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Multitemporal Remote Sensing for Crop Classification and Drought Assessment Using Landsat and Sentinel-2

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Multitemporal Remote Sensing for Crop Classification and Drought Assessment Using Landsat and Sentinel-2

PhD Thesis

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Abstract

This study investigates the use of satellite remote sensing technologies to improve crop classification and assess drought-induced crop failure. Chapter 1 focuses on long-term crop monitoring in the semi-arid region of Barrax, Spain, utilizing Landsat-5, -7, and -8 imagery from 1985 to 2022. To manage the complexity of the data, Principal Component Analysis (PCA) was applied to reduce the dimensionality of time series of the Normalized Difference Vegetation Index (NDVI), followed by the Random Forest classification algorithm to generate annual crop maps. The results demonstrated a notable improvement in classification accuracy, from 94.6% in 1995 using Landsat-5 alone, to 98.7% in 2015 with the integration of Landsat-7 and Landsat-8 data. This study highlights the value of multi-temporal Landsat data for precise crop classification, offering insights into seasonal growth patterns and land use changes, and supporting sustainable agricultural management in semi-arid regions.

Chapter 2 explores the detection of drought impacts on winter cereals in Catalonia, Spain, using Sentinel-2 satellite imagery. During the extreme drought of 2023, ground-truth data on crop failure were collected, and the best Sentinel-2 variables for predicting drought impact classes were identified. Phenological metrics and vegetation indices were extracted, with the NDVI during later stages of crop development found to be a strong predictor of crop failure ($R^2 = 0.66$). The findings suggest that Sentinel-2 data from the latter half of the growing season are critical for accurately detecting drought-induced crop failure. This approach underscores the importance of phenological data in monitoring crop health and identifying agricultural losses due to extreme climatic events.

Together, these chapters demonstrate the essential role of satellite remote sensing in enhancing agricultural monitoring and resilience to climate variability. The integration of Landsat and Sentinel-2 data provides robust tools for improving land management and supporting informed decision-making in drought-prone and semi-arid regions.

Resum

Aquest estudi investiga l'ús de tecnologies de teledetecció per satèl·lit per millorar la classificació de cultius i avaluar el fracàs dels cultius i les pèrdues en la collita a causa de la sequera. El Capítol 1 se centra en el seguiment a llarg termini dels cultius a la regió semiàrida de Barrax, Espanya, utilitzant imatges de Landsat-5, -7 i -8 des del 1985 fins al 2022. Per gestionar la complexitat de les dades, es va aplicar l'Anàlisi de Components Principals (PCA) per reduir la dimensionalitat de les sèries temporals de l'Índex de Vegetació de Diferència Normalitzada (NDVI), seguit de l'ús de l'algorisme de classificació Random Forest per generar mapes anuals de cultius. Els resultats van demostrar una millora notable en la precisió de la classificació, passant del 94,6% l'any 1995 utilitzant només Landsat-5, fins al 98,7% l'any 2015 amb la integració de dades de Landsat-7 i Landsat-8. Aquest estudi ressalta el valor de les dades multitemporals de Landsat per a una classificació precisa dels cultius, proporcionant informació sobre els patrons de creixement estacional i els canvis en l'ús del sòl, donant suport a la gestió agrícola sostenible en regions semiàrides.

El Capítol 2 explora la detecció dels impactes de la sequera en els cereals d'hivern a Catalunya, Espanya, utilitzant imatges del satèl·lit Sentinel-2. Durant la sequera extrema de 2023, es van recollir dades de camp sobre el fracàs dels cultius, i es van identificar les millors variables de Sentinel-2 per predir les classes d'impacte de la sequera. Es van extreure mètriques fenològiques i índexs de vegetació, i es va trobar que l'índex NDVI durant les etapes tardanes del desenvolupament dels cultius és un fort predictor del fracàs dels cultius (R^2 = 0,66). Els resultats suggereixen que les dades de Sentinel-2 de la segona meitat de la temporada de creixement són crucials per detectar amb precisió el fracàs dels cultius induït per la sequera. Aquest enfocament subratlla la importància de les dades fenològiques per monitoritzar la salut dels cultius i identificar pèrdues agrícoles a causa d'esdeveniments climàtics extrems.

En conjunt, aquests capítols demostren el paper essencial de la teledetecció per satèl·lit per millorar el seguiment agrícola i la resiliència davant la variabilitat climàtica. La integració de les dades de Landsat i Sentinel-2 proporciona eines robustes per millorar la gestió agrícola i donar suport a la presa de decisions en regions semiàrides propenses a la sequera.

Resumen

Este estudio investiga el uso de tecnologías de teledetección por satélite para mejorar la clasificación de cultivos y evaluar el fracaso de los cultivos y pérdida de la cosecha debido a la sequía. El Capítulo 1 se centra en el monitoreo a largo plazo de los cultivos en la región semiárida de Barrax, España, utilizando imágenes de Landsat-5, -7 y -8 desde 1985 hasta 2022. Para gestionar la complejidad de los datos, se aplicó el Análisis de Componentes Principales (PCA) para reducir la dimensionalidad de las series temporales del Índice de Vegetación de Diferencia Normalizada (NDVI), seguido del uso del algoritmo de clasificación Random Forest para generar mapas anuales de cultivos. Los resultados demostraron una notable mejora en la precisión de la clasificación, desde un 94.6% en 1995 utilizando únicamente Landsat-5, hasta un 98.7% en 2015 con la integración de datos de Landsat-7 y Landsat-8. Este estudio resalta el valor de los datos multitemporales de Landsat para una clasificación precisa de los cultivos, proporcionando información sobre los patrones de crecimiento estacional y los cambios en el uso de la tierra, apoyando la gestión agrícola sostenible en regiones semiáridas.

El Capítulo 2 explora la detección de los impactos de la sequía en los cereales de invierno en Cataluña, España, utilizando imágenes del satélite Sentinel-2. Durante la sequía extrema de 2023, se recopilaron datos de campo sobre el fracaso de los cultivos, y se identificaron las mejores variables de Sentinel-2 para predecir las clases de impacto de la sequía. Se extrajeron métricas fenológicas e índices de vegetación, y se encontró que el NDVI durante las etapas tardías del desarrollo de los cultivos es un fuerte predictor del fracaso de los cultivos (R^2 = 0.66). Los hallazgos sugieren que los datos de Sentinel-2 de la segunda mitad de la temporada de crecimiento son críticos para detectar con precisión el fracaso de los cultivos inducido por la sequía. Este enfoque subraya la importancia de los datos fenológicos para monitorear la salud de los cultivos e identificar pérdidas agrícolas debido a eventos climáticos extremos.

En conjunto, estos capítulos demuestran el papel esencial de la teledetección satelital para mejorar el monitoreo agrícola y la resiliencia frente a la variabilidad climática. La integración de los datos de Landsat y Sentinel-2 proporciona herramientas robustas para mejorar la gestión agrícola y apoyar la toma de decisiones en regiones semiáridas propensas a la sequía.

General Introduction

Terrestrial ecosystem is experiencing accelerated environmental shifts, primarily driven by climate change and the growing demand for natural resources (Bergstrom et al., 2021). These changes present significant challenges for biodiversity, agriculture, and land management, sectors that are highly sensitive to shifts in environmental conditions.

Agricultural systems are particularly vulnerable to climate change. Temperature alterations, shifts in precipitation patterns, and the increasing frequency of extreme events, such as droughts, floods, and heatwaves, directly affect crop yields (Piao et al., 2010; Zuzulova & Vido, 2018). Recent studies have shown that rising global temperatures and greater climate variability are negatively impacting the yields of staple crops such as wheat, maize, and rice (Zhao et al., 2017; Lobell et al., 2021). These effects highlight the urgent need for more effective monitoring systems that can anticipate and mitigate the impacts of climate change on agricultural production.

Furthermore, as the global population continues to grow, so does the demand for food and agricultural commodities (Foley et al., 2005; Godfray et al., 2010). Feeding a population projected to exceed 9 billion by 2050 will require innovative solutions that not only increase agricultural productivity but also ensure the sustainability of land use practices (Tilman et al., 2011). In the face of these challenges, agriculture must become more resilient and adaptive to environmental changes, particularly in regions where climate impacts are more pronounced, such as semi-arid and arid zones (Yu et al., 2023).

As global temperatures rise and weather patterns become increasingly unpredictable, the ability to monitor these changes accurately and in real-time has become crucial for informed decision-making (IPCC, 2021). In this context, earth observation satellites have proven to be indispensable tools for monitoring land use and crop classifications at large scales (Asner et al., 2002; Jakubauskas et al., 2002; Rodriguez-Galiano et al., 2012a). Such spatial information is essential for applications ranging from crop modelling to yield estimation and the management of cultivated areas (Loveland, 1991; Mkhabela et al., 2011).

Remote sensing technologies, such as Landsat and Sentinel-2, have become essential tools in agricultural monitoring, providing high-resolution data that allow for the assessment of both crop classification and environmental stressors like drought. These satellites offer the capability to monitor large areas over time, offering insights into how agricultural systems respond to changing climatic conditions. By combining long-term data from Landsat with the higher spatial and temporal resolution of Sentinel-2, it is possible to gain a detailed understanding of agricultural dynamics and their interaction with environmental stress factors.

Landsat has provided continuous data since the 1970s, making it ideal for long-term analysis of crop classification. This is especially valuable in semi-arid regions where water scarcity and unpredictable rainfall can significantly influence land-use patterns (Masek et al., 2022). By analysing the NDVI and other vegetation indices derived from Landsat, researchers can track the development and health of crops over time, allowing for the identification of key trends in agricultural productivity. This long-term perspective is essential for understanding how agricultural systems have adapted to historical climatic variations and can help inform future land management strategies in water-scarce regions (Wulder et al., 2022).

Sentinel-2 offers high spatial and temporal resolution data, making it particularly useful for assessing the immediate impacts of environmental stressors such as drought (Drusch et al., 2012). When crops are exposed to drought conditions, their physical and chemical properties change, which alters how they reflect light. By using Sentinel-2's multi-spectral imaging capabilities, it is possible to detect these subtle changes in reflectance and quantify the extent of drought damage in crops. The combination of remote sensing data with land-cover information can significantly enhance the accuracy of drought models, offering a powerful tool for guiding management decisions and improving the resilience of agricultural systems to climate change (EOSDA, 2023).

By integrating data from both Landsat and Sentinel-2, this thesis explores the full potential of remote sensing technologies in addressing two critical challenges: crop classification over long time periods in semi-arid environments, and the real-time assessment of drought impacts on crops. This multi-temporal and multi-sensor approach provide a robust framework for understanding the long-term effects of climate change on agricultural productivity, while also offering immediate solutions for mitigating drought-induced losses.

This thesis aims to explore how remote sensing technologies, particularly Landsat and Sentinel-2, can be applied to monitor and assess the impacts of climate change on agricultural systems.

In Chapter 1, we evaluate crop classification over 1985-2022 period in the semi-arid region of Barrax, Spain, using satellite images provided by Landsat. This analysis takes into account the duration of time that Landsat has been operational, allowing us to assess the effectiveness and consistency of the data over the years. By focusing on this specific region and timeframe, the study aims to provide a comprehensive understanding of how Landsat imagery can be utilized for accurate crop classification in semi-arid environments.

In Chapter 2, we aim to explore whether Sentinel-2 satellite images could help us assess crop losses due to drought, with a particular focus on winter cereals in Catalonia, Spain. When plants are stressed by drought, their physical and chemical responses change, which in turn affects how they reflect light. These changes can be picked up by remote sensing techniques, allowing us to detect and understand the extent of drought damage to crops. Incorporating land-cover information into remote sensing based, drought modeling could enhance its accuracy due to its significant impact on derived remote sensing indices. The use of drought indicators is proposed as an effective tool for guiding management actions and, consequently, for addressing the global challenge of drought.

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Chapter 1

Evaluating long-term crop classification (1985-2022) using Landsat mission in a semi-arid region

Abstract

Accurate crop classification is crucial for monitoring agricultural land use, assessing climate impacts, and ensuring food security. In this study, we employed Landsat-5, -7, and -8 imagery to analyse crop patterns over time. To manage the complexity of the data, we applied Principal Component Analysis (PCA) to reduce the dimensionality of the NDVI time series, followed by the use of Random Forest for generating annual crop maps. Landsat-5, operational from 1984 to 2013, was succeeded by Landsat-7 in 1999 and Landsat-8 in 2013. The advancements in temporal and spectral resolution provided by Landsat-7 and Landsat-8 significantly enhanced the quality of the data. The classification accuracy of crop types improved substantially from 94.6% in 1995, using Landsat-5 data alone, to 98.7% in 2015 with the integration of Landsat-7 and Landsat-8 data. This improvement underscores the progress in satellite technology and the benefits of combining data from multiple sources. By integrating PCA with Random Forest, we achieved more accurate crop classifications through effective data simplification and improved differentiation between crop types. This method facilitates a detailed analysis of seasonal growth patterns and precise land cover mapping. The findings highlight the value of long-term Landsat data for agricultural monitoring, demonstrating how advanced techniques and multi-source data can refine classification accuracy and adapt to various regional characteristics. This approach not only enhances the understanding and management of agricultural landscapes but also supports sustainable land use practices and better decision-making in the context of global change.

1. Introduction

Accurate crop classification holds significant importance in the examination of agricultural land usage for developmental and environmental initiatives, as well as for the mitigation and evaluation of climate-related impacts on crop productivity. Crop classification is also a crucial component in the continuous monitoring and anticipation of food security crises. The classification of crops using remote sensing is part of precision agriculture, a discipline that leverages information technology to combine data from various origins (Li and Chung, 2015; Liaghat et al.,2010).

Landsat imagery has proven to be an essential tool for analyzing the evolution of agricultural expansion and global change. Recent research underscores the significance of Landsat data in monitoring land use and land cover changes. Recent studies highlight the application of Landsat in tracking agricultural expansion, urbanization, and other significant changes (Rogan & Chen, 2022; Lu & Weng, 2021), emphasizing its role in global change management and long-term observation, from deforestation to wetland loss (Wulder et al., 2020; Schott & Strahler, 2019). Finally, Chen and Liu (2018) provide a comprehensive review of the state of the art in long-term land cover change monitoring using Landsat data (Chen & Liu, 2018).

Landsat data has been employed to generate global maps of cropland areas over time (Potapov et al. 2021). Their use allowed for the accurate identification and measurement of the extent of agricultural lands, as well as the analysis of patterns of land cover transformation. Landsat provided a detailed and reliable perspective on land use dynamics, enabling researchers to precisely track cropland expansion and gain a better understanding of the processes involved in this phenomenon on a global scale. However, a limitation of Landsat data lies in its relatively infrequent temporal coverage. Specifically, for each Landsat sensor, revisits to the same geographical location are taken every 16 days. This can produce large gaps in the time series specially in regions with frequent cloud cover (Arvidson, Goward, Gasch, & Williams, 2006). In addition, Landsat-5 and -7 are primarily available within the United States. In contrast, other regions of the world typically have lower frequencies. Furthermore, even when images are acquired, cloud cover often diminishes the utility of the data (Zhang, Rossow, Lacis, Oinas, & Mishchenko, 2004).

Land cover classification stands as one of the extensively explored subjects in remote sensing, with land cover maps serving as the foundation for various applications such as carbon budget modeling, forest management, and crop yield estimation (Jung et al., 2006, Lark and Stafford, 1997, Rogan et al., 2010, Wolter et al., 1995). Although generating a land cover map from remotely sensed data is relatively straightforward, achieving high accuracy in such maps is challenging. The use of multi-temporal images improves classification accuracy, particularly in the case of vegetation, owing to the distinct phenological characteristics exhibited by different vegetation types. This study aims to evaluate the accuracy of annual crop classifications using multitemporal images from Landsat-5, 7, and 8. The study area is the Barrax region in Spain, an area widely used for testing remote sensing algorithms and products and seeks to demonstrate whether Landsat data can provide long-term crop maps.

2. Methods

The methodology used in this study involved two main steps. First, the Landsat NDVI time series were processed annually using a Principal Component Analysis (PCA) to reduce the high dimensionality of the data. The PCA transformed the NDVI values into several principal components, which represent the main temporal variance in the data. We selected the first three principal components as they captured most of the variability and reflected key phenological patterns of different crops.

In the second step, these three principal components were used as input variables for a Random Forest classification. The Random Forest model was trained to classify six different land cover types, including the three main crop types: corn, cereals, and beans. This classification generated annual crop maps for the study area, enabling us to monitor changes in land use and crop distribution over time.

2.1. Study area

This work focuses on Barrax (W2°12'48.49", N39°2'37.32) in the province of Albacete (Spain) (Figure 2). It is located on the plateau that marks the beginning of the Alcaraz mountain range. It is an predominantly agricultural area dominated by vast expanses of cereal crops. There are large uniform crop fields, both irrigated and non-irrigated, consisting mainly of barley, corn, sugar beet, wheat, as well as bare soil (Jimenez-Munoz et al., 2012; Castrillo et al., 2004; Martín et al., 2006).

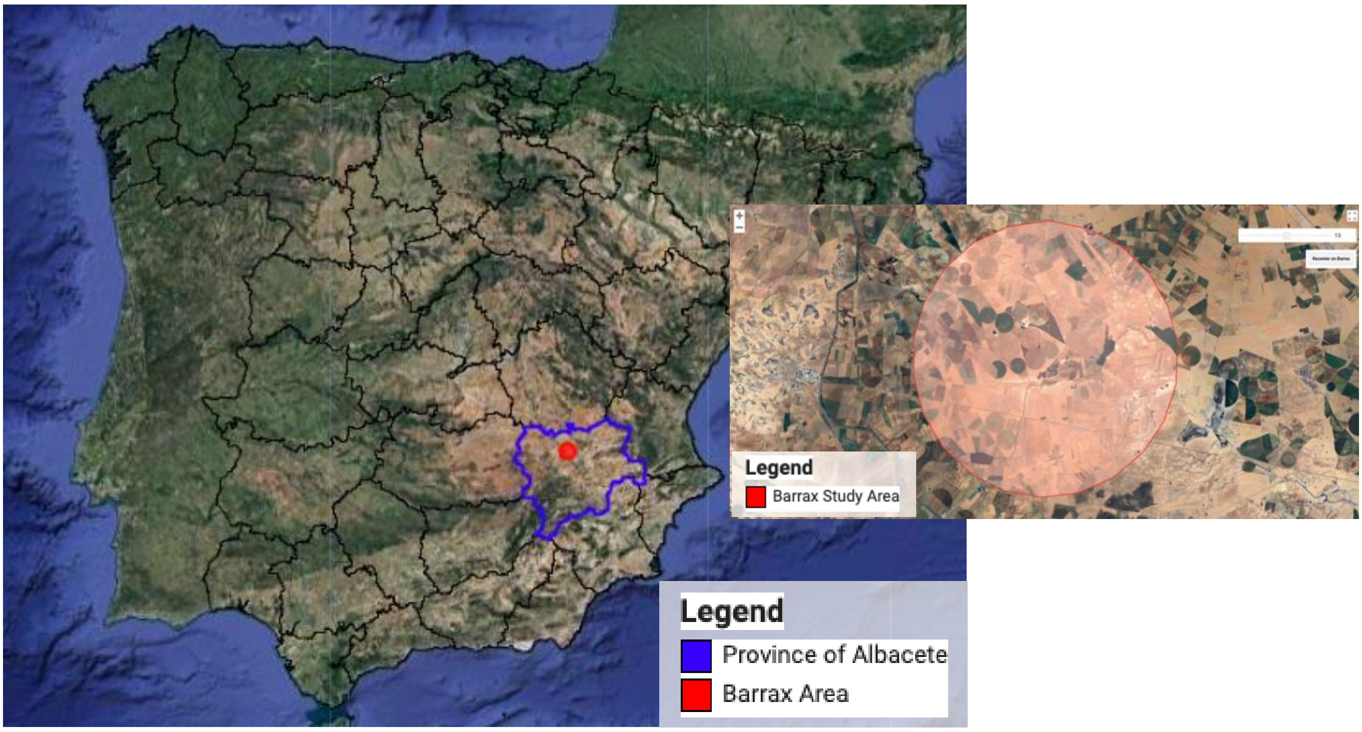

Figure 1. Location map of the study area in Barrax.

The area has been selected for many experiments due to its flat terrain and large, uniform land-use units (Camps-Valls et al., 2014). Barrax experiences a Mediterranean climate, characterized by a rainfall season in spring and autumn, and low rainfall in summer. The area exhibits high continentality, with sudden temperature changes between cold and warm months. Its flat topography is advantageous for correcting and interpreting remotely sensed data.

2.2. Landsat time series

We used Landsat-5, -7, and -8 (Table 1), which are the Landsat satellites that provide a long-term record with frequent images over the study area for the period 1985-2022. We used all Landsat images that overlapped with the study area for the years 1995, 2005, and 2015.

Caracteristic	Landsat 5	Landsat 7	Landsat 8
Launch Date	March 1, 1984	April 15, 1999	February 11, 2013
Mission End	June 5, 2013 (deactivated)	Operational	Operational
Main Instruments	TM (Thematic Mapper), MSS (Multispectral Scanner)	ETM+ (Enhanced Thematic Mapper Plus)	OLI (Operational Land Imager), TIRS (Thermal Infrared Sensor)
Spatial Resolution	30 m (visible and infrared bands), 120 m (thermal band)	30 m (visible and infrared bands), 15 m (panchromatic)	30 m (visible and infrared bands), 15 m (panchromatic), 100 m (thermal band)
Temporal Resolution	16 days	16 days	16 days
Number of Bands	7 (TM), 4 (MSS)	8 (ETM+)	11 (OLI/TIRS)
Orbital Altitude	705 km	705 km	705 km
Swath Width	185 km	185 km	185 km
Orbit Type	Sun-synchronous	Sun-synchronous	Sun-synchronous
Global Coverage	Yes	Yes	Yes

Table 1. Specifications of Landsat satellites used for long-term monitoring of land cover and vegetation change.

2.3. Crop Classification.

2.3.1. Dimensionality reduction using Principal Component Analysis

NDVI (Normalized Difference Vegetation Index) time series data, derived from Landsat satellite images, is essential for analysing seasonal growth patterns of various land cover types. This data is crucial for understanding and monitoring vegetation and land use changes over time, as noted by Zhou et al. (2021) and Gao et al. (2020). To improve the crop classification, we used NDVI time series from Landsat to reflect the characteristic seasonality of each crop. However, using the NDVI from all Landsat images taken in a given year means a high number of variables for the classification model. Given that a Landsat sensor has a 16-day revisit time, the number of valid observations can be as high as 22 NDVI observations per year. To reduce the high dimensionality of the NDVI time series, we used the Principal Component Analysis (PCA). A mathematical derivation and historical review of PCA in the context of remote sensing can be found in the work of Gonzalez and Woods (1993). Examples of PCA applications in remote sensing are also in Lillesand and Kiefer (2000) and Campbell (1996).

A popular method for analyzing images from remote sensing is PCA. It has been applied to land-cover change detection (Lodwick, 1979; Byrne et al., 1980; Richards, 1984; Singh, 1986), data enhancement for geological applications (Gillespie, 1980; Santisteban and Munoz, 1978), and figuring out the underlying dimensions of remotely sensed data (Ready and Wintz, 1973; Anuta et 111., 1984). With its ability to reduce data complexity, identify pertinent variables, detect spatial and temporal patterns, integrate multisensory data, and enhance result interpretation and visualization, PCA is a useful tool for analyzing variables influencing crops studied with remote sensing. In this case, the input data for the crop categorization model consisted of the five first major components of the Landsat NDVI time series.

2.3.2. Random Forest

For classifying land cover, Breiman (2001) employed the random forest (RF) classifier. The RF is a strong algorithm that uses a group of decision trees to provide accurate predictions. High discrimination ability variables can be ranked and chosen using the variable importance measures that the RF produces (Belgiu & Drăguţ, 2016). Due to its benefits in managing high data dimensionality, the RF is frequently utilized in land cover mapping (Belgiu and Drăguţ, 2016; Gong et al., 2013; Wulder et al., 2018). The RF classifier controls over-fitting and enhances predictive performance by fitting multiple decision tree classifiers on different subsamples of the dataset and averaging the results. The Landsat time series was visually interpreted to provide training data for the model, as detailed in Section 2.4.

2.4. Collection of training and validation data

2.4.1. Sampling of training and Validation Points

In this study, training and validation points were collected for three different crop classes: cereals, corn, and beans. These points were taken at three years: 1995, 2005, and 2015. The selection of these points is crucial for evaluating the accuracy of the classification models used to identify cultivated areas (Zhu et al., 2022). For each crop class and each year, 100 points were selected. This stratified sampling method ensures that each crop class is equitably represented, enhancing the robustness of the accuracy assessment (Li et al., 2021). The true class was assigned through visual inspection of the Landsat time series, given the characteristic NDVI seasonality of each crop class (Figure 3).

2.4.2. Accuracy assessment

Landsat satellite images from the years 1995, 2005, and 2015 were used to evaluate the accuracy of the crop classification. We used three metrics to describe the accuracy of the crop classification: overall accuracy

Overall Accuracy: is defined as the proportion of correctly classified validation points out of the total number of points. It is a fundamental metric in the accuracy assessment of classification models. This metric provides a general measure of the classification model’s performance across all categories (Foody, 2021).

Producer's Accuracy (Omission): also known as omission error, measures the ability of a classification model to correctly identify instances of a particular class. It is calculated as the ratio of correctly classified instances of a class to the total number of actual instances of that class in the reference data. High producer's accuracy indicates that the model effectively minimizes omission errors for a given class (Congalton & Green, 2019).

User's Accuracy (Commission): also known as commission error, measures the probability that a point classified as a certain class belongs to that class. It is calculated as the ratio of correctly classified instances of a class to the total instances classified as that class by the model. High user's accuracy indicates that the model effectively minimizes commission errors for a given class (Stehman & Czaplewski, 2020).

3. Results

Each land cover type classified in this study shows a particular NDVI seasonality (Figure 3). For corn, the NDVI data shows a significant peak in mid-2008, corresponding to the summer months when corn reaches its maximum vegetative growth. This peak indicates a distinct growing season characterized by high vegetative activity and healthy, dense vegetation. This pattern aligns with studies correlating NDVI peaks with peak agricultural productivity in corn fields (Johnson et al., 2019).

Cereals exhibit a different NDVI pattern compared to corn, with values peaking earlier in the year. This suggests an earlier planting and harvesting schedule, achieving maximum growth before the height of summer, followed by a decline post-harvest. Such seasonal variations in NDVI values are supported by research emphasizing the phenological differences among crop types (Wang et al., 2019).

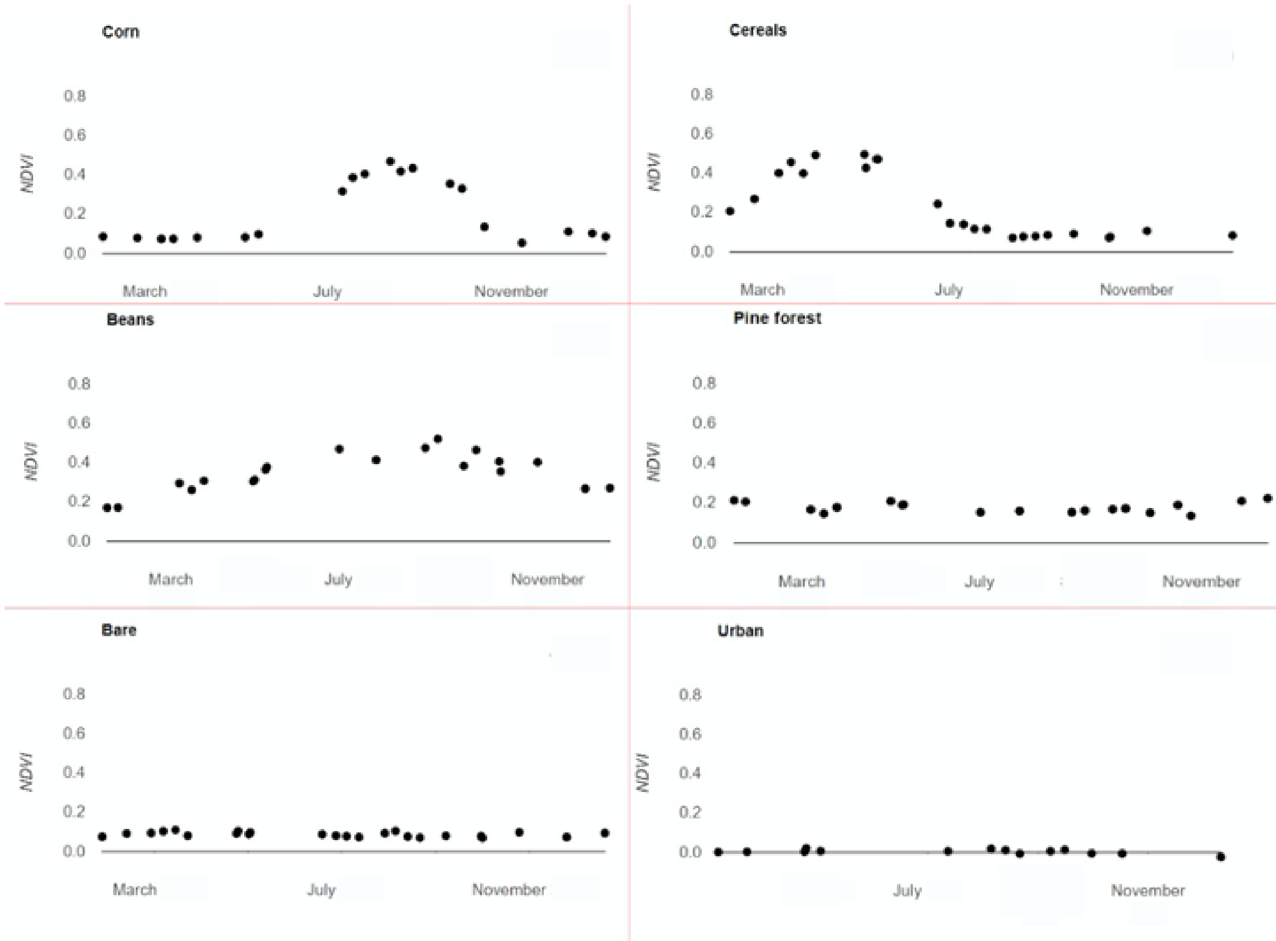

Figure 2. Example of Landsat NDVI time series for the year 2008 for the six land cover types that were classified in this study. The NDVI time series show a different land surface phenology among the vegetated land cover types.

For beans, the NDVI time series displays multiple peaks throughout the year, suggesting multiple growth cycles or a prolonged growing season with distinct phases of vegetative activity. Each peak represents periods of significant vegetative growth, indicating healthy crop conditions. Studies on bean crops confirm that they can have multiple harvests within a year, reflected in their NDVI profiles (Li et al., 2020).

Pine forests exhibit a relatively constant NDVI throughout the year, which is typical of forested areas that do not have a seasonal growth cycle. This stability in NDVI is attributed to the evergreen nature of pine trees, which retain their foliage year-round, unlike deciduous forests that experience more pronounced seasonal fluctuations in NDVI due to leaf shedding and regrowth (Jin et al., 2017; Liu et al., 2016).

Bare land, on the other hand, shows consistently low NDVI values throughout the year, reflecting minimal vegetative activity due to the lack of significant vegetation cover. This is typical for barren or sparsely vegetated areas and is well-documented in NDVI studies (Chen et al., 2018).

Urban areas, similar to bare land, exhibit very low NDVI values. Urban regions typically have limited vegetation due to the prevalence of buildings, roads, and other infrastructure. The low NDVI values in urban areas reflect the minimal presence of vegetative cover, as concrete and asphalt dominate the landscape (Seto et al., 2017).

The NDVI time series data provides a comprehensive view of the vegetative dynamics of different land covers, essential for effective classification, monitoring, and management of agricultural practices, forest conservation, and urban planning. The distinct phenological patterns observed are crucial for understanding and managing diverse landscapes and ensuring sustainable land use practices. Tucker et al. (2020) highlight the importance of NDVI in monitoring vegetation and its implications for effective land management.

Figure 3 depicts true-colour composites form Landsat showing the croplands at different moments of the year. This true-colour composite illustrates crops and vegetation in their natural shades, reflecting early growth stages. Variations in green tones signify different levels of vegetation density and health. Conversely, the second image, taken by Landsat-5 in August 2008, presents the same area later in the year, showing crops in their mature stages. The differences in color intensity and distribution from April to August highlight the progression of growth and increased vegetation density over time, consistent with findings from Bégué et al. (2018) and Wulder et al. (2019). The PCA (Principal Component Analysis) image, derived from NDVI (Normalized Difference Vegetation Index) time series data, evaluates vegetation health by measuring the difference between absorbed and reflected light in specific spectral bands. PCA emphasizes the maximum variability in this data, facilitating a detailed analysis of different growth periods. Different colors in the PCA image correspond to distinct phases of crop growth, with red pixels indicating crops that primarily grow during the summer. This variation helps identify different types of crops and their growth cycles throughout the year, as demonstrated by Zhu et al. (2019) and Lobell et al. (2015).

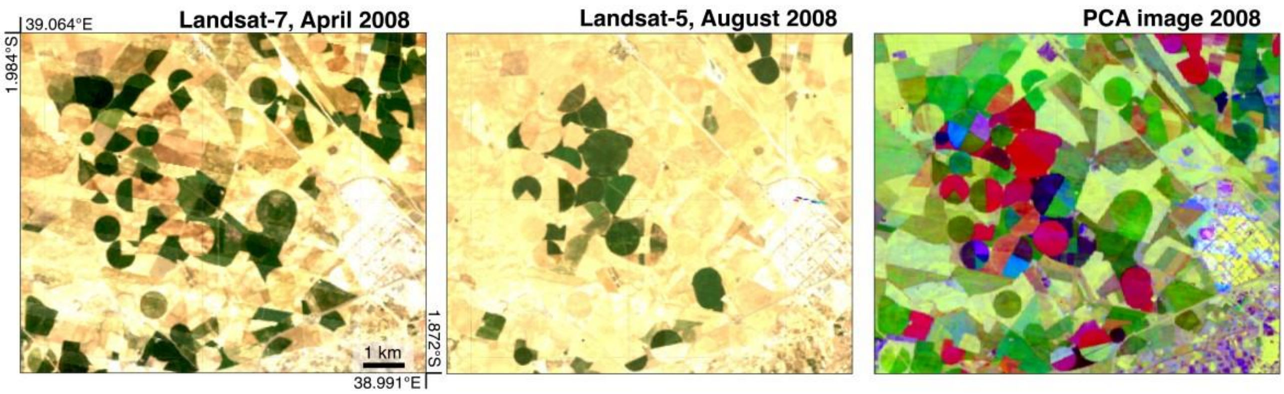

Figure 3. Landsat images were taken in April and August 2008 and PCA image obtained for that same year. The Landsat images are true-color composites depicting crops that grow in different periods of the year. The different growth period is reflected in the different contrasting colors of the PCA image, which reflects the maximum variability in the NDVI time series. For instance, in the PCA image, red-colored pixels depict crops growing in summer.

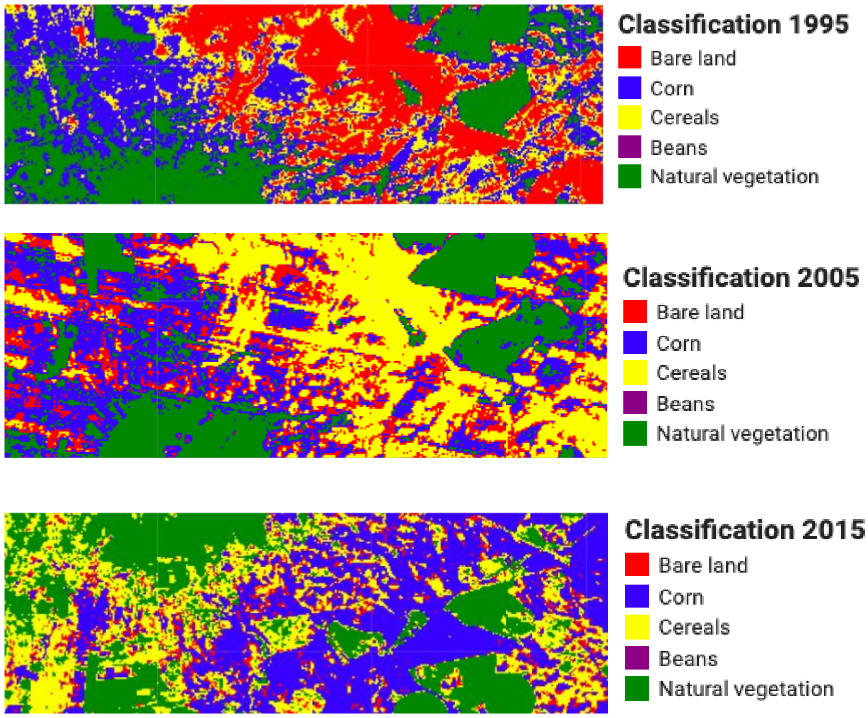

Figure 4. Land cover classification maps for the Barrax area in 1995, 2005 and 2015.

The analysis of land cover classification maps for Barrax from 1995, 2005, and 2015 (Figure 4) reveals a significant shift in land use, where previously classified bare land and natural vegetation areas have been replaced by cultivated land. The expansion of crops, including maize, cereals, and beans, is particularly evident over the two decades. These changes can be attributed to the intensification of agriculture, likely driven by the introduction of irrigation systems in this semi-arid region, which has increased agricultural productivity in response to growing food demand and the impacts of climate change.

In 1995, the overall accuracy of land cover classification was 94.6% (Table 1). This classification relied solely on images from Landsat-5, which, despite its value at the time, had limitations due to older sensor technology. These limitations affected the quality and reliability of the classification. The accuracy for specific land cover types such as beans and natural vegetation was notably lower. The producer's accuracy for beans was 92.1%, while the user's accuracy was 89.6%. For natural vegetation, the producer's accuracy was 90.0%, and the user's accuracy was 94.6%. These figures indicate difficulties in accurately distinguishing these classes, likely due to the spectral similarities between these and other land cover types, as well as the limitations of the Landsat-5 sensor.

In 2005, the overall accuracy improved to 97.2% with the availability of images from both Landsat-5 and Landsat-7. The combination of data from these two satellites provided better spatial and spectral resolution, enhancing the quality of the classification process. The producer's accuracy for maize increased to 95.6%, and the user's accuracy to 96.9%. Natural vegetation also saw improvements, with the producer's accuracy rising to 91.6% and the user's accuracy to 92.6%. These improvements reflect the benefit of increased data availability and enhanced sensor capabilities, allowing for more precise differentiation between land cover types.

By 2015, the overall accuracy had reached 98.7%, benefiting from the advanced sensor technology of Landsat-8, alongside Landsat-7. Landsat-8's improved spectral and spatial resolution, along with its higher frequency of image capture, played a crucial role in achieving the highest overall accuracy of the study period. The classification accuracy for all land cover types in 2015 was remarkably high, underscoring the effectiveness of the advanced sensors. For example, the accuracy for maize was 97.2% for producers and 97.1% for users, reflecting highly reliable classification results. Bare land achieved a producer's accuracy of 99.6% and a user's accuracy of 96.0%, demonstrating the precision made possible by the enhanced capabilities of Landsat-8. Even classes that were previously challenging, such as beans and natural vegetation, showed significant accuracy improvements, with beans achieving a producer's accuracy of 93.5% and a user's accuracy of 90.2%.

	1995	2005	2015
Overall Accuracy (%)	94.6	97.2	98.7
Producers accuracy (%)			
Bare land	96.9	99.4	99.6
Maize	91.4	95.6	97.2
Cerals	92.5	93.1	94.2
Beans	92.1	92.0	93.5
Natural vegetation	90.0	91.6	90.7
Users accuracy (%)			
Bare land	90.4	92.5	96.0
Maize	94.2	96.9	97.1
Cerals	91.7	93.0	94.6
Beans	89.6	88.9	90.2
Natural vegetation	94.6	92.6	94.7

Table 2. Results of the accuracy assessment of the classifications obtained for 1995, 2005, and 2015. The year 1995 only contained images from Landsat-5, explaining the lower accuracies. In 2005, Landsat-5 and -7 were available. The highest accuracies were found in 2015 when Landsat-7 and -8 were available, which provide the highest availability of images during the entire period of study.

4. Discussion

The progression in overall accuracy and the accuracy of individual land cover classes from 1995 to 2015 (Table 1) underscores the advancements in satellite imaging technology and the benefits of integrating data from multiple satellite sources. The increase in accuracy from 94.6% in 1995 to 98.7% in 2015 can be attributed to several factors. Masek et al. (2006) emphasize that improvements in sensor technology, coupled with the integration of data from multiple satellites, have enabled better resolution and quality of images, contributing to higher accuracy in land cover classification.

The use of images from multiple satellites in recent years has provided richer datasets, enabling more robust analysis and classification. Specifically, the availability of Landsat-7 and Landsat-8 data in 2015 provided comprehensive coverage and higher-quality images, which significantly improved classification accuracy (Table 1). Roy et al. (2014) discuss how the transition from Landsat-5 to Landsat-8 brought substantial improvements in sensor technology, including better spectral resolution, enhanced radiometric resolution, and higher temporal frequency. These advancements allowed for more precise and reliable classification of land cover types as shown in Table 1.

The high-resolution imagery provided by Landsat satellites enabled accurate classification of various crop types, supporting the reliability and robustness required for agricultural studies (Zhu et al., 2019; Wulder et al., 2019). Furthermore, advancements in image processing and classification algorithms, such as those utilizing machine learning techniques, have significantly enhanced the accuracy and efficiency of crop classification using Landsat data (Dong et al., 2016; Ma et al., 2019). These techniques are better suited to handle the complexity and variability of multispectral data, leading to more accurate land cover classifications. Belgiu and Drăguţ (2016) highlight that Random Forest is particularly effective for handling large datasets and its non-parametric nature, achieving high levels of accuracy in satellite image classification.

Combining PCA with Random Forest has provided high accuracies of crop classification, allowing a high discrimination between different crop types. This combination has been validated by numerous studies highlighting its efficiency in improving classification outcomes in various contexts. For example, recent research by Liu et al. (2021) demonstrated the effectiveness of using PCA and Random Forest together to enhance crop type classification accuracy. Similarly, Zhao et al. (2019) found that integrating these methods improved the classification of complex agricultural landscapes. The integration of these advanced techniques not only supports more accurate land cover classification but also aids in the detailed monitoring of agricultural practices, forest conservation, and urban development. This approach is crucial for making informed decisions that support sustainable land management practices (Chen et al., 2020; Wang et al., 2021).

This study focuses on regional adaptation, allowing the developed model to be applied in various geographical areas. This approach facilitates the use of the model in different regions, leveraging their specific characteristics and adjusting to local particularities. Therefore, it is crucial that future research efforts concentrate on adapting the proposed model, ensuring its efficacy and accuracy across different study sites. This endeavor will not only broaden the applicability of the classification but also provide a more detailed understanding of regional variations and their specific effects.

Using Landsat images and analyzing NDVI patterns, we observed that uncultivated areas of bare land and natural vegetation have been converted into agricultural lands. The expansion of crops in Barrax study area from 1985 to 2015 is closely linked to the expansion of irrigation systems (Garcia et al., 2022). The use of Landsat images allows monitoring the temporal evolution of NDVI and differentiating between irrigated and non-irrigated crops: irrigated crops exhibit higher and more stwable NDVI values throughout the growing season compared to rainfed crops. This is particularly relevant in semi-arid regions, where water availability is a key factor for agricultural productivity (Smith et al., 2023).

6. Conclusion

The progression in accuracy from 1995 to 2015 highlights significant advancements in Landast satellite imaging technology and the advantages of integrating data from satellite sources. The increase in overall accuracy, as well as in the accuracy of individual land cover classes, underscores the importance of improvements in sensor technology, enhanced spectral and temporal resolution, and more sophisticated image processing for agricultural studies. The ability to adapt this methodology to different region is crucial for ensuring their applicability across diverse geographical areas, ultimately supporting more sustainable land management practice. Future research should continue to focus on refining these models and adapting them to regional specificities, ensuring their effectiveness in a wide range of contexts.

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Chapter 2

Evaluating Sentinel-2 for monitoring drought-induced crop failure in winter cereals

Abstract

Extreme climate events can pose a risk to food production and disrupt supply chains. An example of this is the extreme drought event that occurred in Catalonia in 2023. Farmers and media outlets reported that large extensions of winter cereals wilted and died at early development stages without producing grain. In our study, we evaluated whether Sentinel-2 can detect the failure of winter cereals due to drought events. To do that, we conducted field observations and collected ground-truth data on crop failure. The field data comprised 130 geolocated points, each representing one of three drought impact classes: normal growth, moderate impact, and high impact where the crop failed to produce grain. We then used the field data to explore which Sentinel-2 variables could best predict the drought impact classes. Among these variables, we extracted phenological metrics and 15-day aggregates of vegetation indices. Finally, we estimated the importance of each Sentinel-2 variable in predicting crop drought impacts using single-variable prediction. Our results indicate that drought impacts were not visible during the early stages of crop development. The drought impacts were visible with Sentinel-2 in the second half of the growing season. Specifically, winter cereals affected by drought exhibited a premature decline in several vegetation indices. As a result, the best predictors for drought impact classes were metrics associated with later stages of crop development. The mean Normalized Difference Vegetation Index (NDVI) for the first half of May showed a high correlation with crop failure classes (R^2 = 0.66), although other vegetation indices showed similar correlations. Our findings suggest that phenological data extracted from Sentinel-2 during the second half of the crop development cycle is crucial for evaluating drought impacts on winter cereals. The study identifies specific phenological stages that optical satellite data must observe to accurately identify drought-induced crop failure in winter cereals.

1. Introduction

Climate change has impacted cereal crop yields, reducing global wheat production by 5.5% since 1980 (Lobell, Schlenker, and Costa-Roberts 2011). Specifically, drought directly affects plant and grain growth development, leading to reduced grain yields (Gallagher, Biscoe, and Hunter 1976). As an example, drought conditions were particularly severe in the Mediterranean basin in 2023, affecting winter cereals and resulting in a high likelihood of crop failures (Joint Research Center 2023). As the climate warms, these extreme drought events are expected to increase in the region (Spinoni et al. 2018), highlighting the potential impacts of droughts on food security and food supply chains. Addressing these impacts requires monitoring crop production at the regional and global scale (Park et al. 2016).

Monitoring crop failure due to extreme droughts is critical for ensuring food security, managing water resources, and mitigating economic losses. Effective drought monitoring helps predict crop failures, allowing for proactive measures to secure food supplies and manage resources more efficiently (Ghazaryan et al. 2020; Yagci et al. 2012). In addition, monitoring drought impacts on crop production helps in planning and implementing financial aid and insurance schemes for affected farmers (Bokusheva et al. 2016; Lesk, Rowhani, and Ramankutty 2016). Thus, early monitoring and prediction of potential drought impacts on crop production is crucial and tools that improve the accuracy and timeliness of these monitoring systems are necessary.

Satellite remote sensing has been extensively used to monitor cereal crops and assess drought-related yield losses. Various vegetation indices combined with climate data are used to monitor crop production (Franke and Menz 2007; Yu et al. 2018). In addition, phenology metrics have been proven to be very useful for monitoring the impacts of drought on crop yields, as suboptimal crop growth rates are reflected in an anomalous land surface phenology observed from satellites (Bolton and Friedl 2013). These remote sensing data are often integrated with crop growth and machine learning models that enhance the accuracy of yield predictions (Evans and Shen 2021; Wang et al. 2017). Moreover, recent studies have used phenological metrics derived from Sentinel-2 to further increase the wheat yield estimates (Hunt et al. 2019; Idrissi et al. 2023). The use of Sentinel-2 is particularly useful because its high spatial resolution (10 meters) makes it possible to monitor small plantations and crop production within the plantation (Segarra, Araus, and Kefauver 2022). These studies, however, have a caveat: they estimate drought-induced yield losses and ignore the occurrence of total crop losses that result from extreme drought events. Total crop losses mean that the drought conditions have caused the entire crop to fail, leading to no harvestable yield. Monitoring crop failure and total crop losses using remote sensing remains unexplored. Understanding the capabilities of remote sensing in detecting crop failure is required, as climate change may increase the frequency of extreme droughts and the occurrence of total crop losses.

The aim of this study is to determine whether satellite remote sensing can detect drought-induced crop failure in winter cereals and identify the key variables from Sentinel-2 data that best predict crop failure. This aim entails not estimating yield but rather the complete failure of cereal plantations due to drought. To achieve this, we collected field data on winter cereals in Catalonia, an area that experienced a severe drought in 2023. Then, we extracted phenology metrics from different Sentinel-2 vegetation indices and evaluated the relevance of these variables in predicting crop failure. The purpose of this approach is to develop a reliable method that uses the best predictors from Sentinel-2 data to monitor crop failure.

2. Methods

2.1. Study area

We collected field data within a 1 000-ha study area, which encompassed several municipalities in Catalonia. Winter cereals, which include wheat, barley, oat, and triticale, are the predominant crop in this region. These cereals are sown in January and February, grown from March to May, and harvested in late May and June. The region has a Mediterranean climate, with hot and dry summers that make irrigated crops the only viable option for cultivation in summer. The average annual rainfall is 660 mm, and it usually falls in spring and autumn. Winter cereals are primarily rainfed, with the exception of cereals that are irrigated near rivers and areas with a high water table. Irrigated plantations also cultivate summer crops, primarily maize. The area is covered by family-owned smallholders with properties that rarely exceed 30 hectares. All sampled points were collected in smallholder plantations; the average plantation area was 18.7 ha, with the smallest and largest plantation areas being 0.3 ha and 26.3 ha.

The area experienced a severe drought during the first half of 2023, in particular affecting in March and April during crucial cereal growing stages. According to the ERA5 dataset (Muñoz-Sabater et al. 2021), rainfall in March 2023 was only 3 mm in the study area, while long-term (1980-2023) rainfall was 56 mm. The rainfall in April 2023 amounted to 33 mm, while long-term rainfall was 71 mm. Furthermore, the sparse precipitation fell in late April, during the final stages of crop development. As a result, cereals received little to no rainfall during their growth stages.

2.2. Collection of field data

We conducted field observations to obtain ground truth on crop failure in the study area. The field data consisted of geolocated points that included information on drought affection. Data collection included visits to plantations where winter cereals were grown during the 2023 campaign. The plantations were visited between April 20th and 27th, 2023, when the impacts of the drought were clearly visible in the development stages of the plants. In these plantations, we visually inspected the plantation status and assigned three drought impact classes (Figure 1):

- Class 1 - High drought impact: Plants appeared fully desiccated, exhibiting a complete yellow discoloration. The plants showed no signs of flowering and, thus, no grain was expected. This class represents plantations with total crop losses.
- Class 2 - Moderate drought impact. Most of the plants appeared desiccated, yet signs of flowering stages were evident and reduced grain yield was expected.
- Class 3 - Normal growth. No signs of drought impact were detected.

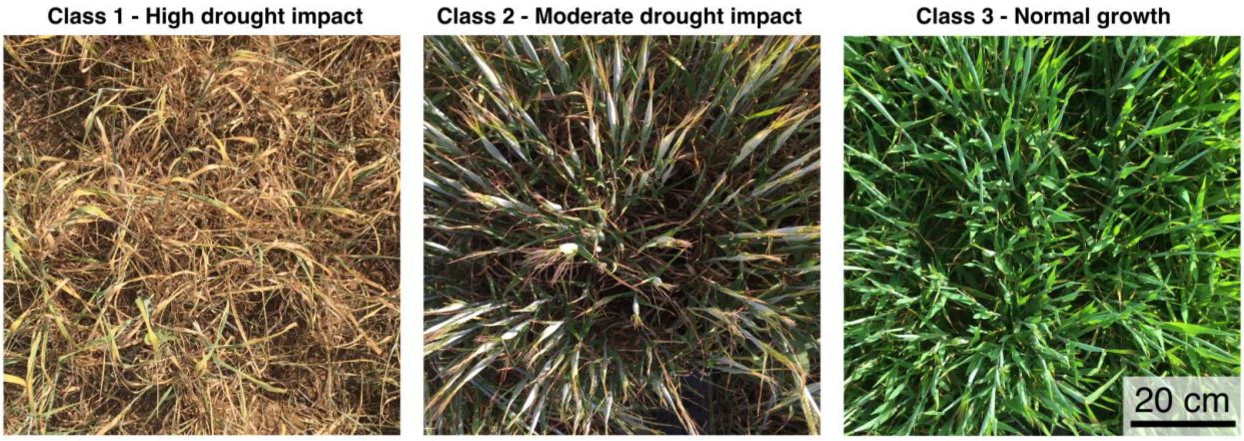

Figure 1. Three images taken during the field visits on 20th April 2023. The images show cereal plantations with different degrees of drought affection.

A total of 130 field observations were collected across the study area (Figure 2). The crops in most of the plantations showed clear signs of desiccation; 76 points were collected for class 1 (high drought impact), 28 for class 2 (moderate drought impact), and 26 for class 3 (normal growth). We found evidence of irrigation, such as pipes and water canals, in the 26 plantations that were growing without signs of drought impact. These plantations were also close to rivers with a high water table.

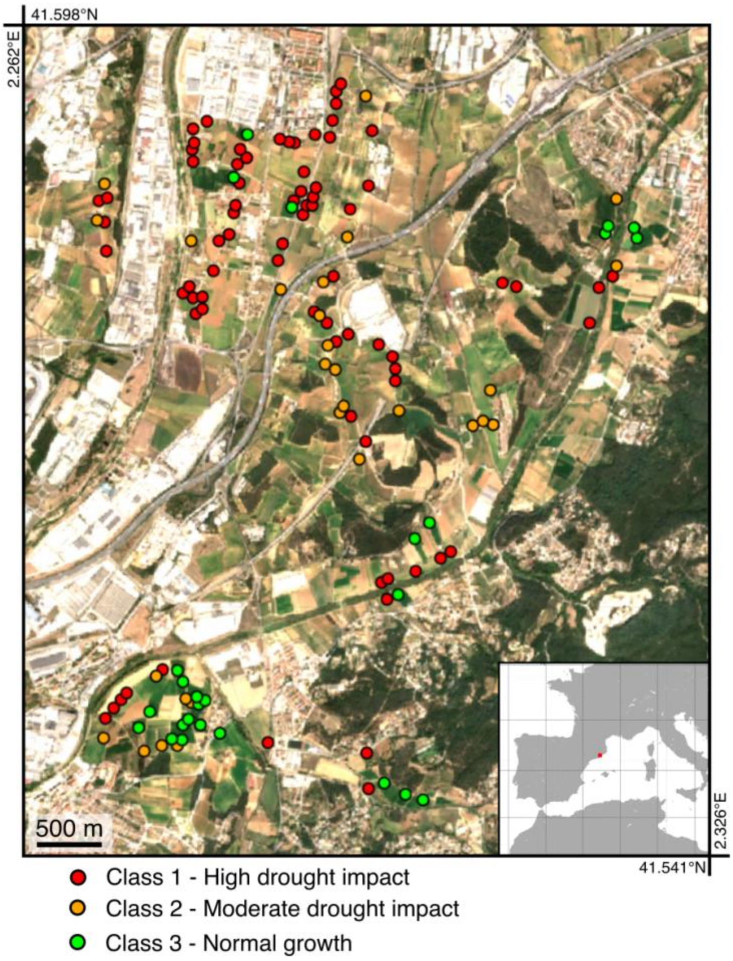

Figure 2. Location of the 130 field observations in the study area. The study area covers an area of 1 000 ha near Barcelona, covering winter cereals in a mediterranean climate region.

2.3. Sentinel-2 time series

We used Sentinel-2 data to examine the seasonality of vegetation indices, the so-called land surface phenology, and determine whether the seasonality differed between the three drought classes. Specifically, we used the Sentinel-2 Level-2A product (Drusch et al. 2012), which includes atmospherically corrected top-of-canopy reflectances. Sentinel-2 has a spatial resolution of 10 meters and a revisit time of five days, allowing the monitoring of changes in leaf phenology within the plantation (Segarra, Araus, and Kefauver 2022). All Sentinel-2 data for 2023 was extracted for the ground truth locations and invalid observations (clouds and cirrus) were masked using the Scene Classification Layer included in the Level-2A product. Finally, we calculated a selection of vegetation indices derived from Sentinel-2 data, specifically the Normalised Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI) (Pamungkas 2023), the Red-Green Vegetation Index (RGVI) (Yin et al. 2022), and the Normalized Difference Moisture Index (NDMI) (Gao 1996).

2.4. Feature extraction

We employed feature extraction techniques to derive temporally explicit variables from Sentinel-2 vegetation indices that can potentially explain the differences among drought impact classes (Figure 3). This process involved generating metrics that captured the vegetation dynamics in response to drought events. First, we computed 15-day composites (COMP), which entailed the mean values for each vegetation index during the first and second halves of each month from January to June. This resulted in 12 variables. Then, from the 15-day aggregates, we used a cubic interpolation (Wongsai, Wongsai, and Huete 2017) to obtain daily values of each vegetation index. From the interpolated daily time series, we estimated the following phenology metrics:

- Start and End of Season (SoS and EoS): These metrics indicate the onset and end of the growing season, respectively. They represent the dates when vegetation activity begins to increase (start of season) and decline (end of season), indicating the transition from dormancy to active growth, and vice versa. The phenology method used for calculating the SoS and EoS was the maximum separation method, which is a phenology extraction method based on thresholds that can be applied to daily nonsmoothed time series without any additional preprocessing (Descals et al. 2020). We calculated the SoS and EoS as the days of the year when the difference in the ratio of observations that exceed a given threshold before and after that date are minimal and maximal, respectively. We used thresholds of 10% to 90% in steps of 10%.
- Peak of Season date (PoS): This metric refers to the date when the vegetation index reaches its maximum during the growing season. The peak of season represents the day of highest vegetation greenness in the interpolated time series.
- Maximum Vegetation Index: The highest value observed in a vegetation index (such as NDVI, EVI, or SAVI) during the growing season. It represents the maximum level of greenness observed in the interpolated time series.

- Growing Season Area (GSA): This metric represents the sum of the daily values during the period when vegetation experiences growth. The period of growth was defined as the lapse of time between the SoS and EoS calculated with a 50% threshold. The growing season area is a proxy of the total productivity of the vegetation for a given pixel.

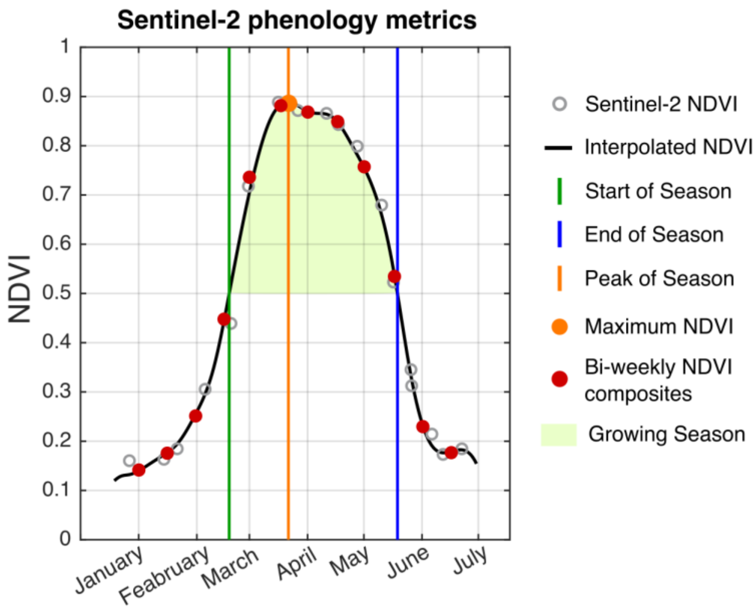

Figure 3. Phenology metrics extracted from the Sentinel-2 NDVI time series. The bi-weekly composites are 15-day aggregates of the interpolated vegetation index.

2.5. Feature selection

We used the single-variable prediction (Parr, Hamrick, and Wilson 2024) to identify the most important features that distinguish the drought impact classes. Single-variable prediction evaluates the model performance when only one feature is used at a time. This allows us to evaluate the feature for its individual predictive capacity. To perform the single-variable prediction, we trained multiple random forests with a single feature in each model. We used random forests (Breiman 2001) because it is a widely-used and robust machine learning model that reduces overfitting by combining predictions from multiple decision trees. After training the random forest models, we used Kendall's correlation coefficient to evaluate the predictive capacity of each feature. Kendall's correlation is a non-parametric correlation measure that evaluates the ordinal association between two variables, making it appropriate for determining the relationship between the predicted variable (drought impact classes) and observed features (phenology metrics extracted from Sentinel-2).

2.6. Evaluation using MODIS and regional yield statistics

We evaluated whether the most effective predictor of crop drought impact, derived from Sentinel-2 imagery, could also explain the interannual variability in common wheat and spelt yield at a regional level. To accomplish this, we investigated the relationship between the mean annual yield in Catalonia from 2000 to 2021 and the variable that showed the highest Kendall's correlation with drought impact. The annual yield was obtained from EUROSTATS (European Commission 2023). Given that Sentinel-2 data is only available since 2016, we used MODIS-derived vegetation indices to cover the entire period from 2001. Since MODIS has a spatial resolution of 500 meters, a mask was required to filter pixels with heterogeneous land cover types and keep only the pure cropland pixels. To do so, we used the ESA Land Cover map at 10-meter resolution and calculated the number of pixels classified as 'cropland' within each MODIS pixel. MODIS pixels with less than 90% coverage of 10-meter 'cropland' pixels were masked. Then, we calculated the feature with the highest Kendall's correlation with drought impact classes using MODIS time series. This calculation was performed on an annual basis from 2000 to 2021 and then spatially aggregated for Catalonia. Finally, we evaluated the coefficient of correlation between crop yield statistics and the features derived from MODIS.

We also calculated the coefficient of correlation between crop yield statistics and the 3-month Standardized Precipitation-Evapotranspiration Index (SPEI) from 2000 to 2021. SPEI is a drought index that incorporates both precipitation and potential evapotranspiration (Vicente-Serrano, Beguería, and López-Moreno 2010). We selected the 3-month SPEI for April, which is the moment when crops started to desiccate in 2023. We conducted this additional analysis to determine whether crop productivity is associated with drought events in Catalonia.

3. Results

The NDVI time series revealed that the three drought impact classes show a similar seasonality at the beginning of the growing season (Figure 4). This suggests that drought affection was not visible at the early stages of the crop development. The main differences among the classes occurred in the second half of the growing season. Class 1 showed a substantial decrease in NDVI in April. Although class 2 does not show a substantial decrease in NDVI, the NDVI values remain low compared to class 3. Maximum NDVI for classes 1, 2, and 3 were 0.76, 0.80, 0.91, respectively, suggesting that the crop growth in classes 1 and 2 did not reach the full potential growth as in class 3.

We also found that some plantations showed a second peak in NDVI during the late stages of the growing season, in particular in class 1. This increase in NDVI was not related to the re-greening of the crops. This re-greening was caused by the small rainfall that occurred at the end of April, which promoted the growth of weeds in the crops that failed. Plantations that were assigned the class 1 had wilted and become completely desiccated by the time of the field visit (20-27 April) as the relative minimum in NDVI indicates.

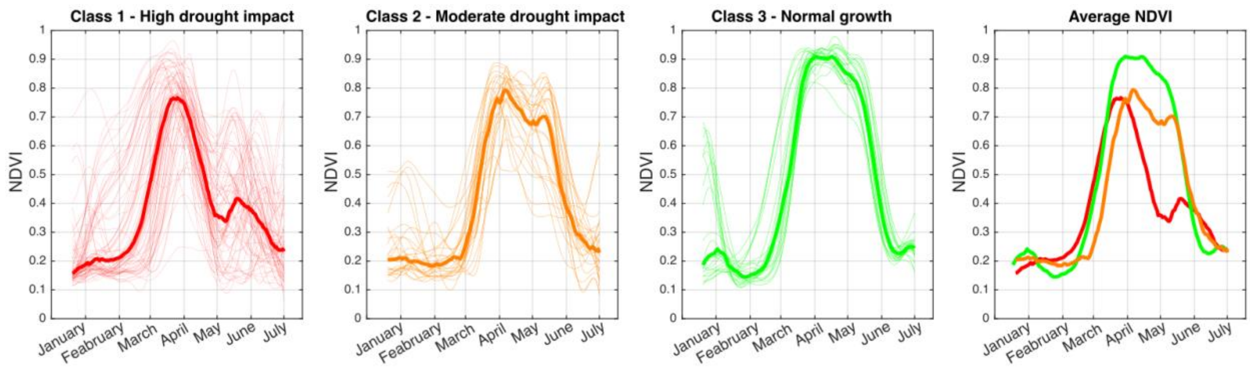

Figure 4. Sentinel-2 NDVI time series for the three drought impact classes on winter cereal development; a) high drought impact, b) moderate drought impact, and c) normal crop growth. Thin lines depict the NDVI time series of individual plantations where field measurements where collected (Figure 2) and thick lines show the average NDVI across plantations. Panel d) shows the average NDVI for the three impact classes.

The results of the feature selection showed that the best predictors for drought impact were COMPMay1 and COMPApr2 (Kendall's correlation of 0.66 and 0.63), which correspond to the NDVI composites for the first half of May and second half of April, respectively. This corroborates what we observed in the NDVI time series (Figure 5): drought induced substantial differences in NDVI among classes during the second half of the crop growing season. In contrast, the NDVI composites for the first half of the crop growing season showed a low Kendall's correlation with drought, indicating that the three classes have similar NDVI during the first stages of plant development. Among the phenology metrics, EoS80 (i.e. the EoS computed using a threshold of 80%) showed the highest Kendall's correlation, followed by GSA, PoS, and maxNDVI. The high importance of EoS metrics further indicates that differences between drought impact classes were mostly observed in the later stages of plant development.

Kendall's correlation did not differ substantially among the vegetation indices. Kendall's correlation calculated with other VIs also gave a high importance to the variables associated to the later stages of crop development (Figure 5). In addition, the highest Kendall's correlation was found for COMPMay2; the correlation was 0.66, 0.66, 0.67, 0.67, and 0.67 for NDVI, EVI, SAVI, RGVI, and NDMI, respectively.

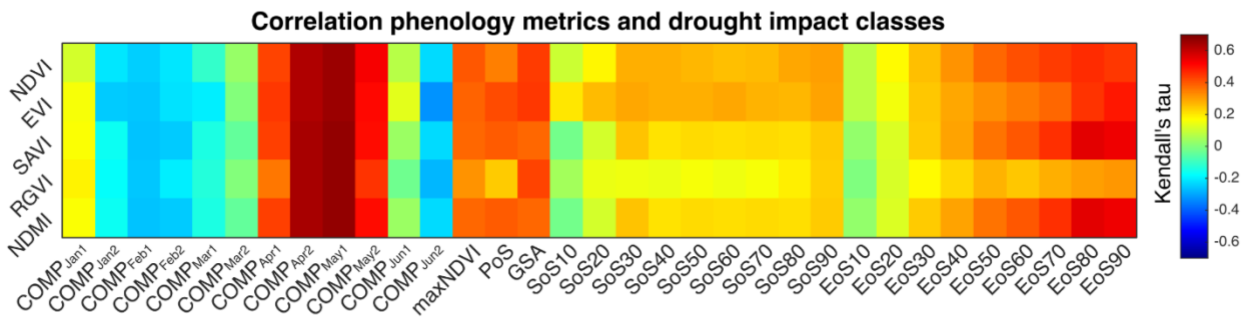

Figure 5: Results of the feature selection by Vegetation index. The feature selection method was the single prediction model, in which Kendall's correlation was calculated between the variables extracted from different vegetation indices (NDVI, EVI, SAVI, RGVI and NDMI) and the drought classes. The variables are composite aggregates

every 15 days (COMP), peak of season (PoS), growing season area (GSA), maximum VIs (maxVI), and the start and end of season (SoS and EoS) calculated at different thresholds (10:10:90 %).

We used the MODIS VIs during COMPMay1 to assess whether this variable explained the interannual variation in crop yield in Catalonia. We found that VIs during the first half of May presented a high correlation with the crop yield for the period 2001-2021 (Figure 6). The highest coefficient of correlation was found for RGVI (R^2 = 0.89), although other VIs showed similar magnitudes; the coefficient of correlation was 0.85, 0.83, 0.84, and 0.80 for NDVI, EVI, SAVI, and NDMI, respectively. The crop yield was also correlated with SPEI (R^2 = 0.41), indicating that droughts partially explain the annual variations in crop yield during the period 2001-2021. These results are important because we can predict the drought impact on winter cereals at regional scale using key phenological metrics.

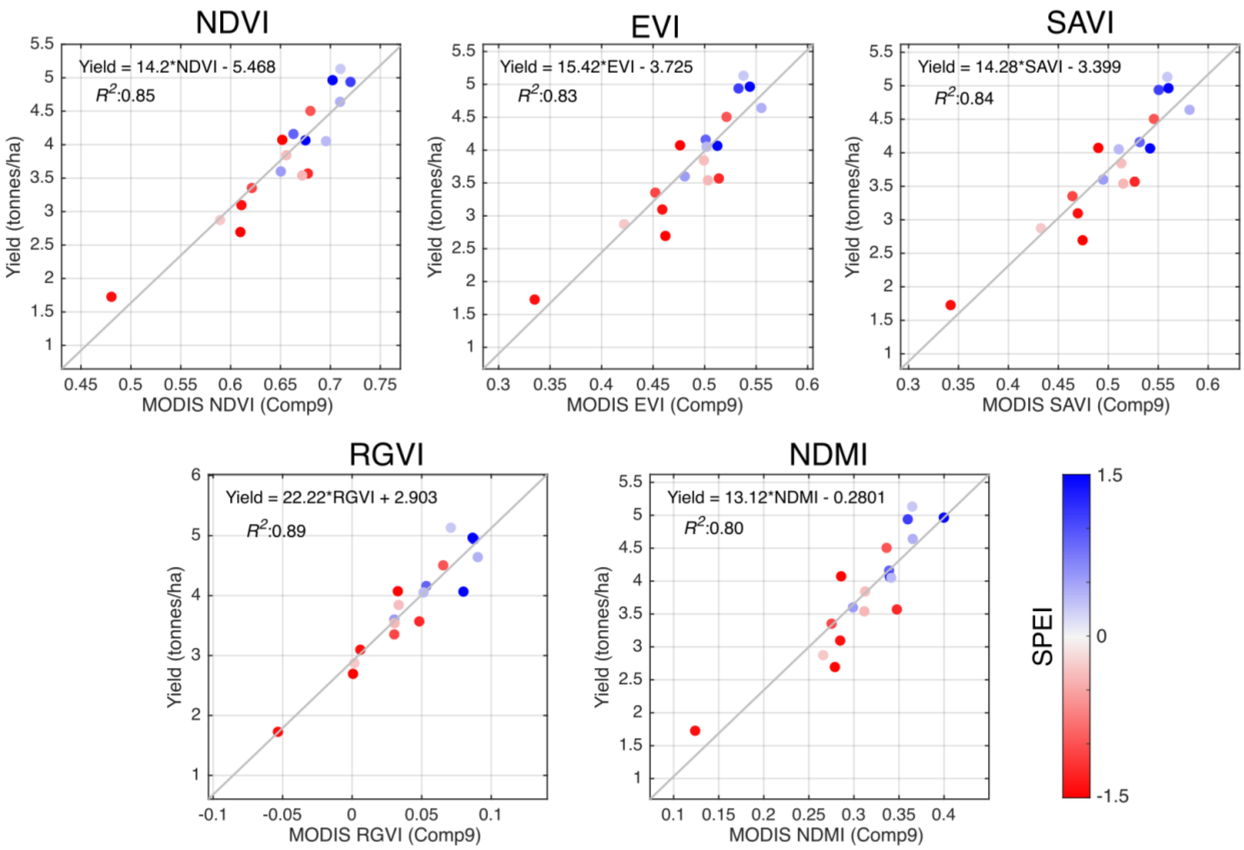

Figure 6. Comparison between Landsat MODIS VIs obtained during the first half of May and annual crop yield of common wheat and spelt in Catalonia during the period 2001-2021. Point colours represent the Standardised Precipitation-Evapotranspiration Index (SPEI). SPEI and the vegetation indices are dimensionless.

4. Discussion

An extreme drought induced a crop failure in winter cereals in the study area in 2023. This was observed in our field visits and from satellite observations. The plantations that suffered a crop failure showed a premature decline in Sentinel-2 NDVI, which occurred during early April. Our results show that phenological data extracted from Sentinel-2 during the second half of the crop development is key to evaluate the drought impacts on winter cereals. Specifically, the VIs values during early May showed the highest correlation with the drought impact classes. In addition, VIs values extracted from MODIS explained the interannual variability in crop yield at the regional scale during the period 2001-2021. This further evidence the importance of satellite remote sensing during the later stages of crop development for monitoring the drought-induced crop failure.

Crop failure is potentially becoming more frequent as the climate warns and crop yields are increasingly susceptible to extreme events (Lobell, Schlenker, and Costa-Roberts 2011). The period that we studied coincided with an extreme drought that occurred in the region (Joint Research Center 2023). We found that all rainfed crops suffered impacts from drought and only irrigated crops presented normal growth. This evidence shows the high impact of the 2023 drought and confirms that rainfed plantations are more susceptible to drought impacts (Jaramillo, Graterol, and Pulver 2020).

Previous research has quantified the relationship between drought impact, as measured by indices such as NDVI (Ghazaryan et al. 2020; Laurila et al. 2010; Yu et al. 2018). However, these studies often omit failed plantations resulting from severe drought. Our study identifies the key phenological stages observable through optical satellite data for effectively detecting drought-induced crop failure in winter cereals. Our findings are in line with a previous study that demonstrated that soil moisture during critical growth stages such as tillering and stem elongation is crucial for yield, and drought during these stages leads to significant yield losses (Benito-Verdugo et al. 2023). Our findings are crucial for the comprehensive mapping of crop failure on a large scale, which is important for ensuring food security. Additionally, our results demonstrate that monitoring drought impacts can be achieved with minimal variables and using a wide range of vegetation indices, facilitating near-real time monitoring of crop failure in winter cereals.

Crop monitoring is important as the effects of climate change on agricultural yields intensify. Crop monitoring using remote sensing techniques has been the subject of numerous scholarly articles. This research is relevant as climate extremes will put significant strain on crop productivity. Our study adds to the existing literature by providing a compelling example of how extreme droughts can have a significant impact on crop yields.

5. Conclusions

Our study provides evidence of the devastating effects of extreme drought on winter cereal production in Catalonia in 2023. Through a combination of field visits and satellite remote sensing, we observed a significant crop failure, particularly in rainfed crops. Our findings highlight the critical importance of spectral data extracted from Sentinel-2 during the later stages of crop development, particularly in May, for evaluating drought impacts on winter cereals. Furthermore, our analysis of MODIS-derived vegetation indices over the period 2001-2021 demonstrates the possibility of quantifying the inter-annual variability in crop yield at the regional-scale. Our study will help design better crop monitoring systems using satellite remote sensing as it elucidates the variables underlying drought-induced crop failure.

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General discussion and conclusions

Remote sensing has the advantage of providing a comprehensive view and broad area coverage, which imparts knowledge about conditions on the Earth's surface and changes in the landscape over time (Campbell & Wynne, 2011; Jensen, 2015). This capability is critical for monitoring environmental changes, agricultural practices, and urban development. GIS allows various manipulations, including map measurements, map overlay transformations, geographic design, and database management (Longley et al., 2015). The integration of remote sensing and GIS technologies provides a powerful toolset for comprehensive spatial analysis and decision-making processes.

The advancement of satellite data records is crucial for improving our understanding of natural and human-induced changes on Earth and their implications. Satellite imagery offers consistent and repeatable observations, enabling long-term monitoring and analysis (Woodcock et al., 2001; Chuvieco, 2016).

Chapter 1 demonstrated the progressive increase in accuracy over the years, from Landsat-5 to Landsat-8, as mentioned by Ryu et al. (2023), where Landsat 5, 7, and 8 data were used to improve land use classification accuracy. The advancements in satellite imaging technology and the integration of data from multiple sources have significantly increased the accuracy of land cover classification between 1995 and 2015. Overall accuracy increased from 94.6% in 1995 to 98.7% in 2015. The evolution from Landsat-5 to Landsat-8 introduced substantial improvements in sensor technology, including better spectral resolution, enhanced radiometric resolution, and higher temporal frequency, enabling more precise and reliable classification of land cover types (Ryu et al., 2023).

The use of images from multiple satellites in later years provided a richer dataset, facilitating more robust analysis and classification. In particular, the availability of Landsat-7 and Landsat-8 data in 2015 provided comprehensive coverage and higher quality images, contributing to significant accuracy improvements. These advancements have been instrumental in enhancing our ability to monitor environmental changes, track land use dynamics, and support sustainable land management practices. Additionally, advancements in analytical techniques and classification algorithms have played a crucial role in enhancing accuracy, being better suited to handle the complexity and variability of multispectral data, resulting in more precise land cover classifications (Maxwell et al., 2018).

Recent developments in machine learning and data processing techniques have further improved the accuracy and efficiency of satellite-based land cover classification. Algorithms such as Random Forest, Support Vector Machines, and Deep Learning models have been successfully applied to large datasets, offering high accuracy and robustness in various environmental applications. advancements in remote sensing technology, particularly with the development of the Landsat and Sentinel-2 satellites, have revolutionized our ability to monitor and classify land use with unprecedented accuracy. The integration of high-resolution imagery and advanced analytical techniques, such as machine learning, has enabled more detailed and effective analysis of land cover changes, which is crucial for the sustainable management of our natural resources. These developments not only improve the accuracy in detecting phenomena like drought and water stress in crops but also provide essential tools for addressing the challenges of climate change. By allowing for early identification of adverse effects and faster response times, these technologies enhance our capacity to adapt to climate impacts, making significant contributions to food security and global environmental management. The continued improvement and application of these tools will be vital for mitigating the effects of climate change and ensuring the sustainable use of land in the future.

Chapter 2 assessed whether Sentinel-2 satellite imagery could detect winter cereal crop failure due to severe drought in Catalonia in 2023, revealing that drought impacts were not visible early in the season but became significant at the end of the growing season. Phenological metrics from later crop stages emerged as reliable predictors of drought impact, highlighting the importance of using Sentinel-2 data for assessing crop failure caused by extreme climate events. This finding aligns with studies conducted in semi-arid regions of Spain, such as Urmeneta et al. (2021), who monitored alfalfa growth in Bardenas Reales using Sentinel-2 images. The results showed that vegetation indices derived from Sentinel-2, such as NDVI, were highly correlated with vegetation cover in advanced stages (Urmeneta et al., 2021).

Remote sensing technologies have evolved significantly over the past few decades. Modern satellites like Sentinel-2 offer high spatial, temporal, and spectral resolution, making them ideal for detailed vegetation monitoring and analysis. Sentinel-2's ability to capture data at various wavelengths allows for the calculation of vegetation indices such as NDVI, which are critical for assessing plant health and detecting stress factors like drought. The integration of these technologies into agricultural monitoring systems enables the identification of early signs of crop stress, allowing for timely interventions and management decisions.

The study demonstrated that drought induced effects mainly occurred in the second half of the growing season. Most affected crops showed a substantial decrease in NDVI in April, suggesting crop failure by that date, considering the different effects of drought stress on growth and grain yield. It was observed that drought during critical growth stages, such as flowering and grain filling, has a significant impact on final yield (Aslam et al., 2017). This finding underscores the importance of continuous monitoring throughout the growing season to accurately assess crop health and predict potential yield losses.

Furthermore, it was emphasized that for this study, the best predictor of drought impact is the NDVI during the first half of May, considering studies that highlight the spatial, temporal, and spectral resolution of Sentinel-2 for drought detection. NDVI derived from Sentinel-2 allows for the identification of early signs of water stress, being especially useful during critical growth months like May (Varghese et al., 2021). This capability is particularly valuable for regions prone to climatic variability and water scarcity, where early detection of drought stress can inform water management practices and mitigate adverse effects on agricultural production.

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