early-season indicators such as May NDVI or SPEI anomalies could serve as triggers for calendar adjustments, enhancing the resilience of rice systems to early stress. The buffering effect observed in 2022—despite severe meteorological drought—suggests that **well-timed irrigation**, guided by integrated climatic and vegetation data, can reduce drought impact and stabilize yields.

Finally, this study emphasizes the importance of **continued investment in irrigation infrastructure**, particularly in subregions identified as persistently vulnerable by NDVI and VCI anomaly maps. These geospatial outputs can be used to **delineate drought-prone zones**, supporting the prioritization of resources such as irrigation upgrades, farmer support programs, or water-saving technologies. In doing so, policymakers can shift from reactive to proactive drought management, leveraging Earth observation data to enhance both short-term response and long-term planning in agricultural landscapes.

While the methodological framework proved effective in capturing spatiotemporal drought dynamics, certain limitations emerged that merit discussion to contextualize the findings and outline future improvement areas.

5.7 Study Limitations

While this study provided valuable insights into drought dynamics and vegetation responses in the Vercelli rice-growing region, several limitations should be acknowledged to contextualize the scope and reliability of the results. These constraints pertain to both data sources and methodological boundaries inherent to remote sensing-based research.

First, the study relied primarily on **optical satellite imagery**, particularly from Sentinel-2, which is known to be susceptible to **cloud contamination**. This limitation was especially pronounced during the summer months, where frequent cloud cover occasionally reduced image availability and continuity, particularly in July. As a result, certain phenological stages may have been underrepresented in the time series, potentially affecting the consistency of seasonal vegetation monitoring.

Secondly, the **NDVI**, while widely used for vegetation health assessment, is known to exhibit a **saturation effect** under dense canopy conditions. This issue was observed during the peak biomass months of **July and August**, when NDVI values plateaued and became less sensitive to incremental differences in chlorophyll or canopy structure. Although complementary indices such as **SAVI and EVI2** were employed to mitigate this effect, the lack of standardized drought thresholds for these indices in flooded rice systems limited the ability to fully resolve high-biomass dynamics.

Another significant limitation was the **absence of ground-truth validation data**. The study did not have access to field-measured observations such as yield data, biomass estimates, or leaf chlorophyll content. Without these reference datasets, it was not possible to quantitatively assess the accuracy of the remote sensing indicators. While temporal and spatial consistency across indices and meteorological indicators (e.g., SPI/SPEI) lends credibility to the findings, the lack of empirical validation restricts the interpretation of results at fine spatial resolutions.

Additionally, the analysis focused on the **core rice-growing period (May to August)**, which includes transplanting, vegetative growth, reproduction, and early maturation. However, important physiological and agronomic processes also occur during the **late-season (September–October)**, including grain filling and harvesting, which were not assessed in this study. Monitoring post-harvest dynamics and residual stress could provide a more comprehensive view of seasonal productivity and crop resilience.

Furthermore, meteorological drought indicators such as SPI and SPEI, though useful for capturing regional-scale climatic trends, are constrained by their **monthly temporal resolution** and dependence on generalized **evapotranspiration models** (Vicente-Serrano et al., 2010). These factors may result in a **temporal mismatch** between climatic drought signals and short-term field-level stress events, particularly during rapid phenological transitions in rice cultivation.

Given these limitations, it is important to exercise **caution when interpreting the findings at the individual field scale**, especially in **non-irrigated or marginal zones**, where stress responses may diverge from regional trends. Despite these challenges, the multi-index framework employed remains a robust and adaptable approach for regional-scale agricultural drought assessment and offers a solid foundation for future refinement.

To build upon this study, the following directions are recommended:

- Incorporate **Sentinel-1 SAR data** to monitor vegetation during cloud-obscured periods and to estimate soil moisture.
- Integrate **ground-based measurements** for validation, particularly yield, phenology observations, and chlorophyll content.
- Explore **machine learning models** that use time-series NDVI, VCI, SPI/SPEI, and weather data for automated drought classification.
- Extend the monitoring framework to cover **September–October**, capturing the full phenological cycle.

- Develop a **web-based decision support system** using QGIS, Python, and Copernicus data, aimed at helping farmers and local planners visualize drought risks in near real-time.

5.8 Future Research Directions

Building on the findings and limitations of this study, three key future research priorities are proposed to enhance the accuracy, resilience, and practical applicability of drought monitoring frameworks in irrigated rice cultivation systems such as those found in Vercelli.

1. Integrating SAR Data for All-Weather Monitoring
The use of Synthetic Aperture Radar (SAR) data—especially from Sentinel-1—should be prioritized to address cloud-related data gaps identified in this study. SAR's ability to capture surface roughness and water content makes it a valuable complement to optical indices during critical stages like transplanting, when rice paddies are flooded and optical signals are often obscured.

2. Field-Based Validation for Vegetation Index Calibration
Ground-truth data such as leaf area index (LAI), chlorophyll content, biomass, and yield should be systematically collected to calibrate and validate satellite-derived indices like NDVI, SAVI, EVI2, and VCI. This would support the development of rice-specific vegetation stress thresholds—especially for indices like SAVI and EVI2 that currently lack standard reference values in flooded systems.

3. Developing an Operational Decision-Support Platform
Future work should also focus on building a GIS-based drought monitoring platform that integrates vegetation indices, SPI/SPEI values, and crop calendars. This platform could support local stakeholders—including farmers, water managers, and policymakers—by providing real-time drought alerts and actionable recommendations on irrigation and cropping decisions. Such systems are especially valuable in Mediterranean and temperate rice-growing regions facing increasing climatic stress.

In summary, these three directions prioritize enhancements to data continuity, index reliability, and real-time operational utility, offering a realistic and scalable path forward for improving agricultural drought preparedness in rice systems.

Chapter 6: Conclusion and Recommandation

6.1 Overview

This concluding chapter synthesizes the key findings, implications, and scientific contributions of the study, which focused on evaluating the spatial and temporal dynamics of agricultural drought in the Vercelli rice-growing region of northwest Italy over the period 2020–2024. The research employed a multi-index, multi-sensor framework by integrating satellite-derived vegetation indices—**NDVI** (Tucker, 1979), **SAVI** (Huete, 1988), **EVI2** (Jiang et al., 2008), and **VCI** (Kogan, 1995)—with meteorological drought indicators, namely the **SPI** and the **Standardized Precipitation SPEI** (Vicente-Serrano et al., 2010).

The principal objective was to detect and analyze vegetation stress across phenological stages of rice, including transplanting, vegetative development, and reproduction. This was achieved through the generation of anomaly maps, time-series graphs, and zonal statistics that together captured interannual and seasonal variability. The integration of remote sensing with phenological timelines allowed for the identification of drought-sensitive periods, particularly June and July, when rice is most vulnerable to hydrometeorological stress. The year 2021, for instance, exhibited pronounced declines in NDVI and VCI during these stages, coinciding with meteorological drought conditions indicated by SPI and SPEI values below –1.5.

The methodology relied on **open-source geospatial platforms**, particularly **QGIS** and **Python scripting**, enabling efficient and transparent processing of satellite imagery. Tools such as the QGIS Graphical Modeler and GDAL utilities facilitated batch processing, spatial clipping, index computation, and map styling, ensuring a scalable and reproducible workflow.

By aligning vegetation dynamics with rice phenology and climate variability, the study produced a robust, high-resolution drought monitoring approach. These results underscore the potential of Earth observation tools to support early-warning systems, adaptive irrigation scheduling, and policy frameworks aimed at enhancing climate resilience in irrigated rice agroecosystems such as those in the Po Valley (Wang et al., 2022).

6.2 Key Findings and Contributions

The findings of this study confirm substantial interannual variability in vegetation health in the Vercelli rice-growing region, closely aligned with meteorological drought trends. The year **2021** was clearly the most drought-impacted period, as evidenced by severe depressions in **NDVI** and **VCI** during the reproductive phase (June–July). These vegetative declines were reinforced by extreme meteorological conditions, with **SPI and SPEI values consistently below –1.5**, indicating acute drought severity (Vicente-Serrano et al., 2010).

In contrast, **2022** presented a notable case of partial vegetation recovery—particularly during July and August—despite continued meteorological drought indicators. This resilience is attributed to adaptive crop management and the buffering capacity of irrigation infrastructure (Wang et al., 2022). These contrasting patterns highlight the importance of combining vegetation and climate indicators to detect both climatic stress and agronomic adaptation.

A progressive improvement in vegetative vigor was observed in **2023**, and by **2024**, NDVI and VCI values had returned to near pre-drought conditions. This trajectory represents a complete **five-year drought cycle**, encompassing:

- **Baseline conditions** (2020),
- **Acute impact** (2021),
- **Adaptation and resilience** (2022–2023), and
- **Full recovery** (2024).

This sequence was further validated through NDVI anomaly maps and VCI spatial analyses, which revealed central and southeastern Vercelli as the most consistently affected sub-regions.

Methodologically, the research demonstrated the efficacy of combining multiple vegetation indices—**NDVI** (Tucker, 1979), **SAVI** (Huete, 1988), **EVI2** (Jiang et al., 2008), and **VCI** (Kogan, 1995)—with SPI/SPEI to produce a nuanced, phenology-aligned characterization of drought. Each index offered distinct analytical strengths: NDVI was highly responsive during early vegetative phases; VCI captured long-term anomalies; EVI2 showed stability under high biomass; and SAVI supported interpretation during low canopy density stages. However, the absence of standardized drought thresholds for SAVI and EVI2 in flooded rice systems remains a methodological gap.

From a practical standpoint, this study demonstrated the potential of **remote sensing** and **climate indices** for real-time drought monitoring and early warning systems in rice-based agriculture. The ability to detect vegetative stress during key phenological windows enables local authorities and water managers to optimize **irrigation scheduling**, **allocate resources strategically**, and adapt **crop calendars** proactively. The identification of spatial drought hotspots also supports **infrastructure investment prioritization**, especially in vulnerable zones like the central and southeastern municipalities of Vercelli.

6.3 Research Contributions

This study contributes meaningfully to the field of agricultural drought monitoring by demonstrating how a multi-index remote sensing framework can be tailored to phenologically sensitive crops, particularly rice, under Mediterranean climate conditions. The integration of **Sentinel-2 high-resolution imagery**, **MODIS-based VCI**, and **climate indicators** such as **SPI and SPEI**, alongside phenological alignment, provides a comprehensive and operationally viable methodology for assessing vegetation stress.

From a **methodological perspective**, the thesis introduces an integrated, scalable, and reproducible workflow for drought monitoring. The use of **QGIS** and **Python scripting** allowed for semi-automated data processing, vegetation index computation, zonal statistics extraction, and anomaly mapping. This open-source setup ensures transparency, cost-efficiency, and adaptability across different geographic regions and crop systems (Huete, 1988; Vicente-Serrano et al., 2010).

The study also advances **applied geospatial analytics** through the production of time-series NDVI trend profiles, vegetation condition anomaly maps, and phenologically segmented drought summaries. These outputs offer spatially explicit insights into drought occurrence, intensity, and recovery across rice fields in the Vercelli region, helping to distinguish between climatic drought and irrigation-buffered resilience.

In terms of **decision-support relevance**, the research translates geospatial observations into actionable insights for agricultural planning. Outputs such as early-warning NDVI drops, spatial drought zoning, and phenology-aligned vegetation stress patterns can support:

- Adjustments in **crop calendars** and planting windows,
- Targeted **irrigation scheduling**, and
- Prioritization of **infrastructure investments** in drought-prone zones.

Moreover, this work enhances our understanding of how irrigated agricultural landscapes respond to **hydroclimatic variability** over time, offering empirical evidence for both vulnerability and resilience. In doing so, it contributes a scientifically grounded, policy-relevant framework for drought assessment and agricultural adaptation in the face of increasing climate uncertainty.

6.4 Policy Implications

The findings of this study offer several important implications for agricultural and water policy in drought-prone, irrigated rice regions such as Vercelli. The integration of remotely sensed vegetation indices (NDVI, VCI, SAVI, EVI2) with meteorological drought indicators (SPI and SPEI) has proven to be an effective strategy for detecting early signs of crop stress. In particular, **NDVI depressions and VCI anomalies** during the vegetative and reproductive stages serve as reliable **early-warning proxies**, offering lead time for local decision-makers to implement adaptive interventions (Jiang et al., 2008; Vicente-Serrano et al., 2010).

One of the most actionable outcomes is the identification of **spatially consistent drought-prone zones**, especially in **central and southeastern Vercelli**, where multi-year stress patterns were observed. These zones represent **priority targets** for agricultural investment, including:

- **Irrigation infrastructure upgrades** (e.g., canal relining, drip systems),
- **Soil moisture monitoring** integration, and
- **Subsidized drought insurance** and support programs for smallholders.

The phenological alignment of the analysis adds further relevance. By focusing on critical rice growth phases—such as **transplanting (May)** and **flowering (July)**—the remote sensing outputs provide **temporal precision** that enhances the operational utility of seasonal irrigation calendars and crop management protocols. In this way, **NDVI- and VCI-triggered alerts** can be embedded into local or regional **irrigation scheduling systems**, improving water-use efficiency during peak sensitivity windows.

From a policy development perspective, this research supports the creation of **data-informed drought zoning frameworks**, which can be integrated into climate resilience strategies at both municipal and provincial levels. Policymakers can use these spatial outputs to prioritize water allocations during drought seasons, plan infrastructural development, and adjust rice production calendars under increasing hydroclimatic stress.

In sum, this study contributes to the growing evidence base that supports the **mainstreaming of satellite-based monitoring tools into agricultural governance frameworks**—advancing precision agriculture and climate-smart planning for food security in Mediterranean rice-growing systems.

6.5 Future Research Directions

While this study has provided valuable insights into drought monitoring within irrigated rice systems, it also reveals several promising directions for future research. These extensions are essential for improving the robustness, operational applicability, and temporal coverage of drought diagnostics, particularly under Mediterranean climatic conditions.

First, **integrating Sentinel-1 SAR (Synthetic Aperture Radar)** data is recommended to complement optical sensors like Sentinel-2, especially during periods of persistent cloud cover. SAR's all-weather, day-and-night imaging capabilities can improve temporal resolution and ensure continuity in phenological tracking—particularly during the critical transplanting and flowering stages when Sentinel-2 imagery is often obstructed by summer cloud interference. Additionally, **soil moisture datasets**, whether retrieved from radar-based missions (e.g., SMAP, ASCAT) or in-situ probes, can enrich the drought modeling framework by capturing sub-surface water stress dynamics.

Second, **ground-truth validation** is crucial to increase the accuracy and credibility of satellite-derived vegetation indices. Future studies should prioritize collecting **field-level observations**, including rice yield records, phenological measurements, and leaf-level spectral signatures. Such empirical data would strengthen model calibration, allow for cross-validation of NDVI, SAVI, and VCI anomalies, and improve the interpretability of remotely sensed outputs under varying soil and crop management conditions.

Third, the incorporation of **machine learning and deep learning algorithms** offers an advanced avenue for multi-index classification and early drought prediction. Techniques such as Random Forest, Support Vector Machines (SVM), or Convolutional Neural Networks (CNNs) can be trained on a combination of vegetation indices, meteorological inputs, and temporal trends to identify complex spatial patterns and provide probabilistic drought alerts at finer resolutions.

Fourth, expanding the **temporal scope** of monitoring beyond the core rice-growing season (May–August) to include **post-harvest months (September–October)** and **winter cover crop cycles** would offer a more comprehensive understanding of vegetation recovery, land-use transitions, and residual drought effects. This would also improve the relevance of remote sensing outputs for adaptive crop scheduling, double-cropping analysis, and land planning strategies.

Finally, future work should emphasize the **co-development of operational decision-support systems (DSS)** in collaboration with local agricultural authorities and farmer cooperatives. By transforming NDVI, VCI, and SPI/SPEI outputs into real-time, user-friendly dashboards, researchers can bridge the gap between geospatial analytics and actionable drought risk management. Such tools could support dynamic irrigation scheduling, early warning systems, and localized drought zoning under projected climate variability.

In sum, these directions align with the ongoing shift toward **integrated, real-time, and stakeholder-driven approaches** to agricultural drought monitoring. They offer a pathway to enhance the scientific, technological, and practical relevance of remote sensing in climate-resilient agricultural landscapes.

6.6 Final Remarks

In an era increasingly shaped by climatic variability, this research underscores the growing relevance of Earth observation technologies in supporting agricultural resilience. By integrating satellite-based vegetation monitoring with crop phenology, the study offers both a methodological contribution and a practical framework for early drought detection and adaptive irrigation planning.

Ultimately, the findings demonstrate that high-resolution, multi-index remote sensing approaches can enable regional stakeholders—particularly policymakers and farmers—to move from reactive drought response to proactive risk management. This transition is essential for sustaining rice production and food security under mounting hydrometeorological stress.

References:

ARPA Piemonte (2022). Dati climatici e idrologici annuali per il Piemonte.

ARPA Piemonte (2023). Drought and Irrigation Bulletin.

ARPA Piemonte. (2022). Relazione di sintesi sulle condizioni di siccità in Piemonte – Estate 2022. Agenzia Regionale per la Protezione Ambientale del Piemonte.

Copernicus Emergency Management Service (CEMS). (n.d.). Drought observatory. European Union.

Copernicus Emergency Management Service.

Didan, K. (2015). MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V006. NASA EOSDIS LP DAAC.

Didan, K. (2015). MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V006. NASA EOSDIS Land Processes DAAC.

ESA WorldCover. (2022). *ESA WorldCover 10m 2021 v200* [Dataset]. European Space Agency.

FAO WaPOR. (n.d.). Water Productivity through Open access of Remotely sensed derived data portal. Food and Agriculture Organization of the United Nations.

Geoportale Piemonte. (2024). Regione Piemonte Geoportal.

Global Drought Observatory. (2024). European and Global Drought Observatories – EU Science Hub. European Commission – Joint Research Centre.

Global Drought Observatory. (n.d.). European Commission – Joint Research Centre. Retrieved from

Hersbach, H. et al. (2020). The ERA5 global reanalysis. Quarterly Journal of the Royal Meteorological Society, 146(730), 1999–2049.

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 25(3), 295–309.

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 25(3), 295–309.

Huete, A. R. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment, 83(1–2), 195–213.

Jha, A. K., & Singh, D. (2022). Sugarcane yield prediction using vegetation indices in Northern Karnataka, India. Universal Journal of Agricultural Research, 10(6), 699–721.

Jha, A., et al. (2022). Sugarcane Yield Prediction Using Vegetation Indices in Northern Karnataka, India. Universal Journal of Agricultural Research, 10(6), 699–721.

Jiang, Z., Huete, A. R., Chen, J., Chen, Y., Li, J., & Yan, G. (2008). Analysis of NDVI and scaled difference vegetation index retrievals of vegetation fraction. Remote Sensing of Environment, 110(3), 318–329.

Jiang, Z., Huete, A. R., Chen, J., Chen, Y., Li, J., & Yan, G. (2008). Analysis of NDVI and scaled difference vegetation index retrievals of vegetation fraction. Remote Sensing of Environment, 112(4), 1365–1375.

Kogan, F. N. (1995). Application of vegetation index and brightness temperature for drought detection. Advances in Space Research, 15(11), 91–100.

Liu, Y., Li, Z., Chen, Y., & Liang, Z. (2020). Integrating Sentinel-2 imagery for rice growth monitoring and yield estimation under varying climatic conditions. Remote Sensing, 12(15), 2480.

Misra, A., Ray, S. S., Jain, N., & Panigrahy, S. (2020). Use of Sentinel-2 data for monitoring rice crop phenology and productivity. Agricultural Water Management, 231, 106004

Mutowo, G., & Chikodzi, D. (2014). Remote sensing based drought monitoring in Zimbabwe. Disaster Prevention and Management, 23(5), 649–659.

NASA LP DAAC (2024). MODIS MOD13Q1 Products.

Pascale, D., & Ragone, M. (2025). National Drought Emergency Report for Northern Italy, 2021–2023. Regional Environmental Observatory.

QGIS Development Team. (2022). QGIS Geographic Information System. Open Source Geospatial Foundation Project.

SNPA (2022). Monitoraggio siccità: condizioni idrologiche in Nord Italia.

SNPA (Sistema Nazionale per la Protezione dell'Ambiente). (2022). Rapporto nazionale sugli eventi estremi e la siccità in Italia.

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment, 8(2), 127–150.

Tuvdendorj, B., Ochir, D., Natsagdorj, E., & Kang, S. (2019). Determination of appropriate remote sensing indices for spring wheat yield estimation in Mongolia. Remote Sensing, 11(21), 2568.

Tuvdendorj, D., et al. (2019). Determination of Appropriate Remote Sensing Indices for Spring Wheat Yield Estimation in Mongolia. Remote Sensing, 11(21), 2568.

UN-SPIDER. (n.d.). United Nations Platform for Space-based Information for Disaster Management and Emergency Response.

Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A multi-scalar drought index sensitive to global warming: The Standardized Precipitation Evapotranspiration Index (SPEI). Journal of Climate, 23(7), 1696–1718.

WMO (2012). Standardized Precipitation Index User Guide. World Meteorological Organization No. 1090.

Wang, F., Wang, L., Zhang, M., & Song, X. (2022). Monitoring phenological dynamics of rice with remote sensing: A review of current status and perspectives. Agricultural and Forest Meteorology, 314, 108777.

Wang, H., Ghosh, A., Linquist, B. A., & Hijmans, R. J. (2020). Satellite-Based Observations Reveal Effects of Weather Variation on Rice Phenology. Remote Sensing, 12(9), 1514.

Wang, H., Ghosh, A., Linquist, B. A., & Hijmans, R. J. (2020). Satellite-based observations reveal effects of weather variation on rice phenology. Remote Sensing, 12(10), 1573.

Wang, M. et al. (2022). Mapping Paddy Rice Phenology with Sentinel-1 SAR. Open Geosciences, 14(1), 414–428.

Wang, M., Wang, J., Chen, L., & Du, Z. (2022). Mapping paddy rice and rice phenology with Sentinel-1 SAR time series using a unified dynamic programming framework. Open Geosciences, 14(1), 414–428.

Wilhite, D. A., & Glantz, M. H. (1985). Understanding the drought phenomenon: The role of definitions. Water International, 10(3), 111–120.

World Meteorological Organization (WMO). (2016). Vegetation indices: A review of current methods for vegetation monitoring using Earth Observation data (WMO-No. 1173). Geneva, Switzerland: WMO.

World Meteorological Organization (WMO). (2020). Vegetation indices and their use in drought monitoring. WMO-No. 1173.

Zhang, J., Wu, H., Zhang, Z., Zhang, L., Luo, Y., Han, J., & Tao, F. (2022). Asian rice calendar dynamics detected by remote sensing and their climate drivers. Remote Sensing, 14(17), 4189.