Optical Remote Sensing Methods for Floating Marine Debris Detection – Review and Bibliography Analysis

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In the last several decades, the disposal and accumulation of debris in the marine and coastal environment has been one of the biggest and fastest-growing threats to the health of the world's oceans. Marine debris is present in all marine habitats and represents a great danger to global environmental and human health. Therefore, this paper aims to support efforts to achieve Good Environmental Status with respect to marine debris in all oceans and seas. The application of optical remote sensing methods for floating marine debris detection was briefly reviewed and the bibliometric analysis of the professional and scientific literature elaborated upon. In the overview part, previously used marine debris detection methods have been listed. The WoSCC (Web of Science Core Collection) and Scopus databases were considered, and the R Studio Bibliometrix and Biblioshiny software tools used for bibliometric analysis. 209 documents that can be classified into 43 research fields were identified in the two databases. Approximately 20% of the documents were published in two journals: the Marine Pollution Bulletin and Remote Sensing. Marine debris research was mainly published in the USA, Portugal, Italy, the United Kingdom, Germany, and China. A total of 54 countries participated in the publication of documents and it should be emphasized that all countries have shown great interest in international cooperation during the scientific research on marine debris. Scientific research on marine debris was found to have increased significantly since 2017, which is highly important for the protection of the environment and human health.

KEY WORDS

~ Marine debris
~ Marine litter
~ Remote sensing
~ Bibliometric analysis

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1. INTRODUCTION

Marine debris is litter that ends up in oceans, seas, and other large bodies of water; it is defined as persistent, manufactured, or processed solid material of anthropogenic origins that has been dumped into the sea or has entered the sea via rivers, waste water, or wind. Therefore, the term marine debris is also referred to as marine litter (Coe, 1997). It is estimated that around 80% (Sheavly and Register, 2007) of marine waste originates from land, while 20% is created at sea (Weiss, 2017).

The artificial debris gets into the water in a number of ways. The source of marine debris is not necessarily limited to human activities on sea and land, but also includes fishing activities, shipping, and offshore facilities such as oil platforms and sewage systems. Furthermore, rivers are known to play a crucial role in carrying land-based plastic waste to the world's oceans, as river ecosystems are also directly affected by plastic pollution. Research on riverine plastic debris transport is relatively new. The first efforts to quantify riverine plastic debris flow were only carried out in the early 2010s and included sampling of waterways in Europe and North America, such as the Los Angeles area (Moore et al., 2011). Rivers are known to play a crucial role in transporting land-based plastic waste to the world's oceans, but riverine ecosystems are also directly affected by plastic pollution. To better quantify global plastic pollution transport and effectively reduce the sources and mitigate risks, a thorough understanding of the origin, transport, fate, and effects of riverine plastic is needed (Abolfathi, 2020). The transport and fate of microplastics in the nearshore environment are predominantly influenced by surface-generated turbulence due to the wave-breaking process, described by Abolfathi (2020). Marine waste can be found throughout the marine environment: on the surface, in the water column, on the seabed, on the coast, and as an integral part of marine biota (van Emmerik and Schwarz, 2019; Madricardo, 2020). Furthermore, only a small fraction of marine debris is thought to float or wash ashore. According to the United Nations Environment Program (UNEP), only 15% of marine debris floats on the sea surface; an additional 15% remains in the water column, and 70% is on the seabed (UNEP, 2018).

The origin of marine debris varies significantly in terms of source and quantity, depending on the region (MadriCardo, 2020). In the Mediterranean, the Baltic, and the Black Sea, the majority of marine waste comes from land-based activities, while in the North Sea, equal quantity of waste is generated by maritime activities (UNEP, 2015).

Plastic waste, as the most abundant type of litter in the ocean, does not decompose but breaks up into smaller fragments. Given that different-sized plastic particles can be found in the natural environment, plastics are divided into macroplastics (particles larger than 2.5 cm), mesoplastics (particles between 2.5 cm and 5 mm), microplastics, and nanoplastics (Eriksen et al., 2014). The maximum size of microplastic particles is usually 5 mm (0.20 inches), while the minimum has not yet been determined (Nerland et al., 2014). The European Commission defines the dimensions of microplastic particles as 5 mm-100 nm, while the size of nanoplastic particles ranges between 1 and 100 nm (Rios Mendoza and Balcer, 2019).

The most environmentally harmful plastic particles are microplastics and nanoplastics. Over time, these fragments float on the sea surface, enter the water column, mix with phytoplankton, and settle in sediments on the seabed and the coast. They permanently and irreversibly become part of the food chain and represent an exceptional and far-reaching danger to the environment and ecosystems. The negative impact of marine debris on the marine environment is also manifested as pollution with hazardous substances and heavy metals.

Several global efforts are currently aimed at reducing and preventing marine litter and mitigating its environmental impacts. There is also a group of specific objectives for reducing marine litter and an associated cohesive set of strategies. The objective is to reduce the amount and impact of overland and marine solid waste entering the marine environment and accumulating in coastal areas, benthic habitats, and pelagic waters.

Some European Union (EU) strategies have focused on marine issues. For example, the aim of the European Union's ambitious Marine Strategy Framework Directive (MSFD, 2008) was to protect the European marine environment more effectively. The MSFD requires member states to take measures to achieve or maintain a Good Environmental Status (GES) by 2020 (EU Directive, 2008). The Barcelona Convention was adopted in 1976, amended in 1995, and re-named the Convention for the Protection of the Marine Environment and the Coastal Region of the Mediterranean, which entered into force in 2004. The convention with seven protocols adopted within the framework of the Mediterranean Action Plan (MAP) is the principal regional legally-binding Multilateral Environmental Agreement (MEA) in the Mediterranean region (UNEP, 2019).

In line with EU directives and the global commitments expressed at the United Nations Conference on Sustainable Development Rio+20 in 2012 (UNEP, 2012), the 7th Action Program of the EU for Environmental Protection (2014-2020) (EUEP, 2014) envisages the establishment of starting values and setting marine litter reduction objectives. The EU has developed the Marine Litter Watch program (MLWP, 2023), an application for monitoring marine litter on European beaches. The application enables gathering data that will be used to clean beaches and contribute to our understanding of marine debris.

Marine debris is a relatively recent subject of scientific research, which has intensified over the last twenty years. Satellite remote sensing systems are a state-of-the-art methodology for marine debris detection. These systems have their physical and technical limitations (radiometric, spatial, and temporal resolution, atmospheric effects, and the appearance of clouds), but they provide promising solutions to this problem. Five to six years later, especially after the Copernicus missions of the European Space Agency, the great opportunities opened by unmanned aerial vehicles (UAV) and drones, and the increasing awareness of the growing pollution of marine areas, automated methods of marine debris detection were introduced.

Remote sensing methods have been intensively used for the last 5 years to identify marine litter and floating plastic. So far, five scientific papers describing methods and algorithms related to this topic have been published. The first review published by Madricardo et al. (2020) presents optical and acoustic methods for identifying marine debris on the sea bed and briefly mentions remote sensing methods. Topouzelis et al. (2021) review paper gives the theoretical basis and an overview of all known methods and different approaches to detecting marine debris. The paper also provides an overview of optical remote sensing algorithms and techniques for marine debris detection based on 14 studies. By analyzing different approaches, the authors attempted to harmonize monitoring methods and show the detection of marine debris protocols. Based on 15 studies over the last ten years, Gonçalves et al. (2022) reviewed the use of UAVs in coastal debris detection. Jia et al. (2023) is based on 34 peer-reviewed journal papers and conference proceedings dealing with artificial intelligence, machine learning, deep learning, and the beginnings of automated detection of micro-plastic litter. Karakus (2023) gives a comprehensive review of marine debris and suspected plastics (MD&SP) remote sensing image analysis, discusses method challenges, and gives a critical analysis of the strengths and weaknesses of each. The paper also gives a review of monitoring applications, namely the use of spectral arithmetic (indexes), computational image analysis, and the methods of analysis used, as well as active and passive remote sensing sensors.

All of the above studies dealing with the methods of optical remote sensing of marine debris were found using the bibliographic analysis of the WoSCC and SCOPUS databases, as described in Chapter 3. The main research objective of this paper is to present the results of the bibliometric analysis of remote sensing methods for detecting floating marine debris in the WoSCC and Scopus databases by using the R Studio Biblioshiny and VOSviewer software tools.

The main goal was to examine the following: scientific production related to the topic of optical (multispectral and hyperspectral) remote sensing methods for floating marine debris/litter detection; research trends in 1991-2022; authors who have published the greatest number of scientific papers and the institutions and countries from which these authors come; an overview of state-of-the-art methods (Vighi et al., 2022; Cózar et al., 2021), and future perspectives. The bibliography revealed which topics scientists should focus on if they intend to deal with marine litter, and which areas require improvement.

The final purpose of this paper is to support research and further activities aimed at achieving Good Environmental Status in all oceans and seas.

2. MARINE DEBRIS MONITORING AND COMPUTATIONAL RESEARCH

A comprehensive overview of optical remote sensing algorithms and techniques in the detection of marine debris was presented by Topouzelis et al. (2021) and Karakus (2023). According to their studies currently, Multispectral satellite images (MSI) Sentinel 2 (S2) and WorldView3 (WV3); Hyperspectral satellite images (HIS) PRISMA and AVIRIS, as well as Unmanned Aerial Vehicle (UAV) images, are mainly used. In their studies, the authors also use the Marine Debris Archive (MERIDA) and active missions Sentinel 1 (S1) and Synthetic-aperture radar (SAR) images.

Topouzelis describes 14 studies published in 2012-2021 (Pichel et al., 2012) that focus on new optical satellite missions (as a basis for the studies, nine papers used S2 data, two used WV3 satellite data, one used Landsat 8 data, and two papers used UAV data). Karakus gives an overview of 24 studies, starting with Acuna-Ruz et al. (2018) and the review ends with two recent studies by Magyar et al. (2023) and Gupta et al. (2023).

The methodology used in most studies can be divided into a preprocessing stage that includes atmospheric correction, land masking, cloud detection, cloud edge and shadow masking, whitecap detection, and glint removal and correction. The next stage is the classification phase, which assumes pixel identification, indexing, and machine learning (ML) techniques for marine debris detection. Studies have used classification methods and indices, like the Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Normalized Difference Water Index (NDWI), Normalized Difference Moisture Index (NDMI), Normalized Difference Build-Up Index (NDBI), Modified Normalized Difference Water Index (MNDWI), Floating Algae Index (FAI), Water Ratio Index (WRI), Automated Water Extraction Index (AWEI), (Floating Debris Index (FDI), Plastic Index (PI), Reversed Normalized Difference Vegetation Index (RNDVI) and Adjusted Plastic Index (API). A list of indexes, acronyms, who proposed them, and when are shown in Table 1.

Many authors have tried to use more than one index type (Acuna-Ruz et al., 2018; Lavander, 2020; Serafino and Bianco, 2021; Freitas et al., 2021; Basu et al., 2021; Jamali and Mahdianpari, 2021; Novelli and Tarantino, 2015; Arias et al., 2019; Le Moigne et al., 2021; Biermann et al., 2020; Martinez-Vicente et al., 2020; Themistocleous et al., 2020; Kremezi et al., 2021), most often NDVI, PI, and FDI indices to find which best suits the detection of marine debris. Some authors have not used spectral arithmetic but other methods (Arias et al., 2019; Aoyama et al., 2016; Topouzelis et al., 2020; Kikaki et al., 2020), most often machine learning methods.

Jia et al. (2023), found 34 peer-reviewed journal papers and conference proceedings on the topic of artificial intelligence, machine learning, and deep learning or the beginning of automated detection of micro-plastic litter in bodies of water, published over the last 5 years. The first paper was published in 2016 (Valdenegro-Toro, 2016). Out of the total number of papers, eight deal with the detection of waste on the shore, six with detection in rivers, while the remaining 20 deal with seas. Deep Learning (DL) methods and their subvariant, ML, used for debris detection, are based on the Computer Vision (CV) methodology which uses three basic methods: image classification (IC), object detection (OD), and image segmentation (IS). The image classification method sorts pixels into one or more categories, object detection is an algorithm that automatically identifies object classes and locations, while image segmentation divides images into multiple segments with similar characteristics.

Based on 15 studies conducted in the last decade, Gonçalves et al. (2022) reviewed the use of UAVs in coastal debris detection. Most studies use multirotor UAVs, and the DJI Phantom Pro is the most commonly used drone. Flight heights vary from 5 to 40 m, and the most common flight altitude is 20 m. Ground Sampling Distance (GSD) varied between 0.01 and 1.2 cm/pixel, and the median value was 0.54 cm/pixel. The same study, as an overview of debris detection methods, can be applied to coastal areas, but not offshore (due to control point (CP) absence and inability to mark the CP, which is necessary for image orthorectification).

2.1. Monitoring research

The authors often detected marine litter by spectral arithmetic (SA), using various indices. Table 1 shows the indexes used and the authors who proposed them. The classification is then subjected to further processing using different methods, which are listed in Table 2.

Index	Full native	References
NDVI	Normalized Difference Vegetation Index	Rouse et al., 1974
SAVI	Soil Adjusted Vegetation Index	Huete, 1988
NDWI	Normalized Difference Water Index	MacFeeters, 1995
NDMI	Normalized Difference Moisture Index	Wilson and Sader, 2002
NDBI	Normalized Difference Build-Up Index	Zha et al., 2003
MNDWI	Modified Normalized Difference Water Index	Xu, 2006
NDWI	Normalized Difference Water Index	MacFeeters, 1995
FAI	Floating Algae Index	Hu, 2009
WRI	Water Ratio Index	Shen & Li, 2010
AWEI	Automated Water Extraction Index	Feyisa et al., 2014
FDI	Floating Debris Index	Biermann et al., 2020
PI	Plastic Index	Thomistoceous et al., 2020
RNDVI	Reversed Normalized Difference Vegetation Index	Thomistoceous et al., 2020
API	Adjusted Plastic Index	Sakti et al., 2023
FAI	Floating Algae Index	Hu, 2009
WRI	Water Ratio Index	Shen & Li, 2010

Table 1. Spectral arithmetic (SA) for marine debris detection

2.2. Computational image analysis research

The methods of computational analysis of remote sensing images, the data or satellite missions used in the analysis, and the achieved accuracy results (which were listed) are shown in Table 2.

Pichel et al. (2012) detected data manually based on the Sea Surface Temperature (SST). Aoyama (2016) used a Spectral angle mapper (SAM) to select marine debris pixels. Acuna-Ruz et al. (2018) used spectral arithmetic, and Random forest (RF), Support vector machines (SVM), and Linear discriminant analysis (LDA) methods for classification. Fallati et al. (2019) used Convolutional Neural Networks (CNN), while Arias et al.

(2019) used the FMask algorithm. Biermann et al. (2020) applied NDVI to S2 data, proposed a novel Floating Debris Index (FDI modified from Floating Algae Index FAI), and performed classification using the Naïve Bayes algorithm. Jakovljević et al. (2020) studied semantic segmentation using UNet architecture and UAV orthophotos. Van Leishout et al. (2020) got the data with camera imagery and then utilized deep learning-based Faster Region-based Convolutional Neural Networks (R-CNN) for object segmentation and Inspection v2 for object detection. Lavender (2020), using S1 and S2 data, employed an artificial neural network (ANN) where RF was used to compare ANN performance. Serafino and Bianco 2021 and Freitas et al. (2021) used machine learning (ML) methods in their study of images obtained from a UAV hyperspectral (HI) sensor. Tasseron et al. (2021) also used HI images and performed a spectral analysis with NDVI and FDI, in which they processed classification with Linear Discriminant Analysis (LDA) methods. Basu et al. (2021), using S2 images, tested four machine learning algorithms: K-means, fuzzy c-means (FCM), support vector regression (SVR), and semi-supervised fuzzy c-means (SFCM). The best results, 97%, were achieved with the application of the SVR method. Kremezi et al. (2021) worked with PRISMA low spatial resolution hyperspectral data, which they improved by pansharpening. They also used Principal component analysis or PCA-based substitution method to detect plastic objects. Jamali and Mahdianpari (2021), using S2 images, applying machine learning algorithms (RF & SVM) and deep learning method generative adversarial network random forest (GAN-RF) achieved a very good overall accuracy of 96%. Mifdal et al. (2021) utilized a deep-learning algorithm. Kikaki et al. (2022) used S2 and MERIDA data and RF and U-Net classification. Kremezi et al. (2022) fused S3 and WV3 data, which processes, coupled with non-negative matrix factorization (CNMF) and Fusion –GAN and Fusion ResNet. Taggio et al. (2022) applied a new combined method of supervised and unsupervised ML algorithms, K-means, and Light Gradient Boosting Machine (LGBM) to HI PRISMA data. Booth et al. (2023) used MERIDA data processes with Map-Mapper algorithm and achieved 95% accuracy. Olyaei et al. (2022) and Nagy et al. (2022) applied an RF classifier to S2 MS and MERIDA data. Sannigrahi et al. (2022) performed the classification of MS data and kernel normalized vegetation index (kNDVI) with SVM and RF models. Gomez et al. (2022), applied UNet and DeeplabV3+ segmentation algorithms to S2 data. Giusti et al. (2022) used CNN and Feature pyramid networks (FPN) for MD detection. Magyar et al. (2023) utilized RF classification. Gupta et al. (2023) proposed a new approach of applying a multi-feature pyramid network (MFPN) to MERIDA data and achieved the accuracy of 84%.

The accuracies achieved by individual studies differ, ranging from 50-57% in Arias et al. (2019) to as many as 97% in Basu et al. (2021).

Reference	Method	Data	Accuracy
Pichel et al., 2012	Manual	SST	N/A
Aoyama, 2016	SAM	WV2, WV3	N/A
Arias et al., 2019	FMask	S2	50-57%
Biermann et al., 2020	NDVI, FDI + Naïve Bayes	S2	86%
Jakovljević et al., 2020	Unet	UAV	85%
van Leishout et al., 2020	Faster R-CNN	Camera	69%
Lavender, 2020	SA + RF and ANN	S1 & S2	95-91%
Serafino & Bianco, 2021	SA + RF, SVM	S1 & S2	N/A
Freitas et al., 2021	SA + RF, SVM	HSI	80%
Tasseron et al., 2021	SA + LDA	HSI	N/A
Basu et al., 2021	SA + K-means, FCM, SVR, SFCM	S2	97%
Kremezi et al., 2021	PCA	HSI, PRISMA	N/A
Jamali & Mahdianpari, 2021	SA + RF, SVM	S2	96%
Mifdal et al., 2021	SA + RF, SVM	S2	N/A
Kikaki et al., 2022	Unet, RF	S2 & MERIDA	N/A
Kremezi et al., 2022	Image Fusion	S2 & WV3	N/A
Taggio et al., 2022	SA + K-means, LGBM	HIS PRISMA	N/A
Booth et al., 2023	Unet	S2 & MERIDA	95%
Olyaei et al., 2022	SA + RF, SVM	S2 & MERIDA	N/A
Nagy et al., 2022	SA + RF	Sim & S2	N/A
Sannigrahi et al., 2022	SA + RF, SVM	S2	80-90%
Gomez et al., 2022	Unet & DeeplabV3+	S2	N/A
Giusti et al., 2022	FPN, CNN	SAR & MSI	N/A
Magyar et al., 2023	SA + RF	S2 & PlanetScope	N/A
Gupta et al., 2023	SA +RF & Unet	S2 & MERIDA	84%

Table 2 List of the methods, and data used, and achieved accuracies (according to Karakus, 2023)

Two recent significant papers on this topic, published in the last 6 months, are Rußwurm et al. (2003) and Kikaki et al. (2024), and can be considered as further research guidelines for this subject. Rußwurm et al. (December 2003) describe the large-scale detection of marine debris in coastal areas and present a detector for marine debris built on a deep segmentation model that calculates the probability for marine debris at the pixel level. This detector was trained on a combination of annotated marine debris datasets and evaluated on specifically selected test sites with highly probable plastic pollution in the detected marine debris. Data-centric artificial intelligence (AI) principles are integrated to yield a deep learning model. Marine pollutant and sea surface feature detection by Deep Learning (DL) using Sentinel-2 imagery was studied by Kikaki et al. (2024). The author assumed that in previous research most remote sensing methods have been designed to detect a single sea surface feature or a small number of categories without taking into account other competing classes, e.g. *Water* formations are classified as *Plastics*, *Water* class is misclassified as *Other* class, etc. This study introduced Marine Debris and Oil Spill (MADOS) dataset and proposed a novel Deep Learning (DP) framework named MariNeXt.

3. BIBLIOGRAPHIC ANALYSIS

In this chapter, marine debris or litter remote sensing detection methods are briefly discussed, followed by the methods of bibliographic analysis.

3.1 Bibliography of remote sensing methods for marine debris detection

In recent years, bibliometric analysis has been extensively used to examine and statistically evaluate published scientific literature and measure the impact and contribution of the previously published scientific literature to a selected scientific topic (Aria and Cuccurullo, 2017).

The proposed bibliometric analysis methodology is divided into four stages that enable the full implementation of bibliometric analysis: (1) defining search criteria by carefully selecting keywords and search periods; (2) data collection using scientific databases; (3) adjusting and improving the criteria to better cover the scientific topic; and (4) exporting obtained results in the form of graphs and the possibility of their analysis and interpretation (Pessin et al., 2022). The bibliographic research period is 2002-2023.

3.2 Bibliographic database

In the bibliometric analysis, the WoSCC (Web of Science Core Collection), and Scopus databases were considered, as they are currently the most reliable (Pessin et al., 2022) for this scientific topic. WOSCC (previously known as Web of Knowledge), launched in 1997, provides access to citation indexes and databases and covers all areas of science from 1945 to the present. The database contains over 20,500 indexed journals and almost a billion records of cited references, including papers, conference proceedings, reports, patents, and more. IT is currently owned by Clarivate Analytics. Scopus is Elsevier's abstract and citation database launched in 2004, covering 1970 and 22,800 peer-reviewed journals from all scientific fields. Both databases cover these sources: books and book chapters, papers, and conference papers (Singh and Piryani, 2023). Each document in the database is stored according to the following attributes: paper author(s), document title, source (ISSN, ISBN), year of publication, volume and issue number, initial and final page of the paper, and DOI number. The database can be searched by these categories.

Documents selected from two scientific databases were additionally analyzed using the R Studio program Bibliometrix (Aria and Cuccurullo, 2017; Bibliometrix, 2023), a program for quantitative research in scientometrics and bibliometrics. In addition, its sub-program Biblioshiny was also used in R studio, a programming language for statistical computing and graphics. For additional analysis, we also used VOSviewer, developed at Leiden University's Centre for Science and Technology Studies (CWTS) (Van Eck et al., 2010). Software importing bibliographic data from different scientific databases such as Scopus, Clarivate Analytics Web of Science, Digital Science Dimensions, Cochrane Library, Lens, and PubMed databases, performed bibliometric analysis, building networks for co-citation, coupling, scientific collaboration, and keyword analysis.

3.2.1. Defining search criteria

The following search parameters were set on three levels: 1) (marine debris OR marine litter); 2) (marine debris OR marine litter) AND (satellite OR remote sensing); 3) (marine debris OR marine litter) AND (satellite OR remote sensing) NOT microwave 4) (“marine debris” OR “marine litter”) AND (satellite OR remote sensing) NOT microwave (see Fig. 1), to answer some questions.

In the first search, WoSCC yielded 13,551 and Scopus 2,702 results. The search shows that the first papers dealing with marine debris or litter appeared in 1975 (Edwards et al., 1975) and 1977 (Morrison et al., 1977) (one paper in each year). When defining marine pollution, scientists mainly use *in situ* measurements to determine the impact of pollution on marine organisms and the marine environment, especially in the coastal zone (Biermann et al., 2020; Moller et al., 2016; Freitas et al., 2021; Maximenko et al., 2019; Murphy et al., 2022). As millennium drew to its end, 1,000 papers on this topic were published by 1999. The production increased slightly until 2019, when 1,000 papers were published, after which the number of papers dealing with this topic has been rapidly increasing. By 2007, thirty years after this topic became part of scientific discourse, approximately 5% of documents were published. 10% were published in the following 5 years, by 2013, and 20% of the total production was achieved in the next two years by 2015. This doubled to approximately 65% of the total number of published papers by 2019. The interest of the scientific community in this topic continues to grow significantly.

Initial bibliometric research was narrowed to the field of remote sensing methods for floating waste detection, yielding 395 WoSCC and 97 Scopus results (Biermann et al., 2020; Moller et al., 2016; Freitas et al., 2021; Maximenko et al., 2019; Swanborn et al., 2021; Madricardo et al., 2020). The first papers in the WoSCC database that dealt with marine debris detection using remote sensing methods were published in 1991 (Raich et al., 1991) and 1992 (Francis, 1992).

In the third search iteration, active remote sensing methods (which have recently begun to be used for this topic) have been excluded (duplicates and irrelevant documents were excluded by reviewing the database and removing them). Ultimately, 391 results were found in the WoSCC and 97 in the Scopus databases, excluding only four papers from the previous search. When data in the two databases were merged, 51 duplicate documents, and 6 irrelevant documents were identified, giving us the final number of 431 documents to analyze.

In the fourth or final search iteration (from 2002 to late 2023), we specified search terms marine debris and marine litter, obtaining 224 papers published by late 2023 (233 by mid-2024) in WoSCC and only 1 paper in the Scopus database. When documents from the databases were merged, 16 duplicates and irrelevant papers (papers written in Korean or those that do not belong to the topic) were identified, which were excluded from further analysis.

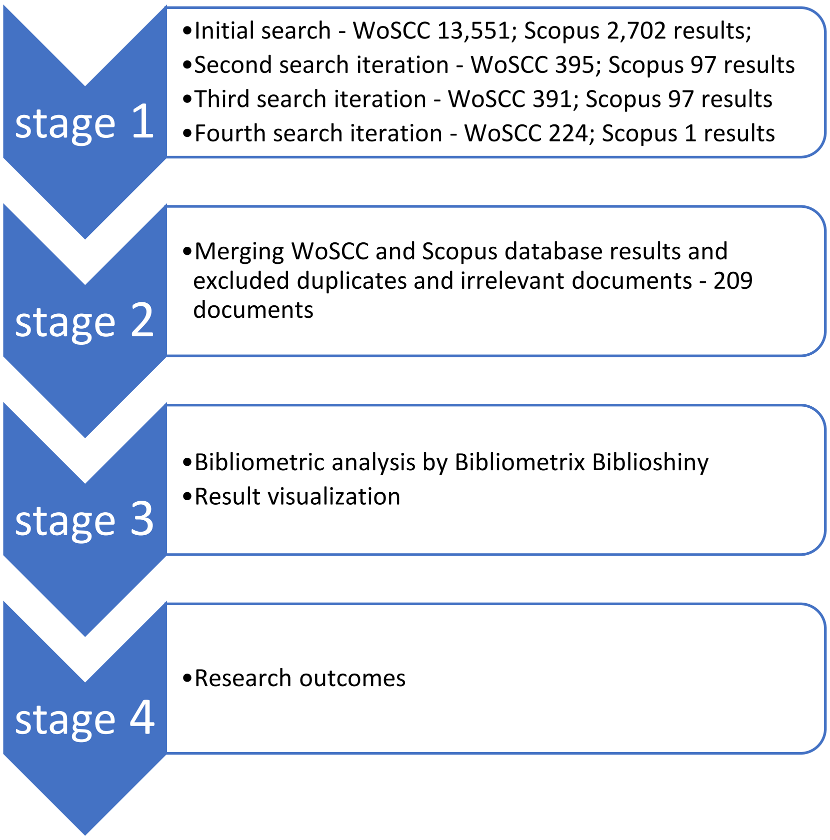


Figure 1. Four levels of bibliometric analysis search parameters

4. RESULTS

The total number of documents obtained by bibliometric analysis can be classified into 32 research areas; more than half, or a total of 121 documents (57.89%), identified the environmental science of ecology as their field of research, around one third, or 66 documents (31.57%), identified remote sensing, while 56 (28.71%) identified marine freshwater biology, 50 (20.77%) imaging science photographic technology, 38 (18.18%) refer to geology, 30 (14.35%) mention engineering, and 19 (9.09%) refer to oceanography. Some of the documents can be classified as belonging to two or more research fields.

Out of the 209 documents identified in the two most important scientific databases, the largest number, 64, i.e. 30.62%, or almost a third of the documents were published in two journals: *Marine Pollution Bulletin* and *Remote Sensing*. The following three journals: *Frontiers in Marine Science*, *Remote Sensing of Environment*, and *Scientific Reports* published more than 5 papers each, giving a total of 19 or 9.09% of papers. The majority of the papers were a collaboration of a large number of scientists, and production has increased significantly in the last four years.

4.1. Analysis of scientific production

By merging the two most important databases, 209 documents from 95 sources (journal papers, books, and conference papers) with a total of 843 authors published over the last twenty years (2002-2023) have been identified. Most of the documents have a larger number of authors from different countries, i.e., approximately 10 authors per paper, which means that most of the documents were created as an international collaboration of authors from approximately 40 countries. This indicates that the authors consider marine litter to be a significant problem. Approximately 8,000 references (a total of 7,819) were made in the papers (see Figure 2).

The average number of paper citations is 25.41, and the annual growth rate of the number of papers is 16.99, suggesting that this topic attracts significant interest in the scientific community.

Figure 2. Main characteristics of the documents retrieved (from Bibliometrix Biblioshiny)

The highest number of all published documents are papers - 168 (78.38%), followed by conference proceedings at 26 (12.44%), and review papers at 12 (5.78%). The remaining 7 documents (3.34% in total) are early access documents (3), book chapters (1), corrections (1) data papers (1), and editorial materials (1) (see Figure 3).

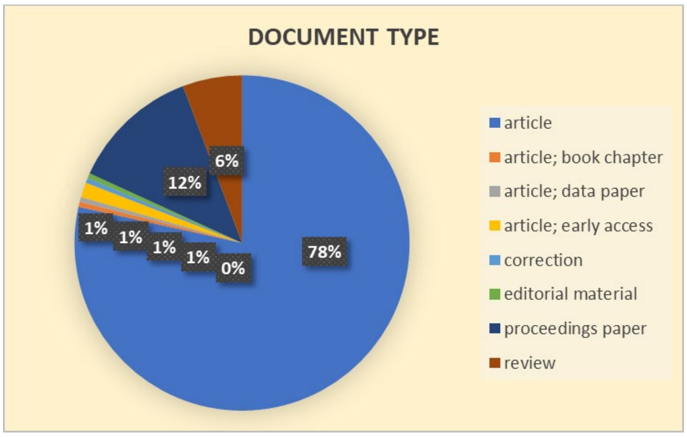


Figure 3. Document type statistics

4.1.1. Annual scientific production

The first documents that report the application of remote sensing methods to marine debris detection date to the beginning of this millennium (see Figure 4). In the last three years, more advanced sensors have been developed and used to detect marine debris, such as the improved spatial resolution of satellite missions, UAV (drone) technology, and hyperspectral missions. Likewise, various automated data methods have begun to be used for the same purpose, while the development of machine learning as the most commonly used automated method resulted in rapid development. As marine anthropogenic waste becomes a huge problem in the environment, a growing number of authors are expected to deal with this topic and publish an increasing number of documents.

The analysis of scientific documents published on the topic of marine debris shows that there have been three distinguishable stages (see Figure 4): 1) the preparation stage from 2002 to 2016, in which less than 10 documents were published per year; 2) a period of growth that lasted from 2016 to 2022, in which the number of published documents per year significantly increased; and 3) the latest period from 2022 on, characterized by a marked decrease of interest in the topic. In 2022, only fifty documents were published, followed by approx. 40 papers or 20% less in the following year, and only 9 in the first half of 2024.

Figure 4 clearly shows that the trend of increasing scientific production on the topic of marine debris began in 2017 and continues to this day. This can be explained by analyzing data on the quantity of plastics observed in the seas and oceans, which significantly increased, ranging from 8 (in 2005) to 170 (in 2022) trillions of plastic particles (mean values) (Eriksen et al., 2023).

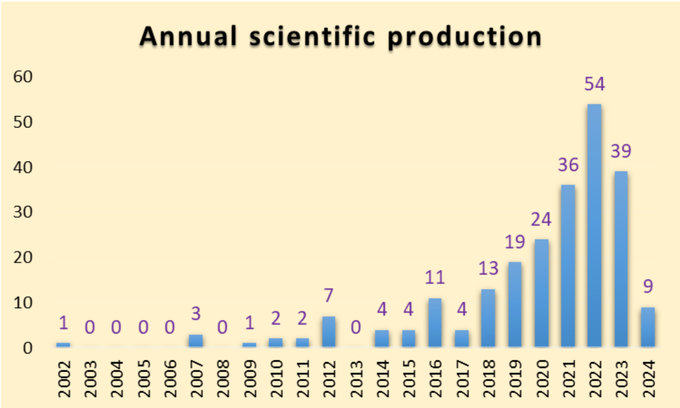


Figure 4. Annual scientific production 2002-2023

A three-field Plot (Sankey diagram) shows an overview of the authors' countries, authors, and the affiliations they belong to (the fifteen most relevant affiliations are presented in Figure 5; Figure 8). The Sankey diagram was created to show the proportions of research topics, which institutions the authors come from and which keywords they use the most. The diagram shows that the main interests of researchers are remote sensing methods in the detection of marine litter plastics and microplastics in the sea and their impact on marine organisms. Marine litter research, although not abundant, was mainly published in the USA, Portugal, Italy, the UK, Germany, and China, i.e. countries with very strong marine environment industries.

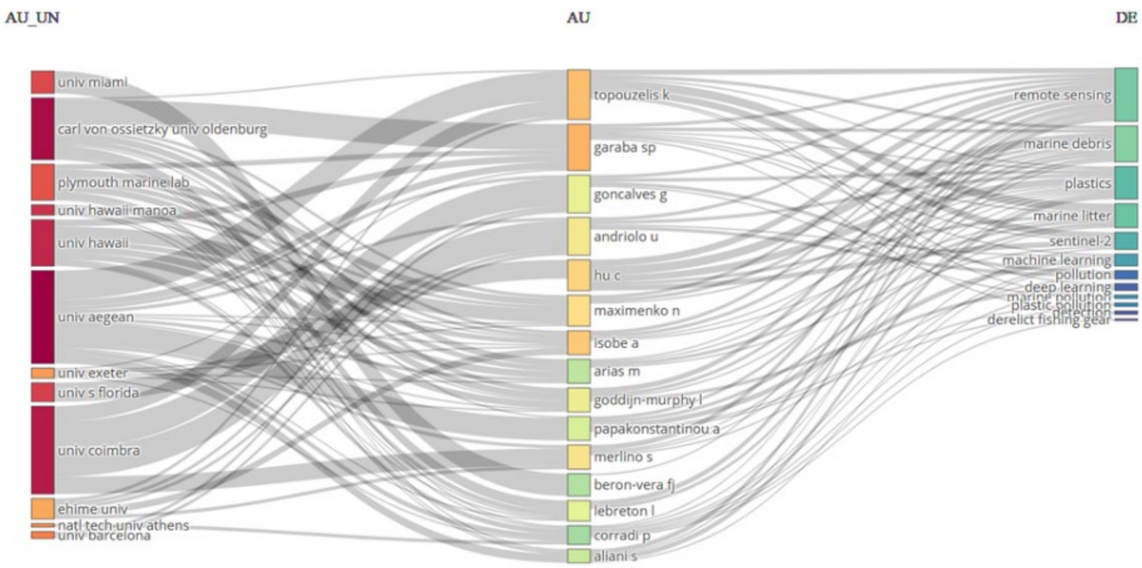


Figure 5. Three-field Plot (Sankey) diagram of author affiliations, authors, and keywords (from Bibliometrix Biblioshiny)

4.2. Analysis by journals, affiliations, and countries

4.2.1. Journals

Through extensive research, we determined that the subject of Optical Remote Sensing Methods for Floating Marine Debris Detection was covered in 102 journals or proceedings, of which two publishers published almost half of the papers, namely *Elsevier* which published 63 papers or 30.14% of all papers, *MDPI* with 38 or 18.18% of all papers, followed by *IEEE* with 23 or 11.00%, *Springer Nature* with 11 or 5.26%, *Frontiers Media Sa* with 9 or 4,30%, *Wiley* with 7 or 5.38%, *Nature Portfolio*, and *Spie-Int Soc Optical Engineering* with 6 or 2.87% of the papers each, *Copernicus Gesellschaft Mbh* and *Taylor & Francis* with 5 or 2.39% of all papers, while other publishers published 33 or 15.79% of all papers (see Figure 6).

A narrowed bibliometric analysis of passive or optical remote sensing methods for the detection of floating marine debris identified 209 papers in WoSCC and Scopus databases. Fig. 6 shows the 15 most relevant journals that published papers on the topic. Overall, a third of the documents were published in two journals, *Marine Pollution Bulletin* (ISSN: 0025-326X), with 37 or 17.70% of all papers, and *Remote Sensing* (online ISSN: 2072-4292) with 27 or 12.92% of all papers. By number of published documents, they are followed by *Frontiers in Marine Science* (online ISSN: 2296-7745) with 8 or 3.82%, *Remote Sensing of Environment* (online ISSN: 1879-0704) with 6 or 2.87%, and *Scientific Reports* (ISSN: 2045-2322) with 5 or 2.39% of all papers. They are followed by four magazines, namely, *Estuarine, Coastal and Shelf Science* (ISSN: 10960015, 02727714), *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* (ISSN: 21511535, 19391404), *Science of the Total Environment* (ISSN: 0048-9697) and *Water* (ISSN 2073-4441) with 4 papers or 1.91% of all papers each. Six magazines have 3 papers or 1.43% of all papers each, and those are 2022 *IEEE International Geoscience and Remote Sensing Symposium* (IGARSS 2022) Kuala Lumpur, Malaysia (ISSN: 2168-6831, 2473-2397, 2373-7468), *Environmental Pollution* (ISSN: 0269-7491), *Environmental Research Letters* (ISSN: 1748-9326), *IEEE Geoscience and Remote Sensing Letters* (ISSN: 1545-598X), *IEEE Transactions on Geoscience and Remote Sensing* (ISSN: 1558-0644) and *International Journal of Applied Earth Observation and Geoinformation* (ISSN: 1872826X, 15698432).

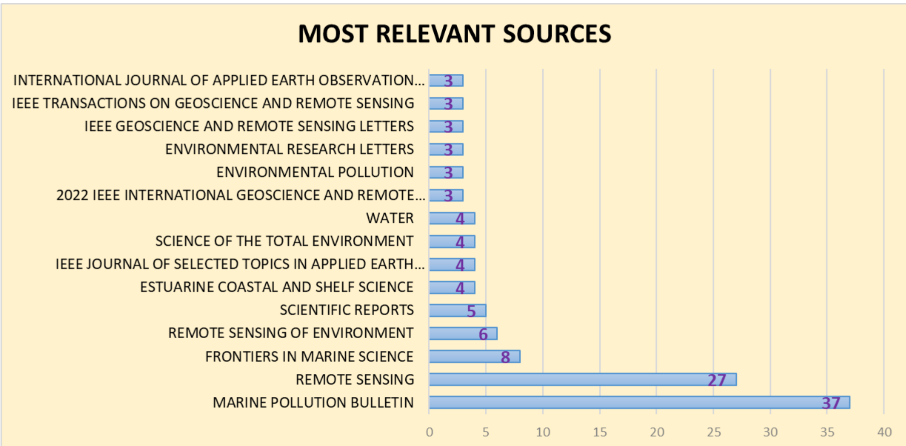


Figure 6. Ten most relevant sources (journals)

The majority of locally cited papers, 1,436 (almost four times more than the second and five times more than the third) on this topic have been published in the *Marine Pollution Bulletin* (ISSN: 0025-326X), a journal published by Elsevier on behalf of the International Maritime Organization (CiteScore 7.9; IF 7.001), followed by the *Remote Sensing* (online ISSN: 2072-4292) MDPI Academic Open Access Publishing journal with 364 citations (CiteScore 7.4; IF 5.349), the *Remote Sensing of Environment* (online ISSN: 1879-0704) Elsevier journal with 286 (CiteScore 20.7; IF 13.85), *Scientific Reports* – SCI REP UK (ISSN online: 2045-2322) published by

Nature Portfolio with 201 (CiteScore; IF 4.996) and *Frontiers in Marine Science* (online ISSN: 2296-7745) with 177 citations (CiteScore 5.2; IF 5.247). The next two journals with 171 cited papers are the *Science of the Total Environment* (ISSN: 0048-9697 (print) 1879-1026 (web)) Elsevier journal (CiteScore 14.1; IF 10.754) and the *Science Magazine* (ISSN: 0036-8075 (print); 1095-9203 (web)) of the American Association for the Advancement of Science (United States) with 321 local citations (CiteScore 57.8; IF 41.84). These are followed by two journals with 162 citations - the *Journal of Geophysical Research-Oceans* (ISSN: 0148-0227 (print) 2156-2202 (web)) of the American Geophysical Union (CiteScore 6.2; IF 3.751), and *PLOS One* (ISSN: 1932-6203) Public Library of Science with 268 citations (CiteScore 5.3; IF 3.24), and *Environment science technology* (ISSN: 0013-936X (print); 1520-5851 (web)) published by the American Chemical Society with 159 citations (CiteScore 14.8; IF 11.357). Other journals have less than 150 local citations (see Figure 7).

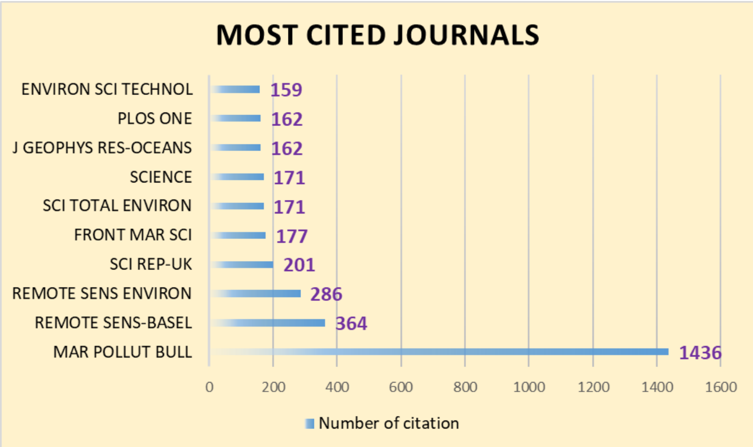


Figure 7. Locally most cited journals

4.2.2. Sources and affiliations

The majority of the papers are the result of collaboration between different countries and affiliations (usually more than 5 authors or 5.06). 224 papers are the result of the efforts of 457 affiliations.

The most productive affiliation with the greatest number of published papers (23 papers (11.00%)) is the *University Aegean*, a public university with multiple campuses located on Lesbos, Chios, Samos, Rhodes, Syros, and Lemnos in Greece. The *Carl von Ossietzky State University* in Oldenburg Germany, founded in 1793, published 17 papers (8.13%). The *University of Coimbra*, a public university in the city of Coimbra, Portugal, one of the oldest continuously operating universities in the world, founded in 1290, and the *University Hawaii* founded in 1907, published 16 papers (7.65%) each.

By the number of published papers, another two US universities follow, namely the *University Hawaii in Mānoa*, founded in 1907, and the *University of South Florida,* a public land grant research university in Gainesville, Florida, founded in 1853, with 14 (6.69%) papers. The *University of Miami*, a private research university in Coral Gables, Florida, established in 1925, published 13 (6.22%) papers, while 12 papers or 5.74% were published by the *Plymouth Marine Lab marine research organization* from Plymouth, Devon, UK, founded in 1988, 10 papers (4.78%) each at the *Ningbo University* located in Jiangbei District, Ningbo, Zhejiang, China established in 1986, and the *University of Lisbon,* a public research university in Lisbon, and the largest university in Portugal originally founded in 1911 (see Figure 8). All other affiliations published less than 10 papers.

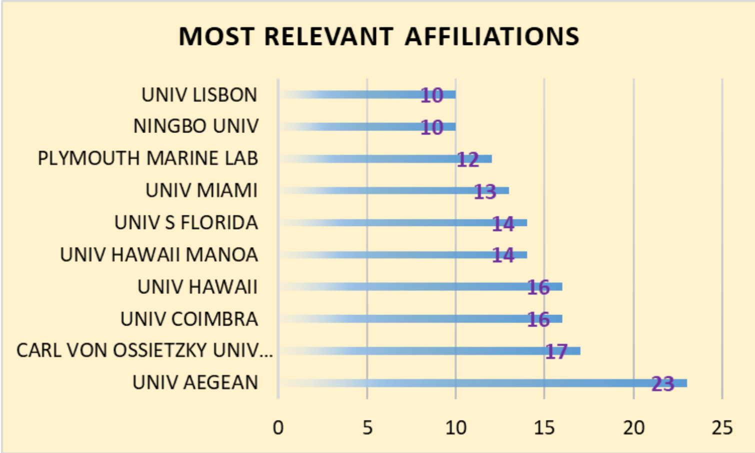


Figure 8. The ten most relevant affiliations

In the last five years, there has been a significant increase in interest in this topic, with growing collaboration between institutions, and an increasing number of institutions joining efforts.

4.2.3. Countries

A total of 54 countries participated in the publication of papers, of which the USA published almost a third of the total number of papers (67 papers or 32.05%), followed by Italy with half as many papers published (30 papers or 14.35%), Germany (22 papers or 10.52%), Japan (20 papers or 9.56%), Spain (19 papers or 9.09%), the United Kingdom and France with 18 papers or 8.61% each, and Greece (17 papers or 8.13%). The Netherlands and Portugal published 16 papers or 7.65% each, Australia 12 papers or 5.74%, and the People's Republic of China 10 papers or 4.78%. All other countries have published less than 10 documents each.

The largest number of cited papers were published in the USA, 1,505, with 32 citations per paper in average, while the Netherlands and the United Kingdom have around 500 cited papers, i.e. 536 (89.30 citations in average) and 484 (37.20 citations in average), respectively. A total of 295 Australian papers were cited, 36.90 citations in average, Greece 258 papers cited 25.80 times in average, Canada 253 papers (126.50 citations in average), France 222 papers (27.80 average), Germany 218 (21.80 average) and Japan 211 (17.60 average) cited papers. Other countries that have a large number of cited papers on this topic are China, Italy, Spain, Portugal, Denmark, and Belgium with 100-200 cited papers (see Figure 9).

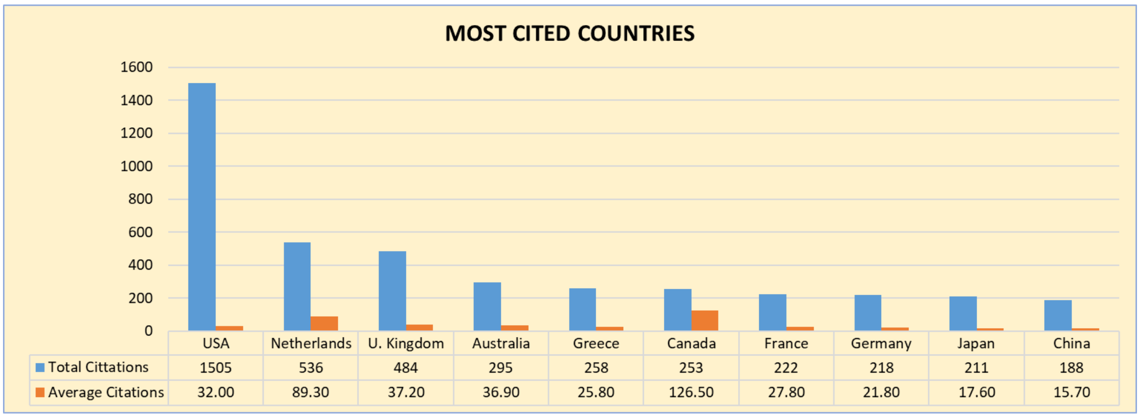
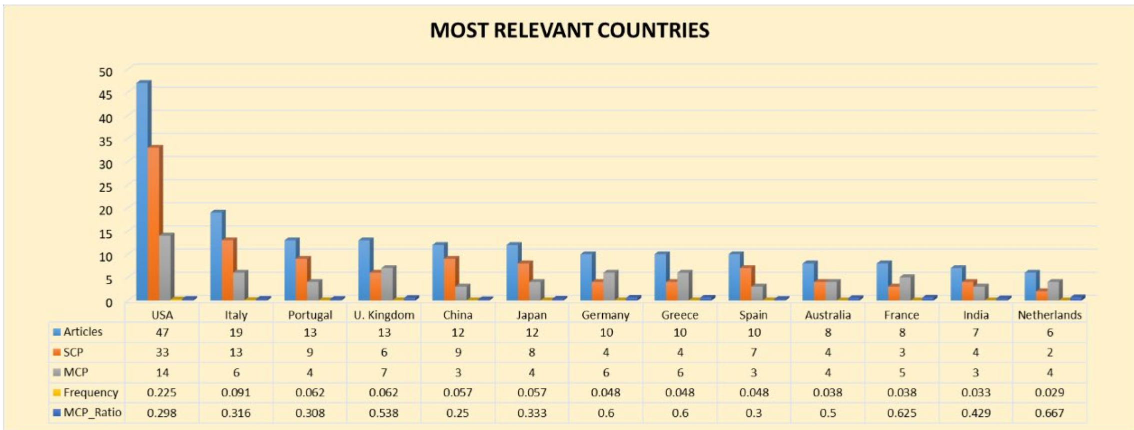


Figure 9. Countries with the greatest number of citations

The USA is in the lead among the countries that collaborate on paper publication, followed by China, the United Kingdom (UK), Japan, Italy, Germany, Greece, France, Spain, the Netherlands, Portugal, Australia, and India. A third of USA production are multiple-country publications (MCP), and two-thirds single-country publications (SCP), in China this ratio is approximately 30% to 70%, and in the UK 45% to 55%. Japan has the ratio of 20% to 80%, Italy 30% to 70%, Germany 50% to 50%, Greece 60% to 40%, France and Spain 60% to 40%, the Netherlands 50% to 50%, Portugal 30% to 70%, Australia 60% to 40%, and India 30% to 70% (see Figure 10).

Out of the total of 209 papers, only 12 have one author, and 22 have 2 authors. All other papers have 3 or more authors, which makes this topic a highly collaborative topic (see Figure 11).



	USA	Italy	Portugal	U. Kingdom	China	Japan	Germany	Greece	Spain	Australia	France	India	Netherlands
Articles	47	19	13	13	12	12	10	10	10	8	8	7	6
SCP	33	13	9	6	9	8	4	4	7	4	3	4	2
MCP	14	6	4	7	3	4	6	6	3	4	5	3	4
Frequency	0.225	0.091	0.062	0.062	0.057	0.057	0.048	0.048	0.048	0.038	0.038	0.033	0.029
MCP_Ratio	0.298	0.316	0.308	0.538	0.25	0.333	0.6	0.6	0.3	0.5	0.625	0.429	0.667

Figure 10. Collaboration between countries on paper publication

The global map of collaboration between countries (see Figure 11) is significant, as is the number of papers published by a large number of scientists. As can be seen in Figure 10, a significant number of papers were published as multiple-country publications, with the USA, Portugal, Spain, and Canada, leading the way. The most intensive collaboration was between the USA and European countries (the United Kingdom, Portugal, Italy, Greece, the Netherlands, and Spain), China, Japan, and Australia.

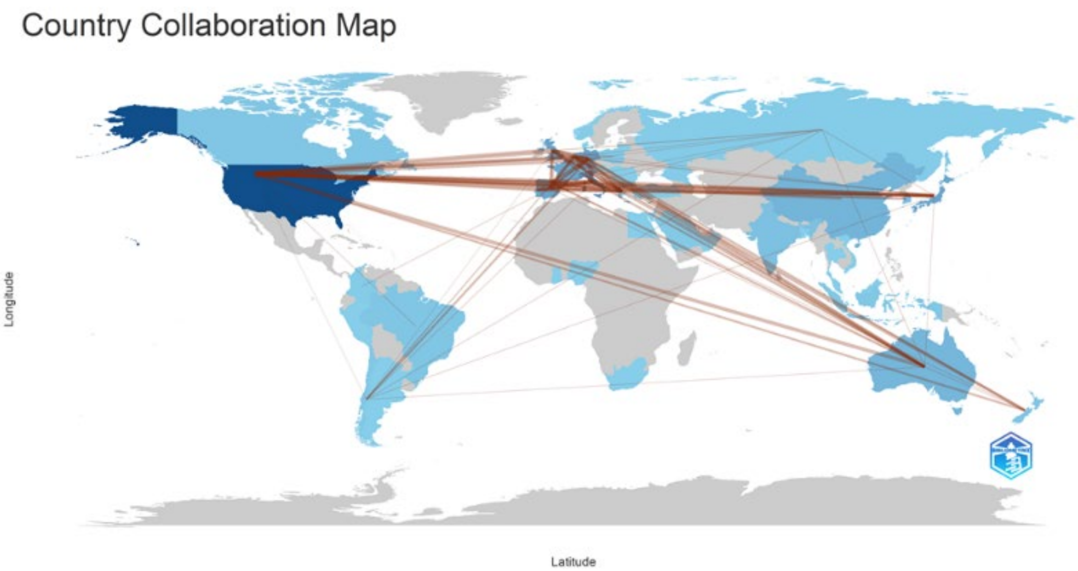


Figure 11. Collaboration between countries (from Bibliometrix Biblioshiny).

4.3. Analysis by authors

The ten most relevant authors, according to the number of published papers, are given in Table 3. The most productive author is Garaba, who has the largest number of published documents on this topic (10), followed by Topouzelis with 8 and Isobe with 7 papers. Three authors published 6 documents each: Hu, Maximenko, and Merlino, while the next four authors published 5 documents each: Andriolo, Goddijn-Murphy, Goncalves, and Lebreton (see Figure 12). Other authors published less than 5 papers. Tab. 4 gives the list of the ten most active authors (surname, name), who published 5 or more papers, the institutions (affiliations) and countries where they work, the number of citations per paper, their H index, and author ORCID number for easier search.

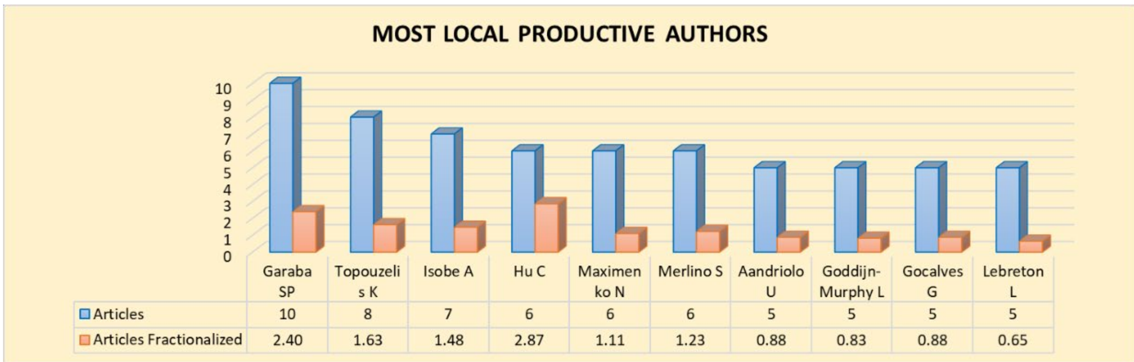


Figure 12. The most productive authors

The ten most locally cited authors (citation papers dealing with optical remote sensing methods for floating marine debris detection) are listed in the graph in Figure 13. The most cited, i.e. the most relevant, author is Garaba with 135 local citations, followed by Isobe with 90 and Goddijn-Murphy with 80 citations. The number of citations of the other seven authors with over 50 citations are given in Figure 13.

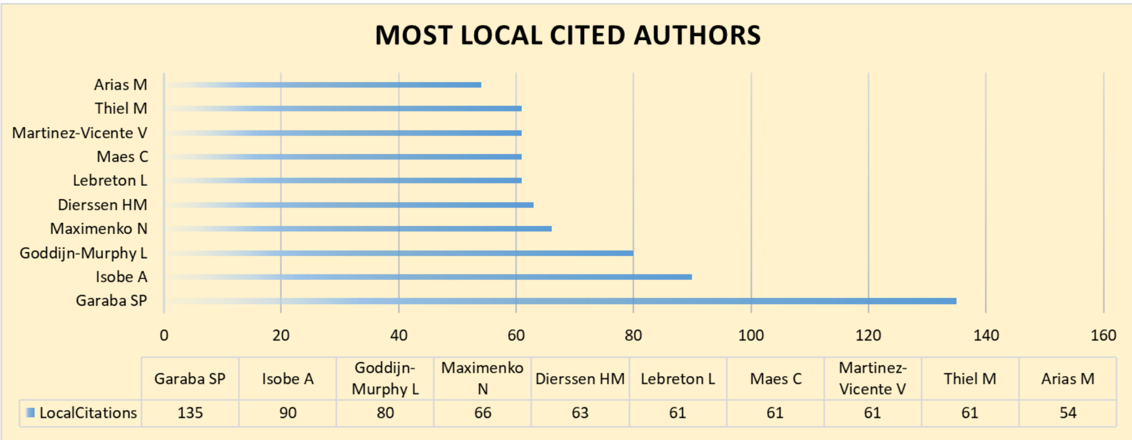


Figure 13. Ten most locally cited authors

AUTHOR/S	AT	AFFILIATION	CO	CI	HI	ORCHID
Garaba, Shungudzemwoyo P.	10	Institute for Chemistry and Biology of the Marine Environment, University of Oldenburg	Germany	1551	19	0000-0002-9656-3881
Topouzelis, Konstantinos	8	Department of Marine Sciences, University of the Aegean	Greece	2759	27	0000-0002-1916-1600
Isobe, Atsuhiko	7	Research Institute for Applied Mechanics, Kyushu University	Japan	4,583	32	0000-0002-9063-9275
Hu, Chuanmin	6	College of Marine Science, University of South Florida, St. Petersburg	USA	24250	84	0000-0003-3949-6560
Maximenko, Nikolai	6	International Pacific Research Center, School of Ocean and Earth Science and Technology, University of Hawaii, Honolulu	USA	8325	36	0000-0001-6017-6807
Merlino, Silvia	6	Istituto di Scienze Marine del Consiglio Nazionale delle Ricerche, ISMAR – CNR	Italy	512	13	0000-0002-4537-2903
Andriolo, Umberto	5	Institute for Systems Engineering and Computers at Coimbra (INESC Coimbra), University of Coimbra	Portugal	685	16	0000-0002-0185-7802
Goddijn-Murphy, Ionneke	5	University of the Highlands and Islands	UK	1618	20	0000-0003-4820-8313
Goncalves, Gil	5	Institute for Systems Engineering and Computers at Coimbra (INESC Coimbra), University of Coimbra	Portugal	1401	20	0000-0001-7757-7308
Lebreton, Laurent C.M.	5	The Ocean Cleanup, Rotterdam	Netherlands	12,141	25	0000-0002-7443-2100

Abbreviations: AT = No. of papers; CO = Country; CI = Citations; HI = H-Index; ORCID number

Table 3 Authors with 5 or more publications related to marine debris (WoSCC and Scopus databases)

The top 15 most productive authors are shown in Figure 14, along with the number of papers (No. papers) per year and the number of citations (TC) per year for each author. The figure also shows the years in which they were active and the scope of their scientific activity. Japanese scientist Atsuhiko Isobe has begun to deal with this topic and has published one paper every couple of years in 2010-2016, and has intensified paper publication since 2019. Nikolai Maximenko has been dealing with this topic since 2012, Eric Van Sebille since 2016 and Apostolos Papakonstantinou since 2017. The most prolific scientists who started to tackle this topic in 2018 are Shungudzemwoyo P. Garaba and Lonneke Goddijin-Murphys. The majority of the authors mentioned started to regularly publish papers on this topic by 2020.

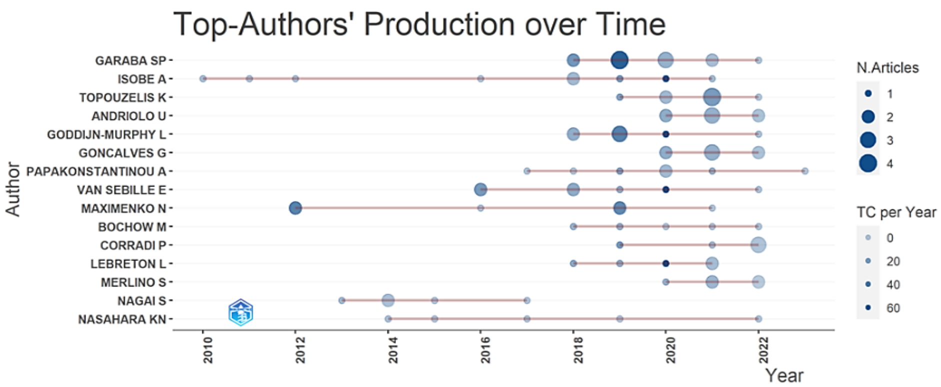


Figure 14. Top authors' production over time (from Bibliometrix Biblioshiny)

The twelve most globally cited documents from the WoSCC and Scopus databases which were cited more than 100 times are shown in Table 4. The first three papers were cited more than 250 times, the next nine were cited more than 100 times. These papers could be considered influential given the sheer number of citations.

AUTHOR/S	YEAR	JOURNAL	PAPERS TITLE / DOI	CI
Maximenko et al.	2012	Mar Pollut Bul, 65, 51–62	Pathways of marine debris derived from trajectories of Lagrangian drifters / doi:10.1016/j.marpolbul.2011.04.016.	415
Van Sebille et al.	2020	Environ Res Lett, 15 023003	The physical oceanography of the transport of floating marine debris / doi:10.1088/1748-9326/ab6d7d.	353
Driedger et al.	2015	J Gt Lakes Res, 41 (1), 9-19.	Plastic debris in the Laurentian Great Lakes: A review / doi:10.1016/j.jglr.2014.12.020.	264
Maximenko et al.	2019	Front Mar Sci, 6, 447.	Towards the Integrated Marine Debris Observing System / doi:10.3389/fmars.2019.00447	138
Pichel et al.	2007	Mar Pollut Bull, 54 (8), 1207-1211.	Marine debris collects within the North Pacific Subtropical Convergence Zone / doi:10.1016/j.marpolbul.2007.04.010	120
Biermann et al.	2020	Scientific Reports, 10, 5364 (2020)	Finding Plastic Patches in Coastal Waters using Optical Satellite Data / doi:10.1038/s41598-020-62298-z	118
Martinez et al.	2009	Mar Pollut Bul, 58 (9) 1347-1355	Floating marine debris surface drift: Convergence and accumulation toward the South Pacific subtropical gyre / doi:10.1016/j.marpolbul.2009.04.022	117
Schuyler et al.	2016	Global Change Biology 22 (2) 567-576	Risk analysis reveals global hotspots for marine debris ingestion by sea turtles / doi:10.1111/gcb.13078	114
Duhec et al.	2015	Mar Pollut Bul 9 (1-2) 76-86	Composition and potential origin of marine debris stranded in the Western Indian Ocean on remote Alphonse Island, Seychelles / doi:10.1016/j.marpolbul.2015.05.042	113
Topouzelis et al.	2019	Int J Appl Earth Obs Geoinf 79 175-183	Detection of floating plastics from satellite and unmanned aerial systems (Plastic Litter Project 2018) / doi:10.1016/j.jag.2019.03.011	103
Henderson and Green	2020	Mar Pollut Bul 152 110908	Making sense of microplastics? Public understandings of plastic pollution / doi:10.1016/j.marpolbul.2020.110908	101

Abbreviations: YEAR = Year of publication; JOURNAL = Journal name, Vol, No, pp; CI = Citations

Table 4. The 12 most globally cited (more than 100 times) papers from the WoS and Scopus databases

The graphic representation of mutual citations of the most important authors, given in Figure 15, is also interesting, as it shows four groups of authors that form co-citation networks. The most important network built around Topouzelis, Bierman, Maximilienko, and Garaba dates back to 2018 and continues to this day (blue in the graph); the second network built around Jambeck and Lebreton was active in 2012-2018 (purple), the third built around Eriksen and Cozar, in 2009-2015 (red), and the fourth around Fallati in 2019-2021 (green).

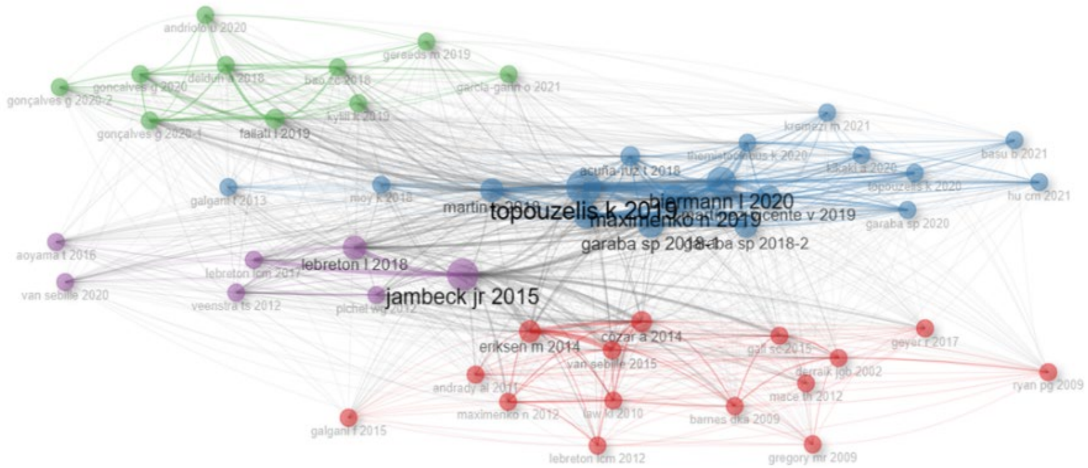


Figure 15. Co-citation network (from Bibliometrix Biblioshiny)

The history of emergence of individual significant authors and their connections in terms of co-authorships and citations is shown in Figure 16. The first authors to systematically deal with this topic, Pichel and Dameron, appeared in 2007. Five years later, in 2012, Maximenko, Veenstra Pichel, and Mace joined them. Three years later, in 2018, papers by Martin Kataoka Goddijn-Murphy and Garab appeared, and in 2019, Maximenko published his paper. A year later, in 2020, papers were published by van Sebile, Wolff, and Garaba, in 2021 by Topouzelis, Garaba, Gardia-Garin, and Papakonstantinou, while, Kikaki published his paper in 2022 (see Figure 16).

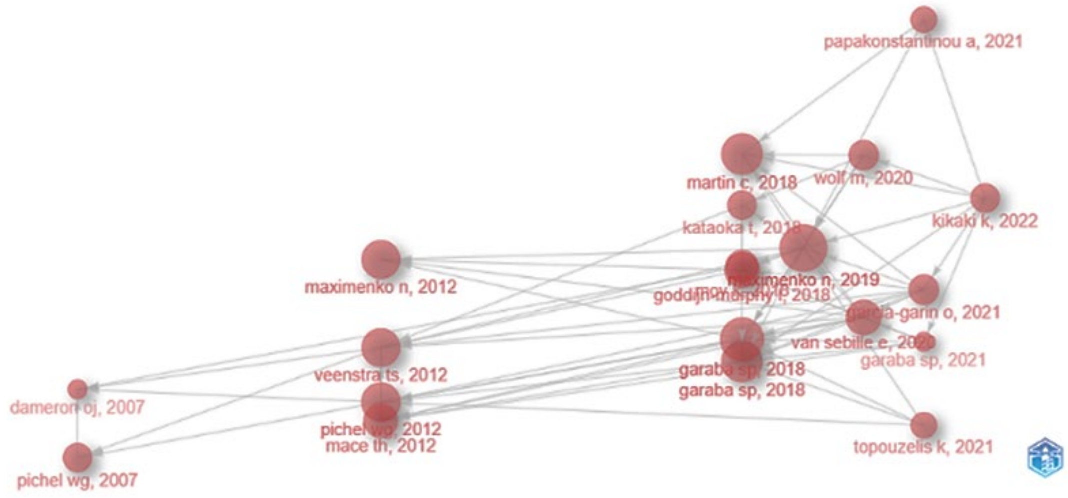


Figure 16. Historiography (from Bibliometrix Biblioshiny)

Figure 17 is an illustration of the author collaboration network, showing that the most productive authors, Garaba, Isobe, and Topouzelis, collaborate the most. These authors gathered around them an enviable number of collaborators. As shown in Figure 17, there are also smaller authors who have formed or have just started to create smaller collaboration groups, such as Andriolo, Merlino, and Hu, and several independent authors who do not collaborate (Acuna-Ruz, Karantzalos) or cooperate with a small number of other authors (Barbone and Ceriola).

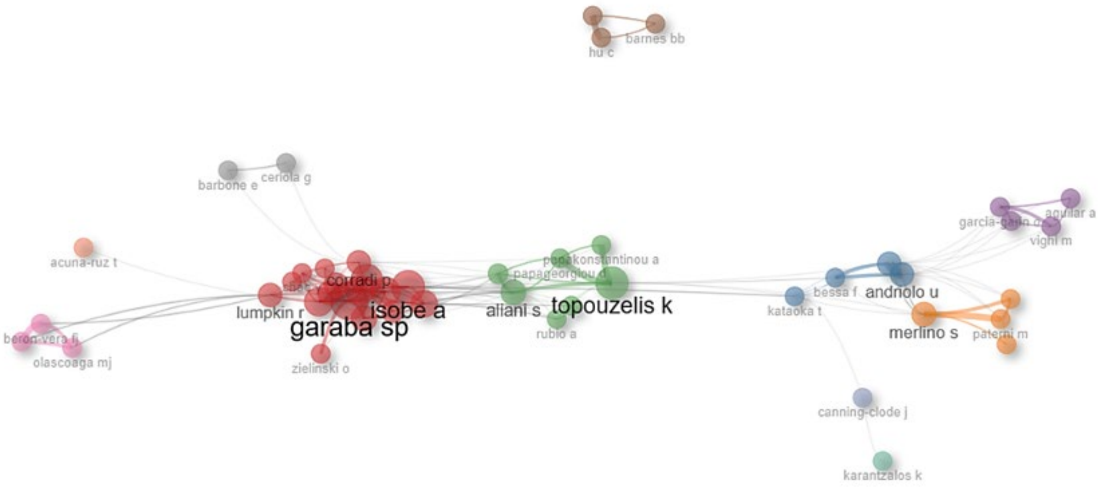


Figure 17. Collaboration network (from Bibliometrix Biblioshiny)

4.4. Analysis by keywords

Keyword analysis aimed to examine the knowledge structure underlying the scientific field of optical remote sensing methods for marine debris detection. Figure 18 shows the frequency of trend topics and their annual changes.

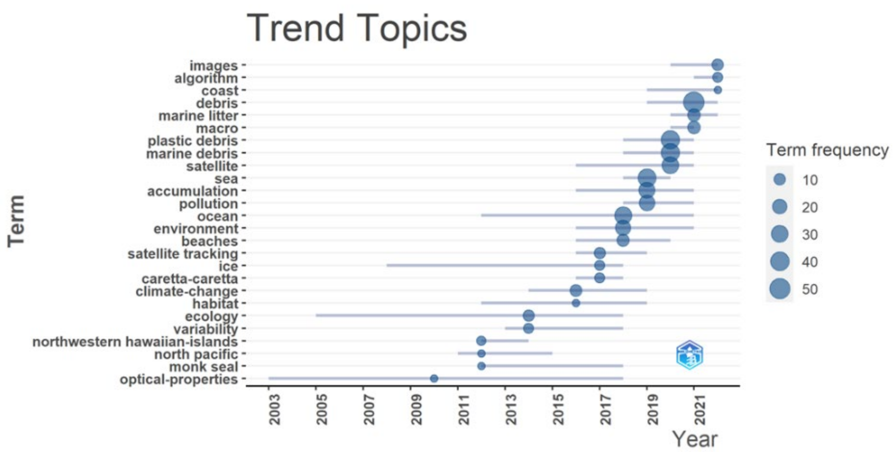


Figure 18. Keyword trends (from Bibliometrix Biblioshiny)

Figure 19 shows the fifty most frequently used Keywords Plus (words or phrases generated by WoS platform algorithms and extracted from paper title and abstract) by search criteria. The terms marine debris, marine litter plastics, and plastic pollution have the highest number of occurrences by far, given that they are the terms or synonyms for the subject of study. Other keywords refer to the methods used, namely machine learning, hyperspectral, and spectroscopy, and the last group of keywords includes platforms used, such as remote sensing and drones.

Figure 19. Keyword frequency in papers (from Bibliometrix Biblioshiny)

The co-occurrence network graph shows the frequency of certain keywords and their mutual connection (see Figure 20) in papers dealing with this topic.

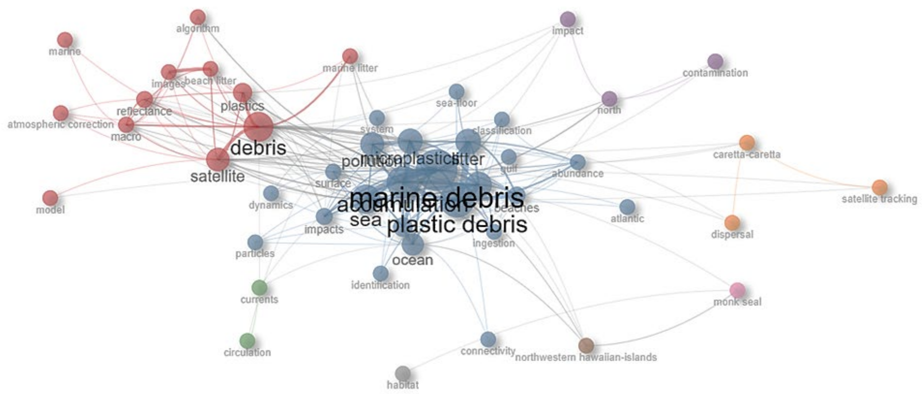


Figure 20. The co-occurrence network (from Bibliometrix Biblioshiny)

5. DISCUSSION

The topic of marine debris in oceans and coastal areas is crucial in the context of global environmental protection. Numerous legislative and advisory initiatives and documents initiated and published by public and scientific institutions have been tackling this issue, which is fast becoming the most significant environmental and health issue. Some scientific studies claim that there will soon be more plastic in the oceans than marine organisms (Eriksen et al., 2023). In the last 5 years, from 2017 to 2022, there has been a significant increase in the number of published documents (papers), by 4 or even 5 times in the WoSCC and Scopus databases, with a tendency for additional increase, as seen in Figure 4. Bibliometric analysis also points to declining scientific interest in this topic in the last 1.5 years. Only 39 papers have been published in 2023, an almost 72% decrease, and as few as 9 papers (33% of papers published in 2022, or 46% of papers published in 2023) in the first half of 2004. The reason for the loss of interest in the topic is that until 2022 different methods, logical approaches, and applications have been proposed and implemented, and more interesting research topics presented themselves in the meantime.

Further studies could use new-generation sensors with improved characteristics (better radiometric, spatial, temporal, and spectral resolutions; e.g. Worldview-3&4 (WV-3&4), commercial satellite sensors from Maxar with sub-meter resolution; Planet Space's SkySat from commercial company Planet Labs (sub-meter resolution and temporal resolution 12 times a day) to detect floating marine litter and better distinguish marine litter from other items.

Optical remote sensing methods are effective as a relatively new trend in floating marine debris detection and problem resolution, especially when combined with new platforms (UAV) and ultimate sensors (hyperspectral, better resolution). Artificial intelligence is trying to solve the problem of automating and accelerating existing methods, especially machine learning.

The leading countries in terms of marine debris research are the USA, Portugal, Italy, the UK, Germany, and China, i.e. countries with a very strong marine industry. Many other countries have been intensively cooperating with these leading countries - a significant progress in marine waste research – as seen in Figures 11 and 12.

Future expectations from the scientific field of marine debris research are progress, automation, and acceleration of remote sensing scene search methods, with emphasis on the use of artificial intelligence. Searching vast ocean surfaces in remote sensing scenes could become the bottleneck of research methods.

6. CONCLUSION

Marine debris, also referred to as marine litter is persistent, manufactured, or processed solid material of anthropogenic origin that ends up in oceans, seas, and other large bodies of water. Around 80% of marine debris originates from land, while 20% is created at sea.

Marine debris is a relatively recent research subject. The first papers dealing with marine debris or litter were published in 1975 (Edwards et al., 1975) and 1977 (Morrison et al., 1977). Historically, various scientific methods have been used in marine debris research, but this paper focused on floating marine debris optical remote detection methods in 2002-2023.

The statistical evaluation of the published scientific literature was carried out using bibliometric analysis that focused on the WoSCC (Web of Science Core Collection) and Scopus databases.

The documents obtained by bibliometric analysis can be classified into 43 research fields. The largest share of the 209 documents identified in the two most important scientific databases, about 25%, was published in two journals: Marine Pollution Bulletin and Remote Sensing. Furthermore, the most frequent type of published documents are papers (168 papers, or 78.38%).

The scientific production of marine debris research documents can be divided into 3 stages: 1) the preparation stage from 2002 to 2011 in which less than 5 documents were published per year; 2) the period of growth from 2011 to 2017, with approximately 10 documents published per year; and 3) the highly productive period from 2017 to the present day (see Figure 4). In the last year and a half, there has been a decline in scientific interest in this topic.

The researchers mostly focused on remote sensing methods for the detection of marine litter plastics and microplastics in the sea. Marine litter research was mainly published in the USA, Italy, Portugal, the UK, China, and Japan i.e. countries that have a very strong industry related to the marine environment. A total of 54 countries participated in the publication of documents, of which the USA published 47, i.e. almost a third of the total number. The USA is in the lead among the countries that collaborate in publishing papers, followed by Italy, Portugal, the United Kingdom, China, Japan, Germany, Greece, Spain, and Australia. Cooperation between the USA and European countries, China, Japan, Australia, and New Zealand has been at an enviable level.

The most productive affiliation with the most published documents is the University Aegean from Greece, with 23 documents.

The most productive author is Garaba SP, who has the largest number of published documents (13), while the most globally cited paper is Elmendorf et al., (2012).

The sharp upward trend of increasing scientific production on the topic of marine debris started in 2017 and continues to this day (see Figure 4). This can be explained by the significant increase in the observed quantity of plastics over time, especially since 2010.

In general, the results of research of marine debris in oceans and coastal areas are of utmost importance in the context of global environmental protection and human health.

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CONFLICT OF INTEREST

Authors declare no conflict of interest.

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