Using Satellite Imagery and Vegetation Indices to Monitor and Quantify the Performance of Different Varieties of Camelina Sativa

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***Abstract*—In recent years, the cropping of *Camelina sativa* has gained popularity among the farmers of rainfed crops. It is an annual and flexible crop, which can grow in different regions. The estimate of the crop yield is essential for farmers. *Camelina sativa* is a small plant that forms a uniform green tapestry of grass. Hence, satellite imagery can be used for monitoring the crops. In this study, we present the use of Sentinel-2 data to monitor the performance of 6 varieties of *Camelina sativa*. Crops have been growing from fall to spring, and the harvest occurred in early June. We include satellite imagery from February to June. In this paper, we include a single image per month. Moreover, due to the size of the plots, we only consider the data from bands with a spatial resolution of 10m and 20m. First of all, the differences in spectral signatures of varieties along the time are presented. Then, we detail the possibilities of correlation between different vegetation indices and crop harvest. Finally, a multivariable statistical analysis to correlate bands of Sentinel-2 with harvested seeds is shown. This analysis estimates the yield with high accuracy.**

Keywords-Sentinel-2; rainfed crops; multivariable statistical analysis; NDWI; NDMI; EVI.

I. INTRODUCTION

Intensive agriculture is vital in our modern societies to produce enough food to sustain the ever-growing population. These cultures are too big to be managed in the same way traditional cultures have. Nevertheless, they do need to be monitored to obtain peak productivity and performance. The consequences of a large estate not being adequately handled are proportional to the magnitude of the field. The bigger the area is, the more losses it will experience with low performance. Therefore, an urgent need for the development of a monitoring system for intensive agriculture has arisen.

Nowadays, the most used method for agricultural monitoring is the use of Wireless Sensor Networks (WSN). Their purpose is focused on monitoring the soil and the chemical characteristics of the plants, such as nitrogen content, though. Instead, our proposed method measures the yield. Unmanned Aerial Vehicles (UAVs) have been proved to be helpful devices for Geographic Information System (GIS) [1]. Environmental variables, such as tree coverage, can be monitored with the use of imaging techniques. The process of obtaining these images was done first by hand until the introduction of UAVs. This innovation allows for these surveys to be done remotely.

The use of airborne multispectral and hyperspectral imagery and high-resolution satellite imagery has been proved to be useful. Moreover, other imaging analysis techniques have been tested lately [2]. A study developed this year managed to detect fruits in trees using image processing [3].

The application of new monitoring techniques to manage intensive agriculture is critical. Not only would it mean diminishing the use of our resources, but it would also translate in an improvement of the yield. Moreover, monitoring the productivity of the crop would help detect problems. It is possible that we should be having more yield than the harvested one. That would mean something is preventing it from being as productive as it should. Besides, estimating the yield has some economic benefits. The cost-benefit ratio could be calculated before the crops are harvested. This could also mean knowing the price at which the product could be sold before other companies and being able to prepare in advance.

The aim of this paper is to determine if the multispectral imaging data, which is obtained from the satellite Sentinel-2B and Sentinel-2A, can be used to determine a key parameter in agricultural productivity and performance. The said parameter is the number of seeds several C*amelina sativa* crops produce, using up to six different varieties. The *Camelina sativa* is a crop that is currently being sown in many dry areas of the world. The plants produce seeds that are used for oil extraction. This plant from the Brassicaceae family is annual, which makes its monitoring easier. It creates a fruit that contains up to sixteen seeds, according to Mostaza-Colado et al. [4]. In order to accomplish our goal, we will obtain the spectral signature of the crops using images taken once per month from February to July. The images used will be taken at the end of each month with the last one representing the bare ground after the seeds are collected. Several vegetation indices will be analyzed using the information from these images to try and relate them with productivity. If necessary, we will create our indices using statistics.

The rest of the paper is structured as follows. The discussion of the related work is presented in Section 2. Section 3 deals with the materials and methods that were used for this experiment. The results are portrayed in Section 4. Finally, Section 5 shows the conclusions of this work.

II. RELATED WORK

In this section, we discuss some papers which deal with different methods to monitor crops. Moreover, other different vegetation indices used nowdays, which could be useful for our purpose, are mentioned.

Mostaza-Colado et al. [4] performed preliminary tests to check if Sentinel-2B images could be used to estimate the growth of *Camelina sativa*. They attempted to correlate the Normalized Difference Vegetation Index (NDVI) with the growth of the plant. They proved a correlation between the acquisition techniques. However, they could not prove the existence of a relationship between the NDVI and the yield.

Sankey et al. [5] used a UAV equipped with a Light Detection and Ranging (LiDAR) sensor, as well as hyperspectral imaging, to monitor a forest in the southwest of the USA. They determined that the data could be analyzed to generate 3D point cloud data, although the differences between ground and trees were not evident in the dense parts of the forest. This is not a problem in the case of intensive cultures, where the coverage is never as thick as a forest.

Vega et al. [6] used a UAV to monitor a sunflower crop and determined that their method could be used in precision agriculture. They managed to extract the NDVI from the images. Moreover, they correlated the NDVI with aerial biomass, plant nitrogen, and grain yield. One of the advantages they remarked from UAVs compared to satellites is the ability to obtain images on cloudy days.

Ashtekar et al. [7] attempted to map the surface water dynamics in the upper Krishna River basin. To do so, they modeled the water dynamics using the Normalized Difference Water Index (NDWI), taking data from 17 years. This index allowed them to classify the water as permanent, seasonal, and new permanent.

A study similar to the one we propose was developed by Yawata et al. [8]. They used satellite images to extract the spectral values and then estimated the rice yield employing a mixed model. Two vegetation indices were implemented as feature values: the NDVI and the Green Normalized Difference Vegetation Index (GNDVI). They managed to reduce the mean absolute error compared to other estimation methods, such as regression methods.

Selbmann et al. [9] used several indices derived from Landsat imaging to monitor wildfire consequences in a wetland tundra ecosystem. The indices they used were the NDVI, the Enhanced Vegetation Index (EVI), the Normalized Difference Moisture Index (NDMI), and the Normalized Burn Ratio (NBR). They managed to relate the EVI and NDVI with the severity of the fires.

Fassnacht et al. [10] attempted to develop a non-destructive method to estimate the carotenoid content on trees. They used the Angular Vegetation Index (AVI) to do so. Said index had to be combined with two other proposed carotenoid indices to give an accurate enough output.

The performance of corn crop fields was estimated by Venancio et al. [11] using the FAO-66 approach and the Soil Adjusted Vegetation Index (SAVI). They used the seventh and eight bands from Landsat to forecast the corn yield at the farm-level in Brazil. The predictions they obtained showed little difference from the real value (between -5% and 5%).

Marin et al. [12] managed to determine the grass coverage in urban lawns with RGB histograms of the lawns. Brightness values between 40 and 60 extracted from the green layer could be used to determine the coverage.

Among the studies mentioned above, several have a similar objective to the one we have. Nevertheless, they used already existing indices while we will test new combinations. Moreover, in our experiment, we will be using *Camelina sativa*, which is an emerging crop. Furthermore, we will be using images from several months. In conclusion, we will estimate the productivity of a *Camelina sativa* crop using geoprocessing, no matter its variety. This will be done using satellite imaging. In order to obtain the desired results, we will compare the value of the bands using several vegetation indices. Moreover, we will create our indices if necessary.

III. MATERIAL AND METHODS

In this section, the utilized images, how they were obtained, and the methodology applied are described.

A. Image obtention

Among the available open-access images from the different satellites, we have selected to work with data from Sentinel-2. The Sentinel-2 was chosen due to its high spectral resolution, up to 12 bands (B), and four generated indices. Furthermore, it has a high spatial resolution, which is 10m (for B2, B3, B4, and B8), 20m (B5, B6, B7, B8A, B11, and B12), and 60m (B1, B9, and B10). Besides, this satellite presents a high temporal resolution, which allows having one set of data every five days. Other satellites that offer open-access images give a lower temporal, spatial, and spectral resolution.

The images are obtained from the Copernicus Open Access Hub webpage [13]. The studied plots *with Camelina sativa* are located in the T30TVK of the grid system. All the images obtained between January and June of 2019 are downloaded. However, the data from January is not used due to the vegetation not yet being visible. First, we discard the images with cloud coverage in the studied area. Next, we select the date of the pictures to have the first picture at the end of February, have all the images separated by 30 days (average), and without cloud coverage. Therefore, the images used correspond to 28-February, 30-March, 29-April, 29-May, and 30-June. The first four images will show the changes in the vegetation, while the last picture will represent the soil status after the harvest.

B. Data gathering

Once the satellite imagery has been obtained and selected, the next step is to get the values of the pixel of different bands for the different *Camelina sativa* varieties. The plots were already digitalized in previous studies [4].

Thus, using ArcMap [14], the satellite imagery and the digitalized plots are opened, see Figure 1. In this figure, we show the plots, identified in yellow borders, and the area which is considered for statistical analysis indicated in red.

This area is smaller to avoid the effect of adjacent surfaces. Every plot contains a single variety of *Camelina sativa*.

The tool Zonal Stadistic as a Table [15] is selected to obtain the values of each band for the different plots. All the statistics are obtained for every band. These data are then exported to an Excel file. In Excel, we generate the different spectral signature for each variety along the time using the mean and median values, including the standard deviation calculated in the previous step. The included varieties in this study were obtained from the Camelina Company España [16]. Purchased seeds were sowed at the beginning of December. The varieties are named 1), 2) 3), 4), 5), and 11).

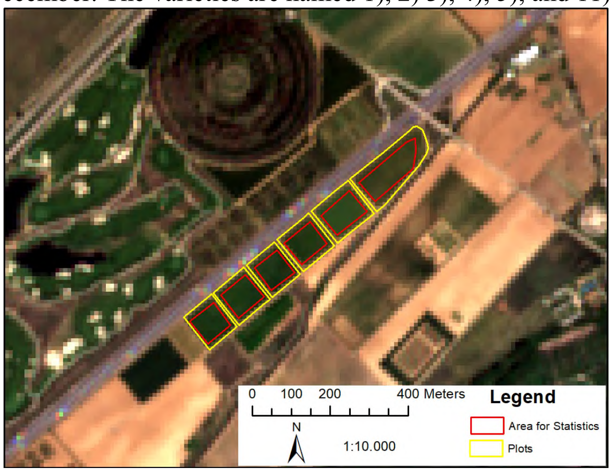

Figure 1. Studied area.

C. Vegetation indices calculation

To obtain a correlation with the harvested seeds, we use the data from the band 1 (B1) to band 12 (B12) of each image to calculate different vegetation indices. Now, we are going to define the utilized indices. Previous works [4] have evaluated the NDVI of these plots. They did not find any relation between NDVI and harvested quantities. Thus, in this paper, we increase the evaluated indices and include the following:

(i) NDWI [17], which is based on the green and Short Wave Infrared (SWIR) bands. In the case of Sentinel-2, the formula to calculate the index is (B3-B8)/(B3+B8). NDWI gives information about the water content in the plants. This index can have values between -1 and 1. The lower the value, the greater the water content. The higher the value, the lower the vegetation cover and water content.

(ii) NDMI [18], which is based on the Near Infrared (NIR) and SWIR. In Sentinel, the formula is (B8–B11)/(B8+B11). This index offers information about vegetation water content. As the previous index, this one can adopt values between -1 and 1. The higher the value, the lower the water stress.

(iii) EVI [19], which was developed by NASA as an alternative to NDVI and similar indices. This index has two main advantages over NDVI-like indices: (i) more sensitive in areas with high biomass and (ii) reduces the influence of atmospheric conditions. It is calculated using the B2, B4, and B8. Besides, some constants are used. The formula is 2.5*((B8A-B4)/((B8A+6*B4-7.5*B2)+1)). In contrast to previous indices, this one is not limited to values from -1 to 1.

D. Obtaining new correlations

Finally, we perform multivariate analysis to find a possible association between different bands and indices and the harvested seeds of the different varieties. The main objective is to have a preliminary result that indicates any potential band or bands for its future use when creating a vegetation index that predicts the harvest. In the case that any band presents a correlation with the harvest, we will use regression tools to define this correlation.

IV. RESULTS

In this section, we discuss the results of this contribution. First, the differences in the spectral signatures are detailed. Next, we present the analysis of the indices. Finally, the multivariate analysis and its outcomes are discussed.

A. Spectral signatures

After obtaining the satellite imagery, some problems were detected. First of all, in images from January to April, the data of band ten was missing. Furthermore, in images from May and June, the data from the calculated indices corresponding to the Level 2A specific bands: Scene-average Water Vapour map (WVP), Aerosol Optical Thickness map (AOT), and Scene Classification (SCL) were not included. Therefore, for the analysis of spectral signatures, the data is not complete for all the time-series. Moreover, we only include the data with a spatial resolution of 10 and 20m. This data can be seen in Figure 2; the name in brackets indicates the variety of *Camelina sativa*. In this figure, the mean value of pixel for each band in different moments of the year is displayed. The months, February to June, are represented in different colors and indicated as 2 to 6. The colors are to show the phenological conditions of the crop. In green, we describe the moments when the *Camelina sativa* has a green coloration and is growing. In yellow, we indicate the period in which plants have very low water content, and they are dry. In late June, the assigned color is brown because the plants are completely dry, and the seeds are already collected.

The first thing that can be noticed when analyzing Figure 2 is that different varieties seem to have different patterns. This might be caused by differences in the phenological characteristics of the different species. Next, we present in detail some of these differences. For example, varieties 3) and 4) present higher variations in the red band between February and March than 1) and 2) (which do not show any change) or 5) and 11) (which decrease to a lesser extent). From March to April, most of the varieties increase their mean value in the green band, nonetheless 5) experiences a decrease.

Apart from that, there are some changes in the region of 705 to 783nm (IR light), which is commonly used for vegetation characterization. While for most of the varieties,

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during the moment in which plants are green, the minimum values in those bands are found in March, 2) has similar data in bands 6 to 8 in February and March. Taking into account that all the plants were sowed at the same moment, the soil was homogenized, and the environmental conditions were the same, the differences found are due to the different varieties. Thus, spectral signatures can be used to characterize the crops.

B. *Vegetation Indices*

The indices above are calculated for the different varieties and different periods of the year.

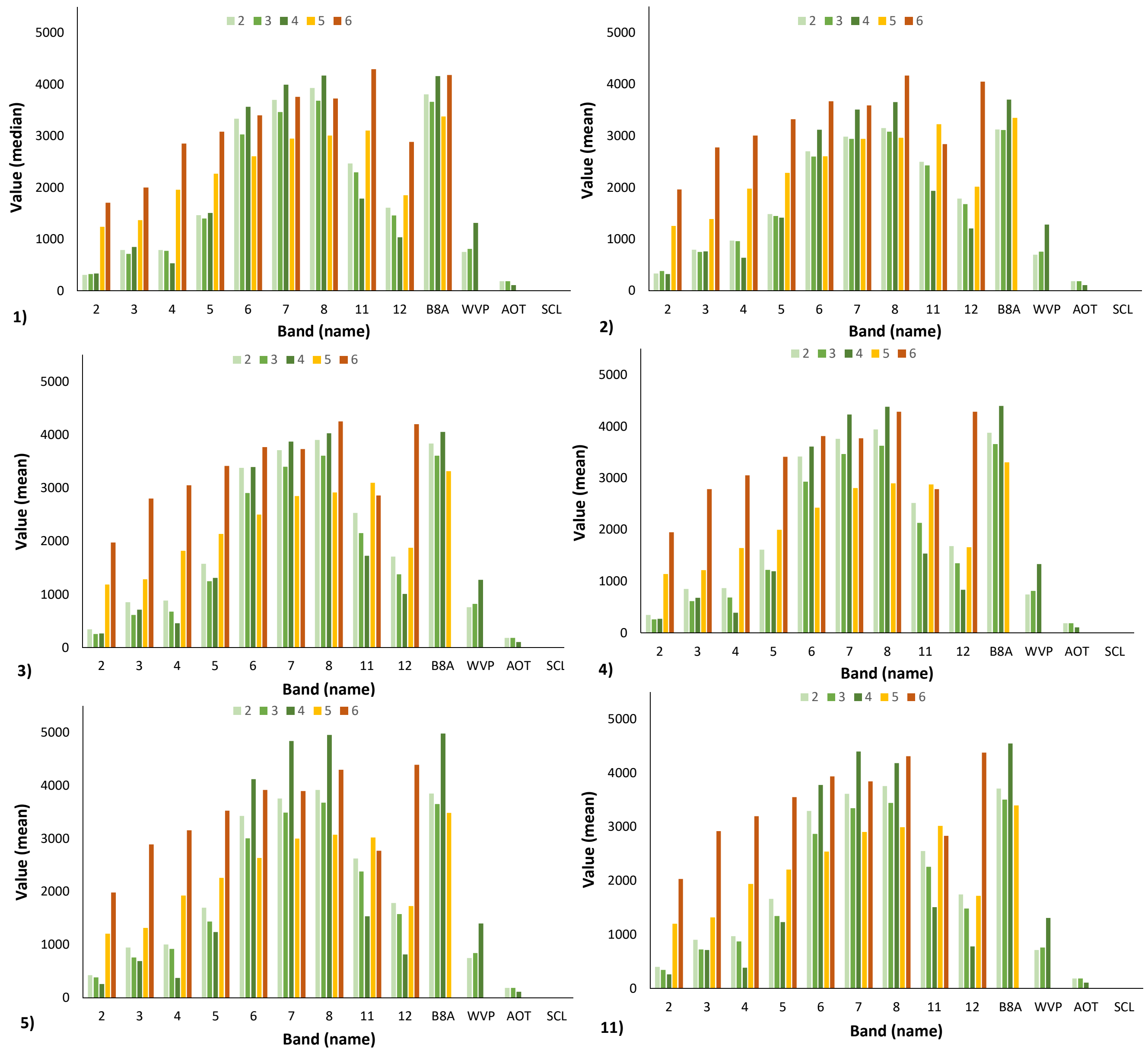

Figure 2. Spectral signatures for different varieties and periods (February to June).

Data from index NDWI is displayed in Table I. This index indicates the changes in the water content of the surface, in this case, the crop. The results of the NDMI index are presented in Table II. The NDMI is an indication of the moisture. For Tables I and II, the varieties were ordered according to the harvested amount of seeds. The variety 5) (620kg/Ha) is the one with the lowest harvest and variety 3) is the one with the highest harvest (1125kg/Ha). The other varieties have a harvest between 914 and 971 kg/Ha. Both indices are similar, and the results of their application offer identical data. The results point out that the healthiest crops are 3), 4), 5), and 11). Nevertheless, there is no relation between the results of the index and the harvested quantity.

Next, the results of EVI are presented in Table III. The higher the value of the index is, the higher the plant vigor is.

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According to EVI, the healthiest crops are 5), 4), and 11). Again, no relation was found between the index and the harvested seeds of different varieties.

TABLE I. VALUES OF NDWI FOR DIFFERENT VARIETIES

Month	NDWI per Varieties					
	5)	*2)*	*1)*	*4)*	*11)*	*3)*
2	-0.61	-0.66	-0.66	-0.65	-0.61	-0.64
3	-0.66	-0.65	-0.67	-0.71	-0.65	-0.71
4	-0.76	-0.68	-0.66	-0.73	-0.72	-0.70
5	-0.40	-0.36	-0.37	-0.41	-0.39	-0.39
6	-0.33	-0.31	-0.30	-0.32	-0.31	-0.31

TABLE II. VALUES OF NDMI FOR DIFFERENT VARIETIES

Month	NDMI per Varieties					
	5)	*2)*	*1)*	*4)*	*11)*	*3)*
2	0.20	0.12	0.23	0.22	0.19	0.21
3	0.21	0.12	0.23	0.26	0.21	0.25
4	0.53	0.31	0.40	0.48	0.49	0.40
5	0.01	-0.04	-0.02	0.00	0.00	-0.03
6	-0.05	-0.07	-0.07	-0.06	-0.06	-0.07

TABLE III. VALUES OF EVI FOR DIFFERENT VARIETIES

Month	EVI per Varieties					
	5)	*2)*	*1)*	*4)*	*11)*	*3)*
2	1.08	0.84	1.23	1.18	1.06	1.14
3	1.09	0.88	1.24	1.27	1.06	1.28
4	2.18	1.49	1.86	2.13	2.12	1.87
5	0.51	0.46	0.48	0.75	0.47	0.56
6	0.29	0.27	0.27	0.31	0.27	0.30

Consequently, we can affirm that there is no correlation between different tested indices and harvested seeds. Thus, the indices cannot be used for the prediction of harvest.

C. *Correlation of bands and the harvest*

Since none of the typical vegetation indices tested in this paper and a previous one [4] has offered a correlation with the harvest, we will perform a multivariate analysis to find a relationship. In this analysis, we will include the harvest quantity in kg/Ha of the six varieties and the value of the included bands in this paper (from February to June).

A multivariate analysis with up to 95 variables (16 bands + 3 indices per 5 months, and the harvest) is conducted with Statgraphics Centurion. The results of the analysis indicate that two bands are correlated with the harvest. The first band is the WVP of April and the second one is on the B1 of June. The one that presents a higher correlation and is meaningful in terms of prediction is the WVP of April (WVP4). According to Statgraphics, the p-value of that correlation is 0.0117, and the correlation coefficient is -0.9103. Figure 3 shows the correlation between the three WVP analyzed and the harvest. There, we can see the correlation that exists among harvest and WVP.

The last step is to perform a simple regression with Statgraphics to obtain a mathematical model that correlates both variables. First, we verify the comparison of regression models available in the software. The one that offers a higher correlation is the reciprocal-Y squared-X model. The graphic that shows this correlation, the mathematical model, and the intervals (prediction and confidence) are shown in Figure 4.

The mathematical equation of this model is Eq (1); its correlation coefficient is 0.926, and the squared-R 85.81. The standard error is 0.0001 and the mean absolute error is 0.00007. Finally, the p-value of the model is 0.0079. All this data confirms that the model is accurate and it can be used to predict in the future the harvest of *Camelina sativa* crops based on data of WVP.

$$\text{Harvest} = 1/(-0.00229478 + 1.95954\text{E-}9 * \text{WVP4}\text{\^{}}2) \quad (1)$$

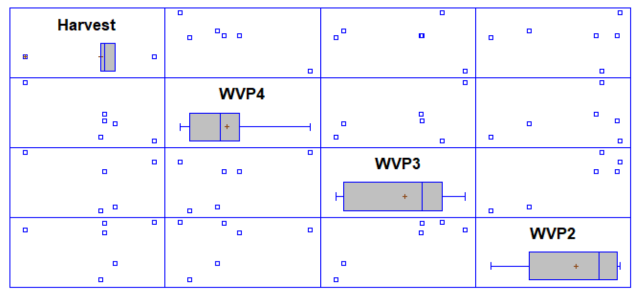

Figure 3. Spectral signatures for different varieties and periods (February (2) to April (4)).

It should be considered that the different varieties of *Camelina sativa* present different seeds size. According to [16], varieties such as 3) and 5) are the ones that give the bigger seeds, and 36 is the one that presents the higher height and larger inflorescences. It is possible that due to the characteristics of the seeds, some have been lost before the harvest because of the wind and other adverse meteorological conditions. On the other hand, 1), 3) and 6) have a smaller size and the loss of seeds due to the wind is minimized. It must be considered that the decision of the harvesting moment is crucial in order to reduce seed loss. This loss might have an impact on the prediction model presented in this paper.

V. CONCLUSION

In this paper, we present the use of satellite imagery for the monitoring of different varieties of *Camelina sativa*. According to the results of the spectral signatures, we identify a different phenology in different varieties. They have different patterns in visible and IR bands. We calculate NDWI, NDMI, and EVI indices to find a possible correlation between indices and harvest. None of the typical vegetation indices tested in this paper present a correlation.

Nevertheless, a multivariate analysis was carried out with Statgraphics. The results point out that the WVP4 is correlated with the harvest. The regression model was obtained with a correlation coefficient of 0. 926. Thus, we have demonstrated the usefulness of the satellite imagery for *Camelina sativa* monitoring and harvest prediction.

For future work, we will extend our study and include more images to evaluate the best moment for WVP measurement to have a more accurate model. Moreover, to avoid the disturbances of clouds and other atmospheric factors, the utility of images obtained with a drone with a thermal camera will be evaluated. Furthermore, the study would be run for several years to eliminate a possible year-specific effect.

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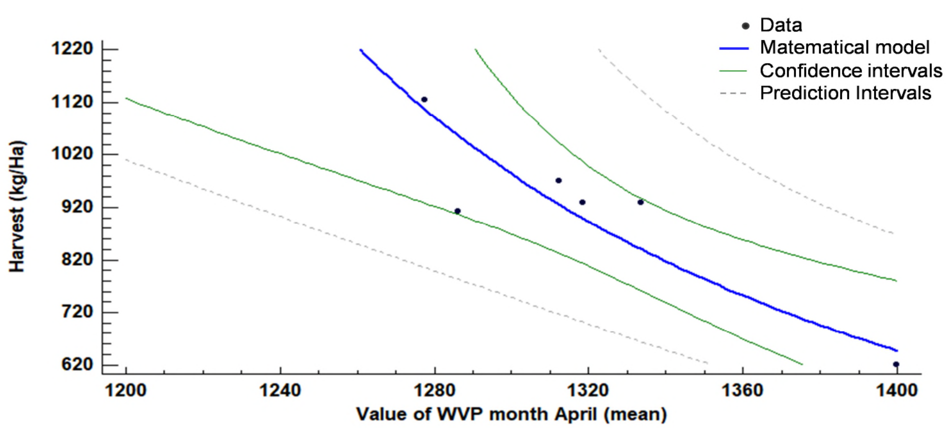

Figure 4. Spectral signatures for different varieties and periods (February to June).

