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Chapter

Dangerous Risk Factors to be Considered for Proper Management of Agroecosystems

Carmine Massarelli, Claudia Campanale and Vito Felice Uricchio

Abstract

Our work aims to identify the main risks existing in the agroecosystems of southern Italy, providing, at the same time, information about innovative and fast methodologies. The goal is to understand the magnitude of the phenomena that could compromise them if no action is taken for water and soil matrices. Regarding the former we will consider plant protection product residues in water bodies and the importance of agroecosystems as source of microplastic pollution and their role as a vector of pollutants; regarding the latter, we will present a rapid and low-cost methodology to detect asbestos-containing materials and significantly transformed areas. Furthermore, indications are provided on how to implement effective monitoring plans in order to certainly identify the problem affecting one or more matrices and provide practical instructions to the administrators to implement the appropriate remediation strategies.

Keywords: remote sensing, microplastic pollution, asbestos, drones, data integration, GIS

1. Introduction

An agroecosystem is an anthropogenic ecosystem which constitutes the basic unit of study in agroecology; it can be defined as a spatial and functionally coherent unit in which different agricultural activities take part that includes living components (few species) and their interactions [1].

Agroecosystems provide products that can be evaluated in economic terms, following agronomic interventions on land and many biological factors.

Although the definition makes us think exclusively of the territory affected by human activity, an agroecosystem is not strictly identifiable with these areas (e.g. the farm), but instead, it includes the regions that are impacted by these activities. These regions are identifiable by changes to the species complexity (simpler species composition), energy flows (aimed at higher productivity) and nutrient balance because the cycles of a few elements are considered often associated with high nutrient input, much of which leads to connected ecosystem eutrophication [2].

For correct management of the agroecosystems, we can not ignore the information deriving from health status of environmental matrices (soil and water) assessable by fast identification of the dangers that can cause contamination to be able to

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suggest possible remediation and bioremediation solutions and many other innovative technologies to improve their functionality.

The presence of harmful or dangerous substances released without any control can become a dangerous source of pollution. Many areas of the Apulia region generally, in southern Italy, are subjected to this type of phenomena. Land monitoring would be carried out in a very long time and would require significant financial resources and considerable effort if done by conventional methods.

The work has been focused on the development of an integrated methodology with a defined and high reliability capable of identifying the presence of dangerous sources of pollution for agroecosystems: asbestos, illegal waste burial for soil and microplastic pollution.

1.1 Asbestos

Asbestos are naturally widespread minerals belonging to inosilicate group (amphibole series) and the phyllosilicate group (serpentine series). At first they have been widely used for their intrinsic resistance to heat and its fibrous structure (suitable for buildings and fireproof fabrics), but later it was ascertained that it is harmful to health at the point of being prohibited in many countries. Dust-containing asbestos fibers are responsible for serious diseases such as asbestosis, pleural mesothelioma and lung cancer.

Before discovering its danger to humans and the environment, asbestos was widely used in several applications; the main one above all is for insulation of buildings and rooftops in the form of composite fiber cement (also known "Eternit"). Given its proven hazard to human health, there are numerous scientific studies in which its presence is investigated through remote sensing technics and sensors, e.g. multispectral visible and infrared imaging spectrometer (MIVIS) [3] or visible and thermal Landsat images [4].

1.2 Illegal waste burial

A severe threat to human health and agroecosystems is represented by illegal waste burial and ground dumping of polluted sludge, especially if it concerns hazardous industrial waste. These illegal activities mainly take place in large areas that undergo large transformation processes in a short time like quarry areas and landfills, even if it is licensed. Unfortunately, since we have witnessed the countryside abandoning phenomenon, such phenomena are increasing because a lot of sites remain increasingly unattended and uncontrolled. Sometimes, entrepreneurs may receive pressure from criminal organizations to buy hectares of farmland in order to have more and more areas to grow the eco-mafia business. In these areas, we have not gone looking for changes such as cultural growth, different photosynthetic activities or other distinctive elements. These elements find more applications in land use-land cover classification, but only in those aspects related to surface soil change, alterations or reshuffle to hide illegal waste dumping that affect the characteristics of vegetation, soil texture and moisture content.

1.3 Microplastic pollution

Both in Europe and many parts of the world, the contamination of soils by plastic is growing. Plastic waste from the terrestrial environment constitutes about 80% of all plastic debris found in the marine environment, representing a source of pollution not only for the seas but also for inland waters and soils, even if the phenomenon is currently less known and studied. The plastic in direct contact with

the soils mainly comes from various widespread practices adopted in agriculture, such as mulching [5], which uses black plastic sheeting positioned on the ground to prevent moisture loss and growth of weeds and to retain heat in spring. Plastic undergoes a series of physical, chemical and biological reactions due to the effects of UV radiation, atmospheric agents and the action of the organisms that inhabit the soils. This cause its embrittlement which leads to the degradation of polymeric waste in smaller and smaller fragments going from macroplastic (>25 mm) to mesoplastic (5–25 mm) and from mesoplastic to microplastic (<5 mm) that creep into agricultural soils and terrestrial ecosystems.

Besides, darker-colored plastic materials, such as mulch sheets and irrigation materials used in agriculture, absorb more sunlight, and the consequent increase in temperature leads to faster decomposition and higher production of meso- and microplastics by fragmentation.

Microplastics can reach terrestrial environments and in particular agroecosystem through various input sources such as soil mulching, the use of compost in agricultural soils, irrigation, rainwater and atmospheric fallout.

Moreover, microplastics, due to their hydrophobic and microscopic size that influence a high S/V ratio, represent ideal vectors for the adsorption of environmental pollutants, especially persistent organic contaminants (chlorinated organ pesticides, PCBs, IPAs) [6], up to several orders of magnitude higher than those present in the surrounding environment [7]. Therefore, agroecosystems, already sensitive to chemical pollution mainly represented by the waste of plant protection products used in agriculture and more exposed to the presence of macro-, meso- and micro-plastics due to the practices used in agriculture, represent excellent tools for studying and investigating the interaction between micropollutants and plastics.

In the absence of global measures to regulate the use of plastic in contact with soils, integrated monitoring of synthetic polymers and adsorbed micropollutants is therefore of fundamental importance in order to investigate the problem of plastics and microplastics in soils, currently almost totally unknown.

2. Materials and methods

2.1 Study areas

For the study areas, we consider three different territories which are all agroecosystems but with different risk factors:

1. The surrounding territory of the municipality of Brindisi in Southern Italy (**Figure 1**). The perimeter is about 22.000 km, the area is 31.00 km^2, and it is characterized by the presence of different farming practices, greenhouses, small structures built primarily for depository purposes, roads (mostly unpaved) and a lot of caves.

2. This study area is particularly affected by abandonment phenomena. It is called Gravina (ravine) of Leucaspide, its extension is approximately 5 ha in Statte municipality (Taranto Province), and it also represents the greatest example of karst in the Taranto area (**Figure 2**).

3. The Ofanto river, the most important river in the Apulia region (Italy) for length, area and abundance of water. Its source is at 715 m above sea level, in the province of Avellino, and it crosses part of Campania and Basilicata regions flowing then into the Adriatic Sea, between the towns of Barletta and

Margherita di Savoia. The shape of the river is trapezoidal with a surface of 2790 sq. km and a mean altitude of 450 m. The length of the main boom is about 165 km, the average annual inflow of 720 mm, and the mean annual temperature is just over 14°C [9]. The region of Ofanto river covers about 88.700 hectares, of which 8% are natural (6.800 ha). The predominant agricultural areas include nonirrigated (30.000 ha) and irrigated (14.000 ha) arable land, which, in total, represent 50% of the territory. In the floodplain of the river, vineyards prevail above all (18.400 ha), followed by the olive groves (14.100 ha) and the orchards (1.600 ha) (**Figure 3**). These permanent crops make up 39% of the area. Lastly, the urbanized district covers 3% (2700 ha) [10].

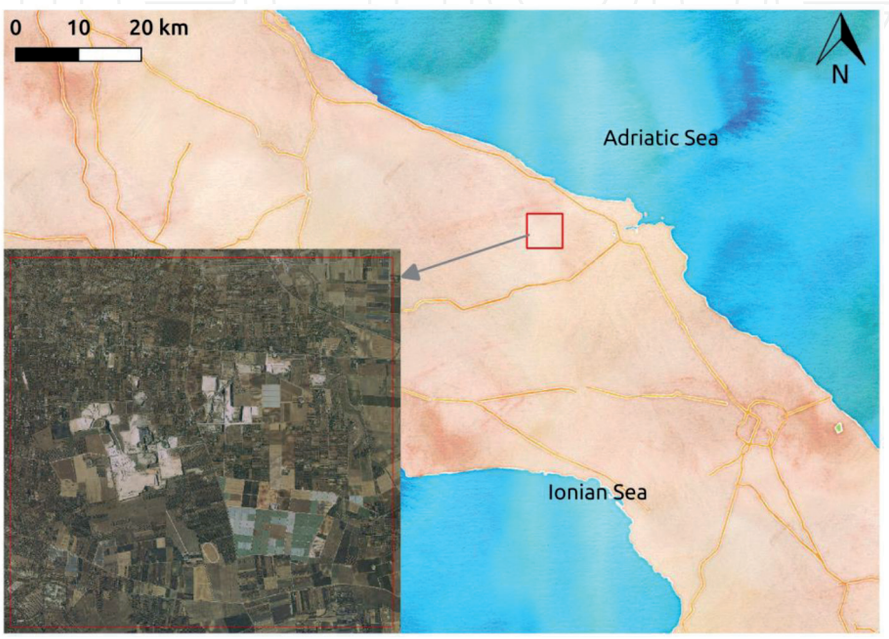


Figure 1.
Study area. Map tiles by stamen design [8], under a creative commons attribution (CC BY 3.0) license. Data by OpenStreetMap, under CC BY SA.



Figure 2.
The perimeter of Gravina of Leucaspide (south of Italy) in red. Map tiles by stamen design [8], under a CC BY 3.0 license. Data by OpenStreetMap, under CC BY SA.

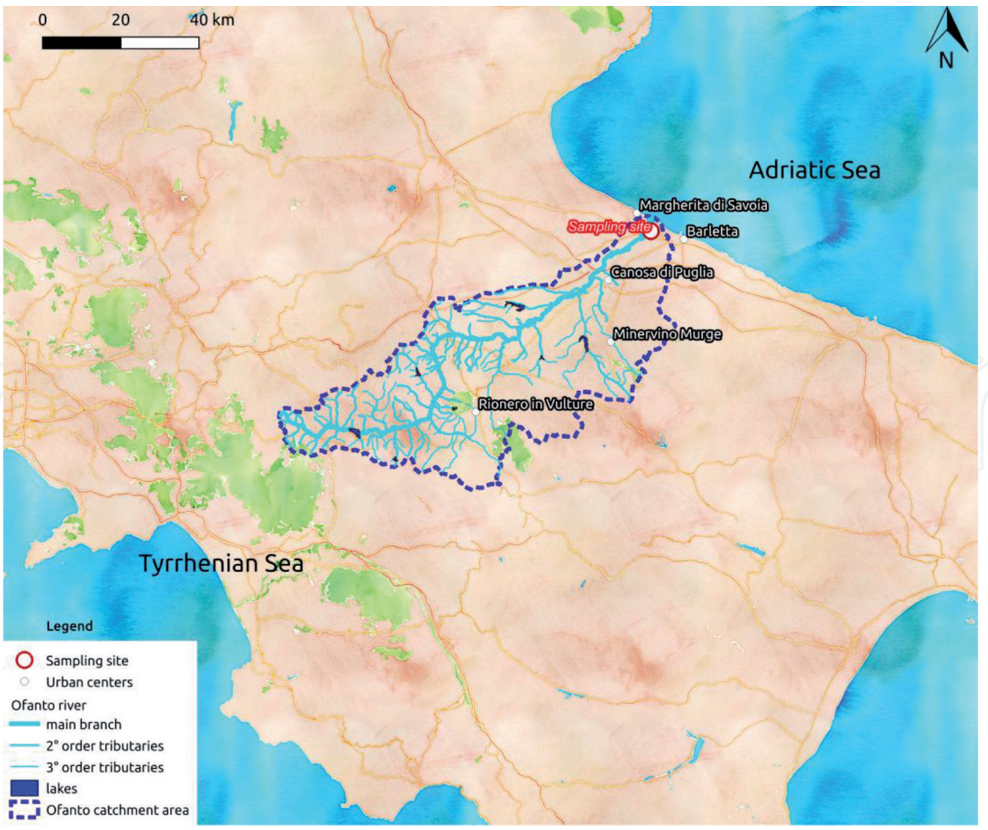


Figure 3.
The study area of Ofanto river. The red fringe represents the river catchment area. Data source: EEA (2018). Map source: Map tile sets are © stamen design, under a CC BY 3.0 license.

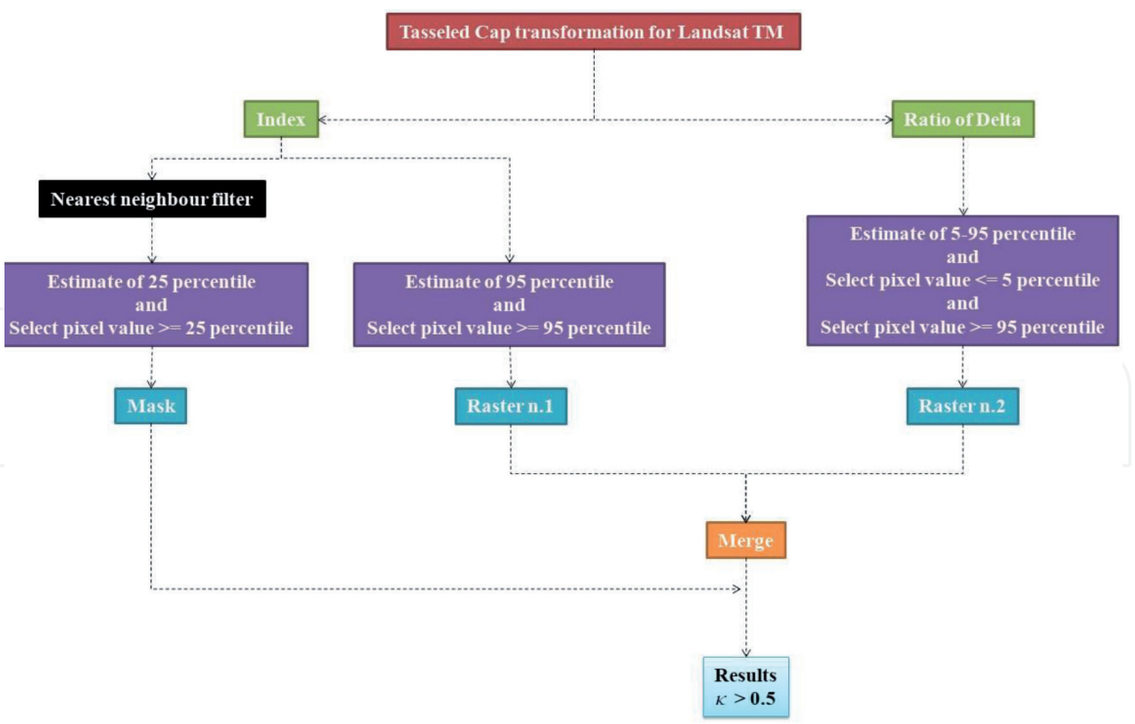


Figure 4.
Operational workflow for illegal waste burial detection.

2.2 Methodology for the soil matrix

For synthesis and completeness reasons, the whole methodology for illegal waste burial detection is shown in **Figure 4**. All the phases will be analyzed in detail in the following sections. All the images processing have been performed with

the Geographic Information System (GIS) software called Geographic Resources Analysis Support System (GRASS) GIS [11, 12] using Landsat images.

The whole methodology adopted to detect asbestos-containing materials (data processing and used sensors) is summarized in **Figure 5**.

Image processing was done in GRASS GIS environment. First of all we found it useful to make a distinction between two ranges of bands: 375–702 nm and from 717 to 1030 nm; later for each one we applied four filters because we noticed that it was possible separate natural elements by asbestos:

- Filter applied to the first 24 of CASI raster bands in the wavelength range 375–702 nm to eliminate background value (no ACM included)
- Filter applied to the second 24 of CASI raster bands in the wavelength range 717–1030 nm to eliminate the emerging rock from ACM reflectance values

For this purpose it was written an algorithm able assigns a value of 1, otherwise 0 to every pixel in each band if not filtered or vice versa if filtered.

Summing all pixel values after this application, we get a raster with only one band with its value ranging from 0 to 24 that we could consider equivalent to 0–100% of fitting pixels in regard to the spectral signature measures.

2.3 Methodology for the water matrix

To monitor the trend of microplastic abundances over a long period, seven seasonal sampling campaigns were carried out. Microplastic samples were collected form river surface water during February, April, October and December 2017, May and December 2018 and April 2019, all of them collected from the same point located at 6 km from the Ofanto river mouth following the sampling strategy reported here [13].

All water samples picked up during each campaign were preserved in glass containers and processed once in laboratory to extract microplastics following

	CASI sensor on airplane	RGB camera on drone	FIELDSPEC Iperspectral sensor	GROUND TRUTH
Preparation for data acquisition	Set configuration relative to the acquisition bands, flight planning	Flight planning	-	-
Data acquisition	4 acquisitions	~100 RGB images	4 sets of asphalt spectra measurements	GPS differential point acquisition over areas containing asbestos
Data pre-processing	Geometric, radiometric and atmospheric correction	Images mosaicking, asbestos identification	Averaging of spectra removing atmospheric influence	Ground truth raster building of known asbestos areas
Data processing	Classifications methods with mask generation and filters applications	-	-	-
Results and statistical analysis				

Figure 5.
Operational workflow for asbestos-containing materials detection.

the method reported by [13]. After processing, all the microplastics were visually identified under a 40× digital microscope (Keyance VH-Z 100 UR). All plastic microparticles detected were counted, photographed, enumerated and categorized based on color (black, transparent and colored) and morphology (fragments, flakes, pellets, lines, fibers, films and foams) (**Figure 6**).

Microplastic concentrations were expressed as mean values (±DEV. ST.) of six replicates for each campaign. Concentrations were indicated as the number of particles per cubic (p/m^3).

Simple regression and Spearman's non-parametric correlation coefficient were used to test significant relations between the concentration of microplastics and the water level of the river for each monitoring campaign. Spearman correlation test was performed by Statgraphics Centurion Software.

2.4 Data integration

The main objective is to evaluate the level of degradation and possible contamination of environment through the combination of different types of investigations in soil and water environmental matrices.

This goal can only be achieved by implementing a data integration procedure to make them comparable and so that each type of investigation, representative factor of the state of a matrix, can be used with others in order to identify compromised environments.

The more representative factors we have, the more reliable the result will be.

In particular our goal is to locate the same zoning areas subject to a different state of degradation.

From the greater knowledge of the environmental component investigated, considerable progress can be derived for the identification and implementation of technologies useful for monitoring and/or for the safety and remediation of polluted matrices.

First of all it is necessary to create data matrices deriving from monitoring and sampling activities. Having the different variables different units of measure (sometimes even of many orders of magnitude), a matrix normalization was carried out [14]: the standard deviation of each variable was first calculated, and each value was subsequently divided for the latter, thus obtaining dimensionless matrices. Later the cluster analysis was carried out. It is a sector of multivariate analysis that

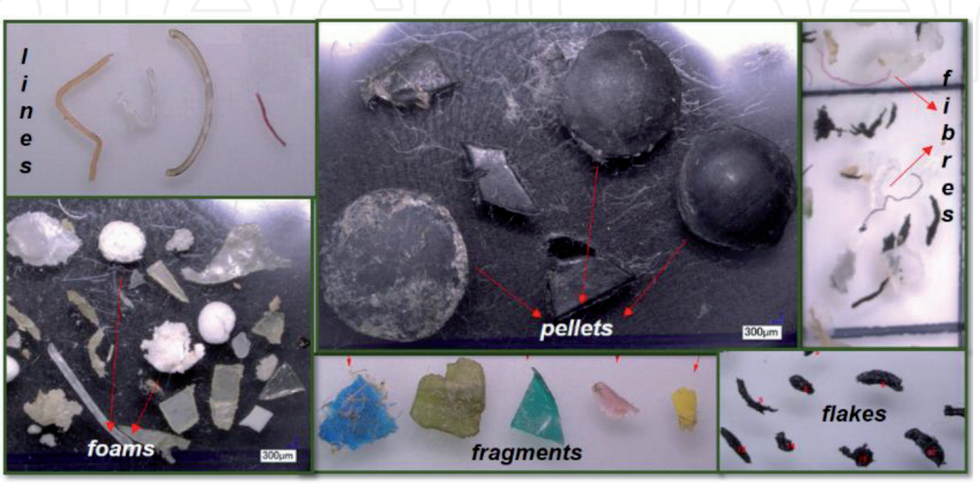


Figure 6.
Microplastic assortment collected by Ofanto river subdivided by morphology as: Fragments and flakes (broken pieces of larger debris), pellets (preproduction pellets), lines and fibers (particles of fishing line and nets and fibers from synthetic textiles) and foams (foam cups, takeout containers, packaging).

groups numerous techniques (k-means, fuzzy k-means, hierarchical cluster, etc.) that allow to group monitoring units (e.g. sampling points) that present characters (the different variables) of similarity between them [15].

Two clustering methods based on very different theoretical approaches have been applied in order to achieve a robust result: hierarchical clustering and k-means [14].

The choice to opt for these methods for the classification of the points investigated was based, above all, on the purpose of the work, i.e. defining homogeneous areas with a priority of intervention (further environmental investigations with more or less immediate action). In this regard, to avoid that, points with similar characteristics are distributed randomly over the territory; we wanted to consider, among the variables, the geographic coordinates that act as "attractors" for the delineation of the clusters.

Through hierarchical cluster analysis and the analysis of the resulting dendrogram, it was possible to identify the optimal number of clusters. This value was equal to 3. Through the clustering procedure, the software groups the dataset into classes based on the similarity index but is not able to independently discriminate the "danger" to be attributed to each of the classes. For this purpose, the centroids of the three classes were analyzed, and it was, therefore, possible to define the "most impacted" class, the "average impacted" class and the "least impact" class that is made based on the interpretation of the distance from the centroids for the dataset relating to the samples.

The results obtained through cluster analysis make it possible to identify geographic areas in which homogeneity of degradation levels is presumed.

The methodology used, starting from the data produced by the cluster analysis, is based on an approach that partially follows that used for the realization of the conceptual model of the site in contaminated areas [16].

Therefore the following steps were carried out in the GIS environment:

1. Distribution of the entire area of interest in different areas of "presumed homogeneity" through the identification of the Voronoi polygons.

2. Attribution to the various polygons of the "Alert" value coming from the cluster analysis.

3. Classification of the different polygons according to the "Alert" value.

4. Identification of an empirical threshold value of 200 Ha with which to identify areas with lower probability of certainty of the result coming from the cluster analysis (these areas would need further sampling).

5. The results of zoning identify areas in which it is necessary to implement short-term (red), medium-term (yellow) and long-term (green) interventions.

Further deductions can be made by considering the adjacency between polygons of different colors (e.g. a green polygon surrounded by red polygons has to be considered red) and assigning different threshold values according to other territorial characteristics.

3. Results and discussion

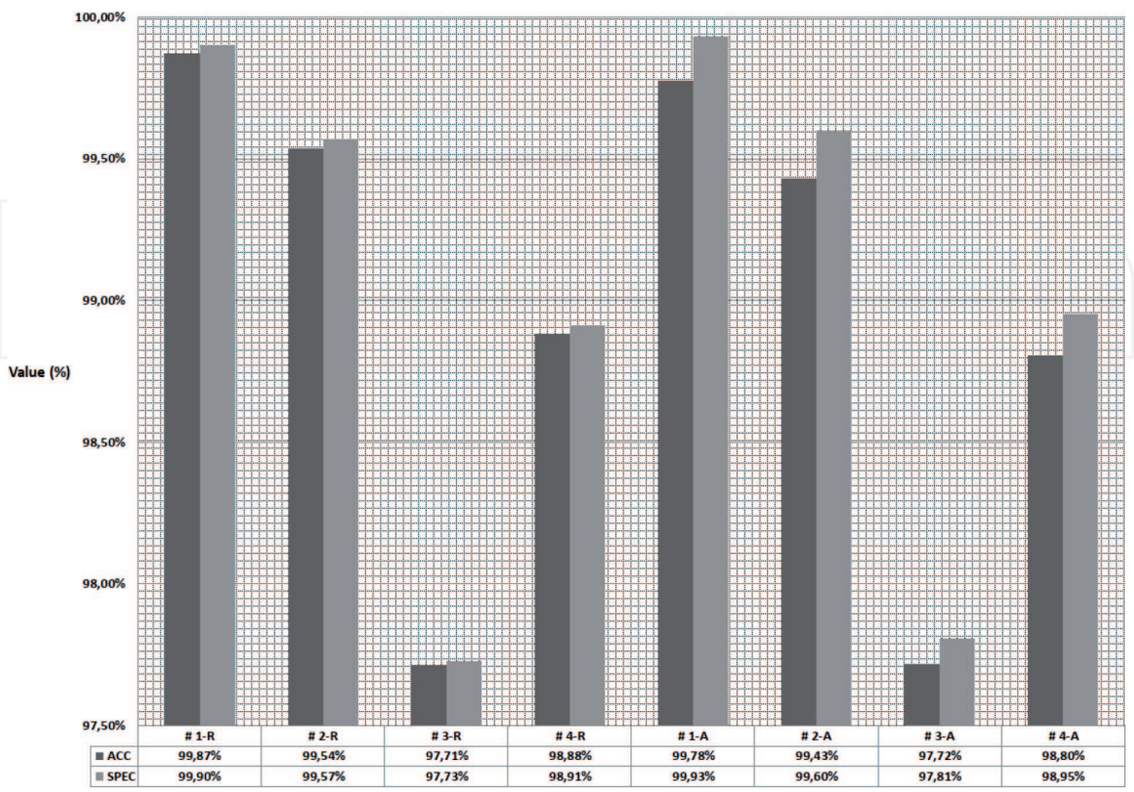
The results obtained for this purpose are considered satisfactory because it is possible to identify not only the potential sites where there may have been illegal

activities but also the complexity of the highly transformed areas. This increases awareness to authorities about all transformation and impacts on our fragile agroecosystems because agricultural activities and related soil processes do not show significant changes compared to those highlighted through the application of these procedures. Although κ may seem low, it should not be overlooked in these procedures because the purpose, with only two Landsat images used in a short time, is to identify certain type of changes relatable to illegal waste disposal; increasing the number of processed images, it is reasonable to think that the accuracy of the results may increase, but on the other hand it will be necessary to invest in more resources (also storage, hardware, staff engaged in work activities). Presence of solar panels and building structures with metal roof alters the result; so, it would be appropriate to exclude them realizing an ad hoc mask to reduce false positives.

The developed methodology for remote sensing analyses the spectral behaviour of materials, highlighting and emphasizing certain features through the use of a procedure based on an if-then-else control structure. It also allows the selection of the most useful features to be combined that significantly reduces the number of false positives.

Here the results of accuracy and specificity for the filters are reported (**Figure** 7).

Results obtained correctly predict 99.87% of cases with 0.13% error for reduced ground truth area and correctly predict 99.78% of cases with 0.22% error for augmented one. We have pixels identifying ACM correctly in 29.49% times in reduced area, while 21.82% in augmented one. Results show a correctness probability of 99.9% with a 0.10% of false alarm probability in the case of reduced ground truth area (99.93 and 0.007%, respectively, for the augmented one). For the other filters that also provide high statistical indices, we have to consider that the number of significant pixels is much higher than those of filter #1. Starting from a computation



	# 1-R	# 2-R	# 3-R	# 4-R	# 1-A	# 2-A	# 3-A	# 4-A
ACC	99,87%	99,54%	97,71%	98,88%	99,78%	99,43%	97,72%	98,80%
SPEC	99,90%	99,57%	97,73%	98,91%	99,93%	99,60%	97,81%	98,95%

Figure 7.
Accuracy (ACC) and specificity (SPEC) values of the different filters for two different ground truth areas: Reduces (R) and augmented (A) [17].

region of 190,437 pixels, filter #1 consists only of 212 pixels, while filter #2 of 830, #3 of 4383, and #4 of 2023. This immediately translates into the lower surface to examine where ground investigations can be focused. Such considerations may also be deduced by the comparison of histogram filters considering the values of accuracy and specificity: filter #1 always shows higher values. This confirmation also means that the photointerpretation by drone is correct and can be used to supplement the investigations.

A summary of the data from the kappa analysis is shown in **Table 1**.

Considering the error matrix [19], we know that the columns represent classification depending on our knowledge and rules given in the supervised method, while the rows represent classification coming from application of the specific algorithm. We look at the negative category column; it reports that 3243 cells were correctly classified as negative; however, 550 cells were classified as positive when they were, in fact, negative. If we sum the pixels number in diagonal, we get 3869 of correctly classified pixels, if we sum the 'col sum', we get 4600 pixels representing all those considered correctly classified. So, dividing the first one by the second, the results is 0.8411, which is equivalent to 84.11%; here we have accuracy value of the classification algorithm. Observing the error statistics section of our table and considering the percentage commission column, we can see how many cells were placed into its class incorrectly: so positive pixels are confused with negative ones 46.77% of the time. This value could be considered high because represents the time that we can mistakenly attribute to the positive pixels, even if the most important thing is not to exclude true positives. This aspect given the purpose of the study is not a limiting factor as it is preferably a false alarm which indicates that the areas after a field survey are not affected by the illegal conduct, rather than a failure alarm where affected areas were not reported. The percentage omission column represents pixels placed incorrectly into other classes.

In section (d), we have the estimated kappa coefficient (κ) as a statistical value of the degree of classifications which are overlapping (more intense training of the dataset which leads to a greater agreement value of the classification results). κ takes into account the agreement of classification versus the possibility that the agreement is just from sheer chance (both classifiers are just randomly guessing the classes). If the classifiers agree on all classifications, then κ would equal to 1. If the classifiers do not agree other than what would be expected by sheer chance, then κ would equal to 0. So, in our case, κ coefficients are reported as 0.53. This could be considered a moderate agreement. A possible interpretation of κ indicates a moderate agreement for the workflow adopted, even if there is no universally agreed-upon range of values that would consider a κ coefficient to be excellent, good, moderate, weak or otherwise and is referred as common thinking. Here is one possible interpretation of κ: weak agreement (<0.20), fair agreement ($0.20 < \kappa < 0.40$), moderate agreement ($0.40 < \kappa < 0.60$), good agreement ($0.60 < \kappa < 0.80$) and excellent agreement ($0.80 < \kappa < 1.00$).

For our purposes concerning the monitoring of microplastics along the Ofanto river, we evaluated the seasonal trend of the concentration of particles hypothesizing their alleged origin. The quantitative analysis showed the presence of MPs in each sample analysed, counting a total of 164,143 microplastic particles during all the campaigns. The lowest abundances were detected in the months of October 2017 (0.93 ± 0.4 p/m^3), December 2017 (1.12 ± 0.37 p/m^3) and December 2018 (2.59 ± 0.34 p/m^3), while the highest ones in the months of May 2018 (12.56 ± 4.83 p/m^3), February (10.21 ± 4.29 p/m^3) and April 2017 (5.16 ± 1.4 p/m^3) with a maximum peak detected in April 2019 (36.05 ± 9.80 p/m^3) (**Figure 8**).

The largest number of microplastics were detected during wet periods (February 2017, May 2018 and April 2019) suggesting a presumable land-based origin from the

	Procedure application		Reference map		
a)	Classification map		*N*	*P*	Row sum
		N	3243	181	3424
		P	550	626	1176
		Col sum	3793	807	4600
b)	Observed corrected	3869			
	Total observed	4600			
	% Observed correct	84.11			
c)		% Commission	% Omission		
	N	5.2	14.5		
	P	46.7	22.4		
d)	*k*	Kappa variance			
	0.53	0.000199			

N, number of negative pixels; P, number of positive pixels

Table 1.
Kappa analysis procedure with site-specific calculated parameters [18].

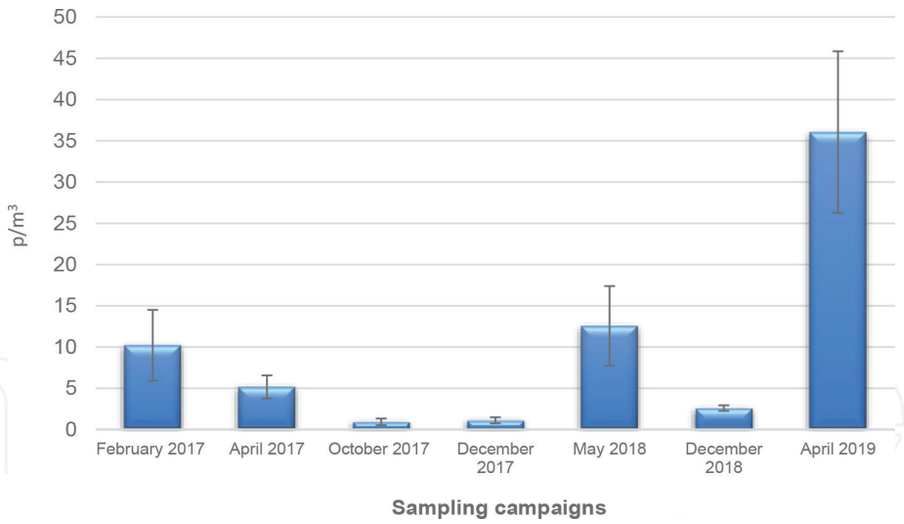


Figure 8.
Microplastic concentrations (mean value of six replicates ± dev. st.) of the sampling campaigns.

surrounding agricultural areas. As already evidenced by [20], Spearman's correlation results show a positive statistically significant correlation between the concentration of MPs and the water level ($r = 0.6583$, $p = 0.01$) of Ofanto river, indicating a marked relationship between the two factors.

It is not surprising that runoff occurring during more abundant rains can transport more microplastic debris from land to water. Indeed, it is recorded that rainy events increase the plastic concentration up to 150 times in an urban part of the Rhone river basin (France) [21, 22].

In the Los Angeles River (USA), microplastic densities were highest in samples collected in the wet season and near the surface of the water rather than samples took in the dry season and in the mid-column or near the bottom of the water column or the riverbank [23].

Others authors [24] investigated the presence of microplastic particles (fragments, foams, films and pellets/beads) in 29 Great Lakes tributaries deepening the role of hydrology in the occurrence of plastic, and they found higher concentrations during runoff events than during low-flow condition.

Different shapes and colors of microplastics were observed and quantified (**Figure 9**). Fragments and flakes were present in all samples of each campaign, constituting the most prevalent morphology identified. The mean percentage of fragments observed during campaigns was of 44%, followed by flake particles (36%) the second most abundant category counted. The percentage distribution of the other categories highlighted an almost equal distribution of lines and fibers (8% of fibers and 9% of lines) followed by pellets, foils and foams ≤3% (**Figure 9**).

Morphological information regarding microplastics is a useful tool to indicate their potential origins.

For example, flake particles, a new plastic morphology observed regularly in Ofanto river [13] in large quantities (**Figure 9**), appeared mainly of black color with an irregular shape and rough embrittled and weathered surface. The aspect of plastic particles usually depends on the fragmentation process occurred as well as the stay time in the environment [25]; breakdown of particles due to biological, chemical and weathering processes causes the degradation and erosion of microplastics through the formation of visible cracks on the plastic surface that produce a wide variety of different shapes [25].

The general irregular aspect of flakes found in Ofanto river seems to suggest an ongoing break-up process probably due to a physical and mechanical degradation

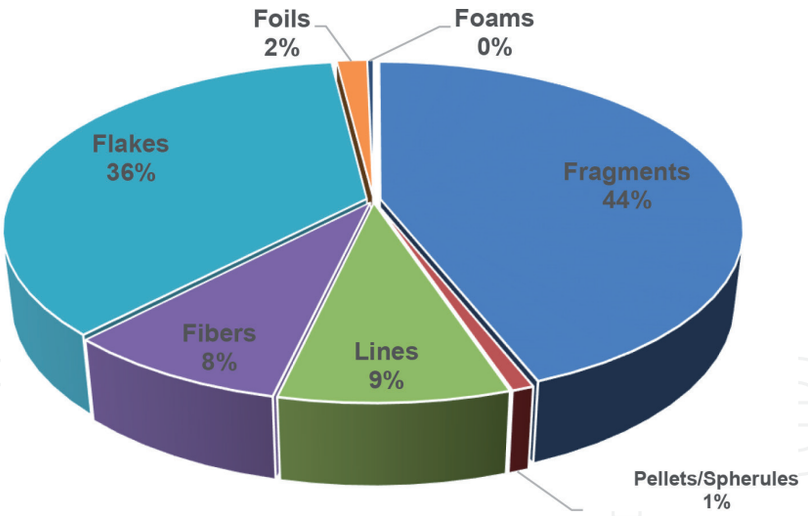


Figure 9.
Shape composition of microplastics in different campaigns, expressed as mean relative abundance in percentage.

(runoff, abrasive forces, heating/cooling, freezing/thawing, wetting/drying) that have continuously scratched their surface.

Moreover, in the presence of sunlight, all plastics undergo photo-oxidation reactions causing embrittlement and reducing the physical stress needed for fragmentation [26, 27]. Plastics exposed to a direct source of solar UV radiation, lied on beaches or soils, undergo a very efficient mechanism of degradation. Moreover, darker-colored plastic objects (e.g. black particles) would be expected to absorb more sunlight, and the resulting increase in temperature leads to more rapid decomposition. Differently, when the same plastic material is exposed to sunlight while floating in the water, degradation is severely slowed due to the fact that all different-colored plastic particles will be at the same river water temperature and decomposition rates will not vary with differential heating caused by the different colouration of microplastics [28]. Therefore, the irregular, jagged and embrittled appearance of flakes observed in the Ofanto river indicate a more advanced decomposition process with respect to transparent particles. This happens because where the plastic debris is pigmented dark, the heat build-up due to solar infrared absorption can raise its temperature even higher. The light-initiated oxidative degradation that is accelerated at higher temperatures by a factor depending on the activation energy E_a of the process, where the $E_a \sim 50$ kJ/mole, for instance, is the rate of degradation that doubles when the temperature rises by only 10°C [26, 28]. The result of this mode of oxidative degradation is a weak, brittle surface layer that develops numerous microcracks [28–31]. This degraded fragile surface is susceptible to fracture by stress induced by humidity or temperature changes as well as abrasion against surfaces [28, 32], generating particles similar to flakes identified in Ofanto river. The same degradation does not occur in plastics exposed while floating in water, suggesting, therefore, a further confirmation of the land-based origin of plastic particles in Ofanto river. The land-based origin of flake particles found in Ofanto river could be associated mainly with agricultural activities, which represent the predominant use of the land area of Ofanto valley. Plastic in direct contact with the soil comes mainly from various practices spread in agriculture, including mulching, which uses black plastic polyethylene sheets placed on the ground to prevent the loss of moisture and the growth of weeds and to retain in spring the heat and irrigation through dripping wings in black polyethylene. Recognition that microplastics (and therefore also nanoplastics) are most likely generated on beaches or riverside or inner lands underlines the importance of cleaning actions

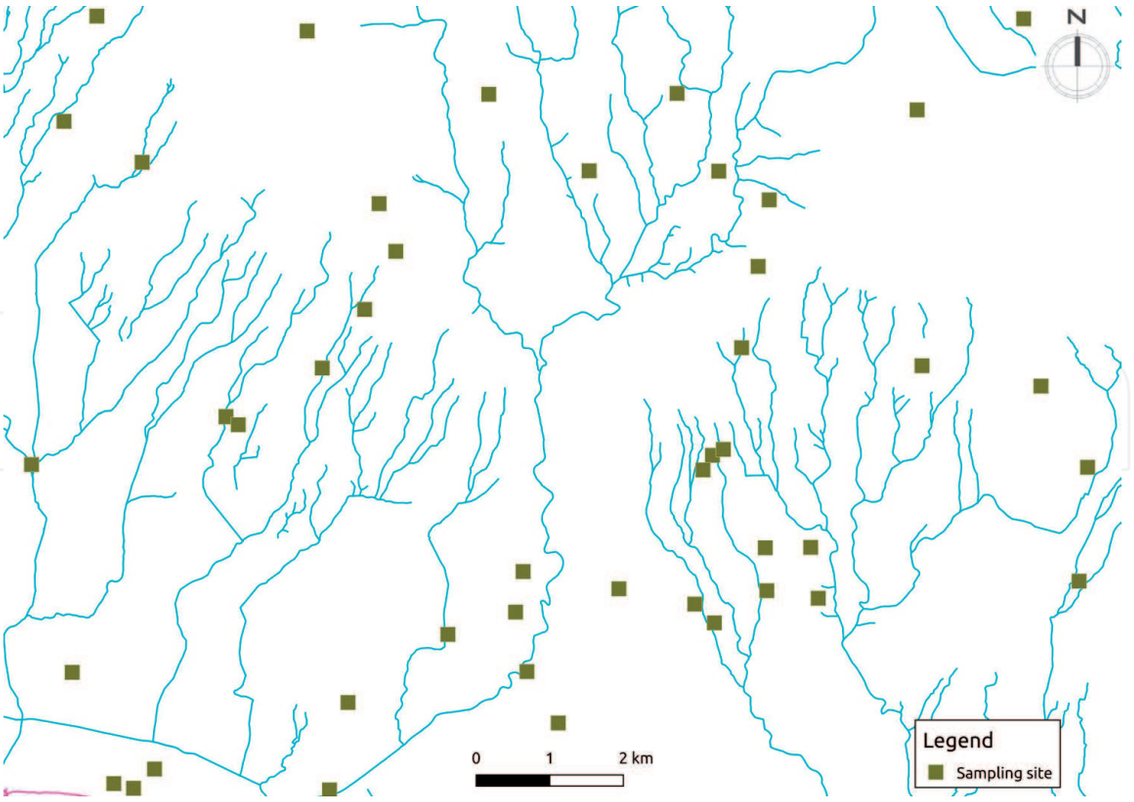


Figure 10.
Test area with rivers.

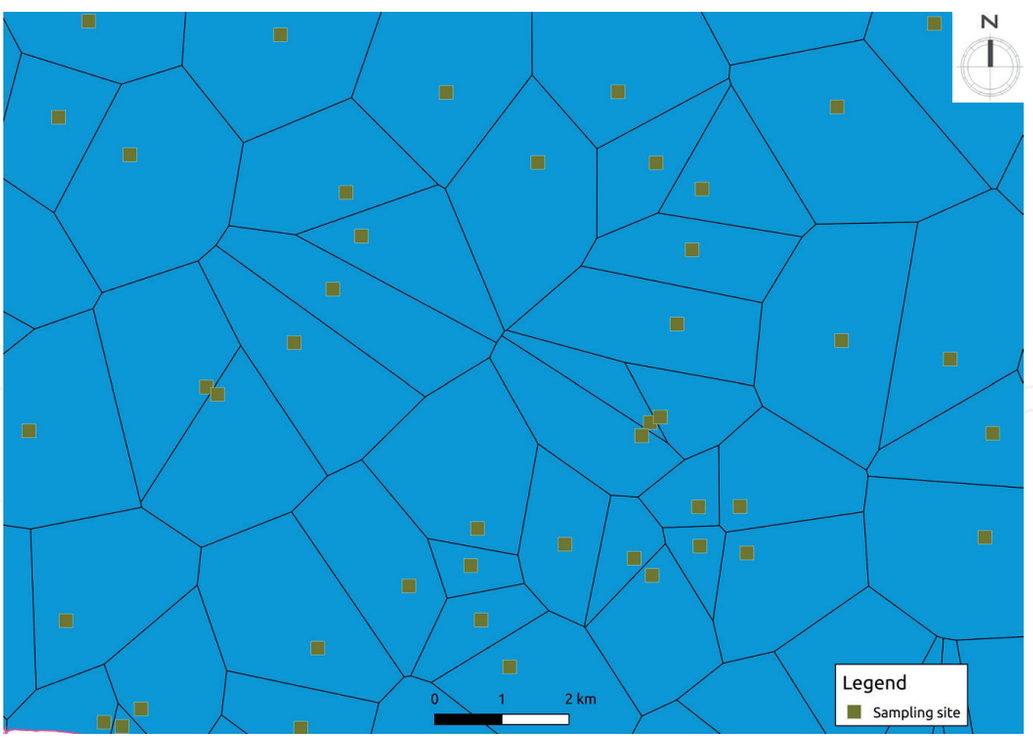


Figure 11.
Division of the test area into Voronoi polygons.

as an effective mitigation strategy contributing towards the health of the food web. The removal of larger pieces of plastic debris from beaches and riversides before these are weathered enough to be surface embrittled can have considerable value in reducing the microplastics that end up in rivers and oceans.

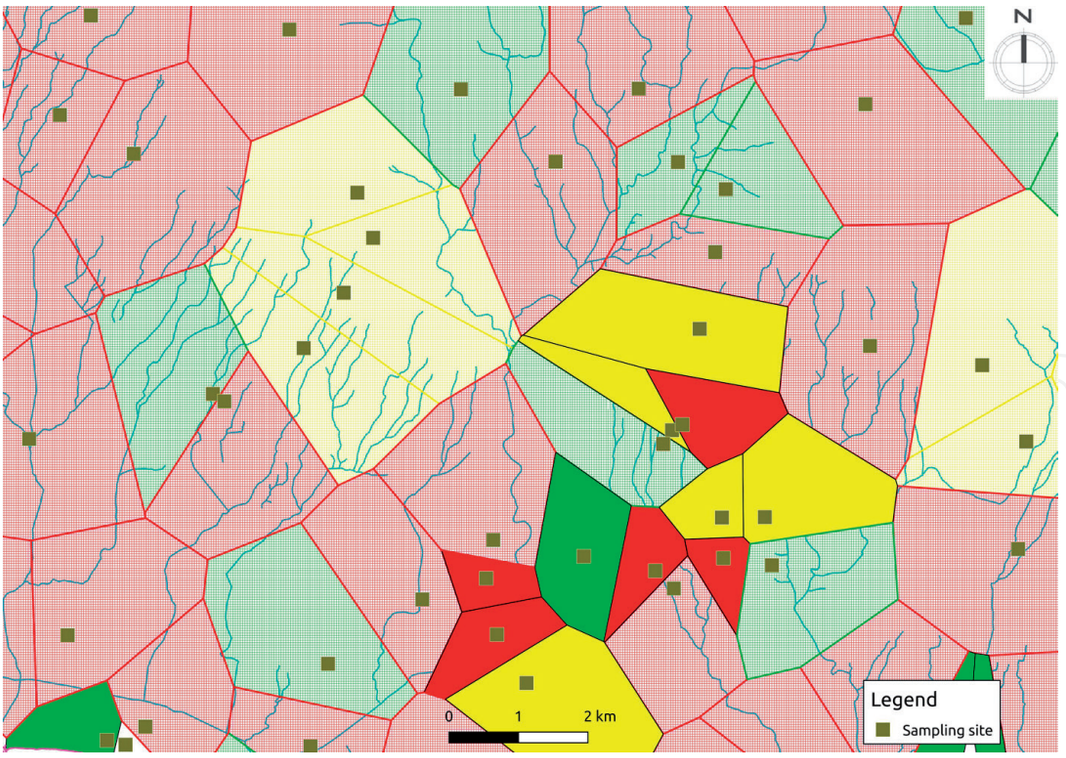


Figure 12.
Results of the classification according to the methodology proposed in the data integration paragraph.

Finally, if we consider a test area with the following sampling sites and rivers (**Figure 10**), we divide the territory with the Voronoi polygons (**Figure 11**), and then applying what is reported in the data integration paragraph, we obtain the result shown in **Figure 12**.

4. Conclusions

The results of the mapping of homogeneous areas of degradation, carried out through the cluster analysis of the data produced by various activities, express a high level of internal coherence evident also concerning the chemical–physical results only. Therefore the radiometric and chemical data are confirmed to be functional for the implementation of methodologies for the rapid identification of degradation levels.

The results of the zoning carried out through the methodological proposal described in this document indicate areas in which it is necessary to implement short-term, medium-term and long-term interventions.

Further deductions can be derived by considering the adjacency between polygons of different colors (e.g. a green polygon surrounded by red polygons is to be considered red, the proximity to inhabited centers, etc.) and attributing different threshold values according to additional territorial characteristics.

In conclusion, the validation of predictive models obtained by integrating chemical-physical analyses with radiometric data is an added value to the methodology proposed here to implement innovative, fast and economically advantageous monitoring technologies. With the proposed methodology, it will be possible to use any data source to obtain evermore precise information on the state of degradation of the environment.

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