Protected horticultural crops characterization through object-based image analysis and satellite imagery time series in Almería (Spain)

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Abstract. Greenhouse farming is an agricultural management system that has showed its efficiency in intensifying food production. The importance of agriculture in the sustainable management of natural resources requires the development of operational methodologies for mapping and monitoring farmland. This study aims to analyze the potential of time series of Sentinel-2 images for monitoring Plastic Covered Greenhouse (PCG) crops in Almería (Spain). For this, a set of 22 Sentinel-2 images taken during 2021 were used. Throughout the year 2021, monthly field visits were made on 32 PCG to know the characteristics of these greenhouses, the crops they contained (i.e., tomato, pepper, cucumber, melon and watermelon) and their evolution over time. By combining both the satellite and the field data, the crops, which are growing into each PCG, can be characterized. Two different spectral indices, NDVI (related to vegetative growth) and Brightness (related to the whitewashing of PCG), derived from the Sentinel-2 images shown their usefulness for differentiating crops growing under plastic sheet. This work could be the first step for discriminating crops through indices derived from Sentinel-2 images for the development of future management strategies for PCG areas.

Keywords: Sentinel-2; horticultural crops; time series; object-based analysis; greenhouse mapping.

1 Introduction

During the last decades, food security has become a crucial global concern driven by projections of population increase and aggravated by the approaching pressure of climate change on agriculture [1,2,3]. Greenhouse farming is an agricultural management system that has showed its efficiency in intensifying food production. These systems constitute a possible alternative to ensure food supply [4].

In 2018, the global surface area of plastic agricultural structures was estimated as ~3,400,000 ha, where 15% of this area was greenhouses and their area is growing. This increase as well as its importance raises the need to map and classify agricultural plastic structures and the type of crops that could be planted [5].

The province of Almería, located in the semi-arid coastal plain of Southeast Spain, has a big plastic covered greenhouses (PCG) area and an even larger crop-growing surface, thanks to the scheduling of two growing cycles per year. These make Almeria the province with the highest concentration of protected crop surface (greenhouses) not only in Spain but in the world [6]. This large concentration of PCG requires transformative solutions for social, economic and environmental challenges and processes. In that sense, remote sensing offers coverage of large areas with precision and is a very efficient and contracted tool to improve management across scales [7].

Agriculture is of increasing importance in the management of sustainable natural resources and requires the development of operational methodologies for mapping and monitoring farmland. [8]. The data obtained by remote sensing offer a significant contribution to provide regular and accurate images of land use and land cover, specifically of the agricultural sector. It takes special relevance considering its applicability in a new era of land cover analysis, which has been enabled by free and open access data (e.g., Sentinel-2 (2A and 2B), Landsat 8 or even Landsat 9 images), analysis-ready data, high-performance computing, and rapidly developing data processing and analysis capabilities [9,10]. For instance, a combination of data from Sentinel-2A, Landsat 8 and Sentinel-2B provides a global median average revisit interval of 2.9 days [11].

In the last ten years, an increasing amount of scientific literature has been published on PCG mapping from remote sensing, that has mainly focused on Landsat imagery and Sentinel-2. A few indices especially adapted to plastic sheet detection, such as the Index Greenhouse Vegetable Land Extraction (Vi), Plastic Greenhouse Index (PGHI), Moment Distance Index (MDI), Normalized Difference Builtup Index (NDBI) and Greenhouse Detection Index (GDI) have been recently proposed [12].

The crop classification via remote sensing from medium resolution satellite imagery (e.g., Landsat or Sentinel-2) was commonly conducted by using pixel-based approaches until more than ten years. As a result of spaceborne sensors was allowing the application of the object-based image analysis (OBIA) model to extract crop types from satellite image time series. Peña-Barragán et al. [13] developed a methodology for outdoor crop identification and mapping using OBIA and decision tree algorithms. This methodology was also applied to a Landsat time series to map sugarcane over large areas [14]. Adapting this research line to PCG horticultural crops (indoor crops), Aguilar et al. [15,16] went one step further by addressing the identification from using a single WorldView-2 satellite image and Sentinel-2 and Landsat 8 Operational Land Imager (OLI) time series.

Satellite based vegetation index data, such as the normalized difference vegetation index (NDVI), is useful for estimating outdoor crop types because it is relatively easy to get and globally scalable. NDVI is a common vegetation index that has been use since the 1970s. Singla et al. [17], identified outdoor types of sugarcane crops efficiently using a temporal profile of NDVI at any given scale.

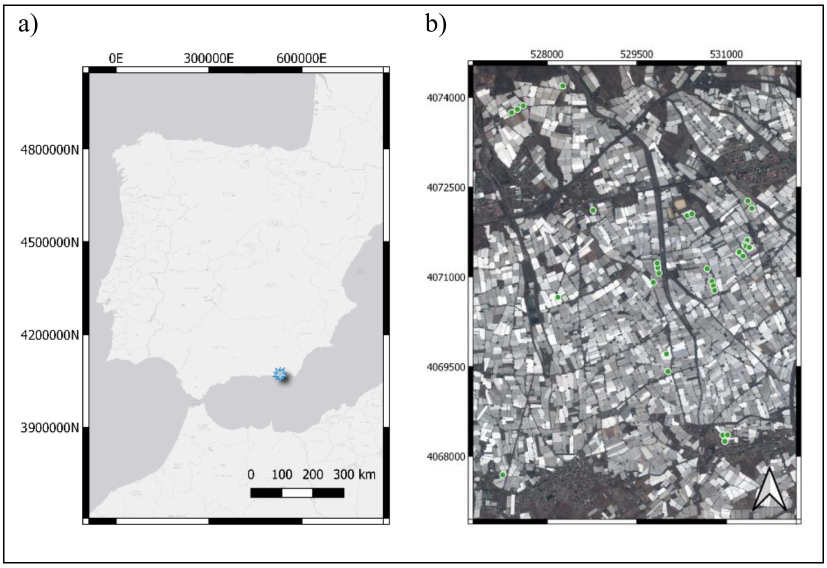
Remote sensing techniques are commonly used in agriculture and agronomy because, agricultural production follows strong seasonal patterns related to the biological lifecycle of crops. The grown crops depend on the physical landscape (e.g., soil type), as well as climatic driving variables and agricultural management practices, among others factors. [18,19]

This work is dealing with the optimized use of Sentinel-2 satellite image data for acquisition of consistent and near in time information associated to the greenhouse crops in spatial and temporal domain. The goal of the proposed study is to discriminate different inside greenhouse crops based on the multi temporal Sentinel-2 remotely sensed data temporal profile of NDVI, Brightness and the agricultural management of PCG.

2 Study area and datasets

The research has been carried out in Almería one of the eight provinces that make up the autonomous community of Andalusia in southern Spain (Fig. 1). Over 32,554 hectares of this province are currently dedicated to greenhouse crops production. Considering the area cultivated by product in the 20/21 season, production was 52,350 hectares of which was 12,575 ha of watermelon, 12,310 ha of pepper, 8423 ha of tomato, 8061 ha of zucchini, 5280 ha of cucumber, 3205 ha of melon, 2277 ha o aubergine, and 219 ha of green bean. About 60.8% of greenhouses cultivated area in Almería in 2020/21 season had two crops grown per year [20].

The study area comprised a rectangle area of about 40 km^2 centered on the WGS84 geographic coordinates of 36.7856°N and 2.6681°W.



(. 1. (a) Location of the study area in Almería (Spain); (b) Detailed view of the study area and location of the reference horticultural crops growing under plastic-covered greenhouses (PCG). Coordinate system: ETRS89 UTM Zone 30N.

2.1 Data set pre-processing

The European Space Agency (ESA) provides free, open access products, for example Sentinel 2 images level 2A (S2), that could be freely downloaded from Copernicus Scientific Data Hub tool, used for this study. The Sentinel-2 mission offer a combination of systematic global coverage of land surfaces, a high revisit of five days at the equator under the same viewing conditions, a wide field of view for multi-spectral observations from 13 bands in the visible, near infrared and short-wave infrared part of the electromagnetic spectrum [21].

A time serie of 22 cloud-free Sentinel-2 satellite images (both Sentinel-2A and 2B) were acquired in different dates (Table 1) during the 2021. In this study, the six 20 m ground sample distance (GSD) bands (Red Edge1, 2 and 3, SWIR 1 and 2 and NIR8a) and four 10 m GSD bands (Blue, Green Red and NIR8) were used. These images were clipped according to the study area.

Table 1. Characteristics of the Sentinel-2A images.

Orbit	*Granule*	*Date of Acquisition*	*Sensor*
R094	*30SFW*	*January 3, 2021*	*2B*
R051	*30SFW*	*January 15, 2021*	*2A*
R094	*30SFW*	*February 7, 2021*	*2A*
R094	*30SFW*	*February 22, 2021*	*2B*
R051	*30SFW*	*March 14, 2021*	*2B*
R051	*30SFW*	*March 24, 2021*	*2B*
R094	*30SFW*	*April 18, 2021*	*2A*
R051	*30SFW*	*May 5, 2021*	*2A*
R051	*30SFW*	*May 25, 2021*	*2A*
R051	*30SFW*	*June 9, 2021*	*2B*
R051	*30SFW*	*June 29, 2021*	*2B*
R051	*30SFW*	*July 4, 2021*	*2A*
R051	*30SFW*	*July 19, 2021*	*2B*
R051	*30SFW*	*August 8, 2021*	*2B*
R051	*30SFW*	*August 28, 2021*	*2B*
R051	*30SFW*	*September 12, 2021*	*2A*
R051	*30SFW*	*September 17, 2021*	*2B*
R051	*30SFW*	*October 7, 2021*	*2B*
R051	*30SFW*	*November 11, 2021*	*2A*
R094	*30SFW*	*November 29, 2021*	*2B*
R051	*30SFW*	*December 6, 2021*	*2B*
R094	*30SFW*	*December 19, 2021*	*2B*

2.2 Horticultural Crops under PCG Reference Data

A variety of data as farming practice, crop growth, agricultural management practices and greenhouse information as type, height, material is essential for carrying out this study. During 2021 were acquired field data to obtain rigorous and real information about 32 controlled greenhouses (Fig. 1b). Ground truth data at regular intervals of a month have been collected to extract the information related to the PCG crop growth cycle of controlled greenhouse.

These greenhouses contained different crops and managements that in turn changed during the course of the year. Among the PCG crops present, the most represented were characterized. In this case, four different crops management: Long cycle (September–April cycles) cherry tomato, Long-cycle bell red pepper (Fig. 2), short crop cycles (two cycles per year autumn to winter cycle and spring to summer cycle) watermelon and cucumber and long cycle zucchini was controlled.

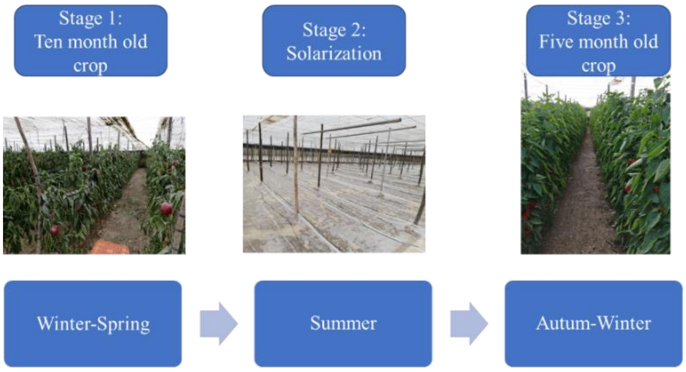


Fig. 2. Grow stage of Long-cycle bell red pepper.

3 Methodology

As shown in Figure 3, the methodology proposed in this article mainly includes three steps, process starts with Sentinel-2 data preprocessing. These satellite images after the preprocessing operations are further used to PCG crop characterization. Trimble eCognition Developer v. 10.1 software was employed for the Object-Based Image Analysis (OBIA) and the extraction of NDVI and Brightness. Finally, an assignment of classes of the horticultural crops studied under PCG in winter-spring 2021 and summer-autumn 2022 is made.

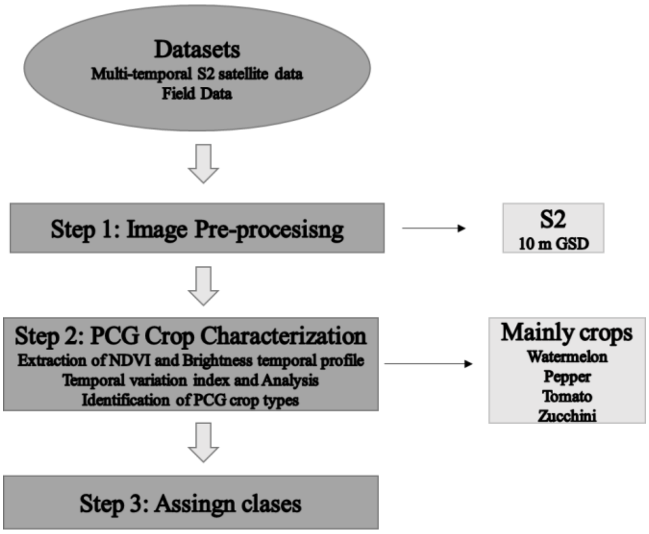


Fig. 3. Flow diagram of the methodology.

The crop characterization was evaluated using 32 polygons over of individual PCG. These polygons were manually segmented on the WV3 pansharpened image generated on July 11 image. Moreover, each polygon was digitized, adapting its boundary to the shape of each PCG. To prevent mixed pixels all the PCG polygons were get smaller by 10 m using the buffer tool in QGIS v 3.16 platform (QGIS Development Team 2021). This technique tried to avoid potentially mixed pixels located at the edges of the sampled PCG, which is a very usual point when working on medium-resolution satellite imagery as S2.

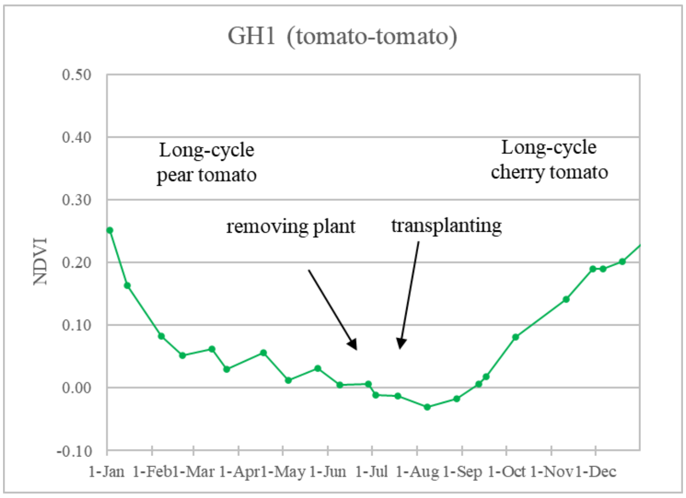
Trimble eCognition Developer v. 10.1 software was employed for the extraction of the mean surface reflectance values of all the pixels inside of each polygon from S2 products. To do this, the chessboard segmentation algorithm included in eCognition was applied to a previously digitized thematic layer containing the 32 reference polygons. The mean values of the Bottom-of-Atmosphere (BOA) reflectance values for all the pixels within an object for each band were labeled as basic spectral information and date. The rest of the features consisted of two spectral and vegetation indices for single images. All the pixels (with an enhanced spatial resolution of about 1.25 m) within the OBIA segments were considered. NDVI and Brightness were also computed for each polygon and date, using the mean values attained from Blue, Green Red, NIR8, SWIR1 and SWIR2 (Equations 1 and 2)

$$\mathrm{NDVI} = \frac{(\mathrm{NIR8\text{-}R})}{(\mathrm{NIR8+R})} \tag{1}$$

$$\mathrm{Brightness} = \frac{(\mathrm{B+G+R+SWIR\ 1+SWIR\ 2})}{5} \tag{2}$$

4 Results and discussion

A review of available literature revealed that the NDVI is the nucleus of land cover related information. Consequently, temporal and spatial variations in the numerical values of the NDVI may be successfully used to crop growth monitoring [17,22] Brightness is another key factor that makes it possible to determine one of the actions on greenhouses that is easiest to detect in remote sensing, whitewashing [23]. These two indices and an exhaustive knowledge of the management tasks carried out in the PCG crops controlled for this study, allow characterizing the crop.



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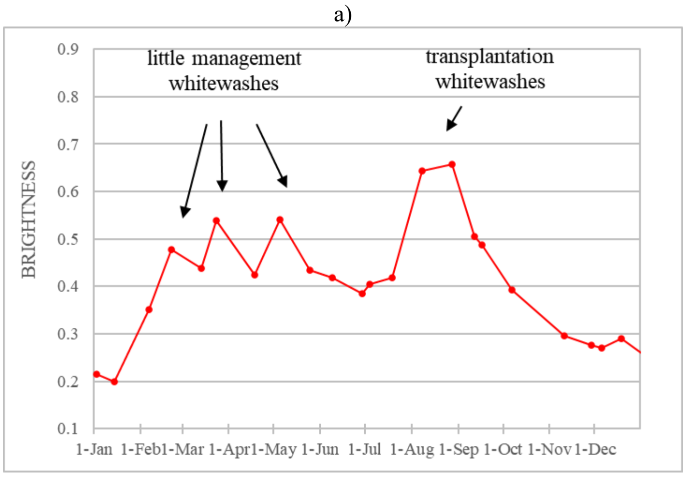
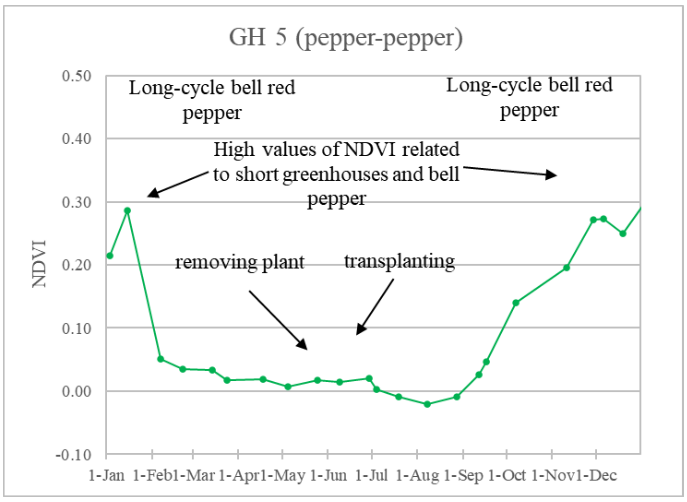


b)

Fig. 4. NDVI temporal profile of a) mean NDVI and b) mean brightness for long-cycle tomato.

Long-cycle tomato crop is characterized by having higher NDVI values around 0.2 in the winter months when the crop shows greater development and brightness peaks at the end of summer with values between 0.6 and 0.7, when whitewashing is carried out to the planting of the crop, as well as small whitewashes in spring that reach brightness values close to 0.5 (Fig. 4).



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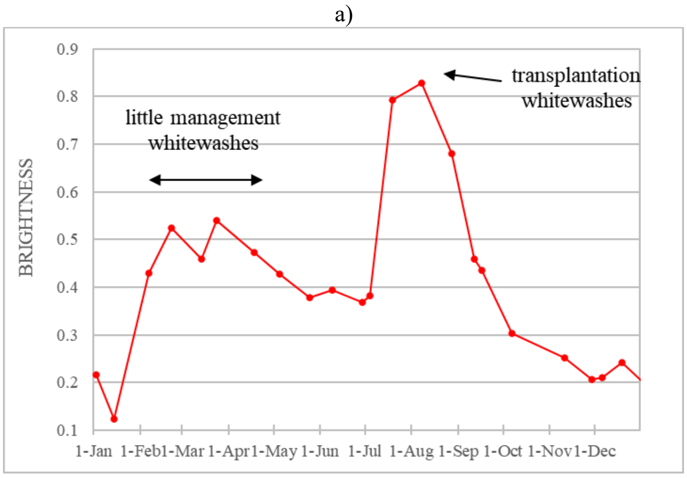
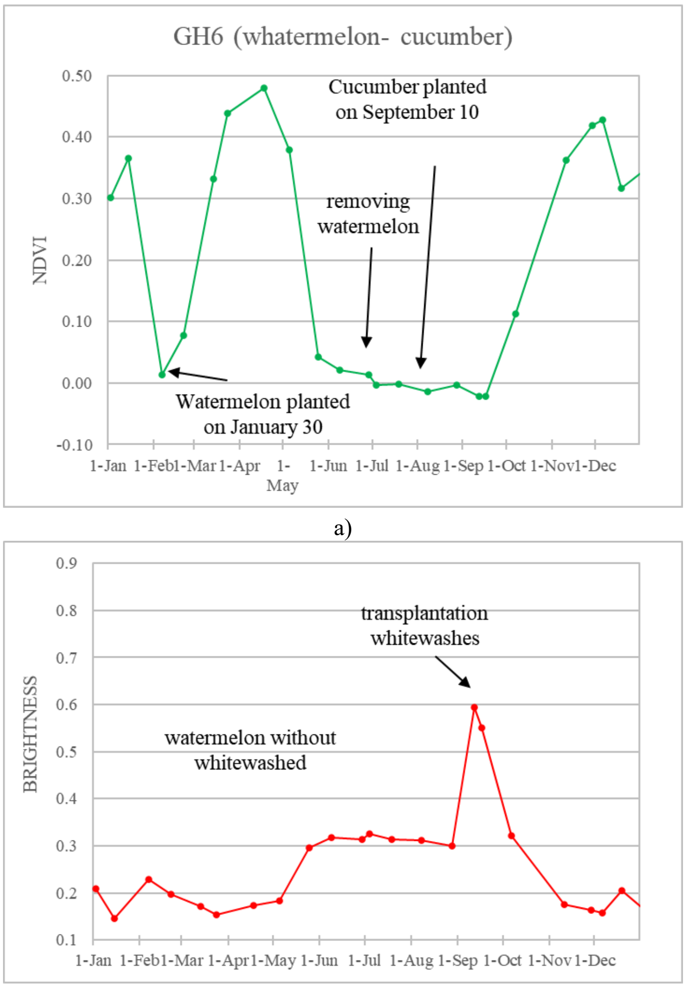


b)

Fig. 5. NDVI temporal profile of a) mean NDVI and b) mean brightness for long-cycle bell red pepper.

Long-cycle bell red pepper is characterized by NDVI values close to 0.30 in the winter months, and by receiving the strongest whitewashes at the end of summer, reaching brightness values above 0.8. Small whitewashes are also carried out in the spring months (Fig. 5).



a)

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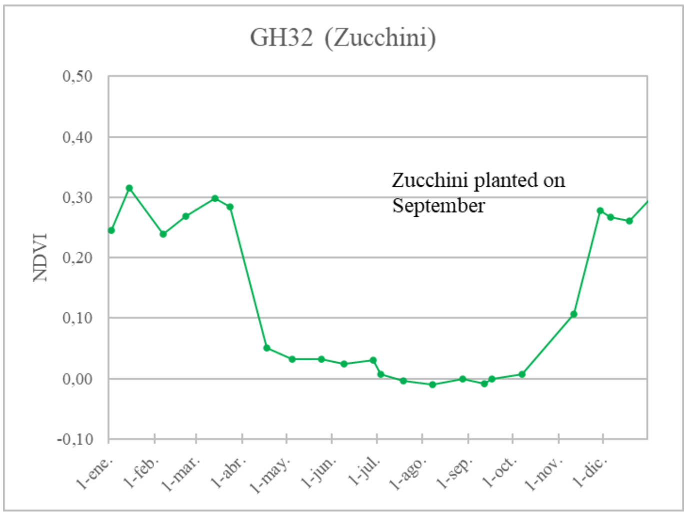
Fig. 6. NDVI temporal profile of a) mean NDVI and b) mean brightness for watermelon-cucumber.

Another widely distributed crop cycle in the study area is the combination of growing watermelon in spring and cucumber in winter. The watermelon crop under plastic is characterized by starting at the end of winter and presenting high NDVI values exceeding 0.4. In addition, it is a crop in which no whitewashing is carried out (Fig. 6). PCG Cucumber crop is a that undergoes whitewashing and also has high NDVI values, although these have greater variability due to the use of management techniques with greenhouse interior plastics. Although the characterization represented in this study is that of the PCG watermelon crop, it was observed that the PCG melon crop presents very similar spectral characteristics and management.



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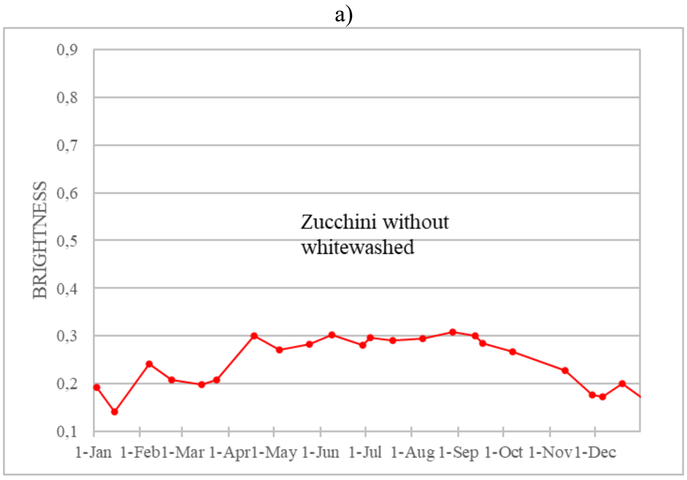

b)

Fig. 7. NDVI temporal profile of a) mean NDVI and b) mean brightness for Zucchini.

The zucchini crop, although less represented, was characterized in this study, presenting high values and NDVI in the winter months and no Whitewashing throughout the year (Fig. 7).

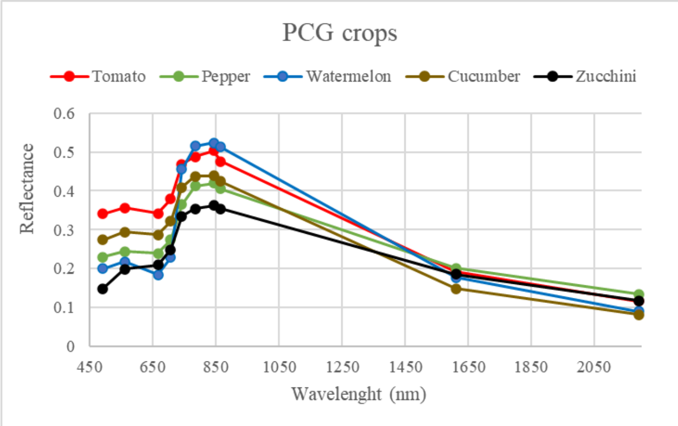

Fig. 8. Spectral signature plots extracted from S2 images for each PCG crop of December 6 S2 image, except the watermelon, in which it was taken from April 18 image.

An analysis of the spectral signature was carried out on Sentinel-2 images of the crops in which the highest NDVI values and lowest Brightness values, the moment where the reflectance values of the crop in the greenhouse are best remotely detected (Fig. 8). Each PCG crop presents a different spectral signature with different reflectance values in each band, these differences are higher in the bands that are in the visible spectrum and in the near infrared. When the spectral signatures of the characterized PCG crops are plotted (Fig. 8), they are characterized by increasing reflectance values as they approach the near-infrared spectrum. Specifically, it is the spectral signature of the PCG watermelon crop that has the largest differences between the reflectance values of the visible spectrum and the near-infrared spectrum, it is also the crop of the characterized ones that presents the highest NDVI values.

Through the characteristics of NDVI and brightness that defined the mainly characterized PCG crops (Fig. 4, 5, 6, and 7), ranges of between 0.05-0.1 were created for these two indices obtained from the values of the S2 images obtained from each of the objects analyzed, generating a decision rule for each PCG crop in each of the two seasons studied.

Through previous studies [24,25], the ability of a vegetation index as robust as the NDVI to detect phenological variations in crops has been demonstrated, allowing outdoor crops and land use to be mapped. By applying this methodology in PCG crops the potential of its application.

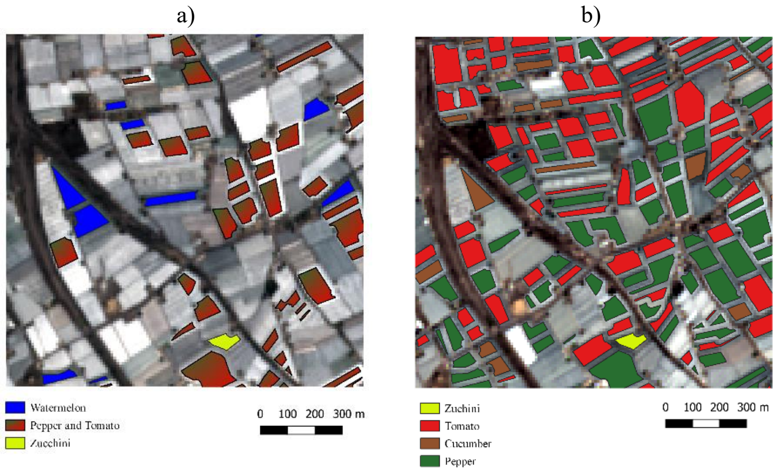

Fig. 9. Classes assigned by PCG crops characterized in the study area over manually digitized greenhouses on two seasons: a) Spring b) Autumn.

In Figure 9 is visually observed that a large number of greenhouses reflect similar characteristics to those extracted from the 32 controlled PCG crops. The year is divided into two seasons, Spring and Autumn, because they present different crops and managements. During the Spring there is no differentiation between tomato and pepper PCG crops and during the autumn months there are no watermelon.

Among the PCG crops used for this study, there was a papaya crop controlled. This PCG crop was characterized by obtaining NDVI values above 0.25 throughout the year and no Whitewashing is done throughout the year. Only the sample greenhouse had these characteristics within the work area.

Through previous studies [17,19,22,24,25], the ability of a vegetation index as robust as the NDVI to detect phenological variations in crops has been demonstrated, allowing outdoor crops and land use to be mapped. This methodology requires the collection of field data and remotely detected data over a period of time.

On the other hand, it is a simple and innovative approach that can be transferred to other work areas.

In addition, this technique could be improved with the application of specific rule-based or automatic classification techniques. Hence, protected horticultural crops characterization approach could be used as a previous step for automatic remote sensing-based classifications.

5 Conclusions

The present study demonstrated that temporal indices as NDVI and Brightness using an OBIA approach may be effectively used for the discrimination of PCG Crops.

The previous analysis of the greenhouse conditions and crop management, as well as the extraction of the correct indices, is necessary for the characterization of the crops.

The process of collecting the field data and extracting the data from the S2 images is laborious and needs to be done simultaneously over time.

Although this study is carried out over one year, the results obtained indicate that studies carried out in longer time series would allow a better characterization of the PCG crops.

Similar approaches could be used in other greenhouse areas and for analysis or estimation of production and yield or environmental parameters of crops.

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