NOVEL TOOLS FOR PORT ENVIRONMENTAL MANAGEMENT SYSTEMS

Doctoral thesis

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Abstract

This thesis addresses the development and evaluation of novel tools and strategies for Environmental Management Systems (EMS) implementation in ports for water quality. Integrating computer vision-based systems with meteorological and hydrodynamic operational models, the research aims to provide efficient and tailored tools for pollution monitoring and management. Three case studies are presented, exploring the feasibility of using meteo-oceanographic operational services as SAMOA, in conjunction with Monte Carlo experiments, for environmental risk analysis; developing robust computer vision systems for spill and waste monitoring; and assessing computer vision systems reliability under different operating conditions. The findings demonstrate the potential of meteo-oceanographic operational services and computer vision for marine pollution monitoring tasks and highlight the significance of progressive implementation in port EMS, leveraging early data collection and adopting an adaptive approach. The research supports sustainable and environmentally conscious practices in port management to protect coastal waters and marine ecosystems.

Resum

Aquesta tesi aborda el desenvolupament i avaluació de noves eines i estratègies per a la implementació de Sistemes de Gestió Ambiental (SGA) en ports per a la qualitat de l'aigua. Integrant sistemes basats en la Visió per Computadora (VC) amb models operatius meteorològics i hidrodinàmics, la recerca té com a objectiu proporcionar eines eficients i personalitzades per al monitoratge i la gestió de la contaminació. Es presenten tres estudis de cas que exploren la viabilitat de l'ús de serveis operatius meteo-oceanogràfics com SAMOA, en conjunció amb experiments de Monte Carlo, per a l'anàlisi de riscos ambientals; desenvolupament de sistemes robustos de VC per al monitoratge de vessaments i residus; i avaluant la fiabilitat dels sistemes de VC sota diferents condicions operatives. Els resultats demostren el potencial dels serveis operatius meteo-oceanogràfics i la VC per a les tasques de monitoratge de la contaminació marina, posant de manifest la importància de la implementació progressiva en els SGA portuaris, aprofitant la recopilació de dades i l'adopció d'un enfocament adaptatiu. La recerca recolza pràctiques sostenibles i conscients del medi ambient en la gestió portuària per protegir les aigües costaneres i els ecosistemes marins.

Resumen

Esta tesis aborda el desarrollo y la evaluación de nuevas herramientas y estrategias para la implementación de Sistemas de Gestión Ambiental (SGA) para la calidad del agua en puertos. Integrando sistemas basados en visión por computadora con modelos operativos meteorológicos e hidrodinámicos, la investigación tiene como objetivo proporcionar herramientas eficientes para la vigilancia y gestión de la contaminación. Se presentan tres estudios de caso que exploran: la viabilidad del uso de servicios operativos meteo-oceanográficos como SAMOA, en conjunto con experimentos de Monte Carlo, para el análisis de riesgos ambientales; el desarrollo de sistemas robustos de visión por computadora para el control de vertidos; y la evaluación de la fiabilidad de los sistemas de visión por computadora bajo diferentes condiciones operativas. Los resultados demuestran el potencial de estas técnicas para las tareas de control de la contaminación marina, destacando la importancia de la implementación progresiva en los SGA portuarios al aprovechar la recopilación de datos y adoptar un enfoque adaptativo. La investigación respalda prácticas sostenibles y conscientes del medio ambiente en la gestión portuaria, para proteger las aguas costeras y los ecosistemas marinos.

Publications

Peer reviewed international journals:

1. Environmental management system for the analysis of oil spill risk using probabilistic simulations: application at Tarragona monobuoy

   Authors: Morell, M.; Espino, M.; Grifoll, M.; Mestres, M.

   Journal of marine science and engineering Vol. 8 num. 4 p. 277:1-277:14

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   Publication date: 04/2020

2. Use of neural networks and computer vision for spill and waste detection in port waters: an application in the Port of Palma (Majorca, Spain)

   Authors: Morell, M.; Portau, P.; Perelló, A.; Espino, M.; Grifoll, M.; Garau, C.

   Applied sciences (Basel) Vol. 13 num. 1, article 80

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1. Análisis del riesgo ambiental por vertidos de hidrocarburos en la zona del puerto de Tarragona en el contexto de la Directiva Marco sobre la Estrategia Marina

   Authors: Morell, M.; Espino, M.; Grifoll, M.; Mestres, M.

   Jornadas Españolas de Ingeniería de Costas y Puertos p. 85-86

   Presentation date: 08/05/2019

2. New strategies for environmental management in harbours: the case of the Tarragona port monobuoy

   Authors: Morell, M.; Espino, M.; Grifoll, M.; Mestres, M.

   International Conference on Maritime Transport p. 491-499

   Presentation date: 09/2020

3. Vigilancia de basura marina y vertidos contaminantes con técnicas de Computer Vision

   Authors: Morell, M.; Portau, P.; Perelló, A.; Espino, M.; Grifoll, M.; Garau, C.

   Jornadas Españolas de Ingeniería de Costas y Puertos p. 99-100

   Presentation date: 11/05/2022

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1. INTRODUCTION

1.1 Background

Ports and coastal areas serve as strategic hubs for economic activities, trade, and transportation, connecting regions and facilitating international commerce. On the other hand, the rapid growth and intensification of port activities have raised concerns about their environmental impact on adjacent waters. Ports are often located in ecologically sensitive areas, adjacent to coastal ecosystems that support a diverse range of marine species and provide essential ecosystem services. These areas face significant environmental challenges due to the concentration of human activities and the operations resulting from interaction between land and sea transport. The complex interplay between natural processes, anthropogenic influences, and limited water renewal rates in ports and adjacent coastal waters makes them highly susceptible to water pollution and the accumulation of solid waste. The discharge of pollutants, the generation of waste, and the degradation of water and sediment quality associated with port operations can have significant adverse effects on marine ecosystems.

Recognizing the environmental challenges posed by port activities, the implementation of effective Environmental Management Systems (EMS) has become increasingly important [Gómez et al. 2015, Wooldridge et al. 1999]. An EMS provides a structured approach to identify, assess, and manage environmental risks and impacts associated with port operations. It encompasses a range of strategies, policies, and practices aimed at minimizing negative environmental effects while maximizing efficiency and sustainability. By integrating environmental considerations into their daily operations, ports can reduce their ecological footprint, protect coastal ecosystems, thus enhancing their long-term viability. Coastal regions play an essential role in the achievement of the UN Sustainable Development Goals given their importance for human habitation, resource provisioning, employment, and cultural practice. In this areas, on the other hand, different ecological, disciplinary and jurisdictional boundaries both overlap and are obscured. So, the land-sea interface is an area where governance systems are most in need of frameworks for systems analysis and governance to integrate complex interdependencies between human livelihoods, energy, transport, food production, and nutrient flows [Singh et al. 2021].

The importance of EMS in port operations extends beyond environmental protection. Ports are complex and multifaceted systems that involve numerous stakeholders, including port authorities, shipping companies, terminal operators and local communities. These stakeholders have diverse interests and objectives, ranging from economic growth and trade facilitation to social well-being and environmental conservation. An EMS provides a common framework for effective communication, collaboration, and decision-making among these stakeholders, helping to address environmental concerns in a balanced and integrated manner. By engaging stakeholders and fostering a culture of environmental responsibility, ports can build trust, enhance their reputation, and promote sustainable development.

Additionally, ports that demonstrate a commitment to environmental stewardship are more likely to attract environmentally conscious customers and investors, thus gaining a competitive advantage in the global market [Puig et al. 2021].

In ports with high recreational activity located in tourist cities, the importance of implementing an effective EMS becomes even more critical. These ports not only serve as hubs for commercial shipping and trade but also attract a significant number of tourists and recreational visitors. The environmental quality status of the port and its surrounding coastal waters directly impacts the tourism industry, which is often a major economic driver for these cities [Mali et al. 2018]. Tourists are drawn to the beauty of coastal environments and pristine condition of port water, and any degradation in water quality or pollution incidents can have detrimental effects on the tourism sector, leading to negative economic consequences for the entire region.

By implementing an EMS, ports with high recreational activity can proactively manage environmental risks and minimize the potential impacts on tourism and recreational activities. A well-designed EMS takes into account the specific needs and characteristics of these ports, considering factors such as water quality monitoring, waste management, noise control, and the protection of sensitive marine habitats. Through effective environmental planning, pollution prevention measures, and regular monitoring, these ports can ensure the maintenance of water quality standards and the preservation of the natural traits that attracts tourists being also valued by residents [Mali et al. 2018]. Thus, safeguarding the quality of the port waters, port operators can enhance the overall visitor experience, attract repeat visitors, and contribute to the long-term sustainability of the tourism industry. By adopting a proactive and systematic approach to environmental management, ports can minimize their ecological footprint, protect coastal ecosystems, and optimize their operations. Through effective stakeholder engagement and the integration of environmental considerations into decision-making processes, ports can achieve a balance between economic growth, social well-being, and environmental conservation.

EMS standards:

Several international standards and guidelines exist to guide ports in the development and implementation of EMS. In this sense, one notable standard for EMS is the ISO 14001 (International Organization for Standardization, 2015) which provides a framework for the establishment, maintenance, and continuous improvement of an. ISO 14001 [Thompson et al. 2020, Johnstone and Hallberg 2020] emphasizes the need for ports to identify and comply with applicable legal and regulatory requirements, assess and manage environmental risks, set objectives for improvement, and engage stakeholders in environmental decision-making processes. Compliance with ISO 14001 not only demonstrates a port's commitment to environmental protection but also enhances its reputation and competitiveness in the global market.

EMS and legal regulations on ports:

In addition to voluntary standards, ports are subject to a wide range of legal regulations aimed at protecting the environment and ensuring the sustainable use of coastal and marine resources. These regulations may include national laws, regional directives, and international conventions addressing various aspects of port activities, such as water quality, air emissions, waste management, and biodiversity conservation. Compliance with these legal requirements is essential for maintaining the social license to operate, preventing environmental harm, and avoiding potential penalties or legal liabilities.

A new challenge in marine pollution monitoring is based on the harmonization of two European Union directives: the Water Framework Directive (WFD) and the Marine Strategy Framework Directive (MSFD). These directives aim to protect marine environments through different approaches, with the WFD following a risk assessment approach and the MSFD adopting an ecosystem approach [Long 2015]. The MSFD establishes a legislative context demanding the use of effect-based tools for the assessment of pollution, shifting the focus towards evaluating ecological effects rather than relying solely on chemical analysis [Diamantini et al. 2018]. A crucial knowledge gap is also the elaboration of internationally agreed assessment criteria for both environmental pollutants and biological responses [Bellas et al. 2020].

Environmental Management Systems (EMS) play a crucial role in ensuring compliance with environmental regulations as well as promoting sustainable practices in port operations. Three main EMS functions can be considered: environmental hazard identification, environmental risk assessment and environmental risk management (see Figure 1.1). An EMS provides a systematic framework for identifying, evaluating, and managing environmental impacts associated with port activities [Gomez et al. 2015] building a framework to support a range of policies, procedures, and practices aimed at minimizing negative environmental effects while promoting resource efficiency and environmental stewardship. Thus, by implementing an EMS, ports can enhance their environmental performance, reduce risks, and foster a culture of environmental responsibility among stakeholders [Puig et al. 2022].

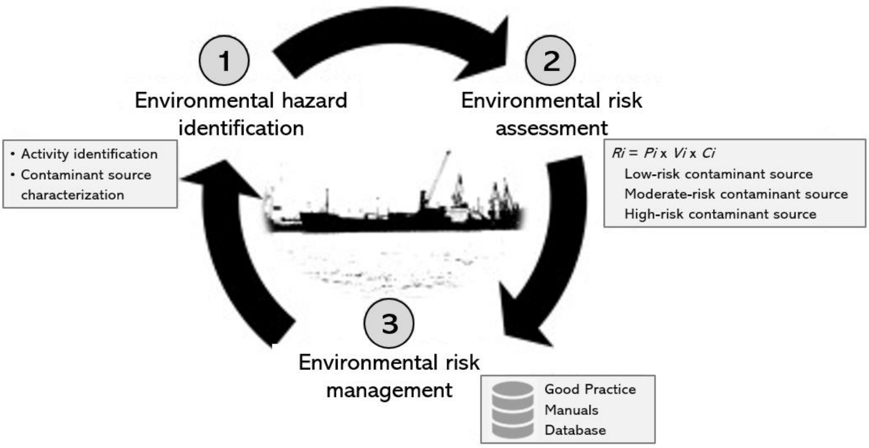


Figure 1.1. Main EMS functions [Gómez et al. 2015].

Traditionally, the assessment of marine pollution relied solely on chemical analysis, but this approach only provides a partial understanding of ecological effects. The study of environmental pollutants and their effects has been hindered by analytical limitations and methodological difficulties, necessitating the development of new techniques. To comprehensively assess the impact on marine organisms and ecosystems, an integrated approach combining chemical and biological state analysis and ecological pressure monitoring tools is necessary. Integrated approach schemes need to improve coastal systems monitoring, which is frequently challenging due to both confounding factors and methodological variability.

Marine pollution monitoring is crucial for effective environmental legislation and the sustainable use of coastal ecosystems. This research explores the challenges and opportunities in this field, emphasizing the need for integrated approaches and the use of effect-based tools in line with the MSFD's ecosystem approach. The development of new approaches and technologies is vital for enhancing marine pollution monitoring efforts and better understanding its environmental behavior and ecotoxicity, including pollutants of emerging concern, such as microplastics. By embracing the MSFD's ecosystem-based approach, marine pollution monitoring can play a fundamental role in preserving and protecting marine ecosystems while promoting their sustainable use.

The integration of efficient automated techniques, such as computer vision-based systems, into EMS can greatly enhance a port's ability to monitor and manage water quality in compliance with legal regulations. These systems can provide real-time and accurate information on surface spills, floating marine waste, and other pollutants, allowing for timely responses and mitigation measures. By incorporating computer vision-based systems into their EMS, ports can improve their environmental performance, streamline monitoring processes, and demonstrate proactive environmental management to regulatory authorities and the public.

By considering EMS and legal regulations as important contextual factors, this study aims to develop and evaluate strategies for environmental management system development for water quality in ports in terms of accordance to the actual needs and requirements that apply to port facilities.

Also, the integration of automated monitoring techniques along with meteorological and hydrodynamic operational systems, will be explored to enhance the effectiveness of environmental monitoring and decision-making processes in port environments. Compliance with legal requirements and alignment with international standards will be taken into account to ensure that the developed strategies contribute to sustainable port operations and the protection of coastal ecosystems [Bean et al. 2017].

Water pollution in port areas:

Conventionally, marine pollution monitoring in ports relies on the collection of in situ water and mud samples, which are then transported to laboratories for subsequent analysis. However, these traditional methods are time-consuming, costly, and often fail to provide real-time information on water quality in port waters. As a result, they are typically implemented at minimum levels to meet regulatory requirements, particularly in ports with limited resources. Traditional monitoring strategy also leaves aside the problem of waste which is a main concern for both user perception and its relations with the production and accumulation of microplastics in the sea.

One of the primary mechanisms of water pollution in port areas is the discharge and accumulation of waste resulting from non-continuous events [Mestres et al. 2010]. These events can occur either intentionally or accidentally, leading to the instantaneous or short-term release of solid or liquid pollutants into the water. Such discharge events pose a considerable threat to the aquatic environment and can have far-reaching socio-economic impacts. The management of water quality in ports and coastal areas, therefore, necessitates robust monitoring techniques capable of addressing the challenges posed by these pollution events.

The problem of microplastics in the Mediterranean is a growing concern due to their ubiquitously distributed and recognized emerging risk for the environment and human health. Marine environments, especially coastal zones, are the most impacted and are subjected to population pressure, tourism, harbors, desalination plants, marine traffic, and fish farms. The Mediterranean Sea is currently considered one of the hotspots of microplastic pollution in the world, due to the high number of plastic marine litter generating activities and its characteristic morphology as a semi-enclosed sea. Microplastics and nanoplastics have been detected not only in surface water and water columns but also in sediments, deep seafloor, and biota, including fish and seafood for human consumption. As a consequence, different European legislative initiatives have been launched in recent years to prevent microplastic and nanoplastic contamination and to address related problems. [Llorca et al. 2020] The menace of plastic pollution has led to initiatives at a global scale, including those taken by the European Marine Strategy Framework Directive and the G7 globe leaders.

In the 21st century, the problem of plastic pollution has emerged as a perilous threat to human and environmental health. The global utilization of plastic polymers was approximately 300 million tons in 2018 and is expected to rise at a compound annual growth rate. The lower rate of recycling activity and enhanced utilization of single-use plastic products are worsening plastic pollution. It is estimated that approximately 79% of plastic waste accumulates in the surrounding environment [Sharma et al. 2021]. The persistent plastic debris undergoes degradation upon exposure to different environmental factors, resulting in the formation of tiny plastic particles known as microplastics. These microplastics act as vectors of various toxic additives and pollutants, posing risks to marine organisms and potentially transferring these toxic microplastics to higher trophic levels. Various scientific reports have been published discussing the existence and estimation of microplastics in aquatic habitats, particularly in the Mediterranean Sea, which has been recognized as a significant accumulation hotspot for marine litter.

The significant problem of microplastic pollution in coastal regions is a matter of concern due to increasing population density, tourism, marine harboring, and coastal activities, which contribute significantly to the release of complex and toxic contaminants, including daily used plastic items. Approximately 8.8 kg per capita per year of macroplastics and 0.18 kg per capita per year of microplastics are released into marine bodies as a result of different coastal activities. Different types of plastic particles are found in coastal areas, beaches, on the sea surface, and on the seafloor, contributing to nearly 30 thousand tons of plastic mass in the Mediterranean basin [Tsiaras et al. 2023]. To overcome the limitations of traditional monitoring methods and obtain real-time information on water quality, there is a growing need for measurement and monitoring techniques that offer timely and accurate data on the spatial distribution of pollutants in port waters. Real-time or near real-time measurement methods are crucial for understanding the dynamics of marine pollutants and their spatial distribution, as well as for managing their environmental impacts.

Plastics and most of marine waste are long enduring floating materials. Thus, it’s feasible to track them, hind and forecasting, with numerical techniques [Amandine et al. 2019, Granado et al. 2019].

By integrating real-time measurement techniques with hydrodynamic models, it becomes possible to develop improved EMS.

Considering the visually perceivable nature of pollution discharge events in ports, there is a potential opportunity to establish automated monitoring systems using computer vision techniques. By installing cameras at strategic locations in ports, it becomes feasible to detect and monitor surface spills and floating marine waste in real-time. Computer vision techniques, combined with automatic image analysis systems, have demonstrated significant potential for detection and recognition tasks across various fields. The rapid evolution of computer vision techniques, particularly the advancements in deep learning and convolutional neural networks, has further bolstered the performance and efficiency of computer vision-based systems.

While remote sensing technology with satellite images has proven effective for detecting and managing pollutants over large surface areas, its applicability in port waters is limited due to the image resolution of satellite images as compared to port basin size.

Consequently, there is a need to develop computer vision-based systems tailored to the smaller scales of port environments. Such systems, supported by "in situ" mounted cameras, offer a robust alternative for continuous and cost-effective monitoring of surface water pollution. Moreover, the practical application of artificial intelligence technology through computer vision in coastal infrastructures can contribute to the digitalization of ports, providing valuable insights for environmental management strategies.

A computer vision-based EMS can go beyond immediate alarms for individual discharge events seeking to provide comprehensive knowledge about the nature and occurrence of discharges threatening the port waters. By leveraging computer vision techniques, particularly image classification based on deep convolutional networks, the system can classify images into categories such as clean water, pollution (spill), or floating waste. Statistical analysis of the occurrence of discharges can be used to assess the critical processes and operations and establish appropriate measures to prevent contamination.

The development of a database of tagged images for training the algorithm is crucial for the successful implementation of the computer vision-based system. However, gathering a substantial database of spill images can be time-consuming, as it requires the installation of cameras in ports to capture images of these events. Consequently, the progressive incorporation of images into the database raises questions about the number and types of images required to achieve an adequate level of confidence in the system.

To evaluate the performance of the computer vision-based system for port environmental management applications, novel performance metrics need to be considered. While traditional metrics like Accuracy, Precision, Recall, and F1-score are commonly used, they may not provide relevant measures for systems with imbalanced class distributions. In the context of water quality monitoring in ports, where clean water images are significantly more abundant than waste and spill images, a different metric is necessary to assess the system's ability to generate accurate alarms for spill and waste instances.

Operational Services and SAMOA project

Operational oceanography encompasses the systematic and long-term routine measurements of the seas, oceans, and atmosphere, rapidly interpreted and disseminated to provide near real-time ocean forecasts. The ocean forecasting systems are founded on the collection of ocean observations, numerical ocean circulation models, and data assimilation tools. This operational approach is essential in supporting various sectors, including marine industry, governments, regulatory authorities, and the public, by providing optimized shipping routes, coastal flood warnings, and forecasts of harmful algae blooms, among other data products. The advancement of Earth observation satellites, supercomputers, and ocean data assimilation has significantly contributed to the development and implementation of basin- and global-scale operational ocean forecasting models. The establishment of a global ocean observing system, combining in situ and remote sensing data, has been pivotal in improving research and forecasting applications, with a focus on climate research as well as marine environment monitoring, weather forecasting, and seasonal and climate predictions. The Global Ocean Data Assimilation Experiment (GODAE) played a significant role in demonstrating the feasibility and utility of global ocean monitoring and forecasting on daily-to-weekly timescales, leading to the establishment of an effective infrastructure for global operational oceanography [Davidson et al. 2019].

The key components of operational oceanography systems involve observation networks, data management and monitoring, prediction and assessment, service delivery and dissemination, and the uptake of products by end-users (see Figure 1.2). Earth observation satellites and the Argo profiling floats have revolutionized the availability of near real-time ocean measurements, providing critical data on sea surface height anomalies, sea surface temperature, ocean color, and other key parameters. Supercomputing technologies have enabled the development of basin- and global-scale numerical ocean circulation models, with a particular focus on eddy-resolving models. These operational oceanography systems have led to substantial advancements in marine research and forecasting applications, supporting various sectors, including maritime safety and pollution forecasting, coastal and shelf-sea forecasting, fisheries management, and the oil and gas industry. Oil spill prevention [Valdor et al. 2015, Valdor et al. 2016a, Valdor et al. 2016b, Xie et al. 2017] and tracking [González et al. 2008] have led to several developments in the implementation of operational oceanography systems in EMS. The successful implementation of operational oceanography systems has contributed to the establishment of a comprehensive infrastructure encompassing observing systems, data assembly and processing centers, modeling and data assimilation centers, and data and product servers [Schiller et al. 2018].

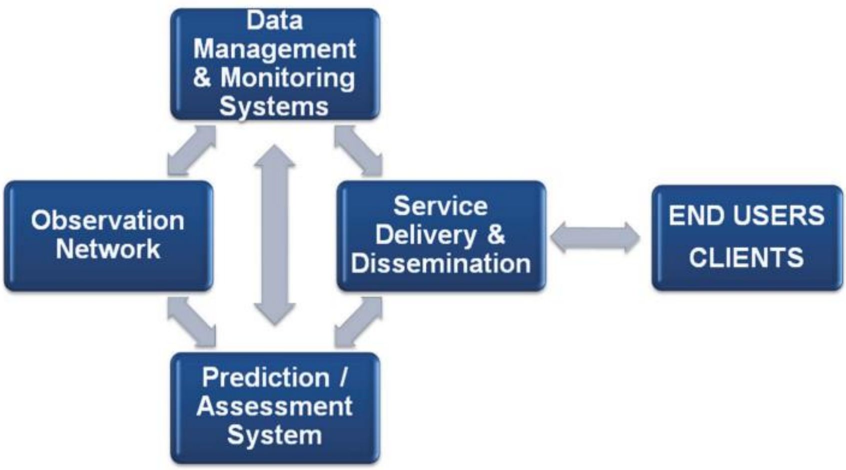


Figure 1.2. Operational oceanography components [Schiller et al. 2018].

The SAMOA service (Sistema de Apoyo Meteorológico y Oceanográfico a las Autoridades portuarias—System of Meteorological and Oceanographic Support for Port Authorities) was initiated by the Spanish Port System to address the complex challenges posed by extreme met-ocean drivers impacting ports. With ports playing a crucial role in global and national economies, it is essential to manage the physical environment effectively to ensure the safety and efficiency of marine activities. SAMOA combines met-ocean observation, ocean modeling, and end-user service tools to provide high-resolution ocean circulation forecast systems, catering to coastal and very local scales within the ports [Sotillo 2020]. The system resolves governing equations for ocean currents, sea level, temperature, salinity, and tracer concentrations, forming a vital component of operational oceanographic systems aimed at forecasting physical coastal processes.

Since its inception in 2017, the SAMOA coastal and port ocean forecast service has been delivering operational ocean forecasts to Spanish Port Authorities, starting with nine ports and eventually expanding to cover practically the entire Spanish Port System, including 31 ports. The ongoing development of the SAMOA service involves updating atmospheric forcing, upgrading the circulation model, and testing new methodologies to nest SAMOA systems in the Copernicus IBI-MFC regional solution. Evaluation of specific model upgrades has shown that SAMOA outperforms IBI-MFC in sea level forecasting at meso- and macro-tidal environments. The continuous efforts to improve the SAMOA service are aimed at enhancing surface currents and sea-surface temperature simulations, ensuring consistency and accuracy in the forecasts provided to support strategic decisions, port adaptation, and planning [García León et al. 2022].

SPILLCONTROL project

Study cases 2 and 3 presented in this thesis have been developed in collaboration with the SPILLCONTROL project, an innovative initiative focused on spill detection and management in port environments and ensuring effective environmental protection. Through real-time monitoring and CV detection algorithms, early intervention becomes possible, preventing spills from spreading and causing further harm to the environment as well as analyzing evolution tendencies and specific risk areas for preventive planification.

Afterword

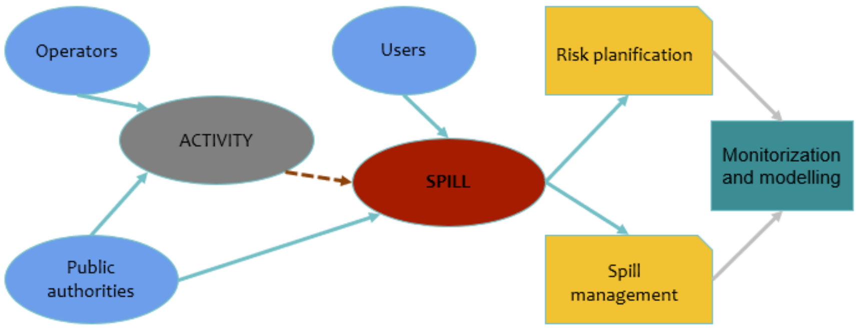
In this thesis, we aim to address the environmental challenges cited by developing and evaluating strategies for an environmental management system that integrates efficient automated techniques, including a computer vision-based system for monitoring surface spills and floating marine waste, as well as meteorological and hydrodynamic operational systems. By harnessing the potential of computer vision and integrating it with operational systems, we seek to enhance the monitoring and management of water quality in ports, enabling real-time decision-making and the development of sustainable environmental management strategies.

1.2 Motivation

The motivation behind this research stems from the need to develop tools to help port authorities and port operators address water quality and pollution concerns in ports and adjacent coastal waters. As major hubs of economic activity, both on the water and on the land, port operations play a crucial role in local and regional economy. However, the environmental impact of these ports, particularly in terms of water pollution and the accumulation of solid waste, poses significant challenges that require immediate attention and innovative solutions.

The adverse effects of water pollution in port areas extend beyond ecological consequences, impacting both the natural environment and the socio-economic well-being of surrounding communities. Pollution discharge events, whether deliberate or accidental, can result in severe ecological damage, degradation of water quality, harm to aquatic species, and disruption of delicate ecosystems. Furthermore, the accumulation of solid waste, including marine litter and debris, not only affects the aesthetic value of coastal areas but also poses threats to marine life, navigation, and the overall health of the coastal ecosystem.

Port activity stakeholders, including Users, Operators, and Public authorities, rely on EMS for control and management of pollution risks and for maintaining the ecological integrity of coastal waters and the surrounding marine ecosystems (see Scheme 1.1). Efficient and reliable monitoring and modeling techniques that can accurately assess and predict environmental impacts must be implemented to achieve this.



Scheme 1.1. Need for efficient EMS tools.

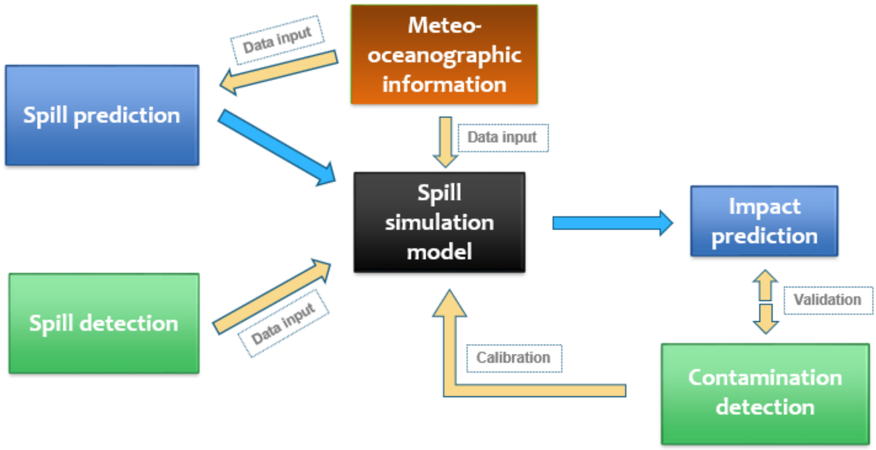
Traditional methods of water quality monitoring in ports, which rely on laborious and time-consuming collection of in situ samples for subsequent laboratory analysis, are inadequate in addressing the dynamic and real-time nature of water pollution events. These conventional techniques often fail to provide timely information on water quality, limiting the effectiveness of environmental management efforts. Moreover, the financial and logistical challenges associated with these methods lead to minimal monitoring levels, compromising the ability to detect and respond to pollution events effectively.

The emergence of computer vision technology and its successful application in various fields has opened up new possibilities for efficient and automated monitoring of water pollution in ports. By leveraging computer vision techniques, such as image classification based on convolutional neural networks, it is now feasible to develop systems capable of real-time monitoring of surface spills and floating marine waste. These computer vision-based systems, supported by strategically placed cameras, offer the potential for continuous and cost-effective monitoring of water quality in port areas, overcoming the limitations of conventional methods.

The integration of computer vision-based systems with meteorological and hydrodynamic operational systems further enhances the understanding of water quality dynamics in ports. By incorporating real-time measurements and monitoring techniques, it becomes possible to assess the spatial distribution of pollutants, predict their movement, and analyze their environmental impacts. This integration provides valuable insights for developing effective environmental management strategies, optimizing response actions, and mitigating the negative consequences of water pollution events.

The potential benefits of implementing computer vision-based systems and meteo-hydrodynamic operational systems on EMS for water quality in ports are extensive as they play an important role in EMS' operation (see Scheme 1.2). They include enhanced environmental management capabilities, timely detection of pollution events, improved understanding of pollution sources and patterns, better decision-making support, and the ability to implement proactive measures for sustainable port operations.

Additionally, the integration of automated monitoring techniques like computer vision enables the digitalization of port infrastructures, aligning with the broader trend of leveraging artificial intelligence and advanced technologies for efficient and sustainable port management.



Scheme 1.2. Monitoring (green) and Operational oceanography components (brown) Integration in a sample EMS.

Considering the significance of water quality in ports and the pressing need for innovative monitoring and management solutions, this research aims to contribute to the development and evaluation of strategies for environmental management system development in port environments. By focusing on the integration of computer vision-based systems for monitoring surface spills and floating marine waste with meteorological and hydrodynamic operational systems, we seek to advance the understanding and capabilities of monitoring water quality in ports. The outcomes of this research have the potential to inform decision-makers, port authorities, and stakeholders in developing effective policies, practices, and interventions to safeguard the ecological integrity and sustainable development of ports and coastal areas.

1.3 Structure of the Thesis

The structure of the thesis is organized as follows:

Chapter 1: Introduction

This chapter serves as foundation for the entire document, providing the reader with information about the context, reasons for undertaking the research, and an overview of the thesis structure. The chapter is divided in three subchapters:

1.1 Background: In this subchapter, the necessary background information related to the topic of the thesis is provided. It sets the stage by providing an overview of the topic, highlighting relevant facts and considerations, as well as previous research in the field. Thus, it gives readers a context that allows them to understand the importance and relevance of the research problem.

1.2 Motivation: The motivation subchapter explains the reasons and driving forces behind conducting the research. It articulates the specific factors that have inspired the researcher to pursue this particular study. Inspiration includes identified gaps in existing knowledge, practical problems, societal concerns, emerging trends, or the desire to explore new ideas. This section is vital as it clarifies the purpose and intention of the research, demonstrating that the study has a clear purpose and is not merely an academic exercise.

1.3 Structure of the Thesis: This present subchapter outlines the organization and contents of the thesis document.

Chapter 2: Objectives

The objectives chapter outlines the aims and goals of the research providing a clear and concise statement of what the researcher intends to achieve through the study. The chapter is divided in three subchapters:

2.1 General Objective: This subchapter presents the overarching and broad aim of the research, the main purpose of the study in a general and synthetic manner.

2.2 Detailed Objectives: This subchapter breaks down the general objective into ten more specific and measurable aims elaborating on the different aspects or components that contribute to achieving the general objective. These detailed objectives are presented in three categories: Scientific Objectives, Methodological Objectives and Technology Transfer / Impact Objectives.

2.3 Specific Objectives: The Specific Objectives subchapter specifies the concrete actions or tasks undertaken to accomplish the thesis conceptual objectives. These objectives are detailed and specific, outlining the tasks performed along the research.

Chapter 3: Environmental Management System for the Analysis of Oil Spill Risk Using Probabilistic Simulations. Application at Tarragona Monobuoy

This chapter presents the first study case of this research which is aimed to develop an EMS for risk analysis of oil spills in Tarragona port oil terminal using a probabilistic analysis of numerical simulations. This study case focuses on the implementation of SAMOA operational service in a planification EMS for oil spill risk in a port near several high environmental value areas.

Chapter 4: Use of neural networks and computer vision for spill and waste detection in port waters: an application in the Port of Palma (Majorca, Spain)

This chapter presents the second study case of this research which aims to implement Computer Vision in an EMS for spill and waste detection in port waters with an experimental application in the Port of Palma. This study case focuses on the assessing the implementation of CV techniques in an EMS for port spill and waste surveillance set in a port area that's closely connected to the touristic center of a city.

Chapter 5: Analysis of the operating conditions for a Computer Vision monitoring system for floating waste detection in port environments. Application at Es Portitxol port in the Bay of Palma (Majorca, Spain)

This chapter presents the third study case of this research which focuses on the operating conditions for a Computer Vision monitoring system for floating waste detection with an experimental application in Es Portitxol port. This study case focuses on the evaluation of the operating conditions of a CV monitoring tool for an EMS for port waste surveillance set in a small recreational port.

Chapter 6: Conclusion and future work

This is the final chapter of a thesis, and it serves as a comprehensive summary of the research findings, followed by recommendations for future research. The chapter is divided in three subchapters:

6.1 General Discussion: Providing is an in-depth analysis of the research's main considerations as well as a comprehensive overview of the key findings and their implications in light of the research objectives.

6.2 Final Conclusions: Presenting a concise summary of the main conclusions drawn from the study and emphasizing their importance in answering the research questions and achieving the objectives.

6.3 Further Investigation: Outlining potential areas for future research and suggesting topics or questions that could be explored to build upon the current study.

2. OBJECTIVES

2.1 General Objective

The main objective of this thesis is to develop a set of methodological tools focused on port environmental management, enabling analysis and decision-making support. These tools aim to enhance the efficiency of environmental management in inland waters of ports and nearby coastal areas, with the ultimate goal of improving water quality by reducing the negative impact of contaminant discharges on people, living organisms, protected areas, and the uses of port and coastal waters.

2.2 Detailed Objectives

This primary objective can be broken down into the following ten objectives, categorized based on their scientific, methodological, or impact nature:

Scientific Objectives:

- Establish a methodology to define the conceptual framework for environmental risk studies related to pollution in ports or maritime areas.
- Set criteria for risk visualization to facilitate the use of study results as decision-making tools.
- Establish a management and regulatory framework.

Methodological Objectives:

- Apply water monitoring systems that are technically and economically feasible and suitable for the proposed analysis approach.

- Identify the most appropriate simulation methodologies for management-oriented analysis based on specific available information.
- Develop mathematical instruments to validate the adequacy of monitoring and simulations for the supporting management instruments.
- Provide results with an operational perspective, offering management-oriented outputs such as risk predictions and spill maps.
- Exploit operational current prediction models within the port [e.g., SAMOA; Sotillo et al., 2019].

Technology Transfer / Impact Objectives:

- Conceptualize the relationship between monitoring and simulation techniques and environmental management instruments in these domains.
- Align the developed tools with the purposes and working methodologies of European guidelines and current state regulations.

2.3 Specific Objectives

As exposed, this thesis is aimed at the development and evaluation of novel tools and specific strategies for their EMS implementation in ports for water quality. Specifically, integrating efficient automated techniques, such as a computer vision-based system for monitoring surface spills and floating marine waste, with meteorological and hydrodynamic operational systems like SAMOA.

This thesis builds upon previous works that have developed management tools and monitoring methods to analyze the behavior of contaminant discharges in port and coastal areas (e.g., Grifoll et al., 2011; Gomez et al., 2015). However, it aims to incorporate new methodologies using innovative sources of information and technologies for management, specifically CNC Computer Vision and SAMOA operational service; providing more powerful, efficient, and tailored tools to meet the current and near future regulatory requirements of environmental managers.

Taking into consideration the current development state of CNC Computer Vision and SAMOA operational service, the overarching objectives can be specified as follows:

- To assess the feasibility of using Computer Vision for water pollution monitoring in ports.

This objective involves conducting a comprehensive investigation into the applicability and potential of computer vision techniques for monitoring water pollution in port environments. The research will explore the capabilities and limitations of computer vision in detecting and recognizing surface spills and floating marine waste. By analyzing random image sets and conducting experiments at the Port of Palma de Mallorca, Spain, the feasibility of implementing computer vision-based systems for water pollution monitoring will be evaluated. The goal is to determine the reliability and development requirements of such systems, establishing their suitability for monitoring tasks in port environments.

- To develop a computer vision-based system for surface spill and marine waste identification.

Building upon the findings of the feasibility assessment, this objective focuses on the development of a robust and efficient computer vision-based system for detecting and classifying surface spills and floating marine waste. Various computer vision techniques based on convolutional neural networks will be evaluated, with particular emphasis on Image Classification as the most promising approach for marine pollution monitoring tasks. The system will utilize a database of tagged images obtained from the Port of Palma de Mallorca, considering the challenges of limited image availability and the progressive implementation of training data. The objective is to create a system that achieves high accuracy rates and low training requirements, facilitating effective and reliable monitoring of water pollution in port environments.

- To integrate the computer vision-based system with SAMOA meteorological and hydrodynamic operational system.

To enhance the understanding and management of water quality in ports, this objective aims to integrate the developed computer vision-based system with meteorological and hydrodynamic operational systems. By incorporating real-time measurements and monitoring techniques, the integrated system will provide valuable insights into the spatial distribution of pollutants, their movement patterns, and the environmental factors influencing their behavior. This integration will enable the development of advanced environmental management strategies by linking computer vision data with hydrodynamic models. The objective is to create a comprehensive system that combines automated monitoring, meteorological data, and hydrodynamic modeling to support informed decision-making and effective pollution management in port environments.

- To analyze the operating conditions for a Computer Vision monitoring system.

This objective focuses on the evaluation of the distance, resolution and angle limitations of the computer vision-based system for detecting and classifying surface spills and floating marine waste. The system will be rigorously tested using experimental scenarios to assess how its overall performance is modified by changes in the operational distance, resolution and angle. The research will also explore strategies to overcome these limitations. The expected benefit of this investigation is to provide valuable insights and recommendations for CV monitoring system implementation and improvement, ensuring its practical applicability and usefulness in port environments.

- To evaluate the performance and effectiveness of the novel tools integrated in the EMS.

This objective focuses on the evaluation of the tool developed for the environmental management system in terms of its performance and effectiveness in monitoring pollution episodes as a pressure on water quality in ports. The tools will be rigorously tested using real-world data and scenarios to assess its reliability in terms of accuracy and overall performance. The research will also explore the impact of different operating conditions on the system's performance and reliability and the possibility to adapt the tool for different operating conditions. By comparing the results against performance of similar tools and considering the unique requirements of port environmental management, a comprehensive evaluation of the system's capabilities will be conducted. The expected benefit of this investigation is to provide valuable insights and recommendations for system optimization and improvement, ensuring its practical applicability and usefulness in real-world port environments.

By accomplishing these objectives, this research aims to contribute to the advancement of environmental management systems for water quality in ports. The outcomes will not only provide valuable knowledge and insights into the feasibility and effectiveness of computer vision-based systems but also offer practical recommendations for their implementation and integration with meteorological and hydrodynamic operational systems. Ultimately, the research aims to support the development of sustainable and environmentally conscious practices in port management, ensuring the protection and preservation of coastal waters and ecosystems.

The following chapter contains an article that has already been published in the following reference:

Environmental management system for the analysis of oil spill risk using probabilistic simulations: application at Tarragona monobuoy

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3. ENVIRONMENTAL MANAGEMENT SYSTEM FOR THE ANALYSIS OF OIL SPILL RISK USING PROBABILISTIC SIMULATIONS. APPLICATION AT TARRAGONA MONOBUOY

3.1 Foreword

Abstract:
Oil spill accidents during port operations are one of the main hydrocarbon pollution threats for coastal waters. Appropriate environmental risk assessment and pollution events management tools are needed to achieve sustainability and environmental protection in port activity. Recent developments in monitoring techniques and accurate meteo-oceanographic prediction systems have been implemented in many ports, providing tools for environmental management. A novel method based on meteo-oceanographic operational services, in conjunction with Monte Carlo experiments using an oil spill model, is implemented to perform probabilistic maps of potential pollution events. Tarragona port area was chosen as the study case for three reasons: it accommodates a hub of petrochemical industry, the availability of high-resolution wind and water current data, and previous studies at the area offer the possibility to check the results' accuracy. The interpretation of the impact probability maps reveals a specific pattern explained by the mean hydrodynamic conditions and the energetic north-westerly wind conditions. The impact probability maps may enhance efficiency in the environmental management of port waters and nearby coastal areas, reducing the negative impact of pollutant discharges.

Keywords:
oil spill; environmental risk assessment; pollution events management; Tarragona port; SAMOA project; MEDSLIK model; Monte Carlo method

3.2 Introduction

The environmental pollution caused by port operational accidents has received increasing attention in the last decades, due to an increased environmental sensibility and shift towards blue growth economy concepts. In particular, pollution by hydrocarbons is relevant because of its frequency (they are present in approximately 57% of accidents involving chemical substances [Lecue and Darbra 2019]) and their toxicity. The oil pollution of marine habitats is an issue, not only for researchers and environmentalists, but is also a main social and political concern, due to the serious impact of oil spills on marine life and on human activity, tourism, and the exploitation of the sea's resources.

The Marine Strategy Framework Directive, adopted at the European Union in 2008, requires member states to establish measures to achieve and maintain a good environmental status of marine waters. The Directive works on an ecosystem-based approach in the regulation and management of the marine environment, marine natural resources, and marine ecological services [Long 2011]. This approach requires the public administration and the private port operators to consider the potential effects of port activities on the marine environment in order to plan and manage port activity. This Directive adds to the Water Framework Directive, which also takes into consideration coastal waters, setting a general scope on marine waters.

Port management policies need models in which the interactions of logistic and environmental factors can be considered, thus integrating the social, economic, legal, technical, and environmental demands together. In this context, environmental risk assessment instruments are meant to become the generalized tool for environmental management and decision-making for port authorities [Gómez et al. 2015]. Several contributions faced risk port management using physical characterization of the oil spill and surrounding meteo-oceanographic conditions [Valdor et al. 2015, Valdor et al. 2016a, Valdor et al. 2016b, Xie et al. 2017, Horrillo et al. 2013].

This management relies on a three-step process of: hazard identification, risk assessment, and risk management. In this sense, environmental risk assessment requires a description of hazards, the determination of the probability of impact, and the vulnerability of the environment, and thus derives the consequences from a hazard. This contribution focuses on the determination of the probability of impact using recent developments in monitoring techniques and accurate meteo-oceanographic information systems. A novel method, based on meteo-oceanographic operational services in conjunction with a Monte Carlo experiment of an oil spill model, is implemented to perform probabilistic studies of potential pollution events. The outcome focuses on the spatial distribution of impact probability of an oil spill in the dock or the monobuoy of the port of Tarragona, using a Monte Carlo method. We took advantage of the operational information available to use modelled wind and current conditions for the simulations. Additionally, the interpretation of the probability maps is carried out, linking with the meteo-oceanographic patterns of the region.

The paper is organized as follows. Section 3.3 introduces the study area, the risk management tool layout, the operational data source, and the oil spill model used. Section 3.4 shows the results of the simulations and a comparison with previous work on the same area. Section 3.5 presents a discussion on the design criteria for the risk management tool. Finally, in Section 3.6, the conclusions of the study are summarized.

3.3 Materials and Methods

a) Study Area

The port of Tarragona is located on the Mediterranean coast of Spain (Figure 3.1); approximate coordinates are: 1°14′ E, 41°05′ N. It is the main petrochemical port in the region, connected to one of the largest Spanish oil refineries, and also an important industrial and commercial port. Repsol Petróleo, SA, owner of the refinery, operates an oil terminal in the port, including a 1489 m long dock with mooring capacity for five vessels and a floating dock (monobuoy) for mooring and unloading larger vessels. This port is optimal for this study due to its activity, the availability of detailed meteo-oceanographic data from operational services, and the availability of previous oil spill environmental risk studies to compare against our results [Valdor et al. 2015, Valdor et al. 2016a, Valdor et al. 2016b, Novelli 2011, Cuesta et al. 1990].

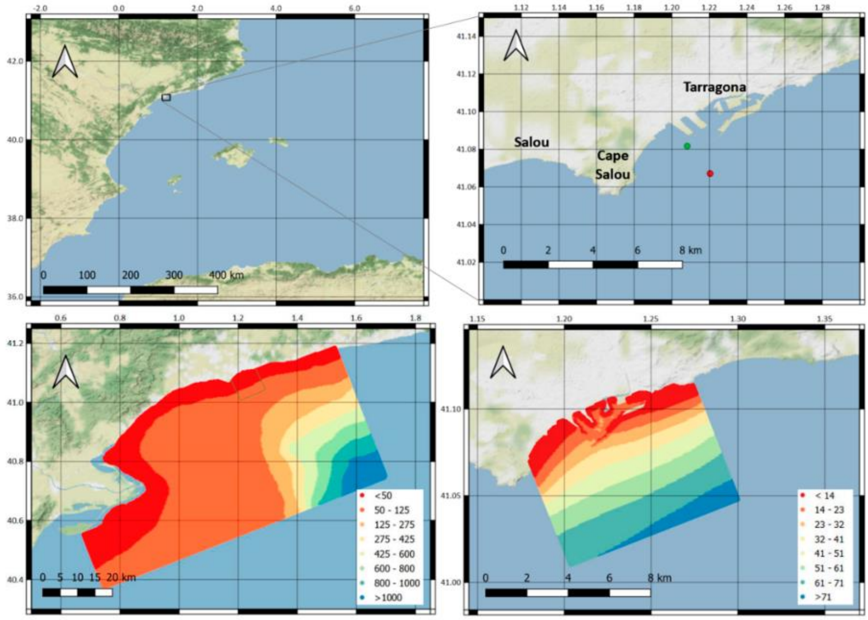


Figure 3.1. (**up-left**) Study location in the western Mediterranean; (**up-right**) situation of the spill points: dock (green dot) and monobuoy (red dot); (**low-left**) coastal and (**low-right**) port numerical domains of SAMOA data in Tarragona with bathymetry (in meters). Green box in the low-left figure represents the numerical boundary of the port domain nested in the coastal domain.

b) Meteo-Oceanographic Services

Wind and water current data for the model is obtained from the SAMOA system (in Spanish: Sistema de Apoyo Meteorológico y Oceanográfico de la Autoridad Portuaria). SAMOA is an initiative of the Spanish Public State Port Agency (Puertos del Estado) to provide port authorities with user-customized operational met-ocean information for harbor safety, environmental management, and operational decisions [Sotillo et al. 2019]. The SAMOA project provides hourly and daily values of meteo-hydrodynamic variables in the Tarragona Port area using two nested domains (see boundaries in Figure 3.1): Coastal domain (with a spatial resolution for currents of 350 m) and Port domain (70 m resolution). Wind data is derived from the Spanish Meteorological Agency (AEMET) forecast services, which use two operational applications of the high resolution limited area model (HIRLAM) model: one is the HNR, covering the Spanish territory, which has a 0.05° resolution and a forecast horizon of + 36 h, while the more extended regional euro-Atlantic ONR application has a 0.16° resolution and a forecast horizon of + 72 h [Sotillo et al. 2019].

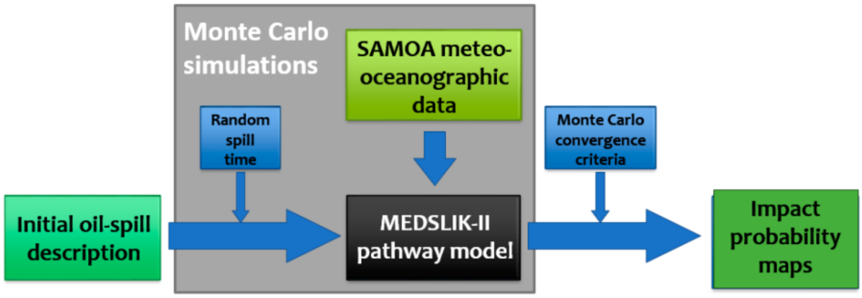
The SAMOA project was inspired by the application of the regional ocean modelling system (ROMS) [Shchepetkin and McWilliams 2005] over port and coastal domains in high-resolution meshes [Grifoll et al. 2011, Grifoll et al. 2013]. Water current data stored in the SAMOA is modelled using ROMS and initialized each day. The forecasts are systematically verified using three monitoring systems: (a) the buoy of Tarragona (REDEXT code 2720, location 1.47 E-40.68 N); (b) the mareograph of Tarragona (REDMAR code 3756, location. 1.21 E-41.08 N); and (c) the high frequency radar system of Delta de l’Ebre (with three stations at Vinaroz, Alfacada, and Salou) [Lorente et al. 2015]. SAMOA provides hourly averaged results, so this frequency was high enough for our probabilistic method when spatial scope was hundreds of meters (or higher resolution) and dispersion effect was considered.

c) Probabilistic Risk Management

Oil spill hazard can be described under source-pathway-receptor-consequence (S-P-R-C) methodology [Horrillo-Caraballo et al. 2013], in which the analysis of the potential pathway between source and receptor is a critical point. In this sense, environmental risk management tools require the hydrodynamic information of the receptor domain [Grifoll et al. 2010]. Several types of environmental risk management instruments have been postulated in recent years in order to mitigate the environmental impact of port activities. These instruments can be classified into nine groups, according to Reference [Moreno Parra et al. 2018], based on their analytical approach: even tree analysis, failure mode and effects analysis, fault tree analysis, risk maps, scenario analysis, Bayesian belief networks, decision tree, bow-tie analysis, and cause-consequence analysis. The support method used may be classified into four groups: analytical hierarchy process, fuzzy theory, evidential reasoning, and simulation methods. This work was directed by the risk map approach, supported by simulation methods. Several examples of such instruments can be found in References [Valdor et al. 2015, Valdor et al. 2016a, Valdor et al. 2016b, Shchepetkin and McWilliams 2005, Grifoll et al. 2013, Grifoll et al. 2010, Abascal et al. 2007]. They vary depending mainly on the perspective adopted, the information available, and the purpose pursued. In any case, all these tools will be articulated by combining a set of constituent elements within an operational layout and the corresponding decision-making criteria.

In general, the common layout of any of the mentioned tools have the same flow chart: information or input variables, one or several numerical simulation models, and one or several outputs that can be used to support the decision making. This modular structure allows improvements in any of its integrating elements to be incorporated into the system. Our contribution focuses on a tool schematized in Scheme 3.1, whose purpose is the elaboration of probability maps associated with oil spills in the oil transfer facilities of the port of

Tarragona. The investigation focuses on the application of an oil spill modelling, the statistical application of meteo-oceanographic operational products, and the physical interpretation of the model output.



Scheme 3.1. Layout of the environmental management tool for accidental spills in the oil transfer facilities of the port of Tarragona.

The environmental management tool is based on a set of Monte Carlo iterations using oil spill simulations obtained from an upgraded version of the MEDSLIK-II model. MEDSLIK-II is an open source Lagrangian model, developed in 2013, to simulate the transport and aging of the slick produced by a spill of oil or a derivate in the sea [Dominicis and Pinardi 2013, Dominicis et al. 2013]. Oil transport is governed by the water currents and the wind and dispersed by turbulent fluctuation components that are parameterized with a random walk scheme. In addition, the model takes in consideration the oil spill evolution due to various physical and chemical processes that transform the oil (i.e., evaporation, emulsification, dispersion in water column, adhesion to coast). MEDSLIK-II is the pathway model chosen for the oil spill module in the SAMOA II project (currently in development). It is also the reference oil spill model adopted by the MONGOOS network, the EMODNET Mediterranean Sea Check Point, and MEDESS-4MS European projects. MEDSLIK-II has also been used in several scientific contributions, e.g., in References [Goldman et al. 2015, Liubartseva et al. 2015, Al Shami et al. 2017, Neves et al. 2015].

The upgraded version used in this article was elaborated in the framework of the CEASELESS H2020 EU research project [Mestres 2020]. The modifications were focused in adapting both forward simulation, to determine the evolution of the spot from a given spill point, and the backtracking procedure, to determine its origin from the point where the spot had been detected.

For the initial oil spill modeling, the premises postulated in the Maritime Interior Plan of the Repsol Terminal of the port of Tarragona (written in 2009) were used. According to this document, a characteristic spill of 5.4 Tn of crude oil (the amount of crude spilled had no incidence on the maps obtained as the impact of pollution was considered without any concentration threshold) during a 5 min period was considered. In this sense, initial conditions were implemented considering the 5 min after the accident, simplifying the initial speed of the spill and the possible movement of the discharge point, etc. In consequence, an initial 10 000 m2 square spilled area was considered at the beginning of the simulation.

The model was forced by the wind and water current fields that were introduced in the upgraded model in either 2 or 3 dimensions; in this case 2-dimensional water currents were used. The wind and water current data used were the historical numerical results obtained from the SAMOA Project [Sotillo et al. 2019]. The output of the oil spill model was the position of the tracer particles used to simulate the oil-spill at different time steps. Thus, the results of different simulations were added in order to obtain the probability maps on the superposition of tracer particles of all the simulations considered at the chosen time steps.

The statistical method adopted to determine the spatial distribution of the probability of impact was the Monte Carlo algorithm. The Monte Carlo algorithm was carried out by simulating a set of spills characterized by a random initial spill time within the simulation period that spanned between October 2017 and September 2018. That is, multiple random combinations of days and hours, representing initial spills that were generated within this period. Then, the evolution of hypothetic spills of the exposed characteristics occurring at these random times were simulated in MEDSLIK-II. To establish this simulation period, the temporal continuity of meteo-oceanographic operational data was analyzed to provide one continuous year of data that allowed us to have an even distribution of the simulations along all seasons. Oil spill simulations were carried out in the two available domains, considering alternatively the dispersion effect. Thus, four types of numerical experiments were designed, as shown in Table 3.1.

Domain	With Dispersion (D)	Without Dispersion (N)
Port (P)	PD	PN
Coast (C)	CD	CN

Table 3.1. Numerical experiment classes.

Numerical experiments for the four experiment classes were carried out considering two spill point options: the monobuoy and the dock (see locations at Figure 3.1). The dock oil-spill location corresponded to its final section of the dock. The model parameters used for each of these four types of experiments and for both spill points are summarized in the Table 3.2.

Parameter	PD	CD	PN	CN
Steps/hour [1]	82	10	82	10
Interval [2]	0.05	0.1	0.05	0.1
Parcels [3]	10	10	1	1
Hz diffusivity [4]	10	10	0	0
Duration [5]	4	8	4	8

Table 3.2. Model parameters for numerical experiments.
[1] Number of time steps per hour used for slick computation.
[2] Interval for output (h). [3] Number of parcels used to model diffusion and dispersion. [4] Horizontal diffusivity (m2/s). [5] Duration of computation from spill start (h).

The number of time steps per hour was determined by computation requirements. The output interval was established according to the scale of the probability map grid. The number of parcels was 1 when dispersion was neglected and 10 when the dispersion was considered. The value adopted for horizontal diffusivity was obtained from the literature [Matsuzaki and Fujita 2017, Dominicis et al. 2012] and a sensitivity analysis was carried out. Finally, the oil spill duration was established according to the size of each domain.

Added to Monte Carlo simulations, numerical experiments were carried out for specific hours and months within the simulation period in order to analyze variations in the distribution of the probability of impact of specific temporal scales (e.g., hourly or seasonal). The results from these non-Monte Carlo numerical experiments were not used for the impact probability maps, but as an interpretation tool.

The results obtained in the port with dispersion (PD) and coast with dispersion (CD) experiments have been used for the generation of impact probability maps using a two-step process. In the first step, particle-count maps were generated by defining a mesh on the domain and obtaining for each cell in the mesh the total count of tracer particles that were in that cell at any step of any simulation. In the second step, impact probability maps (IPMs) were obtained by normalizing the corresponding particle count map, that is, by dividing the value in each cell by the maximum value that corresponds to the cell that contains the initial spill zone. This way, IPMs showed the probability of presence of tracer particles in each cell at any time for simulation lasting 8 h. The cell size used was 100 × 100 m. Probability was defined only in the area where numerical convergence of the Monte Carlo simulations was achieved. For visualization purposes, a logarithmic probability scale was chosen.

3.4 Results

Figure 3.2 and Figure 3.3 show the IPMs for spills in the dock and monobuoy, respectively, evaluated on the coastal numerical domain (see Figure 3.1). Comparison of these maps shows that potential spills occurred in the monobuoy can affect significantly larger areas than spills occurred in the dock. This difference is particularly relevant in the east direction, in which the port constitutes a significant barrier for spills released from the dock. In the south direction, the spill can reach approximately 20% further from the monobuoy than from the dock, apart from the fact that the monobuoy is about 1.5 km south from the dock. In the southwest direction, a spill from the monobuoy can reach approximately 50% further than the spill from the dock.

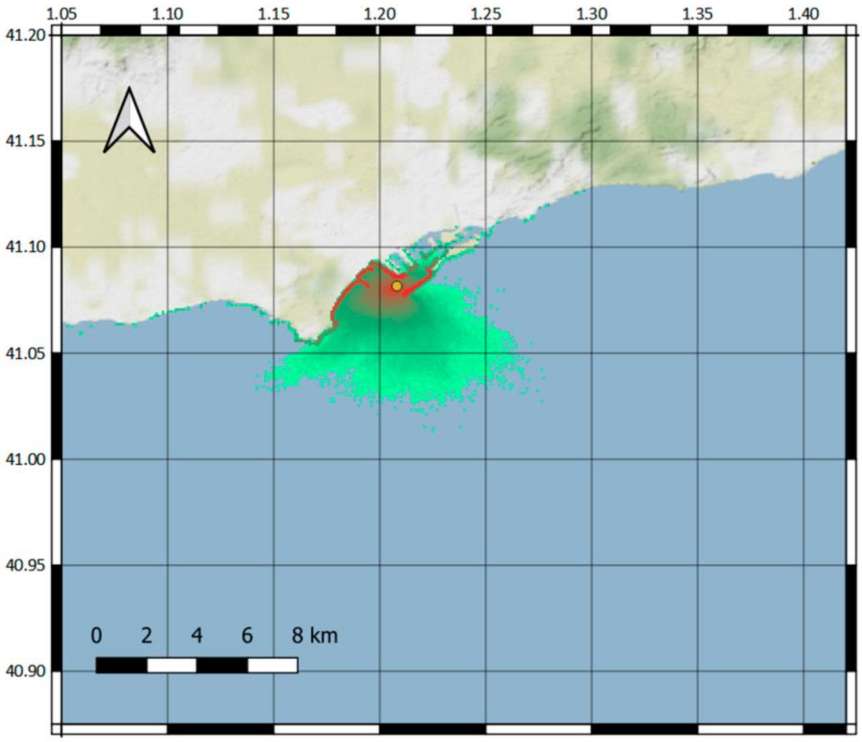


Figure 3.2. Impact probability map (IPM) for spills in the dock (green dot), evaluated on the coastal domain.

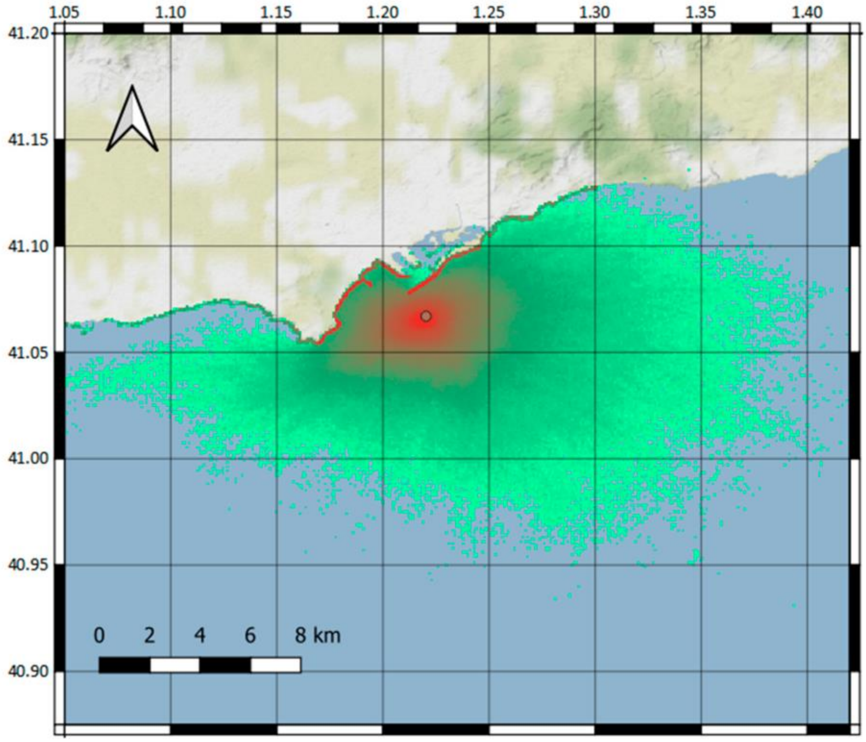


Figure 3.3. IPM for spills in the monobuoy (brown dot), evaluated on the coastal domain.

Figure 3.4 and Figure 3.5 show the IPMs for spills in the dock and monobuoy, respectively, computed on the port numerical domain. In order to avoid the effect of the numerical domain boundary, these maps were defined for a probability of impact higher or equal than 1.5625%, although convergence has already been achieved at lower probabilities (see considerations about convergence in the Discussion section).

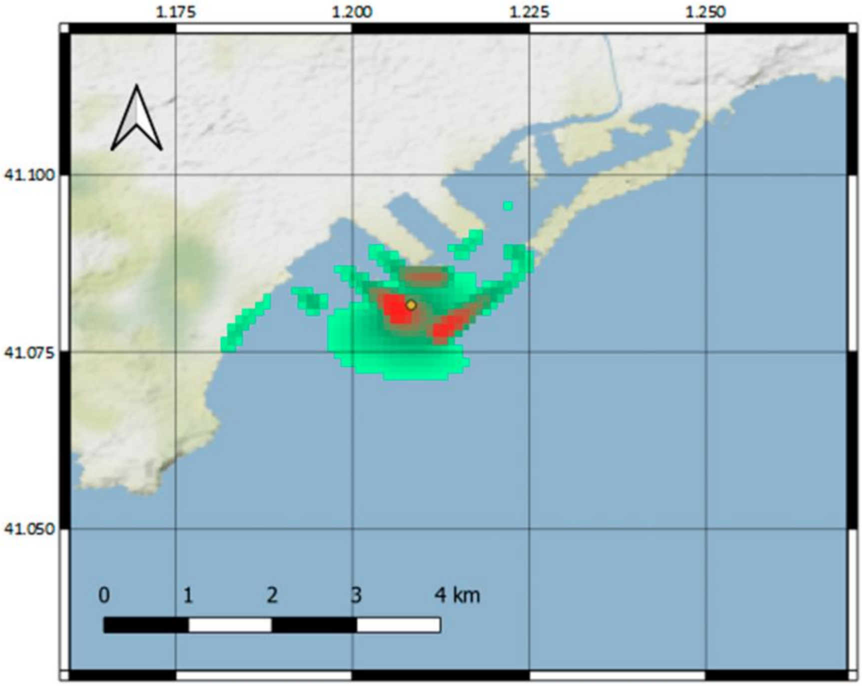


Figure 3.4. IPM for spills in the dock (yellow dot), evaluated on the port domain.

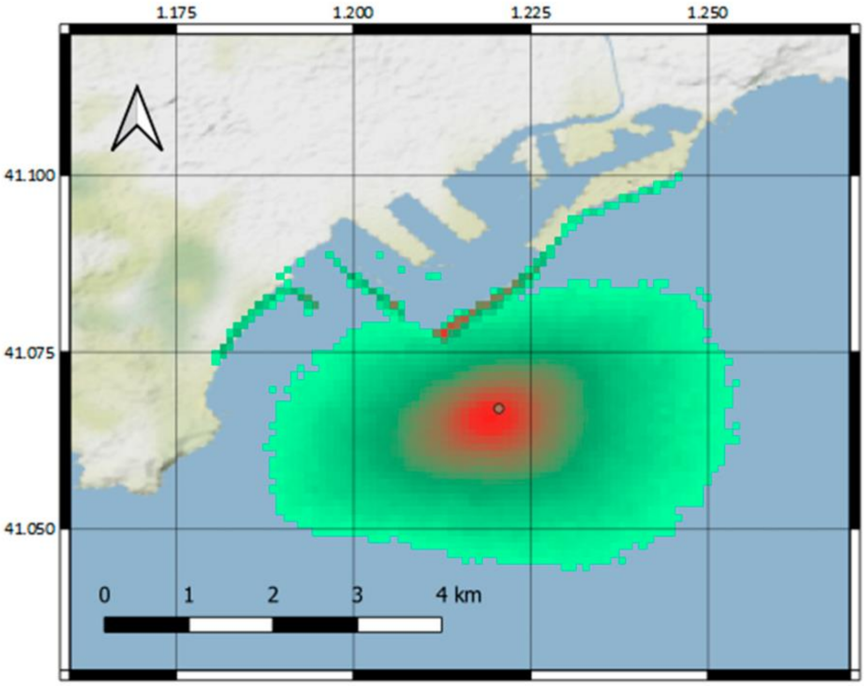


Figure 3.5. IPM for spills in the monobuoy (brown dot), evaluated on the port domain.

Comparison of these maps show again that spills occurred in the monobuoy can potentially affect a significantly larger area than spills occurred in the dock. The relative difference is higher in this case: 55% in the south direction and 85% in the southwest direction, and, again, in the east direction, the port constitutes a significant barrier for spills in the dock.

3.5 Discussion

a) Numerical Resolution Comparison

Previous IPM results have allowed us to evaluate the impact of the numerical resolution of the oil-spill in coastal areas. In these computational experiments, the Port model used a larger resolution to describe the water current in comparison to the Coastal model and expected a more accurate solution in the first case. However, Port domain boundary is a significant limitation to be taken into account. IPM comparison suggests similar maps in both domains for the case of the monobuoy, although this may not be obvious when comparing Figure 3.3 and Figure 3.5 because of the difference in ambit extension and probability representation scale. On the other hand, divergences between IPMs computed using Port and Coastal domains suggest differences of oil spill numerical solutions in the function of the hydrodynamic numerical resolution. The reason is that it seems associated with the hydrodynamics described in the port entrance (i.e., near the oil handling dock), which is quite complex, and there is a significant loss of information in its representation on the coarser mesh (see Figure 3.6).

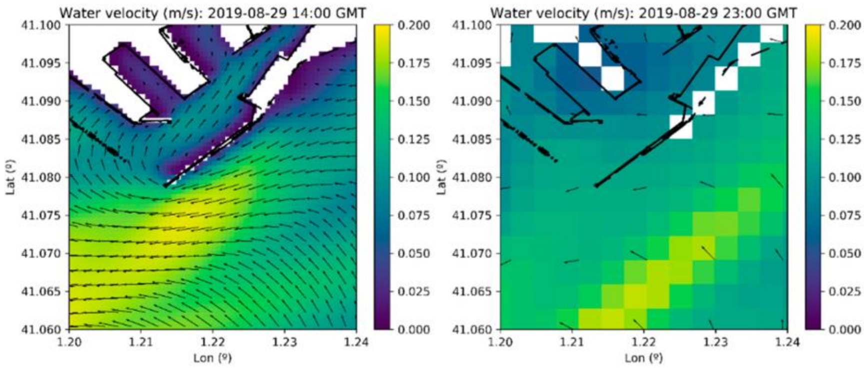


Figure 3.6. Surface water velocity obtained from SAMOA products (**left**: Port model, **right**: Coastal model).

b) Temporal Variability and Hydrodynamic Considerations

The temporal variability of the IPM was investigated in order to determine the prevalent hydrodynamic pattern. In this sense, monthly IPMs were analyzed and compared with the mean water circulation. Variation on IPMs for different seasons could not be clearly established, as the difference between different seasons was apparently no greater than differences observed between consecutive months. The differences detected were not considered significant given that only 1 year of data was analyzed, although, for the same reason, the existence of seasonal variations cannot be ruled out.

The daily variability was also analyzed, obtaining IPMs for oil spills released at different hours. The oil-spill hours considered were 04:00, 10:00, 16:00, and 22:00 GMT. In this analysis, a significant variation was found.

- For spills released at 04:00, the high probability area was slightly displaced away from the coast and the average distance reached was slightly lower.
- For spills released at 10:00, the high probability area was near the coast with a high proportion of particles trapped on the shoreline and the average distance reached was quite a lot lower.
- For spills released at 16:00, there was a wider and more uniform distribution with an average proportion of particles trapped on the coast and the average distance reached was higher.
- For spills released at 22:00, a wider and more uniform distribution (though not as much as at 16:00 spills) was observed and the average proportion of particles trapped on the shore and the average distance reached was higher.

The analysis of water current data from the SAMOA project shows an averaged water circulation southwestward, consistent with the shape of the IPM. Figure 3.7 shows the surface water current averaged for the year 2019, for which the maximum velocities were obtained in the vicinity of the monobuoy. This hydrodynamic pattern is common in the regional water circulation in the inner shelf, where hydrodynamics is modulated by remote sea level gradients and regional winds [Grifoll et al. 2012, Grifoll et al. 2013]. Overlapped to mean water circulation, measured wind data from a meteorological station at Tarragona Port shows how the most energetic wind conditions correspond to the NW component (Figure 3.8). In this sense, a dominant northwesterly component during winter and fall occurs, according to previous studies based on long-term measurements [Grifoll et al. 2015, Ràfols et al. 2017a, Ràfols et al. 2017b]. This would explain the offshore principal direction of the IPM that was consistent with the offshore winds. The additional sea-breeze cycle during summer may provide offshore water flow. However, opposite to onshore flow, offshore flow was neglectable in comparison to long-shelf circulation (see Figure 3.7). Therefore, the spatial variability to IPMs shown previously presumably corresponds to the NW wind component and southwestward averaged water circulation in the surface.

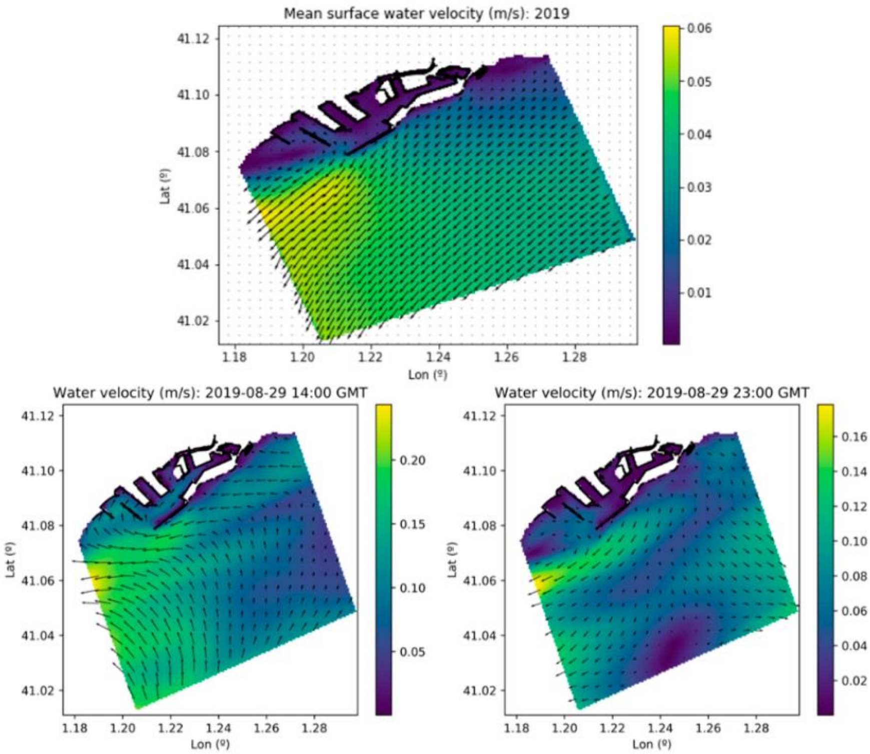


Figure 3.7. (**upper**) Averaged water current from the Port model during 2019. Water current fields during sea-breeze event: 2019-08-29 14:00 GMT (**lower left**) and 2019-08-29 23:00 (**lower right**). Water current fields were obtained from the SAMOA project.

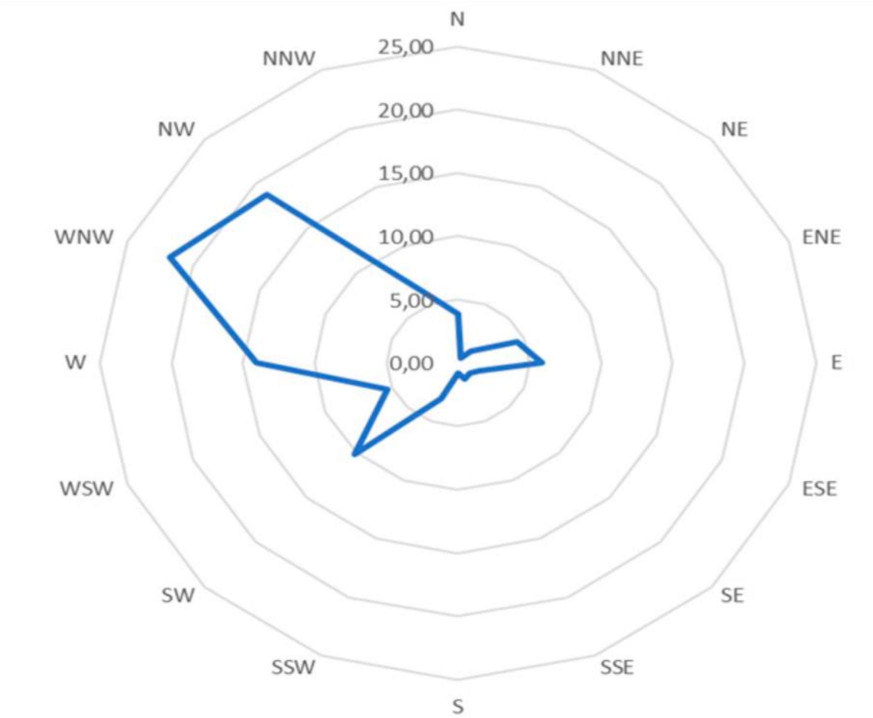


Figure 3.8. Wind direction probability distribution for strong winds (≥ 7.5 m/s). Data obtained from the Spanish Port Agency (Puertos del Estado) during the February 2002–January 2007 period.

c) Convergence Considerations

A key topic when using the Monte Carlo method is the convergence assessment criteria. As any inference based on the Monte Carlo method, the output relies critically upon the assumption that the Markov chain has achieved a steady state (i.e., converged) [Brooks and Roberts 1998].

The first step to consider is whether convergence can be achieved at the same time for all the cells in the IPM. With this method, each cell after a given number of simulations will have a different degree of steadiness. The map does not converge as a whole, but each cell does converge after a certain number of simulations. For a given number of simulations, the map will show an irregular area of converged cells and non-converged cells. Therefore, we established a cell convergence criterium to fulfill the following conditions:

The criteria should be based on relative error in probability, instead of absolute, as it will have to work consistently for different probability values.

If the criterium takes into consideration the probability value, it must be evaluated on the estimate probability obtained at any given number of simulations.

A criterium evaluation with low evaluation cost will be preferred so it can be evaluated after each simulation without a high increase in the time needed for calculation.

To propose a criterium, we compared the number of simulations with the probability obtained for each cell: the number of spill hits in the cell divided by the total number of simulations. This comparison showed a spiked profile (see Figure 3.9) with a spike at each simulation, in which the spill hit the cell. Spike heights decreased as the number of simulations increased.

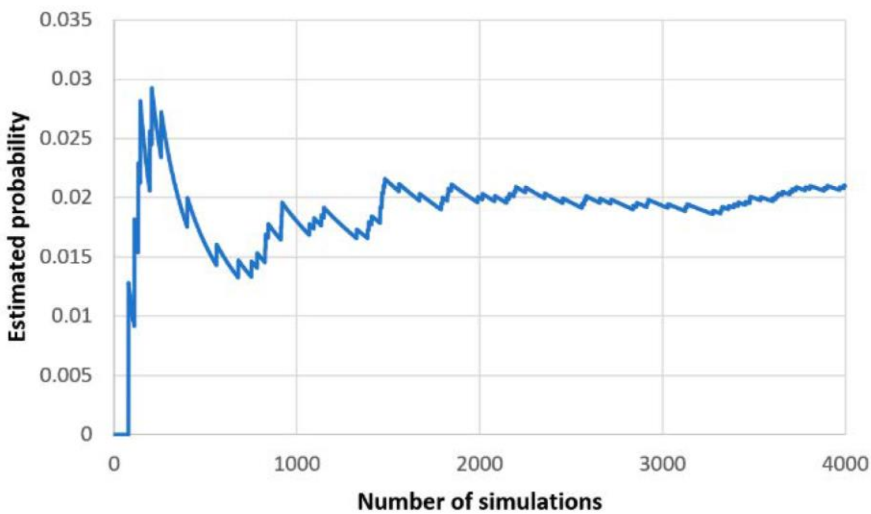


Figure 3.9. Comparison example between number of simulations and the estimated impact probability for a cell.

One reasonable cell convergence criterium that fulfilled the previous conditions was as follows: Convergence was achieved when the expected spike height for a hit was less than a chosen fraction of the probability obtained. This criterium could be considered in terms of the number of hits needed for convergence. This number depended on hit probability as the quotient between expected spike height, and probability obtained increased as probability decreased (see Table 3.3). This value decreased to a threshold of the inverse of the number of hits. These values were obtained by taking into account the properties of the binomial probability distribution. The binomial is a discrete distribution that applies to the number of successes in a sequence of independent experiments. That is the case of Monte Carlo experiments when data from one experiment is not taken into account for other experiments.

Probability	2 Hits	5 Hits	8 Hits	9 Hits	10 Hits	11 Hits
50%	0.333	0.111	0.067	0.059	0.053	0.048
25%	0.429	0.158	0.097	0.086	0.077	0.070
10% [3]	0.474	0.184	0.114	0.101	0.091	0.083
1.0%	0.498	0.198	0.124	0.110	0.099	0.090
<0.10%	0.500	0.200	0.125	0.111	0.010	0.091

Table 3.3. Quotient between expected spike height and probability obtained for different combinations of probability and number of hits.

In this work, a criterium based on an absolute number of hits, equal to 10, was chosen. This criterium set the quotient between expected spike height and probability obtained to the ratios shown in Table 3. This criterium is as demanding as considering one tenth of the probability obtained when the probability was 11.11% or lower, and more demanding with higher probabilities (e.g., with 50% probability, 6 hits would be enough to reach one tenth of the ratio). The actual computational cost of this simplification is quite low as the expected number of simulations to get a hit is the inverse of the probability.

d) Comparison with Previous Works

Potential oil spills from the Tarragona monobuoy have been analyzed previously in several contributions [Valdor et al. 2015, Valdor et al. 2016a, Valdor et al. 2016b]. These works also show an aggregate pattern, and the main directions were E, ESE, and WSW. The IPMs for the monobuoy spill point on both domains (Figure 3.3 and Figure 3.5) were consistent with these contributions showing the probability shape that was elongated on these three directions (Figure 3.10). Reference [Valdor et al. 2015] uses input meteo-oceanographic conditions based on numerical modelling of characteristic scenarios. The TESEO oil spill model [Abascal et al. 2007] shows these prevalent directions in potential oil spills from the modelling of characteristic scenarios. The IPMs for both spill points on the coastal domain (Figure 3.2 and Figure 3.3) were also consistent with the mentioned contributions [Novelli 2011, Cuesta l. 1990], which point out the protection provided by cape Salou to the city of Salou and the nearby beaches.

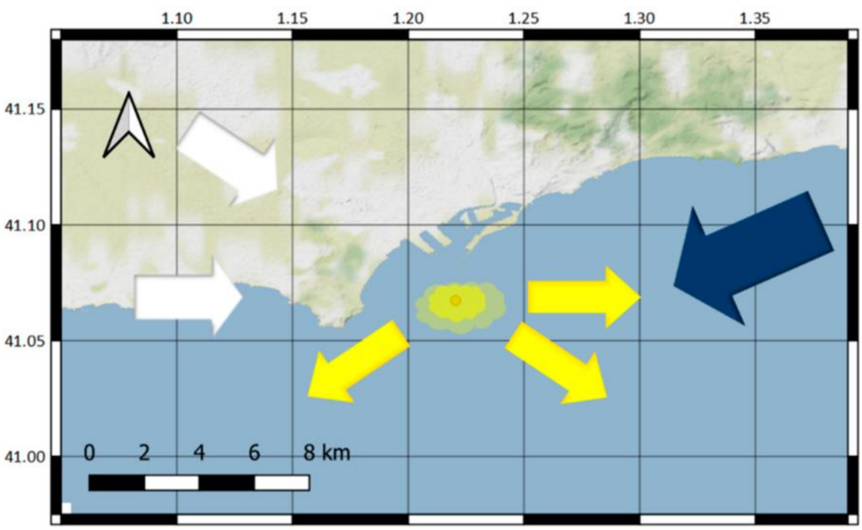


Figure 3.10. Oil transport pattern for spills at the monobuoy. Main directions are represented with yellow arrows. The blue arrow represents the main water current. White arrows represent the main wind directions.

e) Port Management Applications

The statistical methodology based on the Monte Carlo method offers port managers a powerful tool for oil spill risk management, which will result in better compliance with the objectives set by the Marine Strategy Framework Directive. The implementation of this system is facilitated by the implementation of meteo-oceanographic operational models in port areas (e.g., SAMOA). Therefore, the possibility of implementing tools to define the IPMs on the operating models is an added value with low computational effort in comparison to the operational meteo-oceanographic model itself.

Additionally, this methodology has the advantage of automatically improving the output when more historical wind and current data are stored. In consequence, its reliability will grow dynamically without the need to periodically redesign. This advantage also makes it suitable for port environments, where the knowledge of local meteo-oceanographic conditions is limited but operational models are being implemented.

3.6 Conclusions

In this paper, a probabilistic method to obtain IPMs using Monte Carlo simulations is presented. The implementation of the method at oil facilities in Tarragona Port suggests that the IPM is a valid tool for the environmental management in ports. In this case, the IPMs are consistent with the meteo-oceanographic characteristics of the region: south-westward averaged water circulation and NW energetic wind events. The potential of this method will grow in concordance with the development of meteo-oceanographic operational systems models in ports and coastal areas. During the tool design, a compromise has to be reached for the scope and scale of the study, taking into account the available meteo-oceanographic information and the model requirements. Expert judgment will be necessary for analysis of low probability levels in areas with limited data. The analysis of these situations will determine adequate strategies to overcome the limitations being an interesting line for future research.

3.7 Afterword

Author Contributions

Conceptualization, M.M.V., M.E.I. and M.G.C.; methodology, M.M.V., M.E.I. and M.G.C.; software, M.M.V., M.G.C. and M.M.R.; validation, M.E.I. and M.G.C.; formal analysis, M.M.V., M.G.C. and M.M.R.; investigation, M.M.V. and M.M.R.; resources, M.E.I. and M.G.C.; data curation, M.M.V. and M.M.R.; writing—original draft preparation, M.M.V., M.E.I. and M.G.C.; writing—review and editing, M.M.V., M.E.I. and M.G.C.; visualization, M.M.V. and M.G.C.; supervision, M.E.I. and M.G.C.; project administration, M.M.V., M.E.I. and M.G.C.; funding acquisition, M.E.I. and M.G.C. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

The following chapter contains an article that has already been published in the following reference:

Use of neural networks and computer vision for spill and waste detection in port waters: an application in the Port of Palma (Majorca, Spain)

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4. USE OF NEURAL NETWORKS AND COMPUTER VISION FOR SPILL AND WASTE DETECTION IN PORT WATERS: AN APPLICATION IN THE PORT OF PALMA (MAJORCA, SPAIN)

4.1 Foreword

Featured Application:
Port Environmental Management systems; automated spill and waste detection in port waters.

Abstract:
Water quality and pollution is the main environmental concern for ports and adjacent coastal waters. Therefore, the development of Port Environmental Management systems often relies on water pollution monitoring. Computer vision is a powerful and versatile tool for an exhaustive and systematic monitoring task. An investigation has been conducted at the Port of Palma de Mallorca (Spain) to assess the feasibility and evaluate the main opportunities and difficulties of the implementation of water pollution monitoring based on computer vision. Experiments on surface slicks and marine litter identification based on random image sets have been conducted. The reliability and development requirements of the method have been evaluated, concluding that computer vision is suitable for these monitoring tasks. Several computer vision techniques based on convolutional neural networks were assessed, finding that Image Classification is the most adequate for marine pollution monitoring tasks due to its high accuracy rates and low training requirements. Image set size for initial training and the possibility to improve accuracy through retraining with increased image sets were considered due to the difficulty in obtaining port spill images. Thus, we have found that progressive implementation can not only offer functional monitoring systems in a shorter time

frame but also reduce the total development cost for a system with the same accuracy level.

Keywords:
computer vision; marine litter; marine pollution; monitoring technologies; port water quality

4.2 Introduction

Ports and surrounding areas of the coast are zones in which a multitude of human activities are concentrated in a limited space with usually low water renewal rates. In consequence, ports and adjacent waters are very sensitive to pollution and accumulation of solid waste and their impact on the aquatic environment and, in turn, socioeconomic impact [Ng and Song 2010]. A relevant mechanism of water pollution in port areas is waste discharge and accumulation caused by non-continuous discharge events either intentionally or accidentally. This means solid or liquid pollutant waste is discharged into the water instantaneously or during a short period of time. These events constitute one of the most significant aspects to be considered in port and coastal environmental management; thus, economic and robust monitoring techniques are paramount to achieve adequate port water quality [Puig et al. 2021, Hossain et al. 2020]. This issue is especially sensitive in city ports where there is a close relation between port operation and city activity, and where city waste and pollution can easily get into port water [Li et al. 2019]. Currently, the most common approach for marine pollution monitoring in ports relies on conventional methods of collecting in situ water and waste samples for subsequent analysis in a laboratory. Such methods are time-consuming, expensive and do not provide a real-time picture of water quality in port waters. Thus, in practice they tend to be implemented at minimum levels in order to comply with regulations, especially in ports with scarce resources. The consequences of this limited monitoring at environmental management level are in many cases significant [Wooldridge et al. 1999, Puig et al. 2015]. Additionally, real-time or near real-time measurement and monitoring methods for marine pollutants and waste are necessary for managing their environmental impacts and understanding the processes governing their spatial distribution [Hafeez et al. 2019]. These techniques offer a complementary perspective on marine pollution to hydrodynamics-based environmental management techniques [Grifoll et al. 2011, Mali et al. 2018, Morell et al. 2020]. Thus, real-time pollution monitoring techniques can be linked with hydrodynamic models to obtain improved environmental management systems [La Loggia et al. 2011].

Given the nature and frequency of these discharges, management systems will usually consider the statistical parameters of the spatial and temporal distribution of the frequency of discharges instead of individual events. Therefore, these systems do not require very high levels of accuracy in monitoring as opposed to critical systems like biomedical applications, but rather enough to offer statistically significant distributions. Monitoring systems that offer 80% or higher accuracy are considered admissible based on the usual values required in these types of applications [Arribas et al. 2011].

In this context, it is important to note that pollution discharge events in ports are, in most cases, visually perceivable. Consequently, it seems feasible to investigate the possibility of establishing automated monitoring systems for these discharges using cameras installed at strategic points in the port. Associated with automatic image analysis systems, computer vision techniques seem an excellent complement according to previous experiences in other fields for detecting and recognition [Arribas et al. 2011, Eskandari et al. 2020, Storbeck and Daan 2001]. Computer vision techniques have recently experienced a quick evolution, being implemented in a wide range of different applications with high efficiency and performance [Chen and Li 2021, Dong and Na 2021, Ngeljaratan and Moustafa 2021]. Deep learning on convolutional neural networks is proven to achieve very high performance on computer vision tasks [Leonard 2019]. In fact, remote sensing technology is proven to provide spatially synoptic and near real-time measurements that can be effectively used to detect and manage pollutants such as suspended sediments, oil and chemical spills, algal blooms and high suspended solids [Hafeez et al. 2019, Ciappa 2022]. Additionally, recent contributions in waste and pollutant detection used Image Classification based on deep convolutional networks [Panwar et al. 2020, Jiao et al. 2018]. Such approaches have been successful at addressing pollution detection in large surface areas. In the case of port waters, satellite images cannot be used due to poor image resolution, and a monitoring system tailored to smaller scales has to be generated. Specifically, a computer vision system, supported by “in situ” mounted camera images would be a robust alternative for water pollution monitoring at ports. This system would allow continuous and low-cost monitoring of surface water pollution, addressing the limitations of traditional observational techniques. In addition, it would constitute a leap forward in the digitalization of ports through the practical application of artificial intelligence technology in coastal infrastructures at limited cost. It is important to note that the aim of this novel monitoring system is not only to give warnings for each discharge so that immediate action can be taken, especially in particularly relevant episodes that generate a significant risk for health or navigation, but also to obtain knowledge about the discharges that threaten the port waters where and when they happen or if they are related to specific operations. In consequence, computer vision, combined with traditional or Artificial Intelligence based analysis, may provide operational knowledge in specific port areas and facilities, thus allowing development of adequate environmental management strategies.

Computer vision techniques can be classified according to the problem considered [Khan and Al-Habsi 2020]. There are several classifications and the set of problems considered has grown in recent times, but Image Classification is one of the most common applications and, in consequence, is very promising in port environmental management [Lu and Weng 2007]. Image Classification involves assigning a label to an entire image; the labels (i.e., the categories in which images were classified) that should be considered in the context of port environmental management systems are three: clean water, pollution (spill) or floating waste (waste). One of the most important requirements for the implementation of computer vision systems is the generation of a database of tagged images that can be used to train the algorithm. In this respect, it is important to take into account that gathering a significant database of images of spills can be time consuming, as they can only be achieved by installing cameras in the port to record images of eventual spills. Thus, images will be incorporated to the database progressively, and the question arises in terms of how many images—and image types—are required to train the algorithm to achieve an adequate level of confidence on the system. Specifically, it is important to determine whether it is preferable to train the algorithm with all images available even when the number of images in each category is different, or whether optimal results will be obtained only when there is an equal number of images in each category. In the first scenario, the least common class will be underrepresented, potentially affecting proper system performance, and in the second, the number of images to be gathered increases, and consequently so does the time required to achieve a working system.

In addition to image requirements, computer vision systems are evaluated according to specific performance metrics. Four of the most common metrics are Accuracy, Precision, Recall and F1-score [Goutte and Gaussier 2005, Powers 2020]. However, the Accuracy metric does not provide a relevant metric for a port environmental management system because clean water images will be significantly more abundant than waste and spill ones; here Accuracy will provide mostly a measure of how many times clean water is correctly predicted. However, preliminary designs of computer vision systems for port environmental management suggest the need to generate correct alarms on spill and waste instances. Thus, an alternative metric needs to be put forward in order to compare trained algorithms with a set of images that are not evenly distributed between categories, as will be the case in the current application.

The present paper evaluates the results of a set of experiments on surface spills and floating marine waste identification based on random images as an initial stage of the development of a system for port water quality monitoring. After the methodological process (i.e., post-process) has been implemented, image sets have been obtained and analyzed to determine the amount and proportion of each image class that is required. In this sense, several computer vision techniques have been assessed, including Image Classification as the most promising one identified preliminarily. In order to evaluate the performance of the algorithm specifically for port environmental management applications, a novel performance index (the error index) has been proposed. The set of images has been conducted in the port of Palma de Majorca, which suffers important events of water quality degradation.

The paper is organized as follows. Section 4.3 introduces the study area, the computer vision technique used, the spill and waste classification, the system layout, the images used, the algorithm training and the statistical reliability of the algorithms. Section 4.4 shows the results of the training processes and a comparison for different amounts of data available in terms of image set sizes and distribution. Section 4.5 presents a discussion on the design criteria for the system set-up and its further development. Finally, in Section 4.6, the conclusions of the study are summarized.

4.3 Materials and Methods

a) Study Area

The port of Palma de Mallorca is located in the city of Palma, on the island of Majorca (Balearic Islands, Spain; see location in Figure 4.1) in the Western Mediterranean Sea, with approximate coordinates of: 2°38.4′ E, 39°33.7′ N. The management resides at the Port Authority of the Balearic Islands in a landlord governance model. From the impact on water quality degradation and environmental management, the port has the following characteristics: (i) Strong Port–City relation. (ii) Development of several different port activities (i.e., recreational boating, transport of passengers and goods, fishing, repair and maintenance of boats and restoration and services on land). (iii) Sporadic discharges of rainwater through four gullies and several collectors of stormwater drainage networks, in some cases with risk of discharge of mixed rainwater and wastewater.

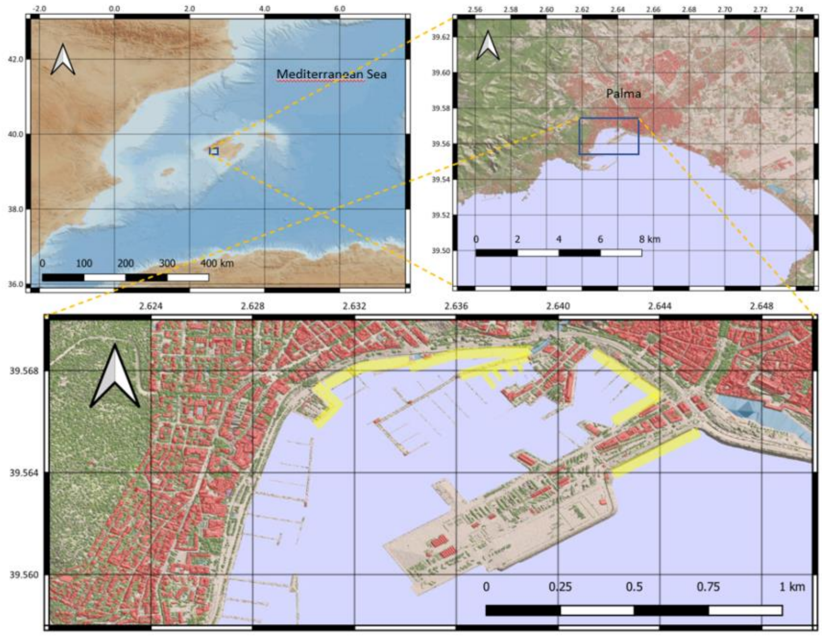

Figure 4.1. Study area location. Zones where images were obtained are highlighted in yellow in the lower panel.

b) Computer Vision Technique and Application to Pollution in Port Waters

Computer vision is a field where applications are developed using convolutional neural networks that are trained using deep learning techniques. Specifically, it can be defined as a set of techniques to automatically obtain descriptions or significant parameters from the images of physical objects; these descriptions can be useful for decision making. This is the case of the current investigation included in the field of marine waste and litter detection. Due to the numerous potential applications of Computer vision, it has experienced an important development in the recent years.

An artificial neural network is a collection of connected nodes which loosely model the neurons in a biological brain [Video]. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. When an artificial neuron receives a signal, it processes it and, as a result, sends outputs (real numbers) to neurons connected to it. In turn, the output signals of each neuron are computed by some non-linear function of the sum of its inputs. Typically, neurons are aggregated into layers; different layers may perform different transformations on their inputs coming from the one before. Signals travel from the first layer (or input layer) to the last one (or output layer). Figure 4.2 depicts schematically how neurons in different layers interact to provide meaningful results.

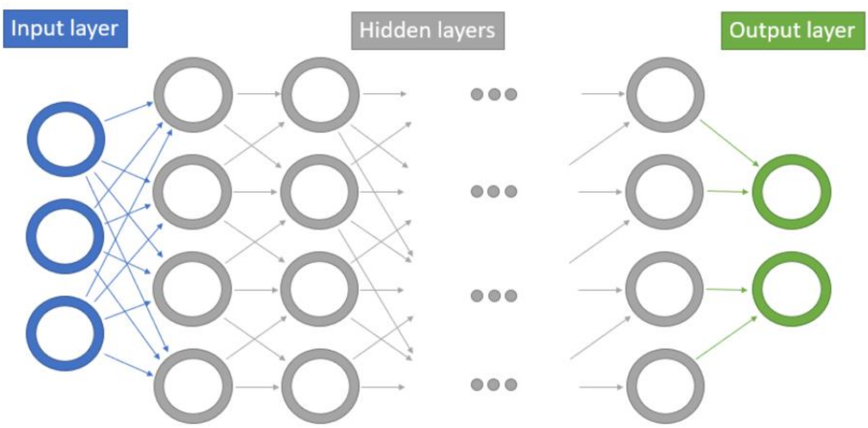

Figure 4.2. Neurons, layers and signal transmissions.

A Convolutional Neural Network (CNN) is a type of artificial neural network most commonly applied to analyze visual imagery because they are shift invariant (or space invariant), meaning that the position of a feature in an image is not important. This is due to the CNN having a shared-weight architecture of the convolution kernels or filters that slide along input features and provide translation equivariant responses known as feature maps. Figure 4.3 shows how the CNN architecture works towards generating relevant information from an input image.

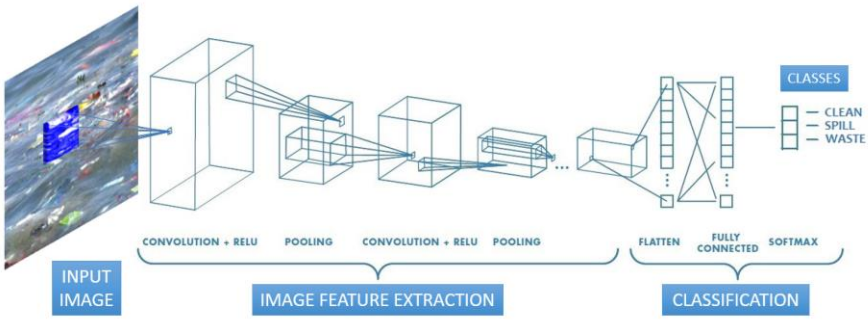

Figure 4.3. Basic CNN architecture (modified from [Video])

The most important computer vision techniques are Image Classification, Object detection, Object tracking, Semantic segmentation and Semantic instance segmentation. Although all these techniques have a potential application in port water quality monitoring, the most appropriate technique according to the input–output information desired is Image Classification. This is due to the fact that the amount of information needed to train the system is lower compared to other techniques, and it allows the classification of images into simple classes that can be used to build temporal and spatial distributions of pollution events [Abiodun et al. 2018].

Thus, the aim of this investigation is to evaluate the efficiency of training Image Classification algorithms that, when taking as input the images of port water provided by a camera monitoring system and operating in real-time, provide as output the class to which each image belongs with the highest probability, according to a classification that is relevant for proper environmental management of port water.

c) Computer Vision Classes Considered

The selection of the clean, spill and waste classes has been carried out after careful consideration of the nature of pollution in ports as well as the level of detail that is useful in port environmental management activities. Specifically, spills in ports have four main origins (although in specific ports or terminals there may be others): users on land, users on boats, discharges of mixed drainage networks and port operations. Considering their physical and chemical nature, there is an enormous variety in waste and contaminants that can reach port waters, including suspended matter, hydrocarbons or eutrophication (not a spill in itself, but a consequence of a nutrient spill) (see Figure 4.4). Identification of both the origins and chemical nature of spills could be pursued, but the applicability of such information is very limited; all these contamination events are managed in a similar fashion and thus their identification would not provide any relevant input in port environmental management. In contrast, a type of pollution that follows a different type of action from a port environmental management perspective is floating waste (see Figure 4.4). Consequently, for the computer vision system designed, two categories of pollution have been considered, namely spill and waste. The spill class (class 1 in this study) refers to liquids mixing and/or diluting in the water, or to clouds of suspended solids. The waste class refers to large individual solids floating on the water or near the surface (class 2 in this study). Finally, clean water has been labelled as class 0. These three classes provide sufficient information for a port environmental management system to take relevant decisions on time and cost.

Figure 4.4. **Right image:** Spill class example. **Center image:** Waste class example. **Left image:** Mixed Spill and Waste example.

The Image Classification technique does not consider the possibility of one image belonging to two or more classes; it simply returns the most likely class. This may constitute a limitation of the method since spill and waste could theoretically appear simultaneously in an image. To overcome this limitation, an additional class should be defined including images with the presence of both (see Figure 4.4). However, this situation is very infrequent in ports, and, in fact, it did not occur in any of the images obtained in this investigation. The most common cases in which we could theoretically find spill and waste together are: (i) pollution originating from two or more independent incidents ending up in an accumulation zone due to the hydrodynamic characteristics of the port; or (ii) mixed pollution released by rivers or collector systems that discharge into the port. In the context of the system proposed in this work, the first case is irrelevant because the main objective is to monitor discharge episodes rather than the persistence of discharges within the port. The second case is limited to specific areas and its processing constitutes a particularity that is to be faced in future research. Therefore, although this limitation exists, it does not seem to be an import limitation at this stage due to the infrequency of the combined (i.e., spill and waste) event. The segregated monitoring system proposed represents the reality of most existing ports and thus is easily scalable to other infrastructures.

d) Dataset Used

The dataset used in the current study consists of images obtained through manual sampling in several different locations in the Port of Palma. About 3400 images were obtained, of which only 1379 were actually used; 660 were selected as instances of clean water class, 389 of spill class and 330 of waste class. Discarded images were too similar to other images that were used or constituted excess clean water class and spill class images. The number of images obtained in spill and waste classes was the main limitation as actual pollution events are required to happen in the port during the fieldwork visit in order to obtain them.

In this study, different amounts of spill/waste and water images have been used, as detailed in Section *e*, in order to investigate the practical applicability of the developed system. The images were gathered using different digital cameras, in 4:3 format and different image resolutions (1 Megapixel and higher). Nevertheless, when using the images for the training and validation of algorithms, they were transformed into square pictures and their resolution was reduced (see Section *e*). Figure 4.5 shows three images from each class with square shape and reduced resolution.

Figure 4.5. Example images for each class.

e) Experiments Description: Algorithm Training and Validation

In order to evaluate the feasibility of implementing a computer vision water quality monitoring system in ports, three experiments have been carried out in the present study using a CNN type system. The experiments intend to evaluate the feasibility of a computer vision system in port environmental management and the performance impact of the results on image set size and distribution. The main characteristics of each experiment are shown in Table 4.1, including the research objectives.

Experiment Number	Research Objective	Number of Images (Spill/Waste/Clean Water)	Image Resolution (Pixels)
Experiment 1	Screening of computer vision system overall performance and feasibility for port environmental management	389/330/660	300 x 300
Experiment 2	Investigating the performance impact of image set distribution	1320 images in different proportions	256 x 256
Experiment 3	Investigating the performance impact of image set size	Different numbers in equal proportions	256 x 256

Table 4.1. Summary of computer vision experiments in the current study.

Keras open-source software library for Python (version: 2.4.3) on Tensorflow Google developed open-source software library (version: 2.3.0) backend framework based on the Anaconda3 platform was used in these experiments. Python 3.8.10 programming language was used for training and validation process programming. The computer used was equipped with an Intel Core i7-6700HQ CPU with 16 GB RAM and a NVIDIA GeForce GTX 960M graphics card. The computer operating system was the 64-bit Windows 10 home edition. In the three experiments, a neural network InceptionV3, with "imagenet" weights and a 3-channel resolution was deployed. InceptionV3 was chosen between Keras available models, after discarding models designed for mobile devices considering the compromise between accuracy and speed according to Keras documentation [WWW Document 2022] and CNN research [He et al. 2019, Hussain et al. 2019]. An additional GlobalAveragePooling2D layer was added with 1024 additional neurons with ReLU activation (0.2 dropout), as well as another layer with 3 neurons with softmax activation. The latter layer is the one bearing the spill/waste/clean water class information. In order to feed the neural network, two image generators were used. For the training images, a series of transformations were applied (rotation, horizontal and vertical shifts, crop, zoom and horizontal reflex) including a standard normalization. In addition, data augmentation techniques were used on the image set [Shorten and Khoshgoftaar 2019]. For image validation purposes, only normalization was applied. Data ingestion was carried out in batches of 8 images. The training set images consisted of 80% of the set and the remaining 20% were used for validation purposes. Firstly, a training of additional layers was conducted and subsequently a fine-tuning was simultaneously carried out of both final inception blocks and additional layers. The cost function used was CategoricalCrossentropy (logit) and Adam was deployed as the optimization algorithm (learning rate of 0.001 and 0.00001 was each of the training phases described previously).

For Experiment 2, 14 algorithms were trained, two for each image set distribution tested. The distributions of images considered in these experiments are the ones shown in Table 4.2.

Image Ratio	Number of Images of Class 0	Number of Images of Class 1	Number of Images of Class 2
1/1	330	330	330
1/2	660	330	330
2/5	660	264	264
1/3	660	196	196
1/4	660	165	165
1/8	660	82	82
1/16	660	41	41

Table 4.2. Distribution of images considered in Experiment 2.

For Experiment 3, 82 trainings based on image sets formed randomly of different sizes (ranging between 18 and 990 total images). Here, one third of the total number of images corresponds to each class.

In experiments 2 and 3, each algorithm training was started from the initial model and not from the previously trained algorithm in order to prevent the propagation of errors or beneficial traits from one algorithm to the next.

2.6. Algorithm Performance Evaluation

Some of the metrics used in this study are the ones commonly reported in the literature and applied investigations when evaluating the performance of computer vision systems [Goutte and Gaussier 2005]. These are the following:

Accuracy: Commonly defined as the ratio of true positives and true negatives to all positive and negative observations. That is, how often we can expect the computer vision system to correctly predict an outcome out of the total number of times it made predictions. Mathematically, it is formulated as the ratio of the sum of true positives and true negatives out of all the predictions, namely:

$$Accuracy = \frac{TP + TN}{(TP + FN + TN + FP)} \tag{1}$$

where TP = true positives; TN = true negatives; FN = false negatives; and FP = false positives.

Precision: It represents the proportion of labels that were correctly predicted to be positive. That is, it is a performance metric that is most useful when trying to control false positives. As well as for Accuracy, Precision is also affected by class distribution; if there are more images for a class that does not happen frequently, precision becomes lower.

Mathematically, it is formulated as the ratio of true positive to the sum of true positives and false positives, namely:

$$Precision = \frac{TP}{(FP + TP)} \tag{2}$$

Recall: It represents the system's capacity to correctly predict the positives from the set of actual positives. Recall is most useful when identifying positives as critical. Mathematically, it represents the ratio of true positive to the sum of true positives and false negatives.

$$Recall = \frac{TP}{(FN + TP)} \quad (3)$$

F1 score: It is obtained as a harmonic mean of the Precision and Recall scores, giving each of them an equal weight. It is often used as a single value that provides high-level information about the model's output quality and Precision/Recall balance.

Mathematically, it is formulated as a harmonic mean of the Precision and Recall scores.

$$F1\ Score = \frac{2 * Precision * Recall}{(Precision + Recall)} \quad (4)$$

In the case of experiment 1, where the objective is to validate the algorithm generated for its application in port environmental management, the prior metrics are relevant and sufficient. However, in experiment 2, as well as in realistic system application, we would need an additional index that evaluates the performance of the system as an alternative to the common Accuracy metric. This is due to the fact that the Accuracy metric is not the most reliable in computer vision models trained on datasets where one event (in this case clean water) is much more frequent than the rest of the events (in this case spill or waste). In this case, Accuracy will mostly determine that clean water is detected correctly most of the time but will not provide decisive information on the spill and waste detection performance. As the latter are the actual events (alarms) to be detected by a computer vision system applied in a port setting, Accuracy is not a parameter that becomes useful in the present study or in real-life applications of the system. Precision, Recall and F1-Score indexes are also not suitable for experiment 2 because they are class specific and for comparison purposes an all-class synthetic index is needed. Consequently, a novel index has been defined for the purpose of this application (as well as others that might face similar issues as the one presented):

the Error index. This index is defined as the ratio of the sum of errors made in providing warnings (either false alarms or alarms that are incorrectly not provided) to the sum of total alarms provided by the system. Adapting for the current application with three classes (i.e., 1, 2 and 3), the *Error index* is defined as:

$$Error\ index = \frac{(FP0 + FP1 + FP2)}{(TP1 + FP1 + TP2 + FP2)} \quad (5)$$

Where *TPi*= true positives for class, *i*; *TNi* = true negatives for class, *i*; *FNi* = false negatives for class *I* and *FPi* = false positives.

The definition corresponds to a parameter that is more meaningful than *Accuracy* for port water quality monitoring applications, as it eliminates the issue of the unequal distribution of images during the application of the system. However, two limitations have been detected: (i) *Error index* is not a normalized parameter and (ii) it overestimates the errors made overall by the system because it eliminates a set of prediction successes. Nevertheless, it is a conservative and meaningful index useful for port managers because of its comprehensiveness.

4.4 Results

a) Experiment 1

The Image Classification algorithm has been trained and validated and an Accuracy of 0.91 has been obtained with an image evaluation time of about one second. Table 4.3 presents the performance metrics for the identification of each of the classes. In general, adequate performance metrics with the Image Classification technique have been achieved, proving that the system is promising. As a shortcoming to be addressed with the validation dataset, a proportion (>10%) of the cases classified as clean water are really contaminated water. This aspect will be improved in the upcoming experiments, where image set distribution and image set size are investigated in order to generate a more applied monitoring technique.

Class	Precision	Recall	F1-Score
0—clean water	0.89	0.94	0.91
1—spill	0.95	0.86	0.90
2—waste	0.93	0.93	0.93

Table 4.3. Performance results for Experiment 1.

b) Experiment 2: Impact of Image Set Distribution

Figure 4.6a shows the Accuracy (y-axis) versus the image class ratio (x-axis) in the different simulations carried out. In this figure, Accuracy remains relatively stable with changing proportions of images in the training and validation dataset. On the other hand, the Error index, formulated in the present study to be able to capture how adequate the system is in correctly detecting contamination alarms, shows that the performance of the system decreases significantly with an increasing disproportion of image classes (see Figure 4.6b).

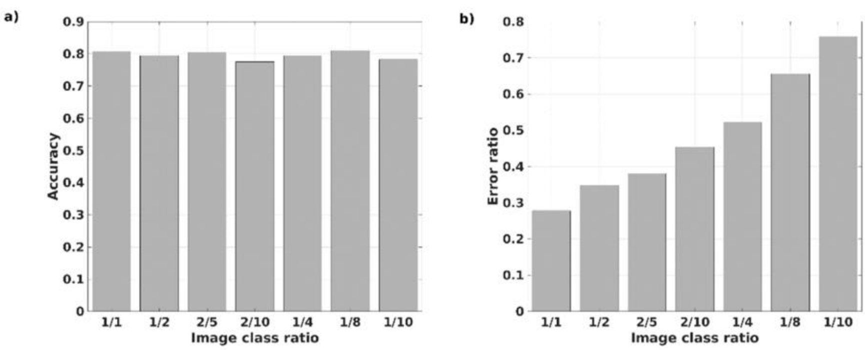

Figure 4.6. **(a)** Accuracy vs. Image class ratio. **(b)** Error ratio vs. Image class ratio.

c) Experiment 3: Impact of Image Set Size

Figure 4.7a shows Accuracy in different simulations where image set sizes vary. Accuracy has been used in this experiment since it is a normalized parameter and thus easier to interpret graphically, but similar conclusions have been reached with the Error index in this case. Figure 4.7b shows how simulations with image set sizes lower than 297 images (99 images per class) generate a significant dispersion in performance. Dispersion shows a decreasing trend up to 99 images per class and from that point on there is no clear trend, remaining at moderate values. The number of 99 images per class is also the closest among those used to the benchmark of 100 images per class usually recommended for training Image Classification algorithms [Abiodun 2018]. With datasets that have a number of images over this amount, Accuracy becomes stable and increases in a linear manner with increasing images provided to train and validate the algorithm. When carrying out a regression in datasets with over 99 images per class (297 total images), both linear and quadratics fits have been considered. Finally, a linear regression, shown in Figure 7a, was selected because the quadratic fit is only marginally better than the linear one and because the linear fit showed significantly more robustness. Robustness was here evaluated as the change in fit parameters when random datapoints are removed from the set of results. Thus, in the range of image set sizes considered in the study, also the relevant range for the application at hand, the Accuracy presents a linear tendency with increasing image set size after a certain number of images have been achieved.

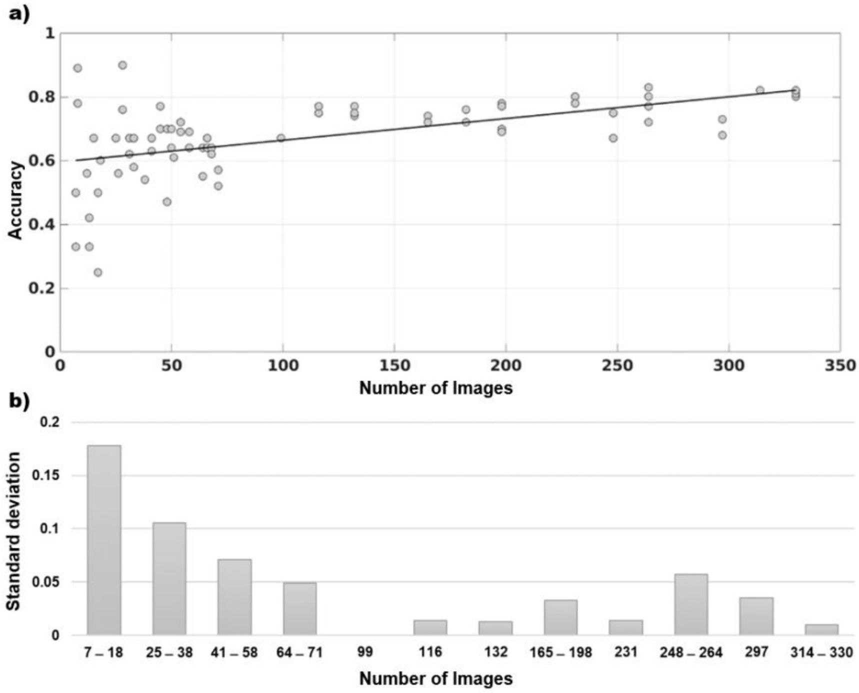

Figure 4.7. (a) Dots: Accuracy vs. Number of Images per class. Line: Regression. (b) Standard deviation of accuracy measures vs. Number of Images per class (when two numbers are displayed it means a number range).

4.4 Discussion

a) Results Discussion System Set-Up

Results showed in Section 4.3 demonstrate that Image Classification is adequate for marine pollution monitoring tasks due to its high Accuracy rates and low training requirements (Table 4.2). The system obtained a 91% accuracy rating, which can be considered a sufficient value for the requirements of a discharge management system in which the use of pollution event data is statistical and, if action is required, it will entail necessary direct validation. The time required by the trained algorithm to classify an image is approximately one second, which is compatible with the needs of real-time monitoring. The best performance was proven to be achieved when image set sizes for all classes are similar (Figure 4.5), providing the first insight into the requirements for adequate system implementation. In practice, spill images are difficult to obtain in great numbers and commonly clean water images will be the most dominant class. Thus, in order to achieve an algorithm that holds optimal performance, spill and waste images have to be obtained to achieve a total number between the three classes which is higher than 297 (Figure 4.6). In this sense, the results of experiments 2 and 3 are consistent with other documented application cases based on computer vision (e.g., [Abiodun 2018]).

The most appropriate performance metric to evaluate these systems in operation is the proposed Error index, since in operating conditions it is foreseeable to find a much higher number of class 0 images than those of classes 1 and 2.

Our work suggests that the most appropriate way for the monitoring system to be implemented is through progressive implementation. In this sense, datasets would be ever increasing when additional spill and waste images were attained. At these points, the algorithm would be retrained with new datasets in order to generate higher Accuracy and lower Error Index rates, improving the information provided by the system in a gradual manner. After a total image data set of 297 (between the three classes considered) has been reached, retraining would be less frequent due to the fact that performance only increases gradually after that point. In this type of progressive implementation, functional monitoring systems would be provided to port decision makers in a shorter time frame while also reducing the total development cost for a system with the same accuracy level.

Considering that the training time of the algorithm is in the order of minutes and that retraining of the algorithm will be carried out very infrequently (due to the difficulty of obtaining pollution images), it is preferable that each training is carried out from the initial model and not from the previously used algorithm in order to prevent error propagation.

Figure 4.8 depicts how the proposed implementation would be carried out in practice. In addition to the image acquisition and identification of the three classes (with alarms generated when spill or waste were detected), with increasing waste and spill images a verification and dataset enhancement step would be prompted in the system. With the enhanced dataset, the algorithm would be revised in order to achieve gradually better Accuracy and Error index performance.

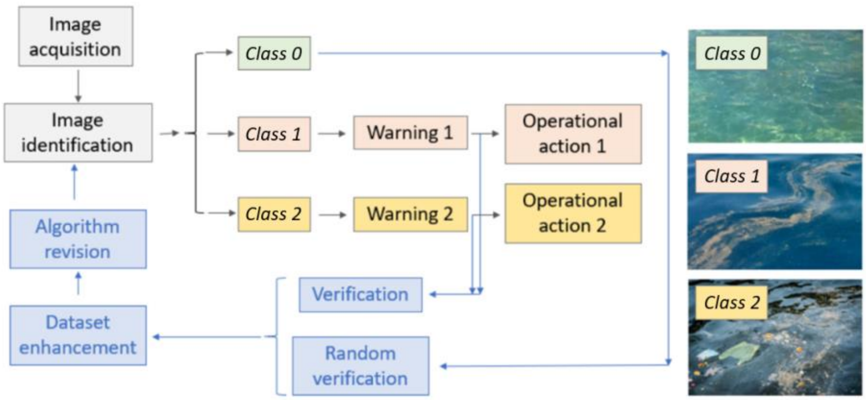

Figure 4.8. Progressive implementation of port water monitoring systems. The operational action refers to eventual anti-pollution measures planned by the port authority.

b) Future Applications

The most critical part of an applied computer vision system for the detection of pollution in ports is the availability of images with spills or floating waste. Therefore, future implementations would include tools and developments that improve upon the speed and cost of image obtention. Specifically, when a spill or floating waste image is detected, considering information on the duration of the pollution event would be critical to accumulate as much images as possible from the same event. This could be achieved either manually when a spill or waste event system was detected by the computer vision system, or a hybrid hydrodynamic computer vision system could be generated. In this sense, a hydrodynamic model in the framework of operational oceanography systems [Sotillo et al. 2019] would automatically provide information on the duration of the pollution event, and the dataset would be increased also in an automatic manner. However, hybrid systems can be complex; thus, proper investigation of the actual practicality of developing such a system should be further investigated. Future implementation in operational mode (with a large amount of images acquired) may entail an increase in the number of classes considered either by subdivision of some of the current classes or even by incorporation of a new class to codify the simultaneous presence of spill and waste as explained in Section 4.3.c. Additionally, pre-filtering and preparation of images could provide better image sets that would increase the performance without relying on algorithm retraining. This would include—for instance—filtering to avoid classification interference by passing boats and port infrastructures and detecting of waste and discharge events located far from the camera location with less loss of image resolution. In addition, pre-filtering may avoid or reduce the effect of sunlight reflections, and other transformation of the images may yield better detail of the contamination event and reduce interference of other less relevant details also contained in the images.

4.5 Conclusions

Experiments on port water quality identification based on random image sets have been conducted. The reliability and development requirements of the method have been evaluated showing that computer vision tools are suitable for these monitoring tasks. Several computer vision techniques were considered for use in real-time marine pollution monitoring, with the decision that Image Classification was the most adequate for such tasks due to its high accuracy rates and low training requirements. These requirements and the possibility to improve accuracy through retraining with increased image sets were considered due to the difficulty in obtaining port spill images, finding that progressive implementation can not only offer functional monitoring systems in a shorter time frame, but also reduce the total development cost for a system with the same accuracy level. A novel performance metric for the case of computer vision systems in the port environmental management application was put forward and tested, providing meaningful conclusions.

Future lines of research include the development of additional methods that improve the time taken to obtain spill and waste images, ultimately increasing the applicability and speed in which it provides meaningful information to port decision makers. In addition, future works include the consideration of a new class for combined spill and waste for those ports that receive mixed (i.e., waste and spills) discharges from waterways or water collection infrastructure. In addition, image preparation and pre-filtering could also yield algorithms with higher performance metrics and help overcome limitations for monitoring systems where camera location is not optimal or where reflected sunlight makes images hard to classify.

4.6 Afterword

Author Contributions

Conceptualization, M.E., M.G. and C.G.; Data curation, M.M. and A.P.; Formal analysis, M.M. and P.P.; Funding acquisition, C.G.; Investigation, M.M. and A.P.; Methodology, P.P., M.E. and M.G.; Project administration, M.M.; Software, A.P.; Supervision, M.E., M.G. and C.G.; Writing—original draft, M.M. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Project datasets are not publicly available as images used are property of Garau Ingenieros, SLU.

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Conflicts of Interest

The authors declare no conflict of interest.

5. ANALYSIS OF THE OPERATING CONDITIONS FOR A COMPUTER VISION MONITORING SYSTEM FOR FLOATING WASTE DETECTION IN PORT ENVIRONMENTS. APPLICATION AT ES PORTITXOL PORT IN THE BAY OF PALMA (MAJORCA, SPAIN)

5.1 Foreword

Featured Application:

Port Environmental Management systems; automated waste detection in port waters.

Abstract:

Water pollution is a main concern for ports and coastal waters and so Port Environmental Management systems often require pollution monitoring. Computer vision offers an efficient tool for automated monitoring of waste discharges in Port waters. An investigation has been conducted at the Port of Es Portitxol in Palma de Mallorca (Spain) to assess the effect of operating conditions of such monitoring systems and evaluate the main limitations and analyze strategies to overcome them. Pretrained algorithms were employed to detect a synthetic waste set released in the surveilled area and system reliability was evaluated. Experiment 1 analyzed the impact of image resolution on waste detection, revealing that appropriate resolutions significantly improved precision. Experiment 2 highlighted the importance of considering the range limitations (distance between waste and the camera) showing a negative correlation with detection accuracy. Experiment 3 involved training new algorithms with different image sets and resolutions, resulting in reliable performance across a range of resolutions. Based on the

results, several strategies for improving the system reliability have been pointed out; including optimizing image resolution, implementing distance-specific algorithms, and combining image sets to enhance reliability. Future research opportunities include exploring burst images for improved detection and extending the system's capabilities to multi-view analysis and other pollution monitoring tasks.

Keywords:
computer vision; marine litter; monitoring technologies; port water quality

5.2 Introduction

Ports and their adjacent coastal areas are hubs that concentrate a multitude of human activities within limited space both on land and water, often characterized by low water renewal rates. As a result, ports and their surrounding waters are highly vulnerable to pollution and the accumulation of solid waste, which can have significant impacts on the aquatic environment and socioeconomic factors [Saliba 2022, Ng and Song 2010]. A critical mechanism contributing to water pollution in port areas is the discharge and accumulation of waste caused by non-continuous events, both intentional and accidental. These events involve the instantaneous or short-term release of solid or liquid pollutants into the water, representing a major concern for port and coastal environmental management. To achieve adequate water quality in ports, it is crucial to surveil such events with efficient and robust monitoring techniques [Puig et al. 2021, Hossain et al. 2020]. This issue becomes particularly sensitive in city ports where the close relationship between port operations and urban activities makes it easier for city waste and pollution to enter the port waters [Li et al. 2019] and increases the sensitivity to water pollution.

The prevalence of plastics in modern society has made them indispensable in various economic sectors due to their versatility, low cost, and durability. However, the excessive production and accumulation of plastics over the past century, often referred to as the "Plastic Age," have resulted in significant negative impacts on the environment and society. Large quantities of plastic waste, estimated to be between 4.8 to 12.7 million tons, enter the oceans annually from land-based sources. Presently, approximately 75% of all marine litter consists of plastics, causing concern for marine ecosystems, human health, and maritime industries [Napper and Thompson 2020].

Marine plastic pollution originates from various sources, including rivers, canals, sewage discharge, litter from ships, and shipping spills. This rise in plastic waste spills has far-reaching consequences, potentially impacting critical marine ecosystem services, such as fisheries and recreation. Addressing marine litter requires a comprehensive approach involving collaboration between industries, policymakers, and global initiatives to curb plastic pollution and safeguard the health of marine environments for future generations.

Currently, the most common approach to marine pollution monitoring in ports relies on periodically collecting water and sediment samples for subsequent analysis in a laboratory and doesn’t specifically consider waste. Also, these methods are time-consuming, expensive, and do not provide a real-time understanding of water quality in port waters. Consequently, they are often implemented at minimal levels to comply with regulations, especially in ports with limited resources. The consequences of such limited monitoring at the environmental management level can be significant [Wooldridge et al. 1999, Puig et al. 2015].

Real-time or near real-time measurement and monitoring methods for marine waste are essential for managing their environmental impacts and comprehending the processes that govern their spatial distribution [Di Vaio et al. 2019, Butt 2007]. These techniques offer a complementary perspective on marine pollution to hydrodynamics-based environmental management techniques, enabling the integration of real-time pollution monitoring with hydrodynamic models to achieve improved environmental management systems [Grifoll et al. 2011, La Loggia et al. 2011].

In this context, it is important to highlight that waste discharge events in ports are usually visually perceptible. Which raises the possibility of establishing automated monitoring systems for these discharges using strategically placed cameras within the port area. Computer vision techniques, associated with automatic image analysis systems, have proven to be excellent tools in other fields for detecting and recognizing objects [Arribas et al. 2011, Eskandari et al. 2020, Storbeck and Daan 2001]. Computer vision techniques have undergone rapid evolution in recent years, demonstrating high efficiency and performance across a wide range of applications [Chen and Li 2021, Dong and Na 2021, Ngeljaratan and Moustafa 2021]. Deep learning on convolutional neural networks has particularly shown exceptional performance in computer vision tasks [Leonard 2019]. In the domain of environmental monitoring, remote sensing technology has proven effective in providing spatially synoptic and near real-time measurements for the detection and management of pollutants, including suspended solid waste and suspended sediments [Ciappa 2022, Hafeez et al. 2019]. Moreover, recent contributions in waste and pollutant detection have utilized Image Classification techniques based on deep convolutional networks [Panwar et al. 2020, Jiao et al. 2018, Morell 2023]. Such approaches have achieved success in addressing waste detection in large surface areas.

However, in the context of port waters, the use of satellite images is limited due to poor image resolution, necessitating the development of monitoring systems tailored to smaller scales. Specifically, a computer vision system supported by "in situ" mounted cameras can provide a robust alternative for monitoring floating waste in ports.

Such a system would enable continuous and cost-effective monitoring, overcoming the limitations of traditional observational techniques. Additionally, the practical application of artificial intelligence technology in port infrastructures at a reasonable cost would represent a significant step toward the digitalization of ports [Heilig 2017, Paulauskas 2021].

The main aim of this novel monitoring system is to obtain knowledge about the discharges threatening the port waters, including when and where they occur, and whether they are related to specific operations, rather than to provide warnings for each discharge for immediate action. Consequently, computer vision, combined with traditional or Artificial Intelligence-based analysis, can offer operational knowledge in specific port areas and facilities, supporting the development of appropriate environmental management strategies.

Computer vision techniques can be classified based on the specific problem they address [Khan and Al-Habsi 2020]. Image Classification is one of the most common applications and holds great promise in the context of port environmental management [Lu and Weng 2007]. Image Classification involves assigning an entire image into an image class, and in the context of port waste management systems, the relevant classes are clean water (clean) or carrying floating waste (waste).

Implementing computer vision monitoring systems in port areas requires careful consideration of the operating conditions to ensure their effectiveness. The successful deployment of such systems relies on strategically choosing camera locations, taking into account the distance and angle of the line of sight to the monitored area. This study case focuses on analyzing the critical operating conditions for a computer vision-based monitoring system, specifically for detecting floating waste in port environments. By understanding these operating conditions, EMS managers can optimize the system's performance and achieve more accurate and reliable results.

The selection of camera locations is a vital aspect of designing a robust and efficient computer vision monitoring system. The positioning of cameras determines the system's field of view and the area covered by the surveillance. It is crucial to identify key areas prone to pollution and waste accumulation within the port and its adjacent waters. Ports are dynamic environments with various human activities concentrated in limited spaces. Consequently, areas with low water renewal rates are susceptible to pollution and waste accumulation, necessitating targeted monitoring [Ng and Song 2010]. By strategically placing cameras, port authorities can ensure comprehensive coverage of critical zones and promptly detect any pollution discharge events.

The line of sight from the cameras to the monitored area plays a pivotal role in the system's performance. The angle and distance of the line of sight influence the clarity and accuracy of the captured images. Obstructions, such as buildings, structures, or other vessels, may obstruct the line of sight and hinder the system's ability to detect floating waste effectively. Additionally, factors like atmospheric conditions and lighting can impact image quality and subsequent classification accuracy.

To optimize the performance of the computer vision monitoring system, careful attention must be paid to camera placement and line of sight considerations. The positioning of cameras should be based on a thorough understanding of the port's layout and the patterns of waste accumulation. High-risk areas and potential pollution hotspots should be prioritized when choosing camera locations. Furthermore, the installation of cameras at elevated positions or utilizing pan-tilt-zoom (PTZ) cameras can enhance the system's flexibility and adaptability to changing environmental conditions.

A well-designed computer vision monitoring system, integrated with environmental management strategies, can significantly contribute to maintaining water quality in ports. Real-time data from the system can enable prompt responses to pollution events, reducing the potential impacts on marine ecosystems and coastal areas. By linking the system with hydrodynamic models, port authorities can gain valuable insights into the spatial distribution and movement of pollutants, facilitating better decision-making and resource allocation.

This chapter evaluates the results of a series of experiments conducted to identify floating marine waste in images taken from a fixed location in the port, with the waste at a variable distance from the camera position; the classifications accuracy for different distance ranges has been compared. Also, the effect of the original resolution of the image on the classification accuracy has been analyzed. To evaluate the algorithm's performance specifically for port environmental management applications, a novel performance index proposed on a former work [Morell 2023] reproduced in chapter 4, the error index, has been considered. The image sets were collected from Es Portitxol Port, located in Palma de Majorca, a recreational port where users and citizen are highly sensitive to water quality degradation events.

The remainder of this chapter is organized as follows. Section 5.3 introduces the study area, the computer vision technique and algorithm employed, the spill and waste classes considered, the field work carried out and the image set obtained, the pretreatment of the images and a description of the three experiments. Section 5.4 presents the results of the experiments (reliability against resolution, reliability against distance and new algorithm training low reliability of the system with pretrained algorithms and. Section 5.5 discusses the reliability of the system with pretrained algorithms, its potential improvement based on experiment 3 and the system’s further development. Finally, Section 5.6 summarizes the conclusions drawn from the study.

5.3 Materials and Methods

a) Study Area

The port of Es Portitxol is located in the city of Palma, adjacent to the Port of Palma, on the island of Majorca (Balearic Islands, Spain; see location in Figure 5.1) in the Western Mediterranean Sea, with approximate coordinates of: 39°33'38"N 2°40'7"E. The management resides at the Port Authority of the Balearic Islands in a landlord governance model. Main aspects to consider about the impact on water quality degradation and environmental management are: (i) Strong Port–City relation. (ii) Focus on sports and recreational boating port activities and related port services (i.e., repair and maintenance of boats and restoration and services on land). (iii) Sporadic discharges of rainwater through one torrent and several collectors of stormwater drainage networks.

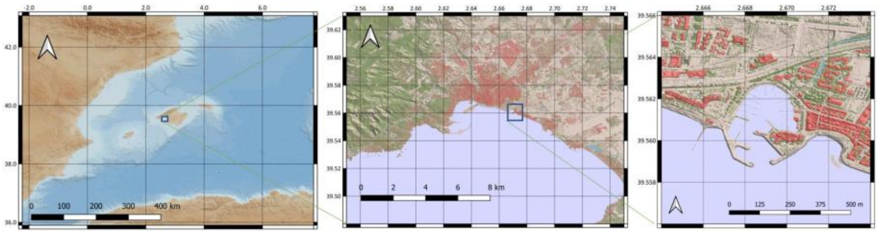

Figure 5.1. Study area location.

b) Computer Vision Technique used

Various computer vision techniques are available, including Image Classification, Object Detection, Object Tracking, Semantic Segmentation, and Semantic Instance Segmentation. While all these techniques have potential applications in port water quality monitoring, Image Classification is deemed the most appropriate technique based on the desired input-output information and the fact that it requires less training data preparation compared to other techniques, allowing for the classification of images into simple classes that can be used to establish temporal and spatial distributions of pollution events.

In the field of computer vision, convolutional neural networks (CNNs) trained using deep learning techniques are often used to develop Image Classification applications. CNNs are a type of artificial neural network commonly used to analyze visual imagery because they are shift invariant, meaning they can analyze images regardless of the position of features within the image.

These algorithms take input images of port water captured by a real-time camera monitoring system and provide output classifications with the highest probability for proper environmental management of port water. The aim is to assess the effectiveness of previously developed Image Classification algorithms in waste monitoring when distance from camera to waste increases from training images and assess the possibility of distance correction using managing port water quality, utilizing the capabilities of computer vision techniques.

c) Computer Vision Algorithm and Classes Considered

Keras open-source software library for Python (version: 2.4.3) on Tensorflow Google developed open-source software library (version: 2.3.0) backend framework based on the Anaconda3 platform was used for training the algoriths used in these experiments. Python 3.8.10 programming language was used for training and validation process programming. The computer used was equipped with an Intel Core i7-6700HQ CPU with 16 GB RAM and a NVIDIA GeForce GTX 960M graphics card. The computer operating system was the 64-bit Windows 10 home edition. A neural network InceptionV3, with "imagenet" weights and a 3-channel resolution was deployed. InceptionV3 was chosen, after discarding models designed for mobile devices, considering the compromise between accuracy and speed according to Keras documentation [WWW Document 2022] and CNN research [He et al. 2019, Hussain et al. 2019]. An additional GlobalAveragePooling2D layer was added with 1024 additional neurons with ReLU activation (0.2 dropout), as well as another layer with 3 neurons with softmax activation. The latter layer is the one bearing the spill/waste/clean water classes information. For the training images, a series of transformations were applied (rotation, horizontal and vertical shifts, crop, zoom and horizontal reflex) including a standard normalization; and data augmentation techniques were used on the image set [Shorten and Khoshgoftaar 2019]. For image validation purposes, only normalization was applied. Data ingestion was carried out in batches of 8 images. The training set images consisted of 80% of the set and the remaining 20% were used for validation purposes. Firstly, a training of additional layers was conducted and subsequently a fine-tuning was simultaneously carried out of both final inception blocks and additional layers. The cost function used was CategoricalCrossentropy (logit) and Adam was deployed as the optimization algorithm (learning rate of 0.001 and 0.00001 was each of the training phases described previously).

For experiments 1 and 2, two computer vision algorithms were used. These algorithms were developed and refined in SPILLCONTROL project, in previous stages of research. The first algorithm (V1) is the compensated image algorithm previously designed and utilized in study case presented in Chapter 4 [Morell, 2023]. This algorithm forms the foundation of the algorithm development process, providing valuable insights and serving as a benchmark for comparison. It leverages a compensated image set obtained from photographs taken by an operator and has shown promising capabilities in detecting and classifying pollution instances in port environments.

In contrast, the second algorithm (V8) represents the most cutting-edge version available within the scope of the SPILLCONTROL project. This advanced version incorporates knowledge obtained from analysis of images from fixed cameras at Es Portitxol port in the Bay of Palma. Through continuous refinement and adaptation to the specific context of Es Portitxol port, V8 aims to surpass the performance of its predecessors, showcasing improved accuracy and reliability in detecting surface spills and floating marine waste.

By employing both V1 and V8, we aim to draw insightful comparisons between the algorithms' performances and assess the possible advantage of using algorithms trained in different operating conditions and different port areas. Furthermore, this approach allows us to evaluate the effectiveness of the novel improvements implemented in V8 and their practical implications for environmental monitoring systems. The comparative analysis will shed light on the strengths and limitations of each algorithm, providing valuable insights to guide future developments and enhance the overall efficiency of computer vision-based environmental management systems. Through a thorough examination of their performance under different conditions and scenarios, we seek to pave the way for the practical implementation of these technologies in port EMSs.

Algorithm development process:

In the initial stages, the compensated image model developed using photographs taken by an operator was adopted (V1). As the number of images obtained from three fixed cameras in the Es Portitxol port increased, new versions of the algorithm (from V2 to V5) were trained, incorporating images from these cameras without maintaining the proportion of compensated images. While this did not improve the statistical reliability parameters of the system, it did enhance the reliability specifically for images from these cameras. However, upon reaching version V5, a significant loss of reliability was observed (see Figure 5.2), attributed to an excess of class 0 images (clean water) that caused a strong imbalance in the training image set.

To address this issue, the class 0 image set was reduced by analyzing the similarity between different images and eliminating redundant ones with a similarity greater than 70% compared to other images. This improved the balance of the training image set, resulting in 2000 class 0 images, 1400 class 1 images, and 1200 class 2 images. Furthermore, to further enhance balance, each image was assigned a weight per class, ensuring equal cumulative weights across the three classes. This technique led to the development of version V6. The addition of new images maintaining compensation brought V7, and finally, the most recent version, V8, which demonstrates good reliability parameters over a set of images with a high proportion obtained from the fixed cameras within Es Portitxol (88.39%).

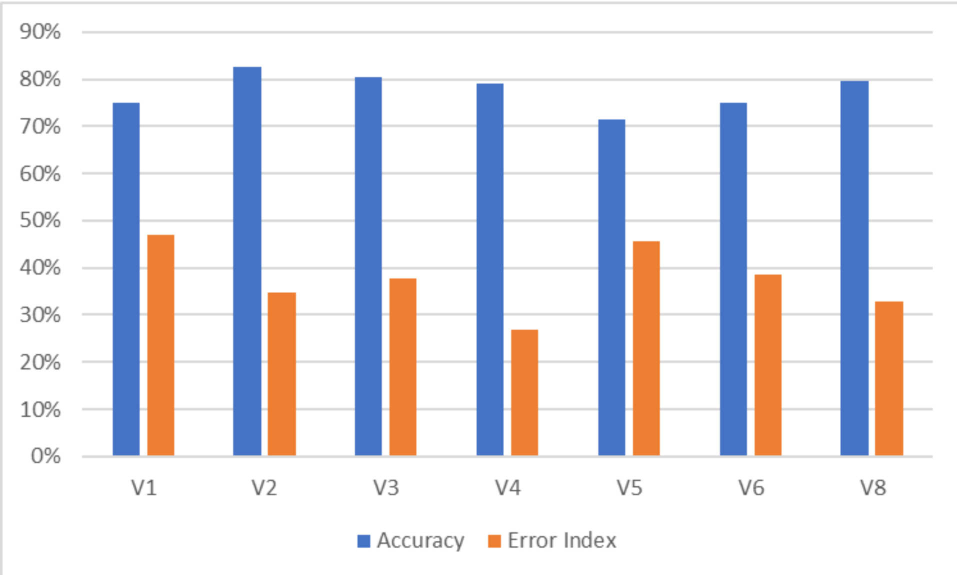

Figure 5.2. Accuracy (blue) and Error Index (orange) evolution during algorithm development. Data for V7 could not be retrieved.

Classes considered:

Although both algorithms were initially trained for a three-class classification, including Class 0 (clean water), Class 1 (spill), and Class 2 (waste), the actual dataset used in this study case presented a variation in the classes available for analysis. As depicted in Figure 5.3, the algorithm training dataset consisted of images representing Class 0 (clean water) and Class 2 (waste), while the Class 1 (spill) instances were notably absent in the experimental dataset for this case.

Despite the absence of Class 1 (spill) images in the dataset, it is important to acknowledge that the algorithms were designed to predict this class. Therefore, there is potential for incorrectly predicting spill instances as this class was considered in the algorithm's design.

Figure 5.3. Example algorithm training images for each class.

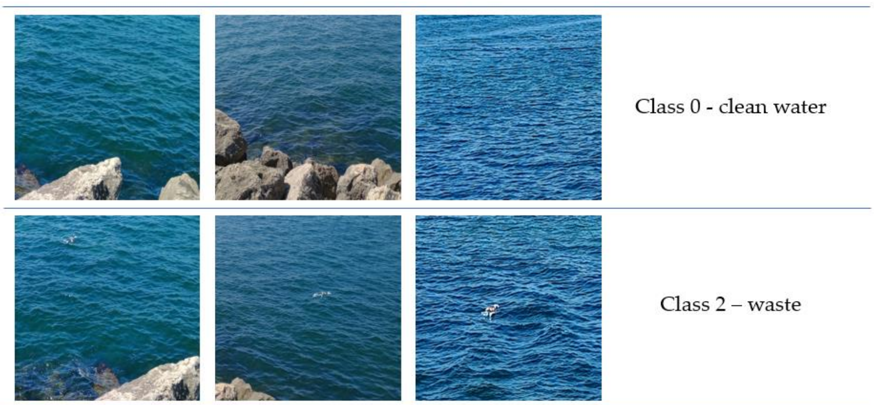

Figure 5.4. Classes present in current experiments.

It must be noted that the lack of Class 1 instances in the dataset could pose certain challenges for the algorithms' reliability measure. However, in real-world scenarios there may be locations where spill occurrences are not expected due to lack of possible sources at some port areas.

d) Fieldwork and Image Set Used

For the fieldwork, a synthetic waste set was employed (see Figure 5.5), comprising eight containers with distinct characteristics securely fastened to a floatation device equipped with a Lagrangian buoy (see Figure 5.6). The buoy served to determine the specific location of the drifting waste during the experiments and evaluate the distance to the camera for each image.

Figure 5.5. Left: Synthetic waste set on the boat. **Right:** Synthetic waste set on sea near the boat.

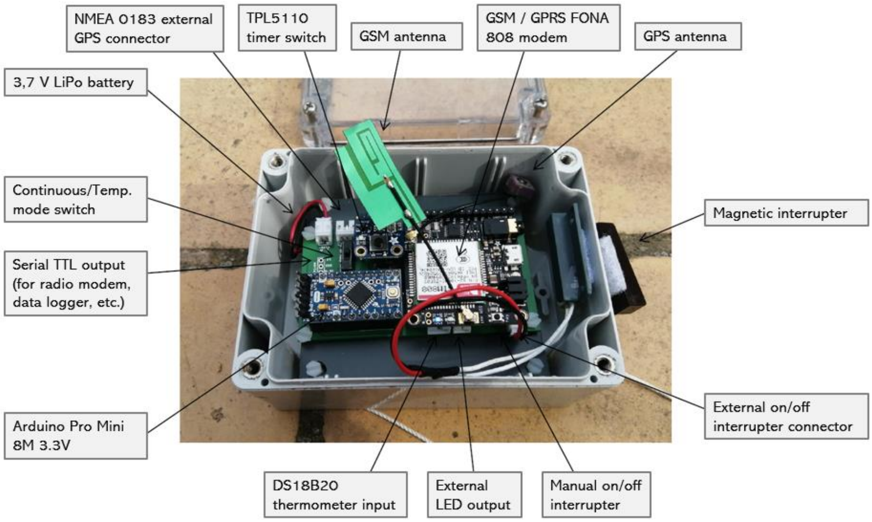

Figure 5.6. Lagrangian buoy device.

This assemblage of synthetic waste was released on five separate occasions, each time launched from a semi-rigid boat and left adrift. Consequently, these five launches resulted in five distinct trajectories, as illustrated in Figure 5.7.

From a fixed vantage point located on the southwest outer breakwater of the Es Portitxol port (see Figure 5.8), a total of 367 photographs were captured, each showing the presence of the synthetic waste as it traversed along the drift trajectories. These photographs were taken at regular intervals, enabling the systematic monitoring and analysis of the synthetic waste's movement.

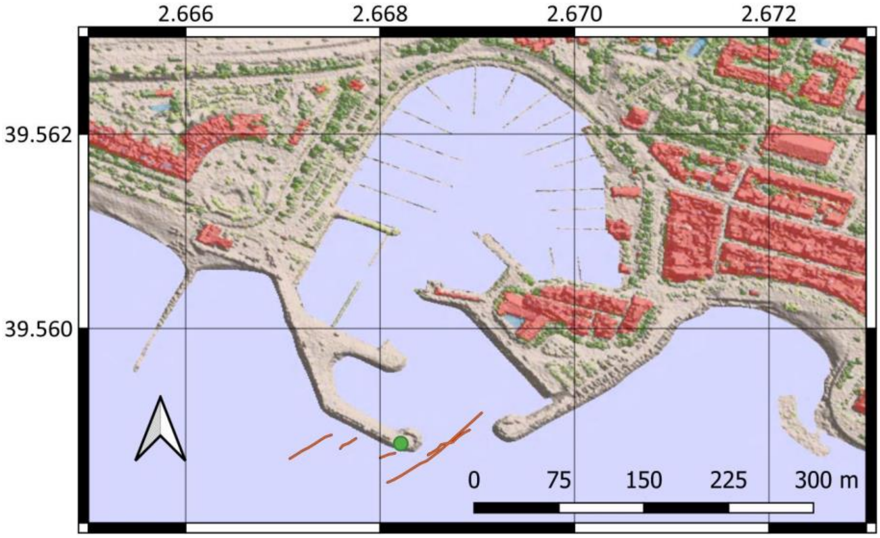

Figure 5.7. Camera location (green dot) and synthetic waste trajectories (orange lines).

Figure 5.8. Classes present in current experiments.

The use of synthetic waste allowed us to create controlled scenarios that mimic real-world waste discharge events and dispersion in a port or coastal setting. This approach enables the assessment of the algorithms' performance and accuracy in detecting and classifying waste instances for environmental monitoring in ports.

The camera employed for this experiment is the rear camera of a TCL 40 SE smartphone, boasting a resolution of 50 MP and possessing the specifications outlined in Table 5.1.

50MP main/macro camera:	PDAF, sensor size 1/2.55”, pixel size 0.7μm, aperture F1.8, field of view 79.4°, 5P lens
2MP depth camera:	FF, sensor size 1/5”, pixel size 1.75μm, aperture F2.4, field of view 88.8°, 3P lens
2MP macro camera:	FF, sensor size 1/5’’, pixel size 1.75μm, aperture F2.4, field of view 88.8°, 3P lens
Video capture:	1080P @30FPS
Video playback:	1080P @30FPS
Features:	Bokeh, HDR, Panorama, AI scene detection, Face detection

Table 5.1. TCL 40 SE smartphone camera specifications.

e) Image Pretreatment

Images were obtained with an original resolution of 12.5 MP (4096 pixels wide and 3072 pixels high). The resolution of these images is much higher than the working resolution of the classification algorithms (0.3 MP with 300 pixels in width and 300 pixels in height). This high resolution allows us to obtain image crops at various resolutions, producing two crops from each image: one containing the synthetic waste (which should be classified in Class 2) and another without the synthetic waste (which should be classified in Class 0). Table 5.2 displays the sizes of the image crops conducted for the experiments described below.

Width (pixels)	**Height** (pixels)	**Resolution** (megapixels)
72	54	0.0039
120	90	0.011
144	108	0.016
216	162	0.035
240	180	0.043
288	216	0.062
360	270	0.097
400	300	0.120
480	360	0.173
800	600	0.480
1200	900	1.080
1600	1200	1.920

Table 5.2. Sizes of the image crops conducted.

f) Experiments Description and metrics considered

Three experiments were conducted with the image sets described in previous section:

- **Experiment 1:** Reliability of the classification algorithm concerning the initial resolution of the classified images.

Since the classification algorithm adjusts the scale of the images to be classified to a resolution of 300x300 pixels (0.09 MP) before performing the classification, the resolution of the image crops does not alter the resolution of the images that will be classified. Instead, it affects the size of the waste in those images based on the scaling factor indicated in Table 5.3.

Resolution (megapixels)	**Scale Factor**
0.0039	481.1 %
0.011	288.7 %
0.016	240.6 %
0.035	160.4 %
0.043	144.3 %
0.062	120.3 %
0.097	96.2 %
0.120	86.6 %
0.173	72.2 %
0.480	43.3 %
1.080	28.9 %
1.920	21.7 %

Table 5.3. Scale factor of the image crops conducted.

For this experiment, two representative indices of algorithm reliability were used: Precision for the Waste class, and the False Positive Rate for this same class. The reason for using these two indices is that they allow us, given the proportion of images with spills in a sample, to determine the Error Index.

- **Experiment 2:** Reliability of the classification algorithm concerning the distance between the waste and the camera.

In this experiment, the images were classified based on the distance between the synthetic waste and the camera. Three distance categories were considered, as shown in Table 5.4. “Near” category was established to represent maximum operating distance of existing SPILLCONTROL cameras used for V8 algorithm training.

Distance category	**Distance range** (m)	**Number of images**
Near	< 30	54
Medium	30 - 60	141
Far	> 60	172

Table 5.4. Distance categories for experiment 2.

The images within these categories were cropped to a size of 288x216 pixels (0.062 MP) and were classified using the V1 algorithm, as this combination of resolution and algorithm yielded the best results in Experiment 1.

For this experiment, as in Experiment 1, Precision for the Waste class, and the False Positive Rate for this same class were used as these two indices allow us to determine the Error Index for a given proportion of images with spills in a sample.

- **Experiment 3:** Training a new algorithm with images from the present case study.

For this experiment, algorithms were trained with different sets of images, and the training cost was evaluated in terms of the number of training epochs required and the reliability of the resulting algorithm using the error index proposed in the previous case [Morell 2023]. The algorithms were trained with image sets of the following resolutions: 0.043 MP, 0.120 MP, 0.480 MP, and 1.080 MP. Additionally, algorithms were trained with combinations of images at 0.043 MP and 0.120 MP, 0.480 MP and 1.080 MP, and all four resolutions together. In all cases, balanced samples of 367 images of clean water and 367 images with the presence of waste were used for training.

For this experiment, the Error Index was used to measure the reliability of the algorithms obtained for the reasons explained in Chapter 4.

5.4 Results

A) Experiment 1: Reliability Versus Resolution

Different sets of images, cropped to the resolutions indicated in Table 5.2 were classified using SPILLCONTROL algorithms V1 and V8 (see section 5.3.c for an explanation on these algorithms) and two reliability indexes were obtained for each case: Precision for the Waste class, and the False Positive Rate for this same class.

Those indexes are presented in Figure 5.9 and 5.10 showing the following features:

- Precision values are low (<20%) for high resolution images (above 360 pixels of height for V1 and 200 pixels of height for V8).
- There is a maximum in Precision for both algorithms (about 210 pixels of height for V1 and 90 pixels of height for V8); bellow that resolutions precision goes down quickly. Maximum precision achieved is around 50 %.
- False Positive Rates are low (<5%) for high resolution images (above 360 pixels of height for V1 and 216 pixels of height for V8) but they increase severely for lower image resolutions.
- For V1 algorithm there is a maximum in 162 pixels of height.

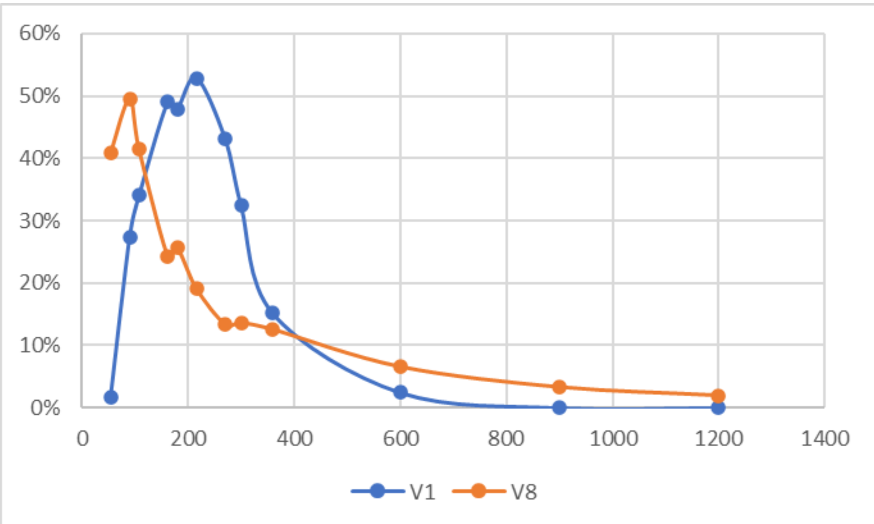

Figure 5.9. Precision for the Waste class against resolution (measured in image height in pixels).

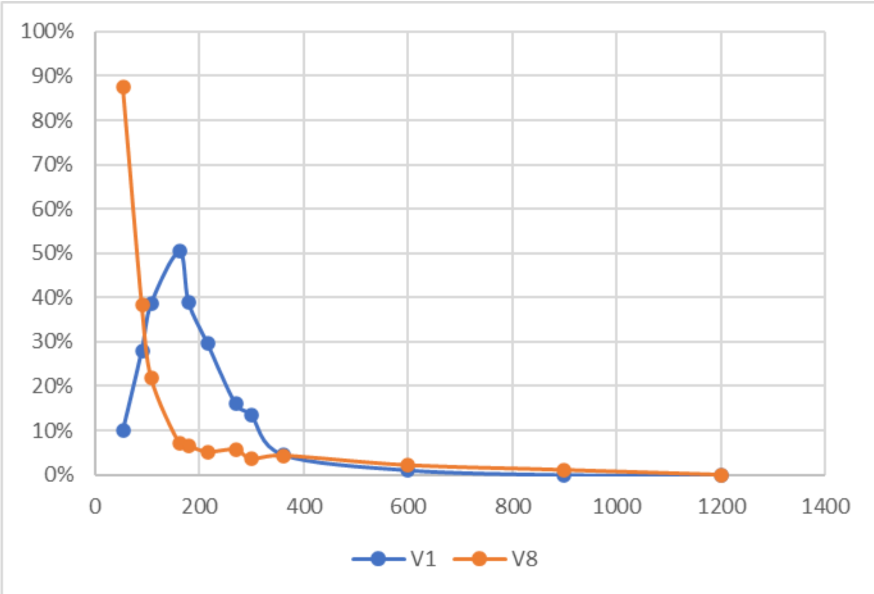

Figure 5.10. False Positive Rate for the Waste class against resolution (measured in image height in pixels).

B) Experiment 2: Reliability Versus Distance

Images have been divided into three Distance categories, cropped to a size of 288x216 pixels (0.062 MP) and classified using the V1 algorithm, as this combination of resolution and algorithm yielded the best results in Experiment 1.

The same two reliability indexes as in Experiment 1 were obtained for each category: Precision for the Waste class, and the False Positive Rate for this same class. Figure 5.11 shows the values of these indexes for each category. The Precision index shows an strong negative correlation with Distance category with Precision decreasing with Distance. The False Positive Rate shows high values for each category and a Not Significant correlation with Distance.

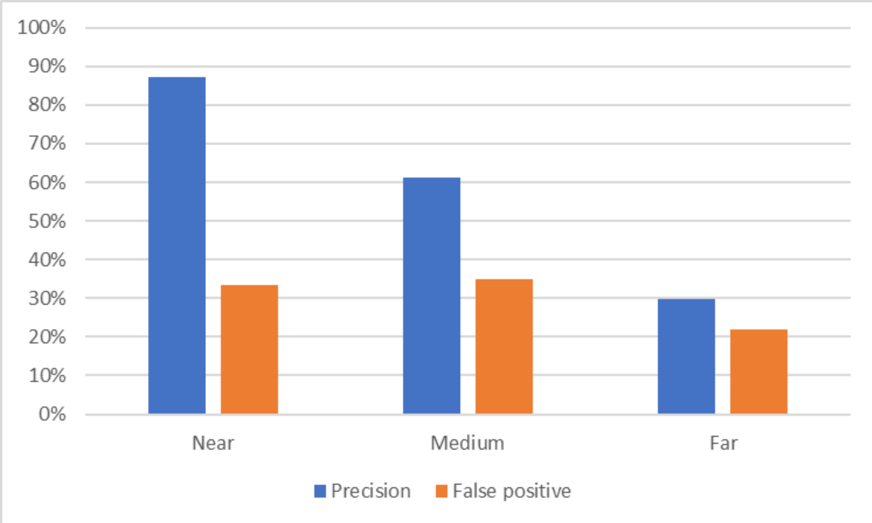

Figure 5.11. Precision and False Positive Rate for the Waste class against Distance category.

C) Experiment 3: New Algorithms Training

New algorithms were trained with seven different sets of images, four wiz fixed resolution of 0.043 MP, 0.120 MP, 0.480 MP, and 1.080 MP; two with combined images of the two lower ant the two higher resolitions considered (0.043 and 0.120 MP and 0.480 and 1.080 MP); and one with combined images of all four resolutions.

For each algorithm, training cost was evaluated in terms of the number of training epochs required; and reliability was evaluated using the Error Index.

Figure 5.12 presents the Error Index and number of training Epochs needed for those algorithms showing the following features:

- Error Index values are low (<30%) for all resolution values and combinations except 1.08 MP and show a positive correlation with image resolution; higher image resolution produce higher Error Index values.

- Image sets combining different image resolutions produce Error Index values that are in the range between those for the resolutions involved.
- Number of Epochs needed for training tend to increase with Image resolution though not severely.

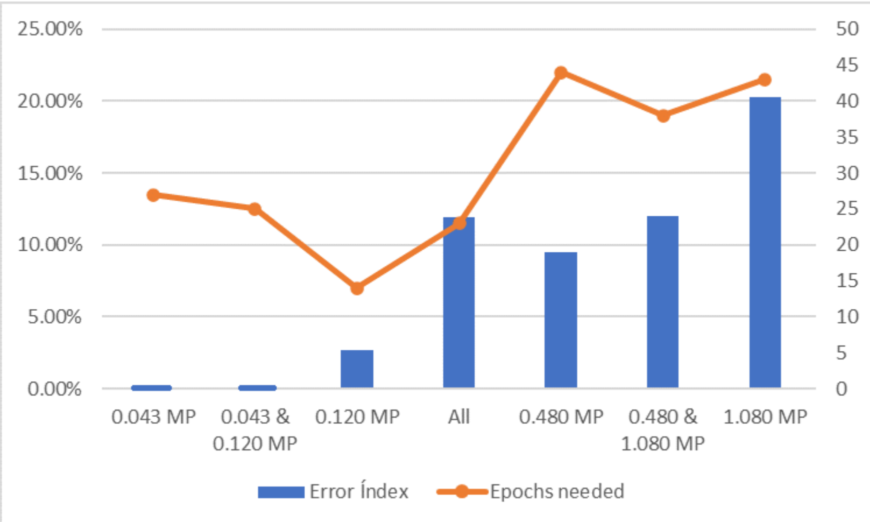

Figure 5.12. Error Index (values on the left) and number of training Epochs needed (values on the right) against resolution (measured in megapixels) of the image sets considered.

5.5 Discussion

a) Reliability of the system with pretrained algorithms

The results from the experiments 1 and 2 in waste detection for the computer vision algorithms pretrained in project SPILLCONTROL show a reduction in the reliability from the values obtained in previous work (see Chapter 4). The obtained Accuracy curves in Experiment 1 align with previous research findings in the field of computer vision applications, highlighting two key features that significantly impact the performance of the algorithms:

- Image cropping plays a crucial role in enhancing Classification Accuracy [Mishra et al., 2020; Thambawita et al., 2021]. When a higher proportion of pixels corresponds to the target feature (waste in this case), the algorithm demonstrates improved accuracy in detecting and classifying the objects of interest. In Experiment 1, this phenomenon is clearly observed in Figure 5.9, where the V1 algorithm achieves its highest Accuracy value when the images are cropped to approximately 0.059 MP (210 pixels in height), and the V8 algorithm reaches its peak at a clipping resolution of about 0.011 MP (90 pixels in height).
- Enlarging lower-resolution images through interpolation does not lead to improved Classification Accuracy [Hashemi, 2019]. In other words, simply increasing the size of images that have a resolution lower than the working resolution of the algorithm does not positively impact the algorithm's ability to accurately detect and classify waste objects. This characteristic is also evident in Experiment 1, where the algorithms' Accuracy values do not improve beyond their respective optimal clipping resolutions.

Furthermore, the optimal cropping sizes identified in Experiment 1 coincide with the image sizes that result in the waste part of the images having a size equal to the average size of the waste in the training images of each algorithm. This is consistent with the fact that the evolution from V1 to V8 involved the incorporation of a high proportion of waste images taken at greater distances, in which waste will on average have a smaller pixel size.

These features are crucial in understanding the behavior of the computer vision algorithms for waste detection in different resolutions and distances and provide valuable insights for practical implementation of the CV monitoring tool:

- Camera resolution should be set at a high enough value to ensure that average waste pixel size for the operational distance is similar to average waste pixel size for the images in the algorithm’s training set after normalization to the algorithms resolution. No improvement can be obtained from a camera resolution higher than that.

- To classify the images, they must be divided in tiles the size of the algorithms resolution rather than resampled. Positive waste classification of any tile leading to waste classification of the image.

Although the False Positive Rate remained low for high-resolution images, which may be indicating the system's ability to correctly identify clean water areas, the significant loss in Accuracy for waste detection invalidates this strategy.

On the other hand, the False Positive Rate increased for lower image resolutions (see Figure 5.10) emphasizes the need to acquire images with enough resolution to ensure that average waste pixel size for the operational distance is similar to average waste pixel size for the images in the algorithm’s training set.

A comparison of the reliability parameters obtained using the V1 algorithm in Experiments 1 and 2 of the current case study with those obtained in Experiments 1 and 2 of the previous case study (Chapter 4), where the same algorithm was also employed, reveals noteworthy differences. Specifically, when analyzing the Precision metrics for both Clean water and Waste classes, the present case images produce lower Precision scores compared to the Control image set used in the previous case study. In the earlier study, the algorithm achieved high Precision scores, with 0.89 Precision for clean water images and 0.93 Precision for Waste images (as indicated in Table 4.3). In contrast, the results obtained in the present case study, even with the optimal clipping size set at 288x216 pixels (0.062 MP), show Precision scores that fall below these (see Table 5.5). The difference in Precision between the two studies suggests variations in the algorithm's performance when applied to images obtained in different conditions, being the distance from Waste to camera the most plausible reason, as Experiment 2 results suggest.

Experiment / distance	Clean water Precision	Waste Precision
1	0.48	0.53
2 / Near	0.33	0.87
2 / Medium	0.63	0.61
2 / Far	0.35	0.30

Table 5.5. Maximum Precision for Clean water and Waste classes reached in experiments 1 and 2.

Experiment 2 emphasized the significance of considering the distance between the waste and the camera in system reliability. The Precision showed a strong negative correlation with Distance, indicating that the system's accuracy decreased as the distance between the waste and the camera increased. So, to improve the system's performance, efforts should be directed towards enhancing object detection capabilities at varying distances from the camera. This could involve training distance-specific algorithms to account for spatial variations and adjusting accordingly the resolution of the images taken according to the results observed in Experiment 3.

What might be considered a limitation of the experiments presented is that, while both V1 and V8 algorithms were trained for a three-class classification (Class 0 - clean water, Class 1 - spill, and Class 2 - waste), the study case in this chapter involved only two classes (Class 0 - clean water and Class 2 - waste). Certainly this limitation might interfere with the measured Precision values; as part of the images inadequately classified as Spill by the algorithm would have been classified properly if that class didn’t exist. However, this limitation does not seem to significantly compromise the conclusions drawn from the experimental results. Also, in the practical application of the system in port environments, it is worth noting that the majority of real-world situations involve both types of pollution, so algorithms shall have to take both classes into consideration.

b) System reliability potential improvement

In Experiment 3, new algorithms were trained using different sets of images at varying resolutions. The Error Index results indicated that the system achieved reliable performance across a range of resolutions, with Error Index values consistently below 30%. Nevertheless, the system's performance tended to decrease slightly with higher image resolutions, suggesting that the analysis of higher resolution images should be performed separately over different sections of each image.

Reliability levels achieved in this Experiment should be taken carefully as all images used for the training and for the reliability evaluation showed the same synthetic waste set and were taken in similar sea and light conditions. So, these reliability levels should be considered as an upper limit rather than an expected value.

Additionally, training the algorithms with combined image sets showed potential for achieving performance levels within the range of the individual resolutions involved, presenting a possible strategy to avoid the need of several analysis of the same images at different resolution and resulting in a more cost-effective system deployment without compromising reliability.

c) Further investigation

While the results of this study provide some insights into the reliability and potential improvements of the SPILLCONTROL computer vision system, there are several areas that warrant further investigation to enhance its performance and broaden its scope of application. The following aspects represent promising directions for future research:

- Expansion to Diverse Port Environments: This study focused on the port of Es Portitxol as a specific case study. To validate the system's robustness and adaptability, further investigations should be conducted in diverse port environments with varying waste characteristics and water conditions. Evaluating the system's performance in different geographical locations and under different environmental conditions will contribute to understanding its generalization capabilities and ensuring reliable waste detection across multiple ports.

- Burst images: Exploring the use of a sequence of images instead of one image at a time and develop algorithms to leverage burst photography for waste detection, aiming to improve the system's reliability and accuracy in identifying pollution incidents.
- Multi-View Analysis: Expanding the system's capabilities to incorporate multi-view analysis can significantly enhance its performance in waste detection. Combining data from multiple cameras with different perspectives can improve object recognition accuracy and provide a more comprehensive understanding of waste distribution in port waters. Investigating multi-view analysis techniques, such as 3D reconstruction or fusion algorithms, will be valuable in capturing a more complete picture of waste occurrences and their spatial distribution.
- Fusion with Other Environmental Data: Integrating the computer vision system with other environmental data sources can provide a holistic approach to marine pollution monitoring. For instance, combining image data with real-time weather, tide, or current information can aid in understanding the dynamics of waste transport and dispersion within port areas. Investigating methods for data fusion and developing hybrid monitoring systems will enable more comprehensive and context-aware waste detection and management.
- Extended Pollution Monitoring: While this study focused on waste detection, the SPILLCONTROL system can be expanded to monitor other types of marine pollution, such as oil spills, dissolved or suspended contaminants, eutrophication and microplastics. Investigating the adaptability of the pretrained algorithms to different pollution types and optimizing their

performance for specific pollution scenarios will contribute to a versatile and comprehensive pollution monitoring platform.

- Environmental Impact Assessment: Assessing the environmental impact of waste occurrences detected by the SPILLCONTROL system is another crucial aspect for further investigation. Understanding the ecological consequences of waste pollution and its effects on marine ecosystems will help in developing targeted mitigation strategies and fostering sustainable environmental management practices.

d) Future Applications

The findings from this study open up exciting possibilities for future applications of the SPILLCONTROL computer vision system. The system's pretrained algorithms exhibit promising reliability in detecting waste in port waters, indicating its potential for practical deployment in real-world scenarios. Future applications could include integrating the system into existing port monitoring infrastructures for efficient and continuous waste detection. By leveraging the pretrained algorithms and incorporating new data from specific port environments, the system can be fine-tuned to adapt to various port configurations and waste characteristics, further enhancing its performance and reliability.

Moreover, the SPILLCONTROL system can serve as a valuable tool in supporting environmental management efforts in port areas. The accurate and timely detection of waste can help authorities take proactive measures to mitigate pollution and preserve marine ecosystems' health. The system's ability to identify waste areas and clean water regions with low False Positive Rates can aid in allocating resources effectively and prioritizing clean-up operations.

Furthermore, the SPILLCONTROL system's potential extends beyond waste detection in port environments. The pretrained algorithms can be applied and adapted for other marine pollution monitoring tasks, such as identifying spills or tracking the spread of hazardous substances from a vessel or drone.

To ensure the reliability and practical applicability of the system, field validation and collaboration with port authorities and environmental agencies are essential. Conducting field trials in real-world port environments will validate the system's performance and provide valuable feedback for further improvements. Collaborating with stakeholders will also aid in tailoring the system to meet specific regulatory and operational requirements.

5.6 Conclusions

The study case presented in this chapter focuses on the operation conditions for a computer vision-based system for waste detection in port waters using pretrained algorithms from the SPILLCONTROL project. The research aimed to assess the limitations of the system and explore potential improvements to correct those limitations.

The results from the experiments demonstrated that the computer vision system achieved under certain conditions promising results in waste detection with Precision values that are lower than those obtained in previous chapter but may be corrected with an appropriate consideration of the resolution of the images according to the distance from the camera to the surveilled area as the reliability of the system showed a clear dependence on image resolution and distance between the waste and the camera. High-resolution images cropped to parts and shorter distances lead to better performance. Additionally, the training of new algorithms with combined resolution image sets presented a viable strategy to achieve reliable performance across different resolutions without compromising accuracy.

The study case demonstrated the feasibility and effectiveness of using computer vision for waste detection in port waters with operating ranges above 30 m. The pretrained algorithms exhibited limited reliability, but potential improvements were identified to enhance the system's performance. Collaborative efforts with port authorities and environmental agencies for field validation and tailoring the system to meet specific regulatory and operational requirements are essential steps for practical implementation. The SPILLCONTROL computer vision system offers a valuable tool for proactive pollution management in port environments, contributing to the preservation of marine ecosystems' health and sustainable port operations.

5.7 Afterword

Data Availability Statement

Project datasets are not publicly available as images used are property of SPILLCONTROL project.

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Conflicts of Interest

No conflict of interest is declared.

6. Conclusion and future work

6.1 General discussion

This thesis aimed to develop and evaluate novel tools and specific strategies for implementing Environmental Management Systems (EMS) in ports to monitor water quality. The primary objectives were to assess the feasibility of using computer vision for water pollution monitoring, develop a computer vision-based system for spill and waste identification, integrate this system with SAMOA meteorological and hydrodynamic operational service, analyze the operating conditions for the computer vision monitoring system, and evaluate the performance and effectiveness of the tools integrated into the EMS.

The research focused on three case studies, each providing valuable insights into the system's capabilities and potential improvements. In Case 1, numerical simulation implementation on operational meteorologic and hydrodynamic service information were investigated. The results demonstrated that the integration of SAMOA operational service supported numerical simulations can provide valuable information on oil spill patterns and their interactions with hydrodynamic conditions. However, the resolution of the numerical model proved to be crucial in achieving accurate results, especially in complex port entrance areas. Understanding the temporal variability of oil spills also offered insights into the impact of time of release on the spreading patterns.

In Case 2, the discussion focused on the system set-up and future applications of the computer vision-based system for pollution monitoring. The study revealed that image classification was suitable for marine pollution monitoring tasks, with high accuracy rates and low training requirements. Progressive implementation of the system with increasing image datasets was proposed as an effective strategy to achieve reliable performance in a shorter time frame. Future applications were discussed, emphasizing the importance of enhancing object detection capabilities and expanding the system to diverse port environments.

Case 3 investigated the effect of operational conditions on the reliability of the SPILLCONTROL computer vision system for waste detection and analyzed potential improvement techniques. The experiments highlighted the importance of image resolution and distance from the camera in achieving reliable waste detection results. Further investigation was suggested to expand the system's capabilities to diverse port environments, explore burst images, incorporate multi-view analysis, and fuse computer vision data with other environmental data sources for comprehensive pollution monitoring.

In general, the research findings showed promising potential for using SAMOA operational service and computer vision-based systems in water quality environmental management systems in ports. The development of robust CV algorithms and the integration with meteorological and hydrodynamic models may provide valuable insights into pollution patterns and dynamics. However, certain challenges and limitations were identified, such as the need for sufficient and diverse image datasets, the importance of optimizing image resolution, and the consideration of distance-dependent algorithms for object detection.

To further enhance the practical applicability and effectiveness of the proposed tools, several future directions were suggested. These include combining SAMOA with CV monitoring, expanding the system to different port environments, implementing burst photography for waste detection, exploring multi-view analysis, integrating computer vision data with other environmental data, and extending pollution monitoring to various types of marine pollution. Additionally, conducting field trials and collaborating with port authorities and environmental agencies were emphasized as essential steps for validation and real-world deployment.

It is essential to underscore the significance of progressive implementation of Environmental Monitoring Systems and the collection of information at early stages for system development. Adopting a progressive approach allows port authorities to initiate environmental monitoring initiatives with the data and technologies available at the time, without delaying the implementation for a perfect, all-encompassing solution. Early data collection provides a valuable baseline and insights into the environmental conditions and pollution patterns specific to the port, enabling tailored system development. As technology rapidly advances, incorporating new or improved technologies into the existing EMS becomes feasible. This adaptability ensures that the environmental monitoring system remains up-to-date and effective, continuously enhancing its capabilities and accuracy over time. Moreover, embracing a progressive implementation strategy can significantly reduce the initial implementation cost, making it more accessible to a broader range of ports, including those with limited resources. By combining early data collection, agile development, and technology evolution, port authorities can embrace an iterative and innovative approach, reinforcing their commitment to sustainable port operations and environmental preservation.

6.2 Final conclusions

This thesis aimed to explore and evaluate the application of computer vision-based systems for environmental management in ports, specifically focusing on spill and waste detection. Three case studies were conducted, each addressing different aspects of the overall objective. The conclusions from each case study, along with the discussions, have contributed valuable insights to the field of port environmental management and computer vision application. The key findings and implications derived from the individual case studies have to be addressed from an integrated perspective as the tools considered have to merge in the EMS development.

Case 1 Conclusion:

The first case study introduced a probabilistic method for obtaining Integrated Pollution Maps (IPMs) using Monte Carlo simulations. The results demonstrated the validity and potential of IPMs as tools for environmental management in ports. The IPMs showed good consistency with the meteo-oceanographic characteristics of the region under consideration, providing valuable information on potential pollution dispersion patterns. The study highlighted the importance of expert judgment in areas with limited data, emphasizing the need for adequate strategies to overcome these limitations. Future research in this area should focus on the integration of meteo-oceanographic operational system models to further enhance the accuracy and applicability of IPMs in port environmental management.

Case 2 Conclusion:

The second case study investigated the use of computer vision techniques for port water quality identification based on random image sets. The study evaluated the reliability of the method and identified Image Classification as the most suitable approach for real-time marine pollution monitoring, given its high accuracy rates and low training requirements. The study emphasized the potential of progressive implementation, which allows for the development of functional monitoring systems in a shorter time frame while maintaining high accuracy levels. Moreover, the proposed performance metric proved to be effective in assessing computer vision system performance for port environmental management. Future research in this area should focus on developing methods to improve the efficiency of obtaining spill and waste images, considering the challenges associated with camera locations and image quality. Additionally, the consideration of mixed discharge classes and image pre-filtering techniques could lead to algorithms with higher performance metrics.

Case 3 Conclusion:

The third case study concentrated on the operation conditions of a computer vision-based system for waste detection in port waters using pretrained algorithms from the SPILLCONTROL project. The study revealed promising results under certain conditions, particularly for waste detection at operating ranges above 30 meters. However, the system's reliability showed a dependency on image resolution and distance between the camera and the surveilled area. High-resolution images and shorter distances led to improved performance. The study also identified the training of new algorithms with combined resolution image sets as a viable strategy to achieve reliable performance across different resolutions without compromising accuracy. This case study highlighted the feasibility and effectiveness of using computer vision for waste detection in ports, offering a valuable tool for proactive pollution management. Collaborative efforts with port authorities and environmental agencies will be crucial for field validation and system tailoring to meet specific regulatory and operational requirements.

Integrated Perspectives and Future Directions:

The three case studies collectively contribute to the advancement of operational services and computer vision applications in port environmental management. They highlight the potential of such systems to support decision-making processes, enhance monitoring capabilities, and foster proactive pollution management. By integrating the findings from all case studies, several overarching themes and future directions emerge:

Multi-modal Integration: The combination of computer vision data with other environmental data sources, such as meteo-oceanographic data, can provide a more comprehensive understanding of pollution dynamics in ports. Integrating data from various sources will facilitate more accurate predictions and early detection of potential pollution events.

Adaptability and Generalization: CV tools development should focus on obtaining computer vision algorithms that are adaptable to diverse port environments and can generalize well across different waste and spill characteristics. This adaptability is crucial for practical implementation in various port configurations.

Collaboration and Validation: Collaboration between researchers, port authorities, and environmental agencies is vital for the successful validation and deployment of computer vision-based systems. Practical implementation will require a strong partnership to ensure the system's reliability and compliance with regulatory standards.

Sustainability and Cost-Effectiveness: Taking profit from the cost-effectiveness of computer vision systems and at the same time identifying ways to reduce the total development cost while maintaining high accuracy levels will be crucial for their widespread adoption.

6.3 Further investigation

The completion of this thesis has shed light on various aspects of operational systems and computer vision applications in environmental management within port settings. The case studies presented have provided valuable insights and recommendations for practical implementation. However, several areas still warrant further investigation to advance the field and address existing limitations.

Advanced Computer Vision Techniques: While the case studies have explored various computer vision techniques, further investigation into advanced methods is essential. Deep learning algorithms, such as Convolutional Neural Networks (CNNs), have shown promising results in image recognition tasks. Investigating the application of CNNs and other deep learning architectures specifically tailored for environmental monitoring in ports can potentially improve accuracy and generalization capabilities.

Fusion of Multimodal Data: To enhance the overall monitoring process, future research should focus on integrating data from multiple sources. Combining computer vision data with meteo-oceanographic data, remote sensing data, and other environmental variables can provide a more comprehensive understanding of pollution dynamics and assist in the early detection of potential incidents. The development of fusion techniques that effectively integrate these disparate data sources is a promising area of investigation.

Citizen Contribution: A promising approach for collecting, integrating, and analyzing environmental data, particularly in the context of long-term data series related to environmental sciences is Citizen Contribution, allowing citizens to actively participate in monitoring water quality. The analysis of optical properties of water such as color and transparency, obtainable from regular camera images, of port and coastal water enable efficient measurements of key environmental descriptors of its environmental condition encouraging further exploration of citizen contribution as a means to enhance environmental data collection and analysis for improved environmental management and decision-making. [Ceccaroni et al. 2020, Soto et al. 2019]

Real-time Data Processing: Efficient real-time data processing is crucial for proactive pollution management in ports. Investigating the use of edge computing and distributed processing techniques can significantly reduce the time delay between pollution occurrence and detection. Additionally, optimizing data transmission and storage strategies will ensure that large volumes of visual data can be processed and analyzed in real-time.

Robustness and Generalization: The robustness and generalization of computer vision algorithms constitute a fundamental development line. Further investigation is needed to test the algorithms in different port environments and under varying pollution scenarios and develop algorithms that can handle diverse environmental conditions, lighting variations, and weather disturbances.

Human-in-the-Loop Systems: Integrating human expertise into computer vision systems can improve the accuracy and reliability of pollution detection. Investigating the development of human-in-the-loop systems, where numerical simulation and computer vision algorithms work in tandem with human operators, can lead to more effective and adaptive EMS solutions.

Validation and Standardization: Validation of the tools presented in real-world port environments is crucial. Collaborative efforts between researchers, port authorities, and environmental agencies are necessary to conduct field trials and assess the systems' performance under practical conditions. Additionally, standardizing evaluation metrics for environmental monitoring with computer vision will facilitate meaningful comparisons across different studies.

Cost-Effectiveness and Scalability: Further investigation into cost-effective and scalable EMS tools will encourage broader adoption in port facilities of varying sizes and resources. Exploring techniques to reduce hardware costs, optimize computational resources, and enhance system scalability will make these solutions more accessible to a wide range of ports.

Decision Support Systems: Integrating operational services and computer vision-based environmental monitoring systems with decision support tools can enhance the overall effectiveness of port pollution management. Investigating the development of intelligent decision support systems that leverage real-time data and predictive analytics will aid port authorities in making timely and informed decisions.

Environmental Impact Assessment: Extending the application of the tools presented to conduct comprehensive environmental impact assessments can provide valuable insights into the long-term effects of port activities on marine ecosystems. Assessing the environmental impact of port operations using these tools can help identify areas that require targeted interventions for environmental preservation.

Interdisciplinary Collaboration: Promoting interdisciplinary collaboration between meteorologists, experts in hydrodynamics, computer vision, environmental science, maritime operations, and policy-making will facilitate a holistic approach to address environmental challenges in ports. Collaborative efforts will help bridge the gap between technology development and real-world applications, leading to more effective and sustainable solutions.

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