

Article

A Principal Components Analysis-Based Method for the Detection of Cannabis Plants Using Representation Data by Remote Sensing

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Abstract: Integrating the representation of the territory, through airborne remote sensing activities with hyperspectral and visible sensors, and managing complex data through dimensionality reduction for the identification of cannabis plantations, in Albania, is the focus of the research proposed by the multidisciplinary group of the Benecon University Consortium. In this study, principal components analysis (PCA) was used to remove redundant spectral information from multiband datasets. This makes it easier to identify the most prevalent spectral characteristics in most bands and those that are specific to only a few bands. The survey and airborne monitoring by hyperspectral sensors is carried out with an Itres CASI 1500 sensor owned by Benecon, characterized by a spectral range of 380–1050 nm and 288 configurable channels. The spectral configuration adopted for the research was developed specifically to maximize the spectral separability of cannabis. The ground resolution of the georeferenced cartographic data varies according to the flight planning, inserted in the aerial platform of an Italian Guardia di Finanza's aircraft, in relation to the orography of the sites under investigation. The geodatabase, wherein the processing of hyperspectral and visible images converge, contains ancillary data such as digital aeronautical maps, digital terrain models, color orthophoto, topographic data and in any case a significant amount of data so that they can be processed synergistically. The goal is to create maps and predictive scenarios, through the application of the spectral angle mapper algorithm, of the cannabis plantations scattered throughout the area. The protocol consists of comparing the spectral data acquired with the CASI1500 airborne sensor and the spectral signature of the cannabis leaves that have been acquired in the laboratory with ASD Fieldspec PRO FR spectrometers. These scientific studies have demonstrated how it is possible to achieve ex ante control of the evolution of the phenomenon itself for monitoring the cultivation of cannabis plantations.

Keywords: remote sensing; machine learning; big data; principal component analysis; cannabis plantations; drug trafficking control



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1. Summary

International organized crime has now taken control of numerous illegal trafficking schemes by exploiting the existing regulatory gaps in international law that can hardly be overcome given the different political orientations of the countries involved. Some activities that were previously linked to national dynamics are now recognized as global security threats. Criminal organizations of various kinds benefit from the inability of different countries to provide national security.

Governments are unable to institute efficient countermeasures due to the instability deriving from historical-economic situations. They are unable to control the entire process of fast modernization, both from a social and economic point of view and, above all, from a technological point of view [1]. The same forces of globalization, those that have guaranteed the immeasurable growth of trade and communications and facilitated all kinds

of displacements, have created unprecedented opportunities for organized crime. In some regions, the enormous profits generated by the illegal activities of criminal organizations have exceeded the gross domestic product of the countries they operate in. The volume of resources that these trades manage to mobilize turns out to be a potentially fatal threat to state authorities and to economic development [2].

Albania has undergone a process of radical change since 1990. Following the dissolution of the communist regime, the desire of Albanian citizens to reintegrate themselves into the great family of Europe after half a century of isolationism was immediately clear. The Albanians have repeatedly shown that they recognize the purely European roots of their national identity, and, in the wake of this new awareness, they have faced a process of radical evolution trying to reproduce in their own country the European social, political and economic structures. The hope was that this would lead to a substantial improvement in the socio-economic situation. This process was not easy at all, and the problems that emerged during of the communist regime created illegal opportunities that could hardly be solved without the help of neighboring countries, including Italy, which has always tried to build solid ties with the Albanian state [3].

In this international context and in the progressive integration of Albania into the European community, international agreements financed by the European community for technological evolution and digital transformation have been implemented for several years [4]. Among these activities, particular attention was paid to fight illegal drug trafficking, which often uses the Balkan countries as routes to reach the markets of the countries of western Europe. These latter, indeed, prove to be important consumers of both soft and hard drugs. Given the territorial conformation of the innermost part of the Albanian territory, this state has not only served as an intermediate stage for the illegal trafficking of narcotic substances from Central Asian countries but has also developed the widespread cultivation of cannabis. Albania, undoubtedly, has, over the years, taken a predominant role in the production of this drug, which is then sorted in Europe through the short stretch of sea that separates Albania from the Italian coasts [5].

Ground investigations to detect illegal cannabis plantations are difficult due to the inaccessibility of illegal planting areas. Most countries carry out this activity through aerial surveillance and local knowledge of the planting areas. These methodologies require an important economic effort due to the instruments used and the men necessary to guarantee the aerial monitoring and the subsequent processing of the detected images. Through remote sensing, it is possible to carry out an environmental monitoring of the areas whose extensions would make it impossible to do so with a direct approach, using a synchronous and spatially distributed characterization of the ground. This investigation can be carried out at distances ranging from a few meters (proximal sensing) up to thousands of kilometers (remote sensing). Azaria et al. [6] used ground-based hyperspectral sensing (an image spectroscopy sensor) for detecting and mapping cannabis crops. The authors revealed that the spectral characteristics of cannabis are unique only within a wavelength range of 500–750 nm. Houmi et al. [7] applied satellite remote sensing to detect cannabis plantations. The authors applied the spectral angle mapper (SAM) method based on a specific angular threshold on Hyperion EO-1 data in well-known cannabis plantation sites. However, there are no relevant studies that have used airplanes for the remote sensing of cannabis plantations.

This article traces the research activity conducted by the Benecon University Consortium, from 2012 to today, demonstrating how it is possible to create a technological platform for a “Knowledge Factory”. It not only responds to the specific need of uprooting cannabis plantations but also contributes to the creation of multidisciplinary applied knowledge to prevent hydrogeological risks and to increase and improve agriculture and urban planning. Good experimental research practices show that human thinking succeeds in governing technology, measuring the dimensions with the corresponding knowledge and using innovative technologies that allow to deeply know the artifacts and the territory. Furthermore, human thinking also succeeds in memorizing the experiences through the

data, coming from the reading of the phenomena on the historical axis, to entrust them as base knowledge to the institutions in order to wisely govern the modification of the territory and the protection of architectural heritage.

2. Data Description

Since 2012, thanks to the agreement signed between the Guardia di Finanza (Air Maritime Exploration Group) and the BENECON SCArL Regional Competence Center, remote sensing activity has been implemented, aimed at identifying cannabis plantations in the Albanian territory, supporting local police forces. These activities use the aircraft available from the Air Maritime Exploration Department of the Guardia di Finanza and the hyperspectral sensors supplied by BENECON Regional Competence Center. The operational protocol provides for:

- the planning of flight campaigns on the Albanian territory
- the acquisition through the use of hyperspectral sensor CASI1500 of hyperspectral images
- the subsequent processing of the acquired data by the researchers of the BENECON Regional Competence Center
- the analysis of the elaborated data and the identification of cannabis plantations
- the writing of the report for Albanian police forces.

3. Methods

3.1. Remote Sensing Flight Planning Phase

The planning of the hyperspectral remote sensing flight represents a fundamental step within the entire activity; it is processed once the overflight area has been identified and circumscribed on a cartographic basis. The flight planning takes into account the orography, the average altitude and the exposure of the land under investigation. These latter parameters are functional to the correct definition of the hyperspectral digital images to be acquired. The spectral mode configuration of the CASI sensor [8] is aimed at maximizing the number of spectral channels that can be acquired. The configuration of the hyperspectral sensor has to take into consideration the 10 conditions imposed by the geometric resolution of the desired ground pixel and the integration time required for detecting the radiant energy reflected from the ground. Specifically, in the case under consideration, the selected bands are uniformly distributed over the entire available spectral range.

The definition of the flight parameters, that is, the configuration of the sensors, the flight attitude and the speed of the aircraft, is followed by the drawing on the cartography of the scan runlines. This last phase consists in the organized representation of runlines series (linear scan trajectory) to be flown with an overlap of 30%. This latter parameter can vary considerably on the basis of the orography of the area.

The flight plan is drawn paying particular attention to the orography of the territory to fly over and the fixed parameters validated during the year, trying to minimize the effect of vegetation anisotropy on the survey (Figure 1). The flight planning concludes with the drafting of the time schedule of the acquisition campaign, which depends on the technical specifications of the sensors installed on board. In fact, the operational acquisition flights with the hyperspectral sensor, to be effective, require the presence of the light source (the Sun) at the moment of maximum radiation, the sunlight at noon, in which the spectral distribution of the emitted light is close to white [9].

Mission Planning

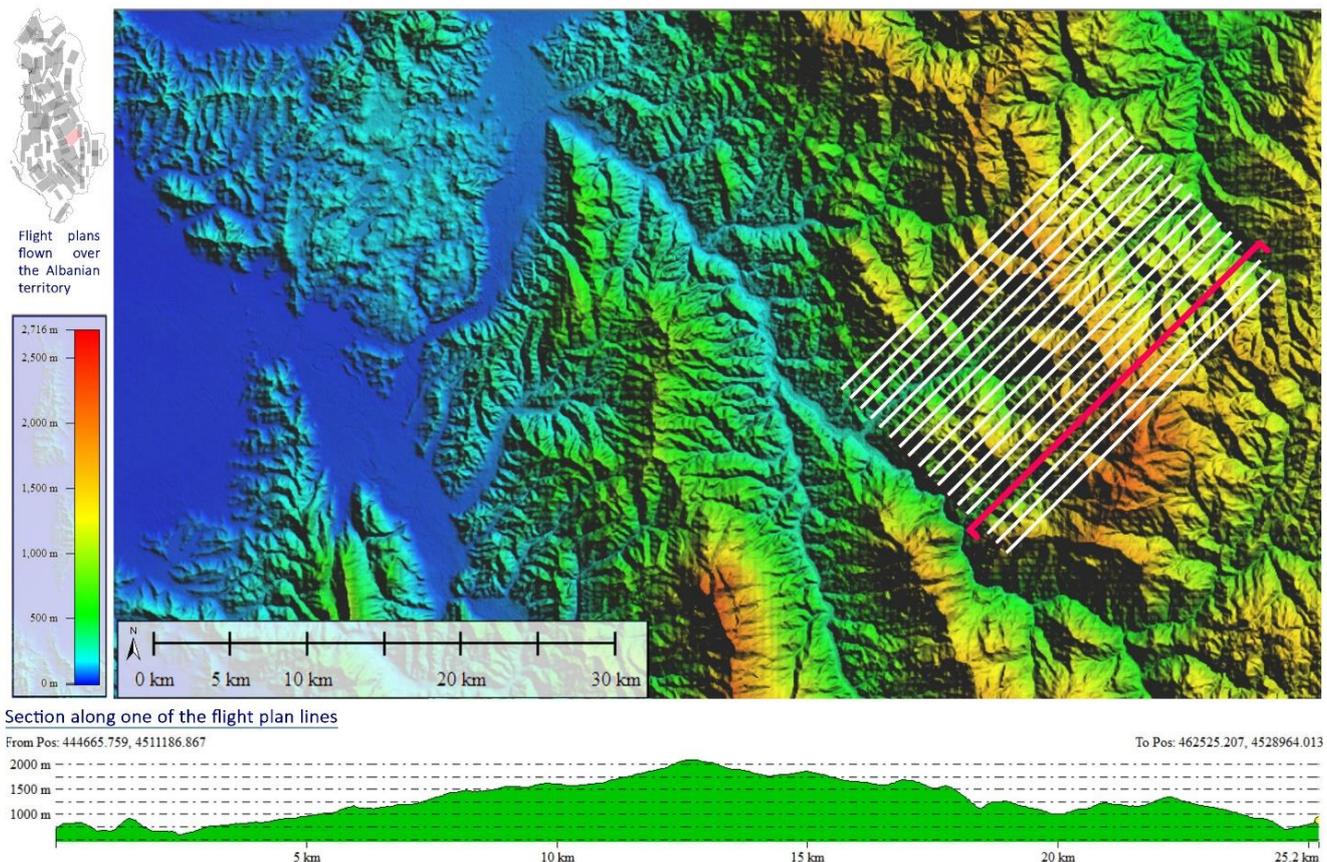


Figure 1. Mission planning: focus on a flight plan designed over the southeast of the Albanian territory. Each flight plan is specifically designed taking into consideration the orography of the territory to fly over. Software used: Global Mapper.

3.2. The Acquisition Phase

The sensors used for remote sensing are generally divided into two large families: active sensors and passive sensors. The active sensors illuminate the surfaces of a spatial map under analysis from the electromagnetic point of view, subsequently detecting the return electromagnetic radiation and measuring the spectral signature in terms of reflectance; a typical example of an active sensor is radar. Passive sensors measure the solar radiation reflected by the surfaces on the ground in a discrete set of wavelength ranges in the visible and near-infrared range. For each element of the detected map, the sensor provides the value of the observed radiative flux measured in terms of radiance, then returns the energy flux per unit of surface and unit of solid angle as a function of the central frequency of each acquisition band [10].

The CASI-1500 hyperspectral sensor (Table 1), owned by BENECON, is a remote sensing instrument, mounted on board the P166 DP1 aircraft of the Guardia di Finanza, capable of measuring the solar radiation reflected by the area overflow, in the wavelengths between the visible and near-infrared. In particular, the CASI sensor measures electromagnetic energy, called reflectance, in the wavelengths between 380 and 1050 nm. It falls into the category of passive systems [11]. The CASI sensor is a so-called pushbroom sensor. Relying on the relative forward motion between the lens and the target, a recognizable hyperspectral “image” is created by the successive build-up of individual scan lines. These scan lines are continually appended to the spatial imagery as the aircraft moves forward. The axes of these scan lines lie perpendicular to the platform’s direction of movement. Each scan line is sensed, measured and recorded from the sensor array across the spectral

bands with a linear resolution of 1500 pixels. Their corresponding wavelengths are chosen between 1 and 288 bands and range from the ultraviolet to the near-infrared field. Thanks to high-quality optics and the use of latest generation CCD sensors, the system can produce images that guarantee a ground resolution of about 25 cm [12].

Table 1. CASI-1500 hyperspectral sensor specifications.

Feature	Specification	Feature	Specification
Airborne sensor	CASI-1500	Band 01	367.2 nm ± 3.6 nm
Aircraft velocity	120 knots	Band 72	1046.7 nm ± 3.6 nm
Aircraft altitude	~3000 m AGL	File output format	.img; .hdr
Bandwidth	7.2 nm	Resolution	1.5 m pixel resolution
Date	1 August 2012	Sky Conditions	clear

The hyperspectral survey and the monitoring of the territory have been made with the airborne sensor Itres CASI 1500, owned by Benecon. The hyperspectral sensor has the characteristics shown in Table 1: wide-array airborne hyperspectral VNIR imager (0.38–1.05 microns), programmable; up to 288 spectral channels; 40° FOV; high signal-to-noise ratio; IFOV 0.49 mrad.

The hyperspectral configuration used for the mission has been developed and perfected throughout the years to enhance and maximize the representation of the spectral signature of the cannabis plant. The ground resolution used is 0.75 m², obtained by optimizing the flight planning and relating the spectral configuration to the orography of the territory. The hyperspectral sensor is boarded on the Guardia di Finanza's Piaggio 166DP1 aircraft with the nadiral PhaseOne iXA camera with an 80 Mpx pixel resolution.

The technological platform, including the GPS instruments, inertial units and hardware input/output devices, is the result of studies and scientific research made in order to deepen the knowledge of the material and immaterial components to represent correctly and in a geo-corrected way the design of the territory.

Benecon University Consortium has, through the years, developed an ever-more precise and efficient protocol. The procedure includes the processing of raw data through radiometric and geometric correction and the creation of the desired processing image up to loading the processed image file into the platform GIS along with auxiliary files such as:

- digital aeronautical maps
- digital elevation models; textured orthophoto
- topographic files in .shp format
- topographic paper maps.

The areas to fly over have been identified according to several factors:

- the existing cartography, the analysis of aerial patrol missions carried out in the early stages of the mission
- critical evaluations that take into consideration elements that characterize the cultivation of cannabis
- the reports of the local police.

The product of the remote sensing data processing phase is a georeferenced multi-layer model in which each homogeneous layer of data corresponds to a wavelength recorded by the sensor and synthesized in each pixel composing the image. The real geometric dimensions of the pixel, and therefore the degree of sintering of the reflected electromagnetic components, are a function of the planning and flight parameters [13].

3.3. Drawing the Territory

The data is collected and systematized in a geo-database, a digital platform for managing remote sensing data, from flight planning to thematic data restitution. During the acquisition phase, the hyperspectral data are recorded according to the position of the GPS and assets of the aircraft. The CASI sensor raw data, the GPS antenna and the inertial

unit data are elaborated along with the flight track to produce a precise geo-located data (Figure 2).

General Data Processing Flow

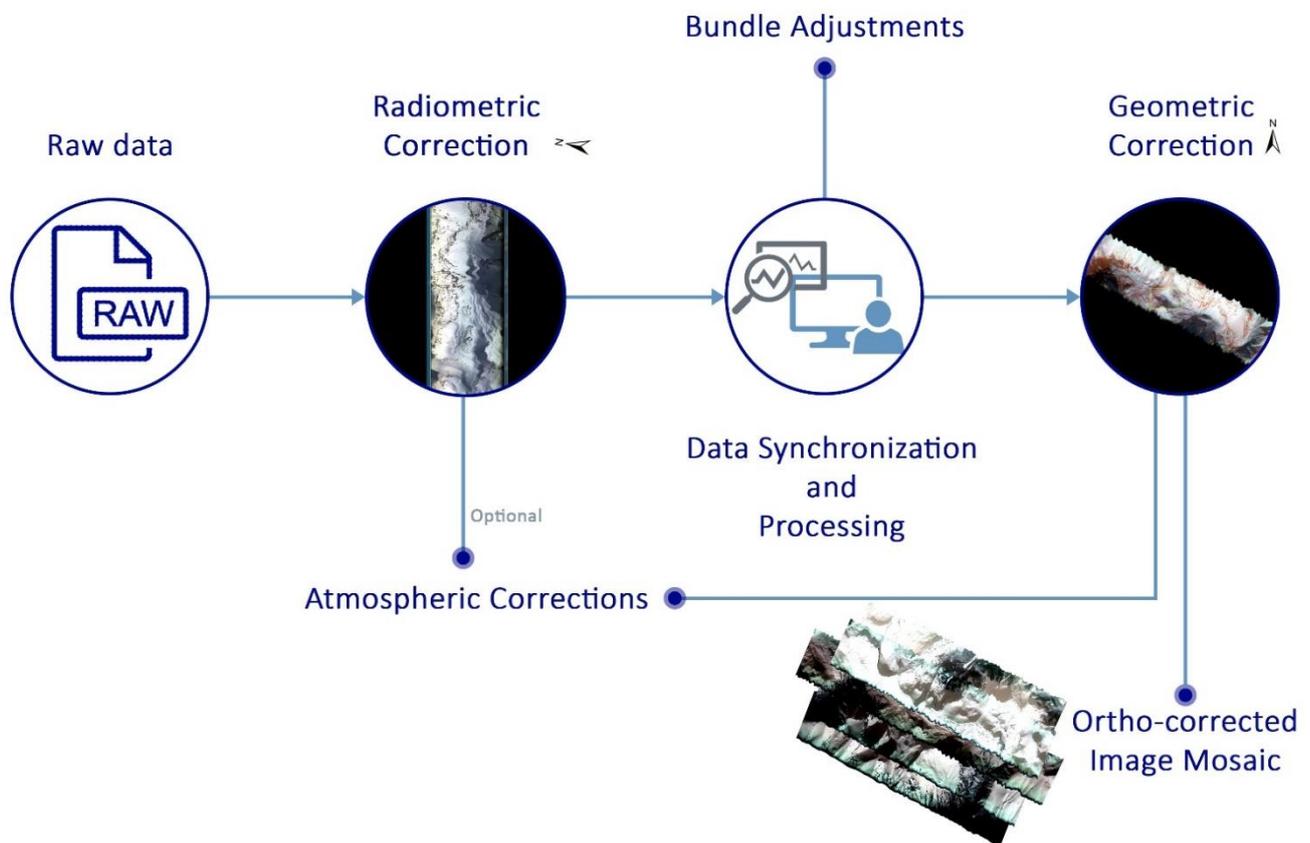


Figure 2. General data processing flow: From the raw data to the ortho-corrected image mosaic.

The hyperspectral images acquired and the aircraft altitude and position in flight data are suitably stored according to organizational rules functional to the subsequent image pre-processing phase. The pre-processing of the image is aimed at correcting radiometric and geometric errors and georeferencing images through the following activities: differential correction of GPS data, processing of inertial data, radiometric calibration (correction) of images and orthorectification [14]. The calculation of the position and altitude of the aircraft is performed through the integration of the data of the permanent GNSS stations (static acquisition) with the raw data of the inertial platform and on-board GNSS (dynamic acquisition). As is known, the former record satellite coverage over the large remote sensing area between the airport and the study area. The latter are combinations of data, measured every second, between the aircraft's position and attitude (roll, pitch, drift), recorded from takeoff to landing. The integrated processing of all these data returns the geo-referenced path made by the plane, so that all the hyperspectral and thermographic images can be automatically referred to the scanned area [15]. The image processing consists of two consecutive software procedures processed with ITRES GUI softwares: radiometric correction and geometric correction. In the radiometric correction of images acquired with the CASI sensor, the raw data (digitized radiance measurements) are transformed into spectral radiance units, thus estimating the true brightness of the target. Converting CASI data to reflectance units requires that the soil spectral measurements coincide with the aerial image data. During the geometric correction, the image (radiometrically corrected)

is aligned with the aircraft's altitude and position data. In this phase, each across-line of the image (linear sequence of pixel-images orthogonal to the runline), acquired in a known instant of the flight (stored in the raw file through the connection to the GNSS antenna of the aircraft) is redrawn and projected in orthographic mode on the XY cartographic plane (with respect to a chosen DATUM) thanks to the software integration with the DEM (digital elevation model) of the territory flown over. The geometric correction makes the acquired image geometrically congruent with the chosen reference, thus establishing a perfect correspondence between the position of the pixel in the image and its location on the territory [16].

3.4. Qualitative and Quantitative Analysis of Hyperspectral Data

The acquired data, then, are uploaded in a geo-database and compared to a big library of cannabis' spectral signature using the ENVI software platform. To gather selectively the complexity of the information contained in the spectral "orthophoto-maps", the data are elaborated and analyzed on image analysis software SNAP, according to some procedures known from the scientific literature:

- "true color" images, sampled in the electromagnetic wavelengths distinguishable by the human eye, for the photo-realistic representation of the territory; this natural color representation associates 700 nm, 550 nm and 450 nm bands respectively to the red, green and blue channels of the monitor;
- redVeg images enhance the greater or lesser density of the vegetation with shades of red [17]. Indeed, for the representation of vegetated areas, this false color representation associates to each red, green and blue channel of the monitor the 789, 675 and 542 nm hyperspectral band respectively (Figure 3).

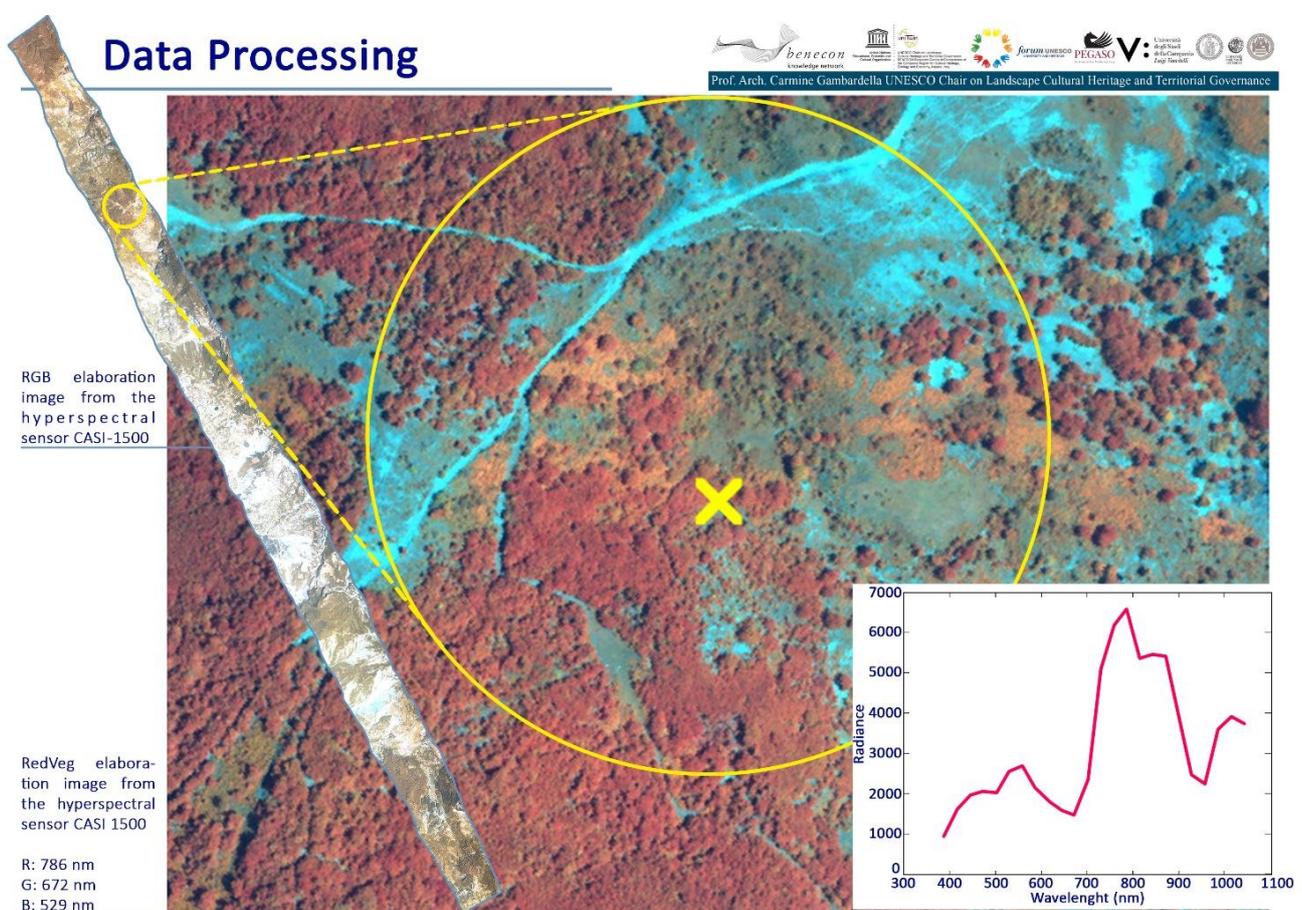


Figure 3. From the ortho-corrected images the protocol considers two type of elaboration: the RGB "true color" elaboration and the "Red-Veg" elaboration, wherein the cannabis plant is enhanced. Moreover, the spectral signature is extracted.

To improve the reliability of the identification procedure of a cannabis plantation, it is necessary to analyze in detail the spectral signature of the scanned areas. To do this, it is essential to first select a region of interest identified based on certain characteristics; these regions are areas that are spectrally anomalous [18,19]. The high number of channels of the CASI allows the use of automatic algorithms for the identification of spectrally anomalous areas. As the spectral signature of the materials and surface conditions to be identified was not known a priori, it was necessary to use an algorithm developed on a statistical basis, which measures the spectral diversity of each pixel of the image with respect to its surroundings [20]. The algorithm used in this study is that of Reed–Xiaoli detector (RXD) [21], well documented in the literature and used in numerous application contexts. Each of the images acquired with the CASI is then processed by the Reed–Xiaoli algorithm, using a comparative window of $50 \times 50 \text{ m}^2$ for each pixel of the image. A total of 0.05% of the spectrally most divergent pixels were selected, and the sequence of morphological filters opening 3×3 and closing 3×3 was applied to remove the isolated pixels and obtain geometrically regular areas. Once the region of interest (ROI) has been identified, it is necessary to analyze in detail the spectrum associated with it. Figure 3 shows the spectral image, as returned by the application of the RedVeg vegetation index in order to enhance the greater or lesser density of the vegetation with shades of red in an area in which a spectrally anomalous region has been identified [22]. The spectral bands selected were: R = 786 nm, G = 672 nm, B = 529 nm. In addition, it is accompanied by zooming into the region of interest with an indication of the longitude and latitude coordinates of the center of that region identified by the yellow symbol. Finally, the spectrum of this region of interest is reported. The spectral signature obtained in this way represents a valid tool for automatically identifying a cannabis plantation from an image detected with the hyperspectral sensor. Its shape is an essential feature of the objects contained in the region of interest and therefore, allows discrimination with respect to others that are contained in the selected scenes. However, we remind you that so far, we have only identified some spectrally anomalous areas since, as indicated above, the spectral signature of the materials and surface conditions to be identified is not known a priori, it is necessary to proceed through a comparison procedure. To be sure that it is a cannabis plantation, it is therefore necessary to be able to compare the spectrum of the spectrally anomalous area with that one of other regions characterized by different elements. Given the difficulties associated with such a procedure, the tables obtained with the application of the Reed–Xiaoli detector (RXD) algorithm [21], relating to regions of interest identified and verified as cannabis plantations, are compared with those relating to regions of interest characterized by different objects.

The areas characterized by a greater spectral similarity with the searched crop are displayed in the GIS environment together with other cartographic information.

The definitive perimeter of the plantation is supported by photographic shots with high spatial resolution. From the geo-database, for each intercepted cannabis plantation, a personal data sheet is extracted with a unique ID, geographical coordinates, spectral and photographic data, areal extension and an estimate of the state of growth of the plants. The file then is shared with the local authority for the uprooting of the plantation [23].

3.5. Principal Component Analysis (PCA)-Based Method

Principal component analysis is a technique used in the field of multivariate statistics [24]; it is a linear transformation that reorganizes the variance in a hyperspectral multiband image into a new set of image bands. The PCA bands are uncorrelated linear combinations of the input bands. Principal components analysis transformation's main goals are:

- the reduction of the original data with the consequent computational simplification
- the reinterpretation of these observations.

If we consider a set of n data on measured on p variables, it is natural to think that exactly p principal components are required to reproduce the total variability of the system. Much of this variability can be quantified by a smaller number of these so-called principal

components, thus arriving at the conclusion that k components (with $k < p$) can replace the initial p variables. We thus obtain that the original set of data, which consisted of n measurements on p characteristics, is transformed into a set consisting of n measurements on k principal components [24].

PCA, once applied, often reveals relationships between observations and new variables that were not originally suspected. It is clear then, that the application of PCA involves a deeper reinterpretation of the data. Like all applications in data analysis, PCA also comes at a cost: the loss of some initial information. On the other hand, it is a technique widely used in the most varied sectors precisely because it reduces this loss within acceptable limits. In other words, if the number of components is chosen wisely, the tradeoff between the loss of information and the simplification of the problem is almost always an advantage.

The primary purpose of this technique is the reduction of a high number of variables, representing as many characteristics of the phenomenon analyzed in some latent variables. This occurs through a linear transformation of the variables that projects the original ones into a new Cartesian system in which the variables are sorted in decreasing order of variance: therefore, the variable with the greatest variance is projected on the first axis, the second on the second axis and so on. The reduction of complexity occurs by limiting itself to analyzing the main (by variance) new variables. Unlike other (linear) transformations of variables practiced in the field of statistics, in this technique it is the same data that determine the transformation vectors [25].

PCA was used as a classification algorithm for the identification of features [20]. In this case, the eigenvectors are computed from a sample set of images, each representing a type of object. In identifying an anomaly, the highest eigenvalue and its associated eigenvector are identified. Each eigenvector represents a feature of the image, and all together represent a feature space. Each image can thus be obtained as a linear combination of eigenvectors and projected into the features space. In the recognition phase, the components of an image are calculated by projecting it into the features space and comparing it with the components of the other images. Every image of the sample set represents a portion of the territory. Every class is represented by several images in the sample set. For the classification to be successful, the classes must be well-separated by a series of features. In the training phase, the system calculates the eigenvectors of the set of training samples to produce an image space. In the classification phase, each new image can be classified by comparing its components in the features space with the components of the sample set that are part of a given class [26].

With the PCA, we represent a set of data with a non-diagonal covariance matrix and of dimension N in a space of dimension less than N in which the same data is represented by a diagonal covariance matrix. Diagonalization is achieved by rotating the coordinates in the base of the eigenvectors representing the principal components. Each eigenvector is associated with an eigenvalue that corresponds to the variance of the associated principal component. If the original variables are partially correlated with each other, some eigenvalues have a negligible value. In practice, the corresponding eigenvectors can be neglected, and we can limit the representation only to the eigenvectors with the largest eigenvalues.

Since the covariance matrix in the principal component base is diagonal, the total variance is the sum of the variances of the individual principal components. It remains necessary to estimate the importance of the residual, or rather of the neglected part of variance. PCA is a second-order method since both the new coordinates and the criterion for size reduction are based solely on the properties of the covariance matrix. In fact, the variance is called the second moment of a distribution and is proportional to the square of the variable. PCA is intrinsically based on the hypothesis that the variable x is normally distributed; in this case the covariate matrix is positive definite and therefore invertible. The average is generally rendered null, and therefore, all statistical information is contained in the covariance matrix (Figure 4).

Data Processing - PCA elaboration

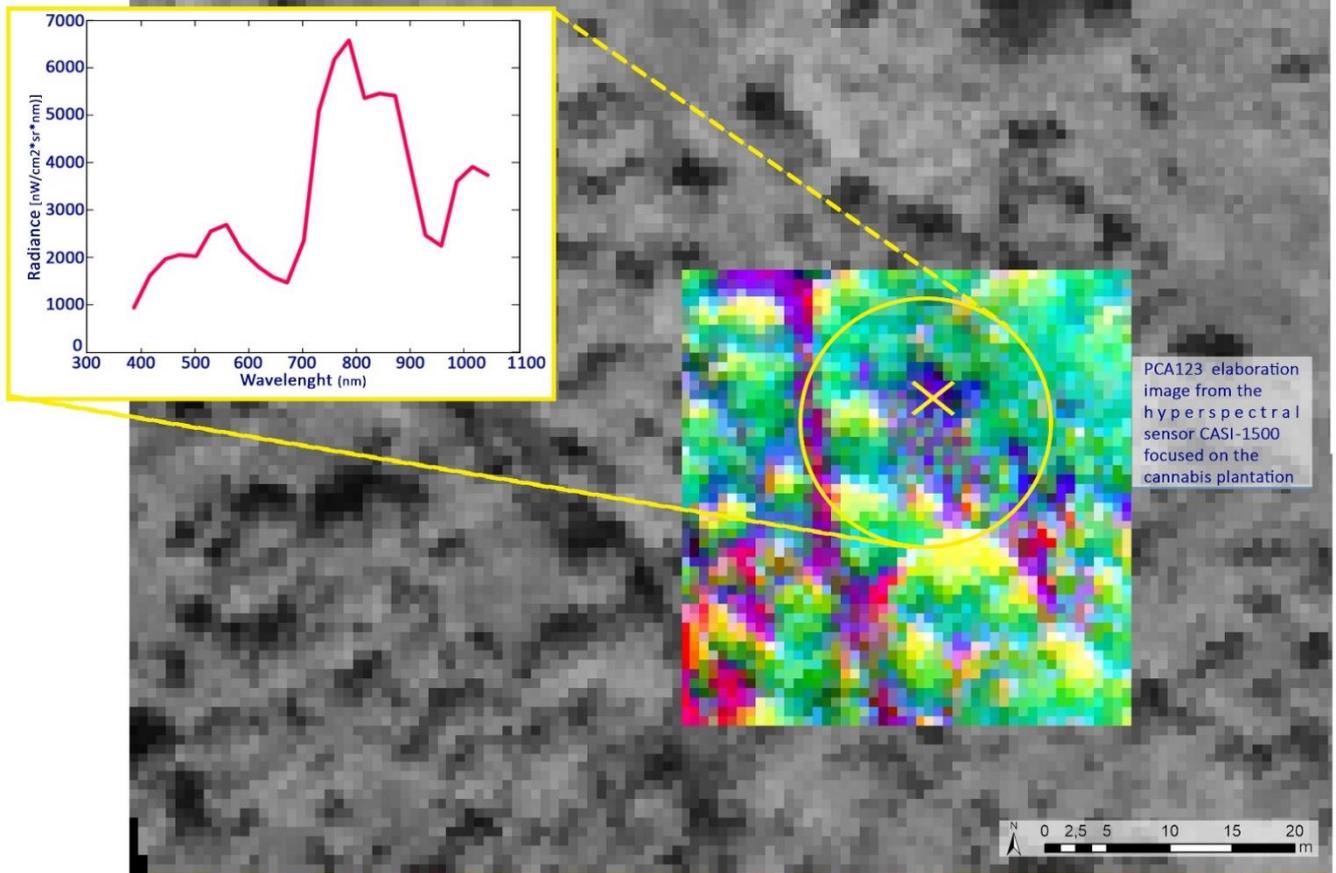


Figure 5. Principal components analysis elaboration with a focus on cannabis planting with the spectral signature.

4. Results and Discussion

Over ten years of missions, aerial remote sensing activities were carried out, reporting the results collected in Table 2.

Table 2. Results and accomplishments of the missions in Albania from 2012 to 2020.

Mission Year	Scanned Area (km ²)	Suspected Plantation Detected
2012	990	62
2013	3618	304
2014	4313	815
2015	4549	1368
2016	5066	2086
2017	7487	90
2018	7336	27
2019	7350	151
2020	5865	189

An analysis of Table 2 shows a progressive increase of the scanned area in the missions that followed in the first part of the monitoring (2012–2016). This increment in the scanned area has led to an exponential increase in the suspected plantations detected. In the second part of the monitoring (2017–2020), despite having scanned an area comparable to the one scanned in 2016, suspicious plantations were drastically reduced (from 2086 in 2016 to 189 in 2020).

only 90 in 2017). This result is certainly a consequence of the monitoring activity that has directed the Albanian police forces in the repression of this illegal activity.

The amount of data collected was fundamental for the subsequent machine learning processing. The ongoing experiments are confirming how starting from the drawing, understood as knowledge of the territory, and the landscape, it is possible to fight a frequent and continuous phenomenon over time until it can be monitored, predicted and anticipated creating forecast scenarios. Thanks to the application of machine learning methodology, we are experimenting with the elaboration of increasingly accurate clusters of the phenomenon in question. Moreover, our main objective is applying machine learning methodology to direct and plan aerial remote sensing flights over increasingly limited areas, in order to reduce the costs and create maps and scenarios forecasting for the identification of cannabis plantations scattered throughout the territory.

5. Conclusions

This work describes the methodology adopted in the research activities carried out by the Benecon University Consortium, from 2012 to 2020, in the fight against illegal cannabis cultivation activities in the Albanian territory. An experimental protocol was developed that used the Itres CASI 1500 hyperspectral sensor mounted on a Piaggio 166 DP1 aircraft. The hyperspectral images detected were subsequently processed for the extraction of the feature. Finally, a principal component analysis (PCA) based methodology was applied to remove redundant spectral information from multiband datasets. This made it easier to identify the spectral characteristics prevalent in most bands and those specific to only a few bands. In nine years of activity (2012–2020) about 46,574 km² of Albanian territory have been scanned, identifying about 5092 suspicious plantations.

In years of experimentation, it has been possible to demonstrate that, through the use of innovative technologies and the work of researchers, it is possible to identify the cannabis cultivation fields and alert local law enforcement officers who can, once the area has been identified, intervene by destroying the plantation. The activity carried out has shown that the application of hyperspectral aerial remote sensing activities not only allows the identification of the plantations but also demonstrates a preventive effectiveness in the sense that it causes a progressive reduction of the activity on the territory.

The future objective of integration between the representation of the territory and the management of complex data has, as a crucial element, the use of artificial intelligence to start a monitoring activity of marine waters as well as of the cultural heritage present throughout Albania to create maps and forecast scenarios. The connection between the different disciplines, knowledge and cultures has made it possible to better understand the Albanian landscape design and also to foresee the future of landscape design.

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