multi-Risk sciEnce for resilienT commUnities undeR a changiNgclimate

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2. ABSTRACT

Environmental degradation has been recognised as a threat to the European and global ecosystems with direct impacts on climate change adaptation, ecosystem conditions, food-security, and social assistance. A lot of scientific effort has been devoted to the concepts and approaches for the monitoring and assessment of environmental degradation and to the question of how the ecosystem resources could be directed towards sustainable use. In addition, within the broad concept of environmental degradation, there are very different processes ranging from air/water/soil contaminants to loss of ecosystem services.

In this regard, the aim of this deliverable is to analyse sources and scale of source of the most prominent environmental degradation processes.

In order to perform such task, we have proceeded in two steps: (i) a preliminary analysis of environmental degradation factors based on bibliometric analysis and (ii) a synoptic view of the outcoming results analysing sources and scale of land degradation.

For the bibliometric analysis, documents type, subject area, documents sources, high-frequency keywords, and the geographical distribution of publications were analysed. The study focused on a total of 19748 articles published from 2016 to 2023, collected through an automated process from the Scopus database and later analysed using techniques such as bibliometric indicators analysis on R and VOSviewer. To identify the sources of environmental degradation and assess the scale and the extent of their dispersion, diverse monitoring techniques have been discussed, highlighting the necessity of a global high spatio-temporal database derived at marine and land scales. Finally, a synoptic analysis has been produced in view of the RETURN project.

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4. State of The Art

4.1 Introduction

In the current years, environmental degradation, an intensifying issue that affected ecosystem services globally, has been actively debated. The term environmental degradation suggests that a change in the environment quality status results in a diminished capacity of the ecosystem to provide goods and services (Hatfield et al., 2017). More precisely, environmental degradation, induced by natural and/or human-caused circumstances, is defined as the process in which the productivity or the potential of ecosystems components' quality and sustainability, including soil, vegetation, air and water, declines partially or completely by losing its physical, chemical, and biological mechanisms (Pereira et al., 2017). The concrete manifestations of environmental degradation are varied, including but not limited to erosion, salinization, pollution, acidification, desertification, nutrient deficiency, compaction, plastics, eutrophication, acidification, and heavy metals contamination. The cited issues are gaining an immense interest in scientific publications and cautions. Few of these factors are explicitly treated in RETURN.

Environmental degradation has been recognized as a threat to the European ecosystems. In addition to that, the European region will have to adapt to climate change impacts, which are continuously and increasingly showing adverse effects on ecosystems conditions (EEA, 2017). The significance of the effects of environmental degradation in the European scale has been discussed in reviews of environmental policy frameworks, assessments by intergovernmental bodies and scientific advisory panels for policy makers, and research projects (Brabant et al., 2010; GIZ, 2023). In response to these concerns, various policy programs, strategies, and guidelines on sustainable management of land and coast is being discussed. Considering the increasingly serious severe extent and impacts of environmental degradation, continuous acquisitions of repeated information on terrestrial and marine components are fundamental, especially on a large-scale. With the further development of environmental degradation-related case studies and research, accurate, high-resolution, and up-to-date datasets was spotted as urgent and essential (Ivits et al., 2018).

The maintenance of ecosystem services should support a more balanced consideration of planning decisions on environmental use and management. Mapping and monitoring of the degradation sources at terrestrial and coastal scales should enable the European Union, countries, regional authorities and environmental organizations to explore the state of environmental degradation phenomena in their areas, and to impose progress towards sustainable ecosystems use. The envisaged use of the mapping outline is to guide towards an identification of hotspot prone regions followed by a design of sustainable management decisions.

In view of that, geospatial information in environmental degradation studies, is becoming increasingly available through high spatial and temporal resolution time series data. With recent advances in earth observation and imaging technology, remotely sensed instruments with high to moderate spatiotemporal and spectral resolution are playing a fundamental role in environmental degradation studies (M. D. Iordache et al., 2011; Quintano et al., 2023; Tasseron et al., 2021a). Latest progress in algorithm and modelling research, accompanied by the rise of cloud-based global remote datasets, have considerably strengthen the application potential of earth observation systems for environmental degradation studies (M. D. Iordache et al., 2022; Stroppiana et al., 2021). Specific uses of remotely sensed techniques in the context of environmental degradation monitoring can include the mapping of large forest fires; the tracking clouds for weather forecasting; the monitoring of erupting volcanoes; the monitoring of dust storms; the mapping of changes in farmland or forests over a defined period of time; and the identification and mapping of the ocean contaminants. In comparison to traditional ground/field/local scale investigation techniques, earth observation systems are presenting a series of benefits particularly by its large global coverage scale. Actually, to date, there are many published literatures on environmental degradation research (aimed to analyze the types, driving factors, and model methods) using earth observation imaging or non/imaging instruments, that is mainly focused on a specific site, rather than a global region (Ferreira et al., 2022).

In this context, the present deliverable aims to provide an overview of the main current contagious sources of environmental degradation; the scale and extent of the defined degradation sources at both terrestrial and marine levels; and the role of mapping approaches (from field /laboratory scale to the global one) in addressing knowledge gaps and driving advances in decision-making motivated by the recent and rapid developments in earth observation technology and the significant advantages of modelling algorithms. Hence, the first goal of this deliverable is to present a bibliometric analysis of articles focusing on environmental degradation research at the European scale focusing on the period 2016-2024. Bibliometrics is a technique that examines all articles that make use of the keywords in question, sorting them by document and source type, year of publication, language, subject area, and most active source titles. The second purpose of this document is to address based on the bibliometrics outputs, the main sources of environmental degradation resulting from land and coastal contaminants. Finally, the main common sources identified from environmental degradation analysis and presented within the aims of the RETURN project, were highlighted and, subsequent discussions about the mapping of these sources were conducted.

4.2 Research Method

The present deliverable aims to assess the main sources of environmental degradation, and the scale of processes of the identified sources. The outputs of the case study are presented based on network visualization and bibliometric indicators. Indeed, this research is built on a bibliometric analysis with the goal to highlight the advances/patterns of the academic bibliography on environmental degradation. We propose an essential contribution for quantifying, understanding, and visualizing trends in this academic field. As will be presented in the following sections, the analysis process includes mainly a study design, data collection, data visualization and analysis, and interpretation.

4.2.1 Bibliometric analysis

Bibliometric analysis is considered one of the most significantly established technique for the survey and investigation of the scientific research productivity, for a well-defined research field (Zyoud et al., 2017). As defined by (Pendlebury, 2010), bibliometrics also called *scientometrics*, is a key tool of quantitative analysis of science databases, generally utilized by university, policy makers, researchers, administrators, research directors and information specialist with the purpose of conducting research performance evaluation. The principle of the bibliometric studies is based on the computation of statistical analysis, from a collection of datasets englobing indicators inherent in publications i.e., authors, sources, geographical distributions and other varied indicators (Dabirian et al., 2016).

For the present study, the bibliometric analysis to measure documents information was conducted using both (i) VOSviewer, a freely available tool to construct and visualize the relationship of networks (www.vosviewer.com), and (ii) a software package *bibliometrix* based on R language.

This VOSviewer software can be used to build a mapping citation data extracted from the established databases e.g., PubMed, Scopus, and Web of Science. VOSviewer produces a visualization of network co-occurrence based on the terms extracted from the literature review. The software obliges a threshold signifying the least number of keywords that must be demonstrate together in a paper (Ciano et al., 2019). The extracted data could also be used to produce co-occurrence and co-authorship networks, based on information of authors, their institutional affiliations, and their respective countries. This allows the identification of the main institutions from which the publications originated, as well as in which manner those authors collaborated, based on their countries of origin. In this research, we utilized the VOS Viewer 1.6.20 software, developed by Leiden University in the Netherlands, to extract the co-authorship networks. For the co-occurrence networks, we limited the search to words occurring in titles and abstracts of the papers analyzed in this study.

The *bibliometrix* software package is a bibliometric software package developed in 2017 based on R language. It can be used for whole-process bibliometric analysis and visual display. The analysis of statistical data, co-occurrence, co-citation, and clusters on documents from the Scopus, Web of Science and other databases are attainable too. Combing the visualization capabilities of a variety of scientific mapping tools, *bibliometrix* performs a complete set of bibliographic data analysis and the interpretation of results (Aria et al., 2017). In this research, the *bibliometrix* software package is used to analyze and visualize the research status and research trends in the field of environmental degradation. In this research, we utilized the *bibliometrix* package to explain the basic laws of environmental degradation from the aspects of annual documents, research power (country, author, journal), research hotspots, and themes.

4.2.2 Data source

In order to achieve the objectives proposed in this research, the construction of a database of papers is the first essential step, and for this, the Scopus database "www.scopus.com" was utilized (accessed on 21 November 2023) to extract the necessary data for this analysis. Because the Scopus database is one of the most prominent academic databases available today, with over 25,100 titles, 5000 editors, more than 77.8 million papers, and tools for information integration, data exportation, and analytics; this study employs the Scopus database as a source for data collection (Vasconcelos et al., 2020; Viana et al., 2017).

The topical scope of this review was delimited to 'environmental degradation'. To build our database of relevant publications, we followed PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines for the document search as presented in Figure 1 (Moher et al., 2009). We selected search terms related with the proposed theme based on two major dimensions: the environmental problem and the geographic region of interest. Therefore, we utilized the expression ("environmental degradation" AND ("Europe"), following the keyword string: (TITLE-ABS-KEY (environmental AND degradation) AND (LIMIT-TOAFFILCOUNTRY, "Europe").

These search terms were required to occur in the paper's title, abstract, or keywords for all available publications until 2023. This Scopus searches generated a total of 31,759 documents (Figure 1). From the listed papers, we focused on Article, Conference paper, Review, Book chapter, and Book, and we excluded the remaining document types. We also excluded the papers published before 2016 and focused on the range time 2016-2024. A total of 19,748 documents were generated and analyzed.

Quantitative metrics of the bibliographic production from the Scopus database were exported such as the overall papers by subject area.

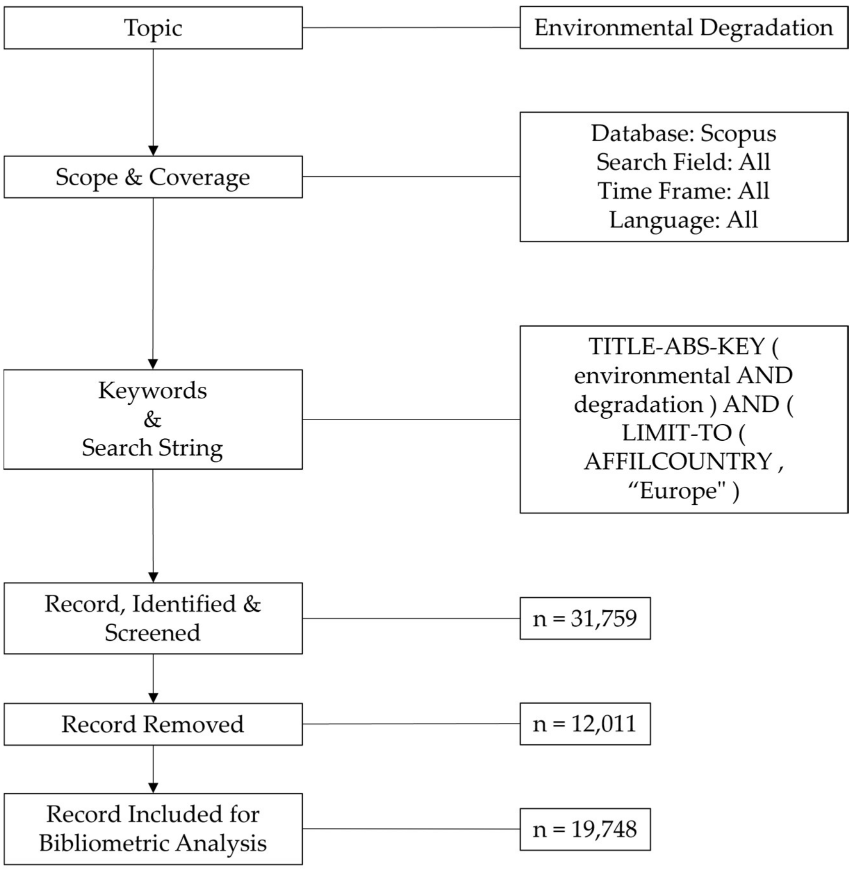

Figure 1 - PRISMA Flow Diagram.

4.3 Results and discussion on bibliographic search

4.3.1 Document types

Results of document type as presented in Table 1, show that most of the studies elaborated on environmental degradation were published as article (76.74%), followed by review (11.82%), and conference paper (5.81%). Others were found as a book chapter and book with 4.91% and 0.72% respectively.

Table 1 – Document Type.

Environmental Degradation		
Document Type	**Total Publications (TP)**	**Percentage (%)**
Article	15154	76.74
Book Chapter	970	4.91
Review	2334	11.82
Conference Paper	1148	5.81
Book	142	0.72
Total	**19748**	**100**

4.3.2 Distribution of Annual Documents

Research productivity is investigated in this research based on the total of documents produced per year. The annual distribution of document number reflects the overall situation and research trends, and the publication year examination of the documents empowers the researcher to comprehend the pattern of the chosen topic over time (Aidi et al., 2019). Research on environmental degradation was firstly published in the year 1968. The year 2022 was the highest year for publication in this area, with the total of the article published 3205 (16.23%). Followed by 2021 (15.02%), 2023 (13.85%), 2020 (12.97%) and 2019 (12.22%) (Table 2).

Table 2 – Environmental degradation research documents published from 2016 to 2024.

Environmental Degradation		
Document Type	**Total Publications (TP)**	**Percentage (%)**
2016	1548	7.84
2017	2066	10.46
2018	2253	11.41
2019	2413	12.22
2020	2562	12.97
2021	2967	15.02
2022	3205	16.23
2023*	2734	13.85
Total	**19748**	**100**

4.3.3 Documents by Subject Area (abbr: * data not complete but included to provide a preliminary first insight)

Table 3 summarizes the publications based on the subject area. It demonstrates that the largest number of publications were categorized under “Environmental Science” with a total percentage of 23.90% publications. This is followed by “Agricultural and Biological Sciences” (9.60%), “Engineering” (8.10%), “Chemistry” and “Social Sciences” (6% each). Other subject areas were below 6% of the total publications, including “biochemistry, genetics, and molecular biology”, “Materials Science”, and “Earth and Planetary Sciences”.

The outcoming results highlights the high trans-disciplinarity nature of environmental degradation studies.

Table 3 – Documents by Subject Area.

Environmental Degradation	
Subject Area	**Percentage (%)**
Environmental Science	23.90
Agricultural and Biological Sciences	9.60
Engineering	8.10
Chemistry	6.70
Social Sciences	6.30
Biochemistry, Genetics and Molecular Biology	5.90
Materials Science	5.30
Earth and Planetary Sciences	4.70
Others	29.5

4.3.4 Most Relevant Sources/Journals Regarding Environmental Degradation

The data of environmental degradation research are separately counted according to the number of documents by journal (Table 4). Figure 2 addresses the most active source of publications on environmental degradation. With the largest document number of 1016 among all journals, the journal Science of The Total Environment is known as a famous journal in the field of novel, hypothesis-driven and high-impact research on the total environment; and consider the main following subject areas as ecotoxicology and risk assessment, wildlife and contaminants, waste or wastewater treatment, nanomaterials, microplastics, and other emerging contaminants. Among the top 10 journals, Chemosphere, Environmental Science and Pollution Research, Journal of Hazardous Materials and Environmental Pollution are core journals in environmental science and environmental contaminant with emphasis on chemical compounds. Journals such as Journal of Environmental Management and Journal of Cleaner Production are core journals in managing environmental systems and improving environmental quality. The journal Water Research refers to the science and technology of the water quality, and its management worldwide.

Table 4 – Top 10 journals with regard to environmental degradation papers.

Environmental Degradation	
Source Title	**Total Publications (TP)**
Science of The Total Environment	1016
Chemosphere	485
Environmental Science and Pollution Research	339
Sustainability	321
Journal of Hazardous Materials	297
Journal of Environmental Management	266
Environmental Pollution	236
Environmental Science and Technology	212
Water Research	193
Journal of Cleaner Production	180

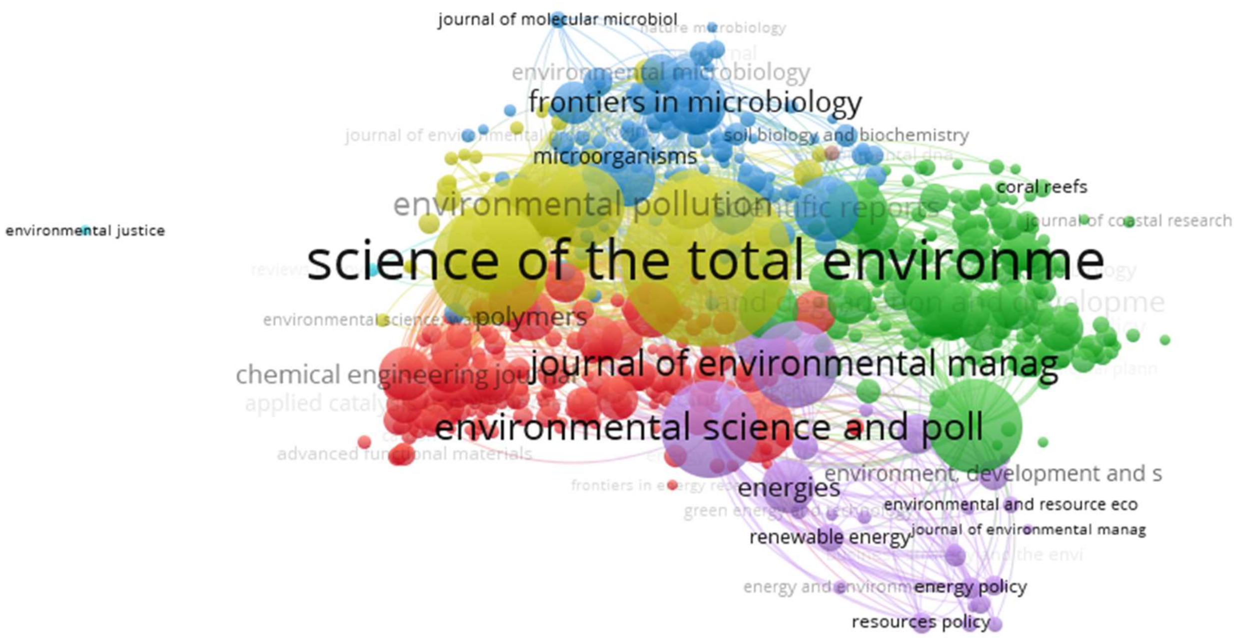

Figure 2 - Most relevant sources/journals regarding environmental degradation (Source: VosViewer).

4.3.5 Analysis of Keywords

4.3.5.1 Analysis of High-Frequency Keywords

Table 5 and Figure 3 show the top keywords that come out as a result of the bibliometric search. The most frequently appeared author keywords involved in the field of environmental degradation are degradation, climate change, land degradation, sustainable development, microplastics, and remote sensing.

The size of each word characterizes the total number of occurrences for the keywords. It is imperative to address that all of the keywords are trending words, or popular words used along with environmental degradation research studies. Thus, we can foresee that future research, investigating this domain, can be concentrated on these keywords.

In table 5 are reported (i) some general terms (e.g., degradation) of little use for this report, (ii) some specific terms related to process of recovery from environmental degradation (e.g., photocalysis, biodegradation), and eventually (iii) key drivers of environmental degradation. For the sake of this deliverable, we shall focus on this last category.

Between the main environmental degradation drivers, the following domains have been extensively studied: climate change, land degradation, microplastics, wastewater.

In view of RETURN objectives, in the footnote[1] we report a focus on some key drivers of special interest.

Table 5 – Analysis of high-frequency keywords as reported by authors of papers.

Author Keywords	Occurrences	Total Link Strength	Author Keywords	Occurrences	Total Link Strength
degradation	636	247	Bioremediation	272	127
biodegradation	561	232	Environment	230	171
climate change	552	298	ecosystem services	215	114
photocatalysis	437	190	**land degradation**	211	103
sustainability	348	186	**sustainable development**	186	109
environmental degradation	317	140	**Microplastics**	185	90

[1] Microplastics, among all the sources of environmental degradation in Europe, presented the highest frequency of mentioned keywords in the published research cases. In this respect, the accumulation and fragmentation of plastics have caused a conflict in managing and directing the deteriorated resources. According to (Bai et al., 2019; Huang et al., 2021), up to 368 million tons of plastic items were manufactured yearly in 2019, with output expected to reach 500 million tons by 2025. In addition, from the entire quantity of plastic waste production, a scares amount is recycled (9%), another part is directed to incineration processes (12%), instead the major remaining quantity is kept in natural environment or sent to landfill sites (Geyer et al., 2017). The majority of the plastic products are photodegraded rather than biodegraded, responsible of the constitution of microplastics, or traces of plastic with a particle size of lower than 5 mm (Ryberg et al., 2019; UNEP, 2018). In view of their detrimental impacts on the ecosystem services, above all oceans, microplastics are proving a developing matter of concern caused by their inappropriate disposal and monitoring operations. In fact, microplastics and nanoplastics exposure in the environment showed strong direct and direct effects on bivalves, copepods, echinoderms as well as auxiliary marine organisms' development and production (Yu et al., 2020; Zhang et al., 2020). Microplastics are considered an emerging environmental concern, and their pollution effects have aroused attention also on freshwater bodies (Dong et al., 2021; Li et al., 2020), wastewater (Patchaiyappan et al., 2020), airspace (Geng et al., 2021), sediments (Wang et al., 2018), and diverse terrestrial ecosystems (Tan et al., 2021). Recent studies proved that nano-/micro-plastics, in addition to their release of toxic additives in the ecosystem, are responsible of the adsorption of various chemicals thus behaving as sinks for different poisonous compounds favorizing their bioavailability, toxicity, and transportation (Amobonye et al., 2021).

Soil, water, and forest are the main land types of environmental degradation (Table 5). The United Nations Food and Agriculture Organization listed soil erosion and its process as the first item of the first category in the "World's Land Degradation Priorities Recommendation" (Xie et al., n.d.). In addition, in 2019, the United Nations reported a drastic soil loss of greater than 24 billion tonnes per year around the globe. The serious increase and dispersion of soil erosion is defined as a challenging sustainability restricting problem through causing a menace to several ecosystems domains, i.e., agricultural production, water quality, hydrology, and other systems. Regarding the case of agricultural areas and considering that land management practices influence hugely the degree of erosion, soil erosion was perceived more advanced on arable land compared to non-arable land. Water erosion and wind erosion accounts for 56% and 25%, respectively global soil degradation (AbdelRahman, 2023). The fine materials produced from the eroded sediments caused by erosion processes, by eventually reaching surface-water bodies, are creating high sedimentation problems that then can led to flooding (Serra et al., 2022). Moreover, in the case that those eroded sediments also contain pesticides or fertilizers, degradation of downstream water quality caused by the consumption of these contaminants by aquatic organisms is also tending to arise. Climate change effects on the environment enhanced the frequency of extreme weather events and hence lead to a drastic spatially differentiated changes in the extent, intensity, and frequency of soil erosion (Seneviratne et al., 2011). A spatio-temporal dynamic management of soil erosion extent and intensity is imposed. The continuous evolution and advancement of quantification tools lead to highly settled information that are available on different scales. Modelling approaches are commonly used for the quantitative measurement of soil erosion. Though, considering the big number of inputs/parameters required by physical and distributed modelling of the soil erosion process and the limited practicality, the USLE/RUSLE model is the most generally used.

Biodiversity	182	128
Conservation	161	76
wastewater treatment	159	113
remote sensing	158	83
soil	158	120
toxicity	156	123
photodegradation	141	77
pollution	137	124
wastewater	131	102
economic growth	123	88
renewable energy	123	61
agriculture	122	120
adsorption	121	108
deforestation	120	80
pesticides	117	109
redd+	115	61
pharmaceuticals	112	115
circular economy	109	49
water quality	104	41
soil degradation	93	40

biochar	92	63
land use	92	72
environmental remediation	91	59
groundwater	91	62
soil erosion	90	45
phytoremediation	89	48
restoration	88	47
heavy metals	86	50
bacteria	83	76
resilience	81	46
water treatment	81	57
advanced oxidation processes	79	61
urbanization	76	55
transformation products	75	58
fungi	71	77
remediation	69	63
water	58	56

The title and abstract from the documents gathered were analyzed using the full counting method via VOSviewer software. The binary counting method is a method where the occurrence of a noun in an article is calculated based on a specific number of times (Waltman et al., 2013). The visualization of the noun occurrences based on the title and abstract is displayed in Figure 3. The strength of the occurrences is indicated by the size of the nodes, while the strength of the relationship is displayed by the thickness of the lines between nodes. Related words are grouped to show their relationship. The results of the analysis show a set of groups of special interest. Between them photocatalysis, bioremediation, climate change, are sustainability are distinguished. The VOSViewer analysis highlights the presence of five major groups of keywords. The differentiation between the groups of keywords is exposed by five community of colors. The main keywords communities are: (i) biodegradation, bioremediation, and germs, (ii) climate change, ecosystem services, and forestry, (iii) environmental degradation and the economic impact, (iv) photocatalysis and chemicals, and (v) degradation materials.

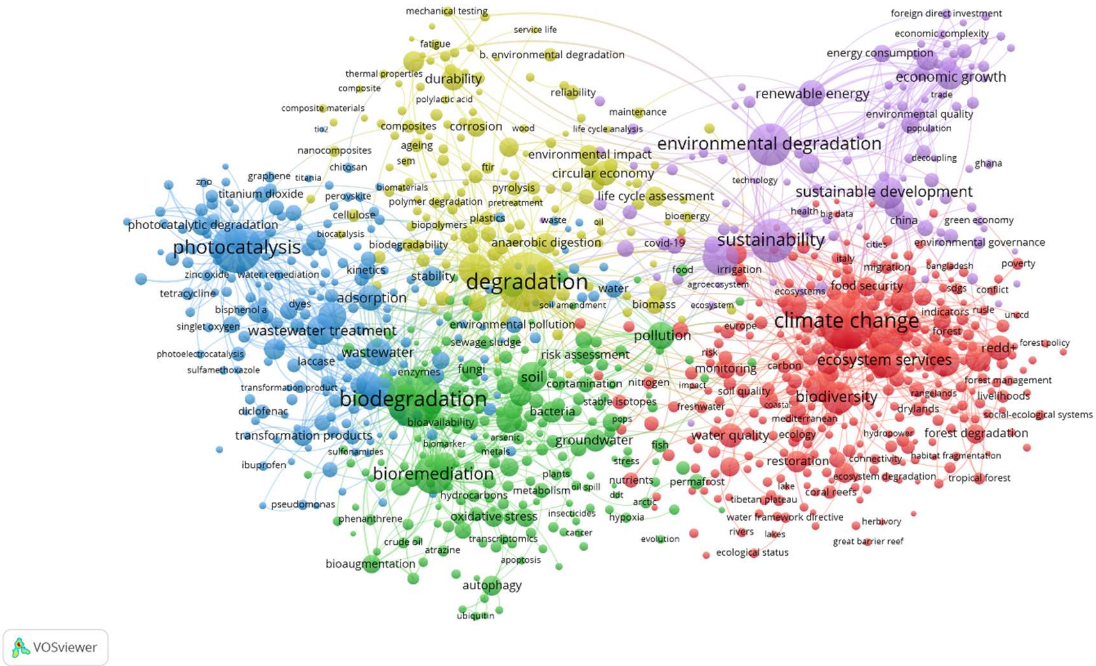

Figure 3 – VOSviewer visualization of a top term co-occurrence network based on title and abstract fields (top 1000 Author Keywords).

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4.3.5.2 Cluster Analysis and Multiple Correspondence Analysis of High-Frequency Keywords

In bibliometrics studies, the cluster analysis is defined based on the frequency of simultaneous occurrence of keywords, using statistical methods with the goal to simplify the complex keyword network relationship into several relatively small groups (Ding, 2011). Multiple correspondence analysis (MCA) is a commonly used sociological approach. It compresses large data with multiple variables into a low-dimensional space to form an intuitive two-dimensional (or three-dimensional) graph that uses plane distance to reflect the similarity between the keywords. Keywords approaching the center point indicate that they have received high attention in recent years. The nearer to the edge, the narrower the study theme, or the transition to other themes (Figure 4) (Mori et al., 2016). Cluster analysis results in relation to the environmental degradation research field can be summarized as follows:

- The first main group of clusters is principally associated with studies in wastewater, wastewater treatment, microplastics, toxicity and pesticides.
- The second general category of cluster is mainly concerning the monitoring of dynamic changes of forest degradation (deforestation) based on remote sensing. Deforestation management research studies, presenting a scientific basis for research-based afforestation and rational conservation supports fully derive the potential of forest land production, achieve the balance of forest ecosystems, improve regional ecosystem services, scientifically formulate land degradation management plans, and realize the sustainable development of forestry management under climate change impacts. Hence, it is essential to periodically assess the spectral characteristics of those areas and their associated spatial and temporal indicators.
- The third main category of cluster is in relation with the research of environmental degradation and sustainable development of land resources. While fully guaranteeing the current land productivity level, it is mandatory to protect its related resources in time without harming its development. Hence, maintaining and enhancing land resource productivity, reducing land production risk, preventing land and water quality degradation, and protecting the potential of natural resources are the main keys to ensure land environmental development goals.
- The fourth group of clusters englobe keywords from the above-mentioned categories. Indeed, the fourth category of clusters, situated at the center of the graph, could be considered as a summary of the main principle occurred keywords.

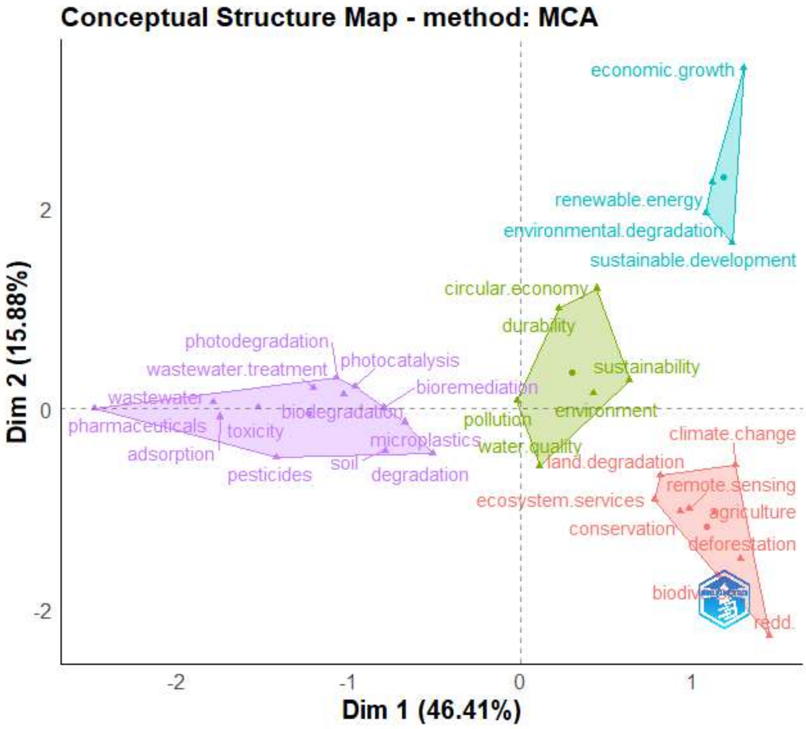

Figure 4 – Cluster Analysis (Multiple correspondence analysis – MCA) of High-Frequency Author Keywords.

4.3.6 Geographical Distribution of Publications

This conducted bibliometric research is considering also the most active countries (here we recall that our subset of analysis refers to papers engaging European countries) in publishing documents related to the environmental degradation. Table 6 highlights the top contributing countries where Germany, China, Italy, United Kingdom, and Spain are the top five co-involved countries with more than 1300 publications.

The percentage of published papers in each country reflects the importance, influence, and the direction of the country in the field of environmental degradation. The outputs of Table 6 reveal that Germany and Italy are among the top European countries that play a leading role in the field of environmental degradation research. Many factors contributed to the rank of Italy on the top countries producing research on environmental degradation. Indeed, the overall Italian environmental situation is presenting that the south-mediterranean country is facing environmental degradation from different sources.

On the base of this bibliographic research findings and in view of RETURN focus on Italy, in the footnote[2] we report a focus on Italian key items concerning environmental degradation.

Table 6 – Top Countries contributed to the publications.

Environmental Degradation				
Country	**Total number of publications**	**Percentage (%)**	**SCP**	**MCP**
Germany	1574	9.02	873	701
China	1563	8.95	32	1531
Italy	1546	8.86	1049	497
United Kingdom	1414	8.1	729	685
Spain	1389	7.96	868	521
Australia	1338	7.66	763	575
France	1038	5.95	633	405
Poland	856	4.9	681	175
Usa	484	2.77	23	461
Netherlands	420	2.41	194	226
Greece	380	2.18	286	94
India	377	2.16	5	372
Switzerland	326	1.87	149	177
Sweden	318	1.82	156	162
Czech Republic	297	1.7	191	106
Denmark	287	1.64	129	158
Romania	257	1.47	212	45
Belgium	255	1.46	104	151
Brazil	254	1.46	9	245
Finland	198	1.13	89	109

SCP: Single Country Publications
MCP: Multiple Country Publications

2 Soil is defined as a limited and very vulnerable resource, facing the challenge of its highest degradation in Italy (Environmental Implementation Review, 2022). Soil protection, sustainable soil management and restoring degraded soils are among the Italian management policies in order to achieve the following entails: (i) preventing further soil degradation; (ii) making sustainable soil management the new normal; and (iii) taking action for ecosystem restoration. The net land take concept combines land take with land return to non-artificial land categories (re-cultivation). The ranking of Italy between the European countries, on net land take, is situated above the average, with 55.2 m2/km2 in 2012-2018 (against the European average of: 83.8 m2/km2) (European Environment Agency, 2023). A preliminary challenge that contributed highly in strengthening biodiversity, is the establishment of forests. Within the Italian territory, forests cover an area equal to 29.97% of land, where over 90% of the statistics show surfaces in a bad to poor status (Environmental Implementation Review, 2022). A significant reduction of the impact of pressures on coastal and fresh waters is required to substantially reduce the negative impacts on sensitive species and habitats in marine ecosystems and to achieve good environmental status. Additionally, ensuring a good status of water bodies will have considered impacts on the efficient management and sustainability of the nutrient cycle. In Italy 41.8% of all surface water bodies achieved acceptable ecological status and 71.7% have good chemical status (WISE Freshwater, 2020). For groundwater, 30.3% failed to achieve good chemical status and 19.0.% are in a poor quantitative status. It is worth mentioning that Italy attained a notable reduction (24.8%) in industrial heavy metals releases like Cd, Hg, Ni, Pb (European Environment Agency, 2023). The increasing demand for water for multiple purposes and the intensification of severe weather conditions due to climate change have put a significant strain on freshwater supplies in Italy. Another challenge causing water degradation in the country is the fact that agriculture is abstracting 42.15% of water, which is accompanied by a high leakage rate in its water supply system (42% leakage rate in 2018), with issues particularly in the south of the country with Campania at 46.7%, and Sicily at 50% (ISTAT, 2021).

The main environmental policies implemented by the Italian government considered an improvement of the waste management and wastewater treatment, and the implementation of site-specific conservation techniques.

4.3.7 Environmental degradation at the European Region (Terrestrial and Marine scales)

In order to analyze environmental degradation processes over terrestrial and marine ecosystems an additional bibliography search was conducted on Scopus, considering 'Terrestrial Environment Degradation' and 'Marine Environment Degradation' (using these terms as topic).

In Figures 5 are given the results from this new bibliographic search reporting the most frequent keywords involved in the field of terrestrial and marine environmental degradation.

Environmental Degradation

Sources

Terrestrial Environmental Degradation

Degradation	183
Biodegradation	162
Climate Change	116
Soil Pollution	116
Environmental Degradation	106
Toxicity	73
Plastic	68
Bacteria	59
Forestry	50
Microplastic	50
Unclassified Drug	50
Soil Pollutant	48
Microplastics	47
Plastics	44
Microbial Community	43
Microbial Degradation	41
Deforestation	38
Anthropogenic Effect	37
Microbial Activity	37
pH	37
Pesticide	26
Ecotoxicity	23
Gas Chromatography	22
Urbanization	22
Soil Microflora	20

Marine Environmental Degradation

Degradation	603
Biodegradation	594
Marine Pollution	393
Water Pollutant	342
Water Pollutants Chemical	334
Plastic	298
Climate Change	276
Bacteria	265
Bacterium	247
Unclassified Drug	223
Microbial Community	195
Petroleum	180
Microplastic	177
Hydrocarbon	164
Toxicity	142
Water Quality	142
Plastic Waste	140
Eutrophication	137
Salinity	108
Gas Chromatography	105
pH	77
Ecotoxicology	68
Oil Spills	62
Heavy Metal	50
Petroleum Pollution	49

Figure 5 - Analysis of high-frequency keywords in relation with "Environmental Degradation".

This analysis gave as results (i) generic terms highly correlated with the search terms and thus having little interest (e.g. Degradation, Environmental Degradation, etc.), (ii) broad drivers or processes connected to environmental degradation (.e.g climate change, biodegradation, toxicity), (iii) more focused drivers of environmental degradation (e.g. soil pollution, microplastic, deforestation).

On the base of this list in figure 5 and focusing on RETURN objective we produced a small focus on key examples of environmental degradation processes of particular interest in RETURN, namely plastics, wildfire e pathogens. These 3 groups are just exemplative cases of the environmental degradation at very diverse scale. In addition, we plotted the resulting papers organized in the three above categories into the following sections which are of a special interest for RETURN: namely Database, Mapping, Transport Model, Innovative Modelling approaches. These can give a global view of the effort of the research in these domains.

Then in the following sections (section 4.3.8 and section 4.3.9), a detailed analysis of few examples of degradation sources found at both terrestrial and marine components resulted from the bibliometric analysis and the degradation sources highlighted on the ambient of the RETURN project is presented.

4.3.8 Terrestrial Environmental Degradation

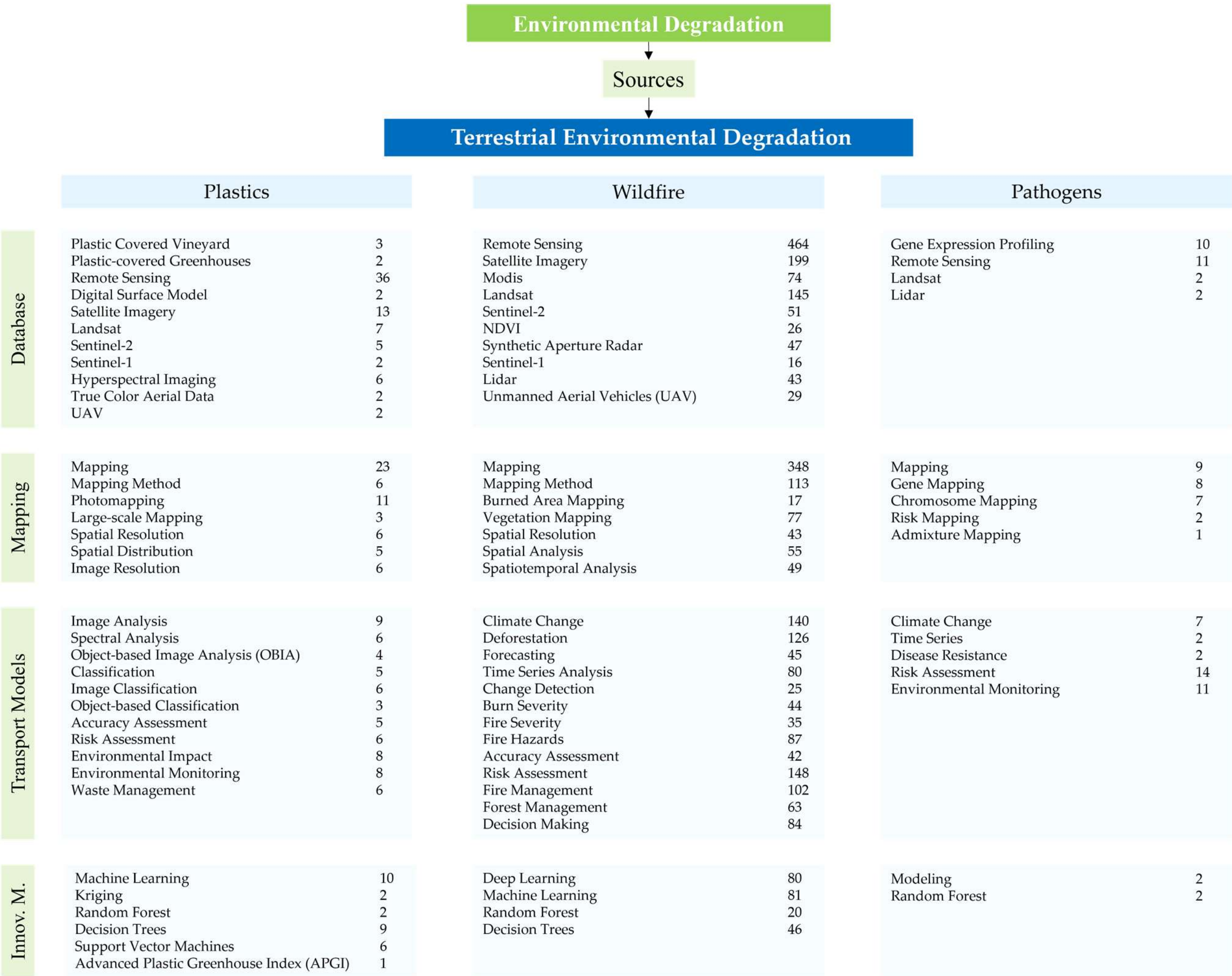

Figure 6 - Analysis of high-frequency keywords in relation with "Terrestrial Environmental Degradation".

4.3.8.1 Plastics

Microplastics (MPs) in terrestrial environment are known to have substantial impacts on soil ecology and agricultural productivity. Accordingly, it is critical to set an efficient, accurate, and reliable assessment methodology of MPs in terrestrial areas. Figure 6 shows that the most frequently appeared groups of keywords involved in the field of terrestrial plastics can be grouped as: (i) field-based database: Plastic-covered Greenhouses and vineyards; (ii) remote sensing database: Landsat, Sentinel-2, Hyperspectral Imaging and UAV; (iii) mapping scales: large-scale mapping; and (iv) innovative management techniques: Machine Learning and Decision Trees.

A more detail accounting of the publications produced under this theme is given in the following note[3].

[3] The presence of plastics in the environment is of rising interest and presents a pressing environmental issue, especially due to the worldwide diffusion of single-use plastic in supply-chains and microplastics releases (Welden, 2020). The current situation, accompanied with incorrect disposal, results in further contamination of terrestrial environments. In 2010, the European plastics industry produced 57 million tonnes of plastic, that represents 21.5% of world production. Five percent of this amount was dedicated to agriculture (Briassoulis et al., 2013). For this purpose, European environmental policies are addressing plastic consumption and the resulting pollution. Following this path, the European Green Deal (European Commission, 2019) includes as political guidelines reducing intentionally added microplastics and unintentional releases of plastics.

Laboratory-based spectroscopy approaches for microplastics assessment such as Scanning electron microscopy, Fourier transform infrared spectroscopy (Simon et al., 2018) and Raman spectroscopy (Anger et al., 2019), were used for MPs estimation. Even though these techniques showed advantages in determining chemical compositions, laboratory spectroscopic techniques are usually labour-intensive, and time and cost consuming (Shi et al.,

4.3.8.2 Wildfire

Although wildfire is an integral part of certain ecosystems, many regions of Europe are facing increasing challenges managing wildfires that are mainly caused by frequent drought and heat wave events as a result of climate change (Abatzoglou et al., 2019; Costa et al., 2020).

A more detail accounting of the publications produced under this theme is given in the following note[4].

2022). Moreover, in order to ensure the mapping of the MPs, laboratory-based spectroscopy need to be coupled with geographic information systems (GIS) approaches.

The identification of the amount and degree plastics waste in the terrestrial environment based on the use of free-of-charge spaceborne earth observation techniques have the potential to map the degradation source at large-scale, thus reducing on-the-ground manual investigation. Indeed, satellite imaging systems have the potential to identify plastic products based on their unique spectral signature. Following these approaches, the assessment can be computed based on the plastic type-specific absorption bands. Most of the publications highlighted the importance of the use of multispectral optical imaging satellites i.e., Landsat and Sentinel-2 (Figure 6), for the mapping of plastic litter in the environment. Landsat satellites are characterised by an earth revisit time equal to 16-days, and a spatial resolution of 30 m (Lanorte et al., 2017). In this regard, Lavender (2022) developed a Machine Learning-based classifier (including an Artificial Neural Network and post-processing decision tree) based on Sentinel-1 and Sentinel -2 data; created a dataset with terrestrial cases by digitizing varying landcover classes alongside plastics under the sub-categories of greenhouses, plastic, tyres and waste sites; and generated high accuracy statistics in mapping the occurrence of plastic waste in terrestrial environments. The findings of Lanorte et al. (2017) revealed encouraging accuracy assessment while estimating plastic waste by means of Support Vector Machines and Landsat 8 imagery. Even though low-moderate spaceborne images are useful in detecting plastic waste, the recent availability of very high-resolution data proved to be very suitable for the mapping of plastic coverings. Thus, depending on the area size of the studied objects, the proper imagery datasets can be detected. Hyperspectral earth observation systems were largely considered in plastic research cases with the objective to assess the size, shape, texture, material composition, morphology, and the spatial distribution of different parameters (Lodhi et al., 2019). The authors of (Schmidt et al., 2023) compared both multispectral imaging systems and hyperspectral sensors in differentiating plastics from other land cover types, and showed the importance of the narrow shortwave infrared bands in the diagnostic of plastics.

Another important factor that appeared in a number of articles is the adequate management of Plastic-covered Greenhouses. An extensive and steadily expanding use of plastic in agriculture, and particularly in protected horticulture, has been reported in the European area. Plastics consumed within the agriculture sector constitute around 2% of the total consumption of plastics in in Europe per year (EUPC, 2007). However, in these countries, there are often inefficient management schemes, with data on the use of plastics in agriculture challenging to obtain. As a matter of fact, a major part of agricultural plastic waste is either buried or ended up in landfills, which in both cases represents a huge threat being a cause for soil contamination and degradation of soil quality characteristics (Briassoulis et al., 2010). Proper mapping and monitoring of Plastic-covered Greenhouses can be particularly beneficial for their proper reuse from an expired greenhouse as a sustainability perspective to mitigate plastic pollution after the harvesting season. Plastic-covered Greenhouses' monitoring can help policymakers mitigate environmental issues directly related to agricultural plastic residues. The advancement in image processing algorithms, e.g., pixel-based, object-based, and Machine Learning approaches presented promising results for the mapping of land use changes in plasticulture areas (Veettil et al., 2023). Remote sensing of plastic coverings is a particular field of application of the automatic mapping techniques of land use due to several peculiarities; it depends strongly on the spatial, temporal and spectral characteristics of the considered objects and of the sensor due to: the similarity of plastic agricultural equipment to other terrestrial objects, the change of the spectral signal of the plastic with the underlying vegetation reflectance properties; and the seasonally dependent use of plastic covering films (Agapiou et al., 2016; Aguilar et al., 2014; Novelli et al., 2016).

As indicated in Figure 6, diverse documents highlighted the importance of the spatial resolution/large-scale mapping in relation with plastic waste mapping. Actually, despite the efforts to expand knowledge in the field of plastic detection and classification, a number of difficulties with regard to the spatial resolution of the litter are still rising. Due to the limited coverage of plastic per pixel that occurs in the majority of the study cases, sensors characterized by a relatively low spatial resolution may make it difficult to detect targeted plastic litter from spaceborne imaging systems. Additionally, the signal-to-noise ratio of operational sensors may also raise concerns for this kind of application (Hu, 2021). Higher spatial resolution in plastic waste research allows for more detailed monitoring of pollution and also provides ways to cancel local microplastics. Although it is possible to deploy airborne hyperspectral sensors that cover the entire electromagnetic spectrum, data collection campaigns may be more expensive and require additional legal procedures. Additionally, data processing consumes more resources compared to multispectral images. In an experiment considering the spatial resolution of the input imagery, Iordache et al. (2022) have shown that the detection of areas polluted with plastic is not only dependent on the spectral-spatial responses of the scanned pixels, but also on the spatial distribution of the contained materials. In other words, mixed pixels containing waste in images with low spatial resolution require adjusting the training data or considering ways to analyse the subpixel composition, such as spectral unmixing. In their research, Iordache et al. (2022) concluded that the discrimination power between litter and natural materials decreases with the degradation of the spatial resolution. When the spatial resolution degrades, more spectral mixing occurs in the area of plastic litter. The problem of mixed pixels can be addressed by including mixed spectra in the training database during the training phase, or by using other techniques based on pure pixels e.g., sparse spectral unmixing (M. D. Iordache et al., 2011; M.-D. Iordache et al., 2011).

[4] Heat waves and forest fires are frequently considered hugely related risks as extreme temperatures play a key part in both events. Forest fires are a familiar issue in Europe (Fernandez-Anez et al., 2021), where most of the burned areas have historically been found in the Mediterranean region (Khabarov et al., 2016; Migliavacca et al., 2013). In this context, 2022 registered the most severe drought for 500 years in Europe, which coincided with an extreme fire season in which a burned area of about 8600 km2 was reported by the European Union (Schumacher et al., 2022). In addition, forest fire models forecast an enlargement in anticipated burned zone and related emissions under future climate scenarios in Europe (Khabarov et al., 2016; Migliavacca et al., 2013). For a better comprehension of the impacts of wildfires, the basis of the fires surveilling systems is the detection and analysis of active fires, burned areas mapping, and the assessment of fire severity, and pre- and post-fire conditions (Lentile et al., 2006). Changing fire regimes impact ecosystem resilience and ecosystem services, including carbon storage, water provision, and erosion protection (Bowman et al., 2020). EU's biodiversity strategy for 2030 is threatened by this fire changing regime, as observed from the 2021 and 2022 fire seasons in Southern Europe and in the Mediterranean biome in general (European Commission, 2020).

Timely and accurate information on ongoing wildfire activity is a crucial requirement for effective decision-making regarding fire hazards and management. Single vegetation and soil indicators can be used to thoroughly assess the severity of a fire in the field (Hammill et al., 2006). On-ground assessment of severity methodologies is used to estimate index values that outline general fire impacts within an area, that can be defined also as the the average burn condition on a plot. Field data makes it possible to sample a representative number of plots over sizable areas. The main goal is to cover as many fire effects and biophysical settings as possible in order to accurately represent the range of variation found within burns (Carl H. Key et al., 2006). Nevertheless, due to the time and resource costs, evaluating large fires based only on field-based indicators is not practical. Independent of the quality of those methods, some of these studies deployed experimental systems, what hampers the operational application for forest surveys and monitoring extents (Szpakowski et al., 2019).

The analysis of the high-frequency keywords described in Figure 6, reveal the huge importance of remote sensing techniques for wildfire studies. Compared to conventional field surveys, remote sensing has shown higher accuracy in mapping forest fires on a regular basis. This is particularly relevant considering recent developments in remote sensing data acquisition and fusion techniques. Remote sensing provides the opportunity of analysing conditions and monitoring changes over large geographic extents, making it useful for studies in fire ecology. As confirmed by the bibliometric analysis, these measurements have been used to assist respectively in (i) fire risk assessment (Gerdzheva, 2014; Jan M Baetens et al., 2022), (ii) fire hazards (Heisig et al., 2022; Laneve et al., 2020), (iii) burn and fire severity (Morresi et al., 2022; Nolè et al., 2022; Schepers et al., 2014), and (iv) burned area mapping (E. Chuvieco et al., 2012). As described below, we will discuss each case separately while referring also to their adequate remote sensing assessment technique and resolution. It is worth mentioning that the bibliometrics presented three main categories of remote sensing sensing systems for wildfire research which are space-based multispectral sensors (i.e., Modis, Landsat and Sentinel-2), followed by Radar and Lidar data, and UAV sensors.

Remote sensing has been used extensively in recent studies to evaluate vegetation conditions, classify land cover, provide elevation data, and validate proposed risk assessments related to wildfires. Given its correlation with fuel types and characteristics, landcover is a critical factor in assessing an area's potential risk of fire events (Vilar et al., 2021). Multispectral based remote sensing information, when paired with other spatial data, enables researchers and land managers to evaluate the risk of fire propagation and ignition for different spatial extents. Given that long- and short-term mapping require distinct spatial and temporal resolutions, selecting the right sensors for fire risk mapping is crucial. Since long-term fire risk maps are not updated regularly, a high temporal resolution is not required. In this context, sensors characterised by a high to moderate spatial resolutions, e.g., Landsat, are capable of providing data for mapping the required inputs for long-term fire risk maps. A spatial resolution at the range of 30 m is considered adequate for classifying inputs such as land cover/land use and so is appropriate for long-term risk maps. For short-term fire risk mapping a higher temporal resolution is required (daily). While it is possible to map the required variables with the previously mentioned sensors, the low temporal resolution limits the user's ability to rapidly update dynamic conditions. As a result, it may be more appropriate to use coarser spatial resolution sensors (>100 m) which have more frequent revisit intervals, such as MODIS (2 days). The sensors onboard the Sentinel-2 satellites have a revisit interval of three to five days, which makes these systems capable of weekly updates to fire risk maps. For short-term mapping, a combination of sensors may be most appropriate, using high to moderate spatial resolution sensors to map static conditions while using coarse spatial resolution sensors to rapidly (daily) update dynamic conditions.

The burn severity in areas affected by wildfires is an important measure of fire's impact on the landscape. All ecosystems and in particular ecosystems in European-Mediterranean climates are affected by fires. For an appropriate planning and management of post-fire response, two main key tools are fundamental i.e., a comprehension of the drivers mostly affecting burn severity trends and accurate mapping of the post-fire consequences. Burn severity is commonly measured in the field using the composite burn index (CBI), which involves an optical assessment of burned areas to determine the fire impacts on ecological conditions. Due to the requirement for a systematic method to evaluate burn severity among various environments, the CBI was developed to provide visual assessments to be conducted by rating the extent of fire damage, as well as the estimated vegetation recovery for the investigated area. CBI estimates are time dependent and demand on-site visits of the burned sites in order to carry out the assessments. Although required, field-based burn severity monitoring is time- and resource-consuming. For that reason, remote sensing-based assessment is currently widely used. Examples include the European Forest Fire Information System (EFFIS, http://effis.jrc.ec.europa.eu) and many research studies (Fernández-García et al., 2022; Quintano et al., 2018). High to moderate spatial resolution imagery is necessary for burn severity assessments since coarser resolutions are unable to recognize patterns in burn severity. This makes sensors on the Landsat series and the Sentinel-2 sensors ideal for burn severity detection. These sensors' long temporal resolution is a restriction that makes it challenging to rapidly collect data on post-fire conditions. Another limitation of the passive satellite sensors is their incapacity to penetrate the forest canopy (Keane et al., 2001). For this purpose, UAV and Lidar techniques may provide effective substitutes to orbital sensors. Fine resolution LiDAR data can provide pre- and post-fire forest structure metrics, which can be altered to various extents based on the degree of the burn. The findings of (García-Llamas et al., 2019) in their study to evaluate whether LiDAR can be a valid tool for understanding how pre-fire vegetation structural characteristics control fire severity, highlighted the potential of low-density LiDAR for evaluating fuel structure throughout the coefficient of variation of heights and concluded the applicability of using pre-fire vegetation structure measurements from LiDAR data for predicting burn severity, as a valid complement to spectral satellite measurements. In order to map the severity of burns, some studies have combined multispectral and hyperspectral imagery with post-fire LiDAR data. Fernandez-Manso et al. (2019) explored the relative influence of pre-fire vegetation structure and topography on burn severity compared to the impact of post-fire damage level and evaluates the utility of the Maximum Entropy (MaxEnt) classifier trained with post-fire EO-1 Hyperion data and pre-fire LiDAR to model three levels of burn severity at high accuracy, on a large fire in central-eastern Spain; and demonstrated the validity of MaxEnt as one-class classifier to model burn severity accurately in Mediterranean countries, when trained with post-fire hyperspectral Hyperion data and pre-fire LiDAR. UAV technology is being adopted by fire researchers to rapidly analyze fire occurrence with innovative approaches. This technology has recently been applied to research focusing on burn severity assessment (Correia et al., 2020). UAV sensors provide a means to acquire hyperspatial datasets at temporal intervals determined by the user. While the limited options for UAS cameras is improving, most current UAV research has been limited to the visible wavelengths, which restricts the types of indices that can be derived from the data (Pérez-Rodríguez et al., 2019). Even though hyperspectral imaging was not mentioned as frequent used keywords on the studies of wildfire mapping, Quintano et al. (2023) revealed that the availability of spaceborne hyperspectral data has great potential to provide fire severity estimates that align with post-fire management needs, overcoming complex logistics and data acquisition costs of airborne hyperspectral sensors, and the suboptimal sensitivity of broadband data to several post-fire ground components. Results revealed that continuum fire severity estimates using PRISMA data clearly outperformed those based on Sentinel-2, the spaceborne mission with multispectral band setting capabilities that has previously provided the most reliable results. Also, the PRISMA-based classification of fire severity was accurate and solved the typical confusion between moderate and low/high fire severity categories when using broadband multispectral data.

Burned area estimates are of critical importance for land managers, climate scientist, and policymakers. Burned area estimates provide accurate spatial representations of fire extents and perimeters. Accurate maps of the areas affected by wildfire are needed for rehabilitation planning, calculating the economic and environmental cost of fires, and for regional and global scale estimates in gas and particulate emissions (Fiorucci et al., 2008; Laneve et al., 2020; Sirca et al., 2018). In fact, accurate data on burned area is essential to determine the factors influencing the changes in fire activity (Andela et al., 2017), estimate fire risk (Lasaponara et al., 2018), and create techniques for predicting fire risk (Turco et al., 2018). Depending on the extent and objective of the assessment, numerous methods are employed to estimate the burned area. Remote sensing technologies provide a means for estimating and mapping burned area at local, regional, and global scales (Szpakowski et al., 2019). At a local scale, burned

4.3.9 Marine Environmental Degradation

Figure 7 groups the most frequently appeared keywords involved in the field of marine environmental degradation, for the case of plastics, eutrophication and pathogens.

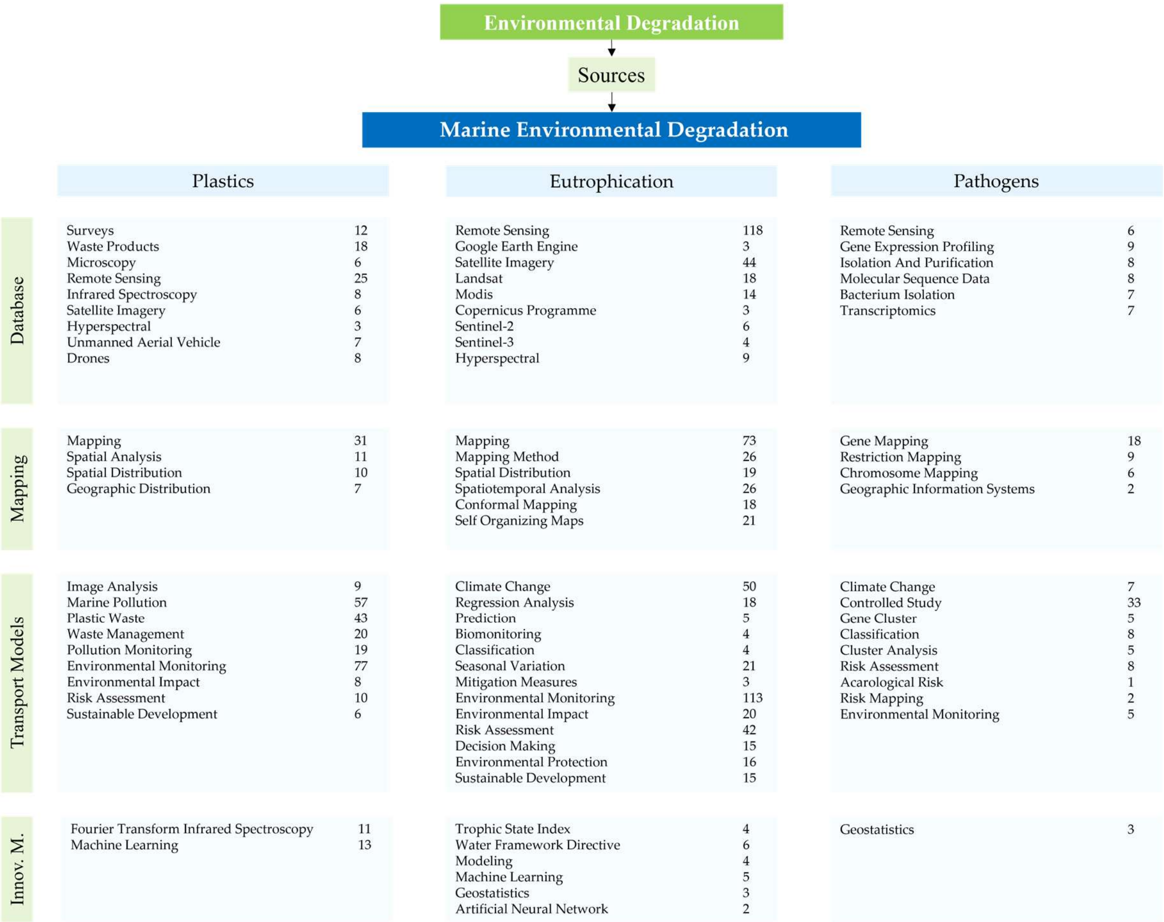

Figure 7 - Analysis of high-frequency keywords in relation with "Marine Environmental Degradation".

4.3.9.1 Plastics

Statistics revealed that within the marine environment of the Mediterranean sea, 3760 t of marine plastics are currently floating on the sea surface, of which 84 % are likely to end up on beaches and the remaining 16 % will end up sinking to the seafloor or are neutrally buoyant in the water column (Tsiaras et al., 2021). This situation imposes a growing global concern over the chemical, biological and ecological impacts of marine plastic pollution on the environment. In the European scale, the Marine Strategy Framework Directive is the main legal instrument to protect the European's marine environment (Frantzi et al., 2021). In this framework, marine litter is one of the eleven qualitative listed descriptors, that is targeted toward achieving Good Environmental Status. To address important scientific queries about the origins,

area estimates can be performed using high and moderate spatial resolution sensors. These sensors are typically used for change detection via spectral index generation and image differencing (Bastarrika et al., 2011). At regional and global scales, coarse spatial resolution orbital sensors, e.g., MODIS are particularly suitable due to their ability to gather data among vast areas over short time periods. In view of this, the majority of regional and global burned area products are produced by analyzing data from coarse spatial resolution orbital sensors, in order to have dense time series, like the FireCCI51 product (Lizundia-Loiola et al., 2020) and the MCD64A1 product (L. Giglio et al., 2018) at 500 m, both derived from MODIS images observation. The FireCCI51 project, which is part of the European Space Agency (ESA) Climate Change Initiative (CCI), has developed long-term time series of burned area products at 250 m. In Italy, since summer 2019, a fully automatic end-to-end processing chain for near real-time burned area mapping from Sentinel-2 data is employed in pre-operational mode by the Italian Department of Civil Protection. Based on change detection, the processor, named AUTOBAM (AUTOmatic Burned Areas Mapper) (Pulvirenti et al., 2020), generates burned area maps in 6-7 hours. The detection of small fires (less than 100 hectares) is the only drawback of the coarse-resolution data (e.g., 250–500 m) used to generate global burned area products (Emilio Chuvieco et al., 2022).

distribution, and movement of plastic in the ocean, efficient mapping and monitoring of plastic objects is required.

Three main groups of techniques could be distinguished from the bibliometrics: (i) laboratory infrared spectroscopy, (ii) spaceborne sensors, and (iii) Unnamed Aerial Vehicle (UAV).

A more detail accounting of the main findings from publications produced under this theme is given in the following note[5].

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[5] Infrared spectroscopy has evolved into a key instrument in the identification of microplastics in environmental samples. Reflectance Fourier Transform Infrared spectroscopy is a perfect approach to recognize micro-plastics given its non-destructive nature, modest sample preparation requirements, and ability to produce IR absorption spectra for thick and opaque materials (Ojeda et al., 2009). Furthermore, reflectance-FTIR spectroscopy may present an alternative to present microplastic analytical methods, since it provides spatially resolved chemical particularity (enabling to identify the particle size, abundance and polymer identity); prevents the issues related to complete infrared absorption by larger particles; and lacks the need for costly infrared-transparent substrates (Willans et al., 2023). In this regard, the capability of spectral reflectance information to discriminate plastic from other targets was driven by the research of (Tasseron et al., 2021). In their publication, the authors provided a hyperspectral laboratory setup to gather spectral signatures of forty microplastic products and recognized absorption peaks of plastics on the 1215 nm and 1410 nm. Still, the analysis of environmental microplastic particles using FTIR microscopy remains a challenging task due to spectral distortion caused by irregularly shaped particles and non-uniform refractive indices in heterogenous samples, as well as the very high number of individual particles within a single sample.

The difficulty in interpreting reflectance spectra is further aggravated by a scarcity of extensive polymer spectral libraries collected in reflectance modes. Therefore, automatable, fast and robust approaches are highly requested.

satellite imagery has begun demonstrating significant possibilities for the identification and tracking of riverine and marine plastic pollution (M. De Giglio et al., 2021; Garaba et al., 2020). In fact, remote sensing imagery occupies an important spot since it offers valuable earth observation products, along with additional crucial development, on finding achievable approaches to marine plastic pollution. Satellite imagery has proven to be a valuable instrument in tracking marine litter and suspected plastics, enabling a more comprehensive assessment and administration of this critical environmental problem. In contrast to conventional ground-based approaches, remote sensing presents a holistic view of debris patterns, enabling the recognition of hot spots and accumulation sites. Furthermore, the non-disruptive nature of remote sensing prevents disturbances to fragile marine environments while collecting data. Thus, the application of remote sensing techniques in monitoring microplastics holds immense promise in advancing our understanding of the issue and guiding effective conservation strategies(Karakuş, 2023). Near to shortwave infrared (NIR-SWIR) imaging from spaceborne systems are expected to be an upcoming source of additional data with a broad spatial coverage for the identification and monitoring of aquatic plastics.

Biermann et al. (2020) demonstrated that spots of floating macroplastics may be identified using optical data gathered by the European Space Agency (ESA) Sentinel-2 satellites and, furthermore, are distinct from naturally occurring materials such as seaweed. The results of the study demonstrate that floating aggregations are able to be identified at sub-pixel scales and seem to be composed of a mix of seaweed, sea foam, and macroplastics. The authors leveraged spectral shape to identify macroplastics, and a Naïve Bayes algorithm to classify mixed materials with an accuracy of 86%. Topouzelis et al. (2019) recently proved that spectra obtained from drone cameras and the Sentinel-2 MSI demonstrated that floating plastic continually reflected light in the near-infrared (NIR). The proportion of floating plastic within pixels appeared to have a major impact on reflectance intensity. As a result, if water covers over 50 to 70% of a specific pixel, it displays poor reflectance in the NIR. Pixels composed of a minimum of 30% of plastic bags/bottles, or 50% of fishing net, the characteristic reflectance and absorption features of floating plastics are noticeable. Multispectral satellite imagery studies, in contrast to hyperspectral imaging systems, are constrained by a fixed number of bands representing central wavelengths, typically with a 20-40 nm range around the central bandwidth (Tasseron et al., 2021b). The capability to exploit narrow spectral features in the near and shortwave infrared regions of the electromagnetic spectrum (800-2500 nm) that are unique to plastic polymers constitutes an advantage of employing optical hyperspectral sources of data. (Kremezi et al., 2021) used satellite hyperspectral data for recognizing small-sized marine plastic waste implementing and assessing 13 pan-sharpening techniques for their capacity to spectrally distinguish plastics from water, and reported that based on the generated indexes, the approach has adequately identified the plastic targets and distinguished them from different substances.

Given the vastity of oceans, the extent of coastal areas, and the time required to process massive amounts of remotely sensed data through conventional approaches, Machine Learning algorithms combined with recently accessible hyperspectral satellite information must be investigated.

In this respect, Kikaki et al. (2022) developed a Marine Debris Archive (MARIDA) dataset that consists of 1381 patches with 837,357 annotated pixels from 63 Sentinel-2 scenes obtained within 2015 and 2021. The patches are distributed over eleven countries. MARIDA dataset is based on Sentinel-2 multi-spectral satellite data providing 15 thematic classes including (marine debris, dense sargassum, natural organic material, clouds, foam, etc.). MARIDA consists of 3339 (0.4%) Marine Debris pixels overall that are described as "floating plastic and polymers, mixed anthropogenic debris". Of these plastic pixels, 1625 pixels were digitised and annotated with high confidence. This study also explored the usefulness of various machine-learning algorithms in identifying marine debris. Three variations of the random forest model were investigated, as well as a U-net model where Random Forest models exceeded the U-net model.

Simultaneously to the aforementioned recent studies on analysing spectral features to discriminate marine debris and floating plastics from others, Scientists also examined the identification ability of aerial and drones. Unmanned Aerial Vehicles (UAV) offer affordable monitoring allowing wide area coverage and very high geospatial resolution collection of information (R. Alenezi et al., 2018). UAV studies confirmed the capability to complement ocean surface net trawl datasets of marine litter (Garaba et al., 2018).

Research using airborne data, optical satellite imagery, remote piloted aerial vehicles (RPAS, also called UAVs) and reflectance models have demonstrated the possibility of identifying macroplastics across vast geographic regions and management catchments. If appropriate models and algorithms can be developed, satellite remote sensing in particular can offer high quality, standardised detection on a global scale.

4.3.9.2 Eutrophication

The immense value of ecological services offered by freshwater bodies is of infinite importance. Yet, the productivity and biodiversity of freshwater bodies are drastically decreasing because of global climate- and anthropogenic-induced changes. Global eutrophication endangers aquatic biodiversity and ecosystem function. Water eutrophication occurs when nutrient levels, particularly nitrogen and phosphorus, are excessively high, which leads to increased productivity and reduced dissolved oxygen levels and affects the normal activities of aquatic organisms. It is essential to develop accurate and efficient research methods for mapping eutrophication.

To target efforts to remediate eutrophication, information is required on its spatial distribution, and temporal development (Figure 7). This information is commonly available at a site or catchment-scale, but seldom available at a regional or national scale. As a matter of fact, high spatial data is crucial to ensure effective decision-making processes concerning, the protection of a particular area from eutrophication effects, the assessment of spatial trade-offs between ecosystem services, and to ensure policies implementation and targets (Townsend et al., 2014). In order to ensure accurate and reliable mapping of the coastal defies, some challenges are important to consider. A first challenge is related with the gathering of enough qualitative and quantitative information to describe all the dimensions of marine ecosystems (Tempera et al., 2016). The second challenge concerns the scale of the mapping. Most studies are performed at the regional or national scale (Martnez-Harms et al., 2012), while there is the need to improve our knowledge regarding marine ecosystem services using global datasets that have higher resolution (Tyberghein et al., 2012).

A more detail accounting of the main findings from publications produced under this theme is given in the following note[6].

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[6] Conventional monitoring methods (monitoring stations, and field and laboratory sampling) for extracting eutrophication processes usually involve taking static samples and performing analysis of bacterial blooms in water, which are limited by traditional site-based temporal and spatial resolution and requires to be interpolated to the entire area (E. J. Tebbs et al., 2015; Emma J. Tebbs et al., 2020). Thus, field and laboratory methods not adequate especially in large lakes, where it may not fully capture the overall water quality due to the limited scope and the exponential raise up of related difficulties (Haji Gholizadeh et al., 2016).

Aside from conventional techniques, remote sensing (as shown by the computed bibliometric analysis – Figure 7) is an effective tool for mapping coastal stresses distributions over large scales. For short- and long-term water quality seasonal variation studies, remote sensing is an approachable and feasible tool, that can be a synergistic, potent, and complementary technique for coastal leaders to enhance up-to-date environmental surveillance along with providing observations over environmental emergencies or crises, as well as for coastal preservation and assessment at a macro spatial scale mapping (Caballero et al., 2022). According to current studies, increased spatial resolution might be employed across complex coastal water areas in order to accurately describe the status of coastal regions by means of images from satellites (Cao et al., 2021; Stumpf et al., 2020). Different sensors onboard on satellites namely the Operational Land Imager (OLI) in Landsat, the Moderate Resolution Imaging Spectroradiometer (MODIS), and Multi-Spectral Instrument (MSI) in Sentinel-2, have been indicated in the literature and by the bibliometrics to map eutrophication. By applying high-resolution satellite imagery, Caballero et al. (2022) observed the quality of the seawater during the September–December 2021 volcanic eruption on La Palma Island (Spain), which has been reported as the longest in the island's history and the most damaging in Europe in the past century.

The Sentinel-2A/B twin satellites and Landsat-8 satellite were jointly used as an optical constellation, which allowed a successful characterization of the short- and medium-term evolution of the new lava delta and subsequent impact on the seawater. The authors concluded that even though there is a tendency towards hyperspectral optical missions use for coastal observations and water quality mapping, the available present multispectral sensors combination strategy is an excellent opportunity to highlight the potential of remote sensing technology as a relevant and powerful tool for future hazard monitoring and assessment during catastrophes and for a better interpretation of their impact on the marine environment.

A mapping technique that was also presented by the bibliometrics is the eutrophication classification. In the literature, classification techniques namely supervised classification (Bermejo et al., 2020), and unsupervised classification (Duffy et al., 2018) have been used in vegetation mapping in coastal and estuarial areas. For both classification types, the results need to be validated with ground-truth data. Despite its simplicity, Schroeder et al. (2019) research concluded that one of the limitations of both supervised and unsupervised classification is that it results in errors due to digital noise and these must be removed carefully.

In recent years, machine learning-based predictions have gained popularity in coastal mapping. They have been used to investigate oceanic, coastal, and inland water environments (Reichstein et al., n.d.). So far, a variety of machine learning methods have been applied to qualitative or quantitative monitoring of various water quality parameters in lakes, including algal bloom, chlorophyll a, Suspended Particulate Matter, Coloured Dissolved Organic Matter, Dissolved Organic Carbon concentration, and Particulate Organic Carbo (Kotta et al., 2018). Artificial Neural Network (ANN) offers the potential to deal with a large number of training samples and model complex relationships taking advantage of multiple input variables (Bourquin et al., 1998). Unlike other models, ANN offers the scope for future additional optimization, by the inclusion of more samples which in turn increases the robustness. Therefore, the addition of more samples and the consideration of further variables provide a learning opportunity to the ANN model which improves predictability over time. These neural networks when adequately trained can model the natural environment making them suitable to big-data applications such as remote sensing. Despite numerous benefits, there are some drawbacks of ANN in relation with the large number of training samples, which may be difficult for smaller scale studies.

4.4 Results and discussion on Synoptic Evaluation of source and scales of environmental degradation

On the base of all above bibliometric analysis, here we have attempted to frame all environmental degradation stressors reported in RETURN VS4 into a synoptic scheme enabling to evaluate source and scale of degradation.

As already known, the main environmental degradation drivers identified in RETURN are the followings: contaminants (traditional and mixtures), plastic (litter, bioplastic), as best (and particulate matter), wildfire, climate change, desertification (land degradation), marine acidification & eutrophication, pathogens (and bio-invasion).

On the base of the bibliographic search, in Figure 8, we reported the main drivers of environmental degradation as formalised in RETURN plotted with respect to both spatial extent and spatial resolution. This figure highlights the large variety of approaches dealing with environmental degradation. In general terms – as expected – there is an inverse relationship between spatial extent and spatial resolution (in some cases, such as the case of soil contamination, it can be assumed that the spatial resolution is the support of the measurement). Explaining further this concept, in Figure 8 climate change approaches are typically characterised by a rather coarse resolution over very large areas while at the other extreme there are most of the studies related to contaminants which – typically – refer (in addition to lab experiments) to specific point in the space (e.g. soil sample in a farm) and this is normally associated to a very small spatial extent (small areas). In between desertification, wildfire.

Considering RETURN ambition in supporting policy related to risk, in Figure 8 we reported some examples of multilevel policy. For instance, climate change data are available at coarse resolution but for the entire EU territory; then any development in this area may contribute towards EU policies. On the other side soil pollution analysis or monitoring typically refer to local side and the outcoming results of this approach maybe of large interest for local policy makers.

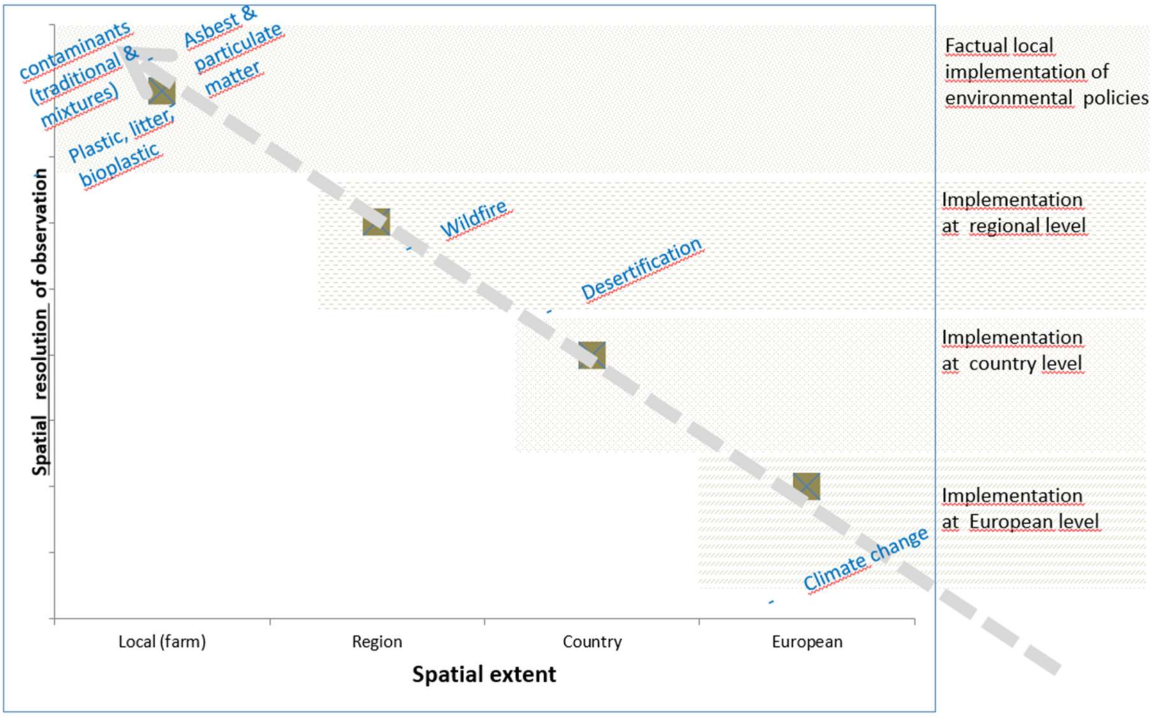

Figure 8 - Main drivers of environmental degradation as formalised in RETURN. These stressors are plotted with respect to both spatial extent and spatial resolution.

In Figure 9, we further implemented Figure 8 plotting the research domains as related all the other RETURN Spokes (VS1,2,3, TS1,2, D1). In most cases, this research remains within the red circle depicted in the figure. The spatial extent and spatial resolution connected with this red circle is particularly important because it is coherent with RETURN objective of "*strengthen Italian governance in managing disaster risk, through the enhancement of basic knowledge (low TRL) towards technology application and exploitation*". Here it is evident that most RETURN spokes having this governance disaster management attitude are well placed covering both regional and national spatial extent with good trade-off in term of spatial resolution.

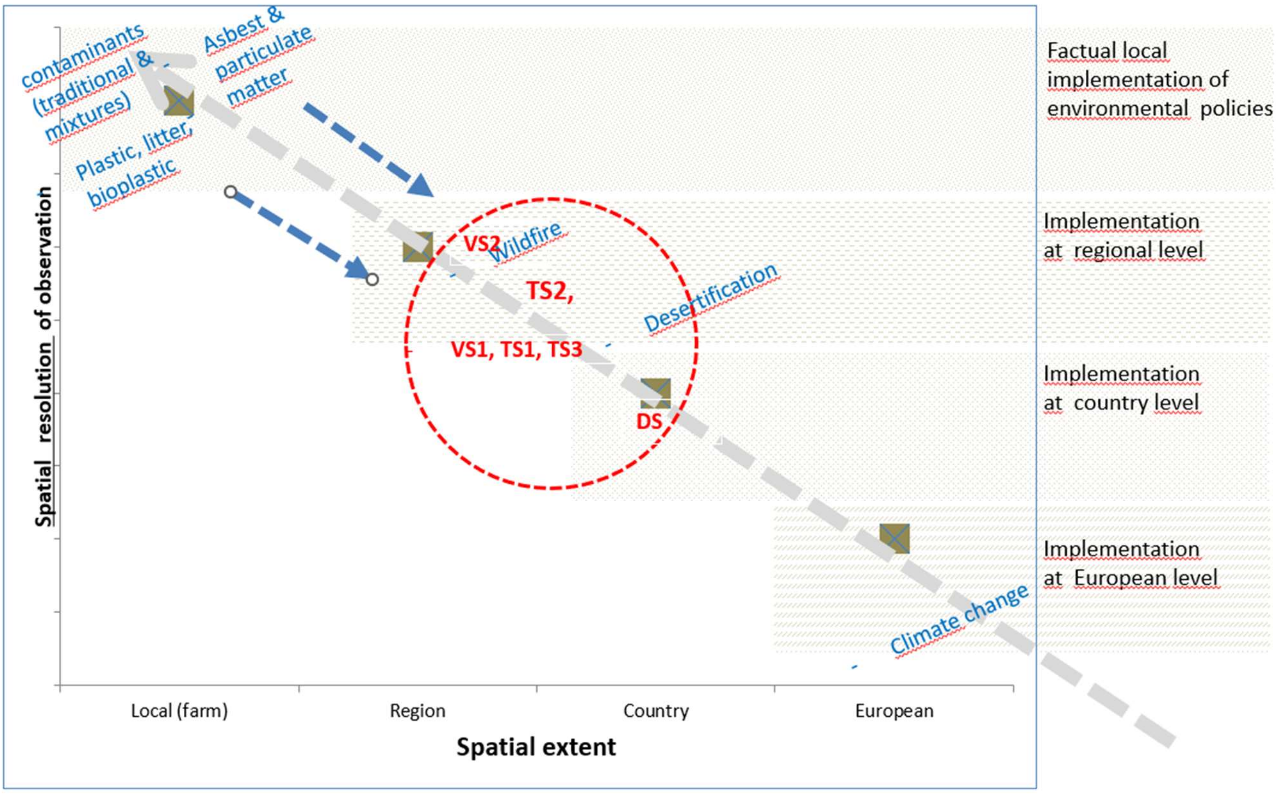

Figure 9 - Here on the same illustration of Figure 8 are reported RETURN Spokes VS1,2,3, TS1,2 and D1.

In view of this evidence, we suggest that – in RETURN - research domains dealing with contaminants and climate change should try to approach the red circle in order to provide operational answer towards risk governance.

5. Conclusions

Large scientific effort has been devoted to the concepts and approaches for the monitoring and assessment of environmental degradation, and to the question of how these threats need to be challenged in order not to cause additional harm to the ecosystem functions and their connection to scales. Here it has been reported (i) a scientific study, based on the bibliometric analysis devoted to examine the main drivers of environmental degradation as occurring in RETURN and (ii) a synoptic evaluation demonstrating the critical trade-off between spatial extent and spatial resolution (or also support of measurements) ads resulting from the analysis of papers with reference to RETURN objectives.

Additional comments have been produced (see notes in the text) on a series of issues such as: scale up from controlled local experiments, the use of high-spatial global coverage information, the use of earth observation sensors aimed at bridging the gaps and improving the management of the terrestrial and marine degradation sources, the use of drones, and satellite multispectral and hyperspectral imagery. In addition, it has been emphasising how papers demonstrate the importance of implementing a general global mapping of the contaminants source using remote sensing.

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