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Golden Seal Project: An IoT-Driven Framework for Marine Litter Monitoring and Public Engagement in Tourist Areas

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Abstract

This paper presents the research outcomes of the Golden Seal project, which addresses the omnipresent issue of plastic pollution in coastal areas while enhancing their touristic value through the deployment of Internet of Things (IoT) technologies integrated into a gamified recycling framework. The developed system employs an IoT-enabled Wireless Sensor Network (WSN) to systematically collect, transmit, and analyze environmental data. A centralized, cloud-based platform supports real-time monitoring and data integration from Unmanned Aerial and Surface Vehicles (UAV and USV) equipped with sensors and high-resolution cameras. The system also introduces the Beach Cleanliness Index (BCI), a composite indicator that integrates quantitative environmental metrics with user-generated feedback to assess coastal cleanliness in real time. A key innovation of the project's architecture is the incorporation of a Serious Game (SG), designed to foster public awareness and encourage active participation by local communities and municipal authorities in sustainable waste management practices. Pilot implementations were conducted at selected sites characterized by high tourism activity and accessibility. The results demonstrated the system's effectiveness in detecting and classifying plastic waste in both coastal and terrestrial settings, while also validating the potential of the Golden Seal initiative to promote sustainable tourism and support marine ecosystem protection.

Keywords: marine plastic pollution (MPP); tourism; internet of things (IoT); unmanned vehicles (UVs); wireless sensor networks (WSNs); serious game (SG); image recognition; environmental sustainability

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1. Introduction

The tourism sector plays a pivotal role in driving socioeconomic growth [1], serving as a catalyst for strengthening international relations [2]. More specifically, this industry creates diverse job opportunities, supports cultural preservation, contributes to the alleviation of poverty, addresses social disparities [3], and may even reduce crime rates by offering alternative income sources [4]. On a worldwide scale, numerous developing nations rely significantly on tourism expenditures, which constitute a major portion of their Gross Domestic Product (GDP) [1]. In 2023, the global travel and tourism sector accounted for 9.1% of GDP, reflecting a 23.2% annual growth and generating approximately 27 million new jobs [5], while in Greece, the sector contributed €42.7 billion to the country's GDP, nearly reaching pre-pandemic levels [6]. However, this economic expansion often comes at the expense of environmental sustainability [1]. Tourist destinations, particularly those in

ecologically sensitive areas, often experience habitat degradation, including deforestation and ecosystem disruption, primarily driven by infrastructure development [7].

Another major environmental side effect of the tourism sector is waste generation, an issue frequently underestimated despite its substantial implications for ecological sustainability. The increasing volume of waste generated by tourists and hospitality establishments, coupled with insufficient disposal infrastructure, significantly contributes to environmental degradation and pollution [8]. Moreover, tourists produce nearly twice the amount of waste as local residents [9], placing immense pressure on waste management systems [10]. Reflecting the magnitude of this environmental concern, the European Union's tourism sector has been shown to produce approximately 35 million tons of solid waste annually, accounting for around 7% of the total [10], which aligns with UNEP's estimate that European tourists generate roughly 1 kg of waste per person per day [11]. This alarming trend is particularly severe in island destinations and coastal regions, where dense populations and seasonal spikes in debris overwhelm collection systems and municipal waste services, many of which are already operating at full capacity [10,12].

Considering that nearly 80% of global tourism activities take place in coastal areas, the resulting waste generation is closely associated with the intensification of marine plastic pollution (MPP) [13]. Plastics, especially, are among the most prevalent materials in marine litter due to their widespread production, extensive use, and long-lasting persistence in the environment [12]. Annually, approximately eight million tons of plastic enter the world's oceans, harming marine life and contaminating the food chain with microplastics [13,14]. On a global scale, assessments indicate that between 75 and 199 million metric tons of plastic waste have accumulated in the oceans [15–19], thus emphasizing the urgent need for improved waste management and monitoring systems [20].

The Mediterranean Sea (MS) is both a top tourism destination and one of the world's largest plastic accumulation zones. In 2022, the region welcomed approximately 265 million tourists, representing 44.4% of all European and 27.6% of global tourist arrivals [21]. Simultaneously, it ranks as the world's fourth-largest producer of plastic products [22] and the sixth-largest accumulation zone for marine litter globally [23]. Annually, nearly 40,000 tons of plastic waste are estimated to leak into the environment, with 11,500 tons ending up in the MS. This type of pollution impacts the blue economy, causing regional economic losses estimated at €641 million annually [22]. Notably, 67% of the plastic pollution entering the MS is deposited back onto Greek shores within a year, due to ocean currents and geography, costing the country an estimated annual loss of €26 million [24].

In light of its severe consequences, the European Union (EU) has prioritized MPP alongside climate change and biodiversity loss [14], establishing binding regulations for all member states to monitor and reduce marine litter [25]. Since the adoption of the EU Plastic Strategy in 2018, significant progress has been made in addressing marine litter [25], further reinforced by the EU's announcement in March 2020 of a new Circular Economy Action Plan aimed at fostering a cleaner and more competitive Europe [26]. As a result, a threshold of 20 litter items per 100 m of coastline was determined to define clean beaches across the EU [27], accompanied by regulatory measures such as Directive (EU) 2019/904, which targets the environmental impact of specific single-use plastic products [28]. Nevertheless, the effectiveness of existing practices remains limited due to insufficient monitoring infrastructure, weak enforcement mechanisms, and a lack of robust community engagement [29–31]. Therefore, the European Commission (EC) has directed its attention to additional measures to mitigate this severe challenge [32].

In response, a wide range of initiatives has emerged, aiming to address the environmental impacts of MPP through state-of-the-art technologies and human-centric methods. The Ocean Cleanup, a non-profit organization, has developed large-scale systems designed

to collect floating plastic debris, primarily targeting accumulation zones such as the Great Pacific Garbage Patch [33]. Similarly, the International Coastal Cleanup (ICC) has incentivized millions of volunteers in coordinated beach clean-up activities, generating extensive data on coastal litter types and distribution [34]. At the same time, the United Nations Environment Program's (UNEP) Clean Seas campaign aims to reduce plastic pollution by encouraging public pledges that focus on behavior change [35]. In addition, the Marine Litter Watch project, developed by the European Environment Agency, engages citizens through a mobile application that allows citizens to collect and share data on beach litter [36], whereas the SeaClear Program emphasizes on the development of an innovative robotic system that utilizes autonomous aerial and underwater vehicles to detect and classify marine debris from the seafloor [37]. While each of these efforts has increased public awareness and participation through clean-up events and data gathering, they typically lack continuous, automated monitoring systems and do not provide ongoing incentives or interactive features to keep users actively involved beyond isolated activities.

To overcome these weaknesses, the Golden Seal Project proposes an integrated framework that combines both environmental monitoring and public engagement. At its core is a robust Internet of Things (IoT) system, including wireless sensors, high-resolution imaging systems, an Unmanned Aerial Vehicle (UAV), and an Unmanned Surface Vehicle (USV). These components enable real-time surveillance of marine and coastal pollution, with visual data transmitted to a cloud-based platform for automated analysis. Advanced Machine Learning (ML) algorithms detect plastic waste, leading to the basis of the Beach Cleanliness Index (BCI), a composite metric that demonstrates plastic waste density, coverage, and abundance, recycling capacity, as well as user feedback. Apart from environmental assessment, the project engages the community through a gamified mobile application, rewarding users for reporting litter, participating in clean-up efforts, and recycling activities. These methodological steps not only support the development of the BCI but also lead to the "Golden Seal" eco-label that recognizes improved cleanliness, serving as a motivational element. By aligning data analytics and citizen participation, the Golden Seal Project overcomes the limitations of earlier initiatives and offers an adaptable model for coastal regions facing environmental and tourism-related pressures.

The structure of this paper is designed to provide a comprehensive overview of the Golden Seal project, emphasizing its novelty, technological backbone, and key findings. Section 2 lays the conceptual basis by reviewing relevant theoretical perspectives and technological advances in environmental behavior, digital engagement, and pollution monitoring. Building upon this foundation, Section 3 transitions to the applied methodology, presenting the system architecture and the progressive development of the project's core technological components. Section 4 describes the pilot implementation phase, detailing how the system was tested and validated under real-world coastal and terrestrial conditions. Subsequently, Section 5 reports on the outcomes of these pilots, focusing on the detection accuracy of the Unmanned Vehicles, the classification performance of the image recognition system, as well as the calculation of the developed Beach Cleanliness Index. Section 6 discusses the broader implications of the project, reflecting on its interdisciplinary contributions, stakeholder engagement strategies, and considerations for scalability. Finally, Section 7 concludes the paper by summarizing the initiative's achievements and limitations, and by outlining directions for future development.

2. Theoretical and Technological Background

Coastal regions, particularly those experiencing high volumes of mass tourism, are increasingly subjected to substantial environmental pressures. These impacts accelerate the degradation of marine ecosystems and the loss of biodiversity, while simultaneously

undermining the natural resources and economic viability that coastal tourism relies upon [38]. As a result, the implementation of sustainable, holistic strategies has become imperative. This requires not only regulatory and infrastructural solutions, but also a deeper understanding of the behavioral patterns that contribute to ecological deterioration, with a focus on promoting Pro-Environmental Behaviors (PEBs) such as recycling, responsible waste disposal, and active participation in conservation activities.

Furthermore, Smart Environment Monitoring (SEM) systems, incorporating technologies such as IoT, Wireless Sensor Networks (WSNs), UAVs, and USVs facilitate continuous data collection and analysis of pollution in coastal areas. These systems are further enhanced by AI-based image recognition, which applies ML and Deep Learning (DL) techniques to detect and measure plastic waste with greater precision. Simultaneously, persuasive tools including Serious Games and gamification methods, have been recognized as effective mechanisms for encouraging PEBs. By embedding motivational elements such as rewards, leaderboards, and social comparison into interactive platforms, the users' attitudes are influenced toward sustainable practices. Nevertheless, their impact depends on how well the technology is designed to support specific behavioral outcomes, rendering them valuable in public awareness campaigns and environmental actions linked to tourism. Together, these technological and behavioral innovations form the backbone of integrative solutions to minimize marine pollution and promote ecological stewardship in tourism-intensive coastal zones.

In response to these challenges and opportunities, this chapter demonstrates the core theoretical and technological concepts that support the Golden Seal project. It begins by examining PEBs, highlighting the psychological, social, and contextual aspects that influence environmentally responsible decision-making. The use of gamification and Serious Games are then presented as innovative strategies for fostering behavioral change and promoting active engagement with sustainability goals. The chapter further explores SEM systems, emphasizing the essential role of IoT technologies and sensor networks in facilitating real-time environmental data acquisition and analysis. Particular attention is given to the capabilities of Unmanned Vehicles, which serve as critical assets for the systematic monitoring of coastal and marine litter. The chapter concludes with an overview of current developments in image recognition and Deep Learning techniques, focusing on their relevance for detecting marine debris and processing large-scale environmental datasets. Collectively, these aspects provide the conceptual and technological foundation for the methodological framework presented in the following chapters.

2.1. Behavior Change and Pro-Environmental Behaviors (PEBs)

Human behavior is arguably a key contributor to ecosystems degradation and global warming [39,40]. On the other hand, PEBs refer to a broad spectrum of actions aimed at reducing negative environmental impacts or contributing positively to ecological prosperity [41]. These include recycling, litter collection, energy preservation, as well as active participation in environmental conservation initiatives [42]. Early frameworks for understanding PEBs were grounded in the assumption that increasing environmental knowledge would directly influence attitudes, which in turn would lead to responsible environmental activities, overlooking the complex and varied perceptions individuals hold [43]. It should also be noted that when the adoption of PEBs involves inconvenience, their consistent application across different contexts becomes less likely [43]. Therefore, for the effective design and implementation of policies promoting PEBs, it is essential to gain a deeper comprehension of how such behaviors are perceived by a broader demographic point of view, as well as to identify the key factors influencing them [44,45].

In view of these ongoing efforts, the authors in [46] identified a variety of parameters influencing PEBs, systematically categorizing them into socio-economic, psychological, geographical, habitual, and contextual domains, thus underscoring its pluralistic nature. For instance, tourists, when situated in unfamiliar environments, often experience a sense of anonymity that can diminish the importance of moral norms and consequently reduce their engagement in environmentally responsible practices [47]. Furthermore, the researchers in [48] assessed tourists' PEBs across four primary domains: recycling, use of environmentally friendly transportation, adoption of sustainable energy and materials, as well as consumption of eco-friendly food. The findings indicated that, although tourists demonstrated positive environmental attitudes in their home settings, this mindset did not consistently translate into similar behaviors while traveling [49]. In reaction to this challenge, identifying effective strategies to cultivate PEBs among tourists has become a pivotal focus in the pursuit of sustainable tourism management [50].

2.2. Gamification and Serious Games (SGs)

Although the significance of encouraging PEBs is widely acknowledged across academic and industry sectors, the fundamental mechanisms and processes that drive sustainable decision-making remain insufficiently investigated [45]. In this context, gamification has emerged as an advanced tool that utilizes diverse game methods and elements (e.g., leaderboards, points, badges, progress bars, etc.) in non-entertainment environments to enhance the users' participation and influence their behavior [45,51]. In recent years, gamification has received increasing attention in the field of sustainability, serving not only as an engagement strategy but also as a practice for behavioral intervention. By leveraging interactive features such as competition, social comparison, and reward-based reinforcement, gamification has proven effective in promoting environmentally responsible behavior and engaging broader audiences that might otherwise remain uninvolved [52].

At the same time, Serious Games are gaining growing recognition across various sectors, notably in the areas of education and environmental awareness, due to their capacity to foster active learning and promote behavioral change [53,54]. Although numerous definitions of SGs exist in the literature, one particularly representative description states that: "a SG is a mental contest, played with a computer in accordance with specific rules, which uses entertainment to further government or corporate training, education, health, public policy, and strategic communication objectives" [55]. When applied to sustainability-related themes, SGs have demonstrated the capacity to significantly enhance user engagement, comprehension of project objectives, and the overall evaluation of training processes [56]. Furthermore, empirical research suggests that participation in SGs, especially those involving activities like waste collection, not only positively impacts environmental conditions but also enhances individuals' confidence in their ability to make environmentally responsible decisions [57].

A successful initiative of a mobile-based SG is the "Protecting the Earth" application, which engages young users in environmental education through interactive stages on waste sorting, recycling, and reduction [58]. Another valuable project is the "Contact from the Future", a 2D tablet-based educational game designed for children aged 8–11, focused on marine conservation and plastic pollution. The game adopts a multi-objective approach by combining environmental education, behavioral change strategies, and emotionally engaging storytelling [59]. Similarly, the Serious Game "SeAdventure" was developed to raise awareness about marine conservation. Through multimedia elements and interactive gameplay, the project aims to enhance motivation and engagement among young children. This approach reflects growing evidence that game-based learning is an effective method for acquiring knowledge and developing new skills [60]. In conclusion, these systems

highlight the potential of Serious Games to function not only as educational instruments but also as impactful drivers of long-term PEBs [61].

2.3. Technological Approaches for Marine Litter Detection

Recent advancements in Artificial Intelligence (AI) have greatly improved the effectiveness of Environmental Monitoring (EM), transforming traditional approaches into intelligent and data-driven systems [62,63]. In the context of marine plastic pollution, conventional monitoring methods remain time-consuming and labor-intensive, limiting their efficiency. To overcome these challenges, AI enables the detection, classification, and quantification of plastic debris through computer vision, Deep Learning algorithms, and advanced data analysis techniques [64]. According to the authors in [65], AI-based models can identify and mitigate pollution sources with 60% greater accuracy than standard methods. Notably, monitoring constitutes the majority of AI applications in this domain (57%), followed by management (24%), and prediction (19%), thus highlighting AI's central role in observation, as well as its expanding influence in forecasting and decision-making processes [64].

A wide range of AI models, including Support Vector Machines (SVM), Random Forest (RF) algorithms, and Deep Learning (DL) techniques, have been employed alongside high-resolution imaging tools, such as reflectance spectrometers and digital cameras to detect marine debris across surface waters, shorelines, and underwater environments. These techniques enable scalable, automated, and continuous monitoring by processing imagery acquired from diverse platforms including drones, satellites, autonomous underwater vehicles, and controlled laboratory settings [66]. Beyond detection, AI-driven remote sensing and predictive modeling tools allow researchers to analyze current and historical datasets to map the extent and distribution of marine pollution. This capability facilitates the identification of high-risk zones, leading to more targeted and timely intervention strategies [67].

Simultaneously, IoT which links physical devices to digital systems [68], offers an integrated solution for evaluating indoor and outdoor environmental conditions [69]. The effectiveness of IoT-based systems depends on appropriate sensor selection and reliable connectivity, which are essential for ensuring accurate data transmission [70]. In this context, WSNs have attracted significant attention for their innovative role in environmental assessment [71], as they consist of distributed nodes that collect data, implement basic processing, and send wirelessly information to central systems for further analysis [72]. In the field of waste management, IoT technologies have proven especially valuable, enabling real-time tracking of waste accumulation, automated sorting, optimized collection scheduling, and better resource allocation [73].

Real-world implementations of these technologies further demonstrate their potential. For instance, solar-powered bins equipped with IoT sensors have been installed along Bondi Beach, in Sydney, to monitor fill levels and automatically compact waste, thereby preventing litter overflow in high-traffic tourist areas [74]. Similarly, to manage seasonal waste surges in Ibiza, mobile "clean point" stations were implemented. Usage data helped optimize collection schedules and locations, improving cleanliness and service efficiency during peak tourist periods [75]. Lastly, the TRACKPLAST project introduced an approach to inland plastic waste tracking through the development of a "smart bottle" embedded with a lightweight LoRa-based IoT sensor. By replicating the behavior of real waste and transmitting geolocation data via a WSN and cloud platform, the system enabled the first non-GPS tracking of plastic pathways from terrestrial origins to marine environments [76].

In parallel, Unmanned Vehicle Platforms (UVPs) have demonstrated considerable potential in collecting environmental data across diverse aquatic settings. As reviewed

by the researchers in [77], these platforms comprising UAVs, USVs, Underwater Gliders (UGs), and Unmanned Ships (USs) offer various advantages in flexibility, spatial coverage, and deployment efficiency compared to conventional satellite-based methods. They have been successfully employed to monitor pollutants, evaluate ecosystem health, and collect data across various depths. UAVs, in particular, have proven to be highly effective tools in coastal pollution assessments, especially for litter detection and spatial mapping [78–81]. Oceana's marine expeditions in Mallorca and Valencia validated the practical application of Unmanned Vehicles (UVs) and Remotely Operated Vehicles (ROVs) in seafloor plastic monitoring. Employing SCUBA and ROV-based imaging, Oceana scientists documented the type, material, and distribution of plastic debris, while identifying benthic species [82]. The combination of AI and UAV integration has also demonstrated notable capabilities in litter detection on shorelines. The authors in [83], employed high-resolution UAV imagery combined with the RF algorithm to detect plastic waste on beaches, achieving detection rates of 44% for drinking containers, 5% for bottle caps, and 3.7% for plastic bags. In the same vein, researchers in [84] utilized UAV images captured at multiple altitudes to manually annotate plastic debris along riverbanks and floating on the water surface.

Deep Learning techniques have significantly improved image recognition by allowing neural networks to automatically learn complex feature representations from large datasets, thereby eliminating the need for manual feature extraction through the use of multiple hidden layers [85]. However, limitations such as poor lighting can degrade image quality and affect model accuracy, highlighting the need for adaptive algorithms that enhance reliability in real-world applications [86]. Building on these efforts, the integration of IoT technologies with ML has been explored to improve the efficiency of waste management systems. For example, an IoT-based waste management system developed by [87] employed ML algorithms to achieve a classification accuracy of 99.34%, demonstrating the potential of combined smart sensing and learning technologies. Furthermore, state-of-the-art DL architectures like AlexNet, VGGNet, ResNet, DenseNet, and Inception have excelled in classification tasks and are often integrated with semantic segmentation frameworks, such as Fully Convolutional Networks (FCN), U-Net, and DeepLab for more detailed environmental analysis [88]. These architectures have also benefited from the growing availability of large-scale, annotated datasets, which are critical to training high-performing AI models [88].

One such dataset is MARIDA [89], a benchmark archive for marine debris detection using multispectral Sentinel-2 satellite imagery. It includes 1381 pixel-level annotated image patches from 63 scenes (2015–2021) across 11 countries, covering marine debris and related surface features. Annotations are accompanied by confidence scores and are validated using high-resolution satellite images and citizen science sources. MARIDA supports both semantic segmentation and multi-label classification and includes baseline implementations such as RF and U-Net. As an open-access resource, it advances the training and validation of AI-driven marine debris detection systems. In addition, authors in [90] investigated the application of low-cost Unmanned Aerial Systems (UAS) for detecting marine litter on coastal sandy beaches using UAVs equipped with RGB cameras to capture high-resolution aerial imagery from a beach in Portugal. The resulting dataset was manually annotated to differentiate litter from the natural background, facilitating the use of supervised ML techniques. Three classification algorithms (i.e., RF, SVM, and k-Nearest Neighbor (KNN)) were evaluated for performance. Among them, RF achieved the highest F-score at 72%, followed by SVM at 68%, and KNN at 65%, establishing the effectiveness of RF. These examples highlight how AI, IoT, and UV technologies, especially when supported by robust datasets and sensor networks, can deliver integrated solutions for monitoring and mitigating marine pollution.

3. Materials and Methods

This section demonstrates the methodological framework and technological components developed to achieve the objectives of the Golden Seal project. It outlines the holistic approach adopted for system design, implementation, and validation, highlighting the deployment of advanced sensing technologies, UVs, AI-based image recognition, and cloud-based data infrastructures. Central to the project are two key innovations, namely the Beach Cleanliness Index, a composite metric that synthesizes environmental and behavioral indicators to evaluate beach pollution levels, and a gamified mobile application designed to foster public participation and encourage PEBs. Finally, a comparative analysis of existing marine litter monitoring initiatives is presented, underscoring how the Golden Seal project addresses current methodological gaps in the field.

3.1. Methodological Approach

The Golden Seal project employed a structured methodology designed to develop, evaluate, and implement an advanced environmental monitoring system for tackling MPP. This methodology encompassed nine distinct phases, each crucial for establishing a robust and replicable solution. By embedding innovative technologies, the project has built a system capable of real-time tracking, data analysis, and public engagement. The strategy initiated with a thorough evaluation of available sensors and IoT technologies suitable for coastal and marine pollution monitoring. The objective of this stage was to identify and select sensors capable of accurately detecting and quantifying plastic waste under challenging environmental conditions, such as high humidity and strong winds. As a result, a wide range of sensors was assessed based on their measurement accuracy, durability, and ability to seamlessly integrate into IoT-based communication frameworks. Each candidate technology was subjected to laboratory testing to ensure functionality, energy efficiency, and resilience in field applications. By forming strict standards for performance and interoperability, this phase laid the technical foundation of the project, ensuring reliable data acquisition and system cohesion in the subsequent phases.

The project then moved forward with the design and integration of the UVs. These were fitted with the chosen sensors to collect data on pollution from both aerial and surface levels. Each vehicle was also equipped with high-resolution cameras, GPS, obstacle-avoidance systems, and autonomous navigation technologies, making it possible to operate effectively in complex and changing coastal environments. A key priority during this stage was ensuring that the UVs were fully compatible with the broader IoT system, so that all collected data could be transmitted smoothly to the cloud-based platform.

The next phase focused on developing and implementing an advanced image recognition system based on DL. Using images captured by the UVs, the system employed Convolutional Neural Networks (CNNs) to automatically identify and classify plastic waste. More specifically, they were trained based on different datasets to improve its ability to recognize various types of debris under diverse environmental conditions. Particular attention was given to challenges like overlapping objects, poor lighting, and image noise, which constitute factors that often interfere with accurate detection. After extensive training and testing, the system achieved strong performance in identifying common plastic items such as bottles, bags, and packaging materials, significantly improving the project's ability to assess pollution levels with great precision.

In the fourth phase, the project deployed a robust WSN to support continuous environmental monitoring and reliable communication between all system components. This network connected both aerial and ground-based sensors, including those installed in smart recycling bins, through standardized IoT protocols to ensure stable and secure data transmission. The WSN was specifically designed to function under the challenging con-

ditions often observed in coastal environments, enabling a steady flow of data from the sensor nodes to the cloud-based platform.

The sensor suite integrated into this network combined high-precision measurement, imaging, and positioning capabilities. Load data from the smart bins was captured by a cylindrical load cell (15 cm × 3.8 cm × 2.4 cm), a minimum measurable load of 50–100 g, 100 g resolution, and 0.1 mV sensitivity. Aerial inspections were supported by an EO/IR UAV payload (ViewPro, Shenzhen, China) operating at 12 V and within a –20 °C to +60 °C range, featuring a 1/3″ Panasonic CMOS sensor (2.48 MP) for Full HD imaging (Panasonic Corporation, Osaka, Japan). Underwater monitoring was conducted using a Barlus ASV camera (Shenzhen Zhiyong Industrial Co., Ltd., Shenzhen, China) with a 2.8 mm lens and 110° horizontal field of view, aided by six adjustable-intensity LEDs. Precise georeferencing across UAV and ASV operations was ensured by the Here3 CubePilot GNSS module (CubePilot Global Pty Ltd., Geelong, Australia), supporting GPS, GLONASS, and BeiDou constellations, with a 3D accuracy of 2.5 m and RTK precision of 0.025 m, operating reliably in temperatures from –40 °C to +85 °C.

Following the deployment of the WSN, a mobile application incorporating serious gaming elements, was developed to promote community engagement and PEBs among both tourists and local residents. The application provides real-time data on key environmental indicators, such as the amount of plastic waste collected, the estimated CO_2 emissions avoided, and the eco-level awarded to each beach. Beyond serving as an informational tool, the app encourages active participation through interactive features, including waste documentation, environmental reviews, beach photo uploads, and an interactive plastic waste collection challenge embedded within the gamified experience. The game design integrates several motivational elements, such as educational material regarding marine pollution and recycling, weekly beach competitions, and progress-based rankings. Users can monitor their personal impact, earn digital badges, and track the environmental performance of participating beaches. Moreover, eco-levels and beach rankings based on measurable criteria (e.g., weight of collected waste or cleanliness ratings) are employed to provide immediate feedback and foster sustained engagement.

Furthermore, the impact of the serious game component is assessed by a combination of usage metrics and behavioral indicators. These include the number of app downloads, user activity levels (e.g., frequency of logins and interactions), waste volumes recorded, user-submitted feedback, and beach cleanliness evaluations. The ranking system itself, comparing beaches by weight of waste collected, user ratings, and AI-supported assessments, also offers indirect insight into community involvement and behavioral shifts. Additionally, the accumulation of user-generated content, such as reviews and photos, contributes qualitative evidence of environmental awareness and engagement. As a consequence, the gamified application functions as both a data collection tool and a behavioral intervention mechanism. By integrating real-time environmental monitoring with user-centered experiences, it strengthens the link between citizen participation and coastal ecosystem protection.

It is also worth mentioning that, in alignment with current regulatory and ethical standards, the Golden Seal system places strong emphasis on safeguarding user privacy and ensuring responsible data management. All users participating in the mobile application are required to provide explicit, informed consent prior to engaging with any functionalities involving data collection, including the submission of geotagged photos or reviews. Personal data collected through the application, such as location metadata and image content, is anonymized before being used in any analysis to ensure that individual users cannot be identified. Moreover, the platform fully complies with the General Data Protection Regulation (GDPR) by incorporating privacy-by-design principles into both

system architecture and user interactions. Data is securely stored, access is restricted to authorized personnel, and usage is limited strictly to research and environmental monitoring purposes. These safeguards are intended to uphold transparency, protect participant rights, and reinforce the ethical integrity of citizen science within the Golden Seal framework.

The sixth phase centered on the creation of a cloud-based platform that would function as the central hub for data collection, processing, storage, and visualization. This platform aggregated inputs from the WSN, UVs, smart bins, and the mobile application, transforming them into structured datasets for analysis. The system enabled both real-time data access and historical trend analysis through a web-based admin console. Administrators could monitor beach performance, configure system settings, and evaluate user engagement, while citizens received relevant updates through the mobile application interface.

Following the successful deployment of the data infrastructure, phase seven focused on developing the BCI, a composite metric designed to evaluate the cleanliness of a beach by collecting several environmental and behavioral indicators into a single score. More specifically, the development of the BCI drew upon and adapted methodologies from pre-existing, well-established BCIs, as outlined in various academic studies [38,91–93]. These indicators reflect both measurable environmental factors such as plastic density, spatial coverage, and recycling activity, as well as human-centric dimensions. As a result, this adaptation ensured that the BCI was both robust and reflective of diverse environmental and contextual factors. The index provided a clear, quantified measure of beach cleanliness, enabling targeted interventions based on standardized assessments. As shown in Equation (1), the BCI was calculated as a weighted sum of five normalized indicators, each capturing a distinct dimension of coastal environmental quality.

$$BCI = W_1 \times PWD' + W_2 \times PWC' + W_3 \times PAI' + W_4 \times URS' + W_5 \times RC' \quad (1)$$

Table 1 presents the five indicators included in the BCI, accompanied by their symbols, definitions, data sources, and the normalization methods used. Specifically, Plastic Waste Density (PWD) and Plastic Waste Coverage (PWC) capture the intensity and spatial extent of plastic litter accumulation, as identified through UV-based image analysis. Plastic Abundance Index (PAI) provides a compositional measure, indicating the dominance of plastic among all detected waste items. User Review Score (URS) incorporates qualitative data from beachgoers, reflecting perceived cleanliness and public satisfaction, while Recycling Capacity (RC) accounts for the operational ability of waste infrastructure to handle and process plastic debris.

Table 1. Composition of the BCI.

Indicator	Symbol	Description	Data Source	Normalization Methods
Plastic Waste Density	PWD	Number of Plastic Items per Square Meter (m^2)	UVs Image Analysis	$PWD' = 1 - \frac{PWD}{\text{Threshold Value}} \times 100$
Plastic Waste Coverage	PWC	Ratio of Plastic-Covered Surface Area to Total Beach Surface Area	UVs Image Analysis	$PWC' = 1 - PWC \times 100$
Plastic Abundance Index	PAI	Ratio of Detected Plastic Waste Items to Total Identified Waste Items	UVs Image Analysis	$PAI' = PAI \times 100$
User Reviews Scores	URS	Average Beach Cleanliness Rating by Users (1–5 scale)	Mobile Application	$URS' = URS \times 20$
Recycling Capacity	RC	Weight of Plastic Waste Disposed in Smart Bins (kg)	Smart Bins	$RC' = \frac{RC}{\text{Threshold Value}} \times 100$

The normalization process relies on clearly defined threshold values tailored to the nature of each indicator. In particular, the threshold value for PWD was based on average plastic litter densities reported in the Mediterranean region. For example, in Greece, values typically range between 0.08 and 0.91 items/m^2, based on [94]. To ensure consistency while maintaining sensitivity to higher pollution levels, a conservative upper threshold of 1 item/m^2 was adopted for normalization purposes. In contrast, the threshold used for the RC indicator reflects the maximum expected waste handling capacity of the infrastructure deployed at each site, ensuring that performance is assessed relative to operational limitations.

The weighting factors (W_1 to W_5) applied in the calculation of the BCI were intentionally designed to be flexible, enabling adaptation to the specific environmental and management priorities of each monitored location. These weights were established collaboratively by system administrators, environmental experts, and beach managers to ensure alignment with both scientific rigor and site-specific operational needs. For instance, user-centric indicators, such as the URS or RC may be emphasized in tourist-heavy areas, while ecologically sensitive zones (e.g., Natura 2000 sites) might prioritize indicators related to plastic presence, such as PWD or PWC.

Moreover, a sensitivity analysis was conducted to evaluate the robustness of the index under varying configurations. This process involved assigning a dominant weight (ranging from 10% to 60%) to each of the five normalized indicators in turn, with the remaining weight distributed equally across the others. The objective was to evaluate how alterations in indicator prioritization would affect the overall BCI score. Even under variable weighting conditions, the results remained balanced, demonstrating the resilience of the BCI framework. This capacity for adjustment, combined with its methodological rigor, underscores the index's value as a reliable and adaptable decision-support tool for integrated coastal monitoring.

In the next step, the project introduced a Mobile Mission Operations Control Unit (MOCU) to support on-site system management and coordination. This specially equipped mobile unit enabled continuous control over UAV and USV deployments, immediate data processing, and rapid performance monitoring in the field. Outfitted with dedicated computing infrastructure, communication hardware, and power systems, the MOCU served as a vital bridge between on-the-ground activities and the cloud-based platform. Its deployment ensured continuity in data collection and system responsiveness during field operations, especially in remote or infrastructure-limited beach locations.

Following the integration and verification of all technological components, the final phase of the methodology focused on the full-scale deployment of the system in selected pilot areas. This step was designed to evaluate the functionality of the developed infrastructure in real-world operational conditions. Field trials were conducted to test the interoperability of all subsystems including UAVs, USVs, the image recognition algorithm, the mobile application, and the centralized data management platform, under varying environmental parameters. These trials also examined user interactions with the system, enabling real-time data transmission and feedback loops that supported continuous monitoring and decision-making. An important aspect of this phase was the practical application of the BCI, which was used to process and integrate environmental and behavioral data into a single evaluative metric. The field implementation served as a testing ground for refining this index and validating its suitability as a decision-support tool for local authorities. The complete methodological flow adopted for this pilot phase is illustrated in Figure 1.

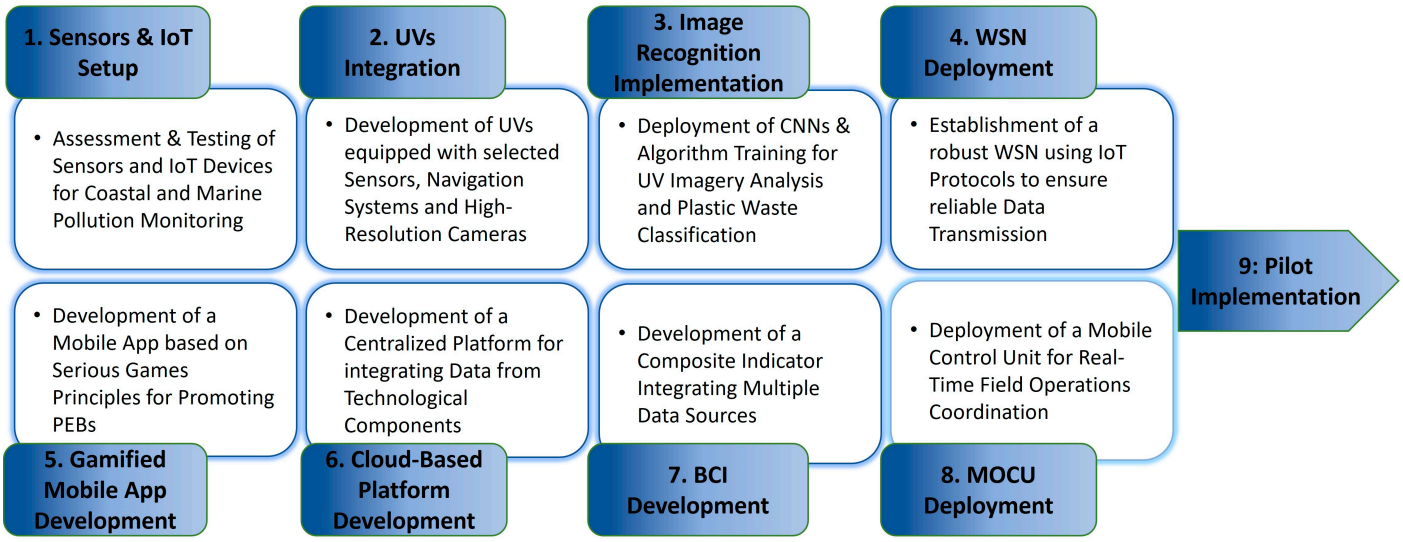


Figure 1. Methodological Approach of the Golden Seal Project.

3.2. Technological Framework

The Golden Seal project's infrastructure is characterized by the seamless integration of IoT technologies, UVPs, ML algorithms, and advanced data management systems. Figure 2 illustrates the core data flow architecture of this project. At the heart of the system was a ASP.NET Core Web API v6.0 that acted as a central communication hub, connecting input sources, UVs, smart bins, and the mobile application, with cloud services and backend data processing tools hosted on Microsoft Azure (App Service v3 and Azure SQL Database Gen 5). UVs equipped with cameras transmitted image files, along with metadata such as beach ID, timestamps, and additional information, via an API to a centralized storage system. At the same time, smart recycling bins equipped with load cells were used to measure the weight of collected plastic waste and transmit this information through the system's WebAPI (ASP.NET Core Web API v6.0).

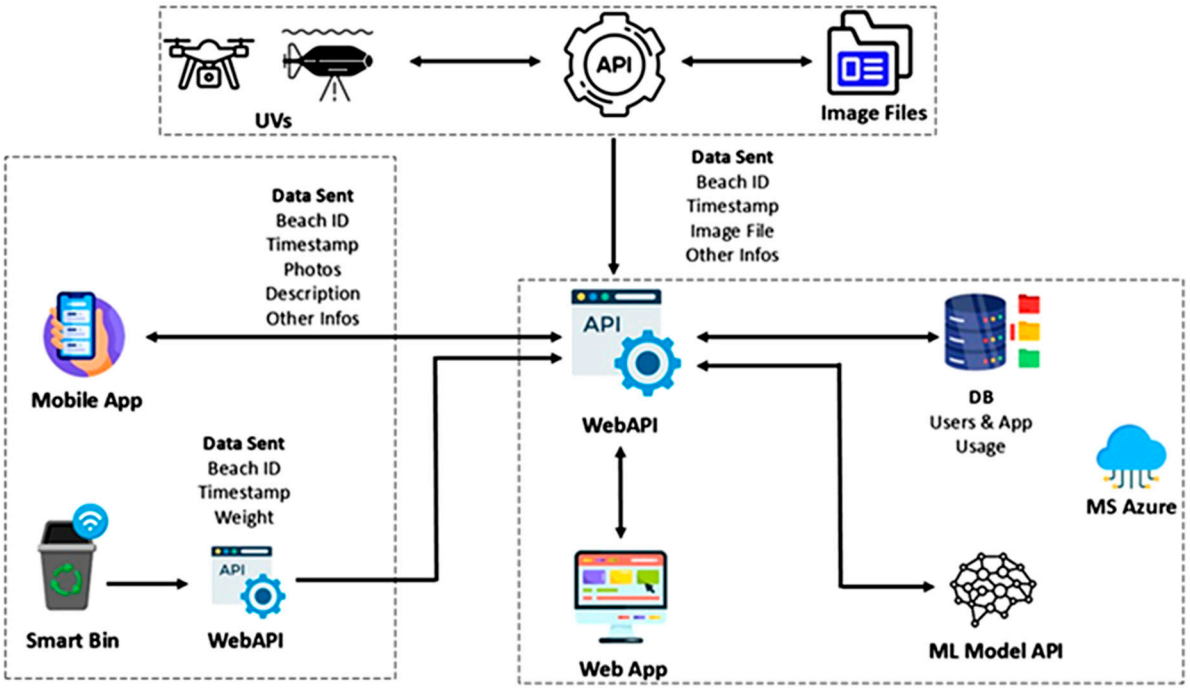


Figure 2. General Architecture of the Golden Seal Project.

In addition, the mobile application allowed users to submit geotagged photos, written descriptions, and incident reports, contributing valuable crowdsourced data to the platform. All incoming data flowed through the WebAPI, which directed it to databases that detected user interactions, system performance, and key environmental indicators. The system also interfaced with ML models via a dedicated API to analyze visual content and extract insights related to pollution levels. A web-based dashboard provided administrators and stakeholders real-time access to this data, effectively closing the loop between data collection, analysis, and environmental decision-making. This integrated approach ensured that the project's technological tools directly supported its environmental goals, while also offering an adaptable solution for sustainable coastal waste management.

The selected UAV was the ATLAS 204 quadcopter (ALTUS LSA S.A., Crete, Greece), due to its robust design and operational suitability in demanding coastal conditions. The drone's structural platform was constructed from high-strength carbon fiber to ensure durability, while its configuration optimized flight stability. The aircraft's landing gear, also made of reinforced carbon fiber, supported safe takeoff and landing operations. The UAV integrated a range of essential electronic subsystems including a Power Distribution Board (PDB), LiPo battery, GPS module, flight controller, and Electronic Speed Controllers (ESCs), all connected through a secure and simplified wiring architecture. The GPS antenna was positioned on the upper section of the fuselage to minimize signal interference, while the flight controller was installed on a vibration-isolated aluminum base to enhance navigational accuracy. The central PDB, located beneath the core systems, distributed power from the battery to critical components, reducing wiring complexity and improving system safety. Each of the four motors was embedded into a carbon fiber arm and connected to the ESCs, which received real-time instructions from the flight controller. These instructions were informed by inputs from multiple onboard sensors such as gyroscopes, accelerometers, as well as barometers. Overall, the ATLAS 204 constitutes a high-performance UAV system suitable for the precise monitoring of MPP and the broader IoT and data analytics infrastructure of the project. Figure 3 illustrates the three-dimensional CAD models of the chosen UAV configuration.

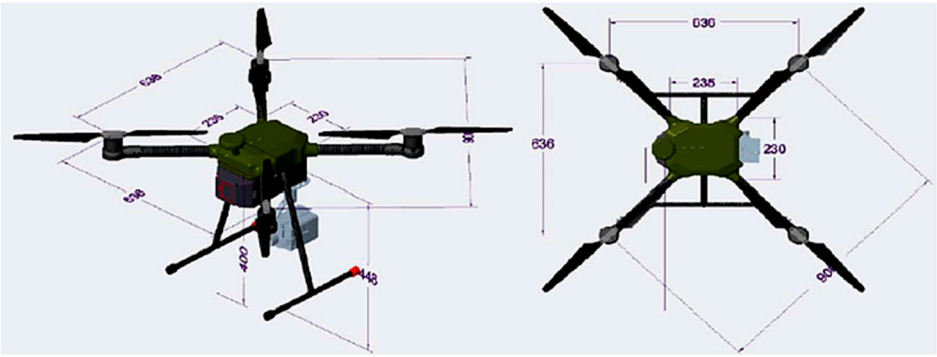


Figure 3. Three-dimensional CAD Simulation of the selected UAV—Side and Top View (mm).

Furthermore, the NIRIIS USV (ALTUS LSA S.A., Crete, Greece) which was developed for the project, was specifically designed to meet the demands of marine operations, focusing on payload capacity, stability, and advanced navigation capabilities. The chosen USV featured a hydrodynamic hull constructed from lightweight and corrosion-resistant materials such as aluminum and fiberglass. Inside the hull, a customized frame secured the arrangement of batteries, controllers, and communication equipment to maintain balance and minimize the center of gravity, which enhanced the vessel's stability during operations. Power was distributed through an integrated system composed of ESCs, Battery Eliminator Circuits (BECs), and a dedicated power distribution network, which guaranteed stable

energy flow across all critical components. Navigation was reinforced by a GPS unit secured on a foldable mast, providing uninterrupted positioning signals and connected to the vehicle's control unit through sealed cabling. Additionally, the USV supported modular integration of payloads such as camera systems and environmental sensors, rendering it suitable for diverse marine monitoring missions.

Following this, an advanced Ground Control Station (GCS) was used to provide reliable operation and coordinated management of both types of UVs. The platform incorporated mission planning, execution, live monitoring, and post-mission analysis within a single software environment. Through a user-friendly Graphical User Interface (GUI), operators could organize autonomous missions, track vehicle locations, monitor system status, and observe data from onboard sensors and cameras. For UAV operations, a portable control unit was utilized to be easily operated by a single user. All telemetry and video transmission components were integrated into the unit and external antennas could be quickly deployed to maintain strong, long-range communication links. USV missions were managed through a tablet-based system that contained the necessary command software and antenna arrays, enabling continuous communication with the vessel during its operation. Together, these systems constitute a reliable and flexible interface for autonomous monitoring of coastal and marine environments. Figure 4 demonstrates the GUI of the system's navigation control software.

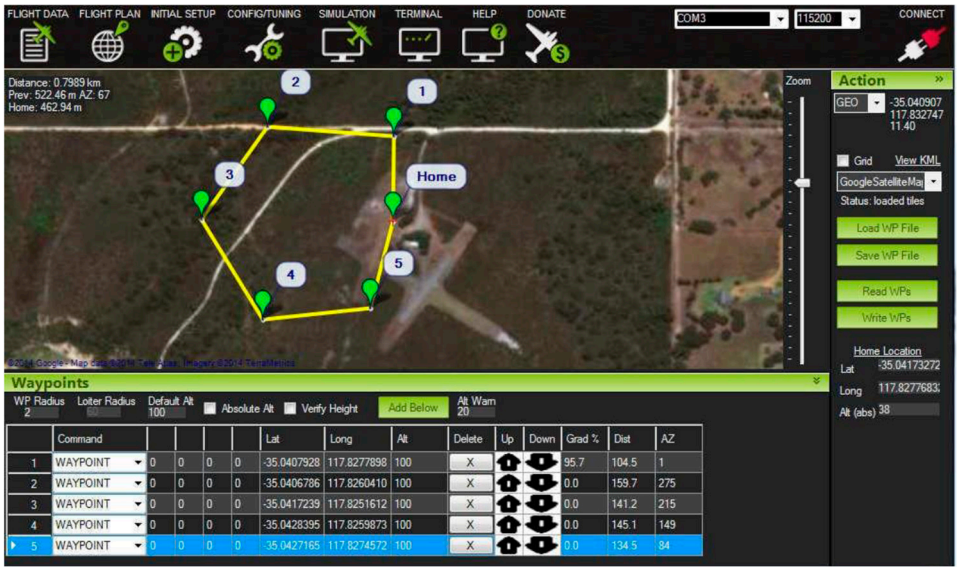


Figure 4. GUI of the System's Mission Planner v1.3.74 Flight Control Software.

In addition, the smart bins used in the project played a key role in supporting on-site waste monitoring and data collection. At the core of their function were high-precision load cells, installed on reinforced weighing platforms. These sensors were sensitive enough to detect even small changes in weight, allowing for accurate measurement of the plastic waste deposited by beach visitors. Each smart bin included a customized electronic board responsible for processing the sensor data in real time and transmitting it to the cloud, even in areas with limited connectivity. To support user-specific tracking, the bins were also equipped with RFID and NFC technologies for user identification. For energy autonomy, the bins were powered by durable, energy-efficient photovoltaic (PV) panels, allowing them to operate continuously, without the need for external power sources.

Subsequently, image processing formed a central part of the project's monitoring system, significantly improving the ability to detect plastic waste. Visual data captured by UVs, along with geolocation information from their navigation systems, was analyzed by

CNNs, which could automatically identify and classify plastic waste with high accuracy. Depending on the situation, this processing was carried out either on-site using embedded computing units or remotely through cloud-based platforms. The results were available through a dedicated API, enabling smooth interconnection with the other elements of the system. All data was securely stored on the Microsoft Azure Cloud, providing safe access for stakeholders and allowing for scalable collaboration.

Lastly, a specially equipped Mission Operations Control Unit was developed to function as a mobile command center for supporting UV deployments in the field. The vehicle's interior was fitted with thermal and sound insulation, as well as an autonomous heating and cooling system, to ensure comfortable working conditions for operators. To ensure continuous power, the unit included a generator, backup batteries, and an Uninterruptible Power Supply (UPS), which could power operations for up to two hours. The MOCU was also fitted with antenna mounts and communication interfaces that supported stable telemetry and live video feeds, thus providing a flexible foundation for real-time coastal monitoring in diverse field conditions.

This synergy between autonomous hardware, intelligent software, and stakeholder-focused interfaces ensured continuous data flow, operational flexibility, and decision-making support for coastal managers. The integration of advanced communication protocols, resilient field equipment, and centralized cloud storage not only enhanced the accuracy and timeliness of monitoring efforts but also demonstrated the feasibility of deploying such systems in dynamic, real-world conditions. Ultimately, the Golden Seal technological framework offers a robust model for replicable and sustainable coastal waste management, aligned with the goals of data-driven environmental stewardship and policy support.

3.3. Comparative Analysis of Marine Litter Monitoring Frameworks

Effective marine litter monitoring is essential to mitigate the escalating threat of plastic pollution to marine ecosystems. Over the last decade, a diverse range of initiatives has emerged, each leveraging distinct technologies and innovative methodologies. The following analysis compares some major projects across Europe and internationally, highlighting their unique contributions, while situating the Golden Seal project as a next-generation framework that synthesizes state-of-the-art technologies, a composite environmental indicator, and behavioral engagement. Table 2 provides a comparative overview of key marine litter monitoring projects, focusing on their technological features, target environments, levels of community involvement, and primary observations.

More specifically, initiatives such as the Oceana Marine Litter Expedition [82] and Saronikos Gulf survey [95] employed conventional methodologies, like ROVs, SCUBA, and vessel-based imaging to document benthic and coastal litter accumulations. These efforts provided valuable empirical data, but were limited in spatial scale, temporal coverage, and automation. In contrast, Golden Seal integrates UVs with AI-based image recognition and IoT infrastructure, enabling continuous monitoring across multiple environmental layers (beach, sea surface, and underwater), thus surpassing static observation frameworks in adaptability.

Furthermore, the SeaClear project [37] advances underwater litter management through robotic autonomy, combining ROVs, a base vessel, smart cable systems, and AI vision for seafloor mapping and waste retrieval. While its technological sophistication in underwater environments is notable, its primary focus remains on autonomous collection. Golden Seal, on the other hand, expands beyond detection and retrieval by incorporating real-time feedback via the Beach Cleanliness Index and citizen involvement through a gamified mobile application. Furthermore, initiatives such as Ocean Cleanup [33] reflect large-scale offshore strategies aimed at macroplastic removal through passive floating sys-

tems and vessel-mounted imaging. However, their operational complexity and dependence on physical infrastructure contrast with Golden Seal's cost-efficient and easily deployable coastal framework suited to regional and nearshore contexts.

Moreover, satellite-based initiatives like MARIDA [89] focus on remote sensing and algorithmic training datasets, offering a benchmark for machine learning applications. Although MARIDA offers detailed image labels and a wide range of environmental categories, rendering it highly valuable for training AI models, it relies on past satellite data and does not update in real time. It also lacks direct involvement from the public or any way to provide feedback from the community. In contrast, the Golden Seal project includes real-time monitoring and actively engages people, making it more dynamic and responsive. Similarly, projects like the Cabedelo Beach survey [96] and the Lake Tollense study [97] utilized UAV imagery and classification models (e.g., Random Forest), but faced limitations in detecting smaller or transparent debris and lacked real-time applications.

While the concept of community engagement is frequently referenced, very few projects meaningfully integrate citizen participation into their operational framework. For instance, Marine Litter Watch [36] incentivizes volunteers across Europe via a mobile app for event-based data collection. Although it promotes awareness, its manual and sporadic approach makes it hard to collect detailed, consistent data across different areas. Similarly, the NPM3 campaign [98] engaged the public through image annotation on the Zooniverse platform, but this involvement was restricted to back-end data labeling, with no direct on-site impact. In contrast, Golden Seal introduces a behavior-based participation model, where citizens contribute through a gamified mobile application, smart recycling bins, and a real-time BCI. This approach offers immediate environmental feedback, thereby creating a closed-loop system that connects user behavior with measurable environmental outcomes. It not only enhances motivation and sustained engagement but also transforms passive observers into active environmental agents.

In conclusion, while each reviewed project offers valuable contributions, they typically focus on either observation, removal, or participation as separate efforts, rather than integrating them into a cohesive approach. On the other hand, Golden Seal combines these elements into an integrated system that not only detects and monitors litter in real-time but also incentivizes behavioral change. By embedding AI, IoT, and gamified citizen interfaces into a unified coastal management framework, the proposed project sets a new benchmark for proactive and participatory marine litter governance. Subsequently, through the systematic use of the BCI, the project enables regular and comparable assessments of beach cleanliness over time, thus supporting data-based decision-making and continuous monitoring efforts.

Table 2. Comparative Overview of Marine Litter Monitoring Initiatives.

Initiative Name & Ref.	Key Technologies	Monitored Environment	Community Involvement	Key Observations
Oceana Marine Litter Expedition [82]	ROVs with HD/4K cameras, SCUBA dives, Image/video analysis	Seafloor (Mallorca, Valencia), Benthic zones	None	Conducted during COVID-19 restrictions, the survey likely underestimated typical levels of plastic pollution.
Marine Litter Watch [36]	Mobile app, Centralized data platform	Beaches across Europe (e.g., Baltic Sea, MS)	Very High (citizen-based clean-up events)	Provides an interactive map of beaches and clean-up events with clickable charts for each site.

Table 2. *Cont.*

Initiative Name & Ref.	Key Technologies	Monitored Environment	Community Involvement	Key Observations
SeaClear/ SeaClear 2.0 [37]	Underwater ROVs, Vessel, UAV, AI algorithms, Smart cable systems	Seafloor	Moderate (SeaClear 2.0 expands with gamified apps)	Demonstrates adaptability to different conditions, including varied water properties and different kinds of litter.
Ocean Cleanup [33]	Floating systems, Active steering, Computer modeling	Oceans, Rivers	Low	Models estimate that 10 full-scale systems are needed to clean the Great Pacific Garbage Patch.
MARIDA [89]	S2 satellite imagery, U-Net architecture, RF model, ResNet, Spectral indices, t-SNE algorithm	Coastal and Ocean surface	Limited (Ground-truth data from citizen science and social media)	A global dataset of over 837,000 pixel-based annotations from Sentinel-2 images for marine debris detection.
[99]	IoT sensors, Satellite communication, WSNs, UAVs, AUVs, MSMs, Data center, AI-driven analytics	Marine ecosystems (Surface to deep sea)	None	The proposed system is highly scalable, covering both small and large ocean areas.
[97]	UAV, D-GPS, ArcGIS, Dataset RGB Images	Freshwater environments	None	In total, plastic items made up 71.5% of all items, followed by glass (9.7%), paper (7.4%), and metal (7.1%)
[96]	UAS, Dataset RGB Images, RF classifier, SfM-MVS Photogrammetry, Hydrodynamic modeling	Coastal beaches	None	Detection accuracy decreased for transparent, decolored, or shadowed items, and performance was notably lower on the vegetated dune area compared to the open beach (F-score: 76% beach vs. 57% dune area).
[95]	Vessel, Digital camera, QGIS Open Source Software for Analysis	Coastal beaches	None	Vessel-based photography, calibrated with in situ sampling, offers a scalable and highly accurate method ($R^2 > 98\%$) for monitoring macro-litter on remote beaches, especially single-use plastics.
NPM3 Mission [98]	Vessel-based imaging, Neural Network models, Geospatial processing, Automated analysis pipeline, Labeling & Data augmentation	Ocean (Eastern North Pacific Ocean)	Moderate (Volunteers contributed to labeling of plastic debris via Zooniverse)	YOLOv5 achieved better detection performance with fewer hyperparameter adjustments, highlighting its suitability for real-time marine plastic detection.

4. Pilot Implementation

This chapter demonstrates the pilot implementation phase of the Golden Seal project, aimed at validating the system's operational performance and technological robustness under real-world conditions. Building upon the conceptual foundation established in Section 2 and the integrated system architecture outlined in Section 3, this phase involved the deployment of the project's components across selected coastal and terrestrial sites. Emphasis is placed on pre-deployment procedures, laboratory validation, scenario development, and field execution, with the objective of assessing detection accuracy, data reliability, and interoperability of the system.

4.1. Pre-Pilot Procedures

The pre-pilot phase focused on preparing and validating the system's core subsystems and technologies through laboratory testing and performance optimization prior to field deployment. These activities aimed to ensure technical reliability and operational readiness under controlled conditions.

4.1.1. Laboratory Testing

Laboratory results often diverge from real-world performance, making rigorous pre-deployment testing essential to ensure a smooth and reliable transition to operational application. In the context of the Golden Seal project, the preliminary validation process was divided into two principal phases: (a) laboratory testing of electronic components and subsystems, and (b) static response testing to evaluate system functionality before field deployment.

The laboratory testing phase was designed to verify the operability and resilience of the electronic systems integrated into both the UAV and the USV. These assessments were implemented in a controlled laboratory environment, equipped with essential safety protocols. Diagnostic tools including multimeters, calibrated power supplies, and specialized instruments were utilized to confirm the accuracy of measurements. Each system component, including flight controllers, electric motors, GPS modules, communication interfaces, and environmental sensors, was subjected to a wide range of functional assessments. Moreover, environmental stress tests were conducted to simulate operational conditions, subjecting subsystems to temperature variability, mechanical vibration, humidity, and electromagnetic interference. Integration tests ensured the compatibility and seamless functionality of power units, actuators, and onboard electronics. These results were comprehensively documented and employed to inform hardware optimization and integration protocols.

Following laboratory validation, the UAV underwent a performance optimization process to align its specifications with mission-specific objectives. The optimization focused primarily on enhancing flight endurance, which required balancing several parameters including platform weight (2700 g), number of motors (4), and physical dimensions (350 mm). A high-capacity battery (22,000 mAh) was selected to provide extended power availability, while motor specifications and propeller size were optimized to increase thrust efficiency and reduce power draw. External variables such as wind resistance were also taken into account during the simulation phase. Careful management of the payload-to-weight ratio further contributed to improved energy efficiency.

At the same time, a similar performance optimization process was carried out for the USV. This task was more complicated due to the additional challenges of hydrodynamic resistance and the constantly changing load conditions encountered during operation on water. Unlike aerial vehicles, predicting energy consumption for surface vessels is more difficult, as factors like hull drag and propeller interaction with water have a continuous

and dynamic impact on the motor's performance. To better understand and optimize these conditions, simulation tools such as the RC Boat Calculator, were used to test different propulsion system configurations (see Figure 5). This enabled the identification of the most efficient powertrain tailored to the specific mission requirements of the project.

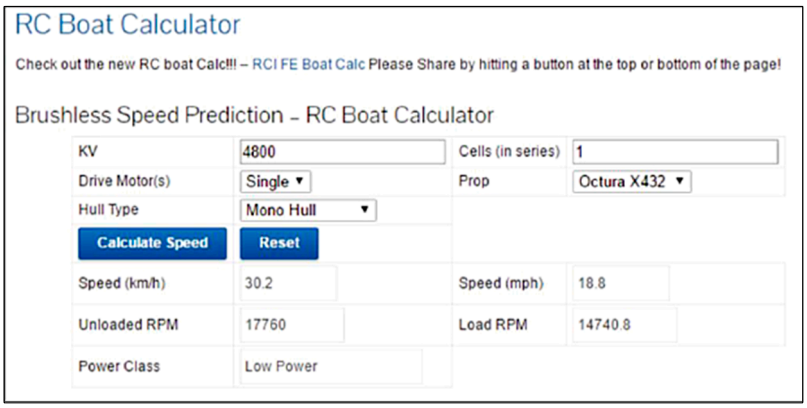


Figure 5. Interface of the USV Performance Optimization Application.

Once both the UAV and USV systems were optimized and validated under laboratory conditions, a static testing phase was conducted to assess the integrity, responsiveness, and interoperability of all integrated subsystems within a semi-operational environment. This phase served as a critical bridge between controlled laboratory testing and real-world deployment. The centralized control center functioned as the mission command hub, enabling bi-directional communication and facilitating real-time telemetry exchange, command execution, and system performance monitoring through a secure and localized network.

During static testing, the UAV remained grounded while executing predefined mission scenarios. These tests were designed to verify the accuracy of sensor data acquisition, the consistency of telemetry transmission, and the responsiveness of control algorithms without the confounding variables of in-flight dynamics. In addition, the USV was tested for the performance of its propulsion system, environmental sensors, and onboard computing architecture. Key parameters such as data latency, signal quality, motor feedback, and energy consumption were continuously monitored.

Moreover, both platforms were evaluated for interoperability, ensuring that simultaneous operation did not introduce signal interference or data collisions. Particular attention was given to stress testing the communication protocols under varying loads to ensure robustness in data routing and command relay, especially under limited-bandwidth conditions typical of remote coastal environments. The centralized control unit played a pivotal role in aggregating telemetry streams, visualizing system diagnostics, and logging all operational data for post-analysis and further system optimization. By simulating mission-relevant scenarios and synchronizing UAV and USV operations in a static environment, this phase validated the readiness of the integrated architecture for dynamic, field-level deployment.

4.1.2. Pilot Scenario Design

To evaluate the performance and reliability of the integrated system under realistic conditions, a structured pilot scenario was developed. Firstly, the beach selection process was carried out based on multiple criteria, including high tourism activity, accessibility, and existing infrastructure. Following the site selection, a controlled distribution of waste was carried out to simulate realistic pollution scenarios. The composition of the waste reflected the typical distribution found on Mediterranean beaches, with plastic comprising 50% of the total, followed by smaller proportions of paper (15%), aluminum (10%), metal (10%), glass

(10%), and wood (5%) [100]. This allocation aimed to test the system's ability to accurately detect plastic waste while differentiating it from other material categories. As a result, a total of 60 waste items were randomly dispersed across the test zones, ensuring they remained visible to the UAV cameras without excessive clustering, except where specific scenarios required testing detection capabilities in densely polluted areas. However, this controlled deposition approach was limited to the coastal environment, as conducting a similar setup within the marine ecosystem was deemed impractical and environmentally unsafe. This stems from the fact that the underwater waste could not be reliably retrieved after the test, unlike on land where each item was geotagged and accounted for during cleanup.

Flight operations were scheduled during early morning or late afternoon hours to take advantage of stable lighting conditions and to minimize glare, which could affect image quality. The UAV followed pre-defined flight paths at a consistent altitude and a steady speed to ensure uniform data acquisition across all regions. Particular focus was placed on evaluating the system's precision in identifying plastic objects. Data processing also assessed the system's overall recognition performance by comparing plastic detection rates against those for other materials. To quantify detection performance, several experimental metrics were established: the percentage of correctly classified waste items per category, the false positive rate (non-plastic items incorrectly identified as plastic), the false negative rate (plastic items not detected), and the proportion of total waste items that remained undetected. This approach allowed for the validation of both the UV-based monitoring workflow and the effectiveness of the image recognition system under semi-controlled yet realistic beach conditions.

4.2. Execution of the Pilot Scenario

The execution phase of the pilot scenario involved the deployment of the integrated system in selected coastal and terrestrial areas under semi-controlled, but realistic conditions. The objective was to evaluate the system's real-world performance in terms of data collection, environmental detection accuracy, and operational coordination.

4.2.1. Pilot Implementation at Coastal Area A

As part of the pilot phase of the Golden Seal project, operations were conducted at Coastal Area A in Attica, Greece, which was selected as the official site for validating the integrated coastal monitoring system under realistic environmental conditions. The selected UAV, depicted in Figure 6a, was equipped with high-resolution optical cameras, smart sensors, and advanced detection algorithms designed to identify and quantify plastic and other commonly encountered coastal waste materials.



(**a**) (**b**)

Figure 6. (**a**) The ATLAS 204 UAV in the Field; (**b**) Mission Planning Interface displaying Automated Waypoints (Blue zone) for Aerial Scanning of the Coastal Area A.

The UAV carried out a fully automated 10 min flight at a constant altitude of 28 m, systematically surveying an area of 721 square meters. The flight path, illustrated in

Figure 6b, was systematically designed using predefined waypoints (Blue zone) to ensure comprehensive aerial coverage of the entire coastal monitoring area. The UAV maintained a steady flight speed of 5 m per second. Favorable environmental conditions during the mission, including clear visibility and low wind intensity, further enhanced the precision of the onboard sensors. The integration of high-resolution imaging and advanced recognition algorithms allowed for accurate differentiation between waste and natural elements, such as sand and vegetation, thereby minimizing false detections and improving data quality.

To assess detection accuracy across different material categories, a controlled placement of waste items was conducted, consistent with the waste composition percentages specified in the pilot scenario. The selected materials included 15 plastic bottles, 5 paper cups, 3 aluminum beverage cans, 3 metal cans, 3 glass bottles, and 1 wooden bar. These items were arranged in predefined locations across the beach to simulate realistic littering scenarios, while permitting a controlled evaluation of the system's classification performance.

The selected USV (see Figure 7a) was deployed to perform a systematic navigation and monitoring mission within the nearshore marine environment on the same day. This operation followed the predefined white-shaded route illustrated in Figure 7b, which was designed to ensure consistent coverage and effective detection of plastic debris across the designated area. This operation formed an integral component of the Golden Seal project's overarching objective to integrate advanced unmanned systems for the effective monitoring and management of marine and coastal environments. The mission aimed to capture real-time data on both underwater and adjacent terrestrial conditions, contributing to a comprehensive understanding of environmental status in this transitional zone.



(**a**) (**b**)

Figure 7. (**a**) The USV NIIRIS in the Field; (**b**) Mission Planning Interface displaying predefined Navigation Route (white-shaded area) for Systematic Scanning of the Nearshore Marine Zone.

For the purposes of the case study, the observation area was defined as extending from the shoreline up to 50 m inland. This zone was selected to facilitate monitoring of the dynamic land–sea interface, where waste tends to accumulate due to tidal movements, anthropogenic activities, and prevailing wind patterns. The USV was programmed to navigate a predefined 500 m route along the coastline, as illustrated in the accompanying figure.

Navigation was guided by a series of waypoints, enabling the USV to follow its designated path with high positional accuracy. While the platform is technically capable of reaching speeds up to 28 m per second (equivalent to 100 km/h), the mission was executed at a significantly reduced speed of approximately 3 m per second. This slower pace was essential for ensuring both navigation precision and the quality of collected data. Operating at reduced speed enabled the USV to acquire detailed imagery and sensor measurements, thereby enhancing the overall reliability and resolution of the environmental dataset.

During operation, the USV's onboard systems continuously collected visual and sensor data, transmitting it in real time to a central gateway for immediate processing and analysis. The resulting dataset provided valuable insights into the state of both the coastal and marine environments and supports the development of data-driven strategies for waste management and pollution mitigation.

4.2.2. Pilot Implementation at Terrestrial Areas

In this phase of the Golden Seal project, a pilot was implemented in a terrestrial area in Attica, Greece to evaluate the adaptability and performance of the project's visual recognition algorithms in detecting plastic waste under non-coastal, vegetated conditions. Although the primary focus of the project is marine pollution, this terrestrial trial was strategically designed to address upstream contributors to marine litter. Many coastal environments, especially those behind beaches, feature significant vegetation and varied terrain that complicate visual detection. These areas often act as transitional zones, where waste is deposited and later, transported into marine ecosystems via wind, surface runoff, or human movement. Thus, validating system performance in such settings aligns with the broader objective of tackling marine pollution at its sources.

This process was conducted using the same UAV, which performed a 12 min autonomous flight at an altitude of 28 m. The operation was executed over two designated zones, referred to as Area A and B, located within a model airfield site characterized by sparse vegetation and heterogeneous terrain. The combined area of both zones covered approximately 776 square meters. To simulate realistic pollution scenarios, a total of 30 waste items were strategically placed across the two test zones. In Area A, which featured more open ground and less obstructive vegetation, 18 items were placed, primarily lightweight and highly visible materials, such as plastic bottles (10 items) and paper cups (4 items), along with 1 glass bottle, 1 metal can, 1 aluminum container, and 1 wooden stick. This distribution aimed to assess the algorithm's performance in conditions that favor direct visibility. In contrast, Area B featured denser vegetation and more textured terrain. The remaining 12 items were distributed here, including 5 plastic bottles, 1 paper cup, 2 metal cans, 2 aluminum containers, and 2 glass items. This setup was designed to assess the system's ability to detect partially obscured objects and to differentiate plastic waste from natural background elements, like vegetation or uneven terrain. By varying the types of materials and the complexity of their placement across the two test zones, the trial aimed to evaluate how well the system could perform detection and classification tasks under realistic land-based conditions.

The recorded data was subsequently processed using the selected visual recognition algorithms, which analyzed the spatial distribution and density of the waste. The outcomes provided critical insights into detection accuracy across varied terrain and environmental conditions. Most importantly, this pilot demonstrated the system's operational flexibility and its relevance beyond strictly marine contexts. By targeting terrestrial zones that often serve as pathways for plastic waste entering the marine environment, the project reinforces a proactive strategy for pollution mitigation.

5. Results

This chapter demonstrates the results of the pilot implementation conducted in both coastal and terrestrial settings, aimed at assessing the operational effectiveness of the Golden Seal system under real-world conditions. The evaluation focuses on the detection accuracy of UVs, the classification performance of the visual recognition algorithms across multiple material categories, and the application of the Beach Cleanliness Index as a composite environmental indicator.

5.1. Detection Results and Cleanliness Assessment at Coastal Area A

After completing the flight mission, the UAV returned to its designated base, where the collected data was reviewed and analyzed by the stakeholders using specialized equipment within the MOCU. This post-flight analysis involved comparing the UAV's detections with the pre-placed waste item inventory, which had been carefully recorded to serve as

the ground truth for evaluating system performance. While minor discrepancies were observed between the expected and detected results, these were largely attributable to environmental variability, such as wind displacement, object orientation, and changes in lighting conditions during the flight.

Figure 8 displays the results of UAV-based plastic waste detection over Coastal Area A, where the system was configured to identify only those items classified with a high level of confidence (80–100%). This threshold was predefined prior to analysis to ensure the reliability of the outputs and to minimize the likelihood of false positives. As shown in Figure 8, each red dot represents an individual plastic item detected within this confidence range, while blue dots indicate the detection of paper items. The green-outlined tiles correspond to separate UAV flight paths, which together form a spatial mosaic covering the entire test area, thereby enabling consistent and systematic monitoring. It also worth mentioning that, the right-hand side of the figure illustrates the interface of the object inference module used during the analysis. This interface allows operators to choose among multiple data layers, including detection polygons, object type classifications, confidence thresholds, and litter density maps, facilitating detailed visual inspection and interpretation of the model's outputs. As a result, the breakdown of detection results by waste category is as follows:

- Plastic bottles (15 items): The algorithm correctly identified 14 plastic bottles, resulting in 93.33% detection accuracy. However, two aluminum cans were misclassified as plastic (see Figure 8), indicating high sensitivity, but some limitations in material discrimination.
- Paper cups (5 items): Three paper cups were detected, yielding a 60% detection rate. The remaining items were likely affected by low contrast against the background or partial occlusion, which can challenge recognition accuracy.
- Aluminum beverage cans (3 items): Only one aluminum can was accurately identified, with the other two misclassified as plastic, indicating a 33% success rate for this category. This suggests that reflective surfaces can be confused with similar-looking plastic waste, highlighting an area for algorithmic improvement.
- Metal cans (3 items): The system detected two out of three metal cans, achieving a 67% accuracy rate. Misidentification appeared to result from overlapping features with plastic containers and suboptimal visibility.
- Glass bottles (3 items): All three glass items were correctly identified, reflecting 100% accuracy. Their unique visual properties, including transparency and light reflection, likely contributed to reliable detection.
- Wooden bar (1 item): The system successfully detected the single wooden item included in the scenario, yielding 100% accuracy. Although the sample size for this category was limited, its proportion was deliberately aligned with observed waste distributions on Mediterranean beaches, where wood typically represents only a small fraction of total litter. As such, its inclusion served to test detection reliability across all expected material types, even those occurring at lower frequencies.



Figure 8. Visualization of UAV-based Plastic Waste Detection Results over Coastal Area A.

These results demonstrate the system's strong capability in detecting visually prominent and high-contrast materials such as plastic, glass, and wood, confirming its reliability in coastal monitoring scenarios. However, the lower detection rates and misclassifications observed for items like aluminum cans and paper cups highlight limitations in the current algorithm's ability to distinguish objects with reflective surfaces or low visual contrast against natural backgrounds. These findings suggest that further refinement of the detection model is needed to enhance material differentiation and maintain consistent accuracy across a broader range of waste types and environmental conditions.

To further assess environmental conditions at the test site, the BCI was calculated using a multi-factor approach that integrates both physical and behavioral indicators of beach quality. For the purposes of this controlled experiment, all components were assigned equal weights of 20% each, allowing for a balanced evaluation of all relevant factors. The calculated input values were:

- Plastic Waste Density: 99.31—Based on the density of plastic items detected per square meter.
- Plastic Waste Coverage: 99.97—Calculated using the total surface area of plastic waste (0.25 m^2).
- Plastic Abundance Index: 61.54—Representing the proportion of plastic items (16) detected relative to the total number of waste items (26) detected across the test area.
- User Reviews Score: 80.00—Based on simulated average user feedback on beach cleanliness.
- Recycling Capacity: 79.18—Determined by available capacity equivalent to three bins, each with a 7 kg weight threshold.

As a result, the BCI for the Coastal Area A pilot was calculated based on the following results:

$$\text{BCI}_{\text{Coastal Area A}} = W1 \times PWD' + W2 \times PWC' + W3 \times PAI' + W4 \times URS' + W5 \times RC'$$

- The actual detected plastic density was extremely low (0.0069 plastic items/m^2), while the threshold value was set at 1 item/m^2, based on relevant literature reporting average beach litter densities in the Mediterranean region [94]. Substituting these values yields:

$$PWD' = \left(1 - \frac{0.0069}{1}\right) \times 100 = 99.31$$

- The total plastic-covered area was calculated to be 0.25 m^2 over a total observed surface of 721 m^2, yielding:

$$\mathrm{PWC} = \frac{0.25}{721} = 0.00035$$

$$\mathrm{PWC}' = (1 - 0.00035) \times 100 = 99.97$$

- In the sample area, 16 plastic items were found among 26 total detected waste items, resulting in:

$$\mathrm{PAI}' = \frac{16}{26} \times 100 = 61.54$$

- User feedback indicated an average cleanliness rating of 4 on a 5-point scale. This score was scaled using the transformation:

$$\mathrm{URS}' = 4 \times 20 = 80.00$$

- Based on the capacity of the deployed bins, the threshold value was set at 21 kg, while the measured collected waste was 16.63 kg, resulting in:

$$\mathrm{RC}' = \frac{16.63}{21} \times 100 = 79.18$$

As a consequence, using the normalized values and equal weighting, the BCI was calculated as:

$$\mathrm{BCI}_{\text{ Coastal Area A}} = 0.20 \times 99.31 + 0.20 \times 99.97 + 0.20 \times 61.54 + 0.20 \times 80.00 + 0.20 \times 79.18 = 84.00$$

Using this methodology, the final BCI score was calculated as 84.00. This value reflects a relatively high cleanliness level within the controlled testing environment, indicating that the integrated monitoring system performed effectively under favorable conditions. The result suggests that the combination of UAV-based image recognition, IoT-enabled data collection, and real-time analysis can provide a reliable foundation for assessing coastal cleanliness. Moreover, this score underscores the potential of the BCI as a responsive and practical tool for evaluating beach litter levels, particularly when applied in structured scenarios with well-defined spatial and environmental parameters.

5.2. Detection Results and Cleanliness Assessment at Terrestrial Areas

In this terrestrial context, the detection system demonstrated solid performance, with detections once again filtered using a predefined confidence threshold of 80–100%. This ensured that only highly reliable visual inferences were included in the analysis, thereby affirming the robustness of the recognition algorithms and supporting sensor configuration (see Figure 9). However, the results also revealed some inconsistencies between the ground-truth dataset and the items identified by the system. These variances were primarily linked to environmental challenges typical of natural land surfaces such as shifting light conditions, intermittent shadowing from surrounding vegetation, and the visual blending of waste materials with textured terrain. These elements made object recognition more complex, particularly from a flight height of 28 m, where smaller or low-contrast items can be partially obscured or misclassified. Despite these limitations, the system's overall accuracy was encouraging and the insights collected from this pilot will inform further improvements aimed at increasing detection precision in real-world terrestrial environments. The detection results were closely examined in relation to the characteristics of the two designated test zones:



Figure 9. Visualization of UAV-based Plastic Waste Detection Results over Terrestrial Area A.

Terrestrial Area A, which featured relatively open ground with minimal vegetation, was populated with 18 waste items, including ten plastic bottles, four paper cups, one glass bottle, one metal can, one aluminum container, and one wooden stick. In this area, the system demonstrated strong performance in detecting plastic materials, correctly identifying 8 out of 10 plastic bottles. However, two bottles were not detected, likely due to poor viewing angles or partial shading. Additionally, the wooden stick was successfully recognized, reflecting the system's capability to detect distinct and high-contrast items. Both the metal can and the aluminum container were detected by the system, but misclassified as plastic, revealing the algorithm's current limitations in distinguishing reflective or similarly shaped materials, particularly under direct sunlight. Conversely, none of the four paper cups nor the glass bottle were detected in this test, likely due to lower contrast with the surrounding terrain or partial occlusion. These results emphasize that while detection of plastics is relatively accurate in open environments, the performance varies significantly with material type, visual texture, and reflectivity.

Terrestrial Area B, which featured denser vegetation and more complex terrain, included 12 waste items: five plastic bottles, one paper cup, two metal cans, two aluminum containers, and two glass bottles. In this zone, the system's performance declined slightly, primarily due to increased visual obstruction, heterogeneous background textures, and shadows cast by vegetation. The detection algorithm successfully identified four out of five plastic bottles, while one remained undetected. Regarding metallic items, only one of the two metal cans and one of the two aluminum containers were correctly classified, while the others were not detected at all. The paper cup was not detected, likely due to low contrast against the background and partial occlusion. These results align with earlier observations, indicating a persistent challenge in distinguishing reflective surfaces under natural lighting conditions. Nevertheless, both glass items were correctly identified, suggesting that their visual properties, such as transparency and distinct reflectivity, enhanced detection reliability, even in a visually cluttered environment.

In summary, the pilot results from both terrestrial test zones underscore the system's promising capabilities in detecting plastic waste under varied environmental conditions, while also revealing certain limitations linked to terrain complexity and material characteristics. Area A, characterized by open ground and minimal vegetation, yielded higher overall detection rates, particularly for plastic items, demonstrating that the system performs reliably in visually unobstructed environments. Area B, despite featuring denser vegetation and more heterogeneous surface textures, also showed strong performance in detecting plastic materials, thus highlighting the system's robustness. However, detection accuracy decreased for other material categories, with reflective items such as metal and aluminum frequently misclassified as plastic and low-contrast objects like paper cups remaining undetected. The consistent recognition of glass items across both sites suggests

that certain visual properties, such as transparency and distinct reflectivity, aid detection despite environmental complexity. Overall, these findings validate the high plastic detection accuracy of the system and confirm its potential for scalable waste monitoring, while also identifying areas for further algorithmic refinement.

To further assess environmental conditions at the terrestrial test site, the BCI was similarly calculated. Although originally developed for coastal monitoring, the BCI was applied in this context to evaluate the overall effectiveness of the waste detection system in a land-based area that may serve as an upstream contributor to marine pollution. To ensure that the BCI remains contextually meaningful and reflective of each environment's specific conditions, the weight coefficients for the terrestrial pilot were adjusted. Unlike coastal zones directly impacted by marine litter, Terrestrial Areas represent inland, semi-natural areas characterized by vegetation and indirect pathways for pollution to reach aquatic ecosystems. Given these characteristics, the weight for Plastic Waste Density (W_1) was reduced from 20% to 15%, as surface density alone is less indicative of long-term environmental impact in open terrestrial zones. Conversely, the Plastic Abundance Index (W_3) was increased to 25%, since the total quantity of waste, regardless of spatial concentration, is a more relevant indicator of potential transport toward coastal areas via wind, runoff, or human activity. Similarly, greater emphasis was maintained for Plastic Waste Coverage (W_2), User Reviews Score (W_4), and Recycling Capacity (W_5), each at 20%, to account for both the public perception of cleanliness in recreational inland areas and the infrastructural capacity to manage waste effectively before it enters marine ecosystems. This weighting strategy aligns with the project's overarching goal of tailoring environmental assessment tools like the BCI to fit both marine and terrestrial use cases, thereby enabling a more comprehensive approach to pollution monitoring and prevention. In parallel, the calculated input values for the Terrestrial Area A and B were as follows:

- The actual detected plastic density was 0.1053 plastic items/m^2. Given a threshold value of 1 plastic item/m^2, based on regional average densities in the Mediterranean [94], the normalized score was computed as:

$$\mathrm{PWD}' = \left(1 - \frac{0.1053}{1}\right) \times 100 = 89.47$$

- The estimated total plastic-covered surface was 0.0874 m^2 over an observed area of 776 m^2, yielding:

$$\mathrm{PWC} = \frac{0.0874}{776} = 0.00011$$

$$\mathrm{PWC}' = (1 - 0.00011) \times 100 = 99.98$$

- In the sample area, 14 plastic items were found among 19 total detected waste items, resulting in:

$$\mathrm{PAI}' = \frac{14}{19} \times 100 = 73.68$$

- User feedback indicated an average cleanliness rating of 4 on a 5-point scale. This score was scaled using the transformation:

$$\mathrm{URS}' = 4 \times 20 = 80.00$$

- Based on the capacity of the deployed bins, the threshold value was set at 21 kg, while the measured collected waste was 15.12 kg, resulting in:

$$RC' = \frac{15.12}{21} \times 100 = 72.00$$

As a consequence, using the normalized values and equal weighting, the BCI was calculated as:

$$BCI_{\text{Terrestrial Areas}} = 0.15 \times 89.47 + 0.20 \times 99.98 + 0.25 \times 73.68 + 0.20 \times 80.00 + 0.20 \times 72.00 = 82.24$$

Using this adjusted methodology, the final BCI score for the terrestrial pilot was calculated as 82.24. Although slightly lower than the score recorded at the Coastal Area A, this result still indicates a relatively high cleanliness level, especially when considering the increased environmental complexity posed by vegetation, uneven terrain, and partial visual obstructions. Furthermore, the lower weight assigned to density and the greater emphasis on abundance enabled a more accurate reflection of terrestrial waste dynamics.

Following the completion of the pilot implementations, all waste items distributed during the experiments were systematically collected. Subsequently, a small-scale cleanup and public outreach campaign was conducted at the test sites, aimed at both restoring the environment and promoting the objectives of the Golden Seal project. As part of this activity, the collected waste was deposited into the smart bins developed under the project, where it was automatically quantified and categorized using the integrated sensor and analytics systems. This post-pilot phase served as a demonstration of the operational capabilities of the developed waste monitoring infrastructure and contributed to raising environmental awareness among local stakeholders.

5.3. Comparative Performance of Waste Detection Across Coastal and Terrestrial Test Areas

The comparative analysis of detection results across the three pilot zones (i.e., Coastal Area A, Terrestrial Area A and B) highlights the impact of environmental characteristics on the performance of the waste detection system. Each zone presented distinct terrain conditions and visibility challenges, which influenced detection accuracy and classification precision across different material categories (see Table 3).

Table 3. Waste Detection Comparison Across Test Areas.

Waste Type	Coastal Area A	Terrestrial Area A	Terrestrial Area B
Plastic Bottles (Initial Number)	15	10	5
Plastic Bottles (Number Detected)	14	8	4
Paper Cups (Initial Number)	5	4	1
Paper Cups (Number Detected)	3	0	0
Aluminum Cans (Initial Number)	3	1	2
Aluminum Cans (Number Detected)	1 (2 Misclassified as plastic)	1 Misclassified as plastic	1
Metal Cans (Initial Number)	3	1	2
Metal Cans (Number Detected)	2	1 Misclassified as plastic	1

Table 3. *Cont.*

Waste Type	Coastal Area A	Terrestrial Area A	Terrestrial Area B
Glass Bottles (Initial Number)	3	1	2
Glass Bottles (Number Detected)	3	0	2
Wooden Items (Initial Number)	1	1	-
Wooden Items (Number Detected)	1	1	-

Coastal Area A, characterized by an open beach terrain with relatively uniform surface textures and minimal visual obstructions, yielded the highest overall detection accuracy. The algorithm correctly identified 14 out of 15 plastic bottles (93.33%) and all three glass items, demonstrating excellent performance for highly visible materials. Paper items showed moderate detectability (60%), while aluminum cans posed a particular challenge, only one out of three was correctly classified, and two were misidentified as plastic. This trend suggests that while the system is highly effective in identifying dominant plastic waste, it tends to overestimate plastic presence in cases of reflective or ambiguous objects. The inclusion of a wooden item, which was correctly identified, further confirmed the system's ability to handle well-contrasted materials under favorable lighting conditions.

Moreover, Terrestrial Area A, an inland zone with open terrain and sparse vegetation, also performed strongly in terms of plastic detection, identifying 8 out of 10 plastic bottles. However, unlike the coastal site, paper and glass items were not detected at all. These results underscore the influence of background blending and light diffusion in non-beach environments. Although the metallic items (one metal can and one aluminum container) were recognized by the system, they were misclassified as plastic, reinforcing the system's sensitivity, but also its vulnerability to material confusion under direct sunlight. The wooden stick, which contrasted sharply with the surrounding terrain, was again detected successfully.

In contrast, Terrestrial Area B introduced greater detection complexity due to dense vegetation, shadows, and heterogeneous ground textures. These conditions led to a slight performance drop, with 4 out of 5 plastic bottles correctly detected, while one was missed, likely due to occlusion. The algorithm accurately identified only one of two aluminum containers and one of two metal cans, with the others remaining undetected. As in Area A, the paper cup was not recognized, while both glass bottles were correctly detected, reaffirming the system's consistent performance with reflective and transparent materials. The complexity of this zone revealed the system's sensitivity to terrain-induced visual noise, which can mask or distort item shapes.

In summary, detection accuracy was highest in Coastal Area A, where minimal obstruction and clear surface contrast supported optimal visual recognition. Performance remained relatively robust in Terrestrial Area A but declined in Terrestrial Area B due to more challenging environmental conditions. Across all areas, plastic items showed consistently high detection rates, affirming the system's core capability, while paper and reflective metallic items highlighted areas for future algorithmic refinement. These findings emphasize the importance of environmental context in UAV-based waste detection and validate the need for adaptive calibration of recognition models depending on terrain complexity and waste type.

6. Discussion

The findings and outcomes of the Golden Seal project confirm its effectiveness as an interdisciplinary response to the challenges of MPP and tourism management. By integrating IoT-enabled sensor networks, UVs, advanced image recognition algorithms, and gamified tools, the project successfully demonstrated a holistic approach to environmental monitoring and stakeholder participation. This comprehensive system strengthened the accurate detection and quantification of plastic waste, the generation of important data through the BCI, and the active involvement of local communities through eco-label methods, educational initiatives, and a serious game.

The selection of indicators used in the BCI was informed by a critical review of established coastal monitoring frameworks, including the Beach Quality Index (BQI) by [92], the Clean Coast Index (CCI) by [91], and the Plastic Abundance Index (PAI) proposed by [93]. While each of these indices focuses on specific environmental or cleanliness attributes, the BCI introduces a novel approach by combining environmental and participatory metrics within a unified structure tailored for UAV-based monitoring. Unlike earlier indices that relied on manual surveys or focused on a single dimension (e.g., litter count or user satisfaction), the BCI combines quantitative data with user-generated reviews and real-time recycling data. In practice, the BCI was applied across two main pilot zones, yielding scores of 84.00 in the coastal test area and 82.24 in the terrestrial pilot. These values reflect relatively high cleanliness levels under semi-controlled conditions, validating the adaptability of the index to different environmental contexts.

Moreover, in line with the authors in [101], who emphasize the need for innovative technological tools in environmental monitoring, the Golden Seal project validated the adaptability of its system across coastal and terrestrial environments. The high detection confidence levels, achieved through real-world testing, build upon and refine existing approaches in image recognition, particularly under complex natural lighting and terrain conditions [102,103]. More specifically, the pilot implementation of the Golden Seal project provided valuable insights into the system's detection capabilities and environmental adaptability. The results demonstrated a consistently high detection accuracy for plastic waste, with detection rates exceeding 90% in Coastal Area A and remaining robust across both terrestrial test zones despite increased terrain complexity and occlusion. Notably, detection performance was strongest in open, minimally obstructed environments, such as sandy beach settings, where item visibility was optimal. Conversely, vegetation density and shadowing in Terrestrial Area B introduced significant challenges, reducing the detection rate for low-contrast materials, such as paper and aluminum. Misclassification of reflective items as plastic was a recurring issue, suggesting a need for improved algorithmic discrimination between materials with similar visual characteristics. These findings confirm the system's reliability for identifying prominent waste types like plastic and glass, while also highlighting the importance of environmental context in determining overall effectiveness.

Furthermore, the project's outreach and eco-labeling strategies directly align with the priorities outlined by the authors in [104] and the UN Mediterranean Action Plan [105], which call for integrated, community-engaged responses to marine litter. By connecting scientific monitoring with citizen involvement and local policy incentives, the project offered a replicable framework for multi-level environmental governance. From a systems integration perspective, the project demonstrated the feasibility of real-time, cloud-enabled data processing and user-friendly interfaces, supporting rapid deployment. As the authors in [106] have noted, bridging technology with community engagement remains a key challenge; the Golden Seal project contributed to this discussion by providing tangible evidence of how gamification and environmental metrics can effectively drive user participation.

In terms of scalability, the Golden Seal architecture has been deliberately designed as a modular system, allowing for implementation across a broad range of geographical and socio-environmental settings. While the initial validation was limited to two pilot sites in Greece, the system was intentionally deployed in areas with contrasting terrain complexities to assess its operational robustness in semi-controlled but realistic conditions. These testbeds allowed for a preliminary evaluation of how key environmental variables such as surface reflectivity, vegetation density, and lighting variability can affect detection accuracy. However, it is evident that detection performance may decline in environments with significantly different features (e.g., tropical coastlines or rocky shores) due to changes in waste typology, background interference, and weather conditions.

To address this, future deployments will involve retraining the image recognition models on locally sourced datasets, collected under site-specific conditions, to ensure accurate generalization. Additional adaptation measures may include optimizing UAV flight paths and altitudes for each context and customizing detection thresholds based on local waste profiles. Similarly, variations in infrastructure availability, internet connectivity, and digital literacy may pose barriers to user participation or system integration. In response, the Golden Seal platform is equipped to handle such constraints through offline data capture capabilities, simplified mobile interfaces, and modular hardware configurations that can operate autonomously with minimal ground support. These design features ensure that the system remains deployable even in resource-limited or remote regions.

From a cost-efficiency perspective, the system enables the reuse of core components, such as UVs and IoT sensors, across multiple nearby monitoring areas, particularly in clustered coastal sites. This reusability significantly reduces per-mission costs and enhances the economic sustainability of long-term monitoring programs. Furthermore, by combining environmental data collection with citizen engagement tools, the platform maximizes the utility of each deployment, generating both technical insights and public awareness.

In conclusion, these elements position the Golden Seal system as a flexible, adaptable, and cost-effective solution for both coastal and inland environmental monitoring. While further validation across more diverse regions and waste conditions remains necessary, the present implementation offers a robust proof of concept and a clear pathway for similar initiatives. More broadly, the project demonstrates how technological innovation, when paired with active stakeholder engagement, can be leveraged to address complex sustainability challenges in marine and coastal ecosystems. Its contributions extend beyond localized impacts, offering a transferable and participatory model to support future efforts in environmental monitoring, marine litter prevention, and responsible tourism.

7. Conclusions

The Golden Seal project demonstrates how integrating advanced technologies with participatory environmental management can effectively address the complex challenge of coastal and MPP. By combining IoT-enabled sensor networks, UAVs, USVs, and intelligent image recognition algorithms with community engagement mechanisms, the project delivered a modular, multi-sensor platform. This platform integrates UAV/USV data, user-generated inputs, and AI-driven analytics for coastal litter monitoring.

Deployed successfully in both coastal and terrestrial environments, the system showed strong adaptability, precise detection, and operational robustness. Tools such as the BCI, eco-labeling mechanisms, and gamified engagement platforms played a key role. They not only enhanced environmental monitoring but also raised public awareness and encouraged collaborative action among local communities, tourism stakeholders, and municipal authorities. From a scientific standpoint, the project contributes novel insights into applying DL algorithms for plastic waste classification in dynamic natural settings.

While the results are promising, scaling the system further will require thoughtful planning. Regulatory variability, deployment costs, and infrastructure readiness in new regions could hinder replication. To overcome these challenges, a modular system design, alignment with strategic policies, and well-chosen partnerships will be essential.

It is also important to acknowledge that both pilot scenarios took place in semi-controlled, small-scale environments using pre-positioned waste items. This approach was necessary to enable systematic evaluation, technical validation, and consistent comparisons across material types and terrain conditions. However, it does introduce some confirmation bias. Future deployments should test the system under real-world, uncontrolled conditions to more accurately assess its robustness.

Additionally, using UAVs, USVs, and image recognition technologies in public areas brings ethical, regulatory, and privacy concerns that must be addressed. Although the pilot activities were conducted in compliance with local operational permits, further attention is required to ensure full alignment with data protection frameworks such as the EU General Data Protection Regulation. This includes addressing bystander privacy, the potential capture of personal data, and the implementation of transparent protocols for the ethical use of surveillance technologies. Future iterations of the project should include privacy impact assessments, community engagement processes, and compliance with national drone regulations.

Ultimately, the Golden Seal project offers a practical and transferable model for addressing environmental degradation in tourism-intensive coastal zones. Its interdisciplinary framework, integrating technology, public participation, and data-driven governance, lays a strong foundation for future advancements in environmental monitoring, marine litter mitigation, and sustainable resource management.

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