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Using remote sensing to map the occurrence of *Cistus salviifolius* L. (Cistaceae) in Armutlu, Yalova, Türkiye

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Abstract

By scientifically grounded nature management, the biodiversity of medicinal plants can be preserved, providing a foundation for the research and development of new therapeutics. Monitoring the condition and distribution of plant communities is one of the contemporary responsibilities of botanical resource research. *Cistus salviifolius* used to mange various ailments in both modern and traditional medicine. Sentinel-2 based on remote sensing techniques, offer promising alternatives to accurately detect, map and monitor the extent of plants. The aim of this study was to investigate the utility of Sentinel-2 data to detect and map *Cistus salviifolius* as a case study in Armutlu. The obtained results reveal the significance of the red-edge and shortwave infrared regions of the spectrum, as well as the inclusion of vegetation indices in the classification for *C. salviifolius* discrimination. Here, we demonstrate the potential of Sentinel-2 data for mapping of medicinal plants.

Keywords: remote sensing, Sentinel-2, *Cistus salviifolius*, classification, spectral signature

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Cistus salviifolius L. (Cistaceae) oluşumunun haritalandırılması için uzaktan algılamanın kullanılması, Armutlu, Yalova, Türkiye

Özet

Bilimsel temelli doğa yönetimiyle tıbbi bitkilerin biyolojik çeşitliliği korunabilir ve yeni tedavi yöntemlerinin araştırılması ve geliştirilmesi için bir temel oluşturulabilir. Bitki topluluklarının durumunu ve dağılımını izlemek, botanik kaynak araştırmasının çağdaş sorumluluklarından biridir. *Cistus salviifolius* hem modern hem de geleneksel tıpta çeşitli rahatsızlıkların tedavisinde kullanılır. Uzaktan algılama tekniklerine dayanan Sentinel-2, bitkilerin dağılımını doğru bir şekilde tespit etmek, haritalamak ve izlemek için umut verici alternatifler sunuyor. Bu çalışmanın amacı, Armutlu'da bir vaka çalışması olarak *Cistus salviifolius*'un tespit edilmesi ve haritalandırılmasında Sentinel-2 verilerinin kullanılabilirliğini araştırmaktır. Elde edilen bulgular, spektrumun kırmızı-kenar ve kısa dalga kızılötesi bölgelerinin öneminin yanı sıra bitki indekslerinin *C. salviifolius* ayrımcılığı sınıflandırmasına dahil edildiğini ortaya koyuyor. Burada Sentinel-2 verilerinin tıbbi bitkilerin haritalandırılmasındaki potansiyeli gösterilmiştir.

Anahtar kelimeler: uzaktan algılama, Sentinel-2, *Cistus salviifolius*, sınıflandırma, spektral imza

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1. Introduction

Due to the fact that the traditional methods for land mapping, especially the preparation of vegetation distribution maps on a regional scale, require detailed field investigations. In addition, allocating a budget and considerable time are required. In the last decade, with the advancement of imaging technologies and the availability of high resolution images, the use of remote sensing methods to produce spatial information for management and micro- and macro-planning has become a common procedure (Figure1). Remote sensing data for vegetation classification and mapping provides accurate results in a time- and cost-effective manner.

Figure 1: Combination of Spectral signatures belonging to different classes and sentinel-2 bands [1], with modification

The use of remote sensing technology to study phenomena on earth is based on different reflectance values of different chemical compounds. Receiving the reflected and emitted waves from the surface of the earth and converting these electromagnetic signals into information that can be used in computers is the basis for preparing these data. In simple words, remote sensing data are the result of measuring energy reflected from the Earth's surface at different wavelengths. The electromagnetic spectrum refers all possible frequencies of electromagnetic energy, which vary from very long wavelengths (such as electric waves) to very short wavelengths (gamma rays). Generally, the spectral behavior of phenomena refers to reflections that occur in the visible and infrared range. In general, electromagnetic waves in any form of the spectrum that we have come across in the types of waves have different characteristics such as how they are produced or radiated, how they interact with the environment, and how they are used. In fact, the electromagnetic spectrum is the frequency range of electromagnetic radiation which includes low radio frequencies to gamma rays. An object's temperature has a direct correlation with the quantity of electromagnetic radiation it emits. The higher the temperature of an object, the shorter its wavelength and the higher its frequency, and vice versa. The visible light includes a very small range of the electromagnetic spectrum, which is between the wavelengths of 380 to 740 nm. The invisible ranges are only detected and recorded by special sensors and cannot be seen by the naked eye [2].

Spectroscopy is one of the methods used to obtain scientific and practical information, using the interaction of electromagnetic energy and the subject of spectroscopy. Because the absorption of electromagnetic energy related to each element or chemical compound occurs a certain wavelength, recording objects surface reflection spectrum and examining their absorption characteristics, it is possible to be helpful in identifying elements and compounds that make up these surfaces. By knowing the spectral behaviors, we can study changes in phenomena that cannot be seen and extracted using the naked eye. The spectral response curve or the so-called spectral signature is a curve that displays the reflectance values of a material at different wavelengths. The behavior of this curve is directly related to the physical and chemical properties of the constituents of the material. As different materials have different components, the spectral response curve of each material is unique. By measuring these curves, we can identify different materials and compounds without expending too much effort or resources (time, money, and effort). One of the main and common methods of identifying and purifying different materials is to create a spectral library and analyze their reflection spectra [3].

The spectral library is considered as a reference for identifying the spectral behavior of various phenomena on the earth's surface and distinguishes them from each other. A spectral library is an assortment of reflectance spectra, often obtained from materials prepared in the field or in a laboratory with compositons. Most researchers collect spectral library materials as part of a project and to facilitate the analysis of multispectral images from the project site. Several high-quality spectral libraries have been prepared for various materials such as minerals, plants and artificial materials, which help us in the spectral classification of images or can be used in the identification of targets for spectral analysis of images. One of the most basic applications of the spectral library is to extract the spectral behaviors of various phenomena. Suppose that we want to extract the spectral behavior of a healthy plant from a reliable reference and use it in our research. In this regard, the spectral library covering thousands of diverse phenomena is the best source from which information can be extracted [4-9]. A spectral signature can be defined as a unique pattern of wavelengths emitted by an object. Function of wavelength (e.g. features and temporal spatial variations, etc.) can be classified as spectral diversity. Each characteristics of electromagnetic radiation may depend on different times or different spectral bands. The measurement of these changes and their correlation with the known characteristics of an object provide the signature of the corresponding object. Knowledge of the polarization state of the reflected radiation plus the spectral signature of various objects in remote sensing adds another dimension to the analysis and interpretation of remote sensing data. These parameters are used in providing valuable data for object recognition and classification. Comprehending and analyzing a remote sensing image requires an awareness of spectral fingerprints. Spectral reflectance is the attribute that is utilized to measure these spectral characteristics. This represents the energy ratio as a function of wavelength between the incident and reflected energy [10].

In recent years, remote sensing and spectrometry data have been widely used in various feilds, especially for natural resource management and sustainable development. This technology has become very important due to providing the possibility of accessing useful information in a desired time frame using non-destructive, cheap and accurate methods. Among these data is the preparation of distribution maps for various important medicinal plants on both large scale and regional scales, which can be one of the important tools in planning and studies of these plants. The Cistaceae family includes the *Cistus* genus, which has 66 accepted species. The native range of this species is South Central Europe, Mediterranean to North-West Iran. It is a shrub and grows primarily in the subtropical biome [11,12]. One of the important species belonging to this genus is *C. salviifolius,* commonly known as Laden Otu (Turkish), Sage-leaf Rock Rose (English). This plant and related species used since ancient times in traditional medicine as antidiarrheic, sedative, expectorant, anti-wound and anti-microbial [13-15].

2. Materials and methods

2.1. Study site

The study area is located to the middle parts of the Armutlu Peninsula in the eastern Marmara region and its territory was investigated. This area geologically is overlain by sedimentary rocks and andesitic volcanic rocks of the Late Cretaceous-Early Tertiary. The investigated area is located near the middle part of the Armutlu Peninsula in the eastern Marmara region. Geologically the area is overlain by sedimentary rocks and andesitic volcanic rocks of the Late Cretaceous-Early Tertiary [16]. Armutlu climate as a subtropical climate is a transition between the Mediterranean climate and the Black Sea. In this province, which has a continental climate in some parts, the summers are dry and hot, and the winters are cool and rainy (Figure 2).

2.2. Plant materials

Field specimens of *C. salviifolius* were collected in Armutlu District, Yalova (40°31'35.7"N 28°47'23.3"E) in June 2022. Authenticated plants were deposited at Istanbul University Faculty of Pharmacy herbarium (voucher number: ISTE-118583) (Figure 3).

Figure 2. Location of the study area, Land-cover classification (S2B_MSIL2A_20230423T085559_N9999_R007_T35TPE_20231108T115522)

Figure 3. The photos of *C. salviifolius* by Ahmet Beyatlı

2.3. Satellite data processing

In this study, the Sentinel-2 satellite images were used, which is one of the most valuable free remote sensing images. This product is a surface reflection, and all necessary pre-processing has already been carried out. The Sentinel satellite is designed to improve missions such as surveying land cover changes, environmental and agricultural monitoring, forest management, and natural disaster management, etc. Sentinel 2 provides images with different spatial resolution, depending on its spectral band, images with a spatial resolution of 10, 20, and 60 meters are provided. This spatial resolution makes it widely used in various fields. The Sentinel-2 satellites are equipped with high-resolution multispectral cameras that record data in several electromagnetic spectrum bands, including visible wavelengths, short-wave infrared and infrared. This feature makes it possible to examine characteristics of plants that exist on the surface of earth with high precision (Figure 4).

Figure 4. The flow chart of research

To process images Snap software has been used. In the first step, we unify the data of different bands that are under different resolutions (Resampling) and then we rectify the image again in the global coordinate system. The processed images required for preparing maps. Image processing steps performed before image classification. The commands used for this step are as follows:

Open Optical from the navigation bar at the top --> Open Processing --> Open S2 Resampling --> Given an Appropriate name to your S2 Resample Result --> Select the Main Imagery as the Input --> Open the Parameters Section from the Menu --> Set the Resolution to 10m --> Run.

The multispectral data of Sentinel-2 images provide information about the reflective behavior of various objects on Earth at 13 different bands. As mentioned earlier, different wavelengths of energy have unique behaviors when they hit the target (object). This difference in spectral behavior is called a spectral signature and is one of the important tools in identifying and distinguishing between different objects in the analysis of digital data of satellite images [17]. The study of spectral signatures has helped to identify different vegetation and non-vegetation classes to understand their spectral resolution, which in turn will give a clue for the final grouping of reflectance spectra during the classification of Sentinel-2 data with SNAP free software. Hence, spectral signature can be considered as one of the important tools in identifying different land covers and distinguishing them in remote sensing studies that deal with digital data. In standard reference-free data collection, field calibration and ground-based spectral measurements are usually performed using portable hand-held spectrometers [9]. Typically, environmental studies and agriculture employ this kind of spectrometer. For the purposes of managing and operating water resources, the acquired spectral fingerprints can be utilized for vegetation classification and mapping, ecosystem productivity, crop kind, and plant stress detection.

It is also possible to obtain the range of statistical changes for each group by studying the spectral data of different dates and generalize obtained information to classify unknown areas of land and vegetation. Image classification is the process of assigning land cover classes to pixels. These classes include the diversity of soil, water, and plants, etc. In Snap software, classification of vegetation and other land surface effects is done using supervised and unsupervised classification methods. Supervised classification involves identifying regions of specific spectral features for each land cover or land use group of interest to the analyst. In comparison, unsupervised image classification into spectral classes is based solely on natural groupings of image values. In addition, land use or vegetation classification is done along with some kind of ground truthing or reference data collection. Unsupervised classification is one of the most basic techniques. Since we don't need samples for unsupervised classification, it is an easy way to segment and understand an image. Indeed, this classification is not considered as an output. It's used only for the general knowledge of study area. In this method, we do not interfere in the classification process except for determining the number of classes, i.e. sampling. In this method, firstly clustering carried out based on the number of pixels and mathematical relations between them, and then each cluster is generalized into classes upon their characteristics. Then, we assign each cluster with a land cover class. By using Snap software, K-mean and ISODATA algorithms are used for image clustering.

After choosing the clustering algorithm [18], we identify the number of groups we want to create. For example, we can create 8, 20 or 42 clusters. Fewer clusters are more like pixels within groups. But more clusters increase the diversity within groups. Because spectral similarities between pixels prevent clusters from being correctly and easily separated from each other. In one of the most common strategies, the user determines the maximum possible number of clusters for an image. Accordingly, the software or computational systems define different statistical information for each class. For example, cluster centers are used in the determination of pixel characterization. Then, each pixel in the feature space that has the minimum distance from the center of the clusters is added to that cluster. At this stage, each pixel is considered a label for that class. Then the calculation process is repeated, and the center of the clusters is continuously recalculated until the best possible clustering is formed. The clustering process stops when the cluster center and the created cluster do not change during subsequent processing (sensitivity analysis). In this regard, by using a threshold, clusters that have less than a certain number of pixels can be removed. After the end of the clustering process, the degree of similarity and separation of the clusters from each other is calculated using the average intra-cluster distance and divergence. The integration of clusters is done to reduce some unnecessary and useless clusters so that the obtained result will be more expressive in this regard. The percentage and amount of consolidation that takes place in this context is a function of the threshold set by the user.

In classification process, we determine the maximum distance between clusters (classes), the distance between the centers of two clusters, the radius of the cluster and the minimum number of pixels in a cluster. Analysis of the distribution of clusters around the average is determined by the average standard deviation of each recorded spectral band. The narrower the clusters created in the feature space are, the more likely they are to be separated in the feature space. The proximity analysis of the clusters in the feature space is determined by measuring the distance between their centers. If the distances between the centers of the clusters are less than the desired threshold, they are combined with each other. Generally, the last cluster obtained from repeating calculations is the best.

Supervised classification is more commonly used for medium resolution images such as Sentinel-2. In this method, we have full control over the classification process. Firstly, samples are taken, and these samples should be taken from homogeneous pixels with the same distribution, and number. Then, after taking the samples, we specify our classifications to the software. In supervised classification, separate samples should be taken for each class. Then the samples are introduced to the software and classified based on their spectral behavior [19] or spectral signature.

3. Results

The area coverage was classified into 7 classes using the K-means method, the results of which are given as a map in the figure 5. As can be seen in the aerial image, these classes include water, soil, forest, cultivated areas, urban areas, asphalt, clouds. To control and validate the prepared map, spectrometry of the classes was done in the order shown in the figure 5. The obtained spectral signatures, except for vegetation areas, do not show significant differences in reflection curves. The observed changes in the recorded vegetations are considered as evidence for the diversity in the plants of the region. According to the results of this classification, the studied area was reclassified in several stages using supervised classification algorithms.

This procedure was used as control points in the supervised classification by considering the sampling and field surveys of the geographical coordinates of the samples. Based on the results of maximum likelihood and random forest methods, at least 8 main classes are classified in vegetation areas. These classes include forest areas with pine trees (e.g. *Pinus pinea*, *Taraxacum turcicum*), cypress trees, deciduous trees, shrubs, and grassland. Based on the surveyed GPS points, *C. salviifolius* is mainly observed in grassland areas and fields roadsides. Grasslands and bush cover areas around Yalova, which were distinguished in the classification, were also evaluated in terms of spectral reflection pattern. The reflection patterns indicate similar vegetation characteristics. *C. salviifolius* reflection was also higher than other species reflection in the whole spectrum (Figure 5).

Figure 5. A) Classified on cover map of Armutlu region using supervised classification, number 1, 2, 3, 4 and 5 vegetation types, 6 build up and 7 water, B) supervised classification methods for grassland of area

The infrared spectral bands (700–1300 nm) showed the highest spectral reflectance, the spectral region (1600–2300 nm) showed the lowest reflectance, and the 1300–2300 nm wavelengths showed very low reflectance. It is noteworthy that there is a great similarity in the spectral reflection pattern between *C. salviifolius* and *T. turcicum*. The reason for this may be the close characteristics and plant structure of these two species. The results of the statistical analysis explained that the near-infrared (NIR) spectral region (700-1150) is the best spectral region to differentiate between the two species. Only one specific spectral region, (710:900 nm for *C. salviifolius* and 730:950 nm for T. turcicum), can be used in the separation between them. At the same time, three spectral bands were sufficient to separate between plants (450:750, 1350:1600, 1900:2350 nm) while three spectral bands were sufficient to separate grassland 480:710, 810:1100, 1300: 1500, 1550:2300 was enough. Simultaneously, three spectral bands were used to separate between plants (450:720, 800:, 1550:2300 nm), while three spectral bands were sufficient to distinguish grassland (450:720, 830:950, 1550:2400 nm) (Figure 6). All measurements were performed at the maximum vegetative growth stage for most plants. Close spectral bands were identified, which can be used to classify grassland. Results show that in the case of classification of close structure plants, using the spectral features of the maximum vegetative growth stage may not be sufficient. There will be a need to evaluate the spectral features in all growth stages.

Figure 6. Spectral view of the *C. salviifolius* in the 4 diferent locaions

Table 1 shows the results from the process of classified images validation using the confusion matrix of classified region matrix and the obtained parameters: producer's accuracy, user's accuracy, and kappa coefficient.

Table 1. Accuracy evaluation results for supervised classification

	Ground Truth (Pixels)											
Class	**ROI:water**	**ROI:veg-1**	**ROI:veg-2**	**ROI:veg-3**	**ROI:veg-4**	**ROI:veg-5**	**ROI:build up**	**Total**	**Prod. Acc. (%)**	**User Acc. (%)**	**Commission (%)**	**Omission (%)**
Unclassified	0	0	0	0	0	0	0	0	0	0	0	0
Water	**22044**	0	0	0	0	0	0	22044	99.57	100.00	0.00	0.43
Veg-1	0	**10368**	662	301	202	0	0	11533	82.61	89.90	10.10	17.39
Veg-2	0	1370	**11592**	0	30	0	0	12992	93.96	89.22	10.78	6.04
Veg-3	0	370	0	**9751**	1	0	0	10122	96.48	96.33	3.67	3.52
Veg-4	0	407	83	24	**4389**	0	0	4903	94.22	89.52	10.48	5.78
Veg-5	0	35	0	31	36	**10469**	273	10844	96.63	96.54	3.46	3.37
Build up	95	1	0	0	0	365	**3471**	3932	92.71	88.28	11.72	7.29
Total	22139	12551	12337	10107	4658	10834	3744	76370	**Overall accuracy = 94.3878%**		**Kappa Coefficient= 0.9316**	

4. Conclusions and discussion

The spectral and spatial characteristics of Sentinel-2 images were used as a standard model to describe and interpret the results and general mapping of the region. Typical spectral reflectance curves for five main types of land features, include vegetation, soil, water, cloud and urban areas (Figure 5). As can be seen from the results, the spectral reflectance of vegetation changes with wavelength. The chlorophyll in the leaf has a strong absorption at 450 nm and 670 nm, and in contrast to the plant structure and the covering of the leaves, it contributes to the high reflectance of the near-infrared region (700-900 nm), which proves the effect of pigments and leaf structure on absorption and reflctivity.

The spectral reflectance curves of healthy vegetation have characteristic shapes that are determined by different plant characteristics. This curve is governed by the absorption properties of chlorophyll and other leaf pigments in the visible part of the spectrum. Stress conditions can produce changes in leaf structure, which vary greatly throughout plant species. Therefore, the species variance, stress, and canopy condition can affect the near infrared reflectance and can be used as an indicator to distinguish between different types of vegetation [20].

In general, the spectral differences of the vegetation covering the study area can be identified in three main reflectance regions: visible region (VIS, 400–680 nm), the near-infrared (NIR, 750–1200 nm), and the shortwave-infrared (SWIR, 1200–2500 nm). For SWIR region is within the range of absorption and physical control of leaf internal structures. Reflectance and transmittance often fall from moderate to low as wavelength increases, whereas absorption typically rises from low to high. Plant water content is the main physical factor controlling vegetation at these mid-infrared wavelengths.

In plants, the curve of the visible spectrum is determined by the plant pigments. For example, the blue (450 nm) and red (670 nm) regions are strongly absorbed by chlorophyll, which is known as chlorophyll absorption [21]. The difference between plant species is slight, but the result of the spectral reflectance shows a significant increase in the red edge (680-800 nm), the plant leaf shows approximately 40-60 % sudden reflectance. The transition zone between red and near-infrared is shown to have a high information content for the vegetation spectrum. This area is generally known as the "red edge". Red edge region represents the region of sudden change in leaf reflectance between 680-780 nm, which is caused by the combined effects of strong absorption of chlorophyll in red wavelengths and high reflectance in bands 5 and 6 (red edge bands) due to the scattering of the internal structure of the leaf. The increased of chlorophyll amount, for example, leads to broadened absorption feature to the center around 680 nm, causing a shift of the red edge slope and the wavelength of the maximum slope towards longer wavelengths, which is mentioned as red edge position (REP). The shift of REP to longer or shorter wavelengths has been used as a means of estimating changes in leaf chlorophyll content and as an indicator of plant stress. Since REP is defined as the turning point of the NIR slope, as can be seen in the figures (6), the shape and slope of the curve change, that includes the bands (5, 6, 7 and 8) is very high and these changes are directly related to the diversity of different species. The correlation and similarity of the GPS points in the curves of this part of the spectral signatures is remarkable. In the NIR region, which includes B7, B8, B8a, and B9 bands a very slight amount of waves is absorbed (about 5%). The structural variation in the leaves in these ranges allows us to distinguish between different species. There are small changes both within and between types of plants due to their phenology, vigor, canopy pattern, and other ecological parameters. These changes are the basis for classifying and distinguishing plant species from each other.

Plants absorb or reflect most incident radiation after 1300 nm, transferring relatively little energy. Three prominent water absorption bands at wavelengths of 1400, 1900, and 2700 nm were found. From NIR to SWIR, the amount of reflection decreases. The reason for the reduction of reflection in SWIR is because of the moisture content of plants. IR waves and SWIR are highly sensitive to water because water strongly absorbs SWIR and thermal waves. The presence of moisture in the soil has caused significant absorption centers to be created in the range between IR and SWIR [4].

Compared to covered soils, the reflectance variance in the bare soil spectral curve is significantly smaller. This is caused by elements that alter soil reflectance in less focused spectral bands, such as moisture, soil texture, surface roughness, iron oxide content, and organic matter content (Figure 1) [22]. Compared to other objects, soil has a spectral behavior without oscillation or low oscillation. The spectral behavior of soil shows a logarithmic trend that increases from short to long wavelength. In other words, as we move from the blue band range to the short wavelength IR band, the amount of wave reflection increases. This increasing process continues with increasing wavelength until a small absorption center is created in the near IR range, which is caused by the moisture that presents. After this absorption center, the increasing process of reflection continues with increasing wavelength. The effect of minerals in the soil can generally be seen in the SWIR range. Accordingly, many satellite sensors designed for mineralogical studies have multiple spectral bands in the SWIR range. Many minerals have similar spectral behavior to each other, but the difference in their absorption centers in the SWIR range is a method to identify and separate them from each other. In general, moisture absorbs electromagnetic waves. The presence of water in the soil reduces reflection and increases absorption of electromagnetic waves. As the amount of water in the plant increases, the reflection ratio decreases in different bands. So, maximum absorption ratio occurs with increasing moisture in the SWIR band. The presence of organic matter in the soil creates an effect like moisture (reducing reflection and increasing absorption) in the soil.

Band ratios or spectral indices have been utilized in a number of studies to highlight particular physiological traits and differentiate between various plant [23-25]. Normalized difference vegetation index (NDVI) and soil adjusted vegetation index (SAVI) are two frequently used indicators. Indices are also used in the classification process of covered areas from remote sensing images. Principal component analysis (PCA) has been used as a data augmentation method when analyzing remote sensing images to separate vegetated and non-vegetated areas [26].

The accuracy rate of the classification calculated by the Maximum likelihood classification (MLC) method. According to this calculations, the accuracy rate of the water class is the highest and the Veg-1 class is the lowest. This can be due to the water class being homogeneity and the Veg-1 class consisting of different plant species. In addition, the Veg-1 control points are fewer than the other plant classes. Our calculations shows the classification agreement between the kappa coefficient result (0.93) and the control points.

Upon the results, it can be concluded that the vegetation indices based on the ratio between NIR, SWIR-I and SWIR-II may be sufficient for grassland separation compared to other indices based on the visible composition. On the other hand, in the case of *C. salviifolius* differentiate, the use of plant indices based on the ratio between the NIR, and any other spectral region (visible or invisible) may give good results.

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