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Monitoring Ocean Pollution: A Comprehensive Review of Satellite Image Analysis Methods

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ABSTRACT

The proliferation of plastic pollution in coastal marine environments has emerged as a significant environmental issue, garnering global focus due to its detrimental impacts on marine ecosystems, human health, and economic endeavors. Coastal regions, characterized by the interaction between terrestrial ecosystems and marine environments, exhibit heightened vulnerability to the accumulation of plastic waste. The origins of this pollution are multifaceted, encompassing terrestrial activities characterized by inadequate waste management, the discharge of industrial effluents, contributions from precipitation, and inputs from river systems. Additionally, marine sources play a significant role, particularly those associated with the fishing industry and various maritime activities. The presence of plastic litter, which includes both large, discernible items and minute particles, poses considerable threats to marine organisms. The ingestion or entanglement of marine species, encompassing organisms from plankton to large mammals, in plastic debris leads to significant injuries, increased mortality rates, and disruptions within their respective food chains. Furthermore, plastics present in marine ecosystems have the capacity to absorb and disseminate toxic chemicals, thereby exacerbating the degradation of aquatic habitats. The ongoing challenges associated with the surveillance and regulation of plastic pollution in marine environments remain a significant concern. Traditional methodologies, such as in-situ sampling and airborne surveys, often present challenges related to labor intensity, time consumption, and limitations in both temporal and spatial dimensions. This scenario presents Earth observation (EO) imagery obtained from satellites as a feasible alternative. Satellites equipped with optical sensors offer a unique vantage point, enabling extensive surveillance of plastic waste distribution across extensive coastal areas with increased temporal resolution. This study investigates the utilization of data from the European Space Agency's Sentinel-2 satellite for the identification and monitoring of floating macro plastics in coastal waterways. The present study aims to evaluate the precision and effectiveness of plastic waste detection utilizing sophisticated remote sensing techniques and machine learning algorithms.

Keywords

Marine Debris, Pollution, Image Processing, macro plastics, multi spectral

1. INTRODUCTION

The primary sources of contaminants entering marine environments are linked to anthropogenic activities occurring in coastal regions as well as inland areas. Non-point source pollution arising from agricultural runoff, industrial discharge, urban wastewater, and stormwater drainage constitutes a significant contributor to marine contamination. Point-source pollution, such as oil spills and chemical leakages, although less frequent, can produce severe environmental impacts on aquatic ecosystems [14], [28], [30].

Marine pollution has emerged as one of the most critical environmental challenges worldwide. Every year, millions of tons of waste materials enter oceans and coastal waters through rivers, coastal settlements, industrial activities, and maritime operations. A significant portion of this debris accumulates along shorelines, while the remaining material is transported by ocean currents and gyres, resulting in large-scale marine debris concentrations [8], [38]. Excessive nutrient enrichment from anthropogenic sources can also trigger harmful algal blooms and hypoxic zones, adversely affecting marine biodiversity and ecosystem stability [16], [33].

Marine debris encompasses a wide variety of waste materials, including plastics, abandoned fishing gear, microplastics, and other anthropogenic litter. These materials pose substantial threats to marine organisms through ingestion, entanglement, habitat degradation, and toxic chemical transfer [6], [8]. According to recent estimates, approximately eight million tons of plastic enter the oceans annually, where they undergo fragmentation due to wave action, ultraviolet radiation, and environmental weathering processes, ultimately generating microplastics that disperse throughout marine ecosystems [1], [10].

One of the most recognized manifestations of marine pollution is the formation of garbage patches within major ocean gyres. Oceanic circulation patterns concentrate floating debris into large accumulation zones such as the Great Pacific Garbage Patch. These regions contain a mixture of macroplastics, microplastics, fishing nets, and other anthropogenic waste distributed throughout the water column [5], [13]. Conventional monitoring approaches, including vessel-based surveys and net sampling, provide valuable information but suffer from limited spatial coverage, high operational costs, and inadequate temporal resolution [10], [11].

Recent advancements in Earth Observation (EO) technologies have significantly enhanced the capability to monitor marine pollution at regional and global scales. Optical satellite missions such as Sentinel-2, Landsat, and PRISMA have demonstrated promising capabilities for detecting floating plastic debris using spectral signatures and plastic-specific indices [2], [3], [10], [21]. Studies have shown that multispectral and hyperspectral remote sensing techniques can effectively distinguish plastic materials from surrounding water bodies through analysis of their spectral characteristics [2], [11], [21].

In addition to optical sensors, radar-based remote sensing systems have emerged as powerful tools for marine pollution monitoring. Synthetic Aperture Radar (SAR) platforms such as Sentinel-1, TerraSAR-X, and RADARSAT-2 enable all-weather and day-night observation capabilities by analyzing variations in sea surface roughness and backscatter characteristics [5], [13], [18], [25]. Several researchers have investigated the use of SAR imagery for detecting oil spills, surfactant layers, and floating debris concentrations in marine environments [27], [28], [39].

Researchers have also explored innovative methods for global marine plastic monitoring. Investigators utilizing NASA’s Cyclone Global Navigation Satellite System (CYGNSS) demonstrated that ocean surface roughness measurements can be employed to estimate microplastic distributions across large oceanic regions. The observed relationship between reduced surface roughness and plastic accumulation zones provides new opportunities for large-scale marine pollution surveillance [9]. Similarly, NASA’s Interagency Implementation and Advanced Concepts Team (IMPACT) developed machine learning-based frameworks using satellite imagery and ground-truth observations for automated marine debris detection and classification.

The integration of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) techniques has further accelerated advancements in marine pollution monitoring. Deep learning architectures, including Convolutional Neural Networks (CNNs), semantic segmentation networks, and attention-based models, have demonstrated improved performance for marine debris detection and localization [4], [7], [17], [31]. These approaches can automatically learn discriminative spatial and spectral features from satellite imagery, enabling more accurate and scalable monitoring solutions.

The increasing severity of marine plastic pollution has attracted significant attention from researchers, policymakers, and environmental organizations. Reports from the United Nations indicate that the volume of plastic entering marine environments may nearly triple by 2040 if effective mitigation strategies are not implemented. Consequently, there is an urgent need for advanced monitoring frameworks capable of supporting sustainable waste management policies, pollution prevention initiatives, and large-scale environmental conservation efforts [23], [40].

This review paper systematically examines recent developments in satellite-based marine debris detection, remote sensing technologies, machine learning algorithms, and deep learning methodologies employed for marine pollution monitoring. Furthermore, the study identifies existing research gaps, evaluates current technological limitations, and highlights future research directions for developing robust, scalable, and intelligent marine debris monitoring systems.

2. RELATED WORK

The proposed review utilized Scopus databases and included academic materials relevant to our research domains. The search was conducted utilizing keywords (Table 1) selected based on preliminary evaluations of their potential efficacy. The preliminary search produced 1230 potential results, from which 400 duplicates were promptly removed, as depicted in Figure 1. An assessment of the actual relevance of research publications to the study topics was essential, given that not all publications were inherently pertinent. The initial screening procedure entailed a thorough examination of titles to exclude studies that were clearly unrelated to our three designated research domains, including those focused exclusively on the biological aspects of marine plastic pollution or on types of marine debris other than plastic. The initial phase of this process led to the removal of 400 items. In light of specific titles complicating the relevance assessment, we advanced to the subsequent stage for further investigation. The evaluation of article summaries involved the application of specific exclusion criteria, which included the omission of publications released prior to 2020, those lacking full text availability, publications in languages other than English, and those deemed irrelevant to the research inquiries. This prompted the removal of an additional 400 studies, culminating in a total of 54 publications identified as probable outcomes. Additionally, we opted to advance certain ambiguous papers to the next selection round for a more comprehensive assessment. Throughout the final evaluation process, all submissions underwent thorough examination. While all selected publications were pertinent to our research questions, we opted to exclude an additional 12 articles that merely described the marine plastic issue without presenting any new study results or evidence. This led to the selection of 30 papers as the primary sources for this study.

Table 1 Keywords employed for SCOPUS database search

Task	Keywords	
Fixed keywords for all searches	“marine plastic”, ”sea pollution”, “marine pollution”	
	“plastic marine litter”, ”marine debris”, ”sea plastic”	
	Empty Cell	“marine litter”, ”sea litter”, “microplastic”, “MP”
	Empty Cell	“public awareness”, “consumer”, “psychology”
Keywords related to the first topic	“public knowledge”, “perception”, “education”,	
	Empty Cell	“corporate responsibility”, “risk perception”
	Empty Cell	“reuse”, “circular economy”, “strategy”
Keywords related to the second topic	“public participation”, “waste treatment”	
	Empty Cell	“fishing for Litter”, “life-cycle”
	Empty Cell	“incentives”, “legislation”, “ecolabels”

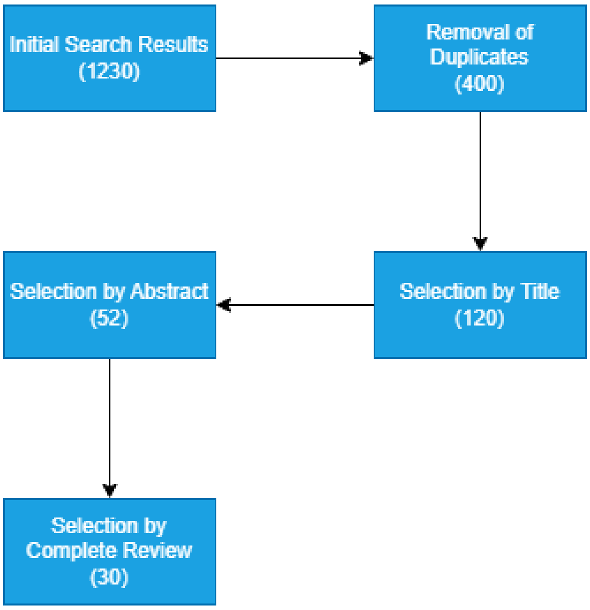

Figure 1. Selection process of the papers.

Table 2 Literature Review for Current international instruments related to marine plastic pollution.

Citation	Title	Remarks	Methodology
[1]	The Design of a Global Oceanic Plastic Debris Monitoring System Using Imaging Spectroscopy Onboard Low-Flying Satellites	•The ocean's 'plastic soup' from river and marine trash is unclear. • Spatiotemporal data is needed to fully comprehend this formation. • A new image spectroscopy method increases plastic spectral fingerprints. • AOTFs are used for remote sensing and imaging. Plans call for a network of low-flying satellites with deployable optics to track plastic growth and motion. 300 km altitude reduces imaging aperture.	High-resolution detection and imaging methods are lacking. Innovative imaging spectroscopic idea. Improve polymers' spectral fingerprints. Creating a high-resolution, long-return optical filtering system. AOTF for satellite navigation and imaging.
[2]	Pansharpening PRISMA Data for Marine Plastic Litter Detection Using Plastic Indexes	• Insufficient evaluation of hyperspectral PRISMA images for marine plastics litter detection. • Insufficient spatial resolution for recognizing tiny plastic particles in the ocean. • The study uses satellite hyperspectral data to locate tiny marine plastic debris. Controlled trials used different-sized plastic targets. • Pan-sharpened hyperspectral images were used to detect plastic items using index combining. Plastic spectrum is distinguished from water without pixels or duplicate edges using PCA-based replacement.	• Experimented with various plastic targets and materials. • Developed pre-processing processes and tested 13 pansharpening approaches for spectrum plastics-water separation. • Pan-sharpened hyperspectral pictures were used to detect plastic items using index combining. Despite plastics and water's spectral similarities, marine plastic waste indexes used certain properties. • Index combining identified plastic targets and separated them from the other materials.
[3]	Comparitive Analysis of Spectral Indices for the Identification of Plastic Patches in the Steam	Indian Ocean Satellite Imaging and Waste Clusters Tracks and evaluates Indian Ocean garbage clusters with Sentinel-2. • Identifies polluted zones using MSI. • Assesses Sentinel-2's Indian Ocean debris surveying capability. Unveils Indian Ocean garbage buildup patterns and evolution.	• Monitor and assess aquatic waste and pollution patterns. MSI remote sensing instrument on Sentinel-2 To locate concentrated pollution zones, collect, prepare, and analyze MSI data. • Discusses maritime debris ecology and Sentinel-2's role in waste management. •

		• Applauds Sentinel-2's marine debris management and countermeasures insights.	Emphasizes MSI data collection, preparation, and analysis.
[4]	Improving marine litter segmentation with limited resolution satellite imagery	Learning-Based Semantic Segmentation for Floating Plastic Litter Detection • Reduces convolutional network parameters. Feeds plastic segmentation indexes. Performs well against other learning methods.	• Create a learning-based categorization approach for marine plastic litter detection. Uses Sentinel-2 data. • Improves plastic segmentation with a neural network with less parameters and particular indexes and multispectral data.
[5]	Monitoring Surfactants Pollution Potentially Related to Plastics in the World Gyres Using Radar Remote Sensing	Ocean Plastic Surfactants: Origins • Microorganisms in ocean plastics produce surfactants, which damper brief capillary wave on the sea surface. • Radar satellites detect this dampening.	• ESA Sentinel-1 or DLR TerraSAR-X satellite data for Atlantic, Pacific, and Indian Ocean gyres. • Gyre surfactants are unrelated to chlorophyll levels. • Surfactants may come from ocean plastics. • Increased surfactant surface flexibility reduces short capillary.
[6]	Coastal Marine Debris Density Mapping using a Segmentation Analysis of High-Resolution Satellite Imagery	• Identification of coastal marine debris • Potential impact on marine life, fisheries, and tourism. High-resolution satellite imaging for debris detection. In situ information regarding local debris removal and segmentation.	• Marine trash classification using segmentation. • Quantifying segmentation uncertainty with Shannon's entropy. Create spectral signatures for marine debris semantic characteristics. • Calculate marine debris density with categorization model.
[7]	Marine Debris Detection in Satellite Surveillance Using Attention Mechanisms	• Marine Debris Detecting and Localization Study • Utilizes YOLOv7's instance segmentation and attention techniques for effective detection. • Compares lightweight coordinate attention, CBAM, and self-attention bottleneck transformer.	• Used YOLOv7 and three attention mechanisms: 1. Light Coordinate Focus 2. CBAM Convolutional Blocks Attention Module 3. Self-attention bottleneck transformer • A carefully tagged satellite picture dataset of ocean trash. • CBAM surpasses other models in box recognition and mask evaluation, as evaluated by F1 scores. • Despite lesser performance, Bottleneck Transformer found manual annotation errors and performed better.
[8]	An Earth Observing System for monitoring the distribution of plastic marine debris	Marine debris effects and solutions • Marine trash causes global warming and navigational dangers. • The Central Pollution Control Board estimates 60% of Indian marine debris is plastic. • Plastics' buoyancy and durability enable long-distance transport. • Some plastics reach beaches, while others are stuck in convergence zones by winds, ocean currents, and drifts.	• Policymakers and organizations need to know marine debris distribution and pathways to make changes. • A hardware model detects and classifies debris pictures in ocean surveillance using YOLO and MobileNet.
[9]	Using Ground Radar Measurements to Measure Plastisphere-Based Surfactant Dampening	• Observing surface roughness variations caused by microbe-produced surfactants on polymers using a ground radar sensor in a semi-natural environment. • Analyzing surfactant damping effects on waves at the ocean's surface to identify marine plastics with radar satellites.	• Surfactant dampening reduces backscatter. • Significant changes in backscattering between plastisphere-based surfactant trials and microbial-free controls. • Ground radar can detect marine plastic surfactant dampening, allowing monitoring of plastic contamination.

[10]	Detection and Monitoring of Floating Plastic Debris on Inland Waters From Sentinel-2 Time Series	• Monitors floating plastic waste in inland waters using multitemporal Earth observation data, including optical satellite image time series. Developed for Google Earth Engine. • Finds damaged locations in entire Sentinel-2 scenes. • Shown on multiple continents.	• Using rule-based detection: - Signal intensity variations Temporal patterns Features of spectrum Fusion of info • Monitors vulnerable locations continuously. - Subpixel plastic cover estimation via spectral unmixing. Temporal frame - Area of interest - No individual image selection or manually region outlining required.
[11]	Automatic Detection and Identification of Floating Marine Debris Using Multispectral Satellite Imagery,	• Use Sentinel-2 satellite data to create tools that can identify and differentiate floating plastic waste from other ocean components. • Classified using severe gradient boosting. Published works and personal satellite image interpretation were training data. • Sensor's mixed bands and subpixel coverage make dataset application difficult. • Expanded dataset with Wasserstein generative adversarial network.	• Supervised synthetic data model classified questionable plastic pixels 83% accurately. • Ensemble model included uncertainty quantification in forecasts. 75% of questionable plastic pixels were classified correctly. • Classification accuracy decreased but misclassifications decreased significantly when compared with the highest quality model. • Used Sentinel-2's two bands and seven indices.
[12]	Detecting Macro Floating Objects on Coastal Water Bodies using Sentinel-2 Data	• Ocean pollution, including manmade litter and natural nitrogen and phosphorus. Coastal Sentinel-1 and Sentinel-2 satellite images detection of floating items. • Region variability hinders consistent recognition of floating patches. • Domain shift concerns complicate detection across varied regions.	• Uses environmental aggregation processes and data-driven deep learning algorithms to predict floating debris spatial properties. Sentinel-1 and Sentinel-2 hand-labeled image database expanded. • Medium-resolution satellite imaging cannot detect floating items. • Remotely detectable floating patches result from aggregation. • Deep learning architecture performance depends on training scenes.
[13]	Monitoring Surfactants Pollution Potentially Related to Plastics in the World Gyres Using Radar Remote Sensing	• Surfactants produced by ocean gyre bacteria colonization plastics. • Plastic in the ocean may produce surfactants.	Gyres of the Atlantic, Pacific, and Indian Oceans. DLR TerraSAR-X and ESA Sentinel-1 data. - Gyre surfactants found many times. - Surfactant presence did not affect medium or high chlorophyll levels. Biogenic slicks do not produce surfactants.
[14]	Characterization of Offshore Oil Seeps Using RADARSAT-2 Polarimetric Features	• Guajira Basin, Colombia, 40 km offshore. Analysis of Polarimetric Features Measures of entropy include conformity and correlation. Coefficient Polarization Degree	• RADARSAT-2 quad-polarized data. • 32 RADARSAT-2 FQW quad-polarized photos. • There were 53 slicks spotted, but only in 2 photos. • Entropy proved most effective.
[15]	Urban Black-Odor Water Remote Sensing Mapping Based on Shadow Removal: A Case Study in Nanjing	• Urban black-odor water is a major environmental concern affecting health and living conditions. • Its distribution is unknown and often mistaken for dark objects due to similar spectral features. • Proven effective in Nanjing City for black-odor water extraction,	• Developed a shadow-free identification approach employing remote sensing photos from the Chinese satellite Gaofen-2 (GF-2). • Measurements of water quality in situ were used for validation. • Proposed technique accuracy: 85.7% • 3.5% false alarm rate

		with potential for urban administration and centralization.	• Outperformed four existing methods by decreasing incorrect extraction of non-black-odor water with excellent accuracy.
[16]	Comparison of the Spatiotemporal Variation of Chl-a in the East China Sea and Bohai Sea based on long time series satellite data	• This study evaluates seas' ecological health and aquatic environment quality using chlorophyll-a (Chl-a) as an indicator. • SeaWiFS and MODIS data were used to track changes in the Bohai Sea (semi-enclosed sea) and East China Sea (open sea) from 1998 to 2020. • Human activities are more quickly reflected in open seas. • Closed sea areas have stronger long-term governance consequences. • Findings support local governments in preventing marine pollution and protecting ecosystems.	• The ecological impact of human activities on the semi-closed Bohai Sea and open East China Sea. • Chlorophyll-a content indicates ecological health and water quality. • Two sensors: SeaWiFS and MODIS. In the Bohai Sea, Chl-a concentration initially increased and then decreased, with no seasonal fluctuations noted. • East China the ocean: Initial rise, fall, then climb; substantial seasonal fluctuations observed.
[17]	Maritime Ship Detection using Convolutional Neural Networks from Satellite Images	• Marine traffic monitoring is crucial for safety and security in global trade and commerce. • Issues include ship hijacking, illegal fishing, border encroachments, illicit cargo exchange, accidents, and military attacks. • This research presents a CNN-based deep learning ship identification model from satellite photos.	• CNN Model 1 and CNN Model 2 are trained, validated, and tested on Airbus satellite pictures. • Both models reach 89.7% accuracy, proving their automatic, rapid, and precise functioning.
[18]	Copernicus and ESA SAR Missions	• Explores SAR performance and interferometry techniques (InSAR). • Explains the ROSE-L SAR instrument's key features.	• The paper reviews the Copernicus SAR missions, focusing on Sentinel-1, ROSE-L, and Sentinel-1 Next Generation (NG). Key points • Explores potential performance improvements and new imaging capabilities.
[19]	Thermal Pollution Monitoring of Tianwan Nuclear Power Plant for the Past 20 Years Based on Landsat Remote Sensed Data	• The study examines Copernicus SAR missions, including Sentinel-1, ROSE-L, and Sentinel-1 Next Generation. Key points • SST changes from thermal discharge from the plant • Trend analysis, seasonal distribution, and environmental impact • No temperature pollution before May 2007 (plant operation start) • SST rise fulfills national marine quality guidelines, with no severe environmental pollution reported.	• Landsat data used • Single-channel algorithm for SST estimation • Calculated and tracked thermal discharge area • Thermally polluted area increased by 66.77 km² from 2001 to 2020 • Spring has the highest thermal pollution, followed by summer, winter, and fall.
[20]	An Assessment of Water Color for Inland Water in China Using a Landsat 8-Derived Forel–Ule Index and the Google Earth Engine Platform	• A 2015 cloud-free composite image of China's aquatic bodies enhanced water quality evaluation. • Developed the first Forel-Ule index (FUI) water color product and conducted the first national-scale study of lakes over 0.01 km2.	• Assessing water color in China, focusing on lakes over 0.01 km². • Processed Landsat-8 imagery in summer 2015 using the BAP compositing technique. • First 30 m resolution Forel-Ule index (FUI) water color product. • Performed a nationwide evaluation of 60,026 natural lakes.

		• Yellow lake proportion: 50% for lakes < 1 km², 28% for lakes ≥ 1 km².	• FUI product vs. in situ water surface reflectance-derived FUI: $R^2 = 0.90$, $P < 0.001$. • $R^2 = 0.90$, $P < 0.001$ for FUI product vs. in situ Secchi depth. • FUI product vs. trophic level index: $R^2 = 0.62$, $P < 0.001$. • The most common lake hues are yellow (49%), and green (41%).
[21]	Pansharpening PRISMA Data for Marine Plastic Litter Detection Using Plastic Indexes	• First use of satellite hyperspectral data to detect small marine plastic litter • Panchromatic data for pansharpening • PCA-based replacement approach efficiently differentiates plastic from water spectra • Plastic targets can be detected at 8% of original hyperspectral pixel coverage. • In panchromatic images, plastic targets are visible but not discernible merely by panchromatic data.	• Hyperspectral PRISMA images are untested for marine litter identification. • Insufficient for small plastic item discrimination • Diverse plastic target controlled trials • The index detects plastic using pan-sharpened hyperspectral spectra. • It differentiates plastic targets from others despite spectral similarities to water.
[22]	Identification of Reef Characteristics Using Remote Sensing Technology in Ayau Islands, Indonesia	• The study uses remote sensing and field measurements from RCO-LIPI to study shallow seas in Indonesia's Ayau Islands. • Due to long tides, the islands' 32,347.08 acres of shallow ground are mixed. • Coral reefs are found in deeper locations, while seagrass grows along the coast. • Highlights major findings and statistical data from the shallow Ayau Islands investigation.	• Shallow water, coral reef, and seagrass distribution characteristics • Landsat 8 OLI primary data • Research Center for Oceanography (RCO-LIPI) field data • Ocean color data for Sea Surface Temperature • MIX dominant class due to lengthy tide times in reef flat zone • Grows in nutrient-rich coastal areas.
[23]	Sustainability Assessment of Marine Aquaculture Based on A Simple Index in Kyushu, Japan	• A simple Aquaculture Intensity Index (AII) and fish production model are used to analyze sustainability and intensity optimization in coastal aquaculture farms. • Distance between fish farms in Kyushu, Japan affects sustainability.	• Aquaculture sustainability is impacted by distance from fish farms to bay mouth. • A simplified Aquaculture Intensity Index (AII) and fish production model are used to analyze and estimate appropriate intensity. • High nutrient loads from coastal aquaculture farms cause self-pollution and reduced production.
[24]	Satellite Remote Sensing Observations of Trans-Atlantic Dust Transport and Deposition: A Multi-Sensor Analysis	• Statistical Aerosol Measurement Summary. • Employs CALIOP, MODIS, MISR, and IASI sensors. • Rates transAtlantic dust transit and deposition. • MODIS and IASI size-based DOD matches closer to AERONET-derived DOD. • The shape-based DOD is 25% smaller and accounts for dust-pollution particles.	• Sensor-specific approaches for determining Dust Optical Depth (DOD) have been grouped by size and form. • Size-based DOD (MODIS, IASI) matches AERONET-derived DOD better. • The shape-based DOD (CALIOP, MISR) is around 25% smaller than the size-based DOD. • Size-based DOD includes coarse-spherical particles, while shape-based DOD eliminates them. • Improve models using analysis.

		• Dust deposition difference is less than DOD, showing constant gradient.	
[25]	Use of SAR Imagery and Artificial Intelligence for a Multi-Components Ocean Monitoring	• High-resolution SAR data from polar earth orbiters. • Single Web platform for monitoring.	• Computing ocean surface environmental parameters • Machine learning methods • Single, operational Web platform for on-demand compute.
[26]	Status of the Kompsat-5 SAR Mission, Utilization and Future Plans	• Expanding imaging modes and maintaining orbit for InSAR beyond scheduled mission. • Using Sigma naught output for multitemporal SAR image analysis. •A paper on mission operation, acquisition, utilization, and application.	• Launched by KARI on August 22, 2013. • Enhances Earth observation and satellite imagery for GIS and environmental monitoring. • International Charter & AOGEO started receiving photographs in 2011. • KOMPSAT-6 and adoption strategies are introduced.
[27]	Towards Automatic Detection of Dark Features in the Barents Sea using Synthetic Aperture Radar	• Discussing results and technique improvements for a fully automated Barents Sea surveillance system for dark features. • Large-scale ocean surveillance for oil spills is necessary due to increased human and commercial activity in the Barents Sea. • Dark spots in SAR photos may indicate spills of oil or similar events.	• Fishing, offshore oil and gas exploration • Large-scale oil spill monitoring using Synthetic Aperture Radar (SAR) due to geographical and climatic constraints • Low backscatter areas indicate potential spills • Accurate lookalike separation is crucial for automatic spill detection.
[28]	Oil Spill Detection from SAR Images by Deep Learning	• Oil spills pose significant threats to maritime and coastal ecosystems. • Satellite synthetic aperture radar (SAR) systems can detect oil spills, but distinguishing between real spills and lookalikes is challenging. • Human operators' visual checks on numerous images are expensive.	• Probabilistic models and machine learning are among the solutions. • An novel image-to-image translation solution using CNNs with an adversarial loss function is presented in this paper. • The method was evaluated utilizing Mediterranean Sea and Atlantic Ocean Radarsat-2 and Sentinel-1 SAR data.
[29]	The Study on Association between Urban Green Space and Temperature Changes in Mega City	• Rise in surface, air, and CO levels over 10 years, especially in Bangkok's core business district.	• Factors impacting green space changes in Bangkok. • Surface, air, and CO levels data from 2007, 2012, and 2019.
[30]	An adversarial learning approach for oil spill detection from SAR images	• Oil spills cause severe harm to coastal and maritime ecosystems. While satellite synthetic aperture radar (SAR) devices may detect oil spills, separating them from fakes is difficult. • High cost of human operators' visual checks on several photos. • The paper presents a novel approach utilizing image-to-image the translation, CNNs, and an adversarial loss function.	• This work presents innovative image-to-image translation using convolutional neural networks trained with an adversarial loss function. • The approach was tested using Mediterranean Sea & Atlantic Ocean Radarsat-2 and Sentinel-1 SAR data. • Probabilistic models & machine learning are among the solutions.
[31]	NASA NeMO-Net's Convolutional Neural Network: Mapping Marine Habitats with Spectrally	• Applied machine learning and computational vision to map benthic habitats. • Implemented deep learning and neural network designs, including NASA NeMO-Net.	• Mapping global shallow benthic tropical marine habitats, especially coral reefs. • Rapid ecological changes from ocean temperatures, acidification, and pollution. • Global datasets may vary according to observation time, atmospheric factors, and

	Heterogeneous Remote Sensing Imagery	• Created an object-based FCN for improved spatial-spectral categorization. • FCNs beat pixel-based approaches in picture classification by identifying relevant spectral and spatial properties.	sensor calibration. • Achieved 85% classification accuracy with WorldView-2 and 80% with Planet satellite imagery.
[32]	Can Mineral Oil Slicks Be Distinguished From Newly Formed Sea Ice Using Synthetic Aperture Radar	A feasibility study will investigate the use of synthetic aperture radar (SAR) imaging to distinguish oil slicks and newly created sea ice.	• Airborne L-band high-resolution UAVSAR • C-band RADARSAT-2 (RS-2) satellite • Utilizing multipolarization characteristics from both SAR datasets. • Determining separability using Kolmogorov-Smirnov test.
[33]	Monitoring Human-Induced Surface Water Disturbance Around Taihu Lake Since 1984 by Time Series Landsat Images	• Inland water dynamics in Taihu Lake region. • Important for water management, ecological balance, and industrial/agricultural development. • Human activity impacts Taihu Lake surface water more than climate variability. • For decades, ecological preservation measures have stabilized natural water quantities. • Disruptions in aquaculture raise concerns about human eutrophication.	• Current water cover products and extraction methods are insufficient for monitoring water distribution and changes in human-disturbed environments. • Developed an expert system to recognize stable water and distinguish aquaculture from natural water using a frequency-based technique for annual maps. Landsat Level-2 photos from 1984-2018 yield steady water products with 30-m resolution. The study evaluated historical changes in water bodies and correlated them with real-world events.
[34]	Roughness Change Analysis of Sea Surface From Visible Images by Fractals	For the first time, the paper examines sea surface roughness utilizing visible picture fractal properties. It quantifies fractal dimensions with box counting, fractional Brownian movement, and area. • The study calculates sea surface roughness using wind speeds and an empirical relation. Wind speed-fractal size correlations are analyzed using field experiment data.	• Evaluated wind speed-fractal dimension correlations using field experiment data. • Introducing four noise kinds to sea surface photos. • Judging noise suppression effectiveness of six ways. Experiments demonstrate the efficacy of fractal approaches and the correlation between winds and fractal dimensions.
[35]	Roughness Analysis of Sea Surface From Visible Images by Texture	• Utilizes six texture measuring methods: gray level, gray level-gradient, Tamura, autocorrelation, edge frequency, and fractional Brownian motion autocorrelation.	Experimental results demonstrate the efficacy of proposed texturing approaches and their relationship. • Demonstrates a correlation between wind speed and image texture roughness.
[36]	Polarized Remote Inversion of the Refractive Index of Marine Spilled Oil From PARASOL Images Under Sunglint	• Detects oil spills utilizing optical polarization remote sensing, focused on refractive index inversion for sunglint reflectance calculations.	• Pixels' equal refractive index predicts seawater and spilled oil. • PARASOL-derived or modeled DOLPs agree significantly when the specular reflection orientation angle (θm) is less than 20°.
[37]	Unmanned Marine Emergency Response System Technology	• Climate change increases coastal emergencies and their severity. • Current equipment and resources not sufficient for timely response. • UAV technology enables unmanned emergency response. • Simulation reveals unmanned system beats subsonic UAV in marine emergencies.	• Implementation of a fast-arriving unmanned crisis response system using high-speed UAVs • Advancements in civil aircraft technology may lead to the usage of fast speeds UAV platforms. • Improve reaction speed for maritime situations (marine research, catastrophe investigation, rescue, surveillance).
[38]	An Earth Observing System for	• Marine debris contributes to global warming and poses navigational	• Marine waste, especially plastics, harms ecosystems and warms the planet.

	monitoring the distribution of plastic marine debris	hazards. • Around 60% of marine litter in India is plastic, according to the Central Pollution Control Board (CPCB). • Plastics' longevity and buoyancy facilitate long-distance transport. • Some plastics are carried to shores, others get trapped in convergence zones created by winds, ocean currents, and drifts.	Ocean navigation is threatened by marine debris. The Central Pollution Control Board reports that 60% of Indian marine litter is plastic. • Due to their buoyancy and durability, plastics are common in marine areas for long-distance transport. • Plastics can wash ashore or get stuck in convergence zones (trash patches) in the five ocean gyres for years. • To make meaningful changes, politicians and organizations must understand marine trash distribution and pathways.
[39]	Insight into Offshore Oil Drift Monitoring Through Combination of Sequential Sentinel-1 Ascending and Descending Images	The paper presents a study on oil drift and the morphological changes of oil slicks offshore Nigeria, utilizing Sentinel-1 satellite imagery.	• Data Collection: Used 12-hour-later descending and ascending photos. • Uses hierarchical split-based oil object identification and contour determination with non-linear filters (mean and standard deviation). • Collocating detected oil from both image kinds estimates oil flow distance and direction.
[40]	Prototype Model of Marine Pollution Monitoring Using Multiple Remote Sensing Platforms	• Prototype Marine Pollution Monitoring Approach • Utilizes multimodal remote sensing data. • Aims for quick, accurate response to marine pollution. • Automatic MPI production and sharing crucial for on-site oil spill response. • Studies oil spills and floating HNS. • Automatic production and sharing of MPI are identified as critical for effectively managing on-site	• The study utilizes various platforms for remote sensing, including satellites, manned aircraft, UAVs, and mobile devices. • The primary goal is to develop a prototype model for monitoring marine pollution, specifically focusing on oil spills and floating Hazardous & Noxious Substances (HNS). • The model aims to generate and visualize Marine Pollution Information (MPI) to enable quick and accurate responses to pollution incidents.

3. COMPARATIVE ANALYSIS OF REVIEWED STUDIES

The reviewed literature demonstrates significant progress in the use of remote sensing technologies, machine learning algorithms, and deep learning approaches for monitoring marine debris and plastic pollution. Optical satellite sensors such as Sentinel-2 and PRISMA have been extensively employed for detecting floating plastics using spectral signatures and plastic-specific indices [2], [10], [11], [21]. These approaches provide good spectral discrimination but remain sensitive to atmospheric conditions, cloud cover, and sea state variations.

Recent studies have increasingly incorporated deep learning techniques for marine debris detection. Costa et al. [4] proposed a semantic segmentation framework capable of improving marine litter segmentation from low-resolution satellite imagery. Similarly, Shen et al. [7] integrated attention mechanisms with YOLO-based architectures and demonstrated improved localization performance for marine debris identification.

Radar-based approaches have also gained attention due to their ability to operate under all-weather conditions. Studies utilizing Sentinel-1 and TerraSAR-X datasets [5], [13], [25] demonstrated the capability of Synthetic Aperture Radar (SAR) to identify surfactant signatures and surface roughness anomalies potentially associated with floating plastic accumulations.

The collective findings suggest that hybrid frameworks combining spectral indices, machine learning classifiers, and deep learning segmentation models provide the most promising direction for future marine pollution monitoring systems.

Table 3 Comparative Analysis of Existing Studies

Ref	Method	Dataset	Accuracy/Performance	Limitation
[2]	PRISMA + Plastic Index	Hyperspectral	Detects plastics at 8% pixel coverage	Limited spatial resolution
[4]	Semantic Segmentation CNN	Sentinel-2	Improved segmentation accuracy	Requires annotated data
[7]	YOLOv7 + Attention	Satellite Images	Highest F1-score among tested models	Computationally intensive

Ref	**Method**	**Dataset**	**Accuracy/Performance**	**Limitation**
[10]	Rule-based Detection	Sentinel-2 Time Series	Continuous monitoring capability	Sensitive to threshold selection
[11]	Gradient Boosting + GAN	Multispectral Imagery	83% classification accuracy	Mixed pixel problem
[17]	CNN-based Detection	Satellite Images	89.7% accuracy	Designed for ship detection
[25]	SAR + AI	SAR Imagery	Robust under adverse weather	Requires specialized processing

The reviewed literature indicates that marine debris monitoring has evolved from traditional spectral-index approaches toward advanced machine learning and deep learning methodologies.

To better understand the distribution of methodologies employed in the reviewed studies, Figure 4 presents the percentage distribution of major detection techniques reported in the literature.

Trend of Marine Debris Detection Techniques

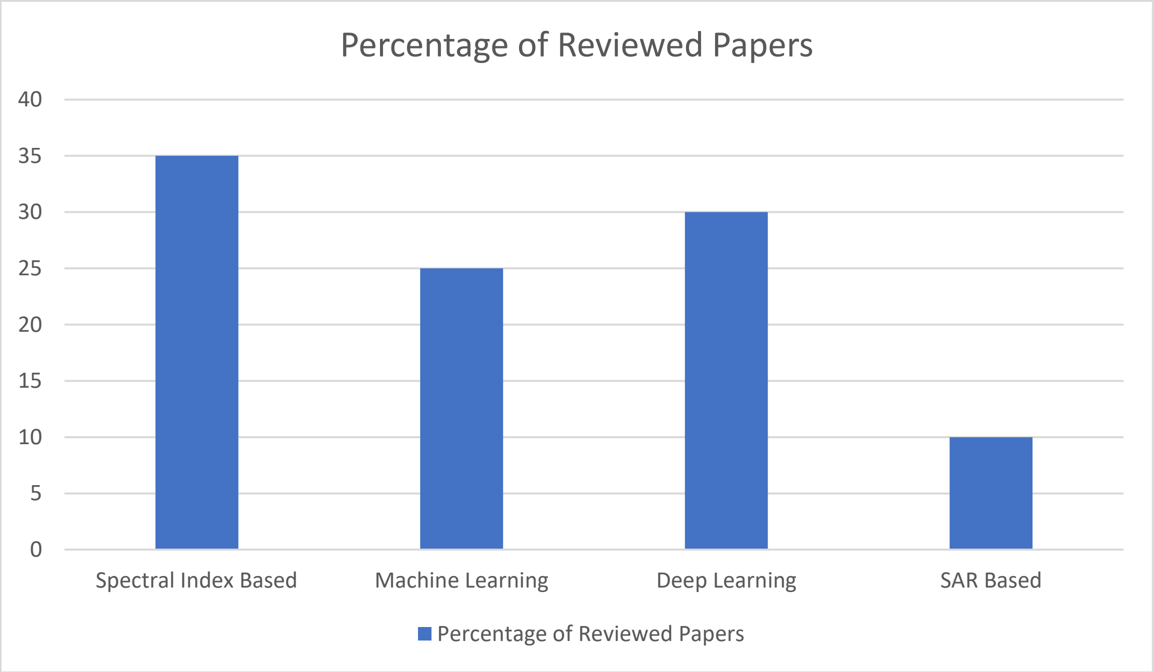

Figure 4. Trend of Marine Debris Detection Techniques in Reviewed Literature

As shown in Figure 4, spectral-index-based approaches account for approximately 35% of the reviewed studies, reflecting their widespread adoption due to simplicity and computational efficiency. Deep learning approaches represent 30% of the literature, demonstrating the growing interest in AI-based marine debris detection. Machine learning methods contribute 25% of the reviewed studies, while SAR-based approaches account for approximately 10%, highlighting their specialized use for all-weather monitoring applications.

4. DISCUSSION

The reviewed studies indicate a clear evolution from traditional image processing approaches toward advanced artificial intelligence techniques. Early research primarily relied on spectral indices and threshold-based methods to identify marine plastics. While such techniques offer simplicity and computational efficiency, their performance deteriorates under varying illumination conditions and complex coastal environments [3], [10].

Machine learning methods such as Gradient Boosting and Random Forest classifiers have improved classification robustness by incorporating multiple spectral and spatial features [11]. However, these methods still depend heavily on handcrafted features and domain expertise.

Deep learning approaches have demonstrated superior performance in recent years. Convolutional Neural Networks (CNNs), semantic segmentation networks, and attention-based architectures have achieved improved detection and localization capabilities [4], [7], [17]. These models automatically learn discriminative features from multispectral imagery and can generalize across different environmental conditions.

Nevertheless, several challenges remain unresolved:

- Lack of standardized benchmark datasets
- Limited availability of labeled marine debris imagery
- Mixed-pixel effects in medium-resolution satellite images
- Atmospheric interference and cloud contamination
- Real-time monitoring constraints

Future research should focus on multimodal frameworks integrating optical imagery, SAR data, and advanced deep learning architectures to improve detection accuracy and operational applicability.

5. RESEARCH GAPS AND FUTURE DIRECTIONS

Based on the reviewed literature, the following research gaps have been identified:

G1. Limited Availability of Annotated Datasets

Most existing studies rely on small datasets with limited geographic diversity. The absence of standardized benchmark datasets restricts fair comparison among different methodologies.

G2. Dependence on Spectral Features

Several approaches rely heavily on spectral indices such as Floating Debris Index (FDI) and NDWI. These indices may fail under changing environmental conditions.

G3. Insufficient Real-Time Monitoring

Current systems primarily perform offline analysis. Real-time operational monitoring remains an open challenge.

G4. Limited Explainability

Many deep learning models operate as black-box systems, reducing interpretability for environmental agencies and policy makers.

G5. Need for Multi-Sensor Fusion

Future systems should integrate Sentinel-1 SAR data, Sentinel-2 optical data, and UAV imagery to improve robustness.

6. CONCLUSION

This review presents a comprehensive analysis of contemporary satellite-based marine plastic pollution monitoring techniques. The literature demonstrates that Earth Observation platforms such as Sentinel-1, Sentinel-2, PRISMA, Landsat, RADARSAT-2, and TerraSAR-X provide valuable capabilities for large-scale marine debris surveillance. Traditional spectral-index-based approaches remain effective for preliminary detection; however, recent advancements in machine learning and deep learning have significantly improved detection accuracy and segmentation performance.

The comparative analysis reveals that semantic segmentation networks, attention-based architectures, and multimodal frameworks offer superior capability for identifying floating marine debris under diverse environmental conditions. Nevertheless, challenges related to dataset availability, mixed-pixel effects, atmospheric interference, and operational deployment remain unresolved.

Future research should focus on explainable artificial intelligence, multimodal sensor fusion, real-time monitoring frameworks, and benchmark dataset development. Such advancements will contribute toward more reliable and scalable solutions for addressing the growing global challenge of marine plastic pollution

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