Sustainability And Resilience for Infrastructure and Logistics networks

D2.4 Integration of monitoring information into green resilience management

Deliverable Number	D2.1
Author(s)	Maria Pina Limongelli, Pier Francesco Giordano, Gonzalo Durán Piñeiro, Raquel Ortega Hita
Due/delivered Date	30/11/2024
Reviewed by	Miltiadis Kontogeorgos, Corinna Köpke
Dissemination Level	PUB
Version of template	1.1

Start Date Project: 2023-06-01 Duration: 36months Project ID: 101103978

This project has received funding from the Horizon Europe program of the European Union under grant agreement ID 101103978.

Document contributors

NO.	Name	Organisation	Role (content contributor, reviewer, other)
1	Maria Pina Limongelli	Polimi	Content contributor
2	Pier Francesco Giordano	Polimi	Content contributor
3	Gonzalo Durán Piñeiro	Uvigo	Content contributor
4	Raquel Ortega Hita	Uvigo	Content contributor
5	Corinna Köpke	Fraunhofer	Internal reviewer
6	Miltiadis Kontogeorgos	RINA-C	Internal reviewer
7	Ana Maia	Rangel	Security officer
8	Benjamin Lickert	Fraunhofer	Quality officer
9	Gonzalo Durán	UVigo	Technical officer

Document revisions

Revision	Date	Comment	Author
01	08/07/2024	Table of Content	Maria Pina Limongelli, Pier Francesco Giordano, Gonzalo Durán Piñeiro, Raquel Ortega Hita
02	20/07/2024	Structure of the deliverable	Maria Pina Limongelli, Pier Francesco Giordano, Gonzalo Durán Piñeiro, Raquel Ortega Hita
03	08/11/2024	Draft version 1	Maria Pina Limongelli, Pier Francesco Giordano, Gonzalo Durán Piñeiro, Raquel Ortega Hita
04	12/11/2024	Draft version 2	Maria Pina Limongelli, Pier Francesco Giordano, Gonzalo Durán Piñeiro, Raquel Ortega Hita
05	13/11/2024	Draft for internal revision	Corinna Köpke, Miltiadis Kontogeorgos
06	28/11/2024	Security control	Ana Maia
07	28/11/2024	Quality control	Benjamin Lickert
08	28/11/2024	Technical control	Gonzalo Durán Piñeiro

Executive summary

This deliverable, D2.4, evaluates how monitoring information can be optimally integrated into the management of green resilience, specifically in transportation and civil infrastructure systems vulnerable to natural disasters like floods and wildfires. It represents the report of Task 2.4, which addresses one main gap identified in D2.1, namely the use of information as a decision support tool for green resilience management. D2.4 also builds on the sustainability integration efforts in Task 2.3, where relevant future mitigation and adaptation measures were identified to address infrastructure, transportation and logistics operation challenges. Task 2.4 extends this work by employing monitoring systems and the Value of Information (VoI) framework to optimize resilience strategies, such as predictive maintenance and emergency response, aligning with the sustainability measures and mitigation actions developed in Task 2.3. Positioned within Work Package 2, this deliverable ensures that monitoring insights support sustainable and adaptive management practices for infrastructure systems. It also informs models and simulations developed in WP3, contributing to a comprehensive resilience framework tested across SARIL's scenarios. Key challenges identified in this document include the economic and environmental costs associated with deploying monitoring technologies, balanced against the benefits these systems offer in data-driven decision-making to ensure infrastructure sustainability and resilience.

Monitoring systems, such as satellites and in-situ sensor-based solutions, offer critical insights into infrastructure conditions and risks. Their data supports timely maintenance, optimizes resource allocation, and minimizes environmental impacts. For example, the deployment of Structural Health Monitoring (SHM) systems on bridges affected by scour provides data on the degradation of structural integrity, which helps infrastructure managers make informed decisions on maintenance versus replacement. Additionally, the use of Earth Observation (EO) satellites in wildfire detection, spread assessment, and post-event evaluation aids in rapid response and infrastructure recovery, underscoring their value in resilience planning.

The cost-effectiveness of monitoring systems is further analysed using the Value of Information (VoI) approach. This Bayesian-based decision model evaluates the benefit of new information from monitoring against the costs of inaction or premature interventions. The model underscores the advantages of predictive maintenance over reactive replacements, which incur higher environmental and economic costs. The report concludes that for infrastructure managers, effective integration of monitoring data allows for optimized decision-making, balancing environmental sustainability with economic pragmatism.

List of Contents

List of Tables

List of Acronyms

Acronym	Definition
EO	Earth Observation
EOSDIS	Earth Observing System Data and Information System
EPA	Environmental Protection Agency
ESA	European Space Agency
EU ETS	European Union's Emissions Trading System
ECMWF	European Centre for Medium-Range Weather Forecasts
Froude Number	Dimensionless number comparing inertial and gravitational forces in open-channel flow
GEE	Google Earth Engine
HEC	Hydraulic Engineering Circular
InSAR	Synthetic Aperture Radar Interferometry
LCA	Life Cycle Assessment
NDT	Non-Destructive Testing
PB	Petabyte
POT	Peaks over Threshold
SCC	Social Cost of Carbon
SHM	Structural Health Monitoring
VoI	Value of Information
VoPI	Value of Perfect Information
WSEL	Water Surface Elevation

Glossary

Term	Definition
Earth Observation	The gathering of information about Earth's physical, chemical, and biological systems via remote sensing technologies, especially satellites, used to monitor and assess environmental changes.
Life Cycle Assessment (LCA)	A technique to assess environmental impacts associated with all stages of a product's life from raw material extraction through production, use, and disposal.
Scour	Erosion or removal of sediment surrounding bridge foundations, caused by fast-flowing water, which can compromise the structural integrity of bridges.
Structural Health Monitoring	Techniques and systems that monitor the condition and performance of infrastructure, such as bridges, in real-time to detect and evaluate damage and degradation over time.
Synthetic Aperture Radar Interferometry	A satellite-based technique used to detect and measure ground movement by analysing radar images taken at different times.
Value of Information	A decision-making tool that quantifies the benefit of information gained from monitoring systems, especially in infrastructure management, by comparing informed to uninformed decisions.
Value of Perfect Information	The theoretical value of complete, error-free information for decision-making, often used as a benchmark to evaluate the benefits of monitoring systems.

1. Introduction

Decision-makers often face the difficult task of making critical decisions with limited knowledge about the current condition of their system. Monitoring systems offer a powerful support to decision-making providing real-time data about the system they monitor: an infrastructure, traffic, transportation, or logistic networks.

However, deploying monitoring systems can be costly, prompting a key question for decision-makers: Should resources be allocated to monitoring, or would other type of actions (e.g. retrofitting or replacing for a damaged bridge) be a more effective approach?

Each of these options has different implications for immediate costs, long-term safety, and sustainability. For instance, while replacing a bridge can significantly improve safety, it often involves substantial economic and environmental costs. In contrast, monitoring systems do not directly enhance safety but provide the critical data needed for informed decision-making. However, the economic and environmental footprint of monitoring systems also needs to be considered in the broader context of sustainability.

As climate-related stresses increase and infrastructure ages, it becomes essential to incorporate sustainability into the management of transportation and logistics networks. Sustainable management does not only ensure that the system remains functional and safe but also helps to mitigate environmental impacts, optimise resource use, and increase the long-term resilience of these systems.

Monitoring linear infrastructures, such as roads and tracks, poses additional challenges due to their vast extent and complexity. Installing sensors along these networks is difficult and costly. Despite this, regular inspections are carried out through methods such as scanning vehicles or visual assessments. While these traditional approaches provide valuable information, they can be time-consuming and do not always offer real-time insights. Modern technologies, such as remote satellite monitoring, are emerging to bridge these gaps. Satellite-based systems offer an efficient way to continuously monitor large-scale infrastructure networks, enabling earlier detection of potential issues and allowing decision-makers to manage infrastructure more sustainably and effectively.

Two specific natural hazards—floods and wildfires—are the primary focus of this document, as they are becoming increasingly significant threats to transportation systems, with their frequency and intensity further increased by climate change. Thus, these hazards require urgent attention in the context of infrastructure management.

Floods can cause severe damage, particularly through bridge scour, where rushing water erodes the foundations of bridges and compromises their structural integrity. In such cases, structural monitoring data is crucial for assessing the extent of the damage and guiding decisions about whether immediate repairs or more drastic actions, like full bridge replacement, are necessary. Monitoring not only provides information about the condition of the structure, but also provides the data needed to evaluate trade-offs between safety, costs, and environmental impacts, potentially avoiding more drastic and costly interventions.

Similarly, wildfires pose a growing risk to transportation infrastructure. The increasing frequency and intensity of wildfires, driven by climate change, can weaken critical infrastructure through heat exposure, damaging materials, and destabilising surrounding landscapes. Remote sensing technologies have become vital in wildfire monitoring, providing essential data throughout the fire's lifecycle—from assessing pre-fire conditions and real-time fire spread to post-fire evaluations of burned areas. For transportation networks, this data is key to assess the impact of fires on infrastructure and ensure timely interventions to prevent further damage, such as landslides or road collapses.

The rising threats posed by floods and wildfires underscore the need for comprehensive, real-time data to support sustainable management of transportation infrastructure. Decision-makers must balance the trade-offs between using monitoring systems and taking direct actions, such as retrofitting or replacing damaged infrastructure. Remote sensing technologies, and other data-driven methods offer critical insights that enable more informed, strategic decision-making. By doing so, decision-makers can avoid unnecessary costs and environmental harm, fostering a more resilient and sustainable infrastructure system for the future.

The first section focuses on the regional scenario, examining the use of monitoring systems and the Value of Information (VoI) they provide, particularly within a sustainability framework. Grounded in Bayesian decision theory, the VoI framework helps quantify the benefits of monitoring data relative to the economic and environmental costs of implementing such systems. The analysis specifically looks at how monitoring data can inform decisions, balancing trade-offs between safety, cost, and environmental impact. This section emphasises bridge management during flood events, where scour is a significant threat to bridge foundations. Monitoring systems allow decision-makers to assess the extent of damage caused by floods and determine whether immediate repairs or more drastic interventions, such as full bridge replacements, are necessary.

In the second section, the national scenario is explored, particularly concerning wildfire risk management. Remote sensing technologies, such as satellite monitoring, play a crucial role in wildfire detection, monitoring, and post-fire assessment. These technologies provide critical data on the burned area, fire spread, and emissions, offering valuable support to decision-makers during the entire lifecycle of a fire. This section draws from remote sensing research and tools, which help assess the impact of wildfires on transportation infrastructure and offer insights for sustainable resilience management. By using these advanced monitoring techniques, decision-makers can better evaluate the risks posed by wildfires and take timely actions to mitigate the effects on transportation networks.

Stakeholder roles have been defined for this project (SARIL, 2024), namely:

- Role 1: Developing and Maintaining Transport Infrastructures
- Role 2: Configuring Transport and Logistics Networks
- Role 3: Managing Logistics Operations

This document focuses on role 1 and differentiates it into (a) infrastructure management and (b) traffic management. The functioning infrastructure and traffic are key for roles 2 and 3. Logistics managers also use sensors to monitor their business, but this would be out of scope of this report. However, this analysis of the trade-off between additional knowledge and sustainability aspects for on-sight and satellite-based monitoring systems, might be adapted to other fields of application.

Finally, in section 4 the work is summarised and conclusion are made, emphasizing the importance of integrating monitoring technologies into infrastructure management and space activities to enhance sustainability, reduce environmental impacts, and support long-term resilience in the face of climate change.

2. Role 1a. Infrastructure Manager

2.1 Decision Problems

Managing civil infrastructure during and after catastrophic events poses a complex challenge, requiring a careful balance between ensuring user safety and minimizing functionality losses (Bocchini & Frangopol, 2012). A significant concern in these scenarios is that the health status of individual structures is often uncertain due to various factors, including disaster magnitude, structural properties (such as materials and geometry), and the models used to assess structural integrity, such as fragility curves (Ganesh Prasad & Banerjee, 2013; Zhong et al., 2012). Consequently, technicians typically perform inspections to evaluate structural conditions. However, in the context of large-scale natural disasters, emergency operations and inspections become increasingly complex, requiring the management of multiple assets and consideration of interdependencies both within and between different civil infrastructures (Hammond et al., 2015; Zhang et al., 2022).

Among the pressing issues for transportation infrastructure operators are scour—the erosion of soil around and under bridge foundations due to the action of water—which is recognized as a leading cause of bridge failures worldwide, and seismic actions, which can lead to significant human and material losses. Scour often occurs in conjunction with other hydraulic phenomena, including uplift and drag forces, the impact of large floating objects, and the accumulation of debris. Consequently, bridge operators must define emergency plans to manage bridges during floods, determining when it is safe to close them to traffic.

In addition to emergency protocols, proactive measures such as retrofitting bridge foundations or, when necessary, replacing the bridge entirely, can significantly enhance capacity against hydraulic forces. Retrofitting may involve strengthening existing foundations by adding materials or structural elements designed to improve stability and resistance to scour. This can include techniques such as underpinning, where additional supports are added below existing foundations, or installing specialized scour countermeasures like rock riprap or concrete mats designed to absorb and deflect erosive forces. Such retrofitting efforts can be undertaken before anticipated flood events, providing a critical safeguard for bridge integrity.

Alternatively, replacing a bridge may be warranted when existing structures are determined to be inadequately designed for current or expected hydraulic conditions. This decision may be guided by comprehensive risk assessments that consider factors such as the bridge's age, current condition, and the anticipated severity of flood events exacerbated by climate change. In these cases, new bridge designs can incorporate modern materials and engineering techniques that enhance their ability to withstand extreme hydrological forces. For instance, elevated bridge designs can minimize the impact of rising floodwaters, and deep foundation designs can mitigate scour effects more effectively than superficial ones.

Floods differ from other disasters like earthquakes, as they are influenced by the intensity and duration of meteorological events, along with the shapes and dimensions of catchment areas. This allows for the use of hydrological forecast models to simulate the formation of flood waves. Typically, emergency management actions are triggered when specific hydraulic parameters reach—or are expected to reach—fixed thresholds. A commonly used parameter for determining whether to close a bridge is the Water Surface Elevation (WSEL). For instance, the Idaho Transportation Department's Field Manual (Ayres Associates, 2004) outlines a bridge flood emergency management plan that includes procedures for bridge closures, monitoring, and positioning emergency protections. Bridges may be closed if scour depth exceeds critical levels, if WSEL surpasses critical levels, if structural anomalies are observed, if existing scour countermeasures show signs of failure, or if hydraulic conditions are critical and a flood wave is imminent.

Once a bridge is closed, it must remain so for the duration of the flood, with pre-defined detour routes established to divert traffic. Before reopening, a thorough inspection of the entire structure, including underwater foundations, is necessary to ensure the bridge is safe. This decision-making process typically involves a monitoring crew working alongside local authorities, who visually assess flow evolution and utilize portable devices to monitor WSEL and scour depths. Unfortunately, emergency management often does not rely on fixed scour monitoring devices or Structural Health Monitoring (SHM) systems, which are rarely available during such critical times.

Recently, automated disaster response strategies have been developed, such as the system implemented on the Oloé Bridge in Sardinia, Italy, where vehicle passage is regulated by an automatic system during floods (CAE, 2020). Although structurally sound, the bridge was found not to fully comply with current hydraulic requirements. Instead of replacement, authorities opted for an automatic traffic management system comprising ultrasonic hydrometers, a meteorological station, and two automatic rising barriers that activate when WSEL exceeds critical thresholds established by Civil Protection Plans.

In summary, current emergency plans, despite their technological advancements, still rely on approximate indicators of hydraulic risk, such as critical WSEL, while measurements of scour depth and structural conditions are generally obtained after the flood through visual inspections. While transportation agencies show growing interest in deploying sensors for scour measurement, the adoption of SHM systems—whether vibration-based monitoring or direct scour monitoring—that provide real-time information on bridge conditions during floods is typically overlooked in current emergency protocols.

2.2 Monitoring Strategies

Bridge scour monitoring is essential for maintaining the integrity of bridges with foundations in waterways, especially given the escalating frequency of extreme weather events due to climate change. These events increase hydraulic loads on bridge foundations, making them more susceptible to scour erosion (Prendergast & Gavin, 2014). Scour, the process by which water flow removes soil around or beneath bridge foundations reducing their load-bearing capacity thus posing a serious threat to bridge stability (Briaud et al., 2011). This makes effective and timely scour detection critical to prevent sudden bridge failures, which could otherwise lead to catastrophic consequences (Cook, 2014; Maddison, 2012).

Traditional scour monitoring is largely reliant on visual inspections, where divers assess the foundation conditions (Iacovino et al., 2022). However, this approach is limited by safety concerns, especially during floods when turbid waters obscure visibility, making it difficult to assess the true extent of scour. Additionally, periodic inspections may miss scour damage that has been refilled by sediment deposits in calmer conditions. These limitations have spurred the adoption of sensor-based systems, which provide real-time data on scour evolution without requiring human intervention (Prendergast & Gavin, 2014). These systems include a variety of radar, electromagnetic, and sound wave devices, which monitor scour hole depths near foundations. While these sensors are valuable, they only provide localized information and lack insight into how scour affects the overall structural performance of the bridge.

Non-Destructive Testing (NDT) techniques such as ultrasonic, thermographic, and radar and sound-based systems, and buried rod systems also offer valuable data on scour conditions (Anderson et al., 2007; Zarafshan et al., 2012). NDT methods can detect material loss or hidden damage in submerged structures, but their applicability is limited to areas where access is possible, and they typically require prior knowledge of damage location. Although NDT methods have proven effective in certain applications, the advent of SHM systems has broadened the scope of scour monitoring (Fitzgerald et al., 2019; Prendergast et al., 2013). SHM systems use local sensors permanently installed on the structure or rely on remote monitoring to continuously track changes in key structural parameters, such as modal frequency and damping. Changes in these parameters can indicate scour-induced degradation in real time, allowing asset managers to make proactive maintenance decisions or even trigger alarms during unexpected events. SHM systems provide a more comprehensive view of structural health than local scour sensors, yet they involve higher installation and maintenance costs.

Recent advances in remote sensing technologies, particularly Synthetic Aperture Radar Interferometry (InSAR), offer significant advantages for scour monitoring. InSAR uses satellite radar data to measure ground displacement at the millimetre scale, enabling near-continuous monitoring of bridges over large areas, even during flood conditions (Selvakumaran et al., 2018). The spatial resolution of InSAR has improved to the point where it can detect movement around bridge piers, capturing both ground and structural displacements caused by scour events. This technology's ability to monitor multiple bridges simultaneously across extensive areas makes it a valuable tool for authorities managing infrastructure networks (Macchiarulo et al., 2022; Miano et al., 2024; Nettis et al., 2023).

To assess the cost-benefit balance of each monitoring approach, it is crucial to consider both the data quality provided and the long-term costs associated with deployment and maintenance. Visual inspections, while affordable, lack reliability; sensor-based systems are more effective for local monitoring but may be limited in scope. NDT provides detailed insight but is logistically challenging for inaccessible areas. SHM systems and remote InSAR monitoring stand out for their potential to assess both scour conditions and structural response, making them valuable for high-risk structures. However, high costs associated with SHM installation, operation, and potential flood damage to contact sensors warrant careful cost analysis (P. F. Giordano et al., 2020b, 2022). The continued development of decision-support tools that quantify the value of monitoring data for managing scour risk represents a critical area of research, facilitating informed, timely interventions that can mitigate the impacts of scour on bridge infrastructure.

2.3 Environmental Impact of Infrastructure Monitoring

Value of Information (VoI) is a concept rooted in Bayesian decision theory, which addresses the rational selection of actions in uncertain environments (Benjamin & Cornell, 1970; Raiffa & Schlaifer, 1961). Depending on the information available, three types of analyses can be conducted: Prior, Posterior, and Pre-Posterior analyses. For this discussion, the source of information is assumed to be a monitoring system. The Prior analysis is performed without monitoring data, relying solely on the decision-maker's prior knowledge. The Posterior analysis is conducted once monitoring information becomes available, while the Pre-Posterior analysis is carried out before acquiring new data but modelling their contribution in the decision problem. Bayesian decision theory facilitates decision-making regarding both actions (e.g., whether to restrict traffic on a bridge) and the collection of additional information (e.g., whether to install a monitoring system). VoI plays a critical role in the latter decision, as it is derived by comparing the results of the Prior and Pre-Posterior analyses.

Bayesian decision analysis

The Bayesian decision theory deals with decision-making in uncertain environments, that is when the state of the system, i.e., the bridge in our case, is not known with certainty. Specifically, the decision-maker must select the optimal action among a set of N actions A_n, $n = 1, \dots, N$ with limited knowledge on the system that can be in one of L damage states DS_l, $l = 1, \dots, L$. The optimal action is the one corresponding to minimum expected costs (i.e., the action which maximizes the expected utility (Verzobio et al., 2021)) The decision-maker assigns a probability to each damage state based on the available knowledge she or he has on the system. A monitoring system, which can provide J possible outcomes O_j, $j = 1, \dots, J$, might give insight into the actual condition of the bridge. According to the amount of information available, different decision analyses can be carried out. The decision analysis performed without additional information from monitoring is referred to as Prior decision analysis. When new information is available, the decision-maker can carry out a Posterior decision analysis. Before collecting new information, the decision-maker can carry out a Pre-Posterior decision analysis. The VoI is one of the most relevant outcomes of the Pre-Posterior analysis. The three types of decision analysis and the VoI are detailed in the following sections.

Prior decision analysis

During the prior analysis, the decision-maker i.e. transport infrastructure operator must select the optimal action $\hat{A}$ using the available information on the state of the bridge, i.e., she or he uses the prior probabilities of the damage states to compute the expected cost of each action A_n, as follows:

$$E[c(A_n)|Q] = \sum_{l=1}^{L} E[c(A_n)|DS_l]P(DS_l|Q) \quad (1)$$

where $E[c(A_n)|DS_l]$ is the expected cost of the action A_n when the state of the bridge is DS_l; and $P(DS_l|Q)$ is the prior probability of DS_l, which in the case of scour emergency management can be conditional on the flow rate Q. The term $E[c(A_n)|DS_l]$ can be computed as:

$$E[c(A_n)|DS_l] = c_F(A_n)P(F|A_n, DS_l) + c_{\bar{F}}(A_n)[1 - P(F|A_n, DS_l)] \quad (2)$$

where $P(F|A_n, DS_l)$ is the probability of failure conditional on the action A_n and the damage state DS_l; and $c_F(A_n)$ and $c_{\bar{F}}(A_n)$ are the costs of bridge failure and survival, respectively, which depend on the action A_n. The optimal action $\hat{A}$ is chosen as the one which minimizes the expected costs according to Eq. 3. In general, the optimal action is conditional on the flow rate Q. The cost corresponding to the optimal action is called c_1, see Eq. 4.

$$\hat{A} = \hat{A}(Q) = \arg\min_n E[c(A_n)|Q] \quad (3)$$

$$c_1(Q) = E\left[c(\hat{A})|Q\right] = \sum_{l=1}^{L} E\left[c(\hat{A})|DS_l\right]P(DS_l|Q) \quad (4)$$

Posterior and Pre-Posterior decision analysis

When new information is available, it can be used to update the prior probabilities of the damage states and thus to carry out a Posterior decision analysis. This is done through the well know Bayes' Theorem (Bayes, 1763), which reads:

$$P\left(DS_l|O_j, Q\right) = \frac{P\left(O_j|DS_l\right)P(DS_l|Q)}{P\left(O_j|Q\right)} \quad (5)$$

where $P\left(DS_l \middle| O_j, Q\right)$ is the posterior, i.e., updated, probabilities of the damage state DS_l; $P\left(O_j|DS_l\right)$ is the probability of observing the monitoring outcome O_j conditional on the damage state DS_l, which is commonly named the likelihood function; and the denominator $P\left(O_j|Q\right)$ is the total probability of the monitoring outcome O_j, which is obtained as:

$$P\left(O_j|Q\right) = \sum_{l=1}^{L} P\left(O_j|DS_l\right)P(DS_l|Q) \tag{6}$$

The expected cost of an action A_n, $E\left[c(A_n)\middle|O_j, Q\right]$, is computed similarly to Eq. 1, but considering the posterior probabilities of the damage states:

$$E\left[c(A_n)\middle|O_j, Q\right] = \sum_{l=1}^{L} E[c(A_n)|DS_l]P\left(DS_l\middle|O_j, Q\right) \tag{7}$$

The optimal action $\breve{A}_{O_j}$ and its expected cost $E\left[c\left(\breve{A}_{O_j}\right)|O_j, Q\right]$ depend on the observed outcome O_j, see Eq. 8 and 9.

$$\breve{A}_{O_j} = \breve{A}\left(O_j, Q\right) = \arg\min_n E\left[c(A_n)\middle|O_j, Q\right] \tag{8}$$

$$E\left[c\left(\breve{A}_{O_j}\right)|O_j, Q\right] = \sum_{l=1}^{L} E\left[c\left(\breve{A}_{O_j}\right)|DS_l\right] P\left(DS_l\middle|O_j, Q\right) \tag{9}$$

Before collecting the new information, the decision-maker and/or an infrastructure engineer can carry out a Pre-Posterior decision analysis, in which they “pretend” that the new information from the monitoring system is available. Specifically, a Posterior decision analysis is made for each possible outcome O_j. After that, the resulting expected costs of the optimal actions are weighted over the corresponding probability of the outcome O_j, as follows:

$$c_0(Q) = \sum_{j=1}^{J} E\left[c\left(\breve{A}_{O_j}\right)|O_j, Q\right] P\left(O_j|Q\right) \tag{10}$$

The resulting expected cost $c_0(Q)$ can be understood as the expected cost of the informed decision-making and can be used to quantify the benefit associated with the new information. This is discussed in the following section.

Value of Information

Before installing a monitoring system, the decision-maker can quantify its benefit by means of the VoI which is computed as the difference between the expected cost of the optimal action from Prior analysis, see Eq. 4, and the expected cost of the informed decision making from Pre-Posterior analysis, see Eq. 10, as follows:

$$\mathrm{VoI}(Q) = c_1(Q) - c_0(Q) \tag{11}$$

In the case of emergency management of scoured bridges, the VoI generally depends on the flow rate Q (due to the dependency of the prior probabilities on this parameter). The expected VoI can be obtained considering the Probability Density Function (PDF) of Q, as follows:

$$\mathrm{VoI} = \int_Q \mathrm{VoI}(Q) f(Q) dQ \tag{12}$$

The VoI computed according to Eq. 12 relates to a single flood event. Instead, the decision-maker might be interested in computing the VoI related to multiple events, over a reference period, e.g., the life cycle of the structure or the monitoring system. To address this issue, the Life-Cycle VoI, $\mathrm{VoI_{LC}}$, is introduced (P. F. Giordano et al., 2020a), as follows:

$$\mathrm{VoI_{LC}} = \sum_{i=1}^{T_{LC}} \lambda \frac{\mathrm{VoI}}{(r+1)^i} \tag{13}$$

where T_{LC} is the reference period (in years) considered in the analysis, λ is the expected number of floods in one year, and r is the discount rate. The $\mathrm{VoI_{LC}}$ should be compared to the expected life-cycle cost of the monitoring system over the reference period, C_{SHM}, to obtain the Net Life-Cycle VoI (Pier Francesco Giordano & Limongelli, 2022), $\mathrm{NVoI_{LC}}$as follows:

$$\mathrm{NVoI_{LC}} = \mathrm{VoI_{LC}} - C_{SHM} \tag{14}$$

If the $\mathrm{NVoI_{LC}}$ is negative, the monitoring system should not be installed. Besides, the $\mathrm{NVoI_{LC}}$ can be used to compare different monitoring systems.

Value of Perfect Information

The framework of the VoI presented so far relates to a monitoring system that provides an “imperfect” outcome, which is commonly the case in real applications due to the effect of several sources of uncertainty (e.g., those due to environmental and operational factors or data processing errors). In the ideal case of a monitoring system that provides “perfect” information, the so-called Value of Perfect Information (VoPI) can be computed (Straub, 2014). It reads:

$$\mathrm{VoPI}(Q) = c_1(Q) - \sum_{l=1}^{L} E[c(A^*)|DS_l] P(DS_l|Q) \tag{15}$$

where the term $E[c(A^*)|DS_l]$ represents the expected cost of the optimal action A^* when the state of the bridge is DS_l. The VoPI constitutes the upper bound for the VoI thereby representing the maximum benefit that can be obtained by installing a monitoring system.

Implementation aspects

The application of the VoI framework in practice requires the definition of several elements, specifically: (i) damage states, (ii) prior probabilities; (iii) probabilities of failure, (iv) cost of failure and survival associated with different management actions, (v) likelihood functions for Bayesian updating, and (vi) modelling of scour hazard. In the context of flood emergency management (P. F. Giordano et al., 2020b, 2022), these elements are defined as follows.

Damage states. The L damage states are determined based on scour depth intervals defined by fixed scour thresholds th_l, $l = 1, \dots, L$, where $th_1 = 0$. For $l \neq L$, the bridge will be in DS_l for scour depths y_s in the interval $[th_l, th_{l+1})$. The bridge will be in damage state L for scour depths higher than th_L.

Prior probabilities. The prior probabilities of the different damage states are computed as:

$$\begin{aligned} &P(DS_l|Q) = P[\{y_s \geq th_l\} \cap \{y_s < th_{l+1}\}] && for\ l \neq L \\ &P(DS_l|Q) = P(y_s \geq th_l) && for\ l = L \end{aligned} \tag{16}$$

The scour depth distribution can be computed using equations available in the literature incorporating the uncertainty in the relevant geometric and hydraulic variables. In this study, the Hydraulic Engineering Circular (HEC-18) design formula (Richardson et al., 1993) is used, which reads

$$\frac{y_s}{y_1} = 2.0\lambda_{y_s} K_1 K_2 K_3 K_4 \left(\frac{a}{y_1}\right)^{0.65} Fr_1^{0.43} \tag{17}$$

where y_1 is the flow depth upstream of the pier; K_1, K_2, K_3, and K_4 are the correction factors for pier nose shape, angle of attack of flow, bed conditions, and armoring by bed material, respectively; a is pier width; Fr_1 is the Froude Number, and λ is the model correction factor. The Froude Number is computed as $Fr_1 = V_1/\sqrt{gy_1}$, where V_1 is the mean velocity of flow upstream of the pier; g is the acceleration due to gravity. In this study, for demonstration purposes, the variable y_1 and V_1 are computed using the following equations valid for a channel with a rectangular cross-section:

$$y_1 = \left(\frac{Qn}{Bs^{0.5}}\right)^{3/5} \tag{18}$$

$$V_1 = \frac{Q}{By_1} \tag{19}$$

where Q is the flow rate; B is the average width of the channel; n is the Manning's coefficient, and s is the slope of the channel.

Probabilities of failure. The probability of failure in each damage state is generally evaluated by comparing the capacity of the bridge with the demand imposed by external actions. Several failure modes might be considered, such as vertical failure, overturning, pile buckling, and bending failure. The presence of scour is expected to reduce the capacity of the bridge. Several reliability methods are available to compute the probability of failure (Ditlevsen & Madsen, 1996).

Costs. As for the cost of failure and survival for different management actions, both direct and indirect costs should be considered. More specifically, the computation of the expected cost of the action A_n requires the evaluation of the cost associated with the failure $c_F(A_n)$ and to the survival $c_{\bar{F}}(A_n)$ of the bridge in relation to action A_n. These costs can be obtained by exploiting the models available in the literature, which are usually developed in the context of risk-based assessment of infrastructures (Imam & Chryssanthopoulos, 2012; NASEM, 2007; Zhu & Frangopol, 2013). The following costs are generally associated with the failure of a bridge: (1) rebuilding cost, (2) traffic delay cost, (3) casualty costs, (4) additional indirect costs.

Rebuilding cost includes the cost of demolition of the existing structure and the cost of the new one. In Reference (NASEM, 2007), the total bridge rebuilding cost C_{RB} is computed as

$$C_{RB} = C_1 W L \tag{20}$$

where C_1 is the unit rebuilding cost (€/m2),W and L are respectively the width and the length in m of the bridge.

In case of collapse, partial or complete closure of a bridge, traffic needs to be redirected to another path. This causes traffic delay costs, which generally include the additional cost of running vehicles C_{RN} and the additional cost of time lost C_{TL} due to the detour, which according to Reference (NASEM, 2007) read

$$C_{RN} = \left[C_2\left(1 - \frac{T}{100}\right) + C_3 \frac{T}{100}\right] DAd \tag{21}$$

$$C_{TL} = \left[C_4 O_{car}\left(1 - \frac{T}{100}\right) + C_5 \frac{T}{100}\right] \frac{DAd}{S} \tag{22}$$

where C_2 is the cost of running cars (€/km per vehicle), C_3 is the cost of running trucks (€/km per vehicle), D is the detour length (km), A is the Average Daily Traffic (vehicles/day), d is the detour duration (days), T is the Average Daily Truck Traffic (% of A), C_4 is the value of time of car passengers (€/h per vehicle), O_{car} is the mean occupancy rate for cars, C_5 is the value of time for truck drivers (€/h), S is the average detour speed (km/h).

The casualty cost represents the economic quantification of the charge on society associated with the fatalities caused by the collapse of the bridge. Assuming that no road or activity is present under the bridge, the casualty cost C_{CC} is related to the vehicles falling from the bridge only. In this case, the casualty cost is computed according to Reference (Zhu & Frangopol, 2013) as follows:

$$C_{CC} = \left(\frac{L}{D_S} + 1\right)\left[O_{car}\left(1 - \frac{T}{100}\right) + O_{trk}\frac{T}{100}\right]C_L \tag{23}$$

where L is the length of the bridge (m), D_S is the stopping distance of vehicles crossing the bridge, O_{trk} is the average occupancy rate for trucks, C_L is the average cost of human life loss.

Additional indirect costs generated by the unavailability of a bridge might be considered (Imam & Chryssanthopoulos, 2012). The computation of these costs generated by the unavailability of a bridge is a complex subject and in general the results depend on the boundaries of the cost analysis, such as the time horizon considered (immediate aftermath of the failure or long-term period) and the definition of the system analysed which can be, for instance the single structure, the transportation network or the societal sphere (e.g. psychologic impact, loss of business).

Likelihood functions. The likelihood functions link the monitoring outcome to the damage state of the bridge. Several methods are available to estimate these quantities, see for instance (Pier Francesco Giordano & Limongelli, 2022). In this work, it is supposed the vibration-based SHM system provides the first natural frequency of the structure. The presence of scour modifies the boundary conditions of the bridge and consequently its dynamic properties, including the modal frequencies. Nevertheless, the values of the natural frequencies of structures are generally affected by several sources of uncertainty including environmental and operational factors and vibration data acquisition and processing. The distribution of this modal parameter in the different damage states must account for the different sources of uncertainty. As for the scour depth monitoring system, it directly provides the scour depth at piers which can be directly associated with a damage state. In this work, as a first approximation, it is supposed that the scour depth monitoring system is not affected by uncertainty.

Flood hazard. The VoI is computed before the actual estimation of a monitoring system thereby future flood events must be "forecasted" through a suitable probabilistic model. In this study, we exploit the properties of the Peaks over Threshold (POT) series model (Kottegoda & Rosso, 2009) which is particularly appropriate to represent multiple flood events. Specifically, a flood event is defined in this context as a river discharge event exceeding a flow threshold, Q_0. The POT model is composed of two probabilistic models: (1) a model for the annual number of flood events and (2) a model for the flood magnitude. Herein, we assume that the number of events in one year follows a Poisson distribution. Instead, the flood magnitude is assumed to be exponentially distributed.

Environmental costs

Bridges are a vital part of transportation infrastructure, yet they pose significant environmental challenges, especially as they approach or surpass their designed service life. Many bridges constructed in the 1950s to 1970s are now deteriorating, leading to increased maintenance needs or even replacement. The replacement of aging bridges can have substantial environmental costs. Bridge construction requires vast amounts of steel, concrete, and other materials that are highly carbon-intensive. For instance, each ton of steel produced emits approximately 1.8 to 2.2 tons of CO_2, and concrete production adds an estimated 0.15 tons of CO_2 per ton of material (García-Segura et al., 2014; Kim et al., 2017).

A case study on medium-span steel girder bridges reveals that replacing a bridge of this type results in around 3,407 to 5,143 tons of CO_2 emissions, primarily due to the production and transport of materials (Raeisi et al., 2021). This calculation underscores the importance of reducing the need for replacement by maintaining existing infrastructure whenever possible. Factors contributing to the high emissions in bridge construction include not only the embodied carbon in materials but also the fuel used for transporting materials to the construction site, operating construction machinery, and detours for traffic during construction. Collectively, these activities make the material production and construction phase of bridges responsible for up to 94% of total CO_2 emissions across their lifecycle (Du et al., 2014).

Furthermore, bridge failure has additional environmental and economic implications. When a bridge fails, urgent replacement is often necessary, which can lead to rushed material procurement, increased energy use, and traffic disruptions that contribute to emissions. This risk of unexpected bridge failure highlights the value of preventive maintenance and the need for tools to monitor bridge health effectively to avoid premature reconstruction.

SHM systems are increasingly used to prolong the lifespan of bridges, thereby mitigating the environmental impact associated with their construction and replacement. SHM technology involves installing sensors on critical elements of a bridge to collect real-time data on structural performance, such as load-bearing capacity and stress distribution. By providing early detection of issues, SHM allows for timely maintenance and reduces the likelihood of unexpected failures that require large-scale interventions (Aujoux & Mesnil, 2023; Raeisi et al., 2021). The environmental benefits of SHM are particularly notable when considered over the extended life of a bridge. Studies demonstrate that implementing SHM can reduce the carbon footprint associated with bridge replacement by 9–17%, if SHM extends the bridge's lifespan by an additional 5–10 years. For example, in a state-wide analysis for Iowa, using SHM to extend the service life of structurally deficient bridges reduced cumulative CO_2 emissions by as much as 35% over a 19-year period, and up to 60% with longer-term use (Aujoux & Mesnil, 2023; Raeisi et al., 2021).

However, SHM systems also have their own environmental footprint. The sensors, data acquisition equipment, and energy sources used to run SHM systems contribute to CO_2 emissions. In a detailed analysis of guided-wave SHM systems, the environmental impact was found to be approximately equivalent to the lifetime emissions of ten laptops, primarily due to sensor production and data transmission needs (Aujoux & Mesnil, 2023). Over a 30-year period, a typical SHM system emits about one ton of CO_2, a relatively modest figure compared to the emissions savings achieved through bridge life extension. Energy-efficient designs and renewable energy sources, like solar power, can further reduce the SHM's operational footprint. In scenarios where SHM systems were solar-powered, the emissions associated with energy use were negligible compared to grid-powered setups.

Expressing CO_2 Emissions in Monetary Terms

Monetizing the environmental impact of CO_2 emissions is an essential practice to internalize the costs of greenhouse gas emissions within economic activities. The purpose of assigning a monetary value to CO_2 emissions is to make the environmental impacts more tangible in financial decision-making, influencing choices in policy, project development, and investment. Two main approaches are commonly used to quantify these emissions financially: The Social Cost of Carbon (SCC) and carbon market pricing.

The Social Cost of Carbon (SCC) estimates the economic damages associated with an incremental increase in CO_2 emissions each year. This metric considers a range of adverse effects from climate change, such as extreme weather, health impacts, ecosystem damages, and agricultural disruptions. By assigning a dollar value to the long-term harm caused by each additional ton of CO_2 released, SCC enables policymakers and businesses to incorporate the environmental costs of emissions directly into economic analyses. The SCC is typically determined by complex integrated assessment models that estimate the future damages of current emissions. These models account for projections on economic growth, climate change impacts, and other socioeconomic factors. For instance, the U.S.

Environmental Protection Agency (EPA) uses SCC values to inform regulatory impact analyses, providing a basis for setting emission standards and other environmental regulations (Interagency Working Group on Social Cost of Greenhouse Gases, 2021). By factoring in SCC, construction projects, for example, can more accurately reflect their long-term environmental costs in project planning, life-cycle assessments, and investment decisions (*Valuing Climate Changes*, 2017).

Unlike the SCC, carbon market pricing is based on supply and demand dynamics within regulated markets, where permits to emit CO_2 can be bought and sold. In these markets, also known as cap-and-trade systems, governments or international bodies cap the total amount of allowable emissions and issue emission allowances to companies, who must then hold permits for their emissions. Companies that reduce their emissions can sell their excess allowances to others, effectively placing a price on carbon that reflects the cost of regulatory compliance.

The price of carbon in these markets fluctuates, reflecting economic conditions and the availability of emissions allowances. For instance, the European Union's Emissions Trading System (EU ETS) serves as a key carbon market, where industries pay a market price per ton of CO_2 emitted, which recently averaged between €50-€80 per ton. Carbon market prices are often used as a basis for calculating the financial impact of emissions in sectors like energy, transportation, and construction, providing a practical framework for integrating emissions costs into project budgets and risk assessments (EU, 2024).

While SCC and carbon market pricing provide valuable tools for monetizing CO_2 emissions, they also face challenges. The SCC is sensitive to assumptions about future economic conditions and discount rates, which can lead to variability in the estimated costs of emissions. Carbon market prices, on the other hand, can be volatile and influenced by policy shifts, limiting their stability for long-term planning. Despite these challenges, these approaches are instrumental in moving toward sustainable development by encouraging carbon-efficient practices across industries, including construction.

2.4 Trade-off Between Economic and Environmental Impact of Monitoring

The environmental costs and benefits of SHM are balanced through its potential to reduce or delay bridge reconstruction. By accurately assessing structural capacity and deterioration, SHM technology enables bridge operators to avoid overly conservative assumptions about bridge strength, which are common in visual inspections. More accurate data allows operators to make informed decisions on whether a bridge can continue to serve safely or if limited repairs are needed, thus preventing unnecessary reconstruction. For example, the deployment of strain gauges on a medium-span bridge revealed that actual loads were about 28% lower than design-based estimates, indicating that the bridge was performing above expected capacity. Such findings can justify service life extensions without compromising safety.

Furthermore, SHM systems contribute to a sustainable infrastructure management approach. The data collected over time informs better maintenance scheduling, thereby reducing the frequency of material-intensive repairs and minimizing traffic disruptions. According to life-cycle assessment (LCA) studies, delaying the need for large-scale maintenance or replacement through SHM not only cuts down on CO_2 emissions but also reduces other environmental impacts, such as acidification and eutrophication potential.

In a comparative analysis (Aujoux & Mesnil, 2023), researchers found that the environmental footprint of deploying SHM for railways and wind turbines was manageable, especially when SHM deferred large maintenance interventions. In the case of rail monitoring, a guided-wave SHM system applied over 30 years demonstrated that the environmental cost was roughly equivalent to that of a single round-trip international flight, reinforcing that SHM's carbon footprint is relatively low in long-term applications.

The replacement of bridges has a substantial environmental impact, mainly from the production of construction materials and the energy use involved in construction. SHM systems provide an effective, lower-emission alternative to frequent bridge replacements by extending the life of existing infrastructure and enabling better maintenance practices. While SHM systems have an inherent environmental footprint, their ability to significantly reduce emissions by deferring the need for bridge replacement often outweighs these initial costs. By using SHM systems, infrastructure managers can make more sustainable decisions, minimizing CO_2 emissions and enhancing the resilience of bridge networks.

3. Role 1b. Traffic Manager

3.1 Decision Problem

Making informed decisions is a crucial challenge in sectors such as environmental sustainability and disaster response. Earth Observation (EO) data generated by satellites provide a solid foundation for resource management and strategic planning in areas like agriculture, disaster management, and urban planning. However, there are still barriers to fully leveraging these data, which require a deeper and more specific understanding of their value.

In Europe, the Copernicus Program and the Galileo navigation system provide essential infrastructure for the availability of EO data. The Copernicus Sentinel satellites, particularly Sentinel-1 and Sentinel-2, offer free and open access to critical real-time information that supports areas like environmental risk assessment and regulatory compliance. Sentinel-1, which uses synthetic aperture radar (SAR) for monitoring under any weather conditions, can detect movements in road infrastructure and assess damage to roads and bridges after disasters. Meanwhile, Sentinel-2, with its high-resolution spectrometer, captures details about vegetation health, facilitating the monitoring of wildfires, assessing affected areas, and planning post-fire recovery (ESA, 2024).

Complementing Copernicus, the Galileo system from the European Space Agency (ESA) provides advanced positioning and navigation capabilities designed for civil control and aimed at improving response capacity in emergency situations, such as wildfires. Galileo enables traffic managers to monitor vehicle flows in real-time and adapt evacuation routes, optimizing the emergency teams' response capacity and enhancing public safety. Its search and rescue function detects emergency signals and notifies affected individuals that help is on the way (ESA, 2024).

At a macroeconomic level, Copernicus has conducted cost-benefit studies to justify its investments, although this analysis often limits itself to aggregate impacts and does not always capture the specific value of the data for end-users. To address this gap, the Sentinel Benefits Study (SeBS) was developed, analysing the impact of Sentinel data on specific organizations through a value chain methodology, evaluating six dimensions of benefit: economic, environmental, regulatory, innovation and entrepreneurship, scientific, and societal (Geoff Sawyer, 2022).

NASA's Earth Observing System (EOS) includes satellites like Terra, Aqua, and Landsat, which are essential for infrastructure management and wildfire monitoring. Landsat, with its detailed monitoring capabilities of land cover, allows for the observation of vegetation status and changes, crucial for identifying risk areas and assessing post-fire impacts. Terra and Aqua, with their thermal sensors and surface change detection capabilities, provide critical information for monitoring drought conditions and detecting active fire hotspots, allowing for early and efficient response (NASA, 2022).

NASA, through the Synergy Program, collaborates with end-users, local agencies, and industry to identify specific needs and develop applications that respond to them. This program focuses on educating and training users in EO to facilitate the adoption of data and technology, overcoming barriers such as costs and lack of skilled personnel. Through this program, NASA aims to provide practical and accessible tools that enhance the capacity for risk management and response in various communities (S. Kalluri, 2003).

Together, Copernicus, Galileo, and EOS underscore the importance of overcoming technical and economic obstacles to effectively integrate satellite data into assessment and planning processes. These programs seek to quantify the social and economic benefits of their use, enabling decision-makers to optimize their strategies and responses in real-time. Thus, EO data not only contribute to solving complex problems in strategic sectors but also improve safety and efficiency in critical situations such as disaster management.

3.2 Monitoring Strategies

Effective monitoring strategies are essential for maintaining the integrity and safety of road infrastructure. With the advancement of satellite technology, the integration of data from missions such as Sentinel-1 and Sentinel-2 has transformed how road conditions are assessed and managed.

Monitoring road infrastructure is based on data coming from Sentinel-1, which carries a Synthetic Aperture Radar (SAR) operating in the C-band and which is used to monitor ground movements. The technique, known as InSAR (Interferometric Synthetic Aperture Radar), uses several observations of the ground at intervals of days, weeks, and sometimes months. By using Multi-Temporal Interferometry (MTI) algorithms, it can detect vertical movements of a few millimetres that have occurred between the observations. The EU Copernicus program utilizes data from many satellites to provide global information. At the heart of the program are the Sentinel satellites, which currently number six. Over the past decades, radar satellite technologies have proven useful for monitoring the Earth due to their all-weather, day-and-night capability and the many applications that can leverage their data. More and more application opportunities have emerged, thanks to the improved capabilities of the new space radar sensors in terms of both resolution and revisit time (Sawyer, 2022).

The specific interest for highway management lies in the capabilities of SAR Interferometry (InSAR), which are attractive for different areas of risk management, such as monitoring subsidence, volcanoes, tectonic movements, urban areas, infrastructure, and slope instabilities.

Sentinel-1 is the latest SAR mission launched by ESA, funded by the EU and ESA Member States, with the first satellite, Sentinel-1A, launched in 2014, followed by S-1B in 2016. The two satellites, Sentinel-1A and 1B, provide highly reliable data with a short revisit time, global coverage, and rapid data dissemination to support operational applications (ESA, 2024). Archive data from earlier radar missions, ERS1/2 and ENVISAT, allows for ground instability analyses to be performed across the globe, dating back in time. It is the only tool capable of developing a historical map of ground movement going back to the 1990s when ERS-1 was operational. The analysis of ground and structural deformations to support the planning, design, construction, and operational phases of developing and maintaining highways can benefit from increased utilization of affordable remote sensing systems. Synthetic Aperture Radars, such as that on Sentinel-1, are playing a crucial and growing role. Sentinel-1 offers regular, global-scale coverage, free imagery, and improved revisit time (less than 6 days) and can now guarantee broader and more efficient application of InSAR for global infrastructure monitoring, which is now being applied to highway management cases in Europe (Sawyer, 2022).

In addition to Sentinel-1, the Copernicus program also includes Sentinel-2 (ESA, 2024), which plays a crucial role in road management by providing high-resolution optical data. Sentinel-2 consists of a constellation of two satellites, Sentinel-2A and Sentinel-2B, equipped with a multispectral imaging sensor capable of capturing images in 13 spectral bands, ranging from the visible to the infrared (visible, near-infrared, and shortwave infrared) (ESA, 2024).

The applications of Sentinel-2 in road management are diverse:

- Monitoring Vegetation and Terrain: Sentinel-2 data allows for the assessment of vegetation cover and changes in land use around road infrastructure. This is particularly important for planning and maintenance, as dense vegetation can affect visibility and safety on roads.

- Natural Resource Management: Information about soil and vegetation conditions can be crucial for managing water resources and preventing landslides. Multispectral images help identify areas prone to erosion and other environmental issues that could impact road infrastructure.
- Impact of Wildfires: Sentinel-2 is especially useful for assessing the impact of wildfires on road infrastructure. High-resolution images allow for the detection of changes in vegetation and terrain, facilitating damage assessment. After a wildfire, Sentinel-2 data can be used to identify affected areas, assess the extent of damages, and plan for recovery and rehabilitation of impacted zones. It can also be used to monitor vegetation regeneration in burned areas, which is vital for environmental restoration.
- Air Quality Analysis: By combining Sentinel-2 data with atmospheric models, estimates of air quality in the vicinity of roads can be made, which is essential for public health and the development of sustainable transport policies.
- Development of Thematic Maps: Sentinel-2 enables the creation of thematic maps that can be used for urban development planning and identifying priority areas for infrastructure investment.

Sentinel-2 uses a data transmission system that ensures the rapid availability of information. Data acquisition is performed with a revisit frequency of 5 days in denser areas, allowing for continuous monitoring. Data is processed and distributed through the Copernicus Platform, ensuring that it is available to users in real-time. Sentinel-2 data products include images at varying levels, from level 1A (raw) to level 2A (which includes atmospheric corrections). This allows users to select the processing level that best suits their needs (ESA, 2024).

The combination of data from Sentinel-1 and Sentinel-2 provides a powerful tool for road infrastructure management. While Sentinel-1 focuses on monitoring ground movements, Sentinel-2 offers a detailed view of the surrounding environment and resources around roads. This synergy allows for more informed decision-making, contributing to the sustainability and resilience of transportation infrastructures.

3.3 Environmental Impact of Earth Observation

The rapid expansion of satellites in orbit, driven by increased connectivity and environmental monitoring, has raised significant concerns about their impacts on the environment. It is important to note that research on the impact of satellites is still in its infancy, with few studies exploring this issue in depth. The results of the first studies in the field of the environmental consequences of satellites re-entering the atmosphere are awaited. During this process, these devices can release toxic substances, such as aluminium and nitrogen oxide compounds, which affect the chemistry of the stratosphere and contribute to environmental degradation (Southampton, 2024).

In addition, the growing number of satellites in orbit intensifies problems such as light pollution, which interferes with astronomical observation and affects the habitat of various species. At the same time, the risk of collisions between satellites and fragments of space debris also increases, which could cause significant damage and further aggravate the amount of debris in space. This creates a dangerous cycle that threatens not only functioning satellites, but also future space missions (Gutterman, 2024).

As the number of satellites in orbit continues to grow, it becomes critical to develop a fuller understanding of these impacts and establish appropriate regulations to ensure the sustainability of space and its influence on Earth.

In this context, Earth observation (EO) has expanded exponentially in recent decades, driven by the launch of high-resolution satellite constellations and the growing demand for data for environmental monitoring and climate change research. This massive growth has brought the volume of EO data to approximately 807 petabytes (PB), with an annual growth rate of 100 PB, representing a significant challenge in terms of storage and processing. In parallel, the migration of this data to cloud platforms raises serious environmental concerns, as the storage and transmission of data generates an impact of 4101 tonnes of CO_2 per year, equivalent to the emissions of 41,000 flights between London and Paris. The processing of this data in the data centres of international agencies and commercial providers has optimised the accessibility and efficiency of analysis. However, these improvements have been accompanied by an increase in energy and resource consumption, especially due to the duplication of data across multiple platforms. In this context, there is a growing need to understand and mitigate the environmental impact of expanding EO data infrastructures, as well as to assess the role of cloud versus local processing in terms of energy efficiency (R. Wilkinson, 2024).

The following are some data from the most used missions for land monitoring:

- Sentinel and the Copernicus programme (https://www.copernicus.eu/en): The Sentinel constellation of the Copernicus programme has eight active satellites, including Sentinel-1 and Sentinel-2, which generate large volumes of daily data. In 2019 alone, Sentinel-1 generated 5.5 petabytes (PB) and Sentinel-2, 4.2 PB. The Copernicus archive grew to 34 PB in 2022 and is projected to reach 80 PB in the next six years. Sentinel data is stored and distributed widely among ESA data centres, 21 national collaborative segments and several cloud platforms, creating redundancy and increasing the carbon footprint.
- NASA and the EOSDIS system: NASA's Earth Observing System Data and Information System (EOSDIS) (NASA, 2022) distributed more than 158 million Sentinel files, equivalent to 52.4 PB, in FY2022. This system also includes data from other major missions, such as Landsat, Terra and Aqua, whose volumes have grown from 5.2 PB in 2012 to 98.2 PB in 2022. Data replication on cloud platforms such as Google Earth Engine and Microsoft Planetary Computer allows global access but increases the environmental impact due to energy consumption at these centres.
- Meteorological missions and ECMWF (https://www.ecmwf.int/): The European Centre for Medium-Range Weather Forecasts (ECMWF) is another large EO data manager, with a total volume of 510 PB. Approximately 10% of this volume is EO data, while the remainder includes data from meteorological models. Meteorological missions, such as geostationary satellites, require constant processing to update temperature, humidity and pressure data, which contributes significantly to the CO_2 emissions associated with the storage and processing of this data.

EO data duplication is one of the main causes of redundancy in Earth observation data storage and processing systems worldwide. This replication occurs across multiple platforms and services, such as the data centres of ESA, NASA, and other commercial global access providers, in order to facilitate access to data from different regions and to ensure continuity of data availability. As mentioned at the beginning of this section (R. Wilkinson, 2024), this practice has a considerable environmental impact, equivalent to the emissions of approximately 41,000 one-person flights between London and Paris, demonstrating the magnitude of the problem.

In addition to storage emissions, EO data processing presents additional challenges. There are clear differences between cloud processing and local processing in terms of energy efficiency. The cloud, used in platforms such as Google Earth Engine (GEE) (https://earthengine.google.com/), allows for a more efficient use of resources by sharing processing capacity among many users and reducing energy use compared to the use of personal computers. Operations such as satellite image processing for calculations of vegetation indices or water surface changes show lower emissions in the cloud, but the lack of transparency on the environmental impact of cloud data centres remains a major problem. Because these data centres are in different parts of the world with different carbon intensities in their power grids, users cannot know the exact environmental impact of their activities, preventing them from making informed decisions. Therefore, while the cloud represents a more efficient option, it is critical that providers make transparent their data on the locations, energy consumption and carbon sources of their data centres to realistically assess the sustainability of cloud versus on-premises processing.

Reducing data duplication in EO to mitigate environmental impact is required. Consolidating archives, especially of common datasets such as Sentinel, MODIS, and Landsat, could alleviate pressure on data centres and facilitate the adoption of more sustainable technologies. In addition, improving the transparency of cloud service providers is critical, as the lack of information on the location and energy efficiency of data centres limits users' ability to make informed decisions about the environmental impact of cloud processing; it is recommended that providers share data on energy consumption and electricity sources, allowing users to choose lower carbon regions. Another important factor is the need to adopt reporting practices on emissions generated and encourage sustainability training, ensuring that future research is conducted in a more responsible manner in terms of data management and environmental impact.

Estimation of the costs and benefits of debris mitigation

Space sustainability refers to the ability to maintain space activities indefinitely in a way that minimizes negative impacts on the orbital environment and ensures equitable and continuous access to the benefits derived from space resources for future generations (OECD, 2022) . In recent decades, the commercial exploitation of space and the increasing number of launches have led to a significant rise in the number of objects in Earth’s orbit, including both active satellites and waste, commonly known as space debris. The growing congestion in certain orbits poses serious environmental and economic risks, as well as a threat to the long-term stability of space activities (Darrel Martin-Lawson, 2024).

Space debris, generated by the accumulation of inactive satellites, rocket remnants, and other fragments, presents a critical challenge to space sustainability. The possibility of cascading collisions, described as the "Kessler Syndrome" (Amrith Mariappan, 2023), could trigger catastrophic events that increase the number of debris to levels that would make operations in certain orbits unfeasible. Despite international efforts and recommendations from organizations like the Inter-Agency Space Debris Coordination Committee (IADC), which suggests mitigation measures such as the deorbiting of satellites at the end of their life cycle, the current legal framework remains insufficient and lacks binding enforcement.

Space debris poses a dual environmental and economic threat to the space economy, increasing risks for spacecraft and satellites. The economic costs of space debris are significant, impacting satellite design, operational expenses, collision avoidance, and insurance, along with missed opportunities due to reduced orbital capacity. Although limited, economic research highlights the potential of models addressing property control and market solutions to mitigate debris.

Table 1: Model's main variables

Variable	Name
π	Profit by period of one satellite π
C	Cost of one satellite
N	Number of active satellites
N_j	Number of active satellites of firm j T
p	Probability of destruction of a satellite due to collision
$(1-p)^N$	Probability that no satellite is destroyed
$p(1-p)^{N-1}$	Probability that exactly one satellite is destroyed
$p^{N-1}(1-p)$	Probability that exactly N-1 satellites are destroyed
p^N	Probability that N satellites are destroyed

A theoretical model is developed to examine how the increasing number of participants in the satellite services market affects the probability of collisions and generates external costs (Victoria Ateca-Amestoy, 2022). Market structures (monopoly, oligopoly, and perfect competition) are compared, showing that while risks can be internalized in a monopoly, they are ignored in competitive markets, leading to an increase in the accumulation of space debris. The loss of value caused by space debris is evaluated, considering the reduction in activity and replacement costs, highlighting the importance of implementing mitigation measures in the space sector. In the following Table 1: Model's main variables**Fehler! Verweisquelle konnte nicht gefunden werden.**, a description of the main variables is provided.

Case 1: Single provider of satellite services

When there is a single provider, the optimal number of satellites N^* is determined by considering the collision probability, which increases with N. The revenue per satellite is given by:

$$\pi = a - bN \tag{24}$$

It is assumed that satellites have an infinite lifespan and can only be destroyed by collisions. In this scenario, there are no external costs, as the impact of the satellites on collision probability is internalized. The profits are expressed as:

$$\Pi = D\pi N - CN - DC\rho(N) \tag{25}$$

To maximize profits, the first-order condition is established as:

$$\frac{\partial\Pi}{\partial N} = \frac{\delta}{1-\delta}\left(a - 2bN - C\frac{d\rho(N)}{dN}\right) - C = 0 \tag{26}$$

The marginal revenue must equal the marginal cost, which includes construction, launch, and replacement costs due to collisions.

Once N^* is determined, the company maintains it even after collisions by replacing destroyed satellites. The decision to launch new satellites depends on space debris, which affects the probability of collision and expected profits.

Case 2: Competing provider of satellite services

In a duopolistic market, two providers, A and B, simultaneously and independently choose the number of satellites to launch, N_A and N_B, respectively. The revenue per satellite is given by:

$$\pi = a - b(N_A + N_B) \tag{27}$$

The profits for providers A and B are expressed as:

$$\rho(p, N_i) = \sum_{j=1}^{N_i} \binom{N_i}{j} p^j (1-p)^{N_i - j} \tag{28}$$

$$a - bN = C\left[1 + \frac{\delta\rho'(p, N)}{1-\delta}\right] \tag{29}$$

$$\Pi_A = \frac{\delta}{1-\delta}[a - b(N_A + N_B)]N_A - CN_A - \frac{\delta}{1-\delta}C\rho(N, N_A) \tag{30}$$

$$\Pi_B = \frac{\delta}{1-\delta}[a - b(N_A + N_B)]N_B - CN_B - \frac{\delta}{1-\delta}C\rho(N, N_B) \tag{31}$$

Where $N = N_A + N_B$ and $\rho(N, N_A)$ represents the expected number of satellites damaged due to collisions, influenced by, N_A and N_B.

The first-order conditions yield the optimal number of satellites each provider will launch, depending on the competitor's choices, and define their response functions:

$$\frac{\partial\Pi}{\partial N_A} = \frac{\delta}{1-\delta}\left(a - 2bN - C\frac{d\rho(N, N_A)}{dN_A}\right) - C = 0 \tag{32}$$

$$\frac{\partial\Pi}{\partial N_B} = \frac{\delta}{1-\delta}\left(a - 2bN - C\frac{d\rho(N, N_B)}{dN_B}\right) - C = 0 \tag{33}$$

The optimal number of active satellites is characterized by the Nash equilibrium in this strategic situation. The decision of provider A on how many satellites to launch implicitly depends on N_B, and vice versa.

This strategic interaction arises from the satellite service market, where a satellite's revenue is affected by the number of competitors, and from the externality created by space debris. The optimal number of satellites decreases with collision probability, which is influenced by the decisions of other providers. Unlike the case of a single provider, external effects are not fully internalized in this scenario.

Case 3: A competitive market for satellite services

As the number of satellite service providers increases, the market becomes more competitive. In this section, the case is analysed where each provider is small compared to the market and has an insignificant impact on both the revenue per satellite π and the collision probability p. Each firm treats both ππ and p as fixed and independent of its own decisions.

Thus, each firm decides N_i to maximize its profits following a price-taking and collision probability-taking behaviour:

$$\Pi_i = \frac{\delta}{1-\delta}\pi N_i - CN_i - \frac{\delta}{1-\delta}C\rho(p, N_i) \tag{34}$$

Where:

$$\rho(p, N_i) = \sum_{j=1}^{N_i} \binom{N_i}{j} p^j (1-p)^{N_i - j} \tag{35}$$

In equilibrium for this market structure, demand equals supply, requiring that the fixed collision probability considered by firms in their optimization problems be consistent with the number of active satellites in equilibrium N:

$$a - bN = C\left[1 + \frac{\delta\rho'(p, N)}{1-\delta}\right] \tag{36}$$

Where $\rho'(p, N)$ is the derivative of **Fehler! Verweisquelle konnte nicht gefunden werden.** with r espect to N. It is noted that the private marginal cost does not account for the effect of new launches on the collision probability p, which is treated as fixed.

In this case, firms do not internalize the impact of their decisions on space debris. The supply curve for satellite services reflects the marginal cost of the industry. The fact that each provider considers the collision probability p as fixed (independent of N_i) implies that there is not even a partial internalization of this impact.

Inefficiency and mitigation measures

The efficient solution corresponds to a level of N such that the social marginal cost equals the social marginal value:

$$a - bN = C\left[1 + \frac{\delta\rho'(p, N)}{1-\delta}\right] \tag{37}$$

Where $\rho'(N)$ is the derivative of $\rho(N) = \sum_{j=1}^{N} \binom{N}{j} p(N)^j \left(1 - p(N)\right)^{N-j}$ with respect to N.

with respect to N. Thus, the social marginal cost of a new satellite considers the impact of new launches on the collision probability.

To implement the efficient solution, a fiscal policy could increase the marginal cost for firms to align it with the social marginal cost, ensuring that the number of satellites in equilibrium is socially optimal:

$$\tau = C\frac{\delta}{1-\delta}\left[\rho'^{(N)} - \rho'(p,N)\right] \tag{38}$$

In this section, the external effects imposed on other firms through collision probability and the necessity to replace damaged spacecraft have been emphasized. However, it is important to note that if the collision probability is sufficiently high, economic activity in space may become unviable or unprofitable, leading to a loss of social surplus. The next paragraph focuses on the lost social surplus due to space debris.

Value of space activity

To calculate the total surplus loss due to space debris, we assume a competitive market. The total surplus is the sum of consumer surplus and producer surplus:

$$\int_0^{N^*}\left(a - bN - C - C\frac{\delta\rho'(p.N)}{1-\delta}\right)dN \tag{39}$$

The total surplus in equilibrium with the total surplus that would be generated in the absence of space debris are compared, resulting in an insignificant collision probability. This comparison reveals the value loss due to space debris, which consists of two parts: 1) the loss of space activity and 2) the increased replacement cost of spacecraft due to collisions:

$$\int_0^{N^{**}}(a - bN - C)dN \; - \int_0^{N^*}\left(a - bN - C - C\frac{\delta\rho'(p.N)}{1-\delta}\right)dN \tag{40}$$

To estimate the economic impact of specific space activities, previous empirical studies have based their valuations on four main indicators: 1) job creation; 2) gross domestic product/value-added gross (GDP/VAG); 3) government revenues; and 4) spillover effects. Table 2: provides measures of impact, estimating how much is generated from a 1 EUR investment (PwC, 2019).

Table 2: Estimated returns on EUR 1 of investment in the ESA's Future EO Programme

GPD	Spillovers	Employment
EUR 1.9	EUR 1.9	EUR 2.3

The concept of a sustainable space involves minimizing the negative externalities of human activity in space while maximizing development opportunities in the exploitation and exploration of this environment. The growing generation of space debris poses a threat, as it increases the probability of collisions and could render certain orbits inaccessible, thereby limiting access to a global public good.

The analysis of different market structures—monopoly, oligopoly, and perfect competition—reveals that in fragmented markets, companies do not fully internalize the risks associated with space debris. This highlights the need for accountability mechanisms. Current mitigation measures have been ineffective as they focus on the design and launch phases, overlooking the removal of accumulated debris.

To achieve a sustainable space, a system of Pigouvian taxes (CFI Team, 2016) is proposed to align the marginal costs of companies with social costs, ensuring that the number of satellites in orbit is optimal. Without global regulation, the increase in competition for satellite services could reduce social welfare, making regulatory intervention urgent. Immediate action is crucial to address the space debris problem and ensure a safe and accessible environment for the future.

3.4 Trade-off Between Economic and Environmental Impact of Monitoring

Satellite monitoring has become a crucial tool for resource management and environmental impact assessment, especially in the context of growing concerns about climate change and sustainability. However, it is essential to consider the balance between the economic benefits derived from these technologies and their environmental impacts. The Earth observation sector generates substantial economic advantages for both Europe and the global community. The European Association of Remote Sensing Companies (EARSC) leads the Sentinel Benefits Study (SeBS) project to measure the total societal impact of Sentinel satellite data products and services. The project follows a systematic approach, starting with the primary users of the data and conducting a detailed analysis of the operations of beneficiaries along the entire value chain, ultimately reaching citizens and society. This comprehensive methodology has revealed that individual services can yield millions of euros in benefits. Currently, the SeBS project has analysed eight full cases and five short cases, highlighting the significant economic contributions of the Earth observation sector, which employs 8,400 people and has a turnover of €1.25 billion, with a steady growth rate of 10% (EARSC, 2022).

The economic benefits of satellite monitoring are significant. The ESA estimates that every euro invested in EO programs generates up to €3.8 in the economies of member states, thanks to direct, indirect, and induced effects. Additionally, the Copernicus program, the largest provider of EO data in the world, is projected to generate at least €56 billion in socio-economic benefits between 2019 and 2035 (ESA, 2018). These figures highlight the potential of satellite technology to stimulate economic growth, create jobs, and drive innovation across multiple sectors, from agriculture to disaster management and public health. NASA also emphasizes the importance of satellite monitoring in environmental protection while generating significant economic benefits. NASA's EO programs not only provide critical data on climate and environmental changes but also contribute to substantial economic value. Estimates suggest that NASA's investments in EO technologies have led to economic growth translating into billions of dollars in benefits for the U.S. economy (Wilcox, 2020). This includes job creation in sectors related to technology and innovation, as well as supporting industries such as agriculture, forestry, and water resource management, which rely on accurate data to maximize efficiency and sustainability.

NASA has demonstrated how its satellite technologies can enhance the global competitiveness of U.S. companies, with an estimated impact on EO data value that could reach $1.4 billion per year in benefits for commercial users. This impact is reflected in improved natural resource management and disaster response, which can, in turn, result in significant savings for governments and communities (Wilcox, 2020).

As satellite monitoring strategies intensify, critical environmental considerations also emerge. The development and launch of satellites contribute to the global carbon footprint, and the accumulation of space debris presents a significant challenge for sustainability in orbital space. ESA estimates that the economic damage caused by moderate space weather events could amount to €13 billion over the next 15 years, with potentially higher costs in extreme events. Here, mitigation strategies, such as Active Debris Removal (ADRIOS), can help reduce these costs and promote more responsible space usage while also creating opportunities in a market that could reach at least €2.5 billion by 2036 (ESASpace Debris Office, 2024).

NASA has adopted a holistic approach to sustainability, integrating environmental considerations into all its EO missions. For example, its satellites are designed to measure not only changes in the climate but also how human activities impact ecosystems and biodiversity. This enables decision-makers to apply a data-driven approach to natural resource management, minimizing negative environmental impacts (NASA, 2020).

Moreover, it is crucial to consider how environmental monitoring can yield tangible benefits in the fight against climate change and the protection of biodiversity. The data obtained from EO missions helps governments and organizations monitor compliance with the Paris Agreement and the United Nations Sustainable Development Goals. New capabilities from missions, such as those derived from the Copernicus program, allow for more precise tracking of CO_2 emissions, land surface temperature, and agricultural production, which not only supports environmental policies but can also lead to significant cost savings in resource management.

Investment in monitoring technologies, such as those developed by ESA and NASA, also carries a technology transfer component, where acquired knowledge can be applied to other sectors, benefiting the economy. For instance, technologies developed for the automation of processes in the space industry can be adapted to optimize industrial processes in sectors such as pharmaceuticals and smart city management.

In conclusion, while satellite monitoring strategies generate considerable economic impact, it is vital that these benefits are accompanied by ongoing assessments of their environmental effects. Initiatives promoting sustainability, such as reducing space debris and the responsible use of orbital resources, are essential for balancing economic interests with the urgent need to protect our environment. Ultimately, a balanced approach that considers both economic growth and environmental responsibility will enable Europe and the world to move toward a more sustainable future, using space not only as an economic resource but also as a heritage that must be preserved for future generations.

4. Discussion and Conclusions

The integration of monitoring data into green resilience management is a crucial step toward ensuring the long-term sustainability and reliability of infrastructure systems, particularly as climate change accelerates the frequency and intensity of natural disasters. This report underscores how monitoring technologies—such as SHM systems and EO data—play an essential role in supporting decision-making processes by providing real-time, accurate data on the condition of critical infrastructure. By enabling timely detection of issues like scour, structural damage, and wildfire risks, these systems allow for more informed, proactive maintenance and reduce the need for costly and environmentally disruptive replacements.

One of the primary sustainability benefits of monitoring systems lies in their ability to optimize the management of infrastructure. These technologies help extend the life of existing assets, reducing the need for resource-intensive construction projects. By identifying risks early, monitoring systems allow infrastructure managers to schedule targeted repairs and preventive maintenance, thus avoiding unnecessary replacements that would otherwise consume vast amounts of materials and energy. In this way, they contribute to a circular approach to infrastructure management, ensuring that resources are used more efficiently, and waste is minimized.

Importantly, while the environmental impact of monitoring systems themselves is an important consideration, available studies have demonstrated that their overall environmental footprint is relatively small. The energy consumption associated with the operation of these systems and the production of their sensors and data centres is minimal in comparison to the environmental benefits they offer through more sustainable infrastructure management practices. For instance, satellite-based monitoring and SHM technologies provide real-time insights without the need for frequent on-site inspections, which would otherwise require travel, equipment, and additional resources. The use of these systems significantly reduces carbon emissions from inspection-related activities and lowers the overall demand for new infrastructure.

As monitoring technologies continue to advance, their integration with renewable energy sources and more efficient data processing systems will further minimize their environmental footprint. Additionally, the continued development of remote sensing and data storage practices promises even greater efficiency, making these systems an increasingly sustainable option for infrastructure management.

Looking ahead, the continued use and development of monitoring systems will play an essential role in the creation of resilient and sustainable infrastructure networks. By empowering infrastructure managers with accurate, real-time data, these systems help prioritize interventions that are not only cost-effective but also environmentally responsible. Ultimately, the adoption of monitoring technologies represents a key strategy for balancing the demands of infrastructure maintenance with the urgent need to reduce environmental impacts, fostering a more sustainable and climate-resilient future.

The expansion of Earth Observation (EO) activities and the growing exploitation of space have led to significant economic and scientific advances but also pose urgent environmental challenges that demand immediate attention (see chapter 3.1). In the case of EO, the increasing volume of data, driven by initiatives such as the Sentinel satellites under the Copernicus programme and NASA's EOSDIS system, has enabled precise monitoring of environmental and climate changes (see chapter 3.2). However, this progress comes with a substantial environmental impact due to the CO_2 emissions associated with data storage, processing, and duplication on digital platforms. While the use of cloud services represents an improvement in efficiency, the lack of transparency regarding energy consumption and the sources of electricity used makes it difficult to adequately assess the environmental impact. Redundant data storage across multiple platforms, though crucial for ensuring accessibility, significantly increases the carbon footprint. Consolidating archives and promoting sustainable practices among service providers could help reduce this impact.

The sustainability of space activities faces the challenge of managing a growing number of orbital debris (see chapter 3.3). The proliferation of waste, including inactive satellites and rocket fragments, threatens the stability of space operations and increases the risk of collisions—a problem exacerbated by the potential for Kessler syndrome. Private companies, driven by competition, often neglect the social costs of this debris, further worsening accumulation in the most frequently used orbits. This issue requires regulatory solutions, such as Pigouvian taxes, to align private costs with social costs and encourage sustainable practices. Initiatives such as active debris removal (ADRIOS) (ESA, 2019) and the design of satellites that can be de-orbited at end-of-life represent important, but insufficient, progress. In addition, stronger international governance is essential to ensure implementation and enforcement of effective measures.

From an economic perspective (see chapter 3.4), EO and space activities generate substantial benefits in sectors such as agriculture, disaster management, and climate change mitigation, contributing to GDP growth and job creation. However, these benefits must be balanced with strategies that mitigate the environmental impacts associated with the satellite lifecycle, from construction and launch to operation and decommissioning. For example, EO data are essential for monitoring climate change and supporting international climate policies, underlining the need to integrate these activities into a global sustainability strategy. Furthermore, the technology for monitoring and storing data must consider not only economic efficiency, but also its environmental impact.

In conclusion, the sustainability of EO and space activities relies on a balanced approach that maximises their benefits while minimising their environmental impacts. Transparency in energy consumption by service providers, data consolidation to reduce emissions, and the development of sustainable technologies are crucial steps towards responsible resource management. At the same time, the implementation of regulatory policies, both at the national and international levels, can promote sustainability in debris management and ensure a viable space environment for future generations. Ultimately, EO and space exploitation must be integrated into a broader sustainability framework, where scientific and economic advances align with environmental protection and the preservation of the space environment as a common heritage.

References

Anderson, N.L., Ismael, A.M., & Thitimakorn, T. (2007). Ground-penetrating radar: A tool for monitoring bridge scour. Environmental Engineering Geosciences, 13(1), 1–10. https://doi.org/10.2113/gseegeosci.13.1.1

Anderson, K., Wilkinson, R., Mleczko, M.M., Brewin, R.J.W., Gaston, K.J., Mueller, M., Shitler, J.D., Yan, X., & Anderson, K. (2024). Environmental impacts of Earth observation data in the constellation and cloud computing era. *Science of the Total Environment, 909*(20), 168584. https://doi.org/10.1016/j.scitotenv.2023.168584

Ateca-Amestoy, V., Boukabouy, C., Ciarreta, A., Eiriz, I., & Espinosa, M.P. (2022). Estimation of the costs and benefits of debris mitigation. In *Earth's orbits at risk: The economics of space sustainability* (pp. 1–10). OECD Publishing. https://doi.org/10.1787/16543990-en

Aujoux, C., & Mesnil, O. (2023). Environmental impact assessment of guided wave-based structural health monitoring. Structural Health Monitoring, 22(2), 913–926. https://doi.org/10.1177/14759217221088774

Ayres Associates. (2004). FIELD MANUAL. Scour Critical Bridges: High-Flow Monitoring and Emergency Procedures. Boise, Idaho: Idaho Department of Transportation. https://www.fhwa.dot.gov/engineering/hydraulics/pubs/idfieldpoa.pdf

Ayres Associates. (2004). Field manual. Scour critical bridges: High-flow monitoring and emergency procedures. Idaho Department of Transportation. https://www.fhwa.dot.gov/engineering/hydraulics/pubs/idfieldpoa.pdf

Bayes, T. (1763). An essay toward solving a problem in the doctrine of chances. Philosophical Transactions of the Royal Society of London, 53, 370–418.

Benjamin, J. R., & Cornell, C. A. (1970). Probability, statistics, and decision for civil engineers. McGraw-Hill.

Benjamin, J.R., & Cornell, C.A. (1970). Probability, statistics, and decision for civil engineers. McGraw-Hill.

Bocchini, P., & Frangopol, D. M. (2012). Optimal Resilience- and Cost-Based Postdisaster Intervention Prioritization for Bridges along a Highway Segment. Journal of Bridge Engineering, 17(1), 117–129. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000201

Bocchini, P., & Frangopol, D.M. (2012). Optimal resilience- and cost-based postdisaster intervention prioritization for bridges along a highway segment. Journal of Bridge Engineering, 17, 117–129. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000201

Briaud, J. L., Hurlebaus, S., Chang, K., Yao, C., Sharma, H., Yu, O., Darby, C., Hunt, B. E., & Price, G. R. (2011). Realtime monitoring of bridge scour using remote monitoring technology. In Report No. FHWA/TX-11/0-6060-1 (Vol. 7, Issue 2). http://tti.tamu.edu/documents/0-6060-1.pdf

Briaud, J.L., Hurlebaus, S., Chang, K., Yao, C., Sharma, H., Yu, O., Darby, C., Hunt, B.E., & Price, G.R. (2011). Realtime monitoring of bridge scour using remote monitoring technology. Texas Transportation Institute. http://tti.tamu.edu/documents/0-6060-1.pdf

CAE. (2020). ROADS AT RISK OF FLOODING? SARDINIA INVESTS IN TECHNOLOGY AND SAFETY. https://www.cae.it/eng/news/roads-at-risk-of-flooding-sardinia-invests-in-technology-and-safety.-nw-1364.html

CFI Team. (2016). Pigouvian tax. *Corporate Finance Institute*. Retrieved from https://corporatefinanceinstitute.com/resources/economics/pigouvian-tax/

Cook, W. (2014). Bridge failure rates, consequences, and predictive trends. Utah State University, Logan, Utah.

Cook, W. (2014). Bridge failure rates, consequences, and predictive trends. Utah State University, Logan, Utah.

Corporate Finance Institute. (2016). Pigouvian tax – Overview, how it works, advantages. Corporate Finance Institute. Retrieved from https://corporatefinanceinstitute.com/resources/economics/pigouvian-tax/

Darrel Martin-Lawson, S., Paladini, S., Saha, K., & Yerushalmi, E. (2024). The cost of (Un)regulation: Shrinking Earth's orbits and the need for sustainable space governance. Journal of Environmental Management, 349, 119382. https://doi.org/10.1016/j.jenvman.2023.119382

Ditlevsen, O., & Madsen, H. (1996). Structural Reliability Methods. Wiley.

Ditlevsen, O., & Madsen, H. (1996). Structural reliability methods. Wiley.

Du, G., Safi, M., Pettersson, L., & Karoumi, R. (2014). Life cycle assessment as a decision support tool for bridge procurement: Environmental impact comparison among five bridge designs. International Journal of Life Cycle Assessment, 19, 1948–1964. https://doi.org/10.1007/s11367-014-0797-z

Du, G., Safi, M., Pettersson, L., & Karoumi, R. (2014). Life cycle assessment as a decision support tool for bridge procurement: environmental impact comparison among five bridge designs. The International Journal of Life Cycle Assessment, 19(12), 1948–1964. https://doi.org/10.1007/s11367-014-0797-z

ESA. (2018). Socio-economic impact of space activities. European Space Agency. Retrieved from https://www.esa.int/Enabling_Support/Preparing_for_the_Future/Discovery_and_Preparation/Socio-economic_impact_of_space_activities

ESA. (2019). La ESA encarga la primera misión de eliminación de basura espacial del mundo. *The European Space Agency*. Retrieved from https://www.esa.int/Space_in_Member_States/Spain/La_ESA_encarga_la_primera_mision_de_eliminacion_de_basura_espacial_del_mundo

ESA. (2024). Sentinel-1. Radar vision for Copernicus. *The European Space Agency*. Retrieved from https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-1

ESA. (2024). Sentinel-2. Colour vision for Copernicus. *The European Space Agency*. Retrieved from https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2

ESA. (2024). Sentinel-2 data products. European Space Agency. Retrieved from https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2/Data_products

ESA. (2024). Sentinel-2. Introducing Sentinel-2. *The European Space Agency*. Retrieved from https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2/Introducing_Sentinel-2

ESA Space Debris Office. (2024). ESA's annual space environment report (GEN-DB-LOG-00288-OPS-SD). European Space Agency. https://www.sdo.esoc.esa.int/environment_report/Space_Environment_Report_latest.pdf

EU. (2024). EU Emissions Trading System (EU ETS). https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets_en

ESA. (2024). What is Galileo?. *The European Space Agency*. Retrieved from https://www.esa.int/Applications/Satellite_navigation/Galileo/What_is_Galileo

European Association of Remote Sensing Companies. (2022). Showing the value of Earth observation. EARSC. Retrieved from https://earsc.org/showing-the-value-of-earth-observation/

Fitzgerald, P. C., Malekjafarian, A., Cantero, D., OBrien, E. J., & Prendergast, L. J. (2019). Drive-by scour monitoring of railway bridges using a wavelet-based approach. Engineering Structures, 191, 1–11. https://doi.org/10.1016/j.engstruct.2019.04.046

Fitzgerald, P.C., Malekjafarian, A., Cantero, D., & O'Brien, E.J. (2019). Drive-by scour monitoring of railway bridges using a wavelet-based approach. Engineering Structures, 191, 1–11. https://doi.org/10.1016/j.engstruct.2019.04.046

Ganesh Prasad, G., & Banerjee, S. (2013). The Impact of Flood-Induced Scour on Seismic Fragility Characteristics of Bridges. Journal of Earthquake Engineering, 17(6), 803–828. https://doi.org/10.1080/13632469.2013.771593

Ganesh Prasad, G., & Banerjee, S. (2013). The impact of flood-induced scour on seismic fragility characteristics of bridges. Journal of Earthquake Engineering, 17, 803–828. https://doi.org/10.1080/13632469.2013.771593

García-Segura, T., Yepes, V., & Alcalá, J. (2014). Life cycle greenhouse gas emissions of blended cement concrete including carbonation and durability. The International Journal of Life Cycle Assessment, 19(1), 3–12. https://doi.org/10.1007/s11367-013-0614-0

Giordano, P. F., Prendergast, L. J., & Limongelli, M. P. (2020a). Impact of climate change on the Value of Information for bridges at risk of scour. IALCCE2020.

Giordano, P. F., Prendergast, L. J., & Limongelli, M. P. (2020b). A framework for assessing the value of information for health monitoring of scoured bridges. Journal of Civil Structural Health Monitoring, 10(3), 485–496. https://doi.org/10.1007/s13349-020-00398-0

Giordano, P. F., Prendergast, L. J., & Limongelli, M. P. (2022). Quantifying the value of SHM information for bridges under flood-induced scour. Structure and Infrastructure Engineering. https://doi.org/10.1080/15732479.2022.2048030

Giordano, P.F., Limongelli, M.P., & Miano, A. (2024). Space-borne DInSAR measurements exploitation for risk classification of bridge networks. Journal of Civil Structural Health Monitoring. https://doi.org/10.1007/s13349-024-00832-7

Giordano, P.F., Prendergast, L.J., & Limongelli, M.P. (2020). A framework for assessing the value of information for health monitoring of scoured bridges. Journal of Civil Structural Health Monitoring, 10, 485–496. https://doi.org/10.1007/s13349-020-00398-0

Giordano, P.F., Prendergast, L.J., & Limongelli, M.P. (2022). Quantifying the value of SHM information for bridges under flood-induced scour. Structural Infrastructures Engineering. https://doi.org/10.1080/15732479.2022.2048030

Giordano, Pier Francesco, & Limongelli, M. P. (2022). The value of structural health monitoring in seismic emergency management of bridges. Structure and Infrastructure Engineering, 18(4), 537–553. https://doi.org/10.1080/15732479.2020.1862251

Gutterman, L. (2024). Are satellites bad for the environment? PIRG. Retrieved from https://pirg.org/edfund/articles/are-satellites-bad-for-the-environment/

Hammond, M. J., Chen, A. S., Djordjević, S., Butler, D., & Mark, O. (2015). Urban flood impact assessment: A state-of-the-art review. Urban Water Journal, 12(1), 14–29. https://doi.org/10.1080/1573062X.2013.857421

Iacovino, C., Turksezer, Z. I., Giordano, P. F., & Limongelli, M. P. (2022). Comparison of Bridge Inspection Policies in terms of Data Quality. Journal of Bridge Engineering, 27(3). https://doi.org/10.1061/(ASCE)BE.1943-5592.0001831

Iacovino, C., Turksezer, Z.I., Giordano, P.F., & Limongelli, M.P. (2022). Comparison of bridge inspection policies in terms of data quality. Journal of Bridge Engineering, 27. https://doi.org/10.1061/(ASCE)BE.1943-5592.0001831

Imam, B. M., & Chryssanthopoulos, M. K. (2012). Causes and Consequences of Metallic Bridge Failures. Structural Engineering International, 22(1), 93–98. https://doi.org/10.2749/101686612X13216060213437

Imam, B.M., & Chryssanthopoulos, M.K. (2012). Causes and consequences of metallic bridge failures. Structural Engineering International, 22, 93–98. https://doi.org/10.2749/101686612X13216060213437

Interagency Working Group on Social Cost of Greenhouse Gases, U. S. G. (2021). Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide Interim Estimates under Executive Order 13990. https://www.whitehouse.gov/wp-content/uploads/2021/02/TechnicalSupportDocument_SocialCostofCarbonMethaneNitrousOxide.pdf

Kalluri, S., Gilruth, P., & Bergman, R. (2003). The potential of remote sensing data for decision makers at the state, local, and tribal level: Experiences from NASA's Synergy program. Environmental Science & Policy, 6(6), 487–500. https://doi.org/10.1016/j.envsci.2003.08.002

Kim, T., Lee, S., Chae, C., Jang, H., & Lee, K. (2017). Development of the CO2 Emission Evaluation Tool for the Life Cycle Assessment of Concrete. Sustainability, 9(11), 2116. https://doi.org/10.3390/su9112116

Kim, T., Lee, S., Chae, C., Jang, H., & Lee, K. (2017). Development of the CO2 emission evaluation tool for the life cycle assessment of concrete. Sustainability, 9, 2116. https://doi.org/10.3390/su9112116

Kottegoda, N. T., & Rosso, R. (2009). Applied Statistics for Civil and Environmental Engineers. Wiley-Blackwell.

Macchiarulo, V., Milillo, P., Blenkinsopp, C., & Giardina, G. (2022). Monitoring deformations of infrastructure networks: A fully automated GIS integration and analysis of InSAR time-series. Structural Health Monitoring, 21(4), 1849–1878. https://doi.org/10.1177/14759217211045912

Maddison, B. (2012). Scour failure of bridges. Proceedings of the Institution of Civil Engineers - Forensic Engineering, 165(1), 39–52. https://doi.org/10.1680/feng.2012.165.1.39

Maddison, B. (2012). Scour failure of bridges. Proceedings of the Institution of Civil Engineers – Forensic Engineering, 165, 39–52. https://doi.org/10.1680/feng.2012.165.1.39

Mariappan, A., & Crassidis, J.L. (2023). Kessler's syndrome: A challenge to humanity. *Frontiers in Space Technology, 4*, 1309940. https://doi.org/10.3389/frspt.2023.1309940

Martin-Lawson, D., Paladini, S., Saha, K., & Yerushalmi, E. (2024). The cost of (Un)regulation: Shrinking Earth's orbits and the need for sustainable space governance. *Journal of Environmental Management, 349*, 119382. https://doi.org/10.1016/j.jenvman.2023.119382

Miano, A., Mele, A., Silla, M., Bonano, M., Striano, P., Lanari, R., Di Ludovico, M., & Prota, A. (2024). Space-borne DInSAR measurements exploitation for risk classification of bridge networks. Journal of Civil Structural Health Monitoring. https://doi.org/10.1007/s13349-024-00832-7

Miano, A., Mele, A., Silla, M., Bonano, M., Striano, P., Lanari, R., Di Ludovico, M., & Prota, A. (2024). Space-borne DInSAR measurements exploitation for risk classification of bridge networks. Journal of Civil Structural Health Monitoring. https://doi.org/10.1007/s13349-024-00832-7

NASA. (2020). Space sustainability. NASA. Retrieved from https://www.nasa.gov/spacesustainability/

NASA. (2022). NASA's Earth Observing System (EOS). NASA Earth Observing System Project Science Office. Retrieved from https://eospso.nasa.gov/content/nasas-earth-observing-system-project-science-office

NASEM. (2007). Risk-Based Management Guidelines for Scour at Bridges with Unknown Foundations. In Risk-Based Management Guidelines for Scour at Bridges with Unknown Foundations. https://doi.org/10.17226/23243

Nettis, A., Massimi, V., Nutricato, R., Nitti, D. O., Samarelli, S., & Uva, G. (2023). Satellite-based interferometry for monitoring structural deformations of bridge portfolios. Automation in Construction, 147, 104707. https://doi.org/10.1016/j.autcon.2022.104707

Nettis, A., Massimi, V., Nutricato, R., Nitti, D.O., Samarelli, S., Uva, G., & Zhang, Z. (2023). Satellite-based interferometry for monitoring structural deformations of bridge portfolios. Automation in Construction, 147, 104707. https://doi.org/10.1016/j.autcon.2022.104707

OECD. (2022). Chapter 1: Space sustainability and the OECD. In Earth's Orbits at Risk: The Economics of Space Sustainability. OECD Publishing, Paris. https://doi.org/10.1787/16543990-en

Prendergast, L. J., & Gavin, K. (2014). A review of bridge scour monitoring techniques. Journal of Rock Mechanics and Geotechnical Engineering, 6(2), 138–149. https://doi.org/10.1016/j.jrmge.2014.01.007

Prendergast, L. J., Hester, D., Gavin, K., & O'Sullivan, J. J. (2013). An investigation of the changes in the natural frequency of a pile affected by scour. Journal of Sound and Vibration. https://doi.org/10.1016/j.jsv.2013.08.020

Prendergast, L.J., Gavin, K., & O'Sullivan, J.J. (2013). An investigation of the impact of flood events on bridge scour: A case study. Engineering Failure Analysis, 31, 116–126. https://doi.org/10.1016/j.engfailanal.2012.12.019

PwC. (2019). Socio-economic impact assessments and accompanying foresight study of selected ESA Earth observation activities: Executive summary. ESA. Retrieved from https://esamultimedia.esa.int/docs/business_with_esa/ESA_EO_activites_Impact_Assessment_Executive_Summary.pdf

Raeisi, F., Algohi, B., Mufti, A., & Thomson, D. J. (2021). Reducing carbon dioxide emissions through structural health monitoring of bridges. Journal of Civil Structural Health Monitoring, 11(3), 679–689. https://doi.org/10.1007/s13349-021-00474-z

Raiffa, H., & Schlaifer, R. (1961). Applied Statistical Decision Theory. Division of Research, Graduate School of Business Administration, Harvard University.

Ramírez, A. (2021). New techniques for monitoring and assessing flood-induced bridge scour. Environmental Monitoring and Assessment, 193, 289. https://doi.org/10.1007/s10661-021-09274-2

Richardson, E. V., Harrison, L. J., Richardson, J. R., & Davis, S. R. (1993). Evaluating Scour at Bridges.

Ruddy, P., & Zhang, Z. (2023). Bridge failure prediction from remote sensing data. Journal of Civil Engineering and Management, 29, 456–467. https://doi.org/10.3846/jcem.2023.11835

SARIL, P. (2024). D1.2 Framework for a sustainability and resilience evaluation of strategic logistics networks.

Sawyer, G. (2022). Road infrastructure monitoring in Italy: Final report. *European Association of Remote Sensing Companies (EARSC)*. Retrieved from https://earsc.org/sebs/wp-content/uploads/2022/05/Road-Infrastructure-monitoring-in-Italy-final.pdf

Sawyer, G., Mamais, E., & Papadakis, D. (2022). The six dimensions of value associated with the use of Copernicus Sentinel data: Key findings from the Sentinel Benefits Study. *Frontiers in Environmental Science*. https://doi.org/10.3389/fenvs.2022.804862

Selvakumaran, S., Plank, S., Geiß, C., Rossi, C., & Middleton, C. (2018). Remote monitoring to predict bridge scour failure using Interferometric Synthetic Aperture Radar (InSAR) stacking techniques. International Journal of Applied Earth Observation and Geoinformation, 73, 463–470. https://doi.org/10.1016/j.jag.2018.07.004

Straub, D. (2014). Value of information analysis with structural reliability methods. Structural Safety, 49, 75–85. https://doi.org/10.1016/j.strusafe.2013.08.006

Thorsen, J., & Soria, F. (2015). High-resolution imagery and space technologies in emergency response for urban resilience. International Journal of Disaster Risk Reduction, 14, 72–80. https://doi.org/10.1016/j.ijdrr.2015.08.003

USA.gov. (2023). Federal Bridge Program. USA.gov. Retrieved from https://www.usa.gov/bridge-safety

Valuing Climate Changes. (2017). National Academies Press. https://doi.org/10.17226/24651

Verzobio, A., Bolognani, D., Quigley, J., & Zonta, D. (2021). Quantifying the benefit of structural health monitoring: can the value of information be negative? Structure and Infrastructure Engineering, 1–22. https://doi.org/10.1080/15732479.2021.1890139

Wilcox, K. (2020, October 15). Report quantifies NASA's far-reaching economic impact. *NASA*. Retrieved from https://appel.nasa.gov/2020/10/15/report-quantifies-nasas-far-reaching-economic-impact/

Wilkinson, R., Mleczko, M.M., Brewin, R.J.W., Gaston, K.J., Mueller, M., Shutler, J.D., Yan, X., & Anderson, K. (2024). Environmental impacts of Earth observation data in the constellation and cloud computing era. *Science of the Total Environment, 909*(20), 168584. https://doi.org/10.1016/j.scitotenv.2023.168584

Zarafshan, A., Iranmanesh, A., & Ansari, F. (2012). Vibration-Based Method and Sensor for Monitoring of Bridge Scour. Journal of Bridge Engineering, 17(6), 829–838. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000362

Zhang, G., Liu, Y., Liu, J., Lan, S., & Yang, J. (2022). Causes and statistical characteristics of bridge failures: A review. Journal of Traffic and Transportation Engineering (English Edition), 9(3), 388–406. https://doi.org/10.1016/j.jtte.2021.12.003

Zhong, J., Gardoni, P., & Rosowsky, D. (2012). Seismic fragility estimates for corroding reinforced concrete bridges. Structure and Infrastructure Engineering, 8(1), 55–69. https://doi.org/10.1080/15732470903241881

Zhu, B., & Frangopol, D. M. (2013). Risk-Based Approach for Optimum Maintenance of Bridges under Traffic and Earthquake Loads. Journal of Structural Engineering, 139(3), 422–434. https://doi.org/10.1061/(ASCE)ST.1943-541X.0000671