WITHIN-SEASON CROP TYPE MAPPING BASED ON THE TIME SERIES OF SENTINEL-1, SENTINEL-2, WEATHER, AND HISTORICAL CROPLAND DATA

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ABSTRACT

Crop classification in remote sensing faces challenges due to limited ground truth labels. However, incorporating historical ground information can help to overcome these challenges. By utilising data from previous seasons or years, classification accuracy can be improved, and the need for costly and time-consuming ground truth data collection can be reduced. Integrating historical information also enables early and in-season mapping, which aids in making pre-harvest decisions.

In this study, within-season crop type mapping was performed by using Sentinel-1 and Sentinel-2 data, historical cropland data together with weather data in the province of Flevoland, Netherlands. The objectives of this study were to explore the influence of weather conditions, satellite sensor characteristics, and temporal shifts on crop dynamics and phenological metrics when historical cropland data is used to train the model and to determine the optimal temporal window for accurate crop classification.

Analysis of phenological metrics derived from both Sentinel-1 (C-band Synthetic Aperture Radar) and Sentinel-2 (multispectral optical) data was conducted. The results revealed distinct patterns and variations in phenological metrics for different crop types. Sentinel-1 data exhibited an advantage in detecting early signs of vegetation growth, attributed to its all-weather capability, as it can capture data regardless of weather conditions, including cloudy or rainy periods. On the other hand, Sentinel-2 data relied on sunlight and was limited by cloud cover during cloudy periods.

The integration of weather parameters, particularly temperature, and precipitation, played a significant role in understanding inter-annual variations in estimated phenology. Warmer conditions were associated with earlier detection of phenological phases, while wet conditions caused delays in reaching phenological stages. Furthermore, this study highlighted the differences between Sentinel-1's backscatter (CR) and Sentinel-2's spectral reflectance normalised difference vegetation index (NDVI) values for various crops emphasising the importance of considering both optical and SAR data for comprehensive vegetation analysis.

Thermal time was introduced as a parameter to mitigate the impact of temporal shifts of crop dynamics caused by weather variability. By aligning thermal time values across different years, refined feature space that enhanced the accuracy of within-season crop type mapping was achieved. June emerged as the optimal temporal window for model performance, although certain crops exhibited early discernibility as early as April. Crop rotation practices influenced growth patterns and phenological stages, which in turn affected classification accuracy.

This study provides valuable insights into within-season crop type mapping and highlights the significance of integrating multiple data sources namely, Sentinel-1, Sentinel-2, weather parameters, and thermal time for accurate and robust crop classification. The findings offer valuable information for stakeholders in agriculture, enabling timely and reliable monitoring of crop types in the region. Continued research in this field will further advance agricultural monitoring and management, ultimately contributing to improved food security and sustainable agricultural practices.

Keywords: crop type mapping, phenological metrics, Sentinel-1, Sentinel-2, synthetic aperture radar (SAR), optical data, weather condition, thermal time, Flevoland, Netherlands.

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1. Introduction

1.1 Background

The global population is rapidly increasing, leading to heightened demand for food production worldwide. This escalating demand places significant pressure on agricultural cultivation to meet the needs of a growing population (Calicioglu et al., 2019).(Schlund & Erasmi, 2020) However, the importance of sustainable agricultural practices cannot be overstated. It is no longer sufficient for agriculture to solely focus on increasing food production; it must also address the critical objectives of biodiversity conservation, maintenance of material cycles, and provision of essential ecosystem services.

Sustainable agriculture aims to strike a delicate balance between meeting the demand for food and protecting the environment (James, 2006; Lafferty, 2015). Minimising the environmental impact of agricultural practices is essential for mitigating ecological degradation, reducing resource depletion, and preserving the integrity of ecosystems. By adopting sustainable farming techniques, farmers can ensure the longevity of their land and mitigate potential negative consequences associated with intensive agricultural production(Foley et al., 2005). Furthermore, as the planet faces evolving environmental conditions, such as climate change and resource scarcity, it becomes imperative for agricultural practices to adapt. Climate change poses challenges such as altered precipitation patterns, increased frequency of extreme weather events, and shifting temperature regimes. These changes necessitate the development and implementation of adaptive measures within agricultural systems to ensure their resilience and productivity in the face of uncertainty. Through the integration of sustainable farming practices and adaptation to changing environmental conditions, crop type mapping serves as a valuable tool for addressing the challenges of global food insecurity.

Accurate information about the types of crops grown, their respective planting times, and locations is crucial for assessing crop production variability and identifying the spatial distribution patterns that correspond to different agricultural areas and crop types. (Zhang et al., 2020). Early crop type mapping is particularly significant in today's farming system monitoring. It allows for timely assessment of crop types during the growing season, enabling proactive management and improvement of farming practices. By mapping crop types at different stages of growth, farmers can make informed decisions regarding irrigation, fertilisation, pest control. This information helps to ensure that crops receive the necessary care and resources at the right time, leading to enhanced productivity. Studies conducted by Zhang et al.(2020), Lin et al. (2022), and Yaramasu et al. (2020) emphasise the importance of accurate crop type mapping in assessing crop production variability, identifying early crop health conditions, and determining specific nutrient requirements. Foerster et al. (2012) and Lin et al.(2022) further highlighted the significance of within-season crop mapping for effective farming system monitoring.

Remote sensing has shown the potential to be a significant information source for crop type mapping as a result of its ability to provide extensive coverage, timely data collection, fast updating, and dynamic data collection (Z. Lin et al., 2022; H. Zhang et al., 2020). Remote sensing provides better spatial resolution and sample frequency, making it much easier to analyse and evaluate cropland's level and condition than traditional in-situ measurements (Chauhan et al., 2019; Foerster et al., 2012). High spatial resolution data can be utilised to perform crop type mapping at a country, continental or global scale. For instance, Sentinel-2 data acquired at 10 m spatial resolution was used for agricultural mapping in Europe (Defourny et al., 2019), Africa (Jin et al., 2019), and Asia (Yi et al., 2020). Sentinel-1 and Sentinel-2 have a high temporal resolution of 5-6 days of revisiting time, thus opening new opportunities for capturing agricultural dynamics through multi-temporal classification techniques (Bargiel, 2017; Clevers et al., 2017).

Several studies have been conducted to explore the timeliness of crop mapping using remote sensing data. These studies have demonstrated the potential of these sensors in providing timely and accurate information for crop mapping purposes. For instance, Blickensdörfer et al. (2022) utilised time series data from Landsat-8 and Sentinel-2, combined with environmental data, to achieve accurate crop type mapping in Germany with overall accuracies between 78% and 80%. In addition, Orynbaikyzy et al. (2022) evaluated the transferability of Random Forest models (RF) for crop type mapping in Germany, their findings showed that the integration of SAR-Optical data improved accuracy and timeliness of crop mapping. Kussul et al. (2018) demonstrated the timeliness advantage of Sentinel-1 (SAR) data in Ukraine, where dense cloud cover impaired the clarity of optical data (Sentinel-2) during within-season crop type mapping. Their findings highlighted that SAR data performed well during early stages of crop growth when obtaining clear optical data was challenging.

Moreover, the integration of Landsat and Sentinel-2 data has shown promise in enhancing the timeliness and accuracy of crop mapping. Johnson & Mueller. (2021) integrated the Cropland Data Layer with a full season's worth of Sentinel-2 and Landsat imagery, achieving improved crop type mapping accuracy in the Great Plains regions and the Corn Belt of the United States. Zhang et al., (2022) utilised Sentinel-2 data and the Cropland Data Layer for within-season crop mapping in the Mississippi Delta area, demonstrating the relevance and scalability of timely crop mapping over a large geographical extent.

Despite the progress made in crop type mapping, research gaps still exist. Limited studies have been conducted for within-crop type mapping, particularly in Europe, and the incorporation of meteorological data remains underexplored.

This study aims to address these gaps by leveraging historical cropland data, Sentinel-1, Sentinel-2, and weather data to enhance the accuracy and applicability of within-season crop type mapping in Flevoland, Netherlands. The findings of this research will contribute to agricultural management practices in the region, providing valuable insights for decision-making processes, crop yield assessments, and sustainable farming practices.

1.2 Problem Statement

Today's crop commodities markets in developed nations like the Netherlands rely on within-season forecasts of planting progress, crop conditions, and anticipated yields. However, this process is fraught with uncertainty during the growing season because the most precise field-level planting information is currently mostly made public after the end of harvesting period (Hao et al., 2018; Whitcraft et al., 2015; Zhong et al., 2016). Furthermore, the classification of crop types utilising remote sensing technologies is a challenging task due to the natural features of most agriculture areas, such as crop rotation and seasonal variations in crop morphology (Dey et al., 2020). Optical sensors have shown a significant application for crop type mapping and agriculture land use monitoring due to their reflectance measurement in the near-infrared and visible range from targets in the electromagnetic spectrum (Shang et al., 2022). Sentinel-2 A/B imaging offers better potential for enhancing crop type classification over heterogeneous agricultural land due to its higher spatial, temporal, and spectral resolution over other optical sensors (Fernández-Manso et al., 2016; Ienco et al., 2019). However, previous studies have revealed the issue of optical data discontinuity during critical growth stages of crops when cloud cover is present (Beamish et al., 2020; McNairn & Shang, 2016). But it is still difficult to effectively identify between crop types using simply spectral information, especially for crop types with similar vegetative growth stages. SAR as an active sensor was employed to address the issue of cloud cover during relevant growth stages (Beamish et al., 2020; Shang et al., 2022). Due to SAR's capacity to penetrate through clouds, cover a large area, and generates its own power to illuminate ground targets, it can collect high-resolution earth observation data at any moment of day or night and practically all-weather conditions (Nasirzadehdizaji et al., 2019). Furthermore, SAR is able to obtain precise information about crops as it is sensitive to crop structure (S. Gao et al., 2013). Sentinel-1 and Sentinel-2 have proven to be effective, and potentially can meet the different observational needs when used to monitor land related activities. But it is not yet known which sensor can perform well in crop type mapping. Previous studies have proven the significance of optical and radar sensors independently for crop-type mapping (Defourny et al., 2019; Ofori-Ampofo et al., 2021). However, integrating data from two sensors can result in better performance compared to the use of only one sensor. Since optical and SAR sensors use distinct data-gathering approaches, the combined data from both can improve discrimination between targets based on reflectance and, structural or moisture characteristics. This is demonstrated by research on crop mapping, urban mapping, and grassland monitoring conducted by (Ienco et al., 2019; Ofori-Ampofo et al., 2021; J. Wang et al., 2020). Furthermore, the issue of incomplete data resulting from the presence of cloud in time series of satellite images can be solved by data fusion (Pohl & Van Genderen, 2010). Additionally, Veloso et al. (2017) and Blickensdörfer et al. (2022) in their studies have shown the importance of data fusion of optical sensors with SAR in crop-type mapping, but there is still few studies that use data fusion of optical sensors (Sentinel-2) and SAR for within-season crop-type mapping in the Netherlands. Furthermore, classification techniques used to produce good-quality crop maps require sufficient ground truth data. However, the acquisition of data requires a lot of time, labour, and money to be collected, which becomes a limitation (C. Zhang et al., 2022). This shows a need of preparing a ground truth dataset from historical cropland data that can be re-adapted to the current year as a solution for reducing cost, labour, and time taken to collect ground truth data.

Previous studies have explored various methods to map crop types within a target year when limited or no ground truth information are available (Cai et al., 2018; Hao et al., 2017; Johnson & Mueller, 2021; Konduri et al., 2020; Waldner et al., 2015; S. Wang et al., 2019). One approach that has been widely used is the utilisation of historical cropland data to train a classifier, which can then be applied to the target year. This method, commonly referred to as "decision boundary-based approach," aim to transfer decision boundaries learned from historical years to classify the target year's data. By training the classifier with historical labels and leveraging the knowledge gained from past observations, this approach enable the estimation of crop types in the absence of ground truth information (Xu et al., 2021; Yaramasu et al., 2020b; You & Dong, 2020; C. Zhang et al., 2021; Zhong et al., 2014). The utilisation of historical data for crop type mapping presents certain challenges and errors due to the variability in crop patterns and spectral features between the historical and target years. These variations can arise from factors such as weather condition variability and crop phenology. Ghazaryan et al.(2018) and Lin et al.(2022) in their studies have confirmed the challenges posed by inter-annual variations in crop growth patterns due to weather conditions. They observed that variations in temperature, precipitation, and sunlight between different years can lead to changes in the spectral response of crops. These variations make it challenging to directly transfer decision boundaries or spectral signatures from historical years to the target year. Also Johnson & Mueller. (2021) and C. Zhang et al. (2021) in their studies showed that while performing within season crop type mapping, using long and simple rotation patterns perform well but it can only be used in a specific area. Additionally, a study by C. Lin et al. (2022) demonstrated the ability to identify crop types early in the season without relying on current-year data as a reference. They achieved this by generating labels from historical data using a topology-based method, which helped reduce the impact of intra and inter-annual variability. The study noted that their approach was not sensitive to crops that exhibited consistent behaviour across different topology features.

The main challenges found to perform the within-season crop type mapping task are:

- There are still few studies that address within-season crop type mapping considering both optical Sentinel-2 data and SAR Sentinel-1 data.
- Although the integration of Sentinel-1 data can mitigate the cloud coverage problem that affects the optical Sentinel-2 data, it is not yet known which crop can be discriminated, when it can be discriminated, and with which sensor (Sentinel-1 and Sentinel-2).

- Using historical cropland data could result in major errors, mainly if cropping patterns and weather conditions shift from one year to another.

1.3 The novelty of the study

- To understand the optimal approach using Sentinel-1, Sentinel-2, or a combination of both data to perform within-season crop type mapping.
- To investigate the reasons behind the potential lack of representativeness of historical cropland data for the target year, attributed to variations in crop phenology and weather conditions.
- To leverage multiple years of historical crop data and weather data to establish a database of phenological trends for different crops with good generalization capabilities.
- To define the novel approach of combining data of Sentinel-1, Sentinel-2, weather data, and historical Cropland data to perform within season crop type mapping in Flevoland.

1.4 Research Objectives

Main Objective

The main objective of this study is to analyse the capability of using Sentinel-1 (SAR-temporal backscatter data), Sentinel-2, weather data and cropland historical data to perform within-season crop type mapping.

Specific objectives

1. Explore the temporal behaviour of SAR backscatter (Vertical- Horizontal (VH), Vertical- Vertical (VV), and VV/VH ratio) and spectral reflectance of Sentinel-2 for different crop types for multiple years.
2. Investigate the best feature space (time invariant) to create a training data set using the historical cropland data that is representative of the target year leveraging crop calendar and weather data information.
3. Determine the optimal temporal window that effectively captures the essential phenological stages for each crop type within the season.
4. Determine the relevance of Sentinel-1, Sentinel-2, and their fusion to enhance in-season crop type classification.

1.5 Research Questions and Hypothesis

1. What is the crop-specific temporal profiles recorded by Sentinel-1 and Sentinel-2 in the considered study area for different years?

Ho: In the study area, there is no variability of crop-specific temporal behaviour from Sentinel-1 and Sentinel-2.

2. What is the most effective approach for creating a time-invariant feature space using historical data, crop calendar information, and weather data to construct a representative training dataset for a specific target year?

Ho: There is no significant difference in the effectiveness of different approaches for creating a time-invariant feature space using historical data, crop calendar information, and weather data to construct a representative training dataset for a specific target year

3. Which temporal window can optimally capture the essential phenological stages per crop type to generate accurate within season crop type mapping?

Ho: There is no phenological stage that can be identified in a temporal window.

4. Does within-season crop type mapping with the integration of Sentinel-1 and Sentinel-2 data perform better than utilising only SAR or optical features?

Ho: Sentinel-1 and Sentinel-2 features together do not improve on employing either SAR or only optical features for in-season crop-type mapping.

2. Study Area and Dataset Description

2.1. Study area

2.1.1. Location

The study area is Flevoland, established in 1986, which is a relatively young province in the Netherlands located in the central part of the country. It occupies the area that was previously the Zuiderzee Bay, a body of water. Geographically, Flevoland is situated between 52°32' North latitude and 5°40' East longitude. One notable characteristic of Flevoland is its low-lying position, with its average elevation about 5 meters below sea level.

Figure 2.1 shows the 5 municipalities of Flevoland, which is divided into three distinct regions: Noordoostpolder, Eastern Flevoland, and Southern Flevoland. Noordoostpolder comprises the municipalities of Noordoostpolder and Urk, while Eastern Flevoland includes Lelystad and Dronten. The municipalities of Almere and Zeewolde fall under Southern Flevoland.

With its predominantly flat terrain, Flevoland is primarily an agricultural region, known for its fertile soil. It offers favourable conditions for farming and crop cultivation. Notably, the province has witnessed extensive land reclamation efforts, creating new land areas. This development has resulted in the establishment of Almere, a modern city within Flevoland.

The figure 2.1 provides a visual representation of the distribution of municipalities within Flevoland, highlighting the spatial layout of the province.

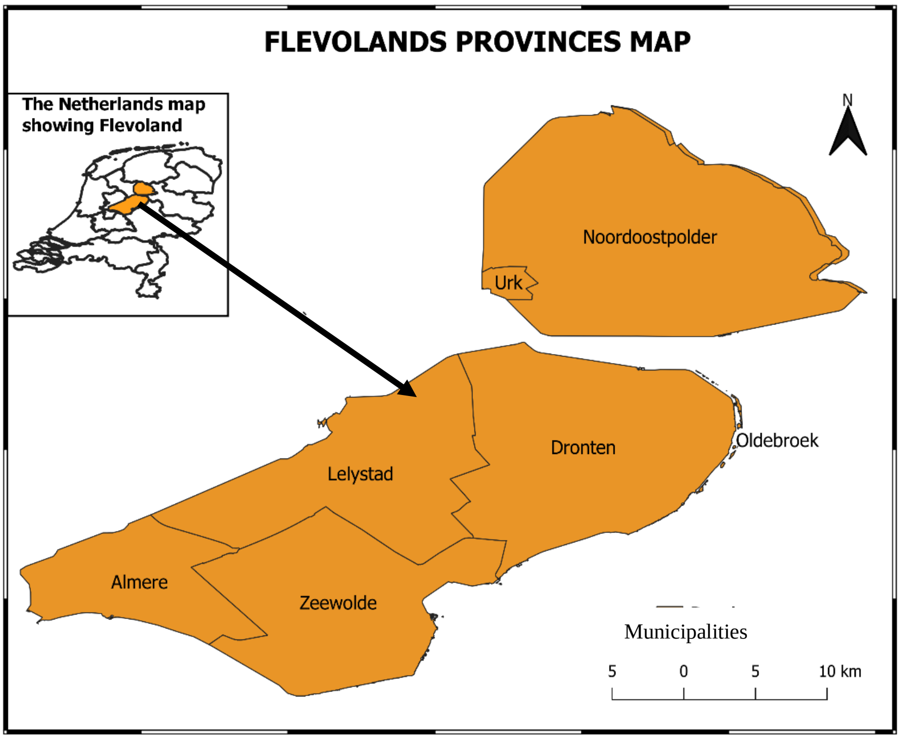


Figure 2.1 Flevoland province map and its 5 municipalities.

2.1.2. Weather condition in Flevoland

Flevoland, a province in the Netherlands, exhibits a temperate climate with distinct seasonal variations. The region experiences four seasons: summer, autumn, winter, and spring. The proximity of Flevoland to Lake IJssel influences its climate, resulting in smaller temperature differences compared to other parts of the country.

During the summer months of July and August, Flevoland sees average temperatures ranging between 20°C and 25°C. This period represents the warmest time of the year in the province. In contrast, the coldest temperatures occur in January and February, with average minimum temperatures varying between 0°C and 2°C. These colder months are accompanied by a decrease in both the minimum and maximum temperatures.

The annual maximum temperatures in Flevoland generally range from 14°C to 16°C, while the annual minimum temperatures range from 5°C to 7°C. These temperature ranges provide an overview of the typical climate in the region throughout the year.

In terms of precipitation, Flevoland receives an average annual rainfall which varies between 700 mm and 800 mm. The driest month is April, with an average rainfall of only 37 mm. This indicates that April experiences significantly less precipitation compared to other months. The weather conditions over a four-years period from 2018 to 2021, were visualised by using bar chart as it is shown on figure 2.2.

Figure 2.2 presents Monthly weather parameters recorded in Flevoland for the year 2018. The Minimum-Temperature, Maximum Temperature, and monthly Precipitation are reported.

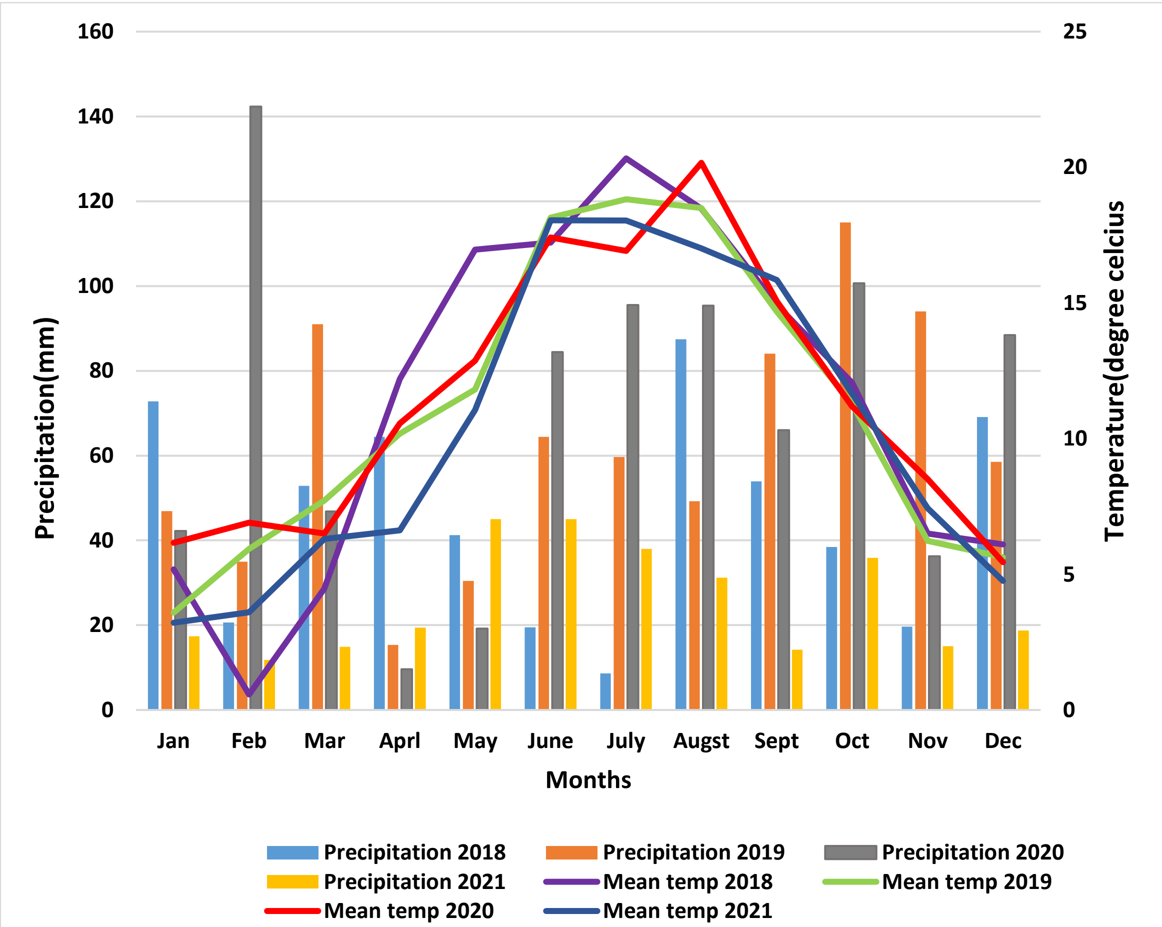


Figure 2.2: Weather data for four years, 2018, 2019, 2020 and 2021 in Flevoland

2.1.3. Agriculture in Flevoland

Flevoland was established to increase agricultural land and mitigate the risk of flooding in the Netherlands. During Second World War, the first farmers moved into the Noordoostpolder region of the newest province. The province was originally intended to serve as a zone for optimal agricultural development. It was able to establish huge, specialised farms because of the availability of water, strong infrastructure, and large, rectangular parcels of land. As a result, Flevoland has favourable agricultural production conditions. Agriculture is important for development and spatial planning in Flevoland. In 2012, Approximately 75% of the land in the province was used for agriculture (Mandryk et al., 2012). In Flevoland, agriculture accounts 6% of employment and 5.5% of the region's gross regional product (means that in 2007 for The Netherlands, these statistics were 1.8 and 3%, respectively) (Mandryk et al., 2012). Arable farming is the most common farm form, accounting 70% of the total farm population and occupying 65% of available agricultural land (Mandryk et al., 2012). Due to urbanisation, the increase of infrastructure, and the creation of natural areas, agricultural land has been reduced during the previous few decades.

As this province is known as the centre of Agriculture in the Netherlands, different crops are grown in this region. This study will focus on the predominant crop types present in Flevoland, such as Potato, corn, Summer Barley, Summer Wheat, Winter Barley, and Winter Wheat. The average field size observed was 5.55 hectares (ha), with the smallest field measuring 0.05 ha and the largest field measuring 28.78 ha. The total area covered by target crop is 35402.92 hectares, which is the 24 % of total area of hall province of Flevoland. The Area of Flevoland is approximately to be 146803.73 hectares. Table 2.1 shows the crop calendar for the main targeted crops, by highlighting their growing season for different phenological stages.

Table 2.1:Crop calendar for the main crops present in Flevoland.

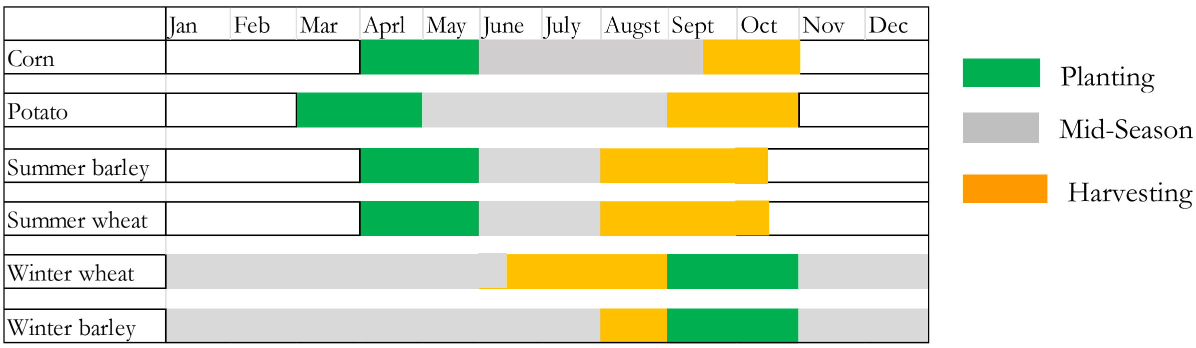


Figure 2.3 provides an overview of the Dutch province of Flevoland, showcasing the spatial distribution of six crop types considered in the year 2020. Flevoland is renowned for its diverse agricultural landscape, and the figure highlights the specific locations and patterns of different crops cultivated within the province. Among these crops, potatoes were found to be the dominant crop, followed by winter wheat in comparison to others. Conversely, summer wheat and summer wheat appeared to be less prevalent in the province.

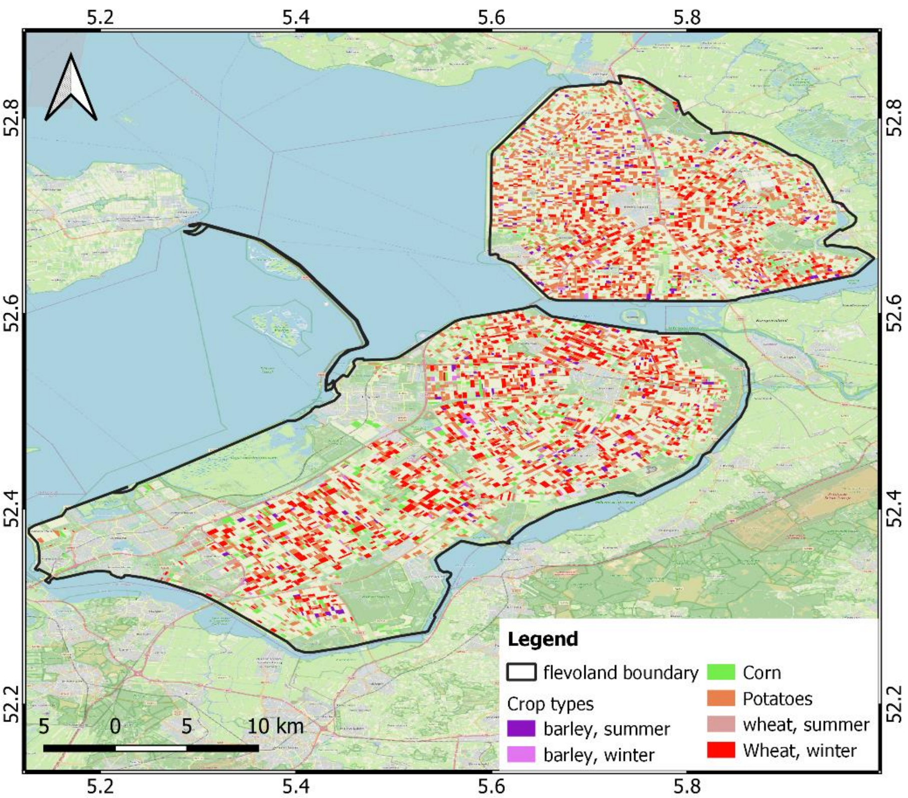


Figure 2.3:Spatial distribution of 6 crops type considered in this study and located in Flevoland for the year 2020.

2.2 Dataset Description

Table 2.2 provides an overview of the datasets employed in the study, highlighting the specific parameters and their respective years. In the following sections, details are given for each data source.

Table 2.2:Selected data to be used in this research study.

Data	Source	Spatial resolution	Date	Type	Reference
Historical cropland data	BRP	-	2018-2021	farmer-based declaration	https://ser-vice.pdok.nl/rvo/brpgewasper-celen/atom/v1_0/ba-sisregistratie_gewasper-celen_brp.xml
Sentinel-1	ESA	10m	2018-2021	SAR	https://develop-ers.google.com/earth-en-gine/datasets/cata-log/COPERNI-CUS_S1_GRD
Sentinel-2	ESA	10m	2018-2021	Optical	https://develop-ers.google.com/earth-en-gine/datasets/cata-log/COPERNI-CUS_S2_SR_HARMO-NIZED
Weather data	KNMI		2018-2021	In-situ	KNMI - Daily weather data in the Netherlands

2.2.1 Cropland reference data

To generate the reference cropland data used for training and validating the results obtained, this study took advantage of the public availability of the Basic Register of Parcel (BRP) databases. In the Netherlands, the BRP offers publicly accessible crop-specific land cover data sets that are updated annually and based on farmer's declaration. Indeed, the crop parcels' owners have the responsibility of registering their agricultural parcels each year and provide information regarding the crops grown in those parcels. This ensures that the data used in the study is up-to-date and reflective of the current agricultural landscape. By leveraging the BRP, researchers can accurately determine the precise locations of farmland and the corresponding crop type for a specific year. For this study, the BRP data were downloaded to represent the spatial distribution of the crop types that were present in Flevoland in the years of 2018, 2019, 2020 and 2021. Since these data are provided by the Netherlands Enterprise Agency, they can be considered a reliable and accurate source of information.

To define the boundaries of the farms, the Agricultural Area of the Netherlands (AAN) dataset was utilised. This dataset provides essential information for mapping out the extents of agricultural land. The AAN dataset provides information or spatial data regarding the agricultural areas or boundaries within the Netherlands, which is used to establish the boundaries of the individual agricultural plots.

For the visualisation of shapefiles, this study used QGIS, a widely adopted free and open-source Geographic Information System (GIS) program. The cropland maps were used to generate the reference labelled data used to train, test, and validate the experiment carried out in this study. The table 3 shows the total number of fields across the years in Flevoland whereby Potato showed to be a dominant crop among other crops. The table 2.3 shows the total number of fields per crop type found in Flevoland over the year 2018 up to 2021.

Table 2.3: The number of fields of each targeted crop in Flevoland present in 2018, 2019, 2020 and 2021.

Crop type	Number of fields			
	2021	2020	2019	2018
Potato	3099	3581	3154	3196
Summer Barley	255	396	199	313
Winter Barley	135	102	111	72
Corn	596	688	589	622
Summer wheat	253	335	129	315
Winter Wheat	1652	1679	1739	1595
TOTAL	5990	6800	5944	6119

2.2.2 Sentinel-1 SAR data

Sentinel-1 Synthetic Aperture Radar (SAR) images have been widely used for agricultural monitoring because of their high temporal density (6-day revisit interval) and spatial resolution in (10 m). This study utilised SAR time series images acquired from Sentinel-1, with a revisit time of 6 days, to cover the growing seasons of 2018, 2019, 2020, and 2021. Pre-processing steps, including range-doppler terrain correction, multi-looking, data calibration, and thermal noise removal, were performed through Google Earth Engine (GEE) to ensure data suitability and maintain measurement accuracy.

To conduct a comprehensive analysis, the study employed the interferometric wide swath mode in combination with dual polarisation. Specifically, the vertical transmission/vertical reception (VV) and vertical transmission/horizontal reception (VH) combinations were utilized. GEE served as the platform for handling large datasets and facilitating efficient data management and analysis. GEE offered access to pre-processed Sentinel-1 backscatter images shortly after their acquisition. The "COPERNICUS/S1 Ground Range Detected" image collection in GEE was utilised to access the SAR data with a spatial resolution of 10 meters. This collection provided the necessary tools for processing and analysing the Sentinel-1 data. Ground Range Detected (GRD) products derived from SAR data that had undergone detection, multi-looking, and projection to surface range using the WGS84 Earth ellipsoid model. The cross-ratio of VV and VH backscatter coefficients derived from the Sentinel-1 SAR data were used in this study to extract SAR-based phenological metrics for each crop.

In addition, the cross-ratio derived from the VV and VH backscatter coefficients was not only used to extract phenological metrics but also played a crucial role in the classification process itself. The cross-ratio was utilised as a feature in conjunction with other relevant data.

2.2.3 Sentinel-2 Multispectral Data

This study employed Sentinel-2, a multi-spectral imaging sensor operated by the European Space Agency, for crop-type mapping. This sensor offered wide-swath, high-resolution imagery with a revisit time of every 5 days (Adrian et al., 2021). Thirteen reflectance bands covering visible, near-infrared (NIR), and short-wave infrared (SWIR) spectral ranges were available. Specific bands were selected based on their significance in crop-type mapping (Maponya et al., 2020; H. Zhang et al., 2020), including visible bands (B2, B3, B4) with 10 m resolution, red edge bands (B5, B6, B7) with 20 m resolution, a near-infrared band (B8) with 10 m resolution, and short-wave infrared bands (B11, B12) with 10 m resolution. The study focused on analysing Sentinel-2 imagery acquired between 2018 and 2021 to investigate temporal changes and patterns in the study area.

The analysis of Sentinel-2 data was conducted using the GEE platform. GEE facilitated access to pre-processed Level 2A Bottom of atmosphere (BOA) reflectance Sentinel-2 data from the COPERNICUS/S2_SR_HARMONIZED collection. This collection contained atmospherically corrected data obtained using the Sen2Cor software (Main-Knorn et al., 2017), which incorporated the libRadtran radiative transfer model for aerosol characterisation (Mayer & Kylling, 2005). The collection also provided a cloud mask to distinguish between cloudy and cloud-free pixels, with different types of clouds identified. Images with less than 40% cloud coverage were selected for further processing.

To ensure data consistency, the red edge band was resampled from its original 20 m resolution to a higher resolution of 10 m using a cubic interpolation approach, where the values within each new pixel were averaged. By aligning the spectral information of the red edge band with the other bands, the spatial resolution throughout the dataset remained consistent. Afterward, a mosaic was generated by combining all the selected images and monthly composites. The average value compositing technique was employed for this purpose. This technique calculates the pixel value for each band by averaging the corresponding pixels in the individual images or composites. By considering the average values over time, the impact of cloud cover was minimised. Ultimately, this process resulted in the creation of an annual time series composite that was utilised to extract phenological metrics and facilitate crop classification.

2.2.4 Weather data

Weather data plays a crucial role in understanding the impact of weather changes on the physical and temporal behaviour of crops. In this study, different weather parameters such as precipitation and temperature were examined to investigate these effects. The weather data used in the analysis were obtained from the Lelystad ground weather station, located in Flevoland. This specific station was selected to accurately represent the weather conditions in the study region under investigation.

By focusing on a single ground weather station, the study can capture localised weather variations that directly influence the growth and development of crops in the region. The weather data were downloaded from KNMI, the authoritative source for daily weather data in the Netherlands.

The weather data were utilised to assess crop development by quantifying the thermal time experienced by crops using Growing Degree Days (GDD). Additionally, precipitation data were employed to understand the influence of weather conditions on crop phenology.

By integrating weather data into the analysis, this study aimed to gain insights into the relationship between weather changes and the observed phenological behaviour of crops recorded by Sentinel-1 and Sentinel-2.

3. Methods

Figure 2 and Figure 3 present the flowcharts of the two main phases of the proposed workflow. The first part of flowchart explains how the cropland data of year 2018-2020 were prepared to generate training and validation datasets (Objective 1 and Objective 2). The second part of flowchart reports the steps carried out to generate the in-season crop type mapping approach (Objective 3 and Objective 4).

Flowchart

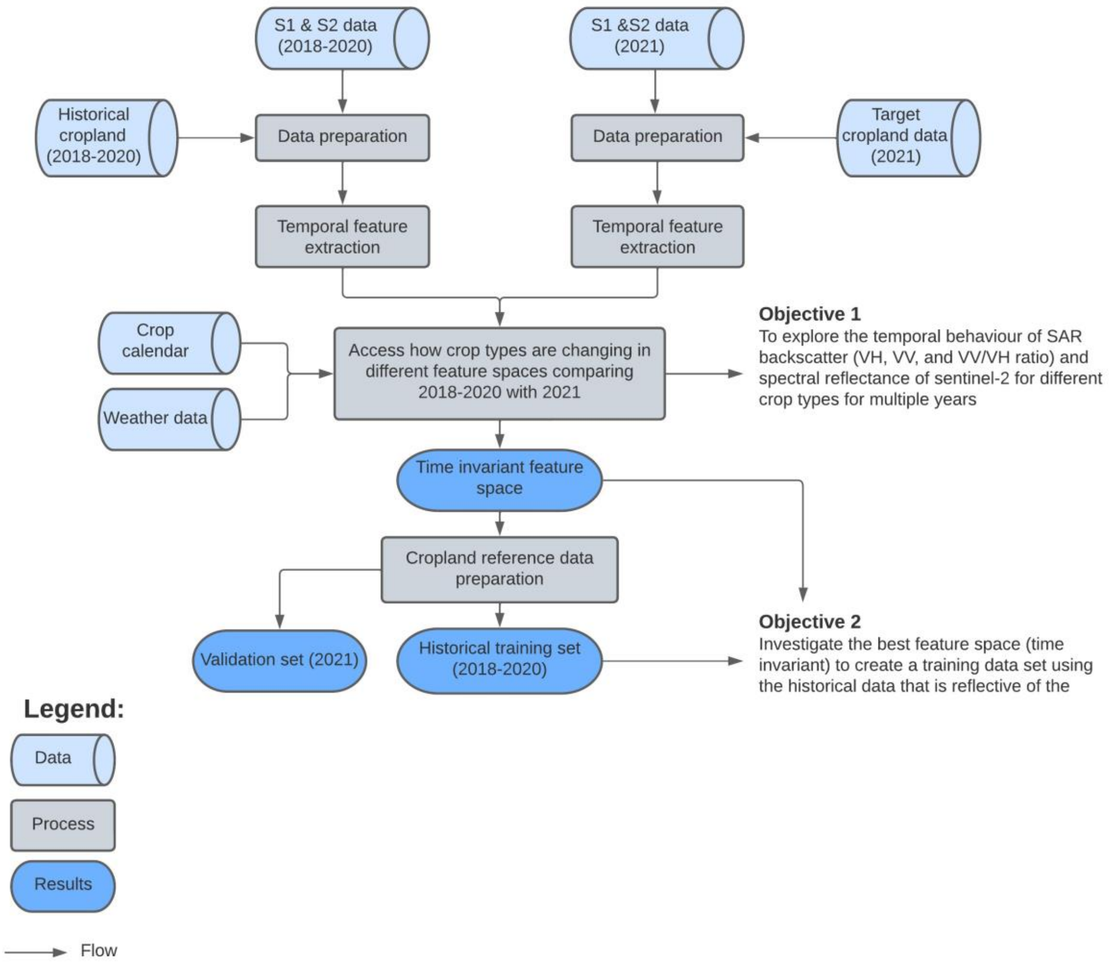


Figure 3.1:Flowchart part1 reporting how the: (1) temporal behaviour of the targeted crops was extracted, and (2) training and validation data set to be used for classification were created.

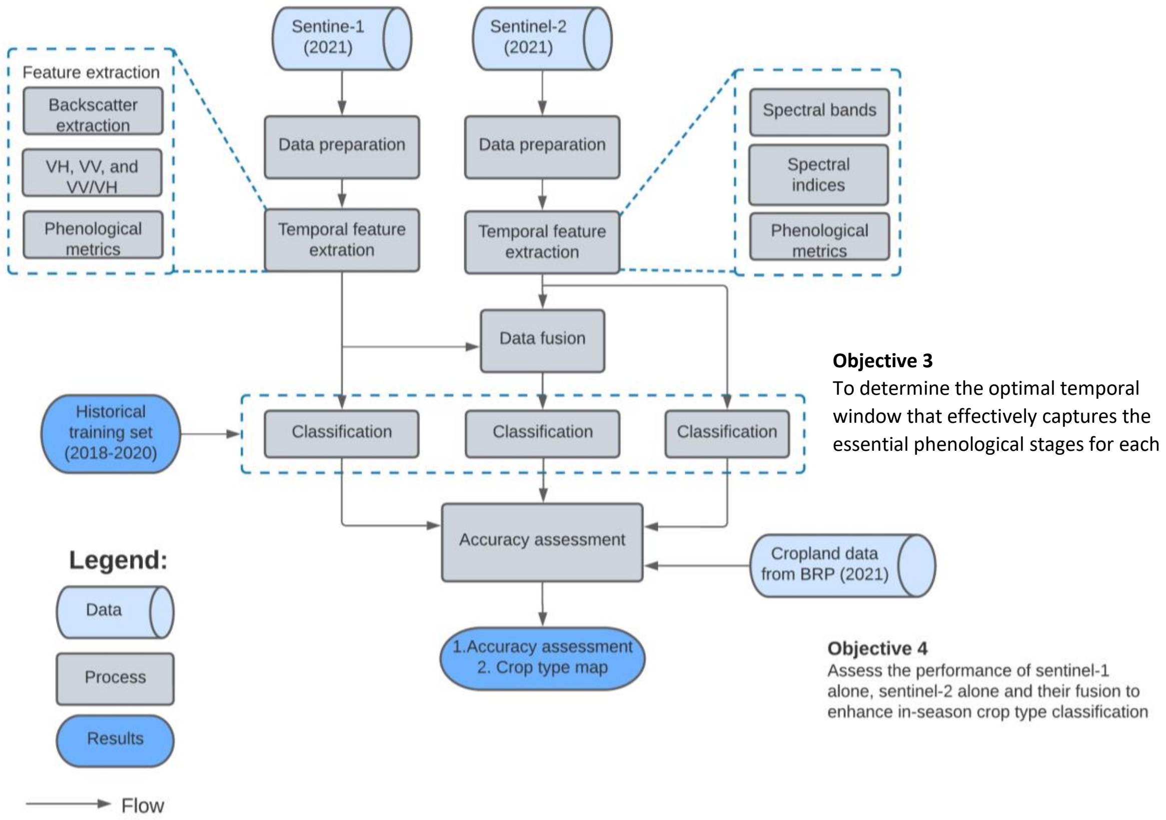


Figure 3.2:Flowchart part 2 representing the crop type classification process implemented to generate the crop map for 2021.

3.1. Data Preparation

Both Sentinel-1 and Sentinel-2 satellites offer frequent acquisitions with a revisit time of approximately 5 days, allowing for regular monitoring of crop phenology. However, cloud coverage often leads to the exclusion of some Sentinel-2 images, necessitating the use of interpolation techniques to fill in the gaps. For interpolating missing data in a time series dataset, dates were converted into day, month, and year components using the strsplit function. Then, it converted the dates to a numerical format represented as the number of days from the start of the year. Finer grids were created by specifying a step value, this creates a more granular time grid for interpolation purposes.

The original dates and the finer grid dates were scaled between 0 and 1 using min-max normalisation. This normalisation ensures that the interpolated data remains within the range of the original data. The min-max normalisation was performed separately for each variable, such as b2, b4, etc.

To interpolate missing values in the data, a loop was used. First, any missing values in the variable were replaced with zeros. This step is necessary as some interpolation methods cannot handle missing values directly. Then, the inpaintCoherent function was applied to estimate the missing values based on the surrounding data points. The inpaintCoherent function was a method used for coherent data inpainting, which fills in missing values in a way that maintains the coherence and smoothness of the data.

After estimating the missing values, the interp1 function is used to interpolate the data from the original dates to a finer grid of dates. The finer grid is obtained by defining a step size (in this case, it is set to 6). Linear interpolation is employed to estimate the values between the original dates based on the available data points. This interpolation process enables the generation of a continuous and spatially explicit representation of variables of interest in the Sentinel-2 data.

To improve data quality in this study, the selection of an appropriate smoothing method is critical. Two commonly used methods, Gaussian and Savitzky-Golay (SGolay), were evaluated for their performance in pre-processing the time series of Sentinel-2 data per crop type. Results show that both methods effectively reduce noise and enhance data quality. However, after careful evaluation and comparison, it was found that the Gaussian smoothing method outperforms the SGolay method in preserving important spatial features and maintaining overall data integrity (see Figure 3 and Figure 3.4). Consequently, the Gaussian smoothing method was chosen as the most suitable approach.

The smoothing operation involved applying a Gaussian filter to the interpolated data after filling in missing or sparse data points to enhance temporal resolution. The Gaussian filter was selected for its noise suppression capabilities while preserving the general shape of the data. A window size of 11 was specifically chosen to strike a balance between capturing relevant information and smoothing out potential noise or outliers.

Once the data underwent the Gaussian smoothing process, noise was effectively reduced, resulting in a clearer representation of the general trend in the temporal behaviour of different crops. This enhanced visualisation and analysis by emphasising underlying patterns and minimising random fluctuations. Consequently, a more accurate assessment of temporal behaviour was possible, facilitating meaningful comparisons between different crops.

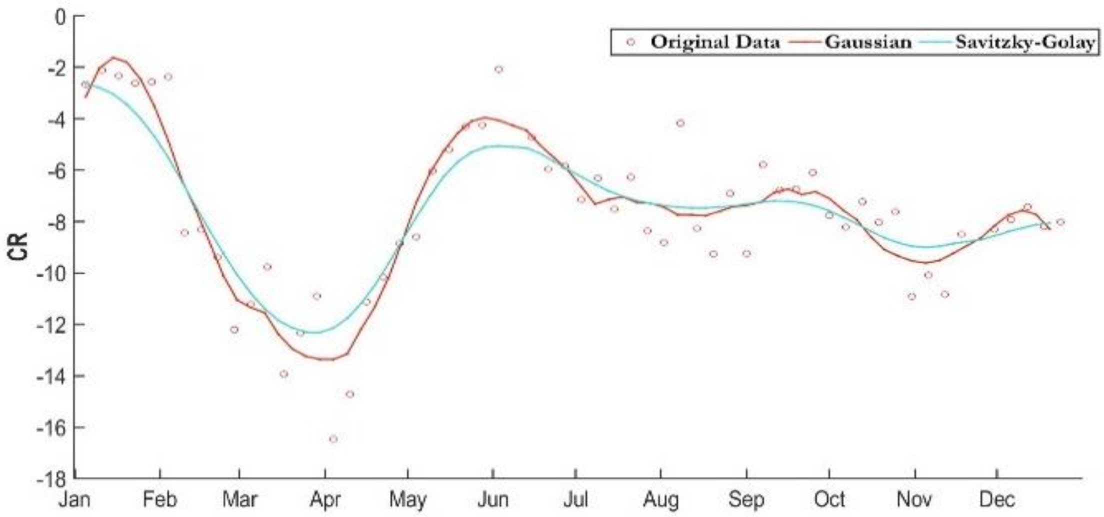


Figure 3.3:Example of median temporal profiles of CR observations for summer wheat with Gaussian and Savitzky-Golay smoothing.

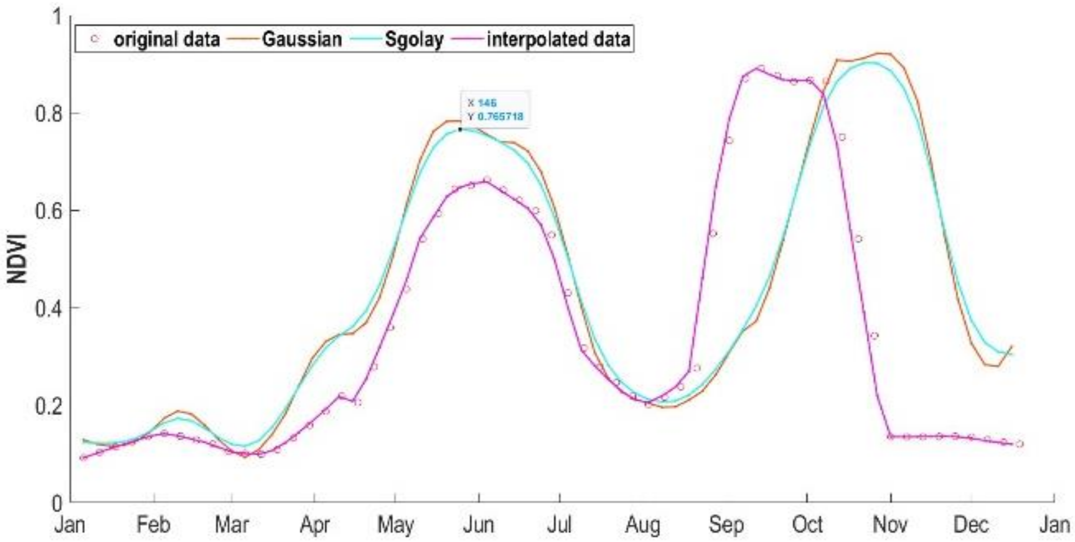


Figure 3.4:Example of median temporal profiles of NDVI observations for summer wheat with Gaussian and Savitzky-Golay smoothing.

3.2. Crop Phenological Metrics

This study focused on vegetation phenology, which examines plant growth and development across seasons. Previous research has shown the value of phenological characteristics in improving crop type mapping accuracy. Using the Google Earth Engine band reflectance and backscatter values were obtained and exported to Excel files. These files were then used in MATLAB to extract phenological metrics from vegetation indices. The process involved deriving measures such as seasonal start, end, and peak. The extracted temporal profiles allowed for evaluating changes in different years due to varying weather conditions and identifying specific crop varieties.

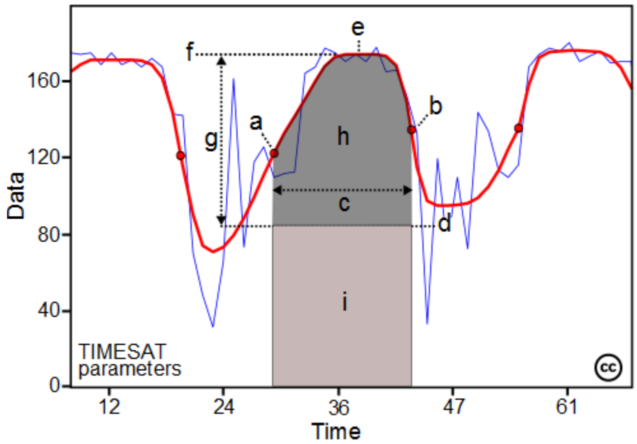


Figure 3.5: Seasonal metrics derived from temporal profile using TIMESAT: (a) start of season, (b) end of season, (c) length of season, (d) base value, (e) time of middle of season, (f) peak value, (g) amplitude, (h) small integrated value, (h þ i) large integrate

The time series of Sentinel-1 and Sentinel-2 data can be used to represent crop growth phenological features by computing vegetation indices. These temporal profiles can be used to collect information on the physiological process of crops from growth and development to maturity and ripeness stages, with variations occurring at different stages of the growth cycle. For this reason, starting of season, peak metrics, and end of season were used to set up a crop calendar at the field level.

The selection and applicability of a vegetation index are often based on its sensitivity to the features of interest and/or its sensitivity to affecting factors (X. Gao et al., 2000). In this study despite NDVI which is the primary vegetation index, and Enhanced vegetation index (EVI) were extracted together with the spectral bands and backscatter (CR, VH, and VV). NDVI together with Cross Ration were used for extracting phenology metrics and for crop classification. Information about NDVI and EVI are summarised in Table 3.1.

Table 3.1:Summary of vegetation indices extracted from the Sentinel-2 time series of images for the considered years.

Abbreviation	Name	Formula	Explanation
NDVI	Normalized Difference Vegetation Index	$NDVI = \frac{NIR - Red}{NIR + Red}$	NDVI is an excellent starting point for understanding crop development during the growing season (Gim et al., 2020).
EVI	Enhanced Vegetation Index	$EVI = \frac{G * (NIR - Red)}{NIR + C1 * Red - C2 * Blue + L}$	EVI is more reliable when applied to crops with a dense canopy or at an advanced growth stage of a vegetation (Huete et al., 2002).

When mapping different crop type, a single spectral indicator like NDVI or EVI may not capture certain crucial phenological stages or define complex crop growth and environmental variables. So, it is important to know how well the different spectral features work for mapping crop types and to figure out if the red edge bands in Sentinel-2 are significant for accurate crop type classification. Table 3.2 shows how red edge indices was calculated.

Table 3.2:Overview of the Red Edge Indices that computed, where B8a is Narrow infrared band and three red-edge bands of vegetation (B5, B6, and B7).

Overview of the Red Edge Indices that computed, where B8a is Narrow infrared band and three red-edge bands of vegetation (B5, B6, and B7).

Vegetation Index	Sentinel-2 Formula
NDVIn1	(B8a - B5)/ (B8a + B5)
NDVIn2	(B8a - B6)/ (B8a + B6)
NDVIn3	(B8a - B7)/ (B8a + B7)

3.3. Calendar Time Feature Space

In the process of remote sensing image classification, constructing an effective feature space is a crucial step that greatly influences the accuracy of the classification results. The selection of informative features plays a vital role in achieving satisfactory classification outcomes. In this study, the feature space for within-season crop type mapping was constructed using Sentinel-1 and Sentinel-2 data, along with the weather and historical cropland data.

To construct the feature space, multiple data sources were utilised. Initially, the original bands from Sentinel-2 imagery were employed which encompass a range of spectral bands capturing electromagnetic radiation across the spectrum. These bands provide valuable spectral signatures that can distinguish different crop types based on their unique reflectance properties.

In this study, the reflectance values from bands 2, 4, 5, 6, 7, 8, 8A, 11, and 12 of Sentinel-2 were combined. This process included concatenating the reflectance values and stacking them vertically, resulting in the creation of a variable representing the combined spectral bands. By assigning class labels to each time series, a labelled time series dataset was generated. This labelled dataset served as the foundation for constructing the feature space specific to the Sentinel-2 data. Moreover, vegetation index (table 3.1 and 3.2) features were extracted from the Sentinel-2 data, supplementing the original bands. These indices were used as an additional feature for classification and discrimination of different crops types.

The incorporation of backscatter values from Sentinel-1 into the analysis involved the creation of a variable through the ratio of VH (vertical transmit, horizontal receive) values to VV (vertical transmit, vertical receive) values. This ratio was computed as an indicator to capture the relationship between the backscatter values. By calculating this ratio, a representative variable that characterises the scattering properties was derived, which played a pivotal role in the analysis. Furthermore, to construct the labelled time series dataset for Sentinel-1, the labels column, and the combined backscatter values were horizontally concatenated. This concatenation process facilitated the integration of the labels representing different crop types with the corresponding backscatter values, resulting in a comprehensive labelled dataset. By incorporating the backscatter information from Sentinel-1, this labelled dataset was used to create feature space for Sentinel-1.

3.4. Thermal Time Feature Space

As the weather condition has a direct influence on the stages of crop growth, it necessitates being considered when assessing the temporal behaviours of crops. The temperature during the growing season is a major factor in determining the rate of crop development, with a maximum rate occurring at an optimal temperature range that varies depending on the crop and stage of development. To analyse crop temporal behaviours, the study adopts the thermal time approach, which quantifies crop development using Growing Degree Days (GDD). Crop thermal time is commonly expressed in terms of GDD, which are calculated by adding up daily average temperatures above a baseline. Since the amount of heat accumulated throughout the growing season significantly affects crop development.

$$GDD = \sum_{i=1}^{t} max \frac{T_{min}^{i} + T_{max}^{i}}{2} - \left(T_{base,0}\right)$$

Where T_{max}^{i} and T_{min}^{i} Th are the minimum and maximum temperatures for day i, accumulated for all the previous days i = 1, 2, ..., t, and T_{base} is temperature base. The temperature must be varied between 0^0C and 30^0C. In this study, the base temperature for all crops was assumed to be zero since the specific crop types were not known. By setting a uniform base temperature, the analysis focuses on the accumulated heat units above this threshold without considering crop-specific temperature requirements. This approach allows for a generalised assessment of crop temporal behaviours based on the thermal time approach using GDD.

By calculating the cumulative thermal time and comparing it across different years, the data were aligned to make it comparable and standardised. This aligning process involves adjusting the values of thermal time to reduce differences between years and enable easier comparison and analysis. The thermal time values were rearranged to reduce differences between years, this is a valid approach to standardise the data. By aligning the values of thermal time for comparable dates across years, the effects of temporal variations were mitigated and make the data more suitable for comparative analysis. This alignment and standardisation process of thermal time data helped to identify patterns, trends, or similarities and differences in crop development across different years in the same region. It provided a consistent basis for crop classification that requires comparative evaluation of thermal time data across multiple years.

Furthermore, the study investigated the relationship between phenological events, such as Start of Season (SOS), Peak of metrics, and End of Season (EOS), and weather conditions. To explore this relationship, a line plot, where the x-axis represents the thermal time and the y-axis represents the median NDVI value for each thermal time interval were used. This type of plot provided a visual representation of the pattern of NDVI values as thermal time progresses. It allowed for a comprehensive understanding of how NDVI behaved in relation to thermal time throughout the growing season. This method assisted in identifying specific crop characteristics, whereby several crops may have the same planting time, development period, and harvesting period during the growing season, but the amount of temperature and precipitation each crop needs to grow is unique, causing them to behave differently. So, the different laws that are based on the characteristics weather of crops can be helpful in determining the period range and classifying the types of crops to some extent.

By incorporating weather data, the thermal time approach, NDVI analysis, assessment, the study aims to provide a comprehensive understanding of crop temporal behaviours. This methodology allows for a deeper exploration of the impact of weather conditions on crop growth and development.

3.5. Sentinel-1 and Sentinel-2 Data fusion

In this study, early fusion was tested and used to determine its effect in crop type mapping. Early fusion combined a common feature vector the Sentinel-2 and Sentinel-1 features before performing the classification.

To perform early fusion, the three datasets (Sentinel-1, Sentinel-2, and Vegetation Indices) were combined by vertically concatenating their respective matrices. This was achieved using the **vertcat** function, which merges the matrices together in a vertical manner. The resulting matrix, referred to as the combined dataset, contains rows that represent individual samples or observations. By vertically concatenating the datasets, the information from Sentinel-1 (radar backscatter measurements), Sentinel-2 (multispectral imagery), and Vegetation Indices were integrated into a single unified dataset. Each row in the combined matrix contains the data associated with a specific sample, including the crop IDs or labels and the corresponding features extracted from the three datasets.

3.6 Historical Cropland Reference Dataset Preparation

The selection of training and test data is a crucial step in the development and evaluation of the Random Forest (RF) model for crop type mapping. In this study, the historical cropland dataset spanning multiple years (2018-2020) was utilised for training the model, while the data from 2021 was reserved for testing and validation. The use of multiple years of historical data for training provides several advantages. It allows for a larger and more representative training dataset, capturing the temporal variability in crop patterns and reducing the influence of specific year-to-year variations. This helps to create a more robust and generalisable model that can accurately classify crops across different growing seasons.

To ensure that the training dataset is representative and balanced, a stratified random sampling strategy was employed. This means that the selection of training samples was based on the proportion of each crop type in the entire Flevoland region. By considering the number of fields available for each crop, the sampling strategy ensures that the training dataset includes a sufficient number of samples for each crop type, preventing any bias towards crops with higher or lower field densities. The use of stratified random sampling helps to capture the diversity of crop types and their spatial distribution within the study area. It ensures that the RF model is trained on a diverse range of samples, allowing it to learn the characteristic spectral and temporal patterns associated with different crops. The table 3.3 shows the total number of fields samples for each crop across the years in Flevoland whereby Potato showed to be a dominant crop among other crops.

Table 3.3:Distribution of field samples over the year in Flevoland.

Crop type	Number of the field sample			
	2021	2020	2019	2018
Potato	1000	1000	900	445
Barley, Summer	105	160	100	68
Barley, Winter	81	66	79	63
Corn	190	259	175	247
wheat, summer	125	106	72	61
Wheat, winter	700	600	800	301
TOTAL	2201	2191	2126	1185

3.7. Important Feature Selection

In this study, we employed the Random Forest algorithm to perform feature selection and identify important features for classifying different crop types based on backscatter data from Sentinel-1, spectral bands, and vegetation indices from Sentinel-2. The methodology used calendar time and thermal time feature space separately.

To identify the important features, a Random Forest model was constructed using a variable representing the combined spectral band's dataset, the ratio of VH and VV together with vegetation indices from Sentinel-2. The model consisted of 100 trees, and the 'OOBPredictorImportance' option was enabled to calculate the feature importance based on out-of-bag predictions.

Based on the RF model, the feature importance values was calculated. To ensure comparability, the importance values was normalised by dividing them by the sum of all importance values. Subsequently, the feature importance values were sorted in descending order to determine the most influential features. To present the results, the feature importance values alongside their corresponding indices were displayed. Furthermore, the feature importance was visualised using a bar plot, which provided a clear representation of the relative importance of each feature (Annex 9).

3.8. Random Forest Algorithm

This study employed the RF algorithm, a supervised non-parametric machine learning approach introduced by Breiman. (2001). RF is an ensemble of decision trees, where each tree is constructed using a randomly selected subset of variables and training data. The study utilised a bootstrapping technique, where two-thirds of the training data, known as the inbag data, were used to build each tree, while the remaining one-third, called the out-of-bag (OOB) data, was used for evaluating the model's performance (Guan et al., 2013). The data used in this study were obtained from satellite images (Synthetic Aperture Radar (SAR) data from Sentinel-1 (S1) and multi-spectral data from Sentinel-2 (S2) captured in 2018, 2019, 2020, and 2021 for various crop types. The SAR data included the vertical and horizontal polarisation bands (VH and VV), while the multispectral data comprised nine spectral bands (B2, B4, B5, B6, B7, B8, B8A, B11, and B12).

For each crop type, the SAR data (VH and VV) were processed to calculate the Cross Ratio of the two polarizations (VH and VV). The Time Series values were computed by subtracting the VV values from the VH values. Similarly, the multispectral data from Sentinel-2 were extracted for each crop type by concatenating the spectral bands to create a time series (TS) for that crop.

To facilitate supervised learning, the labelled datasets were created by assigning class labels to the extracted features. Each crop type was assigned a unique numerical label. For example, for the crop type "corn," a label of 1 was assigned. The same labelling process was repeated for other crop types, including "potato" (label 2), "summer wheat" (label 3), "summer barley" (label 4), "winter barley" (label 5), and "winter wheat" (label 6). The RF algorithm was employed for feature selection using bootstrapping and out-of-bag (OOB) evaluation. The labelled datasets, consisting of the extracted features and corresponding class labels, were split into training and testing sets using a holdout method. The training set comprised 70% of the data, while the remaining 30% was allocated to the testing set.

The RF used 100 trees, as specified by the nTrees parameter. In the TreeBagger function, the default value for the number of nodes in each decision tree of the RF classifier is determined automatically based on the data and the number of trees. The TreeBagger function in MATLAB performs the functionality that can be achieved by specifying parameters such as MinLeafSize, MaxNumSplits, and NumPredictorsToSample in other implementations. The characteristics of the dataset, which include the input features and the corresponding class labels, are considered by the TreeBagger function to automatically determine the number of nodes in each decision tree. For each decision tree in the RF model, two-thirds of the training data (inbag data) were randomly sampled with replacement to build the tree, while the remaining one-third (out-of-bag data) was used to evaluate the model's performance. This bootstrapping technique ensured that each tree had a slightly different training set, allowing for ensemble learning and reducing overfitting.

Once the Random Forest model was trained, it was evaluated using the testing set. The model's performance was assessed by measuring its accuracy, which was calculated as the proportion of correctly classified samples in the testing set. Additionally, the out-of-bag (OOB) error rate was computed to estimate the model's performance without the need for a separate validation set.

3.9. Accuracy Assessment

In this study, several common metrics were utilised to assess the accuracy of the crop type classification results. These metrics provide insights into the performance and agreement between the predicted classifications and the ground truth data. The metrics employed include User Accuracy (UA), Producer Accuracy (PA), Overall Accuracy (OA), kappa coefficient, and F-score.

The confusion error matrix, derived from comparing the predicted classifications with the actual crop types, serves as the basis for calculating these metrics. User Accuracy (UA) represents the proportion of correctly classified pixels for each crop class, indicating the reliability of the model in identifying specific crop types. Producer Accuracy (PA) indicates the proportion of correctly classified pixels for a given crop class out of all the pixels assigned to that class. Overall Accuracy (OA) provides an assessment of the overall correctness of the classification results by considering all crop types. The kappa coefficient is a statistical measure of interclass agreement that takes into account the possibility of agreement occurring by chance. It evaluates the performance of the classification by comparing the observed agreement with the expected agreement, providing a more comprehensive evaluation than OA alone.

$$\boldsymbol{F = 2X(\frac{PA \times UA}{PA + UA})}$$

For crop type classification in this study used historical cropland data of year 2018 to 2020 as training dataset and year 2021 as validation data.

4. Experimental Results

This section provides a comprehensive overview of the main findings regarding the temporal behaviour, phenological metrics, and classification accuracy of different crop types using data from Sentinel-1 and Sentinel-2. The results strongly emphasise the crucial role of pre-processing techniques, thorough temporal analysis, and the consideration of time-invariant characteristics for attaining accurate and reliable crop monitoring and classification.

4.1 Sentinel-1 and Sentinel-2 Crop Phenological Metrics

Phenological metrics are indicators that capture the timing and dynamics of vegetation growth and changes throughout the growing season. Common phenological metrics include the start of the growing season, the end of the growing season, peak vegetation activity, and the length of the growing season. In this study, six different crops were studied and extracted their start of the season, end of the season, and peak metrics. For space constraints, the phenological metrics of potato are reported for both sensors, table 4.1 shows the phenological metrics of potato for Sentinel-1, and Sentinel-2. The remaining crops can be found in Annex 7 and 8.

The results showed that from the phenological metrics extracted from Sentinel-1, the growing season starts earlier while the peak metrics are reached later than the phenological metrics extracted from Sentinel-2. Additionally, the end of the season varied depending on crop type. For corn and potato, their season ended earlier for Sentinel-1 compared to Sentinel-2 while the season of winter wheat, winter barley, summer wheat, and summer barley ended late for Sentinel-1 compared to Sentinel-2. These findings indicate that there are differences in the timing of vegetation growth that can be captured when considering the two data sources.

Table 4.1:Example of the phenological metrics of potato, extracted from Sentinel-1, Sentinel-2.

Sentinel-1

			2018	2019	2020	2021
POTATO	**SOS**		11-May	30-May	18-May	25-May
	EOS		08-Sep	03-Sep	09-Sep	04-Sep
	Peak ratio	ratio value	-6.5	-7	-7.1	-7
		Date	22-Jul	29-July	04-Aug	30-Jul

Sentinel-2

		2018	2019	2020	2021
POTATO	**SOS**	25-May	02-May	28-May	10-Jun
	EOS	10 Sep	17 Sep	20-Aug	14-Sep
	Peak NDVI	0.82	0.84	0.83	0.7
		06-Jul	13-Jul	17-Sep	22-Jul

4.2 Sentinel-1 and Sentinel-2 Calendar Time Feature Space – Analysis

The study aimed to understand the temporal dynamics of SAR backscatter and Sentinel-2 Reflectance for different crop types in the Province of Flevoland, Netherlands. The temporal behaviour of the VV backscatter, VH backscatter, and the ratio of VH and VV backscatter, i.e., the Cross Ratio (CR), are reported since they can provide specific temporal patterns and trend for the considered crop types. In general, the CR and the Normalized Difference Vegetation Index (NDVI) offer a more comprehensive depiction of crop seasons compared to relying solely on VV or VH data. Additionally, both CR and NDVI demonstrate consistent spatial and temporal stability, making them reliable indicators for understanding the temporal behaviour of crops. Therefore, in this study, the analysis focused on utilising the CR and NDVI plots to effectively assess the temporal behaviour of the crops.

To examine the behaviour of the CR and NDVI over time, the temporal behaviour of crops observed from CR and NDVI were compared for the different years with the crop calendar. The results showed significant temporal patterns in the CR and NDVI trends. For space constrain, the example reported in

Figure 4.1 shows the median temporal behaviour computed for the crop type “potato” available in the considered study area over a span of four years. Both indices exhibited a consistent pattern of rising values early in the growing season, followed by a progressive decline as the crops approached maturity. Moreover, this behaviour aligns with the expected growth and development phases of crops reported in the crop calendar (referring to the table 2.1), characterised by an initial period of active growth and subsequent decline as the plants mature. However, because of the different climate conditions, one can notice that the phenological parameters are slightly different across the different years. Interestingly, the growing season of 2019 stood out, displaying notably higher values for NDVI, while the highest CR is observed in 2018 compared to the other three years as can be seen in Figure 4.1.

Similar results are visible for the remaining crop types reported in Annex 1 up to 5. Specifically, when analysing corn, it was observed that it had a high NDVI value in 2020 and 2019, while 2021 had the lowest maximum NDVI value among the four years studied. On the other hand, the CR of corn in 2021 was found to have the highest value, while 2019 had the lowest CR value among the four years. For summer barley, 2018 and 2019 showed high maximum NDVI values, while 2020 had the lowest maximum NDVI value. The CR plot indicated that 2018 and 2021 had the highest CR value, whereas 2020 had the lowest. Similarly, for summer wheat, 2018, 2019, and 2021 exhibited high maximum NDVI values, while 2020 had the lowest. The CR plot showed that 2018 and 2021 had the highest CR value, while 2019 had the lowest. In the case of winter barley, 2019 had a high maximum NDVI value, while 2020 had the lowest. The CR plot indicated that 2018 and 2020 had the highest CR value, whereas 2019 and 2021 had the lowest. Finally, for winter wheat, 2018, 2019, and 2021 showed high maximum NDVI values, while 2020 had the lowest. The CR plot showed that 2018 had the highest CR value, while 2021 had the lowest.

Overall, the observed variations in NDVI and CR values across different years can be attributed to the distinctive growth stages and development patterns of the crops. These insights gained from the analysis aid in identifying and distinguishing different phenological metrics of the crops, providing a deeper understanding of their temporal behaviour.

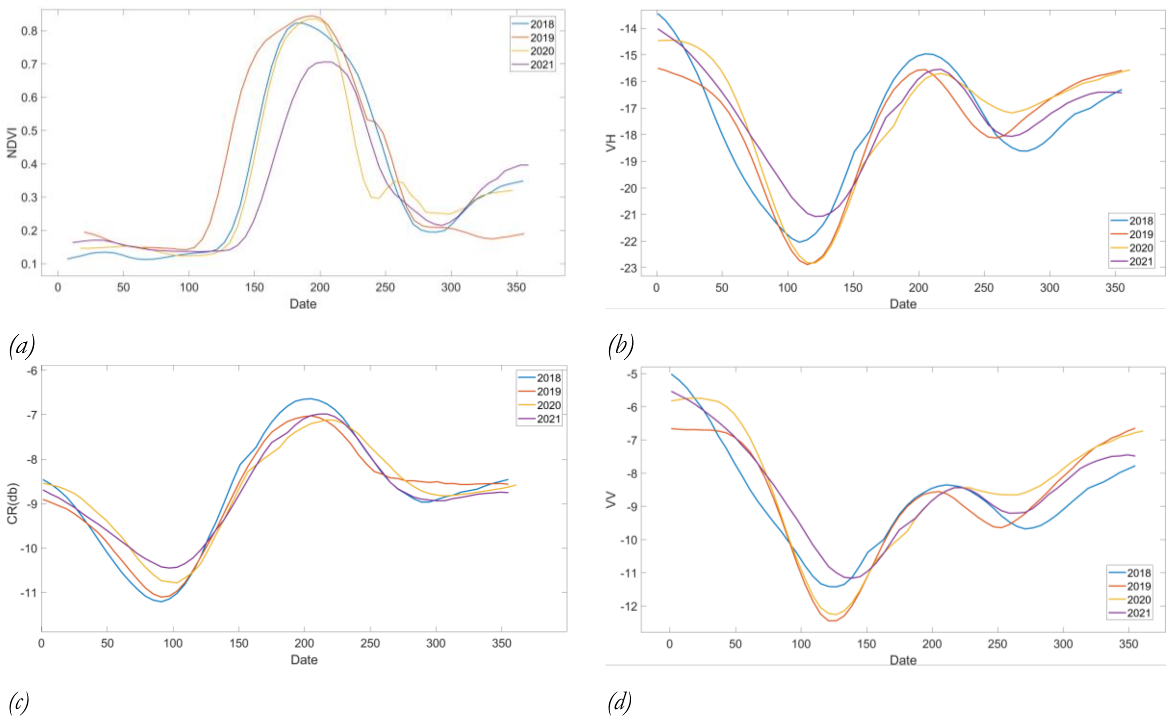


Figure 4.1: Example of median temporal profiles for potato samples available in the considered study area computed for the years 2018, 2019, 2020, and 2021. The profiles included the following parameters: (a) NDVI, (b) VH backscatter (c) CR (VH/VV backscatter ratio), and (d.) VV backscatter.

4.3. Sentinel-1 and Sentinel-2 Thermal Time Feature Space – Analysis

To address weather variability and temporal shifts of crop phenological events across different years, thermal time was employed as a parameter to examine crop behaviour and capture time-invariant characteristics. The study focused on six major crop types in the Flevoland region from 2018 to 2021. A line plot, including NDVI vs Thermal time and CR vs Thermal time, facilitated consistent comparisons of crop dynamics throughout the season, mitigating the influence of weather fluctuations.

The temporal shift of the crop refers to the variation in the timing of crop development and phenological events across different years. This shift can be influenced by weather conditions, such as temperature and precipitation, which can vary from year to year. When using calendar time, the maximum NDVI values are directly associated with specific dates in each year, which can be affected by the temporal shift. This means that the occurrence of maximum NDVI may not consistently align with the same stage of crop growth in different years. The utilisation of thermal time as a metric resulted in a significant reduction in temporal shifts, indicating its effectiveness in providing a consistent measure of crop growth as it can be observed on Figure 4.2 and table 4.2.

The results showed that when considering calendar time, the maximum NDVI values observed in different years showed a range from 0.70 to 0.84. However, when using thermal time as a reference, the maximum NDVI values for each year had a slight variation, ranging from 0.82 to 0.84.

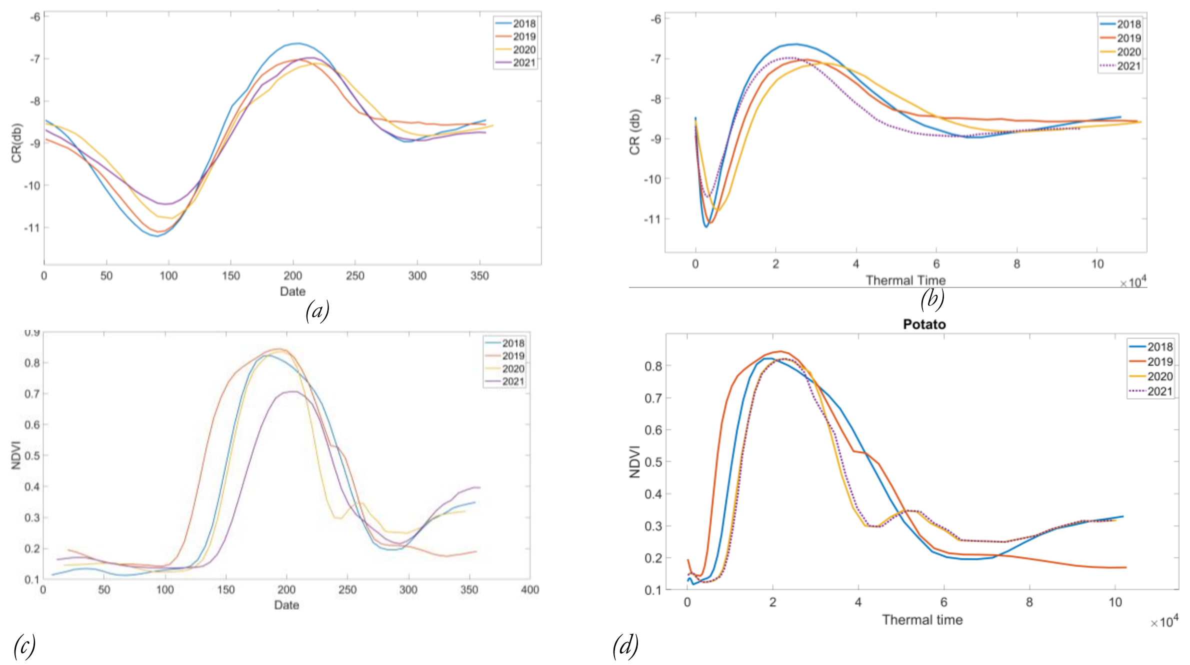


Figure 4.2:Example of median temporal profile for potato sample available in the considered study area computed for the years 2018, 2019, 2020, and 2021. The profiles compare the calendar time vs thermal time across different years for Sentinel-1 and Sentinel-2.

Table 4.2: Maximum median NDVI value observed when calendar time and thermal time used

Potato		
Year	Max NDVI value obtained from Calendar Time	Max NDVI value obtained from Thermal time
2018	0.82	0.83
2019	0.84	0.84
2020	0.83	0.82
2021	0.7	0.82

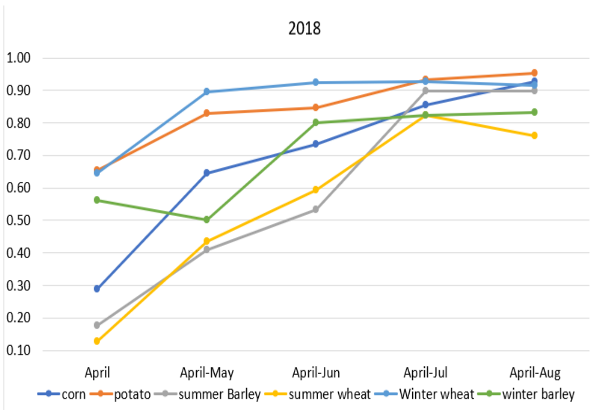
4.4 Within Season Crop Type Mapping – Optimal Temporal Window

In this study, a selective predictor approach using random forest was employed to identify the important features for classifying the six crops under investigation. The results revealed that the optimal temporal window for effectively classifying these crops spanned from April to August.
This temporal window coincided with the crop calendar of the Netherlands, where the study was conducted. It was observed that most of the targeted crops started their growth in April and reached their maturity and harvesting stages in August. By aligning the temporal window with the phenological stages of the crops, the study was able to capture the most discriminative features for accurate classification.

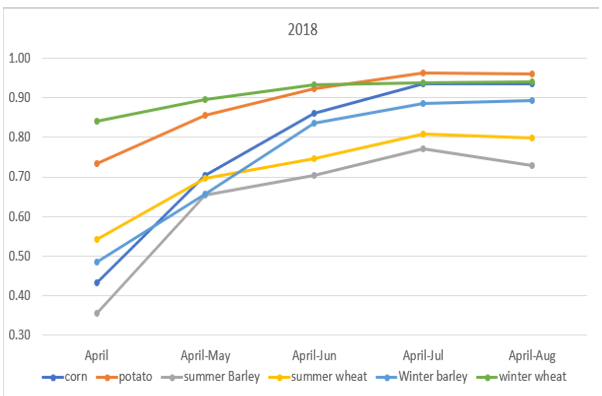
To evaluate the results obtained, the F1-score was used as a performance measure to quantitatively determine the classification window (April to August). The high F1 scores reflect the models' ability to accurately identify and classify crop types within the selected classification window. This is crucial for applications such as crop monitoring and land management. which result in the highest classification accuracy per crop type. The results demonstrated that the highest accuracy can be achieved in June for Sentinel-2 data and in July for Sentinel-1 data. This aligns with the understanding that these months coincide with the maturity stage of most crops, making them easier to distinguish and classify accurately. The figure 4.3 shows F1-score on y-axis and time on x-axis in terms of moth for six crops.

The analysis showed a consistent pattern among various crop types. Potato, winter barley, and winter wheat demonstrated high F-1 scores (above 0.60) as early as April when both Sentinel-1 and Sentinel-2 data were used. On the other hand, Corn, summer barley, and summer wheat showed a clear identification pattern in June for both sensors, with their F1 scores exceeding 0.50.
Moreover, the study found that Potato and winter wheat consistently exhibited excellent classification performance across all years and for both sensors. Additionally, the F1 scores remained stable and consistent from July to August for all crop types for both sensors, as shown in Figure 4.3. This suggests that during this period, the classification models consistently and accurately identified and classified the different crops. Figure 4.3 shows the F1 score trend for different crops in different years within selected window.

SENTINEL 1



SENTINEL 2



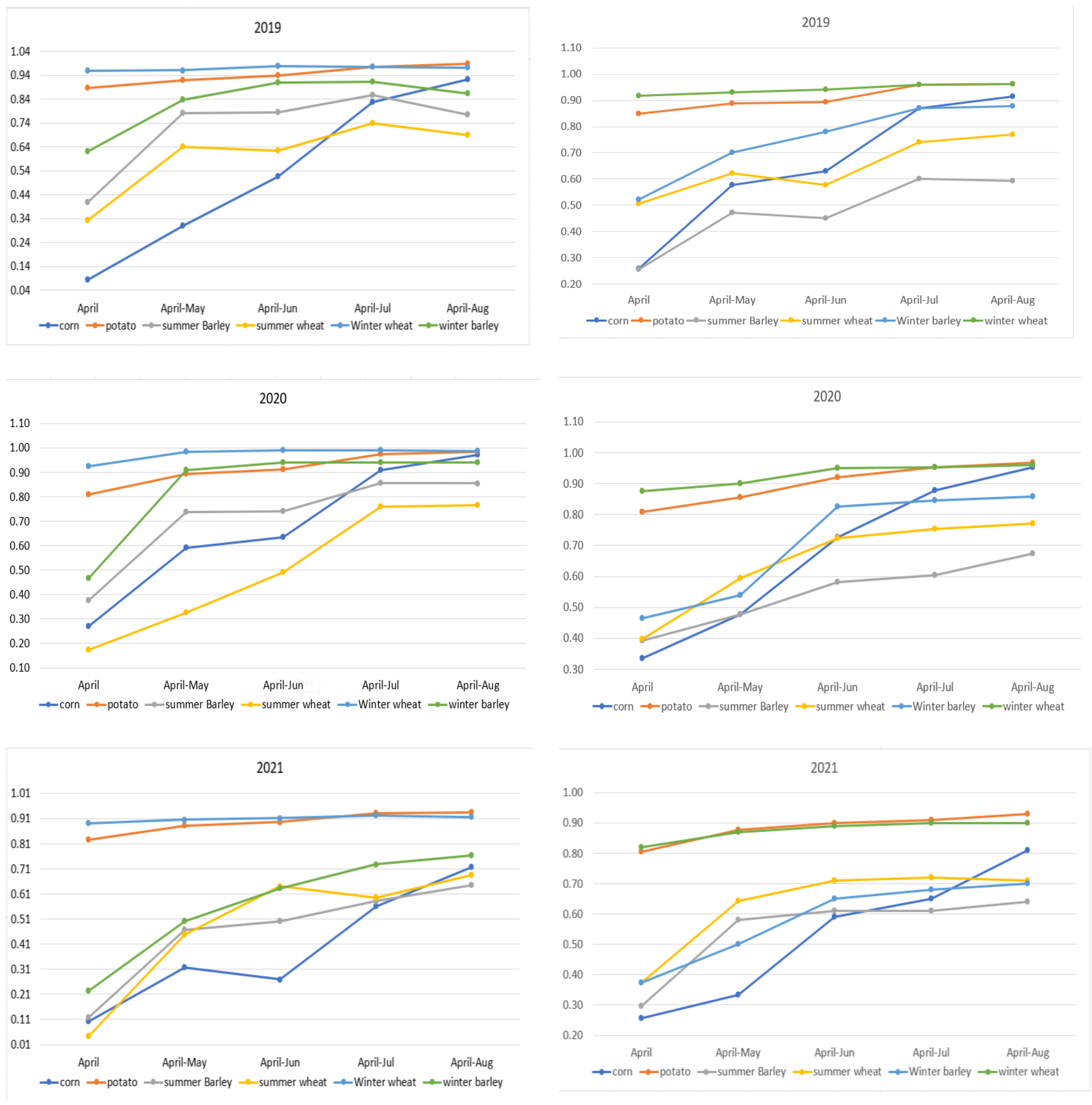


Figure 4.3: F1 scores results obtained per crop type throughout the year when considering different temporal windows. The results are computed using the RF classifier in 2018, 2019, 2020, and 202.

4.5. Inter-annual Crop Type Mapping

In this phase of the study, the inter-annual variation of crop types was examined in the Flevoland region of the Netherlands, comparing the classification results obtained with the calendar time to one achieved when considering the thermal time. The objective was to compare the performance of classification models when weather data were considered and when they were not considered. For each year individually, the data was divided into a training set comprising 70% of the data and a testing set consisting of the remaining 30%. This process was followed separately for both Sentinel-1 and Sentinel-2 data to assess the classification accuracy for each sensor.

4.5.1 Temporal Dynamics of Crop Classification

The experimental results reported in this section analyse the classification results obtained for different crop types when training the model in 2018 and classifying data from subsequent years (2019, 2020, and 2021). The results are represented as a graph bar which displays the F1 scores obtained for each crop type in the different years. The aim of this experiment was to check the effect of using historical crop land data to train targeted year.

In order to perceive the temporal dynamics of crop phenological events, analysis was conducted. A two-step procedure was used in the experiment, which aimed to understand how crops change through time. Initially, the data from the previous year were used as the training dataset to develop and refine the predictive model. Subsequently, the data from the target year were used to evaluate the efficacy of the model. The findings revealed that as the target year progressed further away from the training data, it was observed that the crop classification model's accuracy progressively decreased. In other words, when attempting to predict crop types for a specific year based on historical data from a previous year, the model's effectiveness decreased as the distance between the training and target years increased.

This finding emphasizes the importance of taking into consideration temporal variations in crop phenology when designing predictive models, as their performance may vary over time. The decreasing accuracy observed in the bar graph serves as an indicator of the challenges faced when using the previous year's data as the training dataset and the target years' data as the testing dataset. It highlights the importance of considering the dynamic nature of crop growth and phenology over time. The figure 4.4 shows an example where the training data collected in the year 2018 were used to train the classification algorithm while the data available in 2019, 2020, and 2021 were used as test set.

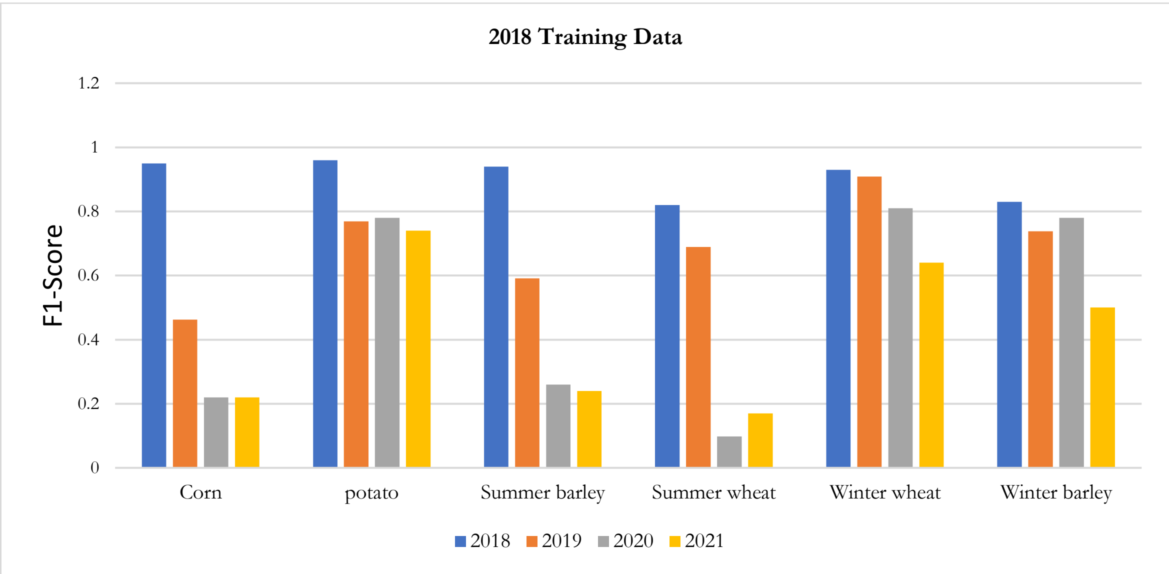


Figure 4.4:Impact of Temporal Shifts on Crop Type Classification Accuracy Over the year 2018-2021 together with weather data across the same time.

4.5.2 Comparison of calendar time and Thermal Time Feature Space

In the study carried out in the Flevoland province, an analysis of the classification results obtained through two different approaches was done. The objective was to determine how taking thermal time into account affected both inter-annual and intra-annual changes in crop behaviour. The figure 4.5 and 4.6 show intra-annual classification when calendar time is considered and when thermal time is considered. By comparing the classification results between the two approaches, the observed results, indicating a greater impact of considering thermal time on inter-annual rather than intra-annual variation of crop behaviour (figure 4.5 and 4.6), can be attributed to several factors specific to the study conducted in the province of Flevoland.

Interannual variation refers to the differences in crop behaviour and growth patterns observed between different years. In Flevoland, various factors such as weather conditions, crop rotation practices, and land management strategies contribute to these interannual variations. By incorporating thermal time, which considers temperature-related growth and development of crops, the classification model becomes more sensitive to these interannual variations. This enables the model to capture and utilise the specific temporal patterns associated with different years, leading to improved classification results.

On the other hand, intra-annual variation refers to the changes and fluctuations in crop behaviour within a single year. In Flevoland, the presence of a well-structured agricultural system, including crop rotation and irrigation practices, can help maintain relatively stable growth patterns and phenological stages of crops throughout the year. As a result, the impact of considering thermal time on capturing intra-annual variations may be less pronounced, as the growth patterns and phenological stages within a single year are relatively consistent. Furthermore, the unique characteristics of the province of Flevoland, such as its fertile soil, flat landscape, and advanced agricultural practices, contribute to the overall stability and predictability of crop behaviour. This stability within a year further reduces the potential impact of thermal time on intra-annual variations.

Overall, the study conducted in the province of Flevoland demonstrates that considering thermal time can have a significant effect on capturing interannual variations in crop behaviour. which will be further analysed and discussed in the next section of the study.

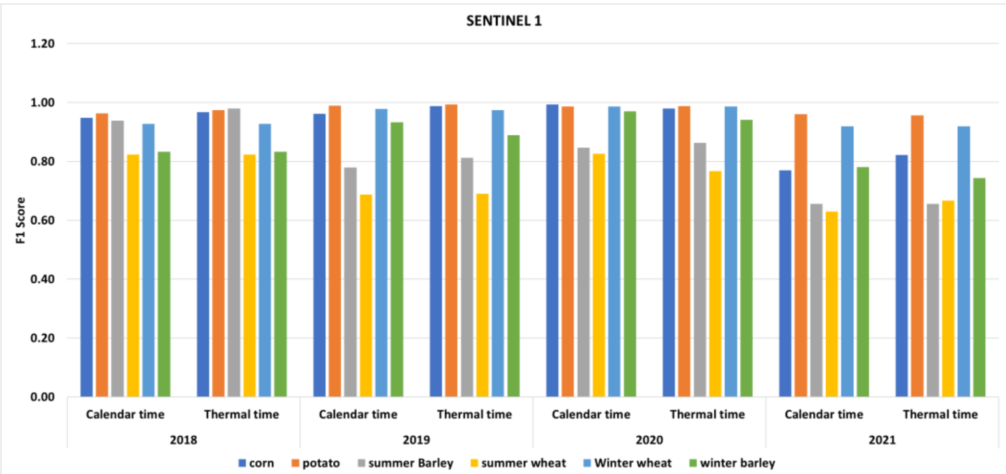


Figure 4.5: The Impact of Thermal Time on Inter-annual Variation of Crop Types for Sentinel-1

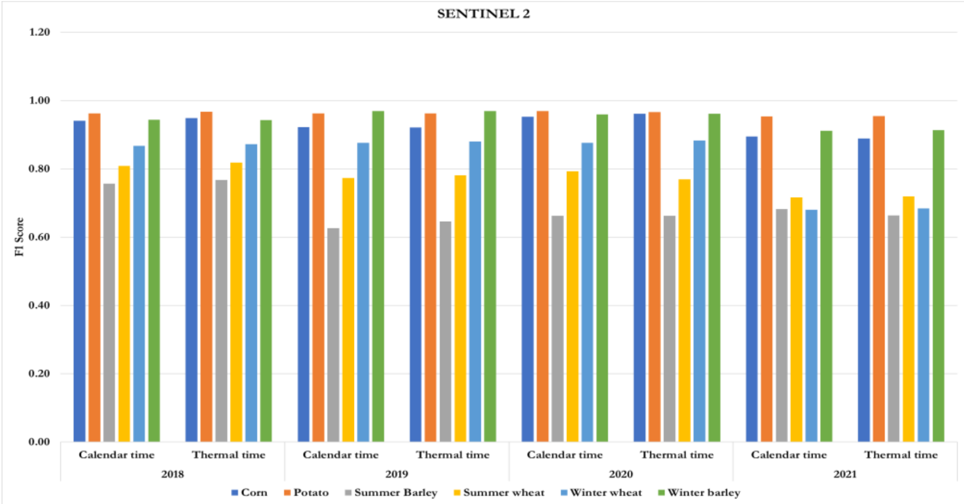


Figure 4.6: The Impact of Thermal Time on Inter-annual Variation of Crop Types for Sentinel-2

4.6 Within Season Crop Type Mapping using Historical Data

This study compared the performance of classification models using calendar time and thermal time approaches. Training was done using data from 2018, 2019, and 2020, and validation was performed using data of 2021. The classification performance was evaluated using the confusion matrix.

4.6.1 Calendar Time Feature Space

The study compared the performance of the classification model with calendar time. Three experiments were conducted: (1) using Sentinel-1 data, (2) using Sentinel-2 data, and (3) using combined Sentinel-1 and Sentinel-2 data.

Sentinel 1-Data

The classification model achieved an overall accuracy of 0.8 and a kappa score of 0.77. The F1 scores varied across different crop classes, with the highest scores observed for potato (0.89) and winter wheat (0.90). Summer wheat (0.34) and summer barley (0.31) had lower F1 scores. Error omission rates ranged from 0.11 for winter wheat to 0.66 for summer wheat. Producer accuracy was highest for potato (0.85) and winter wheat (0.89), while summer wheat (0.34) and summer barley (0.37) had lower producer accuracy. Error commission rates varied from 0.08 for winter wheat to 0.80 for summer barley. User accuracy was highest for winter wheat (0.92) and potato (0.89), while summer barley (0.20) had the lowest user accuracy. The results are interpreted in the table 4.3.

Table 4.3: the confusion matrix results of Sentinel-1 without considering the thermal time.

	Corn	Potato	SW	SB	WB	WW	Total	UA	F1_score
Corn	134	46	2	1	5	2	190	0.72	0.72
potato	35	879	9	71	1	5	1000	0.89	0.89
Summer wheat	7	28	41	35	2	12	125	0.33	0.34
Summer barley	0	15	41	44	2	3	105	0.20	0.31
Winter barley	1	2	0	2	40	36	81	0.75	0.58
Winter wheat	4	16	26	24	7	623	700	0.92	0.90
Total	181	986	119	177	57	681	2201		
Producer Accuracy	0.71	0.85	0.34	0.37	0.53	0.89			
Overall Accuracy					**0.8**				
Overall kappa score					**0.77**				

Sentinel-2 Data

When using only Sentinel-2 data, the classification model achieved an overall accuracy of 0.64 and a kappa score of 0.58. The F1 scores for different crop classes were relatively lower compared to the Sentinel-1 experiment. The highest F1 scores were observed for potato (0.68) and winter wheat (0.78), while summer wheat (0.22) and summer barley (0.30) had lower scores. Error omission rates ranged from 0.18 for winter wheat to 0.84 for summer wheat. Producer accuracy was highest for corn (0.75) and potato (0.62), while summer wheat (0.16) and summer barley (0.26) had lower producer accuracy. Error commission rates varied from 0.16 for potato to 0.71 for summer wheat. User accuracy was highest for potato (0.75) and winter wheat (0.78), while summer barley (0.34) had the lowest user accuracy, As it can be seen from the table 4.4.

Table 4.4: confusion matrix results of Sentinel-2 without considering the thermal time.

	Corn	Potato	SW	SB	WB	WW	Total	UA	F1_score
Corn	712	136	11	5	41	45	950	0.34	0.47
potato	1284	3117	44	33	47	475	5000	0.75	0.68
Summer wheat	15	342	102	40	6	120	625	0.34	0.22
Summer barley	15	222	58	138	8	84	525	0.34	0.30
Winter barley	8	17	1	3	72	304	405	0.35	0.24
Winter wheat	43	289	94	173	31	2870	3500	0.73	0.78
Total	2077	4123	310	392	205	3898	11005		
Producer Accuracy	0.75	0.62	0.16	0.26	0.17	0.82			
Overall Accuracy					**0.64**				
Overall kappa score					**0.58**				

Combined Sentinel-1 and Sentinel-2 Data

Combining Sentinel-1 and Sentinel-2 data resulted in an overall accuracy of 0.7 and a kappa score of 0.65. The F1 scores showed improvements compared to the Sentinel 2 experiment, with higher scores observed for all crop classes. The highest F1 scores were observed for potato (0.78) and winter wheat (0.81), while summer wheat (0.28) and summer barley (0.34) had lower scores. Error omission rates ranged from 0.18 for winter wheat to 0.75 for summer barley. Producer accuracy was highest for potato (0.87) and winter wheat (0.82), while summer wheat (0.26) and summer barley (0.32) had lower producer accuracy. Error commission rates varied from 0.13 for potato to 0.67 for summer wheat. User accuracy was highest for potato (0.87) and winter wheat (0.80), while summer barley (0.39) had the lowest user accuracy. The detailed result is illustrated in the table 4.5.

Table 4.5: the confusion matrix results of the combination of Sentinel-1n and Sentinel-2 without considering the thermal time.

	Corn	Potato	SW	SB	WB	WW	Total	UA	F1_score
Corn	1232	336	18	7	64	53	1710	0.42	0.53
potato	1617	6671	73	77	67	495	9000	0.81	0.78
Summer wheat	33	506	297	125	10	154	1125	0.33	0.28
Summer barley	21	323	181	302	14	104	945	0.39	0.34
Winter barley	14	22	8	9	180	496	729	0.45	0.31
Winter wheat	77	381	332	296	64	5150	6300	0.80	0.81
Total	2994	8239	909	816	399	6452	19809		
Producer Accuracy	0.73	0.75	0.26	0.32	0.25	0.82			
Overall Accuracy					**0.7**				
Overall kappa score					**0.65**				

Thermal-Time Feature Space

The study also considered the impact of time-invariant factors on the classification model. Similar to the previous section, three experiments were conducted: (1) using Sentinel-1 data, (2) using Sentinel-2 data, and (3) using combined Sentinel-1 and Sentinel-2 data.

Sentinel-1 Data

When incorporating time-invariant information with Sentinel-1 data, the classification model achieved an overall accuracy of 0.81 and a kappa score of 0.78. The F1 scores showed improvements compared to the classification without time-invariant information, with higher scores observed for corn (0.67) and potato (0.92). Error omission rates ranged from 0.07 for potato to 0.86 for summer barley. Producer accuracy was highest for potato (0.93) and winter wheat (0.88), while summer barley (0.14) had the lowest producer accuracy. Error commission rates varied from 0.09 for potato to 0.79 for summer barley. User accuracy was highest for corn (0.87) and potato (0.91), while summer barley (0.21) had the lowest user accuracy.

Table 4.6: the confusion matrix results of Sentinel-1 with considering the thermal time.

	Corn	Potato	SW	SB	WB	WW	Total	UA	F1_score
Corn	106	69	6	5	2	2	190	0.87	0.67
potato	12	926	12	38	0	12	1000	0.91	0.92
Summer wheat	3	3	46	5	0	68	125	0.42	0.39
Summer barley	1	3	32	22	4	43	105	0.21	0.24
Winter barley	0	4	0	0	65	12	81	0.50	0.64
Winter wheat	3	8	14	6	51	618	700	0.83	0.85
Total	125	1013	110	76	122	755	2201		
Producer Accuracy	0.54	0.93	0.39	0.14	0.81	0.88			
Overall Accuracy					**0.81**				
Overall kappa score					**0.69**				

Sentinel 2 Data

Incorporating time-invariant information with Sentinel 2 data resulted in an overall accuracy of 0.73 and a kappa score of 0.69. The F1 scores were generally higher compared to the classification without time-invariant information. The highest F1 scores were observed for potato (0.85) and winter wheat (0.78), while summer wheat (0.26) and summer barley (0.19) had lower scores. Error omission rates ranged from 0.16 for potato to 0.87 for summer barley. Producer accuracy was highest for potato (0.84) and winter wheat (0.77), while summer barley (0.13) had the lowest producer accuracy. Error commission rates varied from 0.16 for potato to 0.67 for summer barley. User accuracy was highest for potato (0.84) and winter wheat (0.78), while summer barley (0.33) had the lowest user accuracy.

Table 4.7: the confusion matrix results of Sentinel-2 with considering the thermal time.

	Corn	Potato	SW	SB	WB	WW	Total	UA	F1_score
Corn	619	300	7	3	7	14	950	0.62	0.63
potato	328	4251	190	59	23	149	5000	0.84	0.85
Summer wheat	13	146	142	52	25	247	625	0.29	0.26
Summer barley	11	136	63	69	45	201	525	0.33	0.19
Winter barley	6	22	0	1	269	107	405	0.31	0.43
Winter wheat	28	191	59	21	479	2722	3500	0.78	0.82
Total	1005	5046	461	205	848	3440	11005		
Producer Accuracy	0.68	0.84	0.22	0.13	0.67	0.77			
Overall Accuracy					**0.73**				
Kappa score					**0.66**				

Combined Sentinel-1 and Sentinel-2 Data

Combining Sentinel-1 and Sentinel-2 data with time-invariant information yielded an overall accuracy of 0.77 and a kappa score of 0.73. The F1 scores showed improvements compared to the Sentinel 2 experiment. The highest F1 scores were observed for potato (0.88) and winter wheat (0.82), while summer wheat (0.3) and summer barley (0.31) had lower scores. Error omission rates ranged from 0.13 for potato to 0.75 for summer barley. Producer accuracy was highest for potato (0.87) and winter wheat (0.82), while summer barley (0.25) had the lowest producer accuracy. Error commission rates varied from 0.13 for potato to 0.63 for summer barley. User accuracy was highest for potato (0.87) and winter wheat (0.82), while summer barley (0.39) had the lowest user accuracy.

Table 4.8: the confusion matrix results from the combination of Sentinel-1n and Sentinel-2 by considering the thermal time.

	Corn	Potato	SW	SB	WB	WW	Total	UA	F1-score
Corn	1124	528	17	6	15	20	1710	0.65	0.66
potato	463	7928	250	108	45	206	9000	0.87	0.88
Summer wheat	19	209	291	172	34	400	1125	0.35	0.30
Summer barley	17	168	152	242	64	302	945	0.39	0.31
Winter barley	15	26	3	2	494	189	729	0.37	0.48
Winter wheat	66	260	113	80	672	5109	6300	0.82	0.82
Total	1704	9119	826	610	1324	6226	19809		
Producer Accuracy	0.66	0.87	0.26	0.25	0.67	0.82			
Overall Accuracy					**0.77**				
Kappa score					**0.73**				

5. Discussion

5.1 Sentinel-1 and Sentinel-2 Crop Phenological Metrics

When analysing the phenological metrics extracted from Sentinel-1 data, it was observed that the season starts earlier compared to the phenological metrics extracted from Sentinel-2 data. This differences in season start dates between Sentinel-1 and Sentinel-2 can be attributed to the differences in the capabilities and characteristics of the two satellite sensors. This results align with the study conducted by Mercier et al.(2020) where they confirmed the differences in the capabilities and characteristics of the two satellite sensors, Sentinel-1 and Sentinel-2.

The earlier start dates observed in the phenological metrics derived from Sentinel-1 data can be attributed to its ability to detect changes in surface conditions even under cloudy or unfavourable weather conditions. The studies conducted by Meroni et al.(2021); Schlund & Erasmi.(2020) confirm the capability of Sentinel-1 to detect changes in surface conditions even when faced with cloudy or unfavorable weather conditions. These findings emphasise the advantage of Sentinel-1's all-weather imaging capabilities, allowing for reliable monitoring and analysis of surface changes regardless of atmospheric conditions. This allows for the identification of early signs of vegetation growth or changes in land cover, which may not be captured by Sentinel-2 during cloudy periods. On the other hand, Sentinel-2 is an optical satellite operating in the electromagnetic spectrum's visible and near-infrared regions. It relies on sunlight to capture images and is affected by cloud cover, limiting its observation capabilities during cloudy periods.

The influence of weather parameters, specifically temperature, and precipitation, on the inter-annual variations of estimated phenology is visible in the presented experimental results. The warmer conditions observed in 2018 and 2019 likely contributed to the earlier detection of phenological phases for different crops. The increased temperatures can accelerate the developmental processes, leading to an advance in phenological stages d'Andrimont et al.(2020) have reported similar observations, affirming that elevated temperatures facilitate crop development. Their studies reveal that higher temperatures enhance the progression of phenological stages, including flowering, fruiting, and maturation, in various crop types. These findings align with this study's results, highlighting the consistent impact of increased temperatures on crop phenology.

Conversely, the wet conditions experienced in 2020 and 2021 may have caused delays in reaching the phenology phases. Excessive moisture can result in a slower progression of phenological events. These findings agree with the research conducted by Schlund & Erasmi. (2020) who observed temporal variability in wheat phenology across 2017, 2018, and 2019.

In addition to the earlier start dates observed in phenological metrics extracted from Sentinel-1 data, the results also indicate that the peak metrics were reached later compared to those extracted from Sentinel-2 data. Moreover, the end of the season varied depending on the crop type, with differences between Sentinel-1 and Sentinel-2. The later peak metrics observed in Sentinel-1 data can be attributed to the different characteristics and capabilities of the two satellite sensors. Sentinel-1 provides information based on the backscattered SAR signal, which is influenced by vegetation structure and water content. This signal can be affected by factors such as vegetation density (Gao et al., 2017), biomass (Wang et al., 2019), and moisture content (Veloso et al., 2017b; Wang et al., 2019), which may cause a delay in reaching peak metrics compared to optical sensors like Sentinel-2.

Regarding the end of the season, the variations observed between Sentinel-1 and Sentinel-2 data for different crop types can be attributed to the specific growth and senescence patterns of each crop. Factors such as crop genetics, management practices, and environmental conditions can influence the duration of the growing season as mentioned by Ettinger et al.(2020) and Y. Gao et al.(2022). For instance, in the case of corn and potato, the season ended earlier in Sentinel-1 compared to Sentinel-2. This could be due to the SAR signal capturing changes in vegetation structure and water content associated with crop maturity and senescence earlier than the optical signal captured by Sentinel-2.

These findings emphasise the importance of considering multiple data sources to capture the full range of vegetation dynamics and highlight the potential of Sentinel-1 for detecting early signs of growth and changes in vegetation structure.

5.2 Sentinel-1 and Sentinel-2 Calendar Time Feature Space

The analysis of SAR backscatter (CR) and spectral reflectance (NDVI) from Sentinel-1 and Sentinel-2 data, respectively, revealed distinct patterns and trends for different crop types in the study area. The variations in both NDVI and CR plots provided insights into the growth dynamics, phenological changes, and scattering properties of each crop across the different years.

Winter barley exhibited high CR values in 2020 and 2018, indicating a dense vegetation structure possibly due to favorable weather conditions earlier in the growing season. In contrast, low CR values were observed in 2019 and 2021, suggesting reduced vegetation activity influenced by weather conditions such as below-average precipitation or excessive rainfall. High NDVI in 2018 shows that Winter Barley might have benefited from earlier precipitation or favorable conditions during critical growth stages. These conditions could have led to healthier and more vigorous growth, reflected in higher NDVI values. This disparity can be attributed to the fact that NDVI is primarily influenced by the amount of chlorophyll and overall greenness of the vegetation, whereas CR is more sensitive to structural characteristics such as crop density and compactness. In 2019, despite the lower structural density indicated by the CR values, winter barley might have exhibited higher chlorophyll content or greener leaves, resulting in higher NDVI values.

Corn showed high NDVI in 2019, indicating healthier and more vigorous growth due to favorable weather conditions. In 2021, cooler temperatures and excessive rainfall resulted in lower NDVI values, indicating reduced vegetation activity. However, despite the low NDVI in 2021, corn exhibited high CR values, suggesting a dense vegetation structure. This disparity could be related to factors like crop density or leaf orientation, indicating a different scattering behaviour of the vegetation. Potato displayed high NDVI values in 2018, 2019, and 2020, indicating healthy vegetation and vigorous growth. In 2021, lower NDVI values indicated reduced vegetation vigour, possibly due to factors like excessive rainfall or cooler temperatures. The highest CR value in 2018 indicated a denser vegetation structure compared to subsequent years. Subsequent years showed lower CR values, suggesting a decrease in biomass accumulation and structural density.

In 2018, winter wheat exhibited high CR and NDVI values, potentially because of favorable early-season rainfall and optimal temperature during critical growth stages. These conditions may have compensated for the subsequent dry period, promoting optimal growth, biomass accumulation, and a dense vegetation structure, leading to high CR values. Despite the low precipitation in June and July, winter wheat still showed high NDVI values. This could be attributed to favorable conditions earlier in the growing season or during critical growth stages, potentially increasing chlorophyll content and improving overall vegetation health, resulting in higher NDVI values.

Summer wheat showed high NDVI in 2018, 2019, and 2021. Despite the low precipitation observed in June and July of 2018, Summer Wheat showed high NDVI values in that year. This could be attributed to favorable weather conditions during other parts of the growing season, including early-season rainfall or suitable temperatures that promoted healthy growth and chlorophyll production in the crop. In 2019 and 2021, with higher precipitation compared to 2018, Summer Wheat likely benefited from improved water availability throughout its growth stages, leading to higher NDVI values in those years. The high CR values observed in 2018 and 2021 can be linked to the structural characteristics and biomass accumulation patterns of Summer Wheat (Mandal et al., 2020). In 2018, despite the low precipitation in June and July, Summer Wheat might have exhibited resilience to water stress or benefited from favourable weather conditions earlier in the growing season. These factors could have contributed to denser vegetation and higher biomass, reflected in the high CR values. Similarly, in 2021, with higher overall precipitation, Summer Wheat might have experienced robust growth and dense vegetation, leading to elevated CR values. Summer Barley exhibited high NDVI values in both 2018 and 2019, despite the low precipitation during June and July. This can be attributed to several factors. Firstly, sufficient rainfall in the early stages of the growing season likely promoted healthy growth and chlorophyll production, leading to elevated NDVI values. Additionally, favorable temperature conditions during critical growth stages may have contributed to enhanced photosynthetic activity and higher NDVI values in Summer Barley. Regarding the high CR values observed in 2018 and 2021, they can be linked to the structural characteristics and biomass accumulation patterns of Summer Barley. Despite the low precipitation during June and July, other factors influenced the vegetation structure and biomass, resulting in high CR values. These factors include earlier precipitation, which provided beneficial soil moisture conditions before the dry period, leading to denser vegetation and higher biomass reflected in the high CR values. Moreover, favorable temperature and light conditions during critical growth stages further contributed to the development of a compact and dense vegetation structure, supporting the high CR values. Studies conducted by Mandal et al.(2020) have identified similar patterns, demonstrating that the denser vegetation structure and higher biomass content contribute to a more pronounced response to remote sensing data, resulting in elevated CR values.

The variations in CR and NDVI values across different years revealed the influence of weather conditions on these parameters. By considering factors such as precipitation, and temperature we gained a deeper understanding of the relationships between weather patterns and the observed CR and NDVI trends. These findings enhance our knowledge of the complex interactions between crop growth, environmental factors, and remote sensing indicators, contributing to the broader agricultural monitoring and management field.

5.3 Sentinel-1 and Sentinel-2 Thermal Time Feature Space

When using calendar time, the maximum NDVI values varied across the years, ranging from 0.70 to 0.84. On the other hand, when using thermal time, the maximum NDVI values for each year were slightly different, ranging from 0.82 to 0.84.

The observed differences in the maximum NDVI values between calendar time and thermal time indicate a reduction in a temporal shift of crop phenological events when thermal time is considered. Temporal shift refers to the variation in crop development stages due to weather conditions and temperature fluctuations across different years. By incorporating thermal time, which normalises the effect of temperature, the influence of temporal shifts is minimized. Thermal time allows for a more standardized comparison of crop dynamics throughout the season by aligning the growth stages of crops based on accumulated temperature. It reduces the impact of weather variability on crop development, making it easier to identify consistent patterns and relationships between NDVI and crop behaviour. Therefore, when comparing the maximum NDVI values obtained from calendar time and thermal time, the smaller variation in NDVI values obtained from the thermal time suggests a reduced temporal shift. This indicates that the use of thermal time helps to capture the underlying growth patterns and time-invariant characteristics of the crops, providing a more reliable measure of crop growth across different years.

These findings align with previous research conducted by Nyborg et al., (2022) and Parent et al., (2019) emphasising the significance of using thermal time to minimize the effects of weather variability in time series data. Thermal time as a parameter has the potential to reduce the impact of temporal shifts caused by weather conditions, making it a valuable tool for crop type mapping. The integration of thermal time as a parameter and the alignment of thermal time values across different years demonstrated their effectiveness in addressing weather variability and temporal shifts in crop dynamics. The refined feature space resulting from this approach provided a solid foundation for analysing and interpreting crop behaviour, enabling more reliable insights into the relationship between thermal time, crop growth, and phenological development. Continued research in this area will contribute to the advancement of within-season crop type mapping and enhance our understanding of the role of thermal time in minimizing temporal shifts caused by weather conditions.

The incorporation of thermal time, derived from external weather data, alongside Sentinel-1 and Sentinel-2 data significantly improved the analysis of crop behaviour. While both sensors provided valuable insights, the enhancement was more pronounced in the case of Sentinel-2 data. Moreover, the presence of missing data in the Sentinel-2 dataset necessitated interpolation, which introduced a temporal shift among years. However, the inclusion of thermal time effectively reduced this temporal shift, resulting in a more accurate representation of inter-annual variations. This finding underscores the significance of incorporating temperature information and highlights the potential of integrating different data sources to mitigate data gaps and optimize crop monitoring studies. However, to further validate the robustness of thermal time, additional studies should be conducted across a wider range of crop types and longer time periods. This expanded scope would refine the methodology and assess the usability of thermal time as a parameter in reducing temporal shifts in crop type mapping. Further research will provide a more comprehensive understanding of the applicability and limitations of thermal time as a tool for crop monitoring and mapping.

5.4 Within Season Crop Type Mapping - Optimal Temporal Window

The analysis aimed to determine the optimal temporal window for effectively capturing the essential phenological stages of different crop types in Flevoland, Netherlands. The results, evaluated using the F1-score as a performance measure, provided valuable insights into the classification accuracy within the selected classification window (April to August).

As expected, the highest model performances occurred in June for both Sentinel-1 data and Sentinel-2 data. This is in line with the crop calendar of the considered crop types whereby most crop reach their peak metrics in this time. Indeed, these findings agree with the well-established understanding that these months correspond to the maturity stage of the considered crop types, facilitating their accurate distinction and classification (Kamilaris & Prenafeta-Boldú, 2018). These results demonstrate that for the considered crop types it is possible to perform in-season crop type mapping, thus enabling production of crop type maps before the end of the calendar year. Providing timely and accurate information about the crop types present in the scene is extremely important for various stakeholders such as farmers, agronomists, policy-makers, and researchers. By analysing the results obtained in detail, one can notice that potato, winter barley, and winter wheat showed early discernibility as early as April, compared to other crops. This early identification was evident in both Sentinel-1 and Sentinel-2 data due to the presence of distinctive spectral characteristics and growth patterns. Indeed, their phenological metrics showed that their starting seasons start earlier than the remaining crop (Annex7 and 8), which enables the identification of these crops at an earlier stage. This finding corroborates previous studies that have emphasized the unique phenological behaviour and spectral responses exhibited by these crops as stated by Mercier et al.(2020) and Veloso et al.(2017).

Conversely, corn, summer barley, and summer wheat displayed a more distinct identification pattern in June for both sensors, indicating that their phenological stages and spectral characteristics become more pronounced and distinguishable during this period. Crop rotation practices can influence the growth patterns and phenological stages of crops. As a result, these crops may exhibit unique spectral signatures that remain consistent over time. The consistent and reliable classification performance of certain crops, such as potato and winter wheat, across all years and data from both Sentinel-1 and Sentinel-2, suggests that their growth patterns resulting from crop rotation practices contribute to their distinguishable spectral signatures. These crops have specific characteristics and growth behaviours that make them easily distinguishable from other crop types, regardless of variations in environmental conditions, imaging sensors, or different years of observation. The results are aligned with existing knowledge regarding these crops' spectral separability and unique phenological behaviour conducted by Veloso et al.(2017).

In summary, crop rotation can introduce variations in phenology and growth patterns, which can affect the spectral signatures of crops. While certain crops like winter wheat may exhibit more stable characteristics across years, other crops like corn and summer barley may experience more variability due to their similar phenology and the influence of crop rotation. By considering these approaches, future studies can explore the potential of crop rotation as a strategy to mitigate phenological variation and improve classification accuracy. It is important to conduct systematic investigations and evaluate the effectiveness of different strategies of how incorporating crop rotation in different agricultural contexts to further refine and optimize crop classification methodologies.

Moreover, incorporating ground-based observations or field measurements to validate derived phenological metrics would bolster the accuracy and applicability of within-season crop-type mapping. Additionally, integrating comprehensive weather data, including soil moisture, and cropping patterns, would provide valuable insights into the intricate relationship between crop growth dynamics and weather conditions.

Furthermore, the influence of cover crops specifically was not addressed, it is important to consider their presence and potential impact on the spectral response of agricultural fields. Cover crops are commonly used in the Netherlands after harvesting to protect and improve the soil, enhance sustainability, and provide additional ecosystem services. Integrating cover crop information into future studies could help assess its influence on classification accuracy and improve our understanding of the agricultural landscape's temporal behaviour. This would contribute to more comprehensive crop monitoring and management practices.

5.5 Inter-annual Crop Type Mapping

The observed decrease in F1 score can be attributed to the interannual variability in crop growth patterns, which are influenced by various factors such as weather conditions and land management practices. This agrees with previous studies conducted by (Cai et al., 2018), which highlight the impact of temporal shifts on classification model performance when transitioning from one year to another.

Weather conditions, including temperature, and precipitation, play a significant role in crop growth and phenological development. Variations in weather patterns across different years can lead to differences in crop characteristics, such as growth rates, leaf structure, and water stress responses. These variations subsequently affect the spectral signatures captured by Sentinel-1 and Sentinel-2 sensors, impacting the accuracy of crop classification results. Given the time constraints of this study, conducting field visits to precisely understand the causes of these variations was not feasible. However, our findings provide a foundation for identifying the existence of variations in model performance as we transition from one year to another. To enhance model performance and classification accuracy, future studies should prioritise investigating the underlying causes of changes in crop characteristics during the transition between years. This understanding will allow for the exploration of methods to incorporate these changes into the model effectively.

Overall, acknowledging the influence of temporal shifts and interannual variability in crop behaviour is crucial for improving the reliability and applicability of crop classification techniques, ultimately enhancing our ability to monitor and manage agricultural systems effectively.

5.6 Within Season Crop Type Mapping using Historical Data

The results of the classification experiments carried out considering the calendar time representation revealed varying model performances across different data sources. Using Sentinel-1 data, the model achieved a higher overall accuracy and kappa score compared to Sentinel-2 data. However, the F1-scores were generally lower for most crop classes. Combining both Sentinel 1 and Sentinel 2 data improved the overall accuracy and F1 scores compared to the individual data sources. This suggests that the combination of multiple data sources can provide complementary information for crop classification.

When considering the time-invariant feature space (i.e., thermal time), the model's performance improved compared to ones obtained with the calendar time. The incorporation of time-invariant information led to higher OA of 1%, 11% and 7% when using only Sentinel-1, Sentinel-2 and the combination of Sentinel-1 and Sentinel-2. The F1-scores also showed improvements for most crop classes, indicating better classification performance. This highlights the importance of including time-invariant features in crop classification models.

Among the crop classes, potato consistently exhibited high F1 scores, indicating that it was easier to classify accurately. Winter wheat also achieved relatively high F1 scores in all experiments. On the other hand, summer wheat and summer barley consistently had lower F1-scores, suggesting challenges in accurately distinguishing these classes. This lower accuracy could be attributed to the inconsistent sample size available for these two crops. This observation is in line with findings from previous studies, whereby Kamilaris & Prenafeta-Boldú.(2018) in their study also reported that the inadequate sample size for certain crop classes can negatively impact the classification accuracy of remote sensing-based crop mapping. Unlike other crops, summer wheat and summer barley had a smaller number of samples, which might have affected the overall precision of the results. Results demonstrate the benefits of incorporating time-invariant factors and combining multiple data sources for crop classification. The findings can inform the development of more accurate and robust crop classification models, facilitating agricultural monitoring and management.

Another significant finding was related to the impact of thermal time on the performance of Sentinel-1 and Sentinel-2. When the thermal time was applied, Sentinel-1 showed less improvement compared to Sentinel-2. This could be attributed to the consistent acquisition dates of Sentinel-1, which allowed complete data availability every six days. In contrast, Sentinel-2's acquisition dates were not consistent, requiring interpolation to fill in the gaps. As a result, thermal time exhibited a high positive impact on Sentinel-2. Furthermore, Sentinel-1 consistently demonstrated higher accuracy compared to Sentinel-2. when Sentinel-1 and Sentinel-2 were combined, the overall accuracy did improve, but Sentinel-1 still maintained a higher level of accuracy compared to Sentinel-2. This indicates that Sentinel-1 provided more precise and reliable data for crop assessment and monitoring, even after combining it with Sentinel-2. The differences observed in model performance can be attributed to the distinctive characteristics of Sentinel 1 and Sentinel 2 data. Sentinel 1 data, based on radar technology, provides valuable information on backscatter signals and surface roughness. This information is advantageous for crops with dense canopies or crops with distinct SAR signatures. However, it may not capture certain spectral characteristics that are better captured by Sentinel 2 data, such as variations in chlorophyll content or leaf structure. This discrepancy could explain the lower F1-scores observed for some crop classes in the Sentinel-1 experiment.

Conversely, Sentinel-2 data comprises multispectral imagery that offers rich spectral information for crop classification. The spectral bands in Sentinel-2 data capture reflectance properties related to vegetation health, phenology, and moisture content. However, atmospheric conditions, cloud cover, and shadow effects can impact the quality and accuracy of classification results. The improved performance observed when combining Sentinel-1 and Sentinel-2 data can be attributed to the synergistic effects of integrating both SAR and optical information. The combination of these data sources compensates for the limitations of each individual dataset and provides a more comprehensive understanding of crop characteristics. Our findings align with previous research that emphasizes the benefits of combining SAR and optical data for crop classification, the complementary nature of these data sources in capturing different aspects of crop properties has been widely recognized. Studies have shown that the integration of SAR and optical information can improve classification accuracy and reduce uncertainties associated with using a single data source (Hong et al., 2014; Joshi et al., 2016; McNairn et al., 2009; Nasiri et al., 2022).

To further enhance the classification models, future studies could explore the integration of ancillary data, such as high-resolution imagery, additional climate data, and ground-based observations. Furthermore, changes in land management practices, such as crop rotation, irrigation techniques, and fertilization, also contribute to temporal shifts of crop characteristics. Additionally, it could be better when also these factors can be considered for future studies instead of considering only thermal time. Furthermore, the utilization of advanced machine learning techniques, such as deep learning algorithms, holds promise for improving the accuracy and robustness of crop classification models. By continuously refining these models, we can contribute to advancing agricultural practices and decision-making processes.

5.7. Limitation and Recommendations of the study

Limitation

Small sample size: This study acknowledges that among the six crops analysed, there was variation in the number of samples available. While some crops had a high number of samples, others had a significantly smaller number. This discrepancy in sample size could affect the generalisability of the findings and the overall reliability of the results. For a more robust analysis, it would be preferable for the number of samples to be nearly equal among the different crops. This would ensure a balanced representation and provide a more accurate understanding of the phenological patterns and dynamics across all crops. By achieving a more equitable distribution of samples, future studies can enhance the reliability and generalizability of their findings, enabling more confident conclusions and practical applications.

Absence of fieldwork: The study highlights that due to time constraints, fieldwork was not feasible, which resulted in the absence of direct validation of the remote sensing data and phenological metrics with on-ground observations. This limitation has implications for the comprehensiveness and accuracy of the study's findings. Field data collection plays a crucial role in providing detailed and context-specific information about the crops and their growth stages. By conducting on-site field visits, researchers can assess phenological stages, collect ground-based observations, and measure vegetation indices, thus enabling validation and calibration of the remote sensing data. Moreover, field visits would also facilitate a deeper understanding of the underlying factors that may contribute to crop dynamics, particularly when comparing different years. Factors such as soil conditions, management practices, and localised climate variations can be better captured through field observations, leading to a more holistic analysis of crop growth patterns and their drivers.

Recommendations

Increase sample size: Conducting future studies with a larger sample size would enhance the representativeness and generalisability of the findings. Including a wider range of crop types and multiple locations would provide a more comprehensive understanding of crop dynamics and phenological patterns. By increasing the diversity and number of sample sites, researchers can capture a broader range of environmental and agricultural conditions, thereby improving the reliability and applicability of the study's results. A larger sample size would also allow for more robust statistical analysis and increase confidence in the conclusions drawn.

Validate with field observations: To improve the reliability of the results, it is recommended to conduct fieldwork and collect on-ground observations in conjunction with remote sensing data. Field observations can provide direct validation of the remote sensing-based phenological metrics and enhance the accuracy of the study. By collecting field observations, such as ground truth measurements, field phenology observations, and yield data, researchers can compare and validate the remote sensing-derived results. This validation process would ensure that the remote sensing data accurately reflects the true state of the crops and their phenological stages, providing more confidence in the study's findings.

Explore additional data integration: While the study integrated Sentinel-1, Sentinel-2, and thermal time data, further exploration of additional data sources could provide more comprehensive insights. Consideration of other remote sensing datasets, such as hyperspectral or LiDAR data, could enhance the analysis of crop dynamics and improve the accuracy of crop type mapping. Incorporating additional data sources can provide a more detailed characterization of crop properties, such as vegetation structure, biochemical composition, and canopy density. This richer information can help refine the analysis and improve the understanding of crop growth dynamics, leading to more accurate and precise assessments.

Long-term studies: Conducting long-term studies spanning multiple years would enable a better understanding of inter-annual variability and climate impacts on crop phenology. Long-term data analysis would provide valuable insights into the long-term trends and stability of crop growth patterns, allowing for more accurate predictions and management strategies. By observing and analysing crop dynamics over multiple years, researchers can assess the influence of climate variability and change on crop phenology, identify trends, and develop predictive models. Long-term studies would provide a more comprehensive understanding of the temporal dynamics of crops, enabling policymakers and agricultural stakeholders to make informed decisions and adapt to changing environmental conditions.

6. CONCLUSION

The analysis of Sentinel-1 and Sentinel-2 data in Flevoland, Netherlands has yielded valuable insights into the phenological behaviour, growth patterns, and spectral characteristics of different crop types within a single season. By integrating SAR backscatter (CR), spectral reflectance (NDVI), and thermal time data, a comprehensive understanding of crop dynamics and their relationship with weather conditions has been achieved. This study aimed to investigate crop-specific temporal profiles across multiple years, develop an effective approach to construct a time-invariant feature space using historical data, crop calendar information, and weather data. Moreover, the study intend to determine the optimal temporal window for accurate within-season crop type mapping, and compare the performance of integrating Sentinel-1 and Sentinel-2 data versus using only SAR or optical features. The findings contribute to advancing remote sensing applications in agriculture and provide valuable guidance for future crop monitoring and management practices.

1. What is the crop-specific temporal behaviour recorded by Sentinel-1 and Sentinel-2 in the considered study area for different years?

The analysis of phenological metrics extracted from Sentinel-1 and Sentinel-2 data revealed distinct differences in season start dates and peak metrics between the two satellite sensors. Sentinel-1 exhibited earlier start dates due to its ability to detect changes in surface conditions under cloudy or unfavourable weather conditions. Weather parameters, such as temperature and precipitation, were found to influence inter-annual variations of phenology. Warmer conditions resulted in earlier detection of phenological phases, while wet conditions caused delays. These findings emphasise the importance of considering multiple data sources to capture vegetation dynamics fully. Sentinel-1's ability to detect early signs of growth and changes in vegetation structure is a valuable asset for crop monitoring and management.

2. What is the most effective approach for creating a time-invariant feature space using historical data, crop calendar information, and weather data to construct a representative training dataset for a specific target year?

The analysis of SAR backscatter (CR) and spectral reflectance (NDVI) from Sentinel-1 and Sentinel-2 data, respectively, provided valuable insights into the growth dynamics, phenological changes, and scattering properties of different crop types across different years. Weather data played a crucial role in understanding the variations in CR and NDVI values. For instance, winter barley exhibited high CR values in favorable weather conditions, leading to dense vegetation structure, while low CR values were observed in unfavourable weather conditions. Similarly, variations in NDVI values were associated with healthier and more vigorous growth during favorable weather conditions. These findings highlight the potential of combining SAR and optical data for crop monitoring, as both sensors offer unique insights into vegetation characteristics.

3. Which temporal window can optimally capture the essential phenological stages per crop type to generate accurate within season crop type mapping?

The utilization of thermal time as a parameter and the alignment of thermal time values across different years proved effective in mitigating the impact of weather variability and temporal shifts on crop dynamics. This approach standardized and compared crop behaviour, leading to a more consistent assessment of growth patterns. Thermal time has the potential to reduce the influence of temporal shifts caused by weather conditions, making it a valuable tool for crop type mapping. The integration of thermal time alongside Sentinel-1 and Sentinel-2 data significantly improved the analysis of crop behavior, particularly in the case of Sentinel-2 data. However, further research is needed to validate the robustness of thermal time across a wider range of crop types and time periods.

4. Does within-season crop type mapping with the integration of Sentinel-1 and Sentinel-2 data perform better than utilising only SAR or optical features?

The analysis of the optimal temporal window for capturing essential phenological stages of different crop types in the study area revealed that the highest model performances occurred in June for both Sentinel-1 and Sentinel-2 data. This aligns with the crop calendar of the considered crop types, where most crops reach their peak metrics during this time. This finding allows for the timely and accurate production of crop type maps before the end of the calendar year. Furthermore, the early discernibility of certain crops such as potato, winter barley, and winter wheat as early as April was evident in both Sentinel-1 and Sentinel-2 data. These crops showed distinctive spectral characteristics and growth patterns, enabling their identification at an earlier stage.

In conclusion, the integration of Sentinel-1 and Sentinel-2 data, alongside with weather information, historical cropland data and thermal time, has provided valuable insights into within-season crop type mapping in Flevoland, Netherlands. The analysis has enhanced our understanding of crop dynamics, growth patterns, and their relationship with environmental factors. The findings underscore the importance of considering multiple data sources and weather conditions to capture the full range of vegetation dynamics. These insights can inform decision-making processes related to agricultural management, resource allocation, and crop monitoring, ultimately contributing to more efficient and sustainable agricultural practices.

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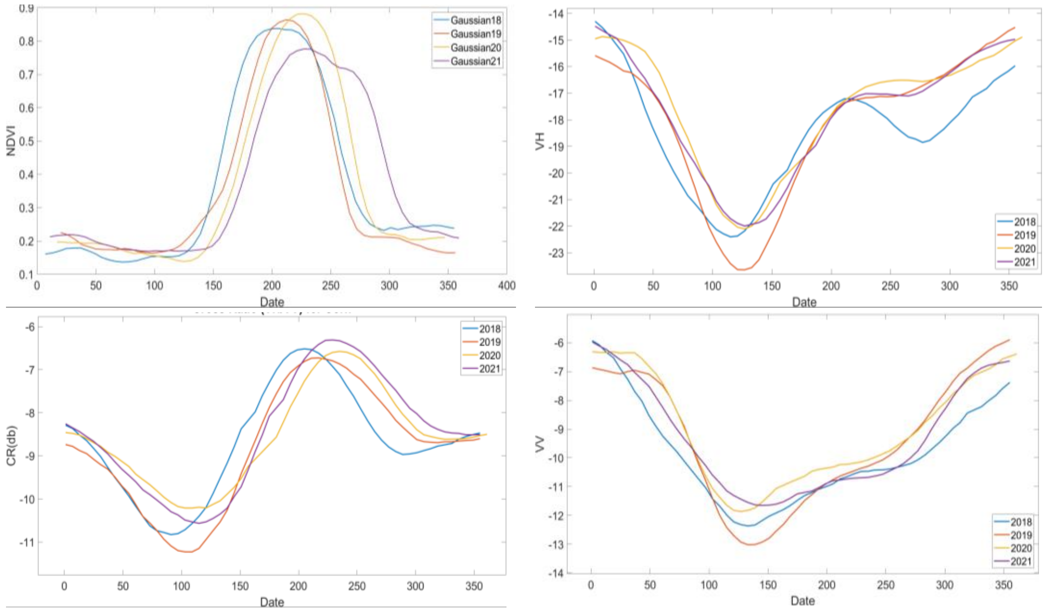
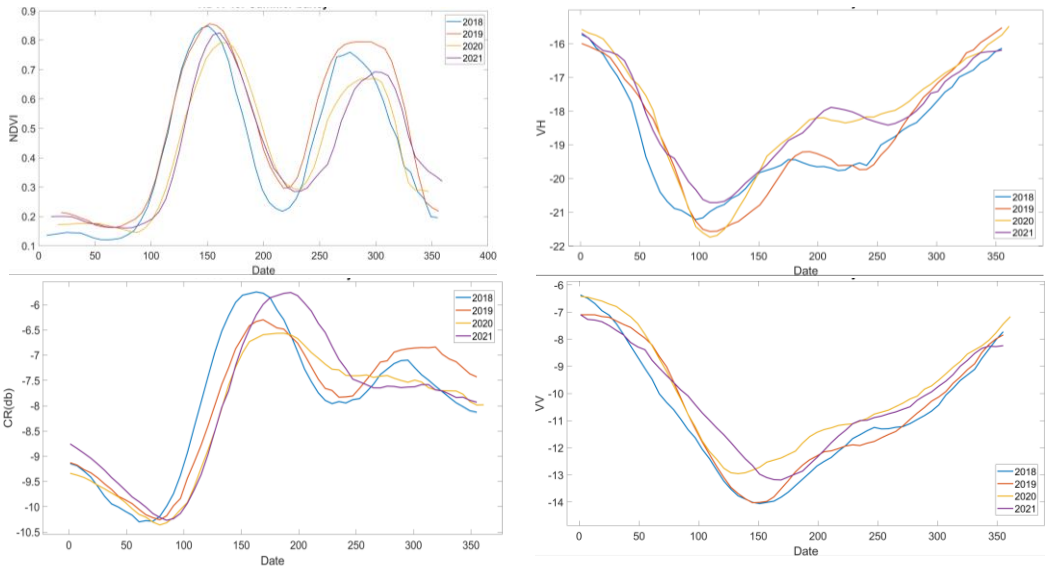
7. APPENDIX

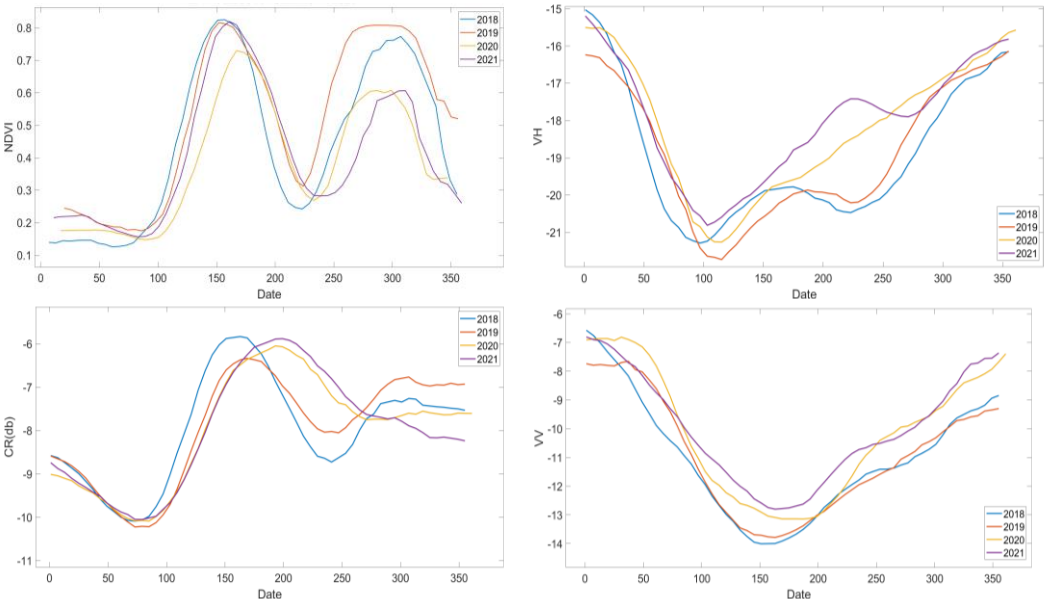
Annex 1: Example of median temporal profiles for Corn samples available in the considered study area computed for the years 2018, 2019, 2020, and 2021. The profiles included the following parameters: NDVI, VH backscatter CR (VH/VV backscatter ratio), and VV backscatter.



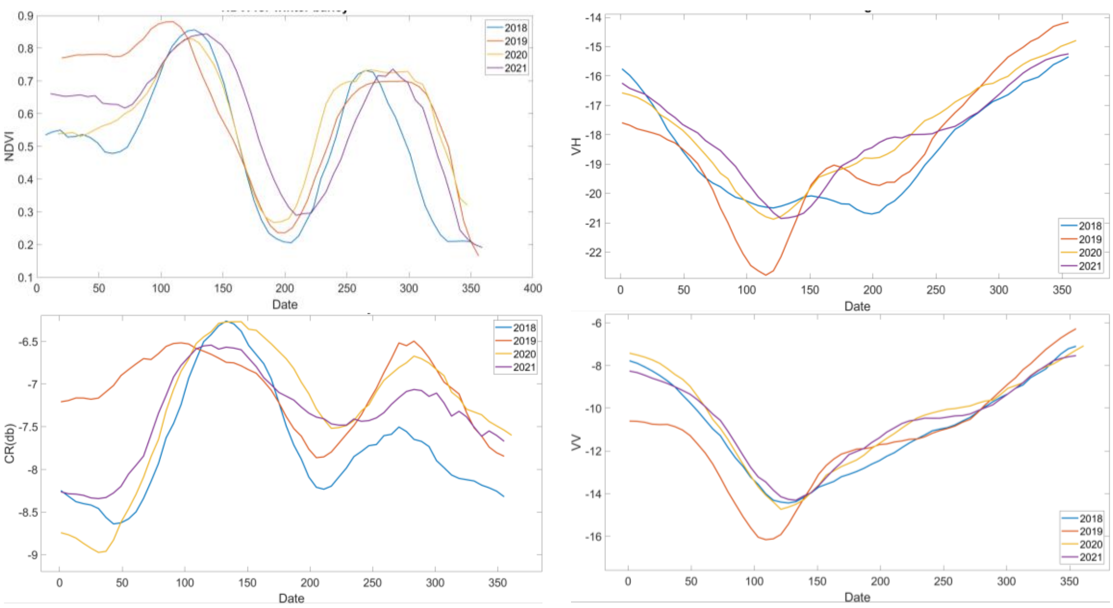
Annex 2: Example of median temporal profiles for Summer barley samples available in the considered study area computed for the years 2018, 2019, 2020, and 2021. The profiles included the following parameters: NDVI, VH backscatter CR (VH/VV backscatter ratio), and VV backscatter.



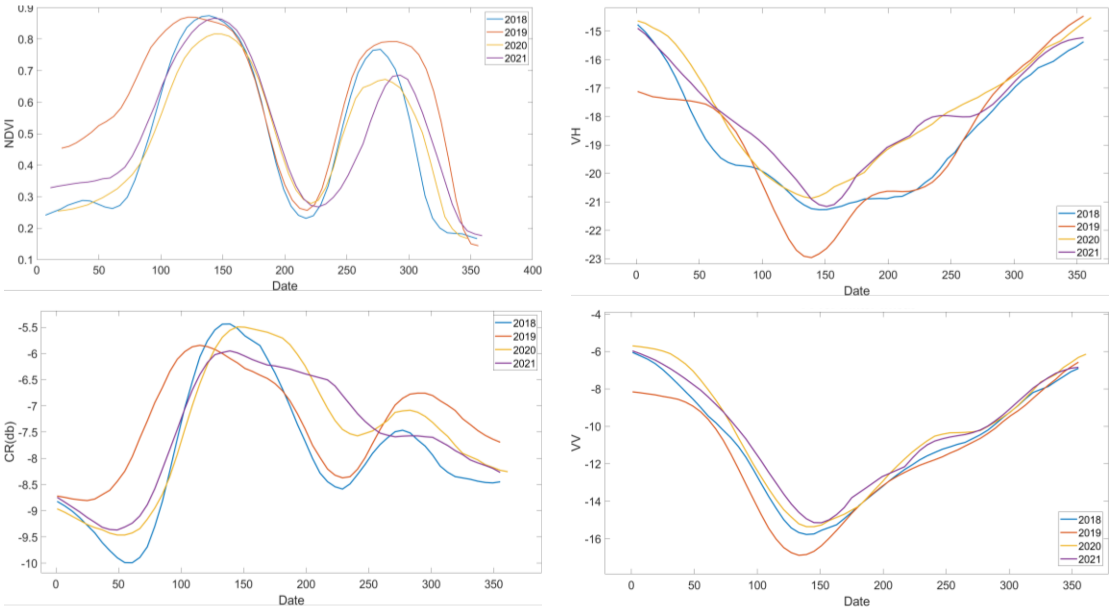
Annex 3: Example of median temporal profiles for Summer wheat samples available in the considered study area computed for the years 2018, 2019, 2020, and 2021. The profiles included the following parameters: NDVI, VH backscatter CR (VH/VV backscatter ratio), and VV backscatter.



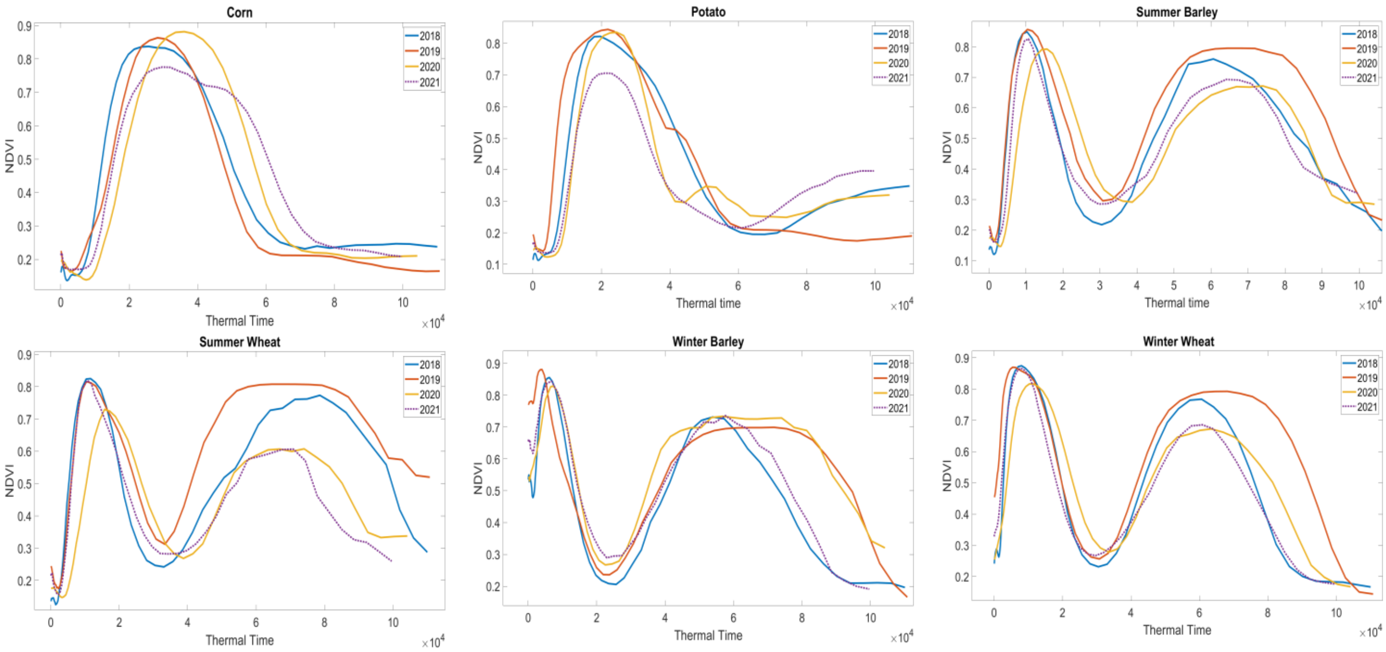
Annex 4: Example of median temporal profiles for Winter Barley samples available in the considered study area computed for the years 2018, 2019, 2020, and 2021. The profiles included the following parameters: NDVI, VH backscatter CR (VH/VV backscatter ratio), and VV backscatter.



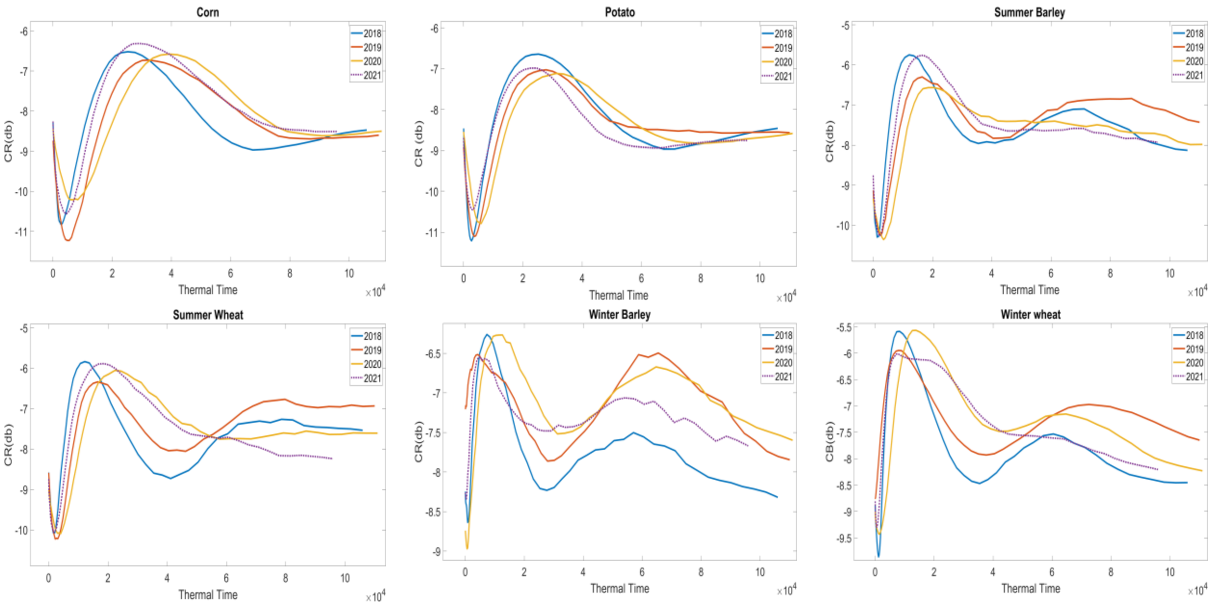
Annex 5: Example of median temporal profiles for Winter wheat samples available in the considered study area computed for the years 2018, 2019, 2020, and 2021. The profiles included the following parameters: NDVI, VH backscatter CR (VH/VV backscatter ratio), and VV backscatter.



Annex6: Example of median temporal profile for six crop sample available in the considered study area computed for the years 2018, 2019, 2020, and 2021. The profiles compare the calendar time vs thermal time across different years for Sentinel-2.



Annex6: Example of median temporal profile for six crop sample available in the considered study area computed for the years 2018, 2019, 2020, and 2021. The profiles compare the calendar time vs thermal time across different years for Sentinel-1.



Annex7: Phenological metrics extracted from Sentinel-1 for six crops.

			2018	2019	2020	2021
Summer wheat	SOS		11-Apr	24-Apr	18-April	19-Apr
	EOS		28-Jul	04-Aug	03-Sep	16-Sep
	Peak CR	value	-5.8	-6.3	-6.00	-5.8
		Date	16-Jun	23-Jun	11-Jul	18-Jul

			2018	2019	2020	2021
Corn	SOS		05-May	18-May	30-May	25-May
	EOS		26-Sep	15-Oct	15-Oct	28-Oct
	Peak CR	value	-6.5	-6.7	-6.50	-6.3
		Date	28-Jul	04-Aug	22-Aug	17-Aug

			2018	2019	2020	2021
Summer barley	SOS		05-Apr	12-Apr	12-Apr	19-Apr
	EOS		03-Aug	04-Aug	04-Aug	17-Aug
	Peak CR	value	-5.7	-6.29	-6.56	-5.75
		Date	16-Jun	23-Jun	29-Jun	12-Jul

			2018	2019	2020	2021
Winter bar-ley	SOS		24-Mar	17-Feb	13-Mar	02-Mar
	EOS		04-Jul	11-Jul	29-Jul	18-Jul
	Peak CR	value	-6.26	-6.5	-6.20	-6.5
		Date	17-May	12-Apr	18-May	01-May

			2018	2019	2020	2021
Winter wheat	SOS		24-Mar	01-Mar	25-Mar	14-Mar
	EOS		04-Jul	05-Jul	23-Jul	23-Aug
	Peak CR	value	-5.60	-6.00	5.60	-6
		Date	23-May	12-May	30-May	19-May

Annex 8: **Phenological metrics extracted from Sentinel-2**

			2018	2019	2020	2021
Summer Wheat	SOS		19-April	26-April	04-May	29-April
	EOS		24-Jul	31-Jul	8-Aug	9-Aug
	Peak NDVI	value	0.82	0.81	0.72	0.81
		Date	06-Jun	01-Jun	15-Jun	10-Jun

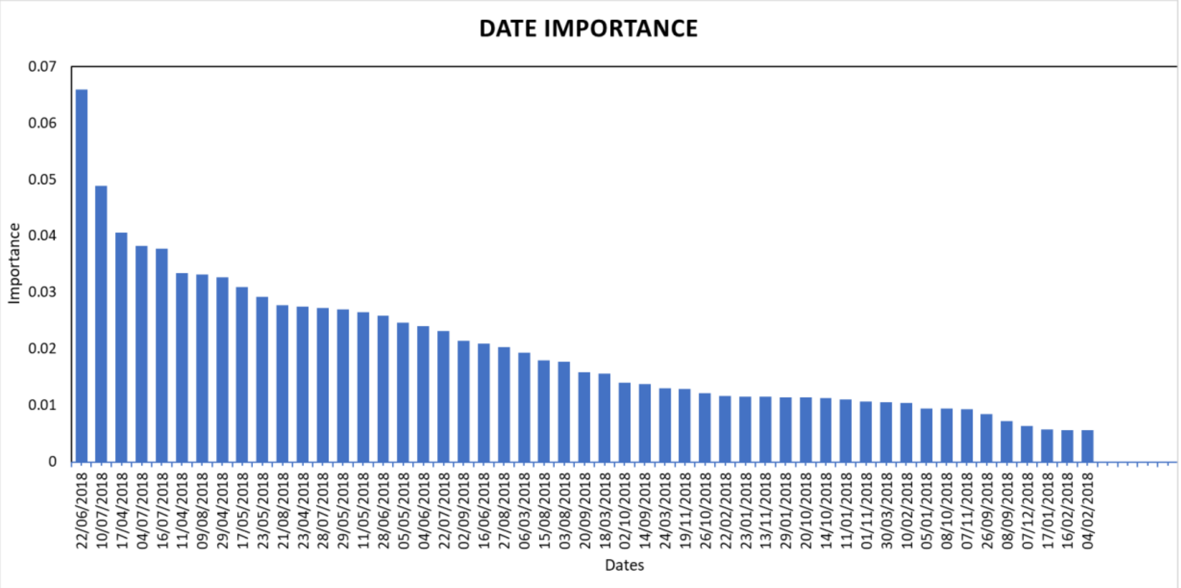
			2018	2019	2020	2021
Corn	SOS		31-May	01-Jun	09-Jun	22-Jun
	EOS		28-Sep	17-Sep	01-Oct	28-Oct
	Peak NDVI	value	0.83	0.86	0.88	0.77
		Date	24-Jul	31-Jul	14-Aug	15-Aug

			2018	2019	2020	2021
Summer bar-ley	SOS		13 Aprl	14 Aprl	28 Aprl	29 Aprl
	EOS		12-Jul	25-Jul	02-Aug	09-Aug
	Peak NDVI	value	0.84	0.85	0.79	0.82
		Date	31-May	01-Jun	15-Jun	10-Jun

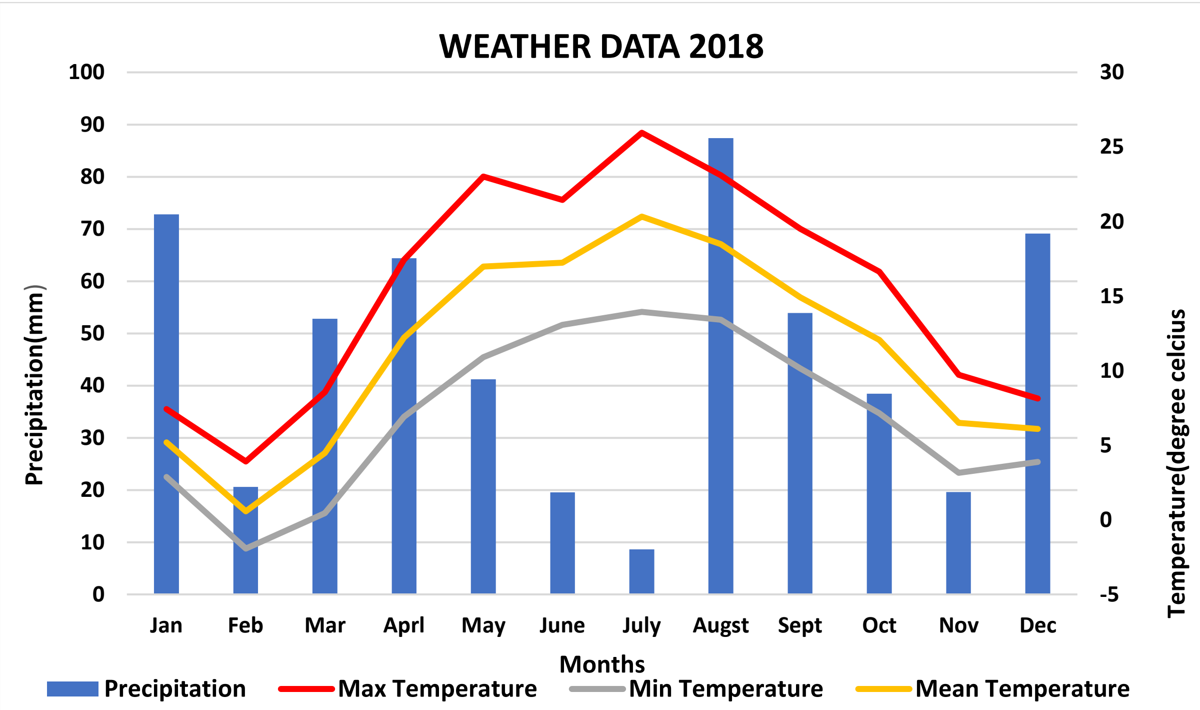
			2018	2019	2020	2021
Winter barley	SOS		26-Mar	15-Mar	17-Mar	24-Mar
	EOS		06-Jun	01-Jul	09-Jun	16-Jul
	Peak NDVI	value	0.85	0.88	0.82	0.84
		Date	07-May	14-Apr	04-May	17-May

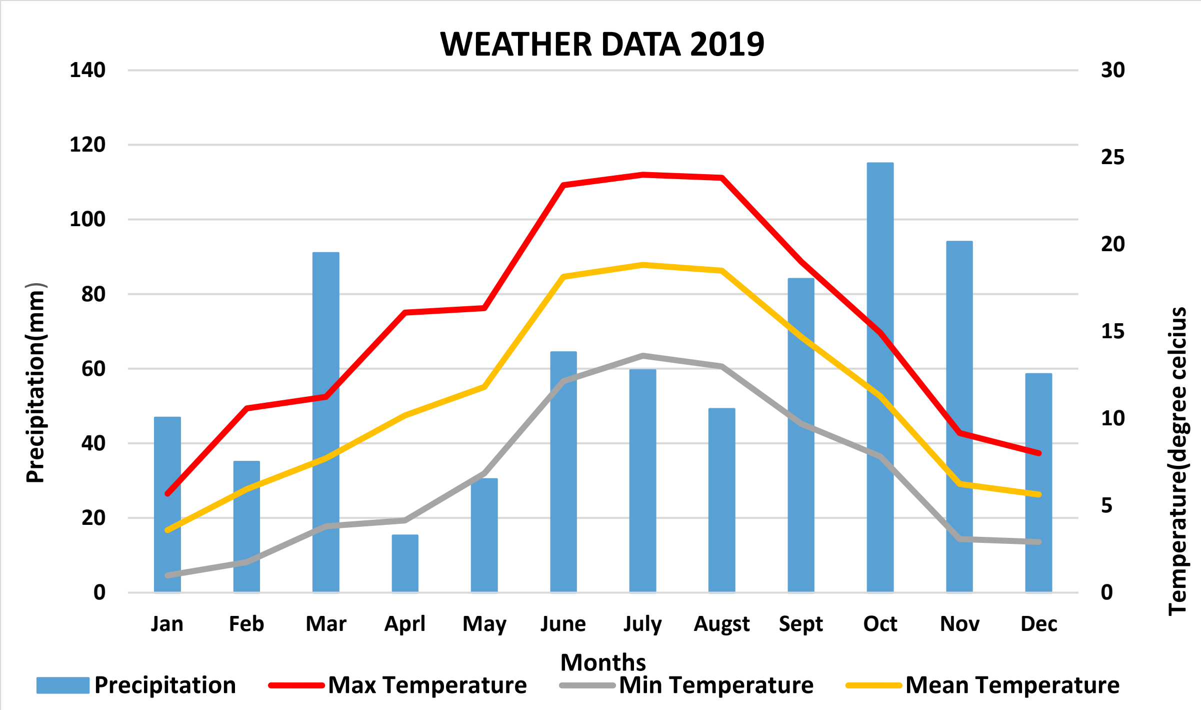
			2018	2019	2020	2021
winter wheat	SOS		26-Mar	03-Mar	23-Mar	18-Mar
	EOS		12-Jul	13-Jul	15-Jul	16-Jul
	Peak NDVI	value	0.87	0.86	0.81	0.86
		Date	19-May	02-May	22-May	23-May

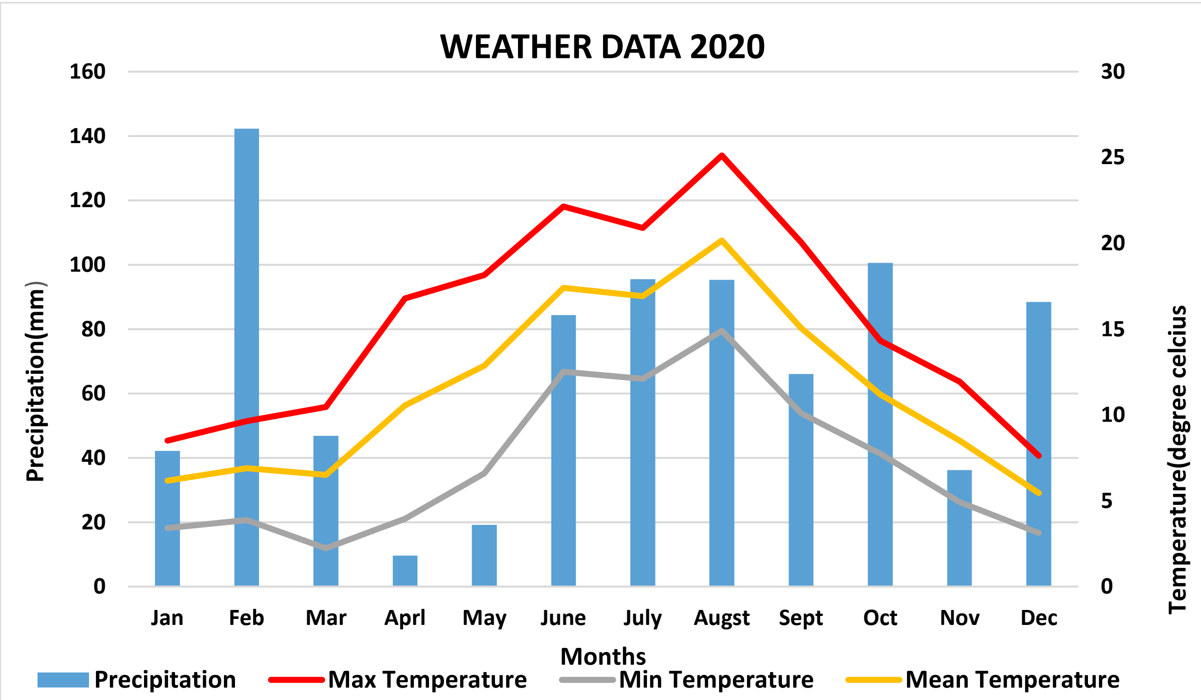
Annex 9: Feature Imporatance

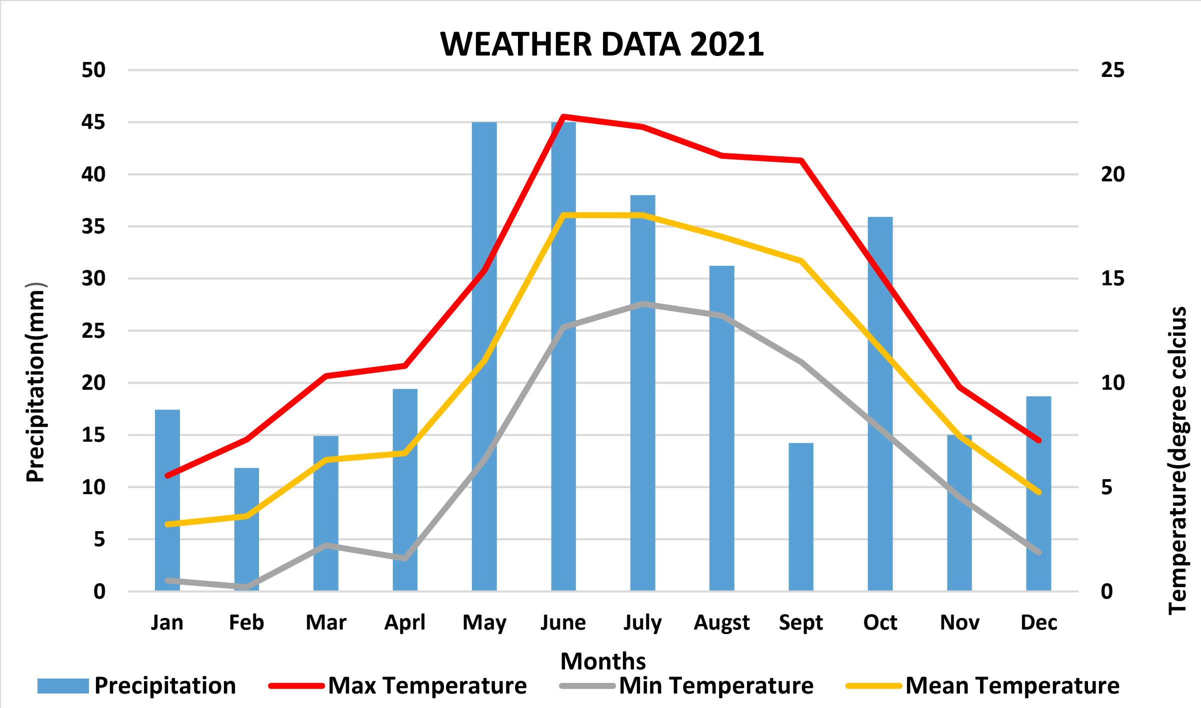


Annex8: Weather data of Flevoland for year 2018 to 2021

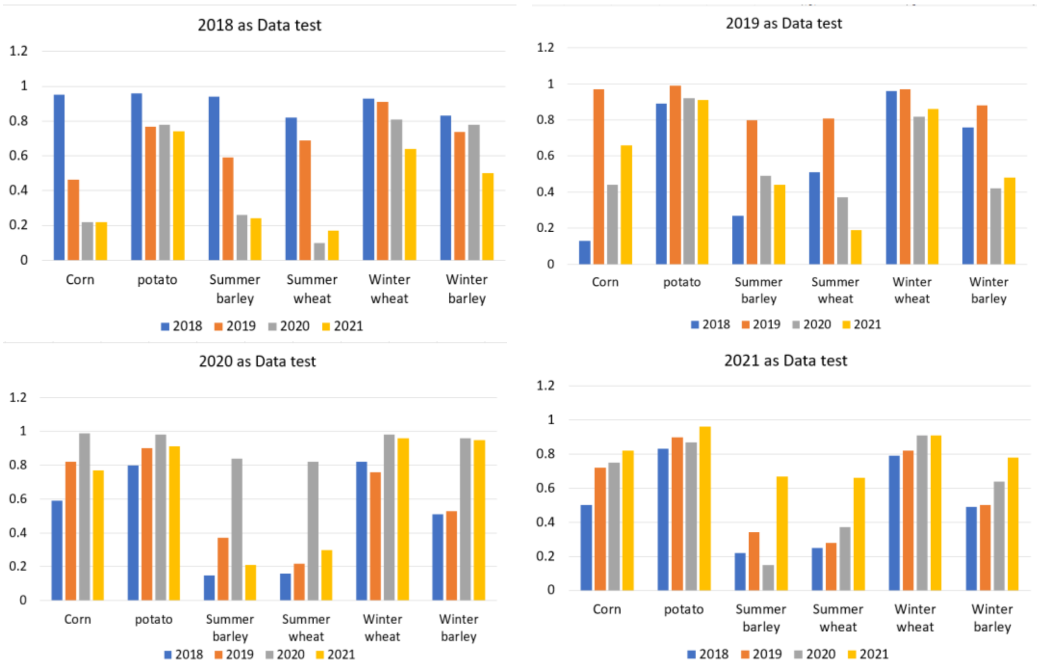



WEATHER DATA 2019
Precipitation(mm)
Temperature(degree celcius
140
120
100
80
60
40
20
0
30
25
20
15
10
5
0
Jan
Feb
Mar
Aprl
May
June
July
Augst
Sept
Oct
Nov
Dec
Months
Precipitation
Max Temperature
Min Temperature
Mean Temperature


WEATHER DATA 2020
Precipitation(mm)
Temperature(degree celcius
160
140
120
100
80
60
40
20
0
30
25
20
15
10
5
0
Jan
Feb
Mar
Aprl
May
June
July
Augst
Sept
Oct
Nov
Dec
Months
Precipitation
Max Temperature
Min Temperature
Mean Temperature



Annex9: Explore how the accuracy changes when previous year is used to train the target year.



Annex 10: Max NDVI value obtained from Calendar Time and Thermal time.

Potato		
	Max NDVI value obtained from Calendar Time	Max NDVI value obtained from Thermal time
2018	0.82	0.83
2019	0.84	0.84
2020	0.83	0.82
2021	0.7	0.82

Corn		
	Max NDVI value obtained from Calendar Time	Max NDVI value obtained from Thermal time
2018	0.83	0.84
2019	0.86	0.86
2020	0.88	0.87
2021	0.77	0.87

Summer Barley		
	Max NDVI value obtained from Calendar Time	Max NDVI value obtained from Thermal time
2018	0.84	0.85
2019	0.85	0.85
2020	0.79	0.8
2021	0.82	0.8

Winter Barley		
	Max NDVI value obtained from Calendar Time	Max NDVI value obtained from Thermal time
2018	0.85	0.85
2019	0.88	0.86
2020	0.82	0.83
2021	0.84	0.83

Summer Wheat		
	Max NDVI value obtained from Calendar Time	Max NDVI value obtained from Thermal time
2018	0.82	0.82
2019	0.81	0.82
2020	0.72	0.75
2021	0.81	0.82

Winter Wheat		
	Max NDVI value obtained from Calendar Time	Max NDVI value obtained from Thermal time
2018	0.87	0.87
2019	0.86	0.87
2020	0.81	0.82
2021	0.86	0.82