THE VALUE OF INFORMATION IN ENVIRONMENTAL CONSERVATION AND MANAGEMENT

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Zusammenfassung

Das Umwelt- und Meeresschutzmanagement stellt die Entscheidungsfindung vor große Herausforderungen. Diese Komplexität ergibt sich nicht nur aus den zahlreichen dringenden Problemen, mit denen Entscheidungsträger konfrontiert sind, sondern auch aus den Unsicherheiten in unserem Verständnis der Ökosystemfunktionen und ihrer Reaktionen auf Stressfaktoren. Die Theorie des Informationswerts (Value of Information, VoI) bietet einen Rahmen für die Bewertung der Auswirkungen dieser Unsicherheiten auf Managemententscheidungen aus der Perspektive des Entscheidungsträgers. Die VoI-Theorie, die in Disziplinen wie der Gesundheitsökonomie und dem Management weit verbreitet ist, gewinnt auch im Umwelt- und Ökosystemmanagement zunehmend an Bedeutung. Als entscheidungsanalytisches Instrument quantifiziert VoI die Vorteile der Beschaffung zusätzlicher Informationen zur Verbesserung von Entscheidungsprozessen. Sie hilft Entscheidungsträgern bei der Auswahl der optimalen Managementstrategie und bei der Entscheidung, ob sofortige Maßnahmen erforderlich sind oder ob es vorteilhaft ist, zu warten und in weitere Datenerfassung und Forschung zu investieren. Diese Arbeit trägt zu dem allgemeinen Verständnis der VoI und deren Anwendung auf Entscheidungsfragen im Umwelt- und Ökosystemmangement bei.

Zu Beginn bietet Kapitel 2 einen umfassenden Überblick über Konzepte und Methoden der VoI, gefolgt von einer systematischen Literaturübersicht über VoI-Anwendungen im Meeresschutzmanagement. Die Ergebnisse zeigen, dass VoI trotz genannter Vorteile nur selten in diesem Bereich eingesetzt wird. Dies könnte auf eine langsame Akzeptanz oder auf Schwierigkeiten bei der Anwendung von VoI auf reale Fallstudien zurückzuführen sein. Dieses Kapitel thematisiert auch potentielle Schwierigkeiten für Entscheidungsträger und die Notwendigkeit weiterer Anwendungen sowie die Berücksichtigung dynamischer Entscheidungsfindung und adaptives Lernen in der zukünftigen Forschung. Die nachfolgenden Kapitel 3 und 4 stellen Anwendungsfälle für VoI für reale Entscheidungsprobleme im Umweltmanagement angewendet dar.

In Kapitel 3 wird der VoI-Rahmen zur Analyse eines konkreten Entscheidungsproblems im Wasserqualitätsmanagement angewendet. Auf der Grundlage von realen Daten wird der VoI von Stickstoff-Monitoring berechnet, der als Indikator für den ökologischen Zustand eines Gewässers verwendet wird. Die Ergebnisse zeigen, dass der VoI in der untersuchten Fallstudie signifikant ist. Ferner wird die Abhängigkeit des VoI von den Bewirtschaftungskosten, dem angenommenen Wert eines guten Zustands und dem Grad der Unsicherheit bezüglich des ökologischen Zustands untersucht. Es besteht ein negativer Zusammenhang zwischen den Managementkos-

ten und der Vorabwahrscheinlichkeit, die den VoI maximiert. Diese Analyse bietet eine Orientierungshilfe für die Informationsbeschaffung bei Ungewissheit und begrenzten Daten.

In Kapitel 4 wird der erwartete Mehrwert aus der Beseitigung von Unsicherheiten über das Auftreten von schädlichen Algenblüten in den deutschen Küstengewässern der Nordsee und deren Auswirkung auf die Entscheidungsfindung bewertet. Ein etabliertes dynamisches Nahrungsnetzmodell mit zwei konkurrierenden Phytoplankton-Konsortien (schädlich und nicht schädlich) und regionalen Überwachungsdaten werden verwendet, um die Vorhersagegenauigkeit verschiedener Indikatoren zu analysieren. In diesem Kapitel wird dann anhand einer VoI-Analyse bewertet, wie sich die Verringerung der Unsicherheit bei diesen Indikatoren (z. B. durch eine erweiterte Überwachung) auf die Managemententscheidungen auswirkt. Es wird festgestellt, dass zusätzliche Informationen in diesem Entscheidungskontext zu einem erwarteten Wohlfahrtsgewinn führen können. Dieser Ansatz liefert wertvolle methodische Erkenntnisse zur Optimierung der Ressourcenallokation zwischen Monitoring und Management und zur Verbesserung von Managementstrategien im Fischereimanagement. Außerdem unterstreicht er die Bedeutung der Berücksichtigung von Unsicherheit in Entscheidungsprozessen.

Das letzte Forschungskapitel, Kapitel 5, erweitert die Anwendung des VoI-Konzepts auf die dynamische Entscheidungsfindung, indem es die Theorie der Optimalen Steuerung (optimal control, OC) verwendet. Traditionell wurde VoI vor allem auf statische Entscheidungsszenarien in der Ökologie und im Umweltschutz angewandt, obwohl diese Themen von Natur aus dynamisch sind. In diesem Kapitel wird eine Methode zur Untersuchung des dynamischen Umweltmanagements unter Unsicherheit vorgestellt, die den Wert der Beschaffung zusätzlicher Informationen in einem sich verändernden Kontext hervorhebt. Durch die Integration der VoI-Analyse mit der Theorie der optimalen Kontrolle im Bereich des Umweltschutzes und des Umweltmanagements zeigt das Kapitel, wie diese Methoden kombiniert werden können und welche Auswirkungen die Lösung der Unsicherheit auf den Nutzen der Entscheidungsträger hat. Dieser neuartige Ansatz bietet eine umfassende Analyse des Zusammenspiels zwischen optimaler Kontrolle und VoI und verdeutlicht die Vorteile der Einbeziehung dynamischer Entscheidungsfindung in Umweltmanagementstrategien.

Summary

Environmental and marine conservation management pose significant challenges for decision-making. This complexity arises not only from the numerous urgent issues confronting decision-makers but also from the uncertainties in our comprehension of ecosystem functions and their responses to stressors. Value of information (VoI) theory provides a framework for evaluating the impact of these uncertainties on management decisions from the perspective of the decision-maker. Widely utilised in disciplines such as health economics and management, VoI is becoming increasingly relevant in environmental and ecosystem management. As a decision-analytic tool, VoI quantifies the advantages of acquiring additional information to enhance decision-making processes. It assists decision-makers in selecting the optimal management strategy and determining whether immediate action is necessary or if it is beneficial to delay and invest in further data collection and research. This thesis contributes to the understanding of VoI and its application to decision problems in environmental and ecosystem management.

To begin, Chapter 2 provides a comprehensive review of concepts and methods of VoI followed by a systematic literature review of VoI applications in marine conservation management. The findings reveal that despite clear benefits, VoI is rarely used in this field. This could be due to slow uptake of methods or difficulties in applying VoI to real case studies. This chapter reflects on difficulties for decision-makers, the need for further applications and the need to consider dynamic decision-making and adaptive learning in future research. The following Chapters 3 and 4 represent cases for the application of VoI to real-world decision problems in environmental management.

In Chapter 3 the VoI framework is applied to analyse a relevant decision problem in water quality management. Based on real-world monitoring data, the VoI of monitoring nitrogen is calculated, which is used as an indicator of the ecological state of water body. The results show that the VoI is significant in the analysed case study. Further, the dependency of the VoI on the management cost, the assumed value of a good state and the level of uncertainty regarding the ecological state are investigated. There is a negative relationship between management cost and the prior probability that maximises VoI. This analysis may provide guidance for decision-makers on information acquisition amidst uncertainty and limited data availability.

In Chapter 4, the expected surplus from resolving uncertainty about the occurrence of harmful algal blooms in the German North Sea coastal waters and its effect on

decision-making is evaluated. An established dynamic food web model with two competing phytoplankton consortia (harmful and non-harmful) and regional monitoring data is used to analyse the prediction accuracy of different indicators. The chapter then evaluates the effect of reducing uncertainty about these indicators (e.g., through extended monitoring) on management decisions by means of a VoI analysis. It is observed that additional information may lead to an expected welfare gain in this decision context. This approach contributes valuable methodological insights for optimising resource allocation between monitoring and management and for improving management strategies in the context of conservation management. It further emphasises the importance of considering uncertainty in decision-making processes.

The last research chapter, Chapter 5, expands the application of the VoI concept to dynamic decision-making by employing optimal control (OC) theory. Traditionally, VoI has been applied primarily to static decision scenarios in ecology and environmental conservation, even though these issues are inherently dynamic. The chapter introduces a method for examining dynamic environmental management under uncertainty, emphasising the value of acquiring additional information in a changing context. By integrating VoI analysis with optimal control theory in environmental conservation and management, the chapter showcases how these methodologies can be combined and the impact of resolving uncertainty on the decision-maker's utility. This novel approach provides a comprehensive analysis of the interplay between optimal control and VoI, highlighting the benefits of incorporating dynamic decision-making in environmental management strategies.

Contents

1 Introduction **1**

1.1 General Introduction 1

1.2 Content and Contribution 3

2 The value of information in marine conservation and management: A literature review **5**

2.1 Abstract 6

2.2 Introduction 7

2.3 Concept and characteristics of VoI 9

2.3.1 Decisions under uncertainty 9

2.3.2 Conceptual Approach 11

2.3.3 VoI in environmental management 14

2.4 Survey of VoI applications in marine conservation management 15

2.5 Discussion 23

2.6 Conclusion 27

3 The value of information in water quality monitoring and management **28**

3.1 Abstract 29

3.2 Introduction 30

3.3 Data and Methods 33

3.3.1 Decision problem and data 33

3.3.2 Concept of the value of information 35

3.4 VoI analysis for the Weser River basin 37

3.4.1 Computing conditional and posterior distributions 37

3.4.2 Value of perfect and imperfect information 38

3.5 Dependence on costs and prior probabilities 40

3.6 Discussion and general insights 44

3.7 Conclusion 47

3.8 Appendix 48

4 The value of information in predicting harmful algal blooms **50**
4.1 Abstract 51
4.2 Introduction 53
4.3 Methods 55
4.3.1 Value of information 55
4.3.2 A conceptual dynamical NPPZ model for a HAB 58
4.3.3 Predicted probabilities and warning likelihood 60
4.4 The value of information for shellfish management 62
4.4.1 Model specification 62
4.4.2 Results 64
4.5 Discussion 68
4.6 Conclusion 71
4.7 Appendix 72
4.7.1 Detailed description of the conceptual NPPZ model 72
4.7.2 Figures 76
4.7.3 Case distinction 77

5 Combining optimal control and value of information for dynamic environmental decision-making **80**
5.1 Abstract 81
5.2 Introduction 82
5.3 Methods 84
5.3.1 Problem Statement 84
5.3.2 Optimal Control with Perfect Information 85
5.3.3 Optimal Control under Prior Information 88
5.3.4 Value of Information 91
5.4 Results 91
5.5 General insights and conclusion 94

6 Discussion and concluding remarks **95**
6.1 General discussion 95
6.2 Outlook 101

Bibliography **102**

List of Figures **118**

List of Tables **120**

Acronyms **121**

1 Introduction

1.1 General Introduction

Anthropogenic pressure and influences on our natural systems require effective management of resources and ecosystems to mitigate degradation and exploitation. Yet, our understanding of the natural world and its functioning is inevitably incomplete due to nature's complexity and stochasticity. Uncertainty is pervasive, and as a result, management decisions in resource management and nature conservation are affected at every level, which makes effective decision-making a difficult task.

One way to attempt to reduce uncertainty is to improve our understanding of the system's state or dynamics by generating or acquiring information that increases our knowledge. From an applied scientist's point of view, advocating for further research and the collection of new data is always desirable. However, data collection is also always an economic consideration. For example, in marine research in particular, we are confronted with a high degree of uncertainty regarding the status of the ecosystem under consideration, while at the same time, data collection, such as on-site measurements, is very elaborate. Especially in remote areas such as the Arctic or Antarctic or the deep sea, research relies heavily on the collection of comprehensive and continuous data, but the collection of these data is characterised by the immense costs of research projects. These costs are often higher than comparable research projects in terrestrial areas because of the mere location and inaccessibility of these places, the specific equipment needed and time resources. To name an example, the total costs of the ice drift expedition MOSAiC (Multidisciplinary drifting Observatory for the Study of Arctic Climate) of the research vessel "Polarstern", which was to study the influence of the Arctic on the global climate, is estimated at about 140 million euros [1].

An additional consideration for decision-makers is not only the significant costs of data collection while budgets are often limited but also the time-sensitivity of environmental issues: many pressing problems require immediate decisions whilst there

[1] https://www.kooperation-international.de/aktuelles/nachrichten/detail/info/ergebnisse-der-mosaic-driftexpedition-veroeffentlicht

is still the opportunity to act to avoid further, perhaps even irreversible, damage to the ecosystem or the potential extinction of species (Martin et al., 2012). Against the background of these considerations, it is imperative for the decision maker to decide what data should be collected, where, when, and to what extent, as well as what information can be derived from it.

Therefore, information has, in addition to its epistemic value, an economic value, and the question arises: When is it worthwhile to invest in the acquisition or collection of additional information or data? Does, from a decision maker's perspective, more information lead to more substantiated decisions? Or would a decision based on current knowledge and estimates result in the same outcome? These questions can be addressed by *Value of Information* (VoI) analysis as a suitable tool for objectifying decisions according to quantifiable criteria. VoI analysis provides a rigorous decision-analytic instrument to quantify the decision maker's expected welfare gain from acquiring additional data. This method has been predominantly applied to decision problems in health economics. An example would be the decision of whether to consider an extensive cancer screening while trading off the benefits of screening and potential early detection and its economic cost and implications for the patient (Hassan et al., 2009). In the literature on environmental management and conservation, VoI analyses appear increasingly but are still widely underrepresented, especially in real decision problems and case studies (Bolam et al., 2019). Possible reasons why VoI remains underused as a tool to improve management include technical challenges of calculations or merely being unfamiliar with decision analytic principles (Canessa et al., 2015).

This thesis explores the concept of VoI, specifically in contexts of environmental conservation decision-making. The objectives of this thesis are twofold:

1. **Demonstrate the applicability of the VoI concept to environmental management and (marine) conservation contexts.** The application of the well-established VoI concepts and methods to current conservation issues is in itself a relevant contribution as these techniques remain underrepresented in environmental contexts.

2. **Identify methods to incorporate dynamical decision-making in VoI analysis.** Applying VoI in a dynamic decision setting is a challenging task, both conceptually from the perspective of modelling and technically in terms of the efficient calculation of values. Yet, environmental problems are characterised by long-term effects and persistence, as well as large uncertainties. This requires flexible policies in the face of uncertainty.

1.2 Content and Contribution

This thesis consists of four research chapters, each an individual scientific manuscript on decision-making and the value of information in conservation management. The chapters are organised in a clear order and build on one another as the complexity of the system under study increases. All the cases are meant to be extendable or adjustable to different decision contexts.

To begin with, Chapter 2 provides an extensive literature review of the developments of VoI theory and applications in different fields of research. A special focus lies on VoI applications in marine conservation and management, and a systematic literature survey is being conducted. Further, Chapter 2 provides a comprehensive overview of the theoretical foundations and concepts of VoI.

The next two Chapters focus on applications of VoI to distinctive problems in environmental management. Chapter 3 treats a decision problem in water quality management, where the decision maker is uncertain about the ecological state of the water body. The focus lies on the Weser, a river in Northern Germany entering the North Sea and hence contributing to the water quality in coastal waters. To reach the target of obtaining or maintaining a 'good status', the decision maker needs to decide on management interventions that are dependent on the current (uncertain) state of the water body. A VoI analysis is conducted to quantify the the utility gain of investing in monitoring activities before deciding on a management action. To base the decision problem on real data, conditional probabilities are estimated from monitoring data of the Weser River. The strong dependency of VoI on crucial parameters such as prior probability and management costs is being highlighted and discussed to help understand how the optimal decision on data acquisition (or, in this case, monitoring activities) depends on the primitives of the decision problem. This chapter not only treats the application of the VoI concept to a real-world decision problem but also contributes generically valid insights for decision problems of similar structure.

In Chapter 4, a VoI analysis is conducted to evaluate the expected benefit of harmful algal bloom (HAB) predictions for fisheries management in the North Sea. HABs can have detrimental economic effects on fisheries, but their occurrence remains uncertain. This analysis is based on a dynamical foodweb model of the North Sea, describing the interplay of two competing phytoplankton consortia (harmful, non-harmful), zooplankton and nutrients over time. In combination with data from literature and regional monitoring data, time series data are simulated to analyse the prediction accuracy of different indicators. The effect of reducing uncertainty about these indicators (e.g. through extended monitoring) on management decisions is assessed by employing a VoI analysis.

In the last research Chapter, VoI theory is embedded in a dynamic, intertemporal decision-making framework. Chapter 5 attempts to combine the optimal management of an ecosystem over time under uncertainty about a parameter of the system and VoI analysis. In a novel approach, optimal control theory (OC) is extended to include uncertainty and the benefit of resolving this uncertainty is evaluated. As this method becomes computationally complex very quickly and only numerical results are available for more complex models, we provide a methodological framework and show the steps involved using the example of a simple optimal control model of an ecological system. This analysis builds on a similar decision problem as presented in Chapter 3 but extends it to incorporate an intertemporal element. In this way, Chapter 5 addresses the second objective of this thesis and offers an extendable framework for combining optimal control of a dynamic system and management under uncertainty.

2 The value of information in marine conservation and management: A literature review

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This chapter in in preparation for submission.

2.1 Abstract

Decision-making in environmental and marine conservation management is a challenging task. Not only because of the many pressing issues that decision-makers face but also because our understanding of ecosystem functioning and its response to stressors is fraught with uncertainty. Value of Information (VoI) theory offers an approach to understanding the impact of uncertainty on the management decision from a decision maker's perspective. VoI is commonly applied in fields such as health economics and management and is increasingly used in environmental and ecosystem management. VoI is a decision-analytic tool to quantify the benefit of additional information collection in order to improve decision-making. It enables decision-makers to select the best management alternative and to assess whether management should take place immediately or if it is worthwhile to postpone management and invest in data collection and further research. This article provides the first comprehensive review of VoI applications related to marine conservation management published in peer-reviewed English language journals by the end of the year 2023. We first provide a broad overview of developments and VoI applications in various fields and we provide a comprehensive conceptual overview on calculating VoI. We then identify applications in marine conservation management, conduct a systematic literature review and characterise various attributes of VoI applications. We show that VoI analysis is still rarely used in marine conservation management, even though its clear benefits are shown in the literature and applications. This may be either due to a slow uptake of methods in the field or due to difficulties in application to real case studies. This article reflects on difficulties for decision-makers and the need to consider dynamic decision-making and adaptive learning in future research. This article offers important insights into VoI applications in marine conservation management.

Keywords: value of information; decision analysis; environmental management; marine conservation; literature review; uncertainty
JEL: C11, C61, D81, Q25, Q57

2.2 Introduction

Not only since the United Nations' call to generate knowledge for the sustainable management of our oceans within the UN Ocean Decade 2020-20230, decision-making and the management of resources and ecosystems have been crucial for sustaining biodiversity and nature's contribution to people (NCP). Environmental management aims to balance the conservation of ecosystems and their natural resources with financial and economic gains. To this end, many resources are invested in generating data and knowledge to enable policymakers to make the most informed decisions.

However, our knowledge is and will always be incomplete, and many uncertainties remain – this is especially true for highly dynamic systems like our oceans. These uncertainties may arise from the system's behaviour in response to stressors, its dynamics or its reaction to management interventions. Therefore, managers are faced with a trade-off: decisions about management interventions can be postponed until some of the uncertainties have been resolved, or they can be made immediately in the face of uncertainty. The latter may seem plausible in the face of many pressing challenges that need immediate intervention to avoid catastrophic outcomes (Martin et al., 2012). However, acting under uncertainty and incomplete or flawed knowledge risks resulting in ineffective or even counteractive management decisions. The other option would imply that managers invest time and resources in gathering additional information to make more substantiated decisions. In this scenario, though, there is a risk of further ecosystem degradation or, at worst, species extinction, making it more difficult to reach management targets – or even impossible in the drastic case of species extinction. Postponing the decisions and waiting for more information can also be used as an avoidance tactic in fear of making the wrong decision (Nichols and Williams, 2006). At the same time, data collection, such as on-site measurements or satellite observations, is frequently very costly and involves many resources. Therefore, acquiring or collecting more information is also a financial consideration – budgets for conservation management are usually limited, making a well-planned allocation of financial (and other) resources crucial. So, as Bolam et al. (2019, p.630) put it, we are faced with "two important questions that are relevant for environmental managers: how should decisions about natural resource management be made in the face of uncertainty, and when is it valuable to reduce the uncertainty before committing to a course of action?".

The concept of *value of information* (VoI) offers a tool to address this trade-off. VoI is concerned with the second question, placing it in the context of the first question:

It quantifies the expected benefit of eliminating or reducing uncertainty by means of information acquisition *before* a decision is made. VoI is, first of all, a decision-theoretical economic concept that allows economic actors to make decisions in situations characterised by substantial uncertainty. Specifically, acknowledging that the decision on the primary problem is conditional on the information available at the time when that decision is made enables us to attribute any piece of information a value, the value that piece has for an improved achievement of the objective function. The secondary problem results from the fact that the piece of information received is not known when the decision of information acquisition is made. Hence, while the state is not known in the first place, the piece of information that is hoped to provide an indication of the state is not known. For this reason, the calculation of VoI involves taking double expectations with respect to the state and to the piece of information (on the likelihood of state) received. In this way, VoI provides a measure for the benefit resulting from the (best) expected action taken on the basis of the unknown information that will be received. Since VoI evaluates information, or more broadly knowledge, only by the consequences induced by the acts chosen on its basis on the resulting payoff, VoI is a purely consequential concept, disregarding any epistemological value of knowledge.

Value is usually understood as a measure in financial terms, however, VoI analysis does not require this restrictiveness and value can be understood in a wider sense: any quantifiable measure that the decision-maker regards as valuable can be incorporated, such as the abundance of fish, the number of species conserved or the reduced risk of extinction. Thus, VoI helps, in the first place, to make more well-judged decisions on the procurement of information, in general, and on data collection, in particular. In this way, VoI paves the ground for enhanced decision-making in the primary problem: to arrive at better decisions on the basis of enhanced information if this enhancement is economic.

The idea that information has both statistical and practical usefulness has been around since the 1950s. The development of these ideas was derived from the fundamental work by Von Neumann and Morgenstern (1947), Wald and Wolfowitz (1948), Blackwell and Girshick (1954) and Savage (1954) to understand decision making under uncertainty. However, it was Raiffa and Schlaifer (1961) who were among the first to formulate the main concepts and coined the term "value of information". They aimed to help corporate executives make better judgments by using statistical inference and sampling techniques in real-world decision-making situations where more knowledge about the state of the world could be gathered through experimentation. Marshak (1974a,b) and Howard (1966, 1967) were also among the earliest contributors to the development of the key ideas of VoI. The economists mainly drove the early development of the concepts and ideas of VoI, with prominent work being done by Howard (1966, 1967); Bellman (1971); Gould (1974); Hanemann (1989). These papers discuss and provide examples of the notion of the value of information that results from concurrently taking into account economic and probabilistic decision-making considerations.

Since its inception, VoI analysis has been increasingly applied in various fields, predominantly in economics and medicine, as well as in agriculture, information science, and engineering. More recently, applications in environmental conservation and ecology have been increasing. Keisler et al. (2014) collected and analysed statistics on the variety of applications of VoI in peer-reviewed publications from 1990 to 2011, discovering trends and patterns and interpreting what this means for scholars and practitioners exploring new endeavours. The concept of VoI has a long and diverse history of development and application, with its roots in decision theory and management science. Over the years, it has proven to be a useful tool for evaluating the worth of obtaining information in various fields, including ecology and environmental economics, where it has helped decision-makers make more informed decisions leading to better environmental outcomes.

In this article, we provide an overview of the concept of VoI and review the VoI literature in environmental management and conservation, specifically applications in marine management. Further, we will reflect on the difficulties when it comes to applying VoI in real-world scenarios, why it may be useful, and how even simplified scenarios may provide valuable insights.

2.3 Concept and characteristics of VoI

2.3.1 Decisions under uncertainty

Most management and policy decisions in environmental conservation, marine management, and biodiversity protection are subject to uncertainty. Over time, the state of the environment changes, and so does the decision maker's information level. As time proceeds, the decision maker acquires new information either through the (automatic) arrival of further data or through the active gathering of new data. Typically, early decision-making is advisable or even required, as pressing environmental issues require decision-makers to act fast, while postponement of decision-making allows for the arrival or the acquisition of new information and data that may lead to more deliberate decisions.

Although uncertainty about the true or future state may dissolve almost automatically as the mere advance of time may reveal more and more information, the decision-maker usually cannot or simply does not want to wait to make their decision until this (distant) point in time. As decisions in conservation management depend on the extent of uncertainty and thus on the available information, it is crucial to identify the sources of uncertainty that have the most decisive influence on the choice of action. Concomitantly, we identify the sources of uncertainty that are most valuable to reduce in order to improve the outcomes of policy or management decisions.

Uncertainties may stem from our imperfect understanding of the natural world and our impact upon it, particularly on the efficacy of policy interventions. Decision makers must, therefore, first identify potential sources of uncertainty regarding the state of the world and our (imperfect) understanding of it, as well as how these sources may influence our actions. These uncertainties can manifest as either irreducible, originating from unforeseen sources (aleatory uncertainty), or reducible, stemming from our incomplete grasp of the system due to knowledge gaps (epistemic uncertainty). Within the category of resolvable uncertainty, uncertainties may be classified as parametric (uncertainty about parameter values), non-parametric (uncertainty about the distribution of state variables), or structural (uncertainty regarding model specifications). (We refer the reader to Morgan et al., 1990 and Regan et al., 2002 for a more detailed description of the categorisation of uncertainties.) Subsequently, upon identifying the resolvable types of uncertainty, decision-makers must capture the extent of uncertainty. Bayesian statistical techniques are valuable for analysing empirical data, as they offer posterior distributions that directly articulate probabilities of parameter values. Alternatively, for analyses reliant on expert judgement, various elicitation and aggregation methods exist to generate estimates (Burgman, 2005; Martin et al., 2012). The next step involves propagating uncertainty through model predictions to derive probability distributions for the state variables of interest. Finally, and most crucially, decision-makers must ascertain how to manage uncertainty in their decision-making process. This involves evaluating whether it is worthwhile to resolve uncertainty and, if so, to what degree before arriving at a decision. At this point, VoI analysis comes into play.

Formalising even a simple VoI problem requires several steps for the decision-maker and analysts:

- definition of the objectives, viz. the objective function

- identification of the relevant uncertainties, viz. the random variables determining "the state (of the world)"
- prior belief about the distribution of the states
- identification of the set of available actions
- analysis of the consequences of each action contingent on the state

These components form the basis of a risk analysis and similarly provide the basis for the VoI analysis. In the next section, we provide the formal approach to calculate VoI.

2.3.2 Conceptual Approach

Considering a system that visits a state $x \in \Omega$, Ω a discrete set (for a continuous set, sums must be replaced by integrals), and that in combination with an action $a \in A$ generates the value (or payoff) $v : A \times \Omega \to \mathbb{R} : (a, x) \mapsto v(a, x)$. Since states are unknown to the decision maker beforehand, they are considered as a realisation of a random variable X that is distributed in Ω according to a prior $p_X(x)$.

Raiffa and Schlaifer (1961) were the first to introduce the concept of the *expected value of perfect information* ($EVPI$) about the true state of the world.

$$\begin{aligned} EVPI : &= \mathbb{E}_X \left[\max_{a \in A} v(a, X) \right] - \max_{a \in A} \mathbb{E}\left[v(a, x)\right] \\ &= \sum_x \max_a v(a, x) p_X(x) - \max_a \sum_x v(a, x) p_X(x) \\ &= \mathbb{E}_X \max_a v(a, X) - \max_a \mathbb{E}_X\, v(a, X) \geq 0\,, \end{aligned}$$

where the first term on the right-hand side, $\mathbb{E}_X \left[\max_{a \in A} v(a, x) \right]$ presents the expected utility after being informed about the realisation of X.

The second term on the right-hand side describes the maximum expected outcome under prior information (i.e., the expected benefit resulting from adopting the management action with the highest expected benefit). The added value beyond the value reached by using only the prior distribution is always non-negative.

The decision maker may face multiple sources of uncertainty. Howard (1966) introduced the idea of perfect information about a single uncertain parameter when multiple uncertain parameters are present in a model: The *expected value of perfect X (partial) information* (EVPXI). Here, X represents an uncertain model input.

$EVPXI$ is a useful measure to identify the relevance of reducing uncertainty about the different inputs.

$$EVPXI := \mathbb{E}_X \left[\max_{a \in A} \mathbb{E}_{Y|X} \left[v(a, X, Y) \right] \right] - \max_{a \in A} \mathbb{E}_{X,Y} \left[v(a, X, Y) \right].$$

Here, the first term represents the situation where the decision maker is informed about the realisation $X = x$ while no (additional) information on Y is revealed before a decision is made. By comparing $EVPXI$ for different subsets, it can provide a measure to evaluate the value of reducing a variety of uncertain components (Runge et al., 2011). Due to the non-additivity effect, $EVPXI$ estimates cannot be derived from $EVPI$ and $EVPI$ can not be yielded by adding up all $EVPXI$ estimates (except in few specific cases) (Howard, 1966; Samson et al., 1989).

As reducing uncertainty to zero is impossible in most cases, the *expected value of sample information* (EVSI) also referred to as the *expected value of imperfect information* (EVII) is a valuable measure. Instead of obtaining perfect information on the state X, one can reduce uncertainty by observing information on a message or indicator m (e.g., from monitoring data), which gives an indication on the probability distribution of X. This could be the case, for example, when we observe a variable that serves as an indicator for the state of the ecosystem (such as Chlorophyll a, which is often used as an indicator for phytoplankton biomass).

Since this information is not known in advance, it represents a realisation of a random variable M with possible values in $\mathcal{M}$ and with probability distribution p_M. This way, any message of M indicates the probability distribution of X and the decision maker updates their belief when receiving message $M = m \in \mathcal{M}$. In the course of belief updating, the prior distribution $p_X(x)$ should be replaced by the more informative posterior distribution $p_{X|M}(x|m)$. We can interpret the probability distribution of the possible message p_M as information/message, which induces the conditional information $p_{X|M}$ on the distribution of X. The excess value beyond the reference set by the prior distribution, $EVSI$, should be calculated as

$$\begin{aligned} EVSI: &= \mathbb{E}_M \left[\max_a \mathbb{E}_{x|m} \left[v(a, X) \right] \right] - \max_a \mathbb{E}_X \left[v(a, X) \right] \\ &= \sum_m \left[\max_a \sum_x v(a, x) p_{X|M}(x|m) \right] p_M(m) - \max_a \sum_x v(a, x) p_X(x) \end{aligned}$$

Since any received information m indicates the distribution of X, the probabilities for realisations of X need to be updated accordingly. By using Bayes' theorem for the process of the belief-updating of the probability of X for all possible sample information, m:

$$p_{X|M}(x|m) = \frac{p_X(x)\, p_{M|X}(m|x)}{p_M(m)},$$

with $p_{MX}(m|x)$ giving the likelihood function of observing m when the state of the world is x, and $p_M(m)$ representing the marginal density of m:

$$p_M(m) = \sum_{x \in \Omega} p_X(x) p_{M|X}(m|x).$$

Similarly to $EVPXI$, the value of resolving uncertainty about an uncertain input of the model can be calculated – but instead of obtaining perfect information, we can estimate *expected value of sample X information* (EVSXI).

$EVPI$ is mostly applied as it is simple to calculate and also yields the highest value, i.e., $EVPI \geq max[EVPXI]$ and $EVPI \geq EVSI \geq max[EVSXI]$). It, therefore, serves as a useful measure for the upper bound of the added value of additional information in any decision. However, as Yokota and Thompson (2004b) point out, even $EVPI$ might "underestimate the true societal value of perfect information since positive externalities from information collection may exist (i.e., additional decisions not directly modeled that may be improved from the information collected)" [p. 289].

Since VoI is a well-established theory, much work has been invested in identifying features of VoI and axiomatic approaches. The well-known results of Radner and Stiglitz (1984) about the non-concavity of VoI are addressed in several papers. Chade and Schlee (2002) develop a general framework for conditions that yield non-concavity in VoI and discuss the robustness of the non-concavity results. Further, they address the difficulties of getting VoI globally concave. De Lara and Gilotte (2007) show that under a certain condition, a positive payoff function exists, for which the marginal VoI at the null is positive under general assumptions. De Lara and Gossner (2020) offer a condition that is both necessary and sufficient to ensure a positive value of information, allowing for the derivation of global estimates of information value across various information structures solely from the local properties of the value function and the optimal actions taken at the prior belief stage.Frankel and Kamenica (2019) axiomatically characterise all valid measures of information and uncertainty. They demonstrate that when measures of information and uncertainty originate from the same decision problem, they are intrinsically linked, such that the anticipated decrease in uncertainty is always equivalent to the expected information produced. Explicit formulas are provided to determine the measure of information associated with any given measure of uncertainty and vice versa. Additionally, it is shown that the only valid measures of information are the payment schemes that consistently avoid incentivising delays in information disclosure. Relations to entropy and measuring VoI can be found in Hellman and Peretz (2020); Cabrales et al. (2013). For introductory economic expositions on the value of information, we refer the interested reader to Laffont (1989, Sec. 4 and Problem 4), Bikhchandani et al. (2013, Sec. 5) and Gollier (2001, Sec. 24 and 25). For a recent overview of the economics of biodiversity, see Dasgupta (2021).

2.3.3 VoI in environmental management

The concept of VoI is well implemented, and many applications exist, especially in health economics (see literature analyses by Yokota and Thompson, 2004a,b; Thorn et al., 2016; Koffijberg et al., 2018). A review by Keisler et al. (2014) showed that applications in environmental topics are not as common. In environmental economics, VoI has been used to evaluate the worth of obtaining information about the environment and the impacts of human activities on the environment (Bounfour and Lambin, 1999) or to evaluate the worth of obtaining information about the costs and benefits of environmental policies (Pannell and Glenn, 2000a). Newbold and Marten (2014) estimate VoI to improve climate-integrated assessment models, while other authors analyse the impacts of climate change on different regions and sectors and the costs and benefits of alternative policy options (Yohe, 1990; Lempert et al., 2000; Quiroga et al., 2011). Macauley (2006) provide a general methodological framework for the use of VoI space-derived earth science data in resource management.

In view of this, it is surprising that although VoI is by no means a new concept, research on marine ecology and biodiversity, as well as on environmental management, often still refrains from using it. An evaluation of the literature on the relevance of VoI by Bolam et al. (2019) showed that the VoI concept was applied to management problems in the field of biodiversity conservation in only 30 studies of which most focused on (single) species management. These include, for example, the conservation of (endangered) species or the management of invasive species. Canessa et al. (2015) provide a step-by-step guide for ecologists to calculate VoI. While Runge et al. (2011) and Johnson et al. (2017) focus on expert elicitation for the conservation of endangered species and invasive species management, Maxwell et al. (2015) rely on a population model to solve structural and parametric uncertainty in conserving Koalas. Polasky and Solow (2001) provide a formal approach to solve a maximal expected coverage problem to the expected number of species in an area. Bal et al. (2018), Bennett et al. (2018), Raymond et al. (2020) and Li et al. (2021) further advance applications of VoI as they consider multiple species, multiple threats, multiple management units or multiple sources of uncertainty in their decision problems. Bal et al. (2018) find that targeted monitoring yielded overall a higher VoI than surveillance monitoring in their case study. Bennett et al. (2018) consider a decision problem in which to choose the optimal unit or combination of units to protect, while Raymond et al. (2020) combine species distribution models with VoI in a multiple threat situation. Li et al. (2021) consider biological and operational uncertainty simultaneously. Adaptive management and learning through the management process itself is applied in a case study by Williams and Johnson (2018). A recent study by Canessa et al. (2020) addresses a common challenge in conserving critically endangered species: high uncertainty impacts management decisions, and the endangered status induces strong risk aversion. This risk aversion limits both the willingness to act on limited information and the capacity for effective learning. While structured methods can enhance transparency, facilitate evaluation, and support decision-making, they cannot fully overcome the inherent objective limitations and subjective attitudes. While most applications focus on species management, as shown in the above-mentioned review by Bolam et al. (2019), there is a need for a broader application of VoI. Topics such as setting research priorities for biodiversity conservation on a global and local level, managing protected area networks, improving funding decisions, and designing or improving protected area networks and their management should be targeted to advance conservation management. In related topics, Davis et al. (2019) apply VoI to social-ecological systems; Venus and Sauer (2022) combine choice experiments with VoI in relation to environmental monitoring and hydropower; Lawson et al. (2022) apply a qualitative VoI framework for in the context of adaptive management and stakeholder involvement to protect a threatened marsh bird species; and Koski et al. (2020); Luhede et al. (2024) use monitoring data to estimate conditional probabilities for managing water quality. The following section gives a systematic overview of VoI applications in the literature with a focus on marine conservation management.

2.4 Survey of VoI applications in marine conservation management

We surveyed VoI applications in the literature by searching the scientific literature databases Web of Science and Google Scholar for the following keywords and combinations of keywords: “value of information,” “value of * information,” “information

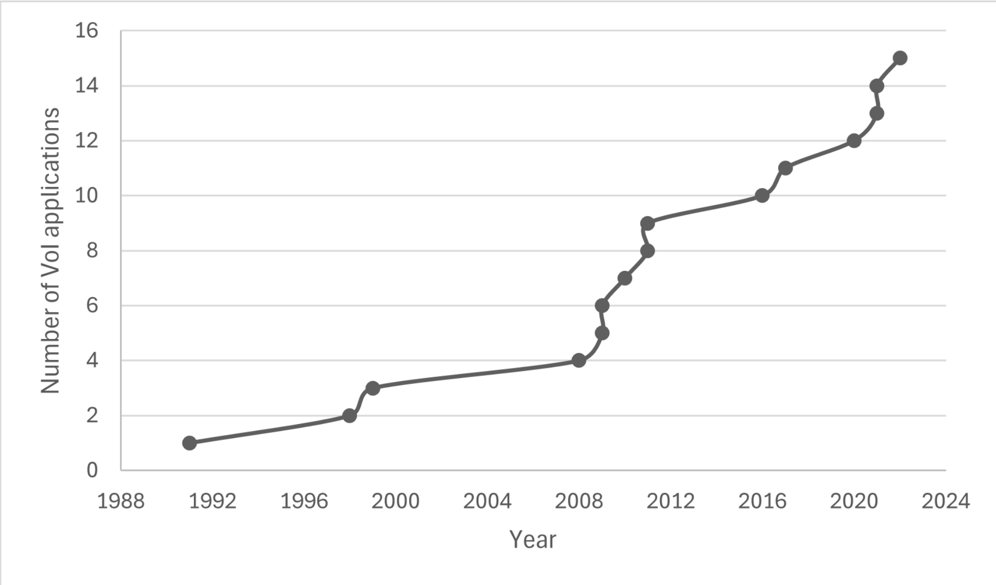

Figure 2.1: Cumulative number of VoI applications in marine conservation management

value," and "value of sampl*." AND (biology OR conservation OR fish OR ecology OR water OR ocean). We scanned the resulting articles for our criteria and inspected any literature that matched our criteria more closely. Our criteria included the following: peer-reviewed, English language, VoI application, focus on the marine environment, including a conservation element. After scanning titles, abstracts and keywords, we removed any literature that is unrelated to the value of information or has no conservation element (e.g. applications to underwater engineering, construction or health economics; articles using "value of information" in the title, but are not related to VoI theory). We grouped the remaining 15 applications and analysed them for the following attributes:

- Journal
- Topic of VoI application
- Objective function
- Description of uncertainty
- Number of management alternatives
- How uncertainty is expressed
- Tye of VoI (EVPI, EVPXI, EVSI)
- Type of model used

Table 2.1: List of journals that published VoI applications.

Journal	#articles
American Journal of Agricultural Economics	1
Canadian Journal of Fisheries and Aquatic Sciences	1
Environmental & Resource Economics	1
Environmental Modelling & Software	1
Fisheries Research	1
Frontiers in Marine Sciences	2
Harmful Algae	1
ICES Journal of Marine Science	1
ICES Marine Science Symposia	1
Journal of Environmental Management	1
Methods in Ecology and Evolution	1
Proceedings of the National Academy of Sciences	1
Science of the Total Environment	2

- Value metric
- Sensitivity analysis
- Time horizon
- Option to revise
- Cost for data collection
- Main findings

The results are summarised in Tables 2.1–2.3. In total, we found 15 articles that matched our criteria and applied VoI to marine conservation management. Table 2.1 lists the 13 journals in which VoI applications have been published. Articles using VoI to analyse decision problems in marine conservation management are published in a variety of journals, whose focus ranges from ecology to environmental modelling or more specific journals that focus on fisheries or agricultural economics. Most journals only have one paper published, and only two journals published two VoI papers. Following the timeline of published articles, we can observe a clear rise in publications since the year 2008 (cf. Fig. 2.1). While the earliest article we found was published in 1989, only four more articles were released until 2008. Between 1999 and 2008, not a single VoI application was published in the field of marine conservation. However, since then, we have seen an increase, and eleven more applications have been published.

For further analysis, we grouped the articles by topic and three categories emerged:

Table 2.2: Summary of VoI applications

	VoI Application	Objective	Uncertainty
Ecosystem Management			
Bouma et al. (2011)	Determine when Earth Observation data has most value.	Decrease sediment discharge into the Great Barrier Reef.	Uncertainty about the difference in sediment discharge between catchments, cost of pollution abatement.
Nygård et al. (2016)	Evaluate the value of ecological status assessments to improve management.	Maximise benefit of choosing optimal set of measures to achieve the target status.	Uncertainty about the current ecological status of the water body.
Fisheries Management			
Bouma et al. (2009)	Evaluate the worth of investing in information from Earth Observation to predict harmful algal blooms and protect fisheries.	Maximise benefits from fisheries.	Uncertainty about the occurrence of a harmful algal bloom.
Costello et al. (1998)	Choose optimal harvest rate under uncertainty about future El Nino events and if uncertainty can be resolved.	Maximise expected net present value of Coho fishery.	Uncertainty about future El Nino occurences.
Costello et al. (2010)	Choose the optimal location and extent of a Marine Protected Area (MPA).	Maximise fishery profits whilst ensuring conservation of species.	Uncertainty about the dispersal of fish larvae.
Haag et al. (2022)	Evaluate the best management strategy to balance socio-economic benefits of coral reef fisheries by taking multiple stakeholder utilities into account.	Maximise utility for different stakeholder preference profiles.	Seven different uncertain predictions of interest for four stakeholder preference profiles.
Jin and Hoagland (2008)	Determine the value of harmful algal bloom predictions in the Gulf of Maine.	Maximise the net revenue of shellfishery.	Uncertainty about the occurrence of a harmful algal bloom.
Kuikka et al. (1999)	Determine the best mesh size for cod fishery.	Minimise risk of spawning biomass going below critical level; Maximise yield.	Uncertainty about the growth rate of cod, recruitment of cod and critical spawning biomass.
Mäntyniemi et al. (2009)	Determine ideal fishing pressure under uncertainty about the stock - recruitment relationship of North Sea herring.	Maximise expected profits over a 20-year period.	Uncertainty about stock-recruitment relationship of North Sea herring.
Prellezo (2017)	Use VoI to measure and understand the economic value of fishery research surveys using the mathematical theory of the expected value of information.	Maximise the revenue or landing with constraints to spawning.	Uncertainty about the stock of anchovy.
Sainsbury (1991)	Find optimal management strategy for fishing by using trap or trawl catch. Using adaptive management to incorperate learning into management process.	Maximise the value of fisheries.	Uncertainty about the effect of intra- and interspecific competition and about the effect of habitat on abundance of different fish species.
Xia et al. (2021)	Assess how different types of information contribute to the management process for Indian Ocean Striped Marlin.	Maximise the relative yield.	Uncertainty about catch and index information.
Others			
Jin et al. (2020)	Understanding the value of marine scientific research to reduce uncertainty regarding the biological carbon pump (BCP) sequestration to improve policy making.	Maximise discounted net economic benefit.	The scale of BCP sequestration.
Punt and Kaiser (2021)	Improve decisions over seismic surveying that may convey economic damages through marine noise pollution.	Maximise the total net value of oil surveys subject to constraints on species population.	Uncertainty about the migration of a whales species.
Sahlin et al. (2011)	Evaluate which species of marcroalgae are likely to become invasive to allocate resources on avoiding their introduction.	Remove species invasive species, leave non-invasive species.	Uncertainty about the base rate of invasiveness.

"Fisheries management", "Ecosystem management", and "Others". The bulk of publications (10 publications) belong to the category of fisheries management. The focus is to enable profitable fishing while taking species conservation into account. Costello et al. (1998) develop a bioeconomic model of a salmon fishery and assess the VoI from improved El Niño forecasting ability. Kuikka et al. (1999) evaluate how different levels of exploitation and mesh sizes in trawl fisheries can affect the management of a fish species. Their modelling approach involves three steps, consisting of: simulating selectivity, using Monte Carlo simulations to estimate uncertainties, and applying decision analysis with Bayesian influence diagrams while emphasizing structural uncertainties and model selection. Their VoI analysis highlights the advantages of using larger mesh sizes as a management strategy. Jin and

Hoagland (2008) assess the value of predicting harmful algal blooms in the Gulf of Maine to avoid losses for shell fisheries by testing different scenarios and management strategies. Mäntyniemi et al. (2009) apply VoI to a case study with uncertainty about stock dynamics and current stock status. Their example analyses the EVPI for information on the type of stock-recruitment function of the North Sea herring population. Costello et al. (2010) develop a general framework to analyse the value of information for spatial fisheries management. They investigate the optimal size and location of a marine protected area for sawfish (*Paralabrax clathratus*) and rockfish (*Sebastes atrovirens*) with regard to maximising the yield from fishing. Bouma et al. (2011) combine Bayesian decision theory with an empirical, stakeholder-oriented approach. Their analysis focuses on the use of satellite data for Dutch water quality management in the North Sea. Prellezo (2017) measures the value of fishery research survey with the objective of maximising landings whilst ensuring a healthy stock of anchovy. Sainsbury (1991) apply VoI to manage a multi-species fishery while considering different fishing gear. Xia et al. (2021) focus on VoI analysis on the Indian Ocean Striped Marlin, exploring how different types of information on parameters contribute to fisheries management. The second category we identified was ecosystem management/conservation. Two articles focus on the improvement conservation of coral reefs via satellite data (Bouma et al., 2009) and the benefit of extensive monitoring for the assessment of the ecological status of marine waters (Nygård et al., 2016). The third category "Others" contains three articles. Jin et al. (2020) focus on ecosystem services and evaluate the value of research on the biological carbon pump to improve policymaking. Punt and Kaiser (2021) apply VoI to a case in seismic oil survey while considering disturbance of marine mammals through noise pollution. The third article in this category focuses on the management of invasive macroalgae species and how to best allocate resources to avoid the introduction of such species (Sahlin et al., 2011). Summaries of the application in each article, as well as the objective and the uncertainties considered, can be found in Table 2.2. Management objectives vary between the applications; however, it is not surprising that in the "Fisheries Management" category, the predominant objective is to maximise the value or benefit of the fishery or to maximise the yield – often with a constraint to some critical element of species conservation. Most studies in the whole sample have the objective of maximising their utility function (13 papers). Three papers consider the objective of minimising either a risk or minimising an invasive species or damaging discharge into the ecosystem. Most studies consider a single management objective (10 studies) in their application, while 5 studies consider multiple management objectives.

Table 2.3: Summary of analysed attributes related to the methodology used in the applications. The first column refers to m.a. = management alternatives. Here, the infinity sign indicates inputs such as continuous levels; the last column "Valuation" refers to the valuation parameter.

	# m.a.	Expression of uncertainty	EVPI	EVPXI	EVSI	Model type	Valuation
Ecosystem Management							
Bouma et al. (2011)	2	discrete	x		x	Four different simulations for cost minimisation model; expert elicitation	monetary
Nygård et al. (2016)	3	discrete	x			Three different hypothetical scenarios for knowledge available for status assessment	monetary
Fisheries Management							
Bouma et al. (2009)	2	discrete	x			Expert elicitations	monetary
Costello et al. (1998)	∞	discrete	x		x	Bioeconomic model of Coho salmon fishery	monetary
Costello et al. (2010)	∞	discrete	x			Stage-structured spatial model, ocean circulation model	net profit (unitless)
Haag et al. (2022)	4	continuous		x		Predictive system model (which integrates an agent-based model of fish stocks and fishing behaviour with a model for benthic community dynamics); preference model	units of utility for particular preference profile
Jin and Hoagland (2008)	2	discrete			x	Six model scenarios	monetary
Kuikka et al. (1999)	100	discrete	x			Bayesian influence diagram, combining three different recruitment models	yield (kt); risk of falling below spawning mass
Mäntyniemi et al. (2009)	2	discrete	x			Bayesian probability model	monetary
Prellezo (2017)	∞	discrete	x		x	Two-stage, biomass-based state-space model	monetary
Sainsbury (1991)	5	discrete & continuous	x			Population growth models	monetary
Xia et al. (2021)	3	discrete	x			State-space age-structured OMs	relative yield
Others							
Jin et al. (2020)	∞	continuous			x	Analytical model of the economic effects of global carbon emissions	monetary
Punt and Kaiser (2021)	2	discrete			x	Biological response model	monetary
Sahlin et al. (2011)	4	continuous			x	Screening model of species invasiveness	cost-ratio: relative loss of avoiding introduction of non-invasive species

Table 2.3 summarises the attributes related to the methods used in the applications that we recorded, with the first columns providing the author's names and year of publication. As shown in the second column, most articles consider a limited set of management alternatives in their studies: five studies involve binary actions, i.e. the decision maker can either "do nothing" or "do something", four studies consider up to 5 different management actions for the decision maker to choose from. One article considered 100 possible combinations of management options. Four studies consider finding optimal levels of emissions or fishing rather than discrete inputs

(these are indicated with ∞ in the table, as in theory, infinite possibilities exist). The majority of articles (12 articles) express uncertainty in a discrete way, such as different possible states or different possible models. Three articles consider continuous parameter values or a continuous prediction space. Most applications use a model to estimate uncertainties (12 papers). These include different ecological or bioeconomic models, preference models, and Bayesian probability models. Two articles make use of expert elicitation methods to estimate uncertainties, while on of those uses a combination of expert knowledge and simulations. One application solely uses hypothetical scenarios to calculate VoI. The most popular choice for the type of VoI is EVPI (11 papers), while EVSI is calculated in 7 applications. Three applications consider two types of VoI and calculate EVPI as well as EVSI. Only one application calculates EVPXI. The last column in Table 2.3 displays the unit of measurement of the valuation parameter. As expected, the majority of the papers use a monetary metric, either directly in EUR, USD or another currency or in relative net profit or relative loss. The remaining articles report performance metrics in units of utility, yield and risk.

Table 2.4 presents information about the attributes related to the results of the VoI applications and to further analyses apart from the sole numerical calculation of VoI. The first attribute we analysed was if analysts make use of a sensitivity analysis to show how certain parameters may influence their results. A little more than half of the applications conduct a sensitivity analysis (9 papers), which is in line with the trend observed by Keisler et al. (2014) suggesting that VoI applications across fields increasingly make use of sensitivity analyses. Although our results do not seem to show a clear development over time, the quantity of applications, including sensitivity analysis, is increasing. Most applications do not consider a time horizon in their analysis. Therefore, the value of the additional information system considered is calculated for the present moment (of the study). Studies that consider a time horizon (7 studies) maximise the objective function over a certain time period or calculate the value under a projection over multiple years (or decades). One article calculates VoI for different finite planning horizons. Another article includes different time intervals for an experimentation period for some of the management alternatives. This application is the only analysis that considers an option to revise the decision after a learning period as part of a management strategy. All the other analyses focus on static decisions, i.e. the decision is made once and will not be revised or changed. The cost for data acquisition is considered in four applications, either it is directly included in the calculation (1 paper) or VoI is later on compared to the cost (3 papers).

Table 2.4: Summary attribute related to the results of VoI applications. Here, S.A. = sensitivity analysis; Revise = option to revise included; m.a. = management alternatives; data cost = cost for collecting or acquiring data/information

	S.A.	Time horizon	Revise	Data cost	Results
Ecosystem Management					
Bouma et al. (2011)	y	n	n	n	VoI of Earths Observations is significant. Depends on decision-makers' perceptions of water quality impacts on the reef.
Nygård et al. (2016)	n	n	n	y	Value of marine monitoring data is an order of magnitude greater than current monitoring investments.
Fisheries Management					
Bouma et al. (2009)	y	n	n	y	Expected welfare impact is positive. Outcomes depend on information accuracy and perceived benefits.
Costello et al. (1998)	y	different finite planning horizons	n	n	Perfect and imperfect forecast result in welfare gain. Optimal management under uncertainty results in lower harvest than under informed management.
Costello et al. (2010)	n	n	n	n	Improved information can increase fishery value significantly. Changes management to spatially targeted fishing.
Haag et al. (2022)	y	3-6 years after implementation	n	n	VoI depends on stakeholder preferences not on attribute's probability distribution.
Jin and Hoagland (2008)	n	annual value, 30 years	n	n	Value of prediction and tracking depends on HAB events frequency, prediction accuracy, and response effectiveness.
Kuikka et al. (1999)	y	n	n	n	VoI analysis supports larger mesh size as a management measure.
Mäntyniemi et al. (2009)	n	20-yr planning period (maximise over 20 yrs)	n	n	VoI is high if it differentiates between consequences of management actions. VoI is low if there's already great certainty about stock state and dynamics.
Prellezo (2017)	n	n	n	n	VoI depends on predictive capacity. The expected economic value of research surveys can be measured, but it with some kind of subjectivity.
Sainsbury (1991)	y	learning period in some m.a. (0-20 yrs), choosing best m.a. afterwards	In some m.a.	y (for some m.a.)	Choosing a management regime with learning yields larger expected value. Experimental periods $>$ 5 years not worthwhile; periods $>$ 15 years too costly.
Xia et al. (2021)	n	yield under 50-yr projection	n	n	VoI from fisheries-dependent parameters is low; similar for fisheries-independent parameters. Relative yield decreases from upper to lower bound of the interval. "Catch at age sample size" parameter had no impact on yield after 134 individuals.
Others					
Jin et al. (2020)	y	20-yr program	n	n	VoI of BCP research program is significant. Depends on prediction accuracy, convexities of climate damage and economic output functions, and initial uncertainty range.
Punt and Kaiser (2021)	y	n	n	y	Cost-effectiveness (CEA) can be used as an alternative to cost-benefit analysis to identify implicit thresholds for marine mammal habitat conservation. Combination with VoI can ease decision making under uncertainty when CBA is not feasible.
Sahlin et al. (2011)	y	n	n	n	Increasing model accuracy generates higher model benefit. Neglecting base rate uncertainty in invasiveness affects cost-benefit analysis of screening model.

In the eleven remaining articles, the cost for information acquisition or data collection is either unknown or difficult to estimate or has not been considered. Different types of information systems serve as the source for information in the applications, ranging from forecasting models and research programs to satellite observations. In the majority of the applications, the value of these additional data or information has significant benefits for the decision maker and is generally welfare-enhancing. One paper reports only a low information value for all tested parameters. As VoI is very dependent on the decision context and input variables, it is not surprising that the results vary. Yet, overall, VoI is positive in most cases, and depending on the cost of information acquisition, it seems worthwhile to invest in additional information. Four papers reflect on the relationship between VoI and the accuracy of the information or prediction: VoI generally increases with the accuracy of the information system. However, not all parameters have a high information value for the decision context, as discussed in Xia et al. (2021). Analytical solutions are generally difficult to derive if decision contexts get more complex - this is as well the case for the applications to marine conservation management considered in this analysis.

2.5 Discussion

This analysis is the first to synthesise applications on VoI in marine conservation management. VoI analysis is a tool that quantifies the net value of additional information in order to provide the decision-maker with a sound basis for his decision in the sense of a comprehensive cost-benefit analysis of information procurement that explicitly takes uncertainty into account and can be objectified. The concept of the VoI is thus problem-oriented and will take a different form depending on the specific issue. Although VoI is a well-established concept and has been around since the 1950s, it is surprising that we found only 15 applications related to marine conservation.

Generally, there seems to be a lack of applications in environmental conservation contexts, as already emphasised in Keisler et al. (2014) and Bolam et al. (2019), and especially in the field of marine conservation. Although the term "value of information" and related versions appear in many papers, the actual application of VoI techniques is rare. This shows that the key ideas and the evaluation of the value of information are quite relevant, but the applications seem to be difficult. Many environmental decision problems, including decisions in marine conservation management, share characteristics that may prevent applications of VoI – however, these characteristics make applications to these decision problems especially relevant (Haag et al., 2022). These challenges include the complexities in their dynamics and the characterisation of uncertain model inputs but also difficulties in attributing values (in every possible sense or metric) to ecosystems and decision outcomes (Yokota and Thompson, 2004a; Koski et al., 2020). Finding suitable models with the right amount of complexity and uncertainty for the decision context, as well as suitable data, makes real applications difficult. This means that the analysts have to carefully consider which model inputs to include – as VoI can, of course, only be evaluated based on the model construction, and other unconsidered relationships cannot be quantified. VoI can only be quantified for information that is considered worthwhile in distinguishing between all possible hypotheses considered (Mäntyniemi et al., 2009). Analytical and technical difficulties arise, especially when attempting to calculate VoI, especially $EVSI$, $EVPXI$ or $EVSXI$ in non-linear or more complex models. Solving these requires sophisticated computational techniques and an advanced understanding of valuation and simulation techniques (Tuffaha et al., 2014). Here, a simplification of models may be helpful as it can also result in meaningful interpretations that may be even more valuable to decision-makers as they are easier to comprehend and adapt. Further, if analytical solutions can be derived, this would help to further advance the overall understanding of VoI. A further challenge is that assumptions may have to be made when estimating VoI. Required inputs, such as the expected benefit from a certain management action, are not easy to assess and often need to be estimated. However, techniques and guidance on how to handle uncertainty surrounding these estimates have been addressed in the literature (Fenwick et al., 2008).

As VoI is dependent on the decision concept, it is not only directed at decision-makers but also requires their participation in the conception and implementation of the VoI approach. This is because, since the aim is to quantify the value of additional information, it requires knowledge of the information available (at the time). However, this information lies either with the decision-makers themselves or with other stakeholders. In addition to identifying the decision problem and the decision maker, it is therefore also necessary to identify the stakeholders involved and the decision-relevant information available to them. Only when the decision-maker(s), the directly or indirectly involved stakeholders, and the information available from all these parties have been identified and brought together, and the further decision-making process has been structured and specified can the determination of the VoI in the respective application case begin. This might pose an issue for applications to real decision contexts as the process of identifying decision problems and framing the decision context takes time and is not always straightforward.

One of the most striking insights of our analysis is that almost all applications focus on a single static decision. Although seven articles consider a time horizon over which utility is being maximised, only the article by Sainsbury (1991) includes the option to revise the decision after a learning period as a management alternative. Some examples exist in the broader field of environmental management. While generally, a large part of the VoI literature assumes rather static systems with one measurement and one decision stage, data and information acquisition are embedded in a dynamic environment. However, this embedding is ignored in the literature in its breadth; few publications assume a dynamic environment in the context of information retrieval. For example, Williams and Johnson (2018) consider a longer period over which repeated measurement (obtaining information) and action or intervention can be taken; in this way, adaptive strategies and existing or resulting options can be considered.

Markov decision processes (MDPs) in combination with stochastic dynamic programming (SDP) can serve as a useful tool in analysing and estimating VoI in dynamic settings (e.g., threatened species populations) to ascertain the optimal policy under uncertainty (McDonald-Madden et al., 2008; Shea and Possingham, 2000; McCarthy et al., 2001; Wilson et al., 2006). Although MDPs do not explicitly address VoI and cannot assess the trade-off between monitoring and management, examples in conservation management and other fields show the applicability (Sledge et al., 2018; Williams and Johnson, 2018; Williams and Brown, 2016; Williams and Johnson, 2015; Johnson et al., 2017). For example, Sledge and Príncipe (2018) propose using the VoI framework in reinforcement learning of MDPs. By modifying a single parameter controlling policy complexity for how that policy trades off with VoI, an agent can learn either risk-averse or risk-seeking behaviours (to greater or lesser degrees), thereby striking an optimal trade-off between the cost of exploration and the expected reward. This approach is computationally more efficient than traditional approaches, as shown in similar examples. Haight and Polasky (2010) use a Partially Observable Markov Decision Process (POMDP) to model the control of invasive species. Given the value of imperfect monitoring information, it can optimally evaluate the management strategy to use, either keeping on monitoring, treating, or doing neither based on the likelihood of infestation, which will then result in the minimisation of long-term costs. Memarzadeh and Pozzi (2016) research the application of VoI in POMDPs for infrastructure management with limited observations. They consider two models for access to information (without a fee but with probability or by paying a fee) and determine VoI in each case, thus enabling a cost-effective choice on the inspection of components and the ordering based on the priority of scheduling for maintenance interventions at the system level. In another infrastructure example, Song et al. (2022) handle the challenge of valuing information in dynamic decision-making for systems with non-stationary deterioration, such as corroding beams. It presents VoI-R-POMDP, a new framework that integrates POMDPs with non-stationary processes, which allows for obtaining more precise estimates concerning VoI than the existing methods, which assume static environments. When faced with uncertainty and needing to make iterative decisions, considerations of VoI can provide a valuable tool for adaptive management (Holling and Walters, 1978; Williams and Brown, 2016). For example, a low VoI might indicate a limited benefit to be gained from adapting strategies based on new information (Williams et al., 2009).

Moreover, combinations of VoI with concepts such as real options have been explored. The idea of real option value is to quantify the option to delay the decision. This seems to be especially relevant in environmental decisions: often, the time to collect information is not favourable, or some of the uncertainty might resolve itself over time – however, there is a severe risk of postponing the decision, such as risking the extinction of a threatened species or further irreversible ecosystem degradation. Jafarizadeh (2012) found out that VoI may differ significantly if a time period is considered instead of a single point in time. Here, VoI has a close link to the uncertainty of the outcomes of the decision of that time period.

Another promising framework for the incorporation of dynamic decision-making processes is optimal control (OC). This approach is used to determine the most effective way to manage and regulate dynamic systems by identifying control variables that influence the system, defining an objective to be achieved, and working within given constraints to find an optimal solution. It answers the question of, given the state of the system, what decision (i.e., harvest rate or pollution rate) is optimal given the long-term objective (e.g. maximising harvest)? In the context of environmental decision-making, OC theory is applied to manage natural resources and ecosystems sustainably. For example, it has been applied in fisheries management (Braack et al., 2018), invasive species management (Hastings et al., 2006), population dynamics (Runge and Johnson, 2002) or problems such as the optimal choice of habitat patch (Clark and Levy, 1988; Houston et al., 1988). By balancing economic, ecological, and regulatory factors, OC theory aids in developing strategies that promote long-term environmental sustainability and resource management. However, even though the methods are there and relevant to decision-making, to our knowledge, there has been so far no attempt to combine OC and VoI in environmental conservation management or other fields.

Although methods to tackle these problems exist, applications of VoI to adaptive management or in dynamic decision problems are still well underrepresented in conservation management. This shows that more applications to decision problems in marine conservation management are needed to improve decision-making and contribute to further advancements in VoI. Studies on dynamic and adaptive decision-making that have been done in other fields urgently need to be implemented in marine conservation management, as issues are characterised by long-term effects and persistence and large uncertainties. Further, in these contexts, data and information may be revealed at a later time, and this can only be captured by dynamic decision-making. The option to postpone the decision to implement policy measures or to revise the decision at a later point are crucial elements of an adaptive policy strategy - this needs to be reflected in future VoI applications.

2.6 Conclusion

Rigorous Value of Information (VoI) analysis provides opportunities to evaluate information collection strategies and offers valuable insights for enhancing conservation management decisions. This article serves as a thorough reference for analysts and decision-makers, addressing the concept and barriers to application. Moreover, this review offers a chance for researchers in marine conservation to benefit from and expand upon the work of other researchers. Despite various challenges for decision-makers, such as choosing quantifiable outcome values, dealing with complexities in environmental decision problems, and possible computational challenges, as the science underlying urgent ecological issues is often incomplete, VoI can be a critical method for assessing uncertainties in conservation management, marine biodiversity, and other ecological areas marked by significant uncertainty. To effectively address ecological challenges through dynamic and adaptive management, further applications and studies of VoI are essential.

3 The value of information in water quality monitoring and management

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Highlights

- The value of imperfect information can be approximated using Monte Carlo simulation.
- We explore the sensitivity of VoI and its maximum on crucial parameters.
- We estimate the likelihood function based on available data.
- We show a significant dependency of VoI on the management cost and the prior probability.

3.1 Abstract

Environmental managers face substantial uncertainty when deciding on management actions. To reduce this uncertainty prior to decision-making, collecting new data may help arrive at more informed decisions. Whether any resulting improvement in the decision will outweigh the cost of collecting the data, and thus make investing in the acquisition of the information worthwhile, is an intricate question. The concept of the value of information (VoI) is a convenient tool to address this problem. We use the VoI framework to analyse a decision problem in water quality management. Based on real-world monitoring data, we calculate the VoI of monitoring nitrogen, which is used as an indicator of the ecological state of water body. We find that the VoI is significant in our case and we further investigate the dependency of the VoI in a similar setting on the management cost, the assumed value of a good state and on the level of uncertainty regarding the ecological state. In addition, we observe a negative relation between the relative management cost and the prior probability that maximises VoI. These insights may help decide on information acquisition in the presence of substantial uncertainties and sparse data.

Keywords: value of information; decision analysis; uncertainty; environmental management; monitoring
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3.2 Introduction

Eutrophication is one of the main problems in the North Sea's coastal waters (OSPAR, 2017). It is caused by increased enrichment of the water with nutrients and can disturb the composition of organisms and eventually reduce the overall quality of the water. Managing aquatic systems threatened by eutrophication is challenging, since there are many inherent uncertainties about its exact causes and effects. Consequently, environmental managers face a high degree of uncertainty when deciding on management actions, but interventions often do not take these uncertainties into account. They may therefore be ineffective or even counterproductive (Cook et al., 2010; Bennett et al., 2018). To reduce anthropogenic stressors and to mitigate eutrophication, legislation, such as the European Marine Strategy Framework Directive (MSFD) and the European Water Framework Directive (WFD), has been enacted (European Parliament, 2000, 2008; Desmit et al., 2020). The WFD requires EU member states to obtain and maintain a "good ecological status" (GES) by 2027, based on a range of biological quality elements that are used to classify the state of a water body as either high, good, moderate, poor or bad. Although the GES target was initially set to be achieved by 2015, only about 40% of European water bodies reached that goal by 2018 (Carvalho et al., 2019; European Environment Agency, 2018). For the coastal waters of the North Sea, the riverine nutrient influx is seen as a reason for eutrophication (Desmit et al., 2020) and hence a cause for the qualities of water bodies falling short of the GES target. These high riverine nutrient concentrations are predominantly due to non-point sources of pollution, from agricultural and other land use activities, or derive from uncontrolled and untreated discharge from sealed surfaces after storm events or heavy rainfall (Carvalho et al., 2019).

In this study, we evaluate the need for monitoring or taking direct actions to manage the water quality in the Weser River basin in Northern Germany. As most of Germany's water bodies still fail to reach the GES, many de-eutrophication measures focus on nitrogen reduction. For rivers entering the North Sea, a special target for nitrogen concentrations has been established in the limnic–marine transition zone to reduce eutrophication in coastal waters and therefore meet the GES targets (BLMP, 2011). Although the ecological and chemical developments of German rivers are closely monitored, few of these rivers have met the GES targets. A thorough assessment of the ecological state is the prerequisite for any recommendation and implementation of restoration measures. However, such an assessment requires reliable data (Koski et al., 2020). The acquisition of a sufficient amount of information through monitoring is therefore essential to evaluate the system's state and to decide whether interventions are necessary or the desired good state of the ecosystem has already been reached. Monitoring activities are at the core of understanding the state of the system and its response to stressors (Nygård et al., 2016). Although monitoring data do not directly solve any environmental problem, they may help facilitate targeted management and policy interventions (Bouma et al., 2009). At the same time, monitoring and data collection involve many resources, while conservation budgets are often limited (Bennett et al., 2018). Additionally, postponing the decision to act may result in missed opportunities for management (Martin et al., 2012) and could result in further degradation of the ecosystem. WFD regulations require extensive monitoring programs, which in turn require significant financial resources, for which governments must find cost-effective, yet qualitatively sufficient solutions (Carvalho et al., 2019). In this context, acquiring new information is only worthwhile if it can be expected to change the choice of the decision maker and, in this way, lead to more effective management. It is therefore mandatory to carefully evaluate whether or not, and if so, to what extent, monitoring – or more broadly, an information service – will be useful for providing valuable information. For this purpose, we can use the Value of information (VoI) analysis. VoI is a decision-analytic tool to determine the value of additional information for decision-making: it computes how much a (rational) decision maker's expected payoff would increase if uncertainty is, at least partially, reduced before the decision is made. The uncertainty here is represented by a probability distribution over possible states of the system (Pannell and Glenn, 2000b). VoI gives the value of an information service, i.e. the expected value of acquiring information before any specific information or data have been received. That is, VoI represents the willingness-to-pay (in terms of payoff or utility) of the decision maker for the acquisition of new data, while not yet knowing what this data will look like. This implies that before the decision-making, more data will only be collected if it is expected to be beneficial. In this way, VoI helps the decision maker enhance their decision through means of a well-judged acquisition of information. Specifically, the expected value of *perfect* information gives the payoff when uncertainty is entirely eliminated, i.e. when complete knowledge about the true state of the world (*clairvoyance*) is achieved; while in contrast, the expected value of *sample* (or imperfect) information gives the increase in the payoff on obtaining some, even though imperfect, information.

Initially formulated by economists (Raiffa and Schlaifer, 1961; Hirshleifer and Riley, 1979), VoI has been widely applied in a variety of fields: for example, in health economics (Yokota and Thompson, 2004a; Fenwick et al., 2020), engineering (Bratvold et al., 2009), fisheries (Clark and Kirkwood, 1986; Costello et al., 2010; Kuikka et al., 1999), water management (Borisova et al., 2005), or invasive species management (Moore and Runge, 2012; Johnson et al., 2017; Li et al., 2021). [1]

In spite of VoI being a well-established theory and its apparent benefits, not many applications exist for conservation management (Runge et al., 2011; Williams et al., 2011; Moore and Runge, 2012) and environmental monitoring (Nygård et al., 2016; Koski et al., 2020; Venus and Sauer, 2022). Even though water management and VoI analysis have a long history and some early applications exist (Slack et al., 1975; Moore and Morzuch, 1982), VoI applications using monitoring data are rare. The reasons for this lack of application may in-

[1] For an overview on the fields of application of VoI, the reader may consult Yokota and Thompson (2004b), Keisler et al. (2014) and Bolam et al. (2019).

clude the difficulty of quantifying the value of an ecological system (Koski et al., 2020) or the high computational costs with the increasing complexity of the decision problem (Canessa et al., 2015; Bolam et al., 2019). Furthermore, the calculation of VoI requires explicitly defining a decision framework: the probabilities of the states of the world, the set of available management actions, and the consequences of each management action, all of which may represent challenging tasks for environmental decision problems. The calculation typically relies on decision-analytic techniques, such as decision trees, Bayesian networks or the use of simulation or other numerical approximation methods, to simulate the anticipated results of various monitoring and information-gathering activities (Yokota and Thompson, 2004b).

Our analysis contributes to the application of VoI in water management. We make use of Monte Carlo sampling techniques, which are widely employed to propagate uncertainty in the parameters throughout the decision model and to estimate VoI (Bates et al., 2014, 2016; Marchese et al., 2018). This method entails drawing samples from the parameter distributions and executing the model with these values to derive an estimate for the outcomes. Through iterative repetitions of this process, a distribution is produced for each outcome, reflecting a potential realization of the truth. The average of these distributions serves as the expected value for each outcome.

For our specific context, we use a VoI framework similar to the one used by Koski et al. (2020) to solve this ecological management problem with available real-world monitoring data. We simplify a complex decision problem on water quality management to a binary system with two possible states of the water body and two management actions. The usage of a binary problem is a wide-spread approach serving as an intuitive starting point for the analysis (see, for example Giordano et al., 2022; Malings and Pozzi, 2016), allowing us to obtain a clear understanding of the problem and the role of VoI. Building on this model, we extend the analysis by performing a sensitivity analysis and showing the interaction between the management cost and the probability distribution of the ecological state. Specifically, we identify the prior probabilities for which VoI is a maximum over a range of management costs. Lastly, transcending our concrete case study, we provide generic results on VoI for all two-state, two-action decision problems under uncertainty with respect to two crucial determinants of VoI: the prior probability distribution and the management costs in relation to the good state.

The remainder of this article is structured as follows: In the next section, we provide information regarding the data and methods used in our investigation. Section 3 provides the results of our VoI analysis along with a detailed sensitivity analysis showing how the VoI depends on the management cost and the prior distribution in Section 4. This is followed by a discussion of the results in Section 5 and a conclusion in Section 6.

3.3 Data and Methods

3.3.1 Decision problem and data

According to the WFD, the state of a water body is determined by several elements of biological quality and supporting chemical-physical parameters. In the case of Germany, coastal waters are prone to high riverine input of nutrients, leading to eutrophication (BLMP, 2011; Desmit et al., 2020) and thus leading to a failure to meet the GES target (BLMP, 2011). Due to a correlation between nitrogen and chlorophyll-a, it is frequently hypothesised that the overall nitrogen concentration in the water body affects the biological quality element phytoplankton (BLMP, 2011). Consequently, water quality management predominantly targets a reduction of nitrogen concentrations to reach the GES in coastal waters. In accordance with this policy focus, we restrict our assessment to total nitrogen because it serves as an indicator of the state of a water body. Our goal is to assess the VoI of monitoring nitrogen data for rivers of the Weser River basin that enter the German Wadden Sea. We use the official and open-source monitoring data provided by Niedersächsischer Landesbetrieb für Wasserwirtschaft, Küsten- und Naturschutz (NLWKN)[2] and of the Flussgebietsgemeinschaft Weser (FGG Weser)[3].

We consider a sample of water bodies within the case study area and differentiate between water bodies within the target state, i.e. fulfilling the criteria of the GES according to the WFD, and those that fail to meet the target state. We consider data for the WFD assessment periods 2000–2018. Since little data is available on water bodies in a good state, we used the raw data and disregarded temporal or spatial differentiation. We acknowledge that in this way, the analysis is biased towards water bodies with a high frequency of measurements or with many measurement stations; also, spatial differences, as well as different river types, cannot be taken into account. However, this approach is still suitable for highlighting the value of monitoring data for environmental management. To base the VoI analysis on empirical data, we assume that total nitrogen is a proxy for the state of the water body. Since the main target of the WFD is that water bodies either maintain or reach the GES, the threshold between the categories GES and non-GES becomes essential; at the same time, subcategories within GES and non-GES are inessential. Consequently, the threshold between GES and non-GES determines whether management interventions must be taken. We, therefore, disregard the original division of the state of a body of water into five categories and consider only two: those that meet the target state (GES) and those that do not (non-GES). We will refer to the latter as *bad state* (x_0) and the former as *good state* (x_1). Accordingly, the state X of a water body may be seen as a random variable taking either of two values: $X \in \Omega = \{x_0, x_1\}$, with a prior probability $p_X(x)$ for state $x \in \Omega$ being true. We assume that for any section of a river,

[2]Lower Saxony Water Management, Coastal Protection and Nature Conservation Agency.
[3]River Basin District Weser.

two management alternatives $a \in A = \{a_0, a_1\}$ can be considered: either no action is taken $a = a_0$ (default), or a specified action is taken $a = a_1$. The resulting payoff then depends on both the action and the state: $v : A \times \Omega \rightarrow \mathbb{R}$, as shown in Table 3.1. We next determine the value of actions, costs and prior probabilities.

Table 3.1: Payoff matrix for the river management problem.

ecological state X	action a		prior belief
	a_0	a_1	p_X
$X = x_0$: bad state	$v(a_0, x_0)$	$v(a_1, x_0)$	$p_X(x_0)$
$X = x_1$: good state	$v(a_0, x_1)$	$v(a_1, x_1)$	$p_X(x_1)$

The estimated cost of action a_1 is retrieved from reports by LAWA (2020) and Flussgebietsgemeinschaft Weser (FGG) (2021) (section “cost for management of pollution from diffuse sources”) and is set to EUR 90 million per year. The cost of action a_0 is set to zero. The value of a water body in good state is estimated from a report by the European Commission (2019). The cost of not reaching GES for Germany, i.e. the benefit forgone, is estimated to range between EUR 820–3304 million per year. Scaled down to the area of the Weser River basin area, this results in a value within the range of roughly EUR 115–450 million per year. We set the value at EUR 200 million per year for our initial analysis. Therefore, the value of a river in good state (x_1), without management cost, is set to EUR 200 million per year.

The payoff for each action is then calculated by subtracting the management cost – $c(a_0) = 0$ in case of action a_0, and $c(a_1) = 90$ in case of action a_1 – from the value of the water body after the action became effective, which is either 0 or 200. We assume that after performing the action a_1, the water body will always reach or maintain the good state, and thus provides a high value; intuitively, a_1 serves as a perfect hedge against a possible bad state of the water body, becoming an unnecessary action in case of a good state. Therefore, the value of the ecological state after management, which we refer to as the payoff, is given by

$$v(a, x) = \begin{cases} 0 & \text{if } (a, x) = (a_0, x_0) \\ 200 & \text{if } (a, x) = (a_0, x_1) \\ 200 - c(a_1) & \text{if } a = a_1, \end{cases}$$

with $c(a_1) = 90$. The prior probabilities for each state are derived from a recent report, highlighting that less than 10% of German water bodies are currently in a good state (Bundesministerium für Umwelt, Naturschutz und nukleare Sicherheit, 2017). Hence, we set the prior belief for a water body to be in a good state to $p_X(x_1) = 0.1$ and for a water body to be in a bad state to $p_X(x_0) = 0.9$. The four possible situations are summarised in Table 3.2 (costs are given in million Euros per year).

Table 3.2: The value of the ecological state after action a_0 or a_1 without additional information.

actions	cost of actions	payoff $v(a,x)$ x_0	x_1
a_0	$c(a_0) = 0$	0	200
a_1	$c(a_1) = 90$	110	110
prior belief	$p_X(x)$	0.9	0.1

3.3.2 Concept of the value of information

In this section, we outline the theory behind the VoI at a more abstract level, to present the general idea behind our approach. As we mentioned already, VoI is used in the case of revisiting a decision via determining whether it is worth investing in more information to reduce the uncertainty or the decision should be based on the current information. This uncertainty about the true state of the system is modelled by the random variable $X : \Omega \to \mathbb{R}^+$, with Ω being the state space, which we assume to be discrete, and corresponding probability measures p_X on Ω. The decision maker can choose any action $a \in A$. The payoff (profit or utility) of the decision maker resulting from state $x \in \Omega$ and action $a \in A$ is denoted by $v : A \times \Omega \to \mathbb{R} : (a,x) \mapsto v(a,x)$.

One of the key measurements of VoI, the *expected value of perfect information* or the expected value of *clairvoyance* about the true state of the world is calculated by

$$VoI^\circ := PoV^\circ - PV,$$

where the prior value (PV) describes the maximum expected outcome under current information; i.e. the expected utility resulting from adopting the action which produces the highest expected utility:

$$PV = \max_{a \in A} \mathbb{E}\left[v(a,x)\right] = \max_{a \in A} \left[\sum_{x \in \Omega} v(a,x) p_X(x)\right],$$

where the expectation is taken with respect to X. In our case, we explicitly calculate the PV by

$$\begin{aligned} PV &= \max_{a \in A} \left[v(a,x_0)(1-p) + v(a,x_1)p\right] \\ &= \max\left[v(a_0,x_0)(1-p) + v(a_0,x_1)p, v(a_1,x_0)(1-p) + v(a_1,x_1)p\right] \\ &= \max(200p, 200 - c(a_1)) \end{aligned}$$

$$PV = \begin{cases} 200 - c(a_1) & \text{if } p < \frac{200 - c(a_1)}{200} \\ 200p & \text{if } p \geq \frac{200 - c(a_1)}{200} \end{cases}$$

Note that PV is not differentiable at the point $p = (200 - c(a_1))/200$. This lack of differentiability in the function will impact the behavior of the variable of interest, which will be introduced later, and can be visually observed in Figure 3.4 and Figure 3.7. On the other hand, the posterior value under perfect information (PoV°) represents the expected utility after being informed about the realisation of X: it gives the expected utility when taking the optimal action for each state of the world $x \in \Omega$ (Yokota and Thompson, 2004a):

$$PoV^\circ = \mathbb{E}\left[\max_{a \in A} v(a, x)\right] = \sum_{x \in \Omega} p_X(x) \max_{a \in A} v(a, x).$$

Here, PoV° represents the probability-weighted sum of the utilities of the optimal actions. Then, the difference between the expected utility under perfect information and under current information gives VoI°, the expected value of perfect information.[4] If perfect information can be obtained, and the value of the perfect information exceeds the cost of acquiring it, then it is worthwhile to acquire this information prior to making a decision.

Calculating the expected value of perfect information is useful for exploring the upper bound of the value of eliminating uncertainty. However, in real-world problems, obtaining perfect information about the state of the world (here, the state of the water body) is almost always impossible (Canessa et al., 2015). Therefore, instead of obtaining perfect information on the realisation of X, the decision maker can reduce, but not entirely eliminate, uncertainty by observing some information (or message) y, which may thus be viewed as specific information about the probability distribution of X. Since the information being received is not known in advance, it represents a realisation of a (continuous) random variable Y with probability distribution p_Y. In this way, any realisation of Y provides some specific indication of the probability distribution of X; we denote this conditional probability distribution of X by $p_{X|Y}$, and specifically, write $p_{X|Y}(\cdot|y)$ if $Y = y$. Intuitively, we may interpret the probability distribution of the possible message p_Y as an *information service*, which induces the conditional information $p_{X|Y}$ on the distribution of X. It is the acquisition of this information service about which the decision maker has to decide before deciding on the action itself.

The VoI concept can be adapted to this situation as well: Yokota and Thompson (2004a) define the value of information, more precisely the value of an information service, as the difference between the expected payoff under current information and the expected payoff when new information is obtained. Specifically, the expected value of imperfect information is the difference between the expected value of the best action based on the posterior probability distribution (PoV) on X induced by the, ex-ante unknown, information Y, and the PV:

$$VoI := PoV - PV.$$

[4] In the literature, the expected value of perfect information is frequently denoted by EVPI (see, e.g. Raiffa and Schlaifer, 1961; Yokota and Thompson, 2004a), we prefer the shorter notation VoI°, though.

Here, a realisation of the random variable Y and the associated probability density p_Y represents some, yet imperfect, information about the state $p_{X|Y}$. This information might be obtained, for example, by means of monitoring or or by conducting an experiment (Raiffa and Schlaifer, 1961). Given the probability density p_Y, PoV is given by

$$PoV := \int \max_{a \in A} \mathbb{E}\left[v(a,x)|y\right] p_Y(y)\,\mathrm{d}y = \int \max_{a \in A} \left(\sum_{x \in \Omega} v(a,x) p_{X|Y}(x|y) \right) p_Y(y)\,\mathrm{d}y,$$

where the expected value of the best outcome is taken over all possible messages (or monitoring results) y weighted by their probabilities of observing $p_Y(y)$. [5]

Since any received message (or information) y provides information on the distribution of X, the probabilities for realisations of X need to be updated accordingly. Bayesian updating reflects the belief-updating process of the probability of X for all possible sample information y:

$$p_{X|Y}(x|y) = \frac{p_X(x)\, p_{Y|X}(y|x)}{p_Y(y)},$$

with $p_{Y|X}(y|x)$ representing the likelihood function of observing y when the state of the world is x, and $p_Y(y)$ representing the marginal density of y:

$$p_Y(y) = \sum_{x \in \Omega} p_X(x) p_{Y|X}(y|x).$$

3.4 VoI analysis for the Weser River basin

We now continue with the VoI analysis for our management problem described in Section 3.3 where we consider two states of a water body $X \in \Omega = \{x_0, x_1\}$ and two actions $a \in A = \{a_0, a_1\}$. For this simplified case, the (prior) probability distribution p_X can be represented by a single probability $p := p_X(x_1) = 1 - p_X(x_0)$. Our initial analysis exemplifies the value of monitoring information based on the prior p and the management cost c.

3.4.1 Computing conditional and posterior distributions

VoI analysis relies on Bayesian updating to compute conditional probabilities, therefore one key aspect is to determine the likelihood of the data. In our case, we fit distributions to the empirical data to simulate monitoring activity by randomly sampling values from these distributions. To choose the best fit for the data, we first compute the descriptive parameters of the empirical data. We use the Cullen and Frey plot – a skewness-kurtosis plot – for a visualisation of the possible best distribution. We then choose from the proposed theoretical

[5] Since PoV depends on the realisation of some experiment (or a message) VoI is frequently referred to as the *expected value of sample information* EVSI (see Raiffa and Schlaifer, 1961; Yokota and Thompson, 2004a).

distribution consistent with the skewness and kurtosis of the empirical data and conduct a goodness-of-fit analysis. We choose the best fit by comparing the maximum likelihood estimators (MLE), log-likelihood, Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC). For the bad state data, the Cullen and Frey graph, in addition to the MLE, suggests a gamma distribution as the best fitting distribution, while the best fit for good state data based on the same criteria is a beta distribution. However, for the fitting process, the data has to be re-scaled to the support of a beta distribution, i.e. rescaled to $[0, 1|$. This is problematic, as there is no way to "scale back" after conducting the VoI analysis. We avoid the need to scale the data by choosing a four-parameter beta distribution, a highly flexible bounded distribution, where the lower and upper limits can be set based on the data. Fitting the best possible distribution to the data is an important part of our VoI analysis as it requires sampling from the distribution and refitting the sampled values.

In order to estimate the posterior value of imperfect information from the available data, that is from sampling values for Y, we estimate $p_{Y|X}\left(y_i|x\right)$ from the distributions fitted to the empirical data using a Monte Carlo approach. Random samples ($n = 10000$) are drawn from the fitted distribution and the distributions are refitted to the random samples. Then, using the estimator $\widehat{p}_{Y|X}\left(y_i|x\right)$, we approximate PoV by

$$\widehat{PoV} = \frac{1}{n}\sum_{i=1}^{n}\max_{a\in A}\mathbb{E}\left[v\left(x,a\right)|y_i\right] = \frac{1}{n}\sum_{i=1}^{n}\max_{a\in A}\left(\sum_{x\in\Omega}v(x,a)\widehat{p}_{X|Y}\left(x|y_i\right)\right),$$

with n being the number of observations. The corresponding confidence intervals (CI) for $\widehat{PoV}$ are estimated using a Monte Carlo bootstrapping approach, for which the procedure is repeated 1000 times and the confidence intervals are obtained by subtracting the value of PV from the calculated PoV in each step.

3.4.2 Value of perfect and imperfect information

We conduct the initial VoI analysis with the estimated prior probabilities and monetary values as given in Table 3.2. We consider the prior belief $p := p_X(x_1) = 0.1$ (see subsection 3.3.1) for the water body being in a good state, meaning that, a priori, the decision maker is fairly certain that the water body is not meeting the desired state $X = x_1$. In view of the prevailing uncertainty and without additional information, the strategy with the highest expected benefit would be to choose the specified action a_1 for the water body. Under current information, this action would result in a maximum expected payoff of 110 million EUR/year. In contrast, the value of perfect information yields a maximum expected value of 119 million EUR/year. If the decision maker could obtain perfect information, it would be worthwhile to pay up to 9 million EUR/year and postpone the decision-making until after additional information is acquired. Lastly, the value of imperfect information, meaning that new information may reduce but not

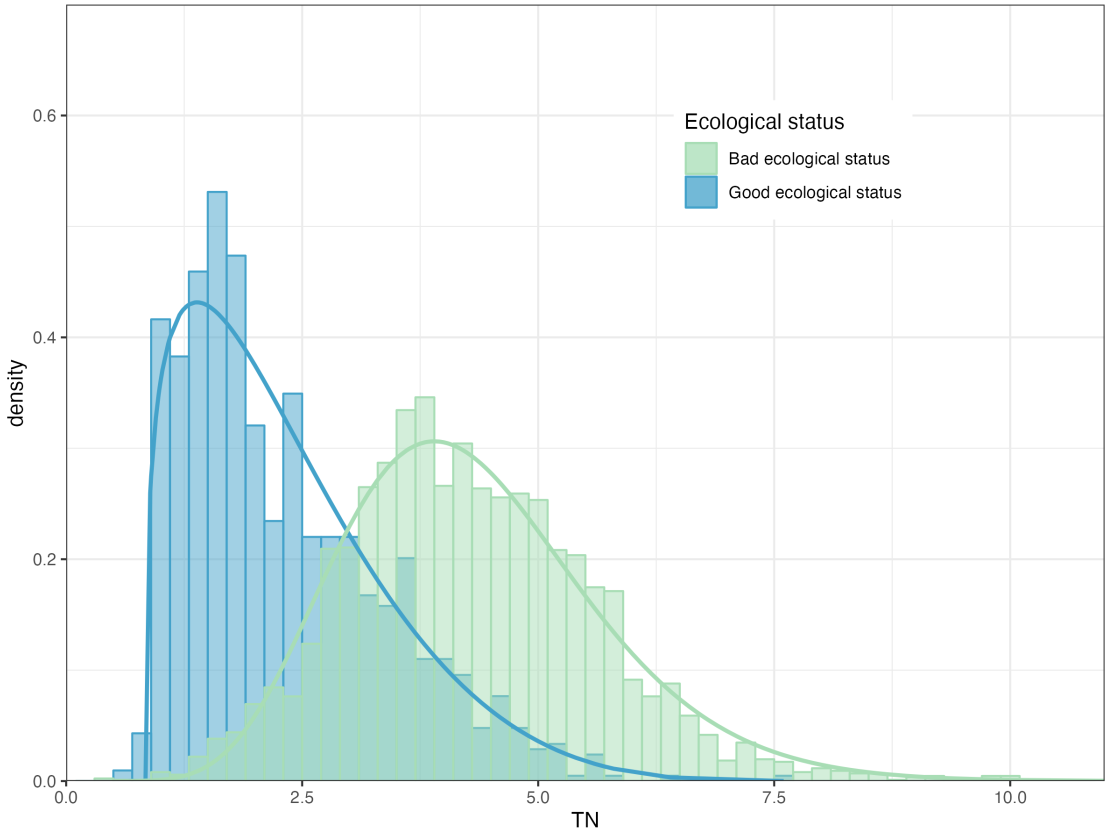

Figure 3.1: Histograms of the empirical data (total nitrogen in mg/l = TN) with fitted four-parameter-beta and gamma distributions. The empirical data is divided into two categories for the ecological state: good ecological status and bad ecological status

eliminate completely the uncertainty, is 112.21 million EUR/year. In this case, the decision maker is willing to pay up to 2.21 million EUR/year (with a 95% CI [2.06, 2.84]) for acquiring information through monitoring in order to be more certain about the true state of the water body, see Table 3.3.

Table 3.3: Value of perfect and imperfect information for the case of the Weser River

Prior $p_X(x)$		Prior value	Perfect information		Imperfect information	
x_1	x_0	PV	PoV°	VoI°	PoV	VoI
0.1	0.9	110	119	9	112.21	2.21 $CI(2.06, 2.84)$

3.5 Dependence on costs and prior probabilities

In real-world applications, the monetary values, management costs and prior probabilities are estimates and are thus themselves subject to uncertainty. A careful sensitivity analysis may help to reduce the uncertainty incorporated in these parameters and to examine the robustness of the VoI analysis with respect to these data. In this section, we, therefore, compute VoI for different management costs c and prior probabilities (for the good state) $p := p_X(x_1)$, and explore the sensitivity of VoI to these two crucial parameters. We assume that the management costs are non-negative and do not exceed the increase in utility achieved from the water body being in the good compared to the bad state. [6] Formally

$$VoI : [0,1] \times [0,v] \to \mathbb{R} : (p,c) \mapsto VoI(p,c).$$

Among other things, this formalisation helps us to find the priors for which VoI is maximised in relation to management costs. Since in the course of our analysis, we vary (p,c) over its domain, we will provide qualitatively generic results for all two-state, two-action decision problems under uncertainty.

Before we present and discuss the properties of VoI for its full parameter range, we begin with computing VoI for specific values of the management cost. Fig. 3.2 displays the values of perfect and imperfect information for low ($c = 50$), medium ($c = 100$), and high ($c = 150$) management costs (all in million EUR/year), along with 95% CI. If the action has a medium cost, VoI reaches its maximum when uncertainty is highest, i.e. at a prior probability of $p = 0.5$, see Fig. 3.2b. In this case, the value of perfect information reaches up to 50 million EUR/year, and the value of imperfect information is up to 30 million EUR/year. In contrast, in the absence of uncertainty, i.e. for either $p = 0$ or $p = 1$, the values of perfect and imperfect information are both zero, as the decision maker already has full knowledge about the true state of the water body.

For low management costs (50 million EUR/year), see Fig. 3.2a, VoI is highest when the ecological state is believed to be likely to meet the target ($p = 0.75$), and the decision maker is therefore relatively confident that there is no need for any action. Intuitively, if the management cost is low, the decision maker is willing to undertake the action a_1 even if the water body is quite likely to be in a good state; only if this probability is sufficiently high does the decision maker omit taking action. It follows that there is a (relatively high) level of this probability at which the decision maker is indifferent between undertaking the action (because its cost is low) and omitting it (because it is seemingly not necessary). But VoI reaches its maximum exactly at the level of p where the decision maker is indifferent between actions a_0 and a_1, because any additional piece of information may flip the decision

[6]The utility function may be transformed by any monotonously increasing function without affecting the DM's preferences and thus the (qualitative) results, as this transformation only scales VoI.

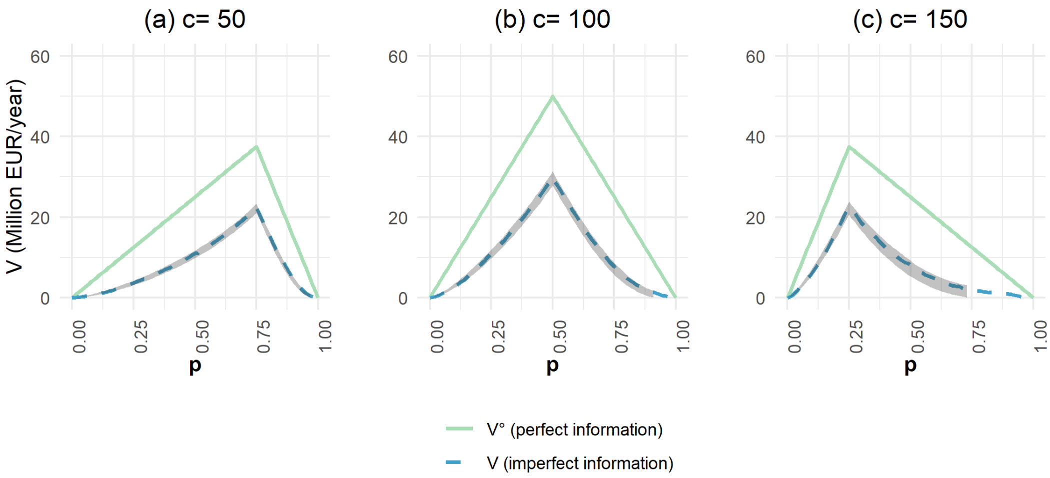

Figure 3.2: The value of perfect and imperfect information (with 95 % confidence intervals) for $c = 50, 100, 150$ and $p \in [0, 1]$.

to either side. Specifically, for $c = 50$, VoI is maximised at $p = 0.75$ with perfect information attaining a value of more than 40 million EUR/year and imperfect information more than 20 million EUR/year. In this case, it is worth getting more information to either confirm or reject the hypothesis that the water body is in good state so that an action can either be justifiably disregarded or undertaken. In this way, the decision maker avoids the risk that either an unnecessary action will be performed, or a beneficial and relatively cheap action will be omitted.

The reverse line of argument holds if the cost of the action is high (here 150 million EUR/year). Then, the action will not be undertaken unless the probability of the water body's being in good state is quite low. The value of p at which the decision maker is indifferent between actions a_0 and a_1 is therefore relatively low – and it is here that VoI reaches its maximum, for any additional indication of the water body's being in the good or in the bad state means changing the decision to one side or the other. Specifically, for $c = 150$, VoI reaches its maximum at $p = 0.25$, see Fig. 3.2c.

Moreover, we infer from Fig. 3.2 that VoI is strictly quasi-concave in p. While VoI depends on p and c, it is true, by the construction of the VoI concept, that the value of perfect information exceeds the value of imperfect information, irrespective of p and c. Yet, for any fixed level of c the location of the maximum, i.e. the prior probability for which VoI is maximum, is the same for both perfect and imperfect information, again see Fig. 3.2. More formally, let us define

$$p^*(c) := \arg\max_p VoI(p, c).$$

Then, for any value of c, VoI has a maximum at $p^*(c)$ with the value of VoI amounting to

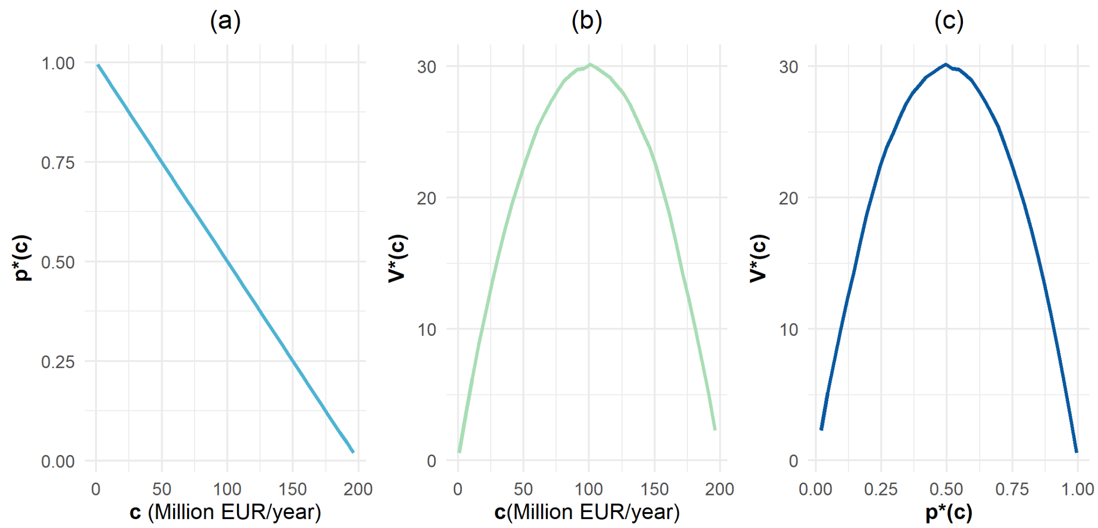

Figure 3.3: (a) Plot of maximum prior probability for which VoI has a maximum, i.e. $p^*(c)$ versus the management cost c; (b) Maximum $VoI^*(c)$ versus the management cost c; (c) Parametric plot of $VoI^*(c)$ and $p^*(c)$.

$VoI^*(c) := VoI(p^*(c), c)$.

We now construct the image of VoI^* step by step. In Fig. 3.2, we display $VoI(\cdot, 50)$, $VoI(\cdot, 100)$ and $VoI(\cdot, 150)$, identifying the corresponding maximisers $p^*(50), p^*(100)$ and $p^*(150)$, and their respective values of VoI: $VoI(p^*(50), 50)$, $VoI(p^*(100), 100)$ and $VoI(p^*(150), 150)$. Proceeding in a similar way, we calculate $p^*(c)$ and $VoI^*(c)$ for all $c \in [0, v]$. The maximiser $p^*(\cdot)$ is shown in Fig. 3.3a., while the maximised function $VoI^*(\cdot)$ is shown in Fig. 3.3b. Finally, we display the graph of the mapping $c \mapsto (p^*(c), VoI(p^*(c), c))$, i.e. a parametric plot of c, in Fig. 3.3c. Fig. 3.3a shows that $p^*(\cdot)$ decreases linearly, with $p^*(0) = 1$ and $p^*(200) = p^*(v) = 0$, while Fig. 3.3b shows that $VoI^*(\cdot)$ is strictly concave, with $VoI^*(0) = 0 = VoI^*(v)$. Lastly, along the path $c \mapsto (p^*(c), VoI^*(c))$, VoI^* is maximum for $(p^*(c), c) = (0.5, 100)$, which can be seen from Fig. 3.3b and 3.3c. Intuitively, if management can be performed at zero cost, the decision maker will undertake the action in any case and is only indifferent between a_0 and a_1 if the water body will be in good state with probability 1. In contrast, if the management cost is equal to the value of the water body in the good state, which happens at $c = v = 200$, the action will never be undertaken, and the decision maker is indifferent between a_0 and a_1 only if the probability of the water body's being in the good state is 0, i.e. the water body is in a bad state almost surely. Reversely, the value of reducing uncertainty as to which is the best decision, a_0 or a_1, is highest when the monitoring costs are neither negligible nor excessive, and a prior uncertainty regarding the state of the water body is high (i.e. $p = 0.5$). In such a situation, any additional data that may give an indication as to what to do best is very valuable.

To summarise our findings, which are valid generically for all two-state, two-actions deci-

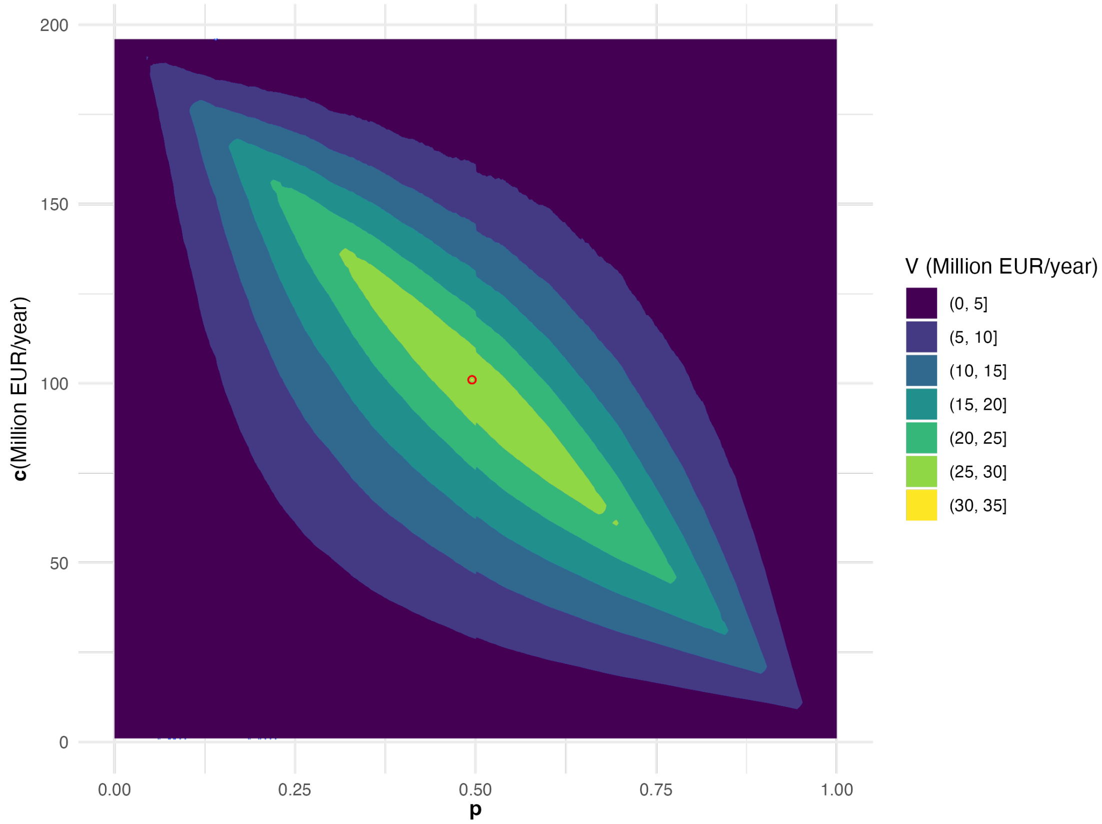

Figure 3.4: Contour plot of the value of imperfect (monitoring) information VoI as a function of the prior probability p and the management cost c.

sion problems under uncertainty: When the cost of management is high, the decision maker does not undertake the action unless the prior probability is quite low (i.e. when the bad state is likely to hold). Therefore, when the cost and the probability of good state are both high, the arrival of new information is unlikely to reverse the decision maker's decision. Yet, when the prior probability is low, there is a significant risk that the actual state is bad, and thus the decision needs to be revised. Hence, given a high cost for management, VoI is largest when the prior probability is low, and therefore the prior probability for which VoI is maximised, p^*, is small. Conversely, when the management cost is low, the decision maker is likely to undertake the protective action. This is especially the case when the prior probability is low, i.e. when the water body is likely to be in a bad state. When the prior probability is high, implying that good state is the probable result, undertaking a costly action, even if relatively cheap, may represent a waste of resources. Given a low value for the management cost, a high probability of good state tends to make the decision to undertake action needless. Consequently, for low management cost, VoI is the largest when the prior probability is high. This explains why there is a negative relation between c and p^*.

This negative relation between c and p^* is also shown in the contour plot in Fig. 3.4, displaying the iso-level curves of VoI for $p \in [0, 1]$ and $c \in [0, v] = [0, 200]$. When the decision maker is a priori quite certain about the state of the water body, i.e. p is either close to 0 or to 1, the value of additional information is relatively low. Even more pronounced is the case when both p and c are simultaneously either low or high. In both of these cases, VoI is low, because of a low [high] probability of the good state, i.e. a high [low] probability of the bad state, together with low [high] management cost makes the decision maker perform [abandon] the action – and the arrival of new information is very unlikely to reverse this decision. In both of these polar cases, it is pretty evident that the action should be performed immediately (when both p and c are small), respectively that the action can be dispensed with (when both p and c are high), so that the arrival of new information is very unlikely to reverse this decision – and thus the value of information is low. On the contrary, VoI is high when the management decision is close, which happens when the state of the water body is very unclear and management costs are moderate. Specifically, VoI is maximised when uncertainty is highest ($p = 0.5$) and when at the same time the action costs are half of the gain in the value of the good over the bad state of the water body ($c = v/2 = 100$).

3.6 Discussion and general insights

Acquiring more information through monitoring can have substantial value, as additional data may improve environmental decision-making. VoI analysis makes this economic benefit of data collection and monitoring activities explicit (Bouma et al., 2009). Decision makers may thereby improve the allocation of resources in monitoring and management and thus enhance returns on investments. Here, VoI represents the decision maker's willingness-to-pay (in terms of payoff or utility) for additional information. Our study aimed at demonstrating how to support an environmental decision problem by means of a VoI analysis. We applied the VoI framework using real-world monitoring data to a simple decision problem with two states of a water body and two decision options, using one variable (total nitrogen concentrations) as an indicator for the state of the water body. We calculated the value of additional monitoring data (or information) for a decision maker deciding on an environmental management action. Improved information, even when imperfect, yields a positive value and may lead to a higher payoff for the decision maker. VoI analysis can be a valuable tool in the light of monitoring being frequently criticised for being too expensive. The fact that these monitoring data may enhance decision making, and may thus have an additional value, is often ignored (Caughlan and Oakley, 2001; Lovett et al., 2007). VoI analysis focuses on this kind of extra value that data may have for environmental management, where investment decisions may be conditional on the collected data.

With our analyses, we obtained interesting methodological and general insights. From a methodological point of view, we see that it is especially difficult to calculate the value of imperfect information when the sample space is continuous. Simplyfing a complex decision

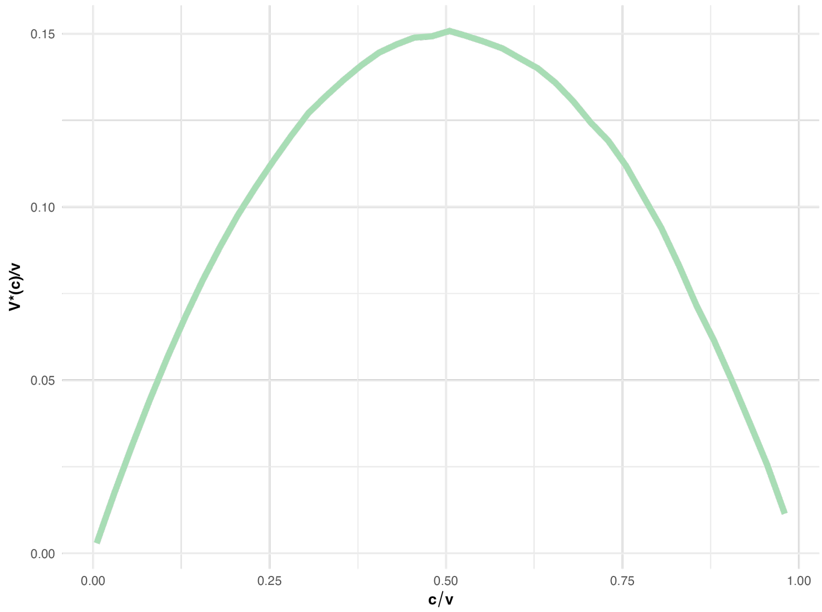

Figure 3.5: Effect of changing management cost on the maximum value of information VoI. The values of both the management cost and the VoI have been normalised with respect to the value of the good state (v).

problem to a binary system with two states and two alternatives is helpful to allow for a clear and intuitive understanding of the problem. Using real-world monitoring data to formulate the likelihood function can be a useful approach and put the analysis in a realistic context. The proposed framework is scalable and not limited to binary systems – it can be applied to systems with any number of states and actions to highlight more realistic scenarios. However, it might not be possible to derive generic insights if the system gets too complex. We showed that a Monte Carlo approach used in conjunction with Bayesian decision theory appears to be suitable for calculating an approximate value for imperfect information. To account for uncertainty incorporated in the estimated prior probabilities and the monetary values, we performed a sensitivity analysis. This method is also beneficial for providing further guidance to decision makers and environmental managers on the value of information for a range of combinations of prior probabilities and management costs. Moreover, this gives insight into the behaviour of VoI in relation to prior probabilities and management costs and highlights the importance of a sensitivity analysis.

Irrespective of the fact that the exact values that result from a VoI analysis are essentially case-specific, there are still some general findings that are worth emphasising: Since VoI crucially depends on the prior probability p and the monitoring cost c, we investigate for which combinations of p and c VoI is maximum. To answer this, we calculate, for any value of c, the level of p for which VoI is maximal. Denoting this maximising prior by $p^* = p^*(c)$, we show that p^* is a decreasing function of c; moreover, VoI is, at least in our decision context, quasi-concave, which is illustrated in Fig. 3.4. We recognise the inherent uncertainties with

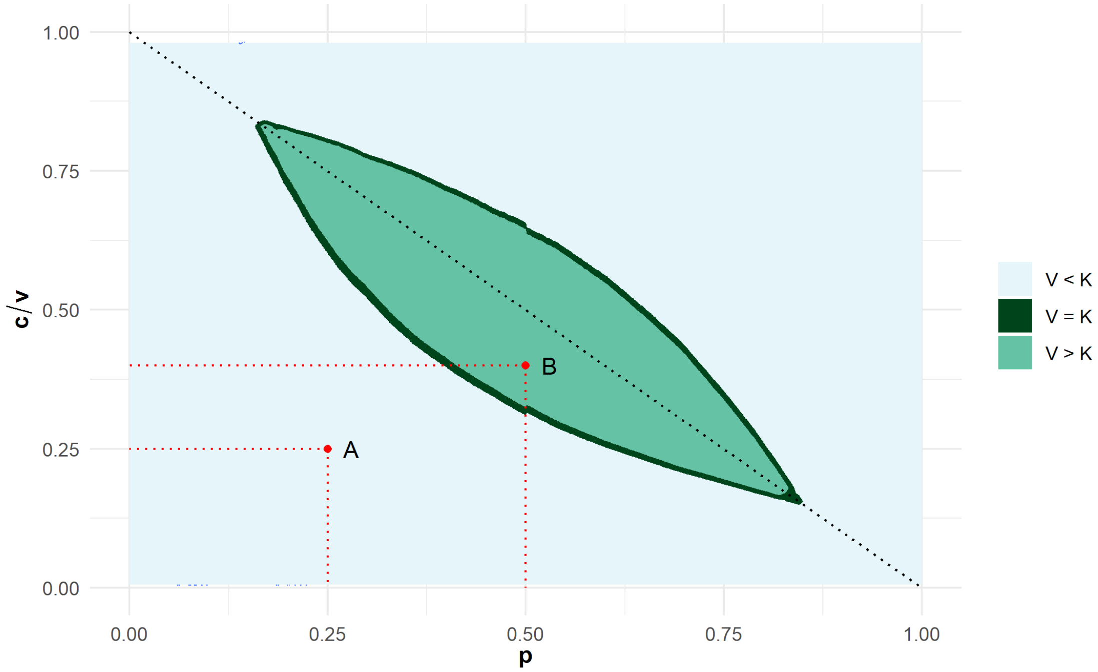

Figure 3.6: Value of information VoI in comparison to monitoring cost K. The black dotted line shows the maximising function $p^*(c/v)$. Example points A and B for parameter combinations where VoI is smaller than K (point A) and VoI is higher than K (point B). The decision maker would decide based on the results of the VoI analysis and the cost for monitoring if investing in additional information is worthwhile ($VoI > K$) or not ($VoI < K$).

regard to estimating prior probabilities, management costs, and the value of the state of the ecosystem. Improving these estimates leads to more confident estimates of the VoI. Intuitively, more informed priors, i.e. p close to either 0 or 1, results in a smaller VoI. The more certain the decision maker is about the state prior to making their choice, the lower the effect of additional information on their choice. However, the highest uncertainty (a prior probability p equal or close to 0.5) does not necessarily imply that VoI is maximal (Canessa et al., 2015) because p^* depends negatively on the management cost c. This finding is in line with Giordano et al. (2022) who discuss the dependence of VoI on management cost and the point of indifference of the decision maker.

To complement our analysis and to obtain more generic results, Fig. 3.5 shows V^* as a function of the ratio of the management cost c and the value of the good state v, i.e. on the relative management cost c/v; it shows that V^* is maximal when $c = v/2$. This generalisation provides us with some interesting and somewhat counter-intuitive insights: Let us assume that both c and p are fixed. If we now vary the value of the good state of the ecosystem, it turns out that increasing the value of the good state may lead to a decrease in the value of information. Intuitively, one might assume that the more relative value the ecosystem has, the more one would be willing to invest in monitoring. Yet, the analysis shows that a higher value leads to the fact that it is more useful to directly invest in actions instead of risking spending resources on monitoring and missing opportunities to act. Hence, the value of the information is relatively low.

So far, our discussion mostly focused on how the value of information is influenced by the key parameters c, v and p. Let us remember that from a decision-making perspective, whether or not the acquisition of additional data is actually worthwhile before a management decision is made, depends on the difference between the VoI and the cost of collecting the data (information acquisition). If the former exceeds the latter, new data should be collected before a decision is made. This is illustrated in Fig. 3.6. It shows the results of a VoI analysis for a case with two states of the world and two actions, similar to our previous example. The vertical axis gives the ratio between the management cost c and the value v of the system. The horizontal axis is the prior probability p of the targeted state of the system. VoI is calculated over the full parameter range ($[0, 1]$) and a fixed cost for monitoring (or information acquisition) K is given. This simple figure exemplifies under which conditions it is worthwhile for the decision maker to invest in monitoring. For a given constellation of parameters, such as in point A, the decision maker would decide against investing in information, as VoI is less than the cost K for monitoring. For another combination of values of the parameters, as in point B, VoI is larger than K and therefore the results suggest that investing in monitoring is welfare enhancing. This figure gives guidance to decision makers under which circumstances information acquisition is valuable. Further, it provides us with a certain amount of sensitivity information: As an example, since point B is relatively far in the interior of the green area, minor variations of parameter values c, v and p do not immediately change the decision to collect additional data.

Finally, we would like to emphasise that the generic results and insights from this discussion regarding the relation between the VoI and the management costs, the value of the good state and the prior probability are not restricted to our case study but apply to decision problems with the same structure. It should be noted, however, that the shape of the ellipse displayed in Figs. 3.4 and 3.6 not only depends on the parameters mentioned before but also on the posterior probability distributions which have to be fitted to the data of the specific decision problem under consideration (see Fig. 3.7 for an example).

3.7 Conclusion

In our study, we demonstrated how value of information (VoI) analysis can serve as a valuable tool to enhance decision-making in environmental management as it may help to arrive at more well-judged decisions. We apply the VoI concept to a decision problem in water quality management in northern Germany. Our case study highlights that the VoI reaches substantial positive values. Even though acquiring data through monitoring may be costly, it may nevertheless be cost efficient to do so if the VoI outweighs the cost of monitoring. As the values and prior probabilities in our case study are estimates and are thus subject to uncertainty – which is the case for most decision problems – a careful and thorough sensitivity analysis is recommendable if not indispensable. Calculating the VoI for a suitable range of costs and prior probabilities enables the decision maker to place the results of the VoI analysis in the specific context and to highlight the specific conditions under which the collection of more data is, in fact, worthwhile. Our approach helps to expand the applications of VoI analysis to environmental management decision problems, especially to the value of imperfect information and monitoring. Even though the numerical results of the VoI analysis are case-specific, important general insights can still be obtained: The VoI has a maximum when the decision maker is indifferent between two alternative policies. In this case, a piece of new information may induce the optimal decision to switch from one action to another; the decision is sensitive to new information, so the VoI is high. Moreover, with a prior for which the maximum VoI is decreasing in the monitoring cost, the maximum VoI is reached when both the prior and the monitoring cost have moderate values. With our analysis, we arrive at qualitatively generic insights that are valid for all management decision problems under uncertainty with two states of the world and two actions.

3.8 Appendix

In our analysis, we arrive at qualitatively generic results for all two-state and two-action decision problems. However, the shape of the ellipse (Fig. 3.4) not only depends on the management cost c and the prior probability p but also depends on the posterior probability. We obtain the posterior probability by sampling random values from distributions fitted to the empirical data. To display this change in shape, we calculate VoI using different distributions. We can see that the shape of the ellipse varies and becomes rounder or narrower depending on the posterior probability (see Fig. 3.7). The maximising function p^* and the structural components remain the same for all decision contexts with two states and two actions. Further, the results displayed in Fig. 3.7 can be interpreted the same way as explained in Section 3.5.

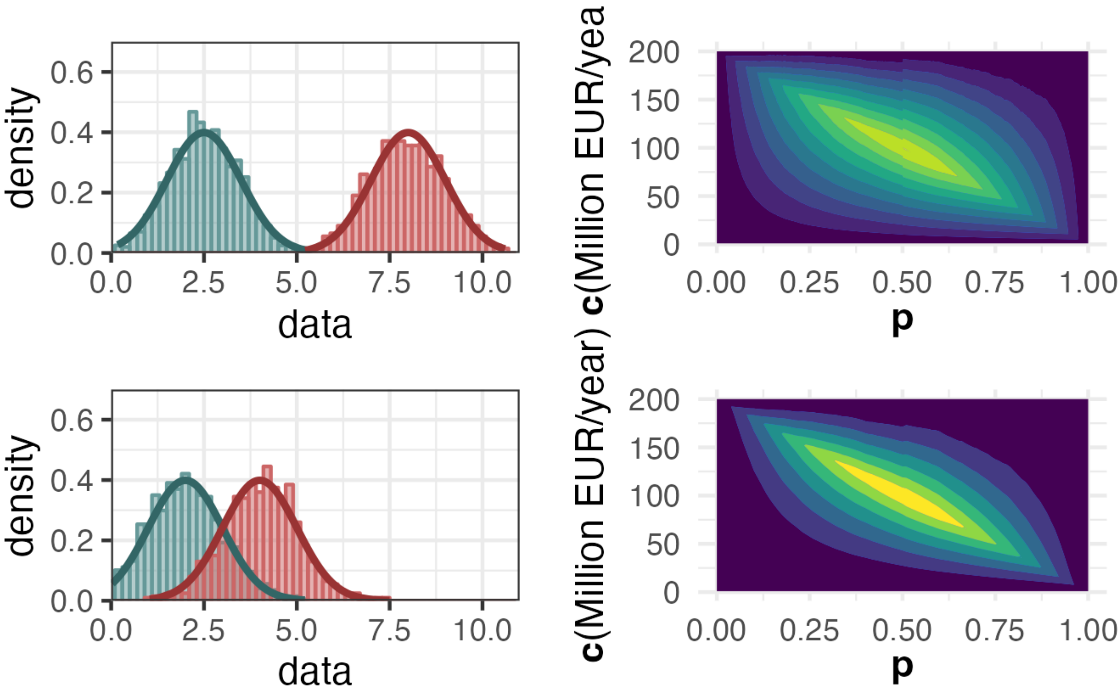

Figure 3.7: Results of two VoI analyses with different distributions of the data. The shape of the ellipse differs depending on the posterior probabilities which is obtained from sampled values from the fitted distributions. Qualitatively, the results of the analyses are generic.

4 The value of information in predicting harmful algal blooms

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Highlights

- Value of Information (VoI) analysis evaluates the benefits of predicting harmful algal blooms.
- Simulation of time series combined with a probit model is a valuable technique for deriving conditional probabilities in VoI analysis.
- Our results show an added value of extended monitoring at a specific seasonal period.
- Information accuracy has a significant influence on VoI.
- We demonstrate how VoI analysis can be used to enable decision-makers to make proactive management strategies to mitigate economic losses and negative impacts of harmful algal blooms.

4.1 Abstract

Environmental decision-making is inherently subject to uncertainty. However, decisions are often urgent, and whether to take direct action or invest in collecting additional data beforehand is pervasive. To make this trade-off explicit, the value of information (VoI) theory offers a powerful decision analytic tool to quantify the expected benefit of resolving uncertainty in a decision context. Although it is mainly used in economic contexts, it can be applied to biodiversity conservation and management.

In our approach, we evaluate the expected surplus in resolving uncertainty about the occurrence of harmful algal blooms in the German North Sea coastal waters and the effect on decision-making. We use an established dynamic foodweb model (NPPZ) with two competing phytoplankton consortia (harmful, non-harmful) and regional monitoring data to analyse the prediction accuracy of different indicators. We then evaluate the effect of reducing uncertainty about these indicators (e.g., through extended monitoring) on management decisions by means of a VoI analysis. We see that additional information may lead to an expected welfare gain in our decision context. Our findings highlight the significant potential for VoI analysis to enhance decision-making in fishery management and provide insights for future monitoring strategies to mitigate the adverse effects of HABs. This approach contributes valuable methodological insights for optimising management strategies and further emphasises the importance of considering uncertainty in decision-making processes.

Keywords: value of information; decision analysis; uncertainty; environmental management; harmful algal bloom
JEL: C11, C61, D81, Q25, Q57
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4.2 Introduction

A feature associated with many phytoplankton species is their ability to rapidly increase in concentration, resulting in substantial plankton blooms. Some algal species bloom regularly during the season and thus produce spring blooms, which is beneficial for the ecosystem since they establish the base of the aquatic food web. By contrast, other algal species bloom only sporadically but can have detrimental effects on the ecosystem. For instance, some of these species release toxins, which can cause substantial mortality of fish or can result in paralysis and death in sea birds and humans or species that damage other organisms physically. These harmful algal blooms (HABs) can negatively affect water quality and may pose severe economic losses for fisheries and tourism, as well as negative health effects for humans and other organisms (Anderson et al., 2000). In recent years, a significant increase in the number of such less predictable and severe HABs has been observed in coastal waters (Anderson, 2007; Anderson et al., 2012). Even though their damage can be severe, the underlying mechanisms of the sudden occurrence of HABs are still poorly understood. Much work has been put into developing modelling approaches to understand their dynamics in order to improve the prediction of HABs and take precautionary management interventions (Chakraborty and Feudel, 2014). At the same time, data collection activities take place to closely monitor the development of HABs (Anderson et al., 2001).

Monitoring data can provide valuable information for understanding the system and its dynamics. However, data collection is often associated with substantial costs, as it relies on frequent observations, water sampling and laboratory tests (Lomax et al., 2005), which is not only costly in financial terms but also in terms of time and resources. Therefore, from a management perspective, a careful evaluation of the benefit of additional data is needed. While additional information may allow the decision-maker to make more substantiated decisions, the time delay induced by continued data collection may be substantial and may thus jeopardise the opportunity for management and intervention decisions in due time.

This trade-off is at the core of the value of information (VoI) analysis, a decision-analytic tool that quantifies the net value gained from information acquired at a certain cost. Based on information theory and statistical decision theory (Hirshleifer and Riley, 1979), VoI has been applied more recently in conservation management (Bolam et al., 2019) and monitoring of water quality (Koski et al., 2020; Luhede et al., 2024). It constitutes a quantitative instrument to evaluate the expected increase in the decision-maker's utility when additional information is collected. The core idea of VoI is to determine the payoff that can be expected in terms of an improvement in the outcome of a decision once based on additional data (or information) that will be collected net of the cost of this data acquisition.

In this study, we focus on reducing uncertainty about the occurrence of a HAB in the German North Sea via extended monitoring. More precisely, we evaluate the value of additional time-resolved data about the top-down control, i.e., zooplankton, to better predict a HAB and to take precautionary management actions in time. Current legislation focuses mainly on nitrogen reduction to prevent further eutrophication and hence the occurrence of severe HABs (Rönn et al., 2023). Therefore, in this study, we investigate the possible improvement of the management decision that may be achieved by adding zooplankton data to previously included nutrient data in order to enhance HAB prediction. Calculating VoI generally involves using decision-analytic methods, for example, decision trees or Bayesian networks, to model the expected outcomes of different monitoring and information-collection activities (Yokota and Thompson, 2004b). Methods to estimate parameters for the decision context include modelling approaches (e.g. Jin et al., 2020) to expert elicitation and surveys (e.g. Nicol et al., 2018); see Bolam et al. (2019) for a literature overview of VoI in biodiversity conservation. We use numerical simulation data with a model fitted to real monitoring data and a literature search to recreate a realistic case study. We base our analysis on an established HAB model by Chakraborty and Feudel (2014), considering a nutrient, toxic phytoplankton, non-toxic phytoplankton, and zooplankton in the North Sea to simulate time series and derive conditional probabilities for the occurrence of a HAB in the framework of a regression model (details in Section 4.3).

Based on the designed case study, we conduct a VoI analysis to quantify the economic value of collecting additional information on zooplankton and the effect of reducing uncertainty in the context of fishery management (in Section 3). Following a discussion of our findings and the sensitivity of the results to changes in parameters (in Section 4), we conclude with an outlook for future monitoring and management and how VoI analysis can contribute to improving management decisions to prevent the consequences of a HAB outbreak (in Section 5).

4.3 Methods

4.3.1 Value of information

Making a decision implies that the decision-maker chooses (at least) one of a set of candidate actions to achieve one or more specified objectives. The decision problem is more complex when the outcome is determined not only by the action but also by the yet unknown state of the system (or, more broadly, the world). In such a situation, the decision maker has to find a suitable way to cope with uncertainty, as an action has to be chosen before uncertainty resolves. This uncertainty can be represented as different beliefs about the (future) state of the system, each with a probability of being true (prior belief). In our setting, the objective is to prevent or at least mitigate the consequences of the occurrence of a HAB by taking precautionary actions. We consider a simple decision problem with two actions $a \in \mathcal{A} := \{a_0, a_1\}$ designed to control two states $x \in \Omega := \{x_0, x_1\}$. Since the state is not known to the decision maker in advance, it may be seen as a random variable X with possible outcomes in Ω, where each state is believed to be the true state with a given prior probability $p_X(x)$. In our case, state x_1 refers to the occurrence of a HAB, and x_0 to the occurrence of no HAB. The decision maker can choose between two management actions: action a_0, which is to do nothing, and action a_1, which is to take a precautionary measure.

As a baseline value for economic activity, a benefit b accrues, irrespective of the action taken. While inactivity is costless, $c(a_0) = 0$, taking the precautionary management action is associated with some cost $c(a_1) > 0$. In case of a HAB, i.e. if x_1 is realised, a damage of an amount d occurs if no precautionary action is taken, while this damage can be avoided if such an action is undertaken. To reduce parameters in our model, we can subtract the constant b from the matrix without loss of generality (see also Eq. (4.17) in the Appendix). This has the advantage that we only need two parameters (d and c). We can interpret the decision maker's payoff $v(a, x)$ as the avoidance of a loss aimed to be maximised.

Table 4.1: Matrix summarising the HAB decision problem.

state of the world X	management action a		prior belief p_X
	a_0	a_1	
$X = x_0$: no event	$v(a_0, x_0) = 0$	$v(a_1, x_0) = -c(a_1)$	$p_X(x_0) = (1 - p)$
$X = x_1$: HAB occurs	$v(a_0, x_1) = -d$	$v(a_1, x_1) = -c(a_1)$	$p_X(x_1) = p$

More formally, the state, together with the action, determines the utility (or the payoff) of the decision maker; that is, utility is a function $v : \mathcal{A} \times \Omega \to \mathbb{R} : (a, x) \mapsto v(a, x)$. Given that the system resides in state x, an optimal decision is to pick the action that maximises utility: $a^*(x) := \arg\max_a v(a, x)$. Since the system visits different states in accordance with $p = p_X$, the average value of optimal decisions is

$$\mathbb{E}_X \left[v(a^*(X), X)\right] = \mathbb{E}_X \left[\max_a v(a, X)\right] = \sum_x p_X(x) \max_a v(a, x) \,. \tag{4.1}$$

Choosing an optimal action $a^*(x)$ requires *perfect information* about the realised state. Therefore this term represents the expected value when the decision maker is informed about the realisation of the state X before making a decision. In this case, the decision can be made contingent on the state (of the world) $X = x \in \Omega$. For this reason, Eq. (4.1) represents the expected payoff under perfect information.

There are several variants of VoI. One of the most prominent is the *expected value of perfect information* ($EVPI$). By acquiring additional information, the decision maker obtains perfect information on the true state of the world. Under perfect information, the decision can be tailored to the actual state so that the decision can be made state-dependent, yet if a decision maker lacks this *clairvoyance* (perfect information), the decision has to compromise on all possible realisations of $X \in \Omega$, viz. to find a "one size fits all" action. In this case, the decision maker can only use the information carried by the prior distribution and select the action that maximises the expected value, i.e., the expected value if the decision is made subject to prior (or present) information. We refer to this value as the *expected payoff under prior information*:

$$\max_a \mathbb{E}_X \left[v(a, X)\right] = \max_a \sum_x v(a, x) p_X(x). \tag{4.2}$$

It is easy to see that $\forall\, a \in \mathcal{A}$:

$$\sum_x \max_a v(a, x) p_X(x) \geq \sum_x v(a, x) p_X(x)$$

hence

$$\sum_x \max_a v(a, x) p_X(x) \geq \max_a \sum_x v(a, x) p_X(x) \,.$$

Therefore, the difference between the expected utility under perfect information and under prior (or current) information yields *the expected value of perfect information*:

$$\begin{aligned} EVPI &:= \sum_x p_X(x)\max_a v(a,x) - \max_a \left[\sum_x v(a,x)p_X(x)\right] \\ &= \mathbb{E}_X\left[\max_a v(a,x)\right] - \max_a \mathbb{E}_X\left[v(a,x)\right] \geq 0\,. \end{aligned} \tag{4.3}$$

Hence, the value added by perfect information beyond the value reached by using only the prior information is always non-negative, and it may be interpreted as the willingness of the decision maker to pay for perfect information. Since perfect information allows for the best decisions to be made, $EVPI$ serves as an upper bound for any investment in information acquisition.

However, only rarely can uncertainty be resolved entirely by information (or data) acquisition. Typically, the arrival of new information reduces the extent of uncertainty but does not eliminate it. The arrival of new information may be seen as a measurement or a message received, providing a better indication of the actual state (of the world), based on which a decision can be made. From an ex-ante point of view, the message received, M, is not known in advance but is a random variable by itself with possible values in $\mathcal{M}$ with probability distribution p_M. Even though the message does not reveal the actual state, it provides an indication of the probability distribution of X. That is, upon receipt of the message $M = m \in \mathcal{M}$, the decision maker updates their belief on the probability distribution of X, yielding the *posterior probabilities*. In this case, the prior distribution p_X should be replaced by the more informative posterior distribution $p_{X|M}$ and the excess value beyond the reference set by the prior distribution, termed *expected value of imperfect information* or *expected value of sample information* ($EVSI$), should be calculated as [1]

$$\begin{aligned} EVSI := \sum_m \left[\max_a \sum_x v(a,x)p_{X|M}(x|m)\right] p_M(m) \quad &- \quad \max_a \sum_x v(a,x)p_X(x) \\ = \mathbb{E}_M\left[\max_a \mathbb{E}_{x|m}\left[v(a,X)\right]\right] \quad &- \quad \max_a \mathbb{E}_X\left[v(a,X)\right]. \end{aligned} \tag{4.4}$$

The transition from $EVSI$ to $EVPI$ is made by enriching the information contained in $p_{X|M}$ until, eventually, there is a surjective function $\mathcal{M} \to \Omega$ which means that $p_{X|M}(x|m) = \delta(x - x(m))$ and also $p_M = p_X$ almost everywhere. In this limit case we

[1] For measurements/messages belonging to a continuum $\mathcal{M}$ the sum $\sum_m \ldots p_M(m)$ should be replaced by the integral $\int_{\mathcal{M}} \ldots p_M(m)dm$)

find

$$\begin{aligned} EVSI &= \sum_m \max_a v(a, x(m)) p_M(m) - \max_a \sum_x v(a, x) p_X(x) \\ &= \sum_x \max_a v(a, x) p_X(x) - \max_a \sum_x v(a, x) p_X(x) \\ &= EVPI \end{aligned}$$

By applying Bayes' theorem, the conditional probability of X on M, *viz* the posterior probability of X, denoted by $p_{X|M}(x|m)$ can be calculated by

$$p_{X|M}(x|m) = \frac{p_{M|X}(m|x)\, p_X(x)}{p_M(m)}, \tag{4.5}$$

$$p_M(m) = \sum_x p_{M|X}(m|x) p_X(x). \tag{4.6}$$

In this way, we can also compute the $EVSI$ via

$$\sum_m \max_a \sum_x v(a, x) p_{M|X}(m|x) p_X(x) - \max_a \sum_x v(a, x) p_X(x)$$

which shows that the additional information introduced via $p_{M|X}$ by M acts by contracting the prior distribution. $EVSI$ can be positive, negative or zero depending on whether signal M is "more, less or equally informative" than the prior information. However, even though mathematically possible, the value of a message is necessarily non-negative, as an information service can never lower the decision maker's utility (Hirshleifer and Riley, 1979, p.1395)

4.3.2 A conceptual dynamical NPPZ model for a HAB

The term HAB refers to a broad class of sporadic bloom events in which a harmful algal species reaches extraordinary abundance, adversely affecting water quality or causing problems for other species of the food web that are relevant to ecological functions or services. These harmful effects can be quite diverse and depend crucially on the specific HAB species, mostly belonging to the groups of dinoflagellates or raphidophytes (e.g. Smayda and Reynolds, 2003); related harmful mechanisms encompass excretion of toxins (e.g. Tillmann and John, 2002; Ma et al., 2011), or allelopathic substances (e.g. Bagoien et al., 1996; Tian et al., 2009), anoxic conditions (e.g. Lemley et al., 2019), or the production of mucus and clogging of gills hampering moving and breathing of target species (e.g. van der Lingen et al., 2016; Bornman et al., 2022).

Plausible explanations for sporadic HAB outbreaks involve abiotic bottom-up factors, eutrophication and global warming, or biotic factors, e.g., a failure of top-down control by reduced grazing pressure. The latter mechanism was investigated early on in a theoretical approach via formulation of process-oriented excitable dynamical systems (Truscott and Brindley, 1994). The occurrence of rapid and massive bloom formations in an excitable bottom-up model dynamics was reported by Huppert et al. (2004). In our paradigmatic approach, we follow a specific model considered by Chakraborty and Feudel (2014). A harmful algal species is modelled as a separate phytoplankton compartment that complements the regular phytoplankton consortium, forming the basis of the marine food web. In a biomass balance approach, the relevant quantities that enter a system of ordinary differential equations (ODEs) are the time-variant concentrations $P_1(t)$ and $P_2(t)$ for non-harmful and harmful phytoplankton, respectively. The growth of both algal species is controlled bottom-up by the availability of a nutrient component (nitrogen) expressed by concentration $N(t)$, and top-down by grazers (zooplankton), quantified by concentration $Z(t)$.

The dynamical system is formulated as the following system of coupled ODEs. The first equation (Eqn. (4.7a)) shows the change in nitrogen (N) over time, which is described by external nutrient inflow N_{ext}, nutrients uptake, respiration and nutrient recycling. The dynamics of non-harmful and harmful phytoplankton, P_1 and P_2, are described by growth, respiration, sinking and grazing (Eqs (4.7b) and (4.7c)). Eqn. (4.7d) describes the change in zooplankton, which is influenced by growth and linear mortality (starvation).

$$\dot{N} = k(N_{ext} - N) - g(f_1 P_1 + f_2 P_2) + r(P_1 + P_2) + \beta(h_1 + h_2)Z + \gamma\delta Z \quad (4.7a)$$

$$\dot{P}_1 = q\,\vartheta_1\,g f_1 P_1 - rP_1 - \sigma_1 P_1 - h_1 Z \quad (4.7b)$$

$$\dot{P}_2 = q\,\vartheta_2\,g f_2 P_2 - rP_2 - \sigma_2 P_2 - h_2 Z \quad (4.7c)$$

$$\dot{Z} = \alpha_1\,h_1 Z + \alpha_2\,h_2 Z - \delta Z. \quad (4.7d)$$

A detailed description of the NPPZ model and a list of all parameters is given in Appendix 4.7.1.

To solve the ODE system (4.7), we numerically integrate it over a time range of hundred years ($100 \times 365\ days$); a typical result is shown in Figure 4.1. Based on empirically reported HAB rates of approximately 10 per 100 years, we assume a concentration of $0.1mg/m^3$ as fixed threshold separating non-HAB years from years with a HAB event (see Section 4.4 for a more detailed explanation).

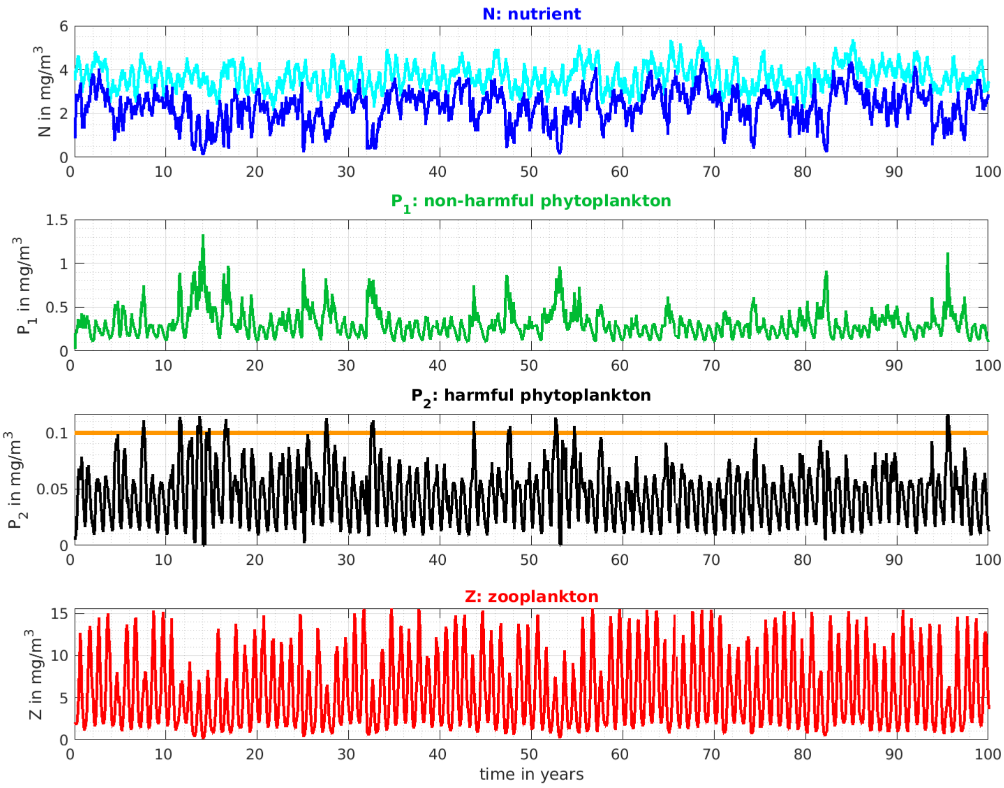

Figure 4.1: Simulated time series of the NPPZ system (panels top to bottom): 1. nutrients $N(t)$ (blue) and $N_{ext(t)}$ (cyan); 2. non-harmful species $P_1(t)$; 3. harmful species $P_2(t)$ (black) together with the threshold $0.1mg/m^3$ (orange) the exceedance of which defines the occurrence of a HAB; 4. zooplankton $Z(t)$

4.3.3 Predicted probabilities and warning likelihood

To improve the available information, the decision maker may invest in an information service providing a valuable message (or signal) on the distribution of X. The message received M, is a random variable with possible values in $\mathcal{M}$ and probability distribution p_M. Upon receipt of the message $M = m$, the decision maker updates their belief on the probability distribution of X, yielding the posterior distribution $p_{X|M}$, which replaces the prior distribution p_X. In order to estimate the value of an information system—here interpreted as an early warning system for a HAB—the conditional probabilities $p_{X|M}$, and specifically the conditional probability $p_{X|M}(x_1|\cdot)$, need to be calculated, i.e. the posterior probabilities (Eq. (4.5)). To do so, we need, in the first step, to obtain the conditional probability $p_{M|X}(m|x)$, i.e. the likelihood of receiving message m given state x. To do so, we use observed concentrations of zooplankton and nitrogen.

Based on the peaks seen in the time series, we define the occurrence of a HAB as a concentration of $0.1\ mg/m^3$ of toxic phytoplankton. Closer inspection of the time series shows that HABs only occur between April and the end of September (weeks 17–39), which is in line with the usual occurrence of HABs in the North Sea in spring to late summer (Richardson, 1989). Hence, we focus on the data from the corresponding weeks. Since the dependent variable is binary, $X \in \{x_0, x_1\}$, we fit a probit regression model, which uses the cumulative standard normal distribution function to model the regression function (Butryn and Fura, 2005) to the data in order to calculate predicted probabilities. We only consider persistent threshold transgressions that last four days as HAB events to exclude a short flickering event that could also be a measurement error. Varying the length of this time interval by a couple of days did not affect our results. This is because, in our simulated data, the HAB threshold was mostly crossed for consecutive days and lasted for a while. Some exceptions did not affect the results due to taking averages over long time series. However, this may be different if real monitoring data is considered and when only shorter time series are available.

To allow the decision manager to take precautionary measures in good time, we are interested in the predictive capacity of the information signal of the warning system. We consider two versions of a warning system: (i) Either the message received only consists of the nutrient data $N(t-\tau)$ as a predictor; (ii) or the message consists of the data of the two covariates nutrient and zooplankton, $N(t-\tau)$ and $Z(t-\tau)$, respectively:

$$p(x_1|N) = \phi(\beta_0 + \beta_1 N) \tag{4.8a}$$

$$p(x_1|N, Z) = \phi(\beta_0 + \beta_1 N + \beta_2 Z), \tag{4.8b}$$

where $\phi(\cdot)$ is the cumulative standard normal distribution function. Both systems provide a warning signal at a certain time in advance of the HAB event (occurring at time t). Accordingly, we run a probit regressions for the selected weeks and with covariates advanced by $\tau = 15, \ldots, 90$ days prior to the average HAB event. We select the optimal time lag for the model based on Bayesian Information Criterion

(BIC) and Akaike Information Criterion (AIC). We compute the predictions for a HAB by fitting the probit model to a collection of 100 independent 100–year time series as realisations of the NPPZ model dynamics (similar to the one depicted in Figure 4.1). To reflect the expected likelihood that the system correctly predicts the occurrence of a HAB, we quantify the possibility of "false warning" and "missed warning" by calculating Type I and Type II errors. To obtain binary signals ('warning' and 'no warning') we set a threshold to divide the continuous probabilities, indicating at which level of probability a positive (warning) signal will be issued. We set the threshold to 0.8, indicating that at a predicted probability of 80% for the occurrence of a HAB, the system would give out a warning signal. We varied the threshold level, but could not see any change in the error statistic unless the threshold was set close to 0 or 1; an effect that is arguably due to the steepness of the probit model (see Figure 4.5). The results of the error statistics of the NZ–model serve as "message likelihoods" $p_{M|X}(m|x)$ for m_1 ("warning") and m_0 ("no warning") for our analysis, see Table 4.2.[2]

4.4 The value of information for shellfish management

4.4.1 Model specification

HABs can have severe economic impacts on fishery and aquaculture (Anderson et al., 2001). While several reports and estimates about the economic consequences of HABs exist, mainly for the US (e.g. Hoagland et al., 2002), there are only limited studies for Europe (Mardones et al., 2020); see Adams et al. (2018) for an overview. For example, Karlson et al. (2021) examine the effects of HABs for Northern Europe with a primary focus on Scandinavian countries, but we did not find any estimates specifically for the German North Sea coast. We, therefore, derive estimates for expected costs from a documented severe HAB event in the Netherlands in 2001. The economic damage to the shellfish industry caused by the event was estimated to be 20 million EUR, whereas mitigation measures could have been implemented at 10% of that cost (van der Woerd et al., 2005). In current terms (year 2023), this amounts to a damage of approximately 30 million EUR, and the associated cost of mitigation measures equals 3 million EUR. Economic losses could be avoided

[2]The ODE system was implemented in MATLAB [version 9.14.0.2206163 (R2023a)]. The calculations for the probit regression model and the predictions were implemented in RStudio [version 2023.06.2] (R Core Team, 2023).

by specific management alternatives such as relocating fishing nets or pre-emptive harvesting and marketing prior to an expected event (Anderson et al., 2001; van der Woerd et al., 2005; Alves de Souza et al., 2022). With early warning, mussel farmers can avoid almost all damage (Konstantinou et al., 2012). Therefore, only the cost for precautionary management c will be accounted for in case of a HAB event.

Our simulated time series (see example in Figure 4.1) shows 11 harmful algae peaks over a period of 100 years, which translates to a probability of 0.11 for the occurrence of a HAB. Based on reports of HAB events in Germany to the IOC-ICES-PICES Harmful Algae Event Database, HAEDAT (http://haedat.iode.org/), 7 out of 86 HAB events were reported as severe and required management, which suggests an occurrence probability of 0.08 for a HAB event. Using expert elicitation, Bouma et al. (2009) estimate the occurrence of one HAB within a period of five years, hence a HAB probability of 0.2. Accordingly, the estimate of the prior probability for our case study seems to be in the right order of magnitude. Nevertheless, we are aware that our estimates for costs and probabilities are themselves subject to uncertainty; we will consider this by testing different scenarios and conducting a sensitivity analysis laterin this article.

As described in Section 4.3.1, the decision maker considers two possible states: x_0 and x_1; in state x_0 no HAB occurs, while in state x_1 a HAB occurs. The respective prior probabilities are given by $p_X(x_0)$ and $p_X(x_1)$. The decision maker will choose one of two management options: to proceed with "business as usual", action a_0; or to take a preventive management action to avoid damage to the fishery, action a_1. The first action involves no cost, while the latter involves cost c, interpreted as the relocation cost of fishing efforts. If no preventive action is undertaken, the damage resulting from a HAB amounts to d, while this damage can be avoided if action a_1 is chosen. We estimate the relocation cost to equal $c = 3$ (million EUR) and the damage of a HAB to equal $d = 30$ (million EUR). The prior probabilities are estimated from the simulated time series and given by $p_X(x_0) = 0.89$ and $p_X(x_1) = 0.11$. The likelihoods of receiving a warning message (m_1) and not receiving a warning message (m_0) are calculated by means of error statistics. The accuracy of the information system is reflected by Type I and Type II errors resulting from the predictions of a HAB occurrence by the probit model (see Sec. 4.3.3). In our case study, the likelihood that the system, based on information about nitrogen and zooplankton ($N(t-\tau)$ and $Z(t-\tau)$ as covariates), predicts the occurrence of a HAB correctly is 0.65. The likelihood that the system will give out a warning even though there is no threat of a HAB is 0.3. The data of the decision problem is summarised in Table 4.2.

Table 4.2: Payoff matrix for the HAB decision problem.

state	action		prior belief	message likelihood $p_{M\|X}$	
X	a_0	a_1	p_X	m_0	m_1
x_0	0	-3	0.89	0.70	0.30
x_1	-30	-3	0.11	0.35	0.65

4.4.2 Results

We next calculate $EVPI$ and $EVSI$ for the problem under consideration. As no estimates on financial losses are available for the German coast, we conduct a sensitivity analysis of $EVSI$ with respect to d. To do so, we start with varying damage d, and then proceed with varying the prior probability p_X and the management cost c.

Under uncertainty, the decision maker chooses the management action that results in the highest expected utility. Specifically, under prior information, a single action that compromises all possible states has to be chosen. Applying the data from Table 4.2 we obtain from Eqn. (4.2):

$$\begin{aligned}\max_a \mathbb{E}_X\left[v(a,X)\right] &= \max_{ain\mathcal{A}}\left[v(a,x_0)p_X(x_0)+v(a,x_1)p_X(x_1)\right]\\ &= \max\left[v(a_0,x_0)p_X(x_0)+v(a_0,x_1)p_X(x_1),v(a_1,x_0)p_X(x_0)+v(a_1,x_1)p_X(x_1)\right]\\ &= \max\left[0\times 0.89+(-30)\times 0.11,(-3)\times 0.89+(-3)\times 0.11\right]\\ &= \max[(-3.3),(-3)]\end{aligned}$$

Under prior information, the best decision is therefore action $a^* = a_1$, i.e., to undertake the precautionary measure, yielding $\mathbb{E}[v(a^*,X)] = -3$.

Under perfect information, the decision maker is informed about the (future) occurrence of a HAB before a decision is made. If a HAB does not occur, the decision maker continues with “business as usual”; that is, a_0 is the best choice for $X = x_0$, i.e. $a^*(x_0) = a_0$, yielding $v(x_0,a_0) = 0$. If, however, a HAB occurs, the best choice is to limit the damage by active management and thus to choose action $a^*(x_1) = a_1$, yielding $v(x_1,a_1) = -3$. Specifically, for the prior belief $p_X = (p_X(x_0),p_X(x_1)) = (0.89,0.11)$, the expected payoff under perfect information (see Eq. (4.1)) equals $\mathbb{E}\left[v(a^*(X),X)\right] = 0\times 0.89+(-3)\times 0.11 = -0.33$. Comparing the expected payoff under perfect information and the expected payoff under prior information, the benefit from perfect information, viz. the expected value of perfect information (see Eq. (4.3)) equals $EVPI = 2.67$; that is, the decision maker is willing to spend up to 2.67 million EUR for being informed about the state of the world in advance of the management decision.

To calculate $EVSI$, we first calculate the updated belief after receiving each possible message or warning. To this end, we plug in the data from Table 4.2 into Eqs. (4.4)–(4.6). A corresponding step-by-step calculation of $EVSI$ is displayed in Table 4.3. Firstly, the marginal probability for each possible message $p_M(m_0)$ and $p_M(m_1)$ is calculated, These values are then used to update the expected payoff after receiving a message, yielding -2.17. Comparing this posterior value with the expected payoff under prior information yields in the expected value of imperfect information: $EVSI = 0.83$. This indicates that it is worth investing up to 0.83 (million Euro) in the collection of additional data.

Table 4.3: Updating prior belief and consequences after receipt of message $M = m$

Updated probabilities

	m_0	m_1
p_M	$p_M(m_0) = p_{M\|X}(m_0\|x_0)p_X(x_0) + p_{M\|X}(m_0\|x_1)p_X(x_1)$ $= 0.7 \times 0.89 + 0.35 \times 0.11 = 0.66$	$p_M(m_1) = p_{M\|X}(m_1\|x_0)p_X(x_0) + p_{M\|X}(m_1\|x_1)p_X(x_1)$ $= 0.3 \times 0.89 + 0.65 \times 0.11 = 0.34$
x_0	$p_{X\|M}(x_0\|m_0) = p_{M\|X}(m_0\|x_0)p_X(x_0)/p_M(m_0)$ $= 0.7 \times 0.89/0.66 = 0.94$	$p_{X\|M}(x_0\|m_1) = p_{M\|X}(m_1\|x_0)p_X(x_0)/p_M(m_1)$ $= 0.3 \times 0.89/0.34 = 0.79$
x_1	$p_{X\|M}(x_1\|m_0) = p_{M\|X}(m_0\|x_1)p_X(x_1)/p_M(m_0)$ $= 0.35 \times 0.11/0.66 = 0.06$	$p_{X\|M}(x_1\|m_1) = p_{M\|X}(m_1\|x_1)p_X(x_1)/p_M(m_1)$ $= 0.65 \times 0.11/0.34 = 0.21$

Updating expected payoff

		x_0	x_1	expected payoff
$p_X(\cdot\|m_0)$		0.94	0.06	
action	a_0	0	-30	$0 \times 0.94 + (-30 \times 0.06) = -1.75$
	a_1	-3	-3	$-3 \times 0.94 + (-3) \times 0.06 = -3$
$p_X(\cdot\|m_1)$		0.79	0.21	
action	a_0	0	-30	$0 \times 0.79 + (-30) \times 0.21 = -6.34$
	a_1	-3	-3	$-3 \times 0.79 + (-3) \times 0.21 = -3$
M		m_0	m_1	
$p_M(\cdot)$		0.66	0.34	
$\mathbb{E}_M\left[\mathbb{E}_{X\|M}\left[v(a^*(M), X)\right]\right]$		-1.75	-3	$-1.75 \times 0.66 + (-3) \times 0.34 = -2.17$
$EVSI$	$-2.17 - (-3) = 0.83$			

For comparison, we calculated the value of information for an information system based on information about nitrogen only ($N(t - \tau)$) as an indicator. Here, the marginal probability of the system giving out a warning message is very close to zero (0.0001). This indicates that this system is not suitable as a warning system. Accordingly, $EVSI$ yields a negative expected payoff of this system: $EVSI = -0.3$, which would lead to the decision not to consider investing in the information system. The following sensitivity analyses, therefore, only consider the more informative NZ–model of our case study.

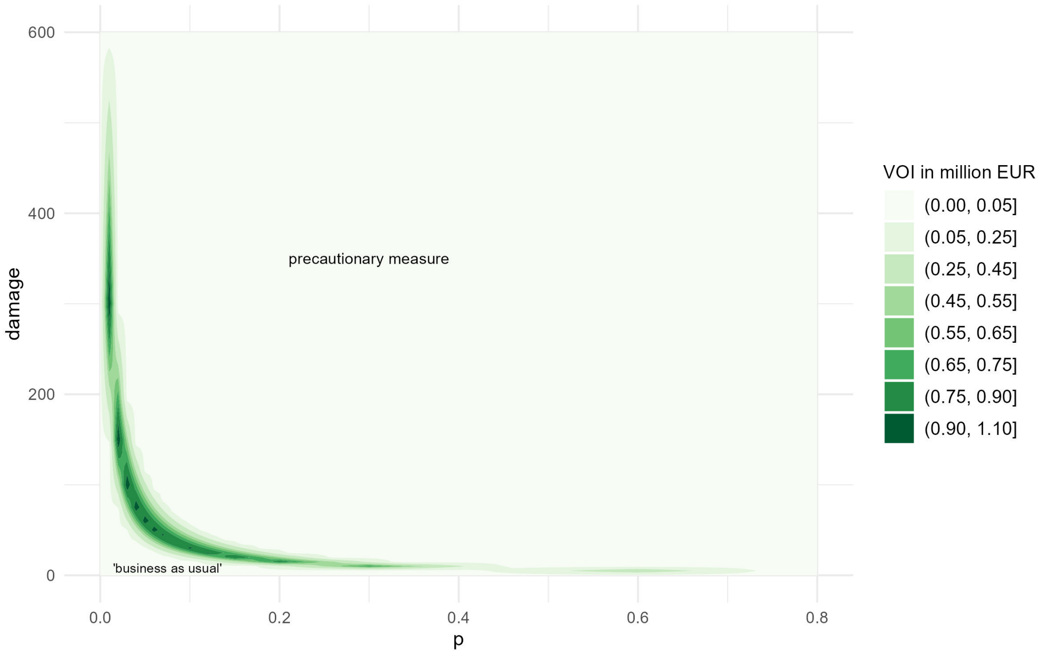

Figure 4.2: VoI as a function of prior probability p of the occurrence of a HAB (x_1) and of the fixed cost of management ($c = 3$) and damage $d \in [0, 600]$.

To account for uncertainties in the estimations of prior probabilities and monetary values for cost and damage, we conduct a sensitivity analysis by varying p, c, and d. Therefore, we calculate $EVSI$ for different scenarios: Figure 4.2 shows the behaviour of $EVSI$ for a range of values of damage $d \in [0, 600]$ (in million EUR) and the prior probability of a HAB $p := p_X(x_1) \in [0, 1]$ while the cost for management c stays fixed.

In the case of low expected damage and low risk of a HAB (lower left corner in Fig. 4.2), $EVSI$ is zero (or negative), and the decision maker would continue with "business as usual" and does not invest in information acquisition. In cases of a sufficiently high prior probability for a HAB, the decision maker would decide on precautionary measures to prevent any large damage, and new information will likely not reverse the decision. In cases where any additional information may change the decision, VoI is positive. This is the case for large expected damages of HAB events and low values of p. Here, $EVSI$ is high in scenarios where the decision maker is a priori quite confident that there is little risk of a HAB, but the damage might be enormous. Therefore, it is worthwhile to invest in additional information before deciding on a management action. The same is true for low values of d and low to medium values of p. In cases of this high uncertainty about a HAB occurrence but low expected damages, additional information may change the decision maker's decision.

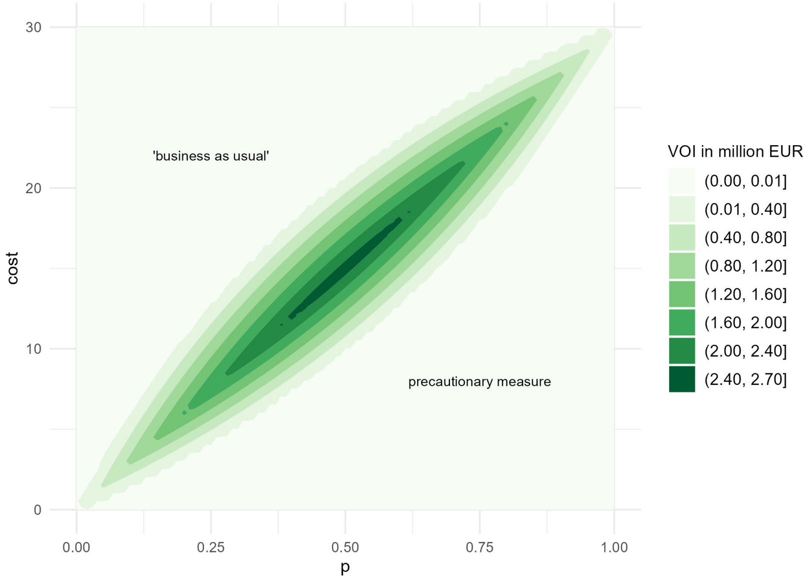

Figure 4.3: $EVSI$ as a function of $p \in [0,1]$ and $c \in [0,30]$. Damage d stays fixed at 30.

Figure 4.3, shows iso-level curves of $EVSI$ with a fixed $d = 30$ for $p \in [0,1]$ and $c \in [0,30]$. When, under prior information, the decision maker is sufficiently confident about the upcoming occurrence of a HAB (when p is close to 1), acquiring additional information is only valuable if management costs are high. On the contrary, for low values of c, $EVSI$ is low: When there is a high probability of a HAB and management costs are low (lower right corner in 4.3), the decision maker will mostly likely perform precautionary management after the receipt of new information; but if the receipt of new information is unlikely to affect the decision, the expected value of this information is marginal, hence $EVSI$ is low. Reversely, if the probability of the unfavourable state is low while management costs are high, the decision maker will continue with "business as usual" without undertaking any expensive precautionary management. As additional information is unlikely to reverse this decision, $EVSI$ is again low. $EVSI$ is high, though, when the decision maker is highly uncertain about the best management policy to be chosen, and this happens if both the probability of the occurrence of a HAB and the management cost are moderate. In this case, additional information is most valuable as any indication about the HAB event might flip the decision. (This strong dependence of $EVSI$ on management costs and prior probabilities has previously been emphasised by Giordano et al., 2022 and Luhede et al., 2024.)

We calculated the analytic expressions on how $EVSI$ and the subsequent management decisions depend on the cost for management and the expected damage of a HAB. Table 4.4 shows the cases in which $EVSI$ is positive and in which scenarios it is not worthwhile to invest in information but in management actions directly. See Section 4.7.3 for the detailed calculation.

Table 4.4: Summary of case distinctions. Substituting the terms of Table 4.2 into Eq. (4.4) yields:
$EVSI = min\{dp(x_1,),c\} - min\{dp(x_1,m_0)\} - min\{d[p(x_1) - p(x_1,m_0)], c(1-p(m_0)\}$
Due to the three $\min$ operators we have to consider eight different cases. Details can be found in the Appendix, Section 4.7.3.

Case							Findings
a)	$c < dp(x_1)$	$\alpha)$	$c < dp(x_1,m_0)$	i)	$c < dp(x_1,m_1)$	$EVSI = 0$	a_1 is chosen without information acquisition
				ii)	$dp(x_1,m_1) < c$	$EVSI > 0$	M is a contra-indicator.
		$\beta)$	$dp(x_1,m_0) < c$	i)	$c < dp(x_1,m_1)$	$EVSI > 0$	Additional information may be worthwhile.
				ii)	$dp(x_1,m_1) < c$	Contradiction.	
b)	$dp(x_1) < c$	$\alpha)$	$c < dp(x_1,m_0)$	i)	$c < (dp(x_1,m_1)$	Contradiction.	
				ii)	$dp(m_1,m_1) < c$	$EVSI > 0$	M is a contra-indicator.
		$\beta)$	$dp(x_1,m_0) < c$	i)	$c < dp(x_1,m_1)$	$EVSI > 0$	Additional information may be worthwhile.
				ii)	$dp(x_1,m_1) < c$	$EVSI = 0$	a_0 is chosen without information acquisition.

To address the dependency on the accuracy of the information system, we calculate $EVSI$ for different combinations of Type I and Type II errors with our initial case study values in Table 4.2. We display VoI in relative terms to obtain more generic results and to shift the focus on the dependencies instead of absolute values. Figure 4.4 shows the 3D plot of $EVSI$ (vertical axis) as a function of Type I and Type II errors. If both error terms are high, $EVSI$ is zero, as a highly flawed indication system does not provide valuable information. $EVSI$ reaches its maximum if the errors are zero, and hence, the information system is perfect. The value of information decreases drastically as the Type II error increases. It decreases slightly less sharply as the Type I error increases.

4.5 Discussion

This study investigates the value of information (VoI) about the occurrence of severe HABs to improve shellfish management. Specifically, we focus on the role of additional information on zooplankton and nutrients to predict HABs prior to the event. The economic implications of HABs on shellfish fisheries underscore the importance of effective decision-making to prevent substantial damages. We compare different models, specifically contrasting the impact of nitrogen-only (the N–model) and the comprehensive model incorporating zooplankton (the NZ–model). This is particu-

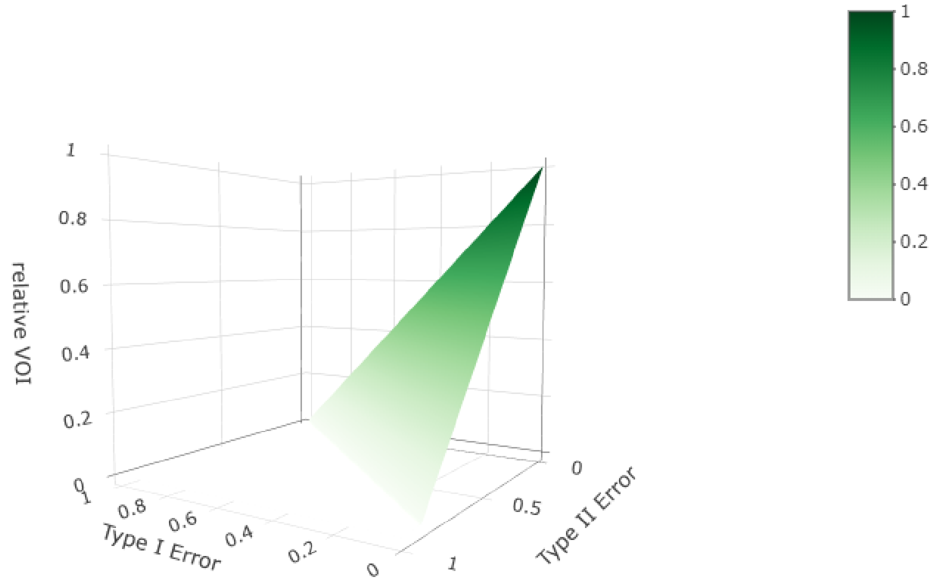

Figure 4.4: The effect of error on $EVSI$. $EVSI$ is calculated with the initial values, see Table 4.2; Type I and Type II Errors range from 0 to 1, $EVSI$ is displayed in relative values.

larly relevant given the common strategy in Germany that predominantly focuses on nitrogen reduction to reach a good ecological status and reduce severe HABs (Rönn et al., 2023). This comparison reveals that in our model scenario, relying solely on nutrient indicators may not adequately predict HAB occurrences. Calculating $EVPI$ and $EVSI$ based on the N–model results in zero additional value suggesting that information on nitrogen only has no benefit for basing precautionary management actions on it. In contrast, the NZ–model yields positive values of up to 2.67 (in million Euros per year). This shows that in our decision context a multivariate approach, considering multiple indicators, is essential for accurate assessments, and spending resources on collecting these data might be worthwhile. Comparing the results of the VoI analysis to the actual cost of monitoring, which is around 85000 Euros per year[3], makes the value of additional data in our case study explicit.

We explore scenarios in which the expected damage of a HAB varies, demonstrating that additional information becomes particularly valuable when the anticipated damage is large while the probability of a HAB is low; and conversely when the dam-

[3]personal communication with a colleague involved in the monitoring program at *Niedersächsischer Landesbetrieb für Wasserwirtschaft, Küsten - und Naturschutz* (NLWKN) in Northern Germany.

age is low but the decision maker is uncertain about the HAB occurrence. Additional information is worthwhile in these cases and may flip the management decision. For higher expected damages, the decision maker is inclined to consider preventive measures and the decision to implement precautionary measures remains unaffected by additional information. The opposite is true for low probabilities of a HAB occurrence and low expected damages: Here, the decision maker will not implement management and continue business as usual; only if the expected damage is substantially greater than the cost for management, additional information becomes valuable as it may affect the decision. By analysing the interplay between $EVSI$ and the cost of management, we see that when decision makers are highly confident about HAB occurrence, additional information proves valuable mainly in cases of high management costs coupled with high probabilities of a HAB event or for low management costs coupled with low probabilities of an occurrence. $EVSI$ is maximum when uncertainty is highest, and the cost is medium.

The second part of the sensitivity analysis shows how strongly $EVSI$ depends on the accuracy of the information system. This emphasises that the benefits of additional information are subject to information reliability. While sensitivity analyses in general have become more common in VoI analyses (Keisler et al., 2014), only a few studies consider the quality of information (e.g. Bouma et al., 2009; Costello et al., 2010; Jin et al., 2020). Considering error statistics and the sensitivity to errors represents a methodological strength, highlighting the importance of the quality of information for VoI. However, the exact values of VoI depend on the study's input values.

Methodologically, we contribute to a better understanding of VoI applications in managing HAB, which can be adjusted to other decision contexts. We are aware that certain assumptions were necessitated during the modelling process. We made careful adjustments to better align the model with available data (see Section 4.7.1). While financial values were unavailable for our case study area, we obtained those values from a neighbouring country. Although not a perfect match, the values still provide a meaningful interpretation of the scale and order of magnitude of VoI. As we test different parameter scenarios, the results offer insights into the potential economic implications of decision-making strategies. We set thresholds for HAB events based on peaks in the simulated time series and a literature review as a crucial part of our methodological approach. These may be limitations to the application. However, we believe that our methods are valuable for gaining insights into the value of additional information in our decision-making. Further, our approach can be easily adjusted to other applications and case studies. We show that simulation of time series combined with a probit model is a suitable technique for deriving conditional probabilities in VoI analysis. This method is relevant in addition to the more conventional sets of techniques, such as expert elicitation, providing a simulation data-driven way to assess uncertainty.

4.6 Conclusion

This article contributes to the understanding of decision-making processes and the effect of uncertainty about the occurrence of HAB in fishery management. VoI analysis offers insights into when and how additional information on indicators of a HAB occurrence can enhance decision outcomes. While acknowledging some simplifications in our model, we derive interesting insights into the behaviour of VoI, which can be useful for decision-makers and practitioners to understand the role of (resolving) uncertainty in decisions. We show that collecting information about top-down (zooplankton) and bottom-up (nitrogen) control provides an early warning indication of the occurrence of a HAB. However, in our model, information on nitrogen alone does not provide additional value. Our results suggest an added value of extended monitoring of multiple indicators at a specific seasonal period. Even though the exact values in the results are specific to our decision context, our findings can serve as guidance for policy development and resource allocation in mitigating the economic impacts of HAB events. The approach can be easily modified and adjusted to different cases and scenarios.

4.7 Appendix

4.7.1 Detailed description of the conceptual NPPZ model

The state variables $N = N(t), P_1 = P_1(t), P_2 = P_2(t), Z = Z(t)$, time dependent quantities $N_{ext} = N_{ext}(t)$, $\delta = \delta(t)$ (detailed below) and

$$g(t) = g\left[P_1(t), P_2(t)\right] = \frac{a}{1 + c\left[P_1(t) + P_2(t)\right]} \tag{4.9}$$

$$q(t) = q\left[T(t)\right] = Q_{10}^{\frac{T(t)-\bar{T}}{10}} \quad \text{with} \quad T(t) = \bar{T} + \Delta T \cos\left[\frac{2\pi(t-t_0)}{365}\right] \tag{4.10}$$

$$f_i(t) = f_i\left[N(t)\right] = \frac{N(t)}{e_i + N(t)} \quad \text{for} \quad i = 1, 2 \tag{4.11}$$

$$h_i(t) = h_i\left[P_i(t)\right] = \frac{\lambda_i P_i^2(t)}{\mu_i^2 + P_i^2(t)} \quad \text{for} \quad i = 1, 2\,. \tag{4.12}$$

By contrast, $k, r, \beta, \gamma, q, \vartheta_i, \sigma_i, \alpha_i$ $(i = 1, 2)$ are constant parameters (values listed below).

The different terms on the right hand side of the ODE system (4.7a-4.7d) reflect the following processes:

- The term $k(N - N_{ext})$ in (4.7a) describes an exponential approach (with constant rate k) of the nutrient concentration $N(t)$ to an external nutrient concentration $N_{ext}(t)$ that reflects nutrient inflow by rivers and surface water following precipitation.

- The term $-g(f_1 P_1 + f_2 P_2)$ in (4.7a) models the nutrient uptake that, via photosynthesis, is converted with factors $q\vartheta_1$ and $q\vartheta_2$ to biomass of primary producers (non-harmful and harmful) entering (4.7b) and (4.7c).

- The terms $-rP_1$ and $-rP_2$ in (4.7b-4.7c) resp. account for respiration (with constant rate r) and replenish the nutrient pool with the term $r(P_1{+}P_2)$ reflecting recycling by bacteria.

- The terms $-\sigma_1 P_1$ and $-\sigma_2 P_2$ in (4.7b-4.7c) account for the loss of phytoplankton due to sinking with specific sinking rates σ_1 and σ_2 resp.

- the terms $h_1 Z$ and $h_2 Z$ in (4.7b-4.7c) model the grazing of phytoplankton by zooplankton which are converted with efficiency α_1 and α_2 resp. into zooplankton biomass in (4.7d).

- Growth of zooplankton following grazing is balancing the linear zooplankton mortality δZ in (4.7d).
- Through bacterial recycling a fraction γ of dead zooplankton is fed back to nutrients in (4.7a).

This ODE system combines four state variables with several constant parameters and three time variant parameters as external drives:

- A deterministic process in the form of a Q_{10}-law (Mundim et al., 2020) with a temperature that is seasonally modulated as a harmonic signal (cf. Eq. (4.10) in App. 4.7.1).
- A stochastic process modelling riverine import of an essential nutrient concentration $N_{ext}(t)$ (cf. Eq. (4.13) in App. 4.7.1).
- A stochastic process modelling slow variations of the *per capita* mortality rate δ_t (cf. Eq. (4.15) in App. 4.7.1) of zooplankton reflecting slowly fluctuating environmental conditions thus introducing inter-annual variability of top-down control of the harmful species.

The functions defined in (4.9-4.12) have the following meaning:

- The function $g[P_1(t), P_2(t)]$ in (4.9) describes growth limitation of both phytoplankton species due to light limitation caused by self-shading, where it is assumed that cells of both phytoplankton species contribute equally to the shading effect.
- The function $q[T(t)]$ modulates the conversion of assimilated nutrients into phytoplankton biomass in the form of a temperature dependent Q_{10}-law. The average seasonal temperature profile is modelled as a harmonic oscillation around mean temperature $\bar{T}$ with amplitude ΔT and seasonal maxima at $t_0 + 365k$ and minima at $t_0 + 365/2 + 365k,\ k \in \mathbb{Z}$, (we have assumed an integer year length of 365 days instead of a more realistic fractional astronomical year). Since $q(\bar{T}) = 1$ the constant parameters ϑ_1 and ϑ_2 constitute respective translation factors $q\vartheta_i$ at mean temperature.
- The functions $f_i[N(t)]$ models the nutrient uptake via a Monod kinetics, i.e. initial linear increase leading into saturation (at unity), with phytoplankton specific half-saturation constants e_i.

- The functions $h_i[P_i(t)]$ describe the grazer's functional response to varying prey concentration and is here modelled as a Holling-type III, i.e. starting as a parabola before saturating at maximal ingestion rate λ_i, with phytoplankton specific half-saturation constants μ_i. Differences between maximal ingestion rates λ_1 and λ_2 can be interpreted as split preferences of zooplankton for non-harmful vs harmful phytoplankton species.

Aside from the seasonal drive via $q[T(t)]$ the deterministic ODE system is driven by two stochastic processes:

- The external nutrient inflow $N_{ext}(t)$ (in units gCm^{-3}) is modelled as a harmonic with red noise added to it, i.e.

$$N_{ext}(t) = 0.9 + 0.1\cos\left[\frac{2\pi(t-92)}{365}\right] + \zeta(t) \tag{4.13}$$

  where all parameters were fitted to measured time series from the coastal region of the German bight. The anomalies $\zeta(t)$ (red noise) are obtained via interpolation from uniformly sampled (sampling rate $f_s = 1/day$) values ζ_t resulting from an auto-regressive process of order 1 (AR[1])

$$\zeta_t = \alpha\ \zeta_{t-1} + \epsilon_t \qquad (t = 2, 3, \ldots) \tag{4.14}$$

  with $\alpha = \mathrm{e}^{-1/(f_s\tau_c)}$ to match the empirical correlation time $\tau_c = 280\ days$ and zero-mean Gaussian white noise ϵ_t of intensity $\sigma_\epsilon^2 = 10^{-4}$.

- The *per capita* mortality rate of zooplankton $\delta(t)$ (in units $1/day$) is modelled as a slowly varying random process created through interpolating the following uniformly sampled (sampling rate $f_s = 1/day$) values δ_t resulting from the recursion

$$\delta_t = 0.02 + 0.3\ \eta_t^2 \tag{4.15}$$

  with random terms η_t again following from an AR[1]

$$\eta_t = \beta\ \eta_{t-1} + \hat{\epsilon}_t \qquad (t = 2, 3, \ldots) \tag{4.16}$$

  with $\beta = \mathrm{e}^{-1/(f_s\hat{\tau}_c)}$ tuning the correlation time of η_t to $\hat{\tau}_c = 365\ days$ and zero-mean Gaussian white noise $\hat{\epsilon}_t$ of intensity $\sigma_{\hat{\epsilon}}^2 = 5.5 \times 10^{-4}$.

Numerical integration was applied to the system of ODEs (4.7a-4.7d) with initial values: $N(0) = \frac{1}{4}N_{ext}(0)$, $P_1(0) = 0.025\ gm^{-3}$, $P_2(0) = 0.005\ gm^{-3}$, $Z(0) = 2\ gm^{-3}$ and using the following list of parameters:

parameter	value	unit
a	1.5	day^{-1}
c	0.05	$[gm^{-3}]^{-1}$
e_1	0.1	gm^{-3}
e_2	0.1	gm^{-3}
k	0.25	day^{-1}
r	0.01	day^{-1}
α_1	0.25	dimensionless
α_2	0.1	dimensionless
β	0.03	dimensionless
γ	0.5	dimensionless
λ_1	2	day^{-1}
λ_2	4	day^{-1}
μ_1	1	gm^{-3}
μ_2	1	gm^{-3}
σ_1	0.5	day^{-1}
σ_2	0.5	day^{-1}
θ_1	2	dimensionless
θ_2	1	dimensionless
Q_{10}	3	dimensionless
$\bar{T}$	11	^oC
ΔT	8	^oC
t_0	212	July 31^{st}

4.7.2 Figures

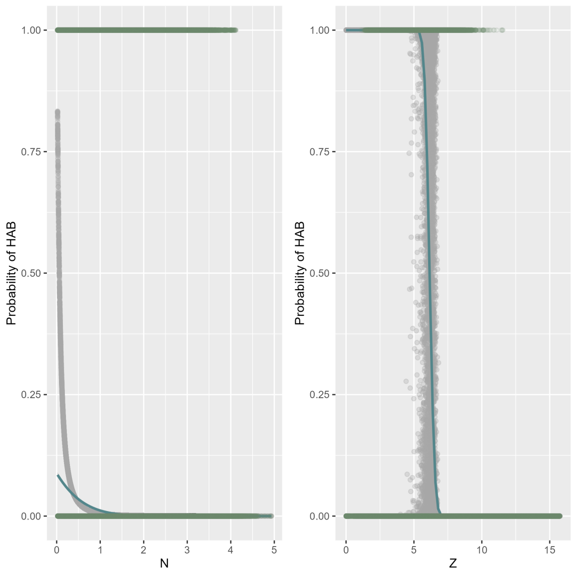

Figure 4.5: Probit regression: comparison of N–model and NZ–model. The grey dots show the predicted probabilities for the occurrence of a HAB. The green dots show the actual values for a HAB (0 = no HAB, 1 = HAB). The blue line shows the trend line. We can see that for low values of Zooplankton (Z) HABs are more likely to occur based on the model.

4.7.3 Case distinction

To recapitulate, we have:

$$\Omega = \{x_0, x_1\}, \quad M = \{m_0, m_1\}, \quad \mathcal{A} = \{a_0, a_1\},$$
$$v(a_0, x_0) = b, \quad v(a_1, x_0) = v(a_1, x_1) = b - c, \quad v(a_0, x_1) = b - d.$$

Substituting these terms into Eq. (4.4) yields

$$\begin{aligned}
EVSI =& \sum_m \max_a \sum_x v(a,x)p(x,m) - \max_a \sum_x v(a,x)p(x) \\
=& \max\{v(a_0,x_0)p(x_0,m_0) + v(a_0,x_1)p(x_1,m_0), v(a_1,x_0)p(x_0,m_0) + v(a_1,x_1)p(x_1,m_0)\} \\
&+ \max\{v(a_0,x_0)p(x_0,m_1) + v(a_0,x_1)p(x_1,m_1), v(a_1,x_0)p(x_0,m_1) + v(a_1,x_1)p(x_1,m_1)\} \\
&- \max\{p(x_0)v(a_0,x_0) + p(x_1)v(a_0,x_1), p(x_0)v(a_1,x_0) + p(x_1)v(a_1,x_1)\} \\
=& \max\{(b-c)p(x_0,m_0) + (b-c)p(x_1,m_0), (b-d)p(x_1,m_0) + bp(x_0,m_0))\} \\
&+ \max\{(b-c)p(x_0,m_1) + (b-c)p(x_1,m_1), (b-d)p(x_1,m_1) + bp(x_0,m_1)\} \\
&- \max\{(b-c)p(x_0) + (b-c)p(x_1), (b-d)p(x_1) + bp(x_0)\} \\
=& \max\{(b-c)p(m_0), bp(m_0) - dp(x_1,m_0)\} + \max\{(b-c)p(m_1), bp(m_1) - dp(x_1,m_1)\} \\
&- \max\{b-c, b-dp(x_1)\} \\
=& bp(m_0) - \min\{dp(x_1,m_0), cp(m_0)\} + bp(m_1) - \min\{dp(x_1,m_1), cp(m_1)\} \\
&- b + \min\{dp(x_1), c\} \\
=& \min\{dp(x_1), c\} - \min\{dp(x_1,m_0), cp(m_0)\} - \min\{dp(x_1,m_1), cp(m_1)\}
\end{aligned} \tag{4.17}$$

Due to the three $\min$ operators we have to consider eight different cases:

Case a) $c < dp(x_1)$**:** The management cost is lower than the expected damage.

α)

$$cp(m_0) < dp(x_1, m_0) \;\Leftrightarrow\; c < dp(x_1|m_0) \tag{4.18a}$$

Management cost is lower than the expected damage in case of a negative signal.

i)

$$cp(m_1) < dp(x_1, m_1) \;\Leftrightarrow\; c < dp(x_1|m_1) \tag{4.18b}$$

Management cost is lower than the expected damage in case of a positive signal. In this case, we have $EVSI = c - cp(m_0) - cp(m_1) = 0$. It follows from (4.18a) and (4.18b) that management cost is lower than the expected damage irrespective of the signal. In view of this, information acquisition is not economic (unless it is costless), so that precautionary management, action a_1, is undertake without information acquisition.

ii)

$$dp(x_1, m_1) < cp(m_1) \;\Leftrightarrow\; dp(x_1|m_1) < c \tag{4.18c}$$

Management cost is higher than the expected damage in case of a positive signal. It follows from (4.18c) that $EVSI = c - cp(m_0) - dp(x_1, m_1) = cp(m_1) - dp(x_1, m_1) > 0$. However, combining (4.18a) and (4.18b) we have $dp(x_1|m_1) < c < dp(x_1|m_0)$, which can only be true if $p(x_1|m_1) < p(x_1|m_0)$. But this means that the signal M is a *contra-indicator* for the occurrence of a HAB. Hence, information acquisition may be economic, but the signal should be interpreted in a reverse way.

β)

$$dp(x_1, m_0) < cp(m_0) \;\Leftrightarrow\; dp(x_1|m_0) < c \tag{4.18d}$$

Management cost is higher than the expected damage in case of a negative signal.

i) Eq. (4.18b) holds, so that management cost is lower than the expected damage in case of a positive signal. In this case, we have $EVSI = c - dp(x_1, m_0) - cp(m_1) = cp(m_0) - dp(x_1, m_0)$, which is positive by assumption (4.18d). Hence, depending on the cost of information acquisition, it may, or may not be beneficial to do so.

ii) Eq. (4.18c) holds, so that management cost is higher than the expected damage in case of a positive signal. In this case, we have $EVSI = c - dp(x_1, m_0) - dp(x_1, m_1) = c - dp(x_1)$, which is negative by assumption, as Case a) specifies $c < dp(x_1)$. Moreover, Eqs (4.18d) and (4.18c) together imply $dp(x_1) < c$, contradicting the assumption of Case a). Hence, this case does not exist.

Case b) $dp(x_1) < c$: The management cost is higher than the expected damage. It immediately follow that it does not pay to perform management action a_1 without getting a signal indicating that the expected damage will be higher.

α) Eq. (4.18a) holds, implying that the management cost is lower than the expected damage in case of a negative signal.

i) Eq. (4.18b) holds, so that the management cost is lower than the expected damage in case of a positive signal. In this case, we have $EVSI = dp(x_1) - cp(m_0) - cp(m_1) = dp(x_1) - c < 0$, because $dp(x_1) < c$ due to Case b). However, Eqs (4.18a) and (4.18b) together imply $c < dp(x_1)$, contradicting the assumption of Case b). Hence, this case does not exist.

ii) Eq. (4.18c) holds, so that management cost is higher than the expected damage in case of a positive signal. In this case, we have $EVSI = dp(x_1) - cp(m_0) - dp(x_1, m_1) = dp(x_1, m_0) - cp(m_0) > 0$, due to Eq. (4.18a). Hence, information acquisition may be economic. However, Eqs (4.18c) and (4.18a) imply $dp(x_1|m_1) < c < dp(x_1|m_0)$ and thus $p(x_1|m_1) < p(x_1|m_0)$. But this means that the signal M is a *contra-indicator* for the occurrence of a HAB. Hence, information acquisition may be economic, but the signal should be interpreted in a reverse way.

β) Eq. (4.18d) holds, i.e., management cost is higher than the expected damage in case of a negative signal.

i) Eq. (4.18b) holds, so that the management cost is lower than the expected damage in case of a positive signal. In this case, we have $EVSI = dp(x_1) - dp(x_1, m_0) - cp(m_1) = dp(x_1, m_1) - cp(m_1) > 0$ by assumption. Hence, depending on the cost of information acquisition, it may, or may not be beneficial to acquire information.

ii) Eq. (4.18c) holds, so that management cost is higher than the expected damage in case of a positive signal. In this case, we have $EVSI = dp(x_1) - dp(x_1, m_0) - dp(x_1, m_1) = c - dp(x_1) = 0$. Hence, information acquisition is not economic (unless it is costless). Moreover, we have from Eqs (4.18d) and (4.18c) that the management cost exceed the expected damage irrespective of the signal received, i.e., $dp(x_1|m_0) < c$ and $dp(x_1|m_1) < c$. It follows that precautionary management, action a_1, is never performed, neither on an ex ante nor on an ex post basis.

5 Combining optimal control and value of information for dynamic environmental decision-making

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5.1 Abstract

Uncertainty in environmental decision problems is prevalent and can have a large impact on management. The value of information (VoI) theory provides a tool for evaluating the expected benefit of resolving uncertain aspects of the decision problem. To this point, VoI has been mostly applied to static decision problems in ecology or environmental conservation, although environmental issues are dynamic. We present a method that can be used to study dynamic environmental management under uncertainty to explore the value of additional information in a dynamic setting. In a novel approach, we integrate VoI analysis in the context of applications of optimal control in environmental conservation and management. We show how optimal control and value of information can be analysed for a relevant decision problem and what the effect of resolving uncertainty can have on the decision maker's utility.

Keywords: value of information; optimal control; decision analysis; uncertainty; environmental management

5.2 Introduction

Dynamic decision-making is required for most environmental decision problems, as urgent environmental issues usually persist over a long time, and the ecosystem under study itself never behaves static. Pressing issues such as increased nutrient pollution of water bodies from agricultural runoff or other non-point sources have been a major cause in the degradation of aquatic ecosystems and their biodiversity (Grizzetti et al., 2017; Poikane et al., 2019). Reaching a good ecological and environmental status in inland or coastal waters is the goal of international regulative frameworks, such as the Clean Water Act in the U.S. (United States Congress, 1972) or the EU Water Framework Directive (European Parliament, 2000), and is addressed by many studies on pollution control (e.g. Gaddis et al., 2014; Han et al., 2021). However, as many aspects of the managed ecosystem are uncertain, decision-makers do not only need to consider a dynamic emission control strategy but also consider uncertainty in their policy plan. Assessments, monitoring, and research programmes can help decision-makers reduce uncertainty. However, they often come with high financial expenses. The value of information (VoI) theory is a concept that evaluates the potential benefit of management that has been forgone under uncertainty. VoI offers a tool to quantify the expected benefit of resolving uncertainty prior to making the decision. For example, VoI can evaluate the utility gain by reducing uncertainty compared to other costs that are associated with collecting information to decide whether monitoring should take place. The concept was developed several decades ago and was coined by Raiffa and Schlaifer (1961), and has since then been applied mostly in economics, health risk management and many other fields (e.g. Frauendorfer, 1992; Yokota and Thompson, 2004a; Eidsvik et al., 2015). Still, relatively few applications have been found in ecology and environmental management, and almost none of them include a dynamic decision framework. For example, the work by Williams and Johnson (2018) employ a Markov Decision Process as the base model, where the state of the system evolves according to state transition probabilities. In contrast, we use a more deterministic framework based on differential equations and optimal control (OC) theory, while uncertainty is introduced through a parameter of the system dynamics. To the best of our knowledge, (OC) has never been used to calculate VoI before, and our objective is to extend the valuation to include dynamic decision-making. The framework developed here goes beyond current treatments of VoI in the literature in its emphasis on the management of dynamic environmental systems by combining OC theory and VoI. Optimal control theory is a framework used to determine the best possible way to manage and regulate dynamic systems by finding a series of optimal actions throughout time. It involves the system's dynamics, which defines how the current state and the selected action influence the future state, control variables that influence the system and can be executed at any moment, defining an objective to be achieved, and working within given constraints to find an optimal solution (Shastri and Diwekar, 2006). In environmental decision-making, optimal control theory is applied to manage natural resources and ecosystems sustainably (Richards et al., 1999; Brock et al., 2014; Runge and Johnson, 2002; Shastri and Diwekar, 2006). In contrast to static decisions, optimal control allows one to find a dynamic optimal management strategy over a (finite or infinite) time horizon and calculates the decision-maker's utility over time. This approach is more realistic because it accounts for the continuous nature of real-world processes and the need for finding optimal policy (a series of actions over time) in response to uncertain conditions. By incorporating dynamic elements, our method can better capture the complexities and uncertainties inherent in the system, leading to more informed and effective decision-making.

This analysis serves as a continuation of the literature on the value of information in environmental conservation and management. For illustration purposes, we use a decision problem context similar to the one analysed by Luhede et al. (2024) and extend it to a dynamic framework. To do so, we choose a simple model of a dynamic system that is prone to nutrient influx (pollution/emission), which influences the state of the ecosystem. This system can be interpreted as a coastal water body that is influenced by nutrient influx from rivers. The system can be influenced by a control variable (e.g. management of nutrient influx). Our paper expands the standard linear-quadratic model of pollution control, studied by Dockner and Van Long (1993), among many others, to allow for uncertainty about the system's dynamics and for the comparison of the optimal control strategy under uncertainty (i.e. finding the optimal control that yields the highest expected payoff across all possible scenarios) with the maximum value of the expected problem. Athanassoglou and Xepapadeas (2012) build on the same model to introduce uncertainty in the system's dynamics. In their work, uncertainty is expressed by an added noise term representing natural variability and stochasticity. As this represents an unresolvable type of uncertainty, we introduce a different kind of uncertainty that can be resolved by collecting additional information.

We assume the presence of a decision-maker who makes a decision about a mitigation intervention at time zero and subsequently decides on a desirable dynamic emissions policy. In our case, the decision maker is uncertain about the nutrient absorption rate. This is expressed in our model by allowing for two possible values (high and low absorption rate), and we study the effect of resolving uncertainty on optimal mitigation and damage-control decisions.

Our primary focus is to introduce the methodology and provide a framework for combining OC theory and VoI. We showcase the approach by a relevant decision problem in environmental management. Here, we aim to show analytical results and understand the effect of uncertainty on the optimal policy instead of focusing only on numerical results. To guide the reader and demonstrate our approach step by step, we first calculate the cases of optimal management with full certainty or perfect information about the absorption rates. Next, we introduce uncertainty: we consider two possible natural absorption rates of nutrients (i.e., high or low), which impact the ecological status of the water body. The decision-maker has no knowledge about the exact absorption rate governing the system but only has prior information regarding the probabilities of the two possible rates. We calculate the optimal control strategy for a decision-maker to maintain the equilibrium state of the system over infinite time – i.e. to find the optimal emission rate to avoid ecosystem degradation. We then compute the value of information as the difference between the optimal management strategy under perfect information and the optimal management under uncertainty.

5.3 Methods

We introduce the step-by-step method of optimal control, given the example of nutrient pollution. Here, we provide all the necessary equations and refer the reader to Kirk (2004) for a more detailed explanation of the theory of optional control. A detailed overview of the calculation of VoI in an ecological context can be found in Canessa et al. (2015).

5.3.1 Problem Statement

We consider the problem of pollution control (Dockner and Van Long, 1993; Dockner et al., 2000) where the agent produces a single good (i.e. nutrients from artificial fertilisers in agriculture) which contributes to the increase in the pollution stock (here, the nutrient concentration in the water body) while also decaying at a natural rate. The dynamics governing the nutrient stock is given by:

$$\dot{x}(t) = f(x,u) = b\,u(t) - a\,x(t) \qquad\qquad x(0) = x_0 \geq 0 \tag{5.1}$$

where $u(t) \geq 0$ is the rate of production of the good, $b > 0$ is the contribution to nutrient stock due to the production activity, and $a \geq 0$ is the environmental absorption rate of the nutrient. Here, $b\,u(t)$ can be interpreted as the emission rate due to the production activity.

We choose the profit function as $\pi(u) = \left(c\,u - \frac{u^2}{2}\right)$. For $u \in [0, c]$, $\pi(u)$ is concave and has the property of decreasing marginal returns. Additionally, we assume that the cost function is quadratic in the nutrient pollution stock $\left(\frac{q}{2}x^2\right)$, i.e. the fines or tax imposed vary in a quadratic manner with respect to the nutrient pollution level and weighted by a factor of q. With these assumptions, our instantaneous objective function becomes a linear-quadratic problem:

$$J_c := \left(cu - \frac{u^2}{2}\right) - \frac{q}{2}x^2 \tag{5.2}$$

5.3.2 Optimal Control with Perfect Information

The objective functional for the discounted net profit for an infinite time horizon is:

$$J(x_0, u(t)) = \max_{u(t)} \int_0^{\infty} e^{-\rho t} J_c \, \mathrm{d}t \tag{5.3}$$

Next, we calculate the Hamiltonian function, which combines the system dynamics, the control variables, and the objective function into a single comprehensive function. The Hamiltonian for the above problem, incorporating the state dynamics (5.1) and the instantaneous objective function (5.2), is given by

$$H \coloneqq J_c + \lambda f(x, u) = c\, u - \frac{qx^2}{2} - \frac{u^2}{2} + \lambda\, (b\, u - a\, x) \tag{5.4}$$

Here λ is the adjoint variable or the co-state variable. The adjoint variables are crucial components in OC, as they help integrate the system dynamics and the objective function within the Hamiltonian and provide the necessary conditions for optimality through the adjoint equation. They measure the sensitivity of the objective function to changes in the state variables and, hence, guide the determination of the optimal strategy.

By solving for the adjoint variables along with the state and control variables, one can determine the optimal trajectory and control actions for the system.

If $u : [0, \infty) \to \mathbb{R}$ is an optimal solution, Pontryagin's necessary conditions state that $\lambda(t), x(t)$, and $u(t)$ are such that for each $t, u = u(t)$ maximises the function $H(\lambda(t), x(t), u)$, then:

$$\dot{x}(t) = \frac{\partial H}{\partial \lambda} = b\, u(t) - a\, x(t), \tag{5.5a}$$

$$\dot{\lambda}(t) = \rho\lambda(t) - \frac{\partial H}{\partial x} = qx(t) + \lambda(t)\, (a + \rho). \tag{5.5b}$$

Next, we find the necessary first-order condition, which gives the control variables at each moment to achieve the optimal outcome. It involves maximising (or, in other cases, minimising) the Hamiltonian. The necessary first-order condition for a control maximising H is given by

$$\frac{\partial H}{\partial u} = 0 = c - u(t) + b\, \lambda(t), \tag{5.6}$$

whence the optimal control is

$$u^*(t) = c + b\, \lambda(t). \tag{5.7}$$

Substituting above into Eq. (5.1) yields the *canonical system* (CS):

$$\dot{x}(t) = -a\,x(t) + b\,(c + b\,\lambda(t)), \tag{5.8a}$$

$$\dot{\lambda}(t) = q\,x(t) + \lambda(t)\,(a + \rho). \tag{5.8b}$$

The canonical system refers to a set of differential equations that are derived from the necessary first-order conditions for optimality. They include both the state equations and the adjoint equations, forming a complete system that describes the evolution of the state and adjoint variables over time. The canonical system is essential for finding the optimal control strategy. Solving the canonical system gives the optimal control strategy.

Transversality Condition

The transversality condition is a boundary condition in optimal control theory that applies to the adjoint variables at the endpoints of the time horizon. It ensures that the optimal solution not only meets the dynamic constraints and optimality conditions but also appropriately considers the final state of the system. The transversality condition can be seen as a way to incorporate information about the desired state of the system at the end of the control period. It helps determine the appropriate values of the co-state variables at the terminal time, which is particularly important when the final state is not fixed or when dealing with infinite horizon problems. It ensures that the optimisation problem is properly solved by considering the value of the objective function at the boundaries. We choose the transversality condition to be zero, to ensure that the present value of the adjoint variable, which can be interpreted as the shadow price of the state variable at the end of the planning horizon (i.e., infinity) is zero. This is essential for the existence of a well-defined and finite optimal solution to the control problem over an infinite horizon (Benveniste and Scheinkman, 1982; Grass et al., 2008).

$$e^{-\rho t}\,\lambda(t) \to 0 \qquad\qquad (t \to \infty) \tag{5.9}$$

Canonical Steady States (CSS)

Canonical steady states refer to equilibrium points where the state and adjoint variables, as well as the control variables, remain constant over time. At these points, the system is in a dynamic balance where the rates of change of both the state and adjoint variables are zero. Finding the canonical system states is needed as we are analysing the long-term behaviour of controlled dynamic systems. At steady state, the dynamics of the canonical system Eq. (5.8) is zero, which gives,

$$x^{\infty} = \frac{b\,c\,(a+\rho)}{b^2\,q + a\,(a+\rho)}, \tag{5.10a}$$

$$\lambda^{\infty} = -\frac{b\,c\,q}{b^2\,q + a\,(a+\rho)}. \tag{5.10b}$$

where x^{∞} and λ^{∞} are the fixed points of the Eq. (5.8). Putting Eq. (5.10) in Eq. (5.7) and Eq. (5.2) and using Eq. (5.4) , we have,

$$u^{\infty} = \frac{a\,c\,(a+\rho)}{a^2 + b^2 q + a\,\rho}. \tag{5.11a}$$

Noting that $f(x^{\infty}, u^{\infty}) = 0$, we get,

$$J_c^{\infty} = H^{\infty} = \frac{c^2(a+\rho)\left(a^3 + ab^2q + a^2\rho - b^2q\rho\right)}{2\left(a^2 + b^2q + a\rho\right)^2}, \tag{5.11b}$$

Since J_c^{∞} is constant, we can easily compute $J(x^{\infty}, u^{\infty})$ as

$$J(x^{\infty}, u^{\infty}) = \int_0^{\infty} \mathrm{e}^{-\rho t} J_c^{\infty} \mathrm{d}t = J_c^{\infty} \int_0^{\infty} \mathrm{e}^{-\rho t} \mathrm{d}t = \frac{1}{\rho} J_c^{\infty} \tag{5.12}$$

which agrees with the discussed result (Grass et al., 2008, Proposition 3.75). In the following, we will refer to the J_c^{∞} for perfect information as J_c^{fix} and corresponding u^{∞} under prefect information will be $u^{\infty}_{posterior}$.

Figure 5.1 illustrates $J_c = H$ as a function of parameter a, where $b = 1$, $q = 1$, $c = 1$, and $\rho = \frac{1}{40}$. The plot demonstrates that J_c increases with increasing values of a.

The scenario discussed in Fig. 5.1 should be interpreted with the caveat that x^{∞} and u^{∞} also changes a. This means that the plot in Fig. 5.1 must be understood as plotting J_c^{∞} against the triple $(a, x^{\infty}(a), u^{\infty}(a))$.

Qualitative Analysis of the Equilibrium Point

As the aim is to calculate the value of information at the equilibrium point, it is necessary to ascertain that the equilibrium point is a saddle point, which implies that the computed fixed point will indeed be the solution for the optimal control problem (Grass et al., 2008). Here, the Jacobian matrix is used to analyse the stability of the equilibrium point. By examining the eigenvalues of the Jacobian matrix evaluated at these points, we can determine whether they are stable or unstable.

The Jacobian matrix of the CS, i.e., Eq. (5.8) computed at $(x^{\infty}, \lambda^{\infty})$ is given by:

$$\mathbf{J}_m = \begin{pmatrix} -a & b^2 \\ q & a+\rho \end{pmatrix} \tag{5.13}$$

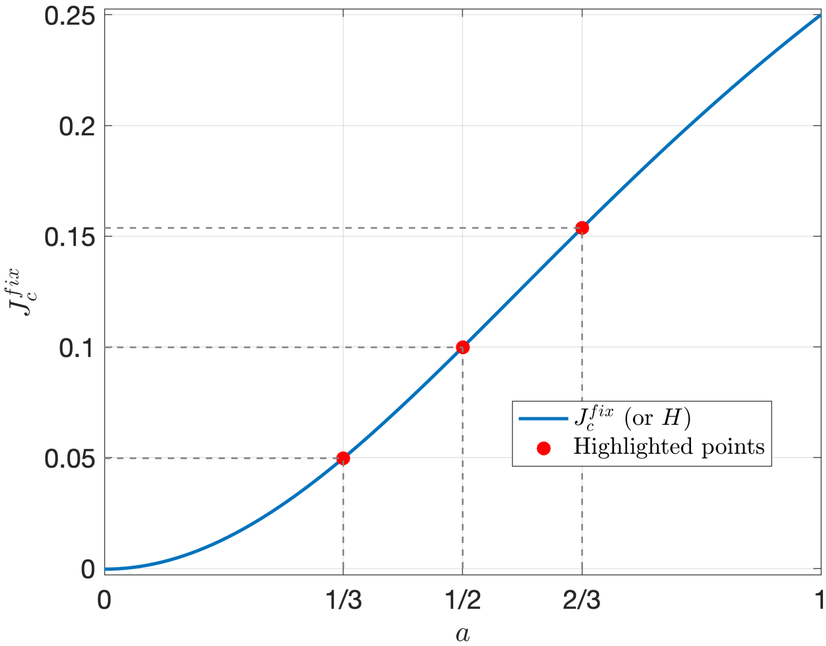

Figure 5.1: Plot of J_c (or H) as a function of a. The function J_c increases with increasing values of a, here we highlight specific example points at $a = \frac{1}{2}$, $a = \frac{1}{3}$, and $a = \frac{2}{3}$ with red markers and grey dashed lines. Other parameter are fixed: $b = 1$, $q = 1$, $c = 1$, and $\rho = \frac{1}{40}$.

Let us evaluate the eigenvalues and the associated eigenvectors for the above Jacobian matrix.

The eigenvalues are:

$$\mu_1 = \frac{1}{2}\left(\rho - \sqrt{4b^2q + (2a+\rho)^2}\right) \tag{5.14a}$$

$$\mu_2 = \frac{1}{2}\left(\rho + \sqrt{4b^2q + (2a+\rho)^2}\right) \tag{5.14b}$$

Since $4b^2q + (2a+\rho)^2 > \rho^2$, we have one positive ($\mu_2$) and one negative ($\mu_1$) eigenvalue, therefore, $(x^\infty, \lambda^\infty)$ is a saddle point.

5.3.3 Optimal Control under Prior Information

Now consider the problem of finding an optimal control when the parameter a of the canonical system is uncertain and may assume any of the two values $\{a_1, a_2\}$ with equal probability (generally, the probability might be expressed as p and $1-p$). The following state dynamics can be assumed:

$$\dot{x}_1(t) = f(x_1, u_1) = b\, u_1(t) - a_1\, x_1(t) \qquad x_1(0) = x_0 \geq 0 \tag{5.15a}$$

$$\dot{x}_2(t) = f(x_2, u_2) = b\, u_2(t) - a_2\, x_2(t) \qquad x_2(0) = x_0 \geq 0 \tag{5.15b}$$

The instantaneous objective function for the uncertain system then becomes:

$$J_c^u := \left(cu - \frac{u^2}{2}\right) - \frac{q}{2}\left(p\,x_1^2 + (1-p)\,x_2^2\right) \tag{5.16}$$

The goal will then be to minimise the following sample averaged cost functional (justification and theory from Phelps et al. (2016)):

$$J[\mathbf{x}, u] = \mathbb{E}^P\left[\int_0^\infty \mathrm{e}^{-\rho t}\left(\left(cu - \frac{u^2}{2}\right) - \frac{q}{2}\,x(t,a)^2\right)\,\mathrm{d}t\right] \tag{5.17}$$

where $\mathbb{E}^P$ is the expectation on the complete probability space (Phelps et al., 2016) and $x_i = x(t, a_i)$ for $i = \{1, 2\}$ and $\mathbf{x} = [x_1, x_2]$. In other words, we approximate the cost functional for the uncertain parameter a as the sample averaged version of the fixed a but with a common optimal control function $u(t)$. The Hamiltonian for uncertain a is then given by:

$$\begin{aligned} H &:= J_c^u + \lambda_1 f(x_1, u_1) + \lambda_2 f(x_2, u_2) \\ &= cu - \frac{u^2}{2} - \frac{1}{2}q\left(px_1^2 + (1-p)x_2^2\right) + (bu - a_1 x_1)\,\lambda_1 + (bu - a_2 x_2)\,\lambda_2 \end{aligned} \tag{5.18}$$

Using a similar procedure as before, the first-order condition for a control maximising H for an uncertain system is given by

$$u^\infty = c + b\,\lambda_1(t) + b\,\lambda_2(t) \tag{5.19}$$

Substituting above into Eq. (5.15) yields the CS for the uncertain a:

$$\dot{x}_1(t) = b\,u_1(t) - a_1\,x_1(t) \tag{5.20a}$$

$$\dot{x}_2(t) = b\,u_2(t) - a_2\,x_2(t) \tag{5.20b}$$

$$\dot{\lambda}_1(t) = p\,q\,x_1(t) + \lambda_1(t)\,(a_1 + \rho). \tag{5.20c}$$

$$\dot{\lambda}_2(t) = (1-p)\,q\,x_2(t) + \lambda_2(t)\,(a_2 + \rho). \tag{5.20d}$$

Following a similar procedure as for perfect information, we next evaluate the CSS and check for stability for the uncertain case.

Canonical Steady States (CSS)

At steady state, we obtain:

$$x_1^\infty = -\frac{bc\,(\rho + a_1)\,a_2\,(\rho + a_2)}{b^2(-1+p)qa_1\,(\rho + a_1) - \rho\,(b^2pq + a_1\,(\rho + a_1))\,a_2 - (b^2pq + a_1\,(\rho + a_1))\,a_2^2}, \tag{5.21a}$$

$$x_2^\infty = -\frac{bca_1\,(\rho + a_1)\,(\rho + a_2)}{b^2(-1+p)qa_1\,(\rho + a_1) - \rho\,(b^2pq + a_1\,(\rho + a_1))\,a_2 - (b^2pq + a_1\,(\rho + a_1))\,a_2^2}, \tag{5.21b}$$

$$\lambda_1^\infty = -\frac{bcpqa_2\,(\rho + a_2)}{-b^2(-1+p)qa_1\,(\rho + a_1) + \rho\,(b^2pq + a_1\,(\rho + a_1))\,a_2 + (b^2pq + a_1\,(\rho + a_1))\,a_2^2}, \tag{5.21c}$$

$$\lambda_2^\infty = -\frac{bc(-1+p)qa_1\,(\rho + a_1)}{b^2(-1+p)qa_1\,(\rho + a_1) - \rho\,(b^2pq + a_1\,(\rho + a_1))\,a_2 - (b^2pq + a_1\,(\rho + a_1))\,a_2^2} \tag{5.21d}$$

Substituting $(x_1^\infty, x_2^\infty, \lambda_1^\infty, \lambda_2^\infty)$ into Eq. (5.19) and resulting expression of u^∞ into Eq. (5.16) then one can obtain the expressions for both u^∞_{prior} and J_c^u for the prior information. Note that similar to the perfect information case (See Eq. (5.12)) , the prior value is $J[\mathbf{x}^\infty, u^\infty_{prior}] = \frac{J_c^u}{\rho}$.

Stability Analysis

The Jacobian matrix of the CS of the uncertain system, i.e. Eq. (5.20) is given by:

$$\mathbf{J}_m^u = \begin{pmatrix} -a_1 & 0 & b^2 & b^2 \\ 0 & -a_2 & b^2 & b^2 \\ pq & 0 & \rho + a_1 & 0 \\ 0 & q - pq & 0 & \rho + a_2 \end{pmatrix} \tag{5.22}$$

Assuming $p = 0.5$, Eigenvalues:

$$\mu_1 = \frac{1}{2}\left(\rho - \sqrt{\psi - 2\sqrt{\phi}}\right) \tag{5.23a}$$

$$\mu_2 = \frac{1}{2}\left(\rho + \sqrt{\psi - 2\sqrt{\phi}}\right) \tag{5.23b}$$

$$\mu_3 = \frac{1}{2}\left(\rho - \sqrt{\psi + 2\sqrt{\phi}}\right) \tag{5.23c}$$

$$\mu_4 = \frac{1}{2}\left(\rho + \sqrt{\psi + 2\sqrt{\phi}}\right) \tag{5.23d}$$

, where ϕ, ψ are defined as follows: $\psi = 2b^2q + \rho^2 + 2\left(\rho a_1 + a_1^2 + a_2(\rho + a_2)\right)$, $\phi = b^4q^2 + (a_1 - a_2)^2(\rho + a_1 + a_2)^2$, and $\xi = b^4q^2 + (a_1 - a_2)^2(\rho + a_1 + a_2)^2$.

The eigenvalues and the associated eigenvectors do not depend on state or adjoint variables but are constant. If $-2\sqrt{\phi} + \psi > \rho$, we have two positive and two negative eigenvalues, and hence a saddle-point.

5.3.4 Value of Information

To calculate the *expected value of perfect information* ($EVPI$), we subtract the maximum expected outcome under prior information (prior value) from the expected value under perfect information (posterior value). The general formula to calculate $EVPI$ is:

$$EVPI = \max_{u \in U} \mathbb{E}\left[v(u,a)\right] - \mathbb{E}\left[\max_{u \in U} v(u,a)\right] \tag{5.24}$$

where the expected value under uncertainty is the sum of the possible values for action u across all possible values for $a \in A$ of the uncertainty parameter, each weighted by the respective probability p_a of each a being true. The expected value under perfect information represents the expected utility after being informed about the realisation of a; it gives the expected benefit when taking the optimal action for each a. This posterior value gives the probability-weighted utility sum of optimal management actions. The difference between the expected utility under perfect information and under prior information results in the expected value of perfect information. For detailed explanations on the calculation of VoI, see, for example, Hirshleifer and Riley (1979); Yokota and Thompson (2004b); Canessa et al. (2015).

In our case, the prior value is J_c^u, divided by the discount rate ρ. The value under perfect information is given by J_c^{fix} divided by ρ. Hence in our case, $EVPI = VoI = \frac{1}{\rho}(J_c^{fix} - J_c^u)$.

5.4 Results

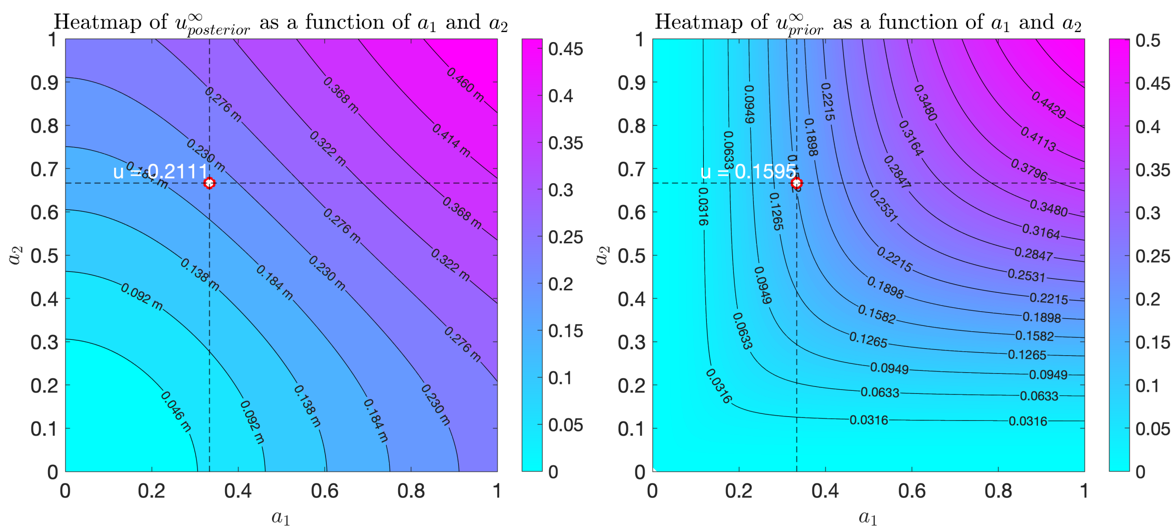

Figure 5.2: Contour plot of a) $u^{\infty}_{posterior}$ as a function of a_1 and a_2 and b) u^{∞}_{prior} as a function of a_1 and a_2. Here we highlight the point corresponding to $a_1 = \frac{1}{3}$, $a_2 = \frac{2}{3}$ with a white-red circle. Other parameter are fixed: $p = 0.5$, $b = 1$, $q = 1$, $c = 1$, and $\rho = \frac{1}{40}$.

We calculate the optimal rate of emissions u^{∞} to stay at the equilibrium point for different values of a under uncertainty (prior information) and with perfect knowledge about a. Figure 5.2 shows the optimal control under prior and posterior information as a function of a_1 and a_2. For low values of a, indicating a low natural nutrient absorption rate, the optimal policy is to emit at a low rate. For higher natural absorption rates, the decision-maker can choose a higher emission rate. Under perfect information, the decision-maker may choose a higher rate of emission because they have perfect information about the absorption rate.

Under uncertainty, the optimal control for the emission is relatively lower compared to the perfect information case because it could be either absorption rate, and the decision-maker needs to find the optimal rate that would perform best on average. Comparing different uncertain values for a, Figure 5.2 shows that possible values for a that are far apart result in a lower optimal emission rate. For values of a that are closer to one another, the emission rate may be higher for high values of a_1 and a_2. Next, we compare the expected utility for choosing the optimal policy under uncertainty and under perfect information.

Under uncertainty, the decision-maker chooses the average optimal control that maximises their utility. This means that the decision-maker would allow for a nutrient influx rate that gives the, on average, highest expected benefit. Figure 5.3a shows a contour plot of the expected utility J_c^u/ρ if the absorption rate of the water body a is uncertain. The higher the range of possible values for a, the lower the expected utility, as the decision maker would have to choose a control that meets, on average, the optimal value, which can be interpreted as a 'one kind fits all' control. Under perfect information, the expected payoff depends on the value of a. For high values of a indicating that the water body has a high absorption capacity of nutrients, the expected payoff is higher, as the decision maker could choose an increased nutrient influx without ecosystem degradation. Accordingly, for low values, the expected payoff is lower (see Figure 5.3b). The expected value of information, if one would resolve uncertainty about a completely, is the difference between the expected value under perfect information (or posterior value) and the expected value under uncertainty (or prior value). Figure 5.3c shows the iso-level curves of VoI as a function of a_1 and a_2. The higher the difference between the uncertain values of a_1 and a_2, the higher the VoI, as obtaining perfect information about the value would increase the expected utility. Conversely, the closer the values of a_1 and a_2 to one another, the lower the VoI, as additional information might only have minor implications on the optimal control level. As the values are only the result of a hypothetical example, the exact numerical values do not need to be interpreted. Figure 5.3 merely presents the outcome of a VoI analysis with hypothetical values but provides insights about how VoI relates to values of a.

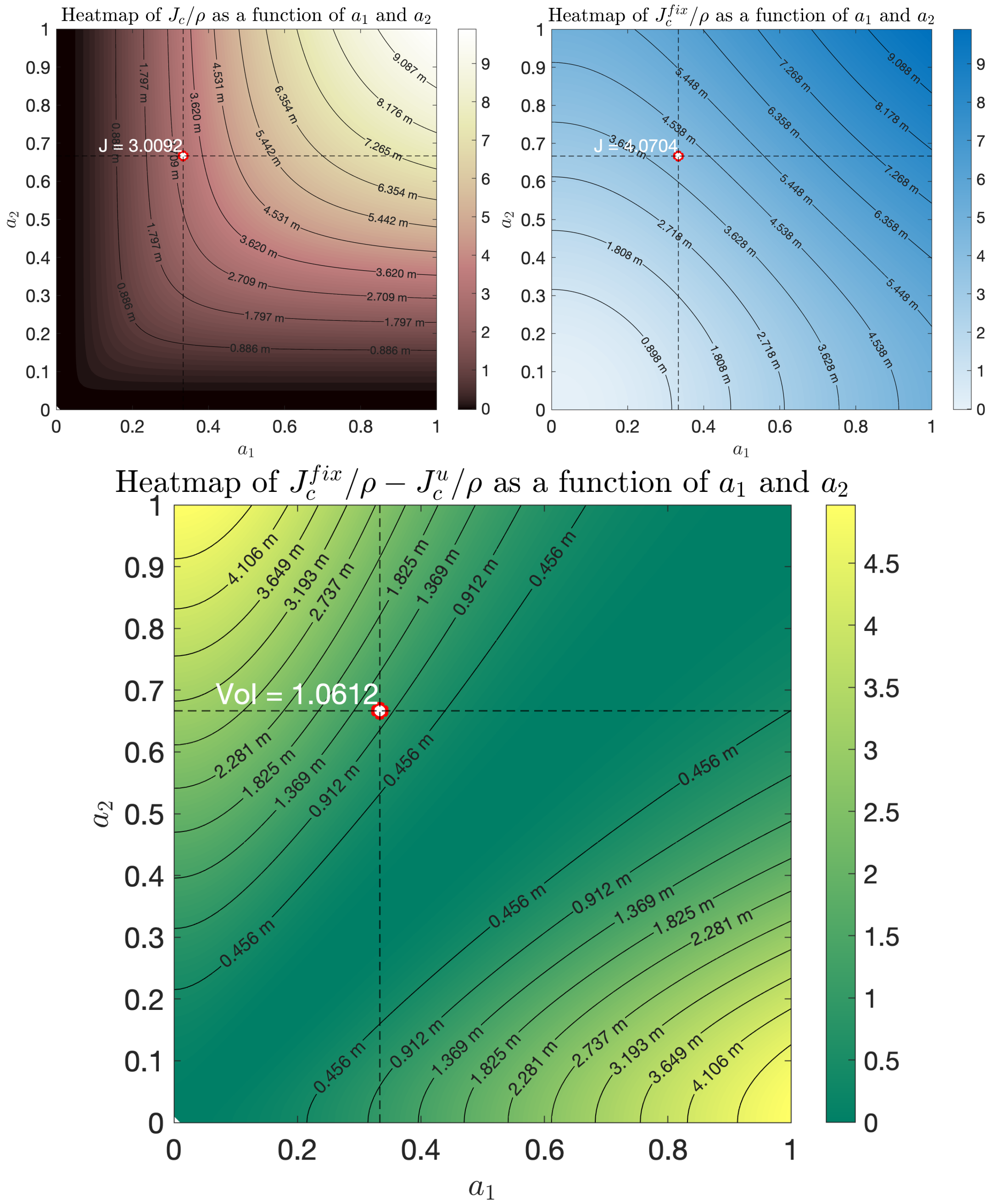

Figure 5.3: (a) (upper left) Contour plot of J_c^u/ρ (or H/ρ) as a function of a_1 and a_2 for uncertain system. (b) (upper right) Contour plot of J_c^*/ρ as a function of a_1 and a_2 for known a. (c) (down) Contour plot of Vol $= (J_c^* - J_c^u)/\rho$ as a function of a_1 and a_2. For all the plots, we highlight the example point corresponding to $a_1 = \frac{1}{3}$, $a_2 = \frac{2}{3}$ with a white-red circle. Other parameter are fixed: $p = 0.5$, $b = 1$, $q = 1$, $c = 1$, and $\rho = \frac{1}{40}$.

5.5 General insights and conclusion

The value of information can serve as a useful tool to guide and improve decision-making. In environmental decision-making, it is often unclear if information collection strategies such as additional research or monitoring would be a justifiable investment regarding the additional costs (Runge et al., 2011). VoI can, therefore, be a useful tool for evaluating the value of additional data collection and assessing whether or not to invest in additional monitoring or data collection activities. The aim of this study was to provide a methodological framework for incorporating VoI and optimal control at steady state in an environmental management context. This is a novel approach to introducing the evaluation of reducing uncertainty within intertemporal decision-making. We use a hypothetical extension of a decision problem similar to the one analysed by Luhede et al. (2024), introducing intertemporal management and building on an established pollution control model by Dockner and Van Long (1993). Here, uncertainty about the natural nutrient absorption rate exists, and the decision maker wants to choose the optimal control strategy for managing the ecosystem. The question of whether it is financially worthwhile to resolve uncertainty about the uncertain aspect of the ecosystem is quantified by the calculation of VoI. The results show that resolving uncertainty can result in a higher expected payoff, especially if the possible values for the uncertain parameter differ greatly. Even though calculating VoI at the steady state may not be the most realistic example but it serves as a starting point for demonstrating the methods and for future analyses. Analysing systems in optimal control and their steady state has frequently been the focus of many studies, and mathematical resource economics and theoretical ecology devote considerable effort to analysing the stability properties of the respective steady states. However, as emphasised by Hastings et al. (2018), focusing solely on steady states and their properties may provide little help in reality for environmental and ecological management. Both models and real-world observations show that transient behaviour may persist over long time periods, making transition paths much more relevant than remote long-term behaviour. Only a few authors, though, have explicitly considered transition dynamics; that is, the optimal path towards a steady state, e.g., Castilho and Srinivasu (2007), Grass and Uecker (2017) and Dragicevic (2019). The properties of these paths are of particular interest in the presence of nonlinear dynamics with multiple steady states, as demonstrated by Grass et al. (2019); Upmann et al. (2021); Uecker (2022). Considering optimal transition paths under uncertainty and calculating the value of the information would be an important next step. This work can serve as a starting point for future research.

6 Discussion and concluding remarks

6.1 General discussion

Uncertainty is prevalent in our understanding of our highly dynamic ecosystems. Decision-makers and environmental managers have to deal with these uncertainties when deciding upon management strategies and policies. Resolving or reducing uncertainties about some aspects of the system under study could lead to more substantiated decisions and enhance decision-making. The intricate question of whether and to what extent one should invest in more accurate information about uncertain aspects of the ecosystem under study can be assessed using the concept of VoI. VoI analysis provides a quantitative instrument to evaluate the expected increase in the decision maker's utility when additional data or information is collected. It, therefore, provides an individual assessment of the decision-maker's willingness to pay for this information against the background of their current level of information. In ecology or environmental management, VoI is a tool to evaluate the cost-effectiveness of different monitoring and data collection strategies and to optimise the allocation of resources. Yet, besides the apparent benefits of VoI analysis, it remains widely unused in the field of environmental management and conservation. This thesis contributes to the applications of VoI analysis for decision problems in environmental conservation management.

Applicability of VoI to conservation management

The first objective of this thesis is to demonstrate the applicability of VoI methods in environmental conservation contexts and, more specifically, to decision problems related to marine conservation management. To provide an overview of VoI and the developments in the field, Chapter 2 provides a basis for the following VoI applications. It gives a comprehensive methodological overview of the concept of VoI, followed by a systematic review of VoI applications in marine conservation management. As it turns out, little attention has been given to the benefits of VoI in this field. Even though the benefits of VoI have been shown in many studies in related fields, such as applied ecology or (terrestrial) biodiversity conservation, in the field of marine conservation, VoI has only been applied in 15 studies since the year 1991. The predominant topic throughout the studies is fisheries management, which might be the most intuitive topic if one thinks of economic-ecological management decisions in the marine realm and many data exist on fisheries as they are usually closely monitored. Yet, other interesting cases in marine conservation management, such as water quality in coral reefs or the investigation of the benefits of more research about the functioning of the biological carbon pump, have been analysed in the past years. This shows the scope of possible VoI applications, yet only a limited number of case studies exist so far. Chapter 2 highlights some of the possible barriers for analysts and decision-makers to incorporate VoI analysis as a tool to enhance decision-making processes. One of the probably most difficult tasks is the formulation of a precise decision problem, as well as identifying and quantifying the relevant parameters. This step requires estimating probabilities and values for the decision context and needs interdisciplinary collaboration. Technical and computational issues may pose another challenge when attempting to calculate $EVSI$ or $EVPXI$; however, as the review shows, a variety of methods exist to estimate VoI. This chapter ends with a call for more applications of VoI to further advance the field and increase the number of VoI applications in marine conservation management. Further, the need for case studies tackling dynamic decision problems is being discussed, as environmental challenges and management decisions need to be adaptive.

Building on this literature analysis and the introduced methodology, Chapter 3 addresses a decision problem in water quality management, where the current ecological status is uncertain. The decision maker's objective is to reach a 'good ecological status' in the coastal waters of the German North Sea. Currently, most of these waters do not reach the targeted status due to eutrophication as a result of high nutrient influx from rivers. This application highlights the value of additional monitoring data on nutrients in rivers flowing into the North Sea in order to improve management decisions and reach the desired good ecological status. The analysis demonstrates how conditional probabilities can be estimated by fitting distributions to monitoring data, therefore basing the analysis on real data.

In Chapter 4, VoI is applied to evaluate the effect of reducing uncertainty about the occurrence of harmful algal blooms via extended monitoring about decisions on mitigating economic effects on fisheries. Due to anthropogenic pressures and climate change, there is an increased risk of detrimental algal blooms. These harmful algal blooms (HABs) can have a significant negative effect on ecosystems, water quality and, among others, can pose severe economic losses for fisheries. The focus of the study is the German North Sea, and the VoI framework is applied to evaluate the value of additional time-resolved data about the top-down control, i.e. zooplankton, to better predict a HAB and to take precautionary management actions in time. Current legislation focuses mostly on nitrogen reduction to prevent further eutrophication and hence the occurrence of severe HABs (Rönn et al., 2023). Therefore, the possible improvement of the management decision that may be achieved by adding zooplankton data to previously included nutrient data in order to enhance HAB prediction is investigated. A food web model of the North Sea fitted to regional monitoring data is the basis for the analysis. Coupled with economic data extracted from a previous HAB event in the neighbouring country, a realistic case study is constructed. Conditional probabilities are calculated by estimating the prediction accuracy of zooplankton and nitrogen data by evaluating the error statistics of a fitted probit regression model. The results suggest that monitoring of multivariate indicators is welfare enhancing, and compared with the actual cost of monitoring, it is worthwhile to do so. Monitoring data on nitrogen alone does not have any additional value in the analysed decision context, as this data has no predictive capacity. This analysis provides another example of how VoI can be applied in an environmental decision context and provides a different method of extracting conditional probabilities. This analysis is constructed in a way that is easily extendable and adjustable to different decision contexts.

Chapters 3 and 4 provide interesting insights into how uncertainty affects management decisions in different environmental contexts. It is important to remember that the numerical results of VoI analysis are always context-dependent and are highly sensitive to model parameters such as costs and prior probabilities. Therefore, sensitivity analyses are crucial in the interpretation of the results. As VoI does not directly incorporate the cost for data collection (unless explicitly considered in the model), the resulting values should be interpreted as the maximum willingness to pay for information acquisition and need to be compared to the monitoring cost. Even a small VoI can, therefore, be interpreted as a valuable investment in additional information if the cost of data acquisition is lower. At the same time, a VoI equal to zero does not mean no monitoring activities should take place at all – as VoI is evaluated against the background of the current information level, maintaining this information level is crucial. Decision-makers and practitioners need to carefully evaluate the results of VoI analysis in their specific decision context.

Simplifying models

This thesis intentionally considers simplified models for VoI analysis, the reasons are twofold: First, simple models are suitable to demonstrate the methods and they have the advantage of facilitating better interpretation and insightful analysis whilst still displaying a sufficiently accurate decision context. In practice, this would allow decision-makers to focus on the most relevant aspects of the decision. Further, computational efficiency allows for more detailed sensitivity analyses and reproducibility.

Chapter 3, deals with the analysis of a static VoI decision problem with binary states and actions. The chapter contributes conceptually to the VoI framework as it shows how conditional probabilities can be derived from distributions fitted to monitoring data. In this way, the analysis can be based on monitoring data and places the decision problem in a real-world context. Naturally, environmental systems are more complex and not binary, but the benefits of simplifying the decision-making process have their merits. Firstly, in political discussions and decisions, we are often confronted with binary decisions, i.e. do something or do nothing. More specific management alternatives or additional states can be easily added to the existing decision context, but the 'binarised' version allows us to derive interesting generic insights. For example, investigating the behaviour of the maximised VoI as a function of relative management costs, i.e. the ratio of costs and the value of the ecosystem, provides somewhat counter-intuitive insights. Assuming a fixed prior probability and a fixed cost for management, it shows that increasing the value of the ecosystem leads to a decrease in VoI. This seems surprising on first glance as the intuitive assumption is that a higher relative value of the ecosystem is associated with a higher willingness to pay for monitoring. Yet, the analysis reveals that at a higher value of the ecosystem, it would be more worthwhile to invest in management activities to avoid missed management opportunities and risk degradation of the valuable ecosystem while monitoring takes place. Using a binary decision problem as the intuitive basis for this VoI analysis allows us to clearly understand the problem and derive general valid insights relevant to the field.

Therefore, choosing a two-state, two-action problem in Chapter 4 is the natural starting point. The difference from the previous chapter is not only the case study considered but also clear methodological differences. This chapter investigates the value of HAB predictions by combining simulated time series of a dynamic model on HAB developments and a linear probit regression model. To obtain the message probabilities for each signal, error statistics from the predicted probabilities are calculated. This allows to assess the effect of information accuracy on VoI on the management decision. Here, the results show that the higher the prediction accuracy, the higher the VoI, i.e., the more willing a decision-maker is to pay for an information system. This is an intuitive result, as a less reliable prediction would not be very beneficial for the decision-maker. However, the sensitivity of VoI to the error depends on the consequences of the error for the expected outcome or damage. In the analysed case study, a false negative prediction causes far more damage than a false positive signal. Therefore, VoI is more sensitive to this type of error.

These two applications consider static decision problems; however, dynamic systems such as our ecosystem require dynamic decisions. Incorporating dynamic decisions in VoI applications in conservation management, and more precisely, marine conservation management, is rarely done. Therefore, the second objective of this thesis is to study ways to incorporate dynamic decision-making in VoI analysis.

Intertemporal decision making

One of the most distinct findings in the literature search presented in Chapter 2 is the absence of intertemporal decision-making in VoI applications in environmental conservation management. Even though environmental issues are persistent over long time periods and policy strategies that take system dynamics into account are needed, most VoI applications do not explicitly consider a time horizon or a dynamic policy. There are only a few examples of embedding VoI analysis in a dynamic decision framework. For example, Williams and Johnson (2018) use MDPs to analyse VoI in a dynamic setting aiming to arrive at adaptive management strategies and Haight and Polasky (2010) use a POMDP to model the control of invasive species.

Another promising avenue for dynamic decision-making is optimal control theory, a method used to identify the most effective strategies for managing and regulating dynamic systems over time. It addresses the question of what decision (e.g., harvest rate or pollution rate) is optimal, given the system's state, to achieve a long-term goal (e.g., maximising harvest). It has been applied in many branches of environmental and ecosystem management (e.g. Loehle, 2006; Hastings et al., 2006; Braack et al., 2018) and examples of OC problems in ecology or environmental management that incorporate uncertainty exist (e.g. Richards et al., 1999; Runge and Johnson, 2002; Shastri and Diwekar, 2006; Athanassoglou and Xepapadeas, 2012); however, no study in the literature has so far explicitly calculated the value of resolving uncertainty.

To address this, Chapter 5 introduces a novel approach to include the optimal management of an environmental system over a time period in VoI analysis. By using a relevant example of nutrient pollution control of a coastal water body, the methodology of first calculating optimal control under certainty and uncertainty and the evaluation of VoI at the steady state is introduced step by step. The example emphasises the applicability of the approach, even though the resulting values are purely hypothetical. Chapter 5, provides a base for decision-making in a dynamic context. Frameworks in VoI that consider dynamic decisions, especially in environmental management, are rare, and therefore, there is a need for additional applications. Yet, with more complex models, one must potentially rely solely on numerical results as analytical solutions are most likely not available.

Chapter 5 offers many opportunities for exploring different scenarios and more realistic cases. First, instead of calculating the value of perfect information, one could extend the analysis to introduce imperfect information. This would require adding probability distributions for each possible scenario and belief-updating to the model. Further complexities could be introduced to the model to make the analysis more realistic. For example, the uncertain absorption rate could be changed to be a function or expressed as a cyclic dynamic, such as explored in a similar model by Gromov et al. (2024). Considering and calculating VoI at steady states is an intuitive starting point; however, it is not the most realistic scenario. Even though many analyses on optimal control systems in mathematical resource economics and theoretical ecology focus on steady states and their stability properties, Hastings et al. (2018) emphasise that an exclusive focus on steady states and their properties may offer limited guidance to environmental and ecological management. Both theoretical models and empirical data suggest that transient behaviour can endure for prolonged periods, underscoring the importance of transition paths over long-term equilibrium states. Nonetheless, the examination of transition dynamics, which entails determining the optimal trajectory to a steady state, has been relatively scarce in the literature (Castilho and Srinivasu, 2007; Grass and Uecker, 2017; Dragicevic, 2019). Understanding these transition paths is crucial, especially in the context of nonlinear dynamics with multiple equilibria, as highlighted by Grass et al. (2019); Upmann et al. (2021); Uecker (2022). For the more realistic scenario to analyse the VoI in the context of transitory policies or optimal paths, it is to start from a fixed value and find the transition paths. However, finding the optimal solution for transition paths is difficult. They can only be calculated numerically and involve the use of algorithms to find the optimal solutions. Algorithms might find local minima instead of the global minimum, resulting in the OC not being the global optima. By definition, VoI compares the optimal solutions under uncertainty and with information. This problem exists especially for non-linear systems. Therefore, this kind of analysis requires a careful interpretation of results and might not be without flaws.

Limitations to VoI

Despite VoI's general applicability to decision-making in conservation management, it has several key limitations for real-world problems and applications. Firstly, most VoI applications focus on single-species management, and conventional VoI theory is not fully developed for management, which involves managing multiple species or habitat patches. Existing literature on multi-unit problems often relies on strict assumptions or simulations rather than generalised, broadly applicable theory. In the literature on environmental management, VoI has not been focusing on individual decisions among units, complicating its implementation in real-world scenarios (Bennett et al., 2018).

Secondly, VoI does not explicitly relate monitoring results to financial or time costs, potentially diminishing the perceived value of data collection if monitoring is expensive or the time frame for management is limited. Therefore, it is necessary to interpret VoI in relation to the actual cost of monitoring.

Moreover, one has to keep in mind that VoI is a purely consequential tool that disregards epistemological values. Therefore, it cannot account for all possible uncertainties if they are not explicitly considered in the context of the framed decision. For example, there might be a wider societal value of information or a value of further research for the field in general. Further, VoI analysis assumes that the decision problem and context are formally structured and can only account for the elements explicitly included in the decision framework; i.e., no external influences or uncertainties can be evaluated. This requires careful construction of the decision context and, in case of real-world decision problems, needs transdisciplinary cooperation, While some methods consider different stakeholder preferences and societal impacts (e.g. Haag et al., 2022), these aspects need further research and incorporation into decision problems. Lastly, $EVPI$ is mostly characterised as an upper bound for the $EVSI$ and other VoI variants. However, this might be neglecting some important aspects. The optimal information collection strategy from a utility-maximising perspective often overlooks the societal perspective. Not considering the wider societal value of information can underestimate its overall value Yokota and Thompson (2004a).

6.2 Outlook

This thesis provides opportunities to build upon and highlights possible pathways for future research opportunities. Given the benefit of VoI for decision-making and research in conservation management, it is surprising that this method has hardly been used to date. As highlighted in Chapter 2, this may be due to the fact that it is an interdisciplinary issue in which economic, decision-theoretical, statistical and ecological research come together. For interdisciplinary research in general and especially in the field of environmental conservation and management, the concept of VoI provides many opportunities to implement projects and identify measures to address the changing problems with the help of the methods mentioned in the previous Chapters. In principle, further applications of the known VoI concepts and methods to decision problems in conservation management are interesting and relevant and would be an important contribution to research. Building on simple models enables us to derive general insights into VoI's behaviour and characteristics, which can and should be further explored. Beyond that, the exploration of applications to complex ecological-economic problems is certainly an interesting challenge for research, both conceptually from the perspective of modelling and technically (computationally). Further, exploring VoI in contexts of dynamic decision-making is an exciting path. Even in comparatively simpler models such as those used for the analysis and identification of optimal intervention and control measures, the information values of the individual parameters are equally important, as they are policy-determining, difficult to determine, and as each parameter change can result in a discrete policy change and thus lead to discontinuities. For example, the empirically determined parameter values on which the modelling is based significantly influence the resulting policies. Examples for applications could be the planning of marine protected areas or the allocation of fishing rights. Another interesting avenue would be to explore the optimal timing of triggering policy interventions. This is related to optimal stopping problems, i.e. at what point in time should the information collection end and an intervention be triggered. In this scenario there is the option to trigger an intervention immediately, which mitigates the situation but incurs substantial cost. Alternatively, waiting for more information to arrive would reduces the risk of unnecessary intervention but increase the risk of missing opportunities to act, incurring additional costs or damages. Here, optimal optimal solution to this problem, could be computed depending on the cost of the intervention, the damage done by waiting too long, the likelihood that intervention is necessary and the information gained by delaying the decision. Applications for this could be for example cases with regime shifts and warning signals. This thesis provides a base for further exciting applications and extension of VoI in conservation management.

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List of Figures

2.1 Cumulative number of VoI applications in marine conservation management . 16

3.1 Histograms of the empirical data (total nitrogen in mg/l = TN) with fitted four-parameter-beta and gamma distributions. The empirical data is divided into two categories for the ecological state: good ecological status and bad ecological status 39

3.2 The value of perfect and imperfect information (with 95 % confidence intervals) for $c = 50, 100, 150$ and $p \in [0, 1]$. 41

3.3 (a) Plot of maximum prior probability for which VoI has a maximum, i.e. $p^*(c)$ versus the management cost c; (b) Maximum $VoI^*(c)$ versus the management cost c; (c) Parametric plot of $VoI^*(c)$ and $p^*(c)$. 42

3.4 Contour plot of the value of imperfect (monitoring) information VoI as a function of the prior probability p and the management cost c. 43

3.5 Effect of changing management cost on the maximum value of information VoI. The values of both the management cost and the VoI have been normalised with respect to the value of the good state (v). 45

3.6 Value of information VoI in comparison to monitoring cost K. The black dotted line shows the maximising function $p^*(c/v)$. Example points A and B for parameter combinations where VoI is smaller than K (point A) and VoI is higher than K (point B). The decision maker would decide based on the results of the VoI analysis and the cost for monitoring if investing in additional information is worthwhile ($VoI > K$) or not ($VoI < K$). 46

3.7 Results of two VoI analyses with different distributions of the data. The shape of the ellipse differs depending on the posterior probabilities which is obtained from sampled values from the fitted distributions. Qualitatively, the results of the analyses are generic. 49

4.1 Simulated time series of the NPPZ system (panels top to bottom): 1. nutrients $N(t)$ (blue) and $N_{ext(t)}$ (cyan); 2. non-harmful species $P_1(t)$; 3. harmful species $P_2(t)$ (black) together with the threshold $0.1mg/m^3$ (orange) the exceedance of which defines the occurrence of a HAB; 4. zooplankton $Z(t)$ . . 60

4.2 VoI as a function of prior probability p of the occurrence of a HAB (x_1) and of the fixed cost of management ($c = 3$) and damage $d \in [0, 600]$. 66

4.3 $EVSI$ as a function of $p \in [0,1]$ and $c \in [0,30]$. Damage d stays fixed at 30. . . 67

4.4 The effect of error on $EVSI$. $EVSI$ is calculated with the initial values, see Table 4.2; Type I and Type II Errors range from 0 to 1, $EVSI$ is displayed in relative values. 69

4.5 Probit regression: comparison of N–model and NZ–model. The grey dots show the predicted probabilities for the occurrence of a HAB. The green dots show the actual values for a HAB (0 = no HAB, 1 = HAB). The blue line shows the trend line. We can see that for low values of Zooplankton (Z) HABs are more likely to occur based on the model. 76

5.1 Plot of J_c (or H) as a function of a. The function J_c increases with increasing values of a, here we highlight specific example points at $a = \frac{1}{2}$, $a = \frac{1}{3}$, and $a = \frac{2}{3}$ with red markers and grey dashed lines. Other parameter are fixed: $b = 1$, $q = 1$, $c = 1$, and $\rho = \frac{1}{40}$. 88

5.2 Contour plot of a) $u^{\infty}_{posterior}$ as a function of a_1 and a_2 and b) u^{∞}_{prior} as a function of a_1 and a_2. Here we highlight the point corresponding to $a_1 = \frac{1}{3}$, $a_2 = \frac{2}{3}$ with a white-red circle. Other parameter are fixed: $p = 0.5$, $b = 1$, $q = 1$, $c = 1$, and $\rho = \frac{1}{40}$. 91

5.3 (a) (upper left) Contour plot of J^u_c/ρ (or H/ρ) as a function of a_1 and a_2 for uncertain system. (b) (upper right) Contour plot of J^*_c/ρ as a function of a_1 and a_2 for known a. (c) (down) Contour plot of VoI $= (J^*_c - J^u_c)/\rho$ as a function of a_1 and a_2. For all the plots, we highlight the example point corresponding to $a_1 = \frac{1}{3}$, $a_2 = \frac{2}{3}$ with a white-red circle. Other parameter are fixed: $p = 0.5$, $b = 1$, $q = 1$, $c = 1$, and $\rho = \frac{1}{40}$. 93

List of Tables

2.1 List of journals that published VoI applications. 17
2.2 Summary of VoI applications 18
2.3 Summary of analysed attributes related to the methodology used in the applications. The first column refers to m.a. = management alternatives. Here, the infinity sign indicates inputs such as continuous levels; the last column "Valuation" refers to the valuation parameter. 20
2.4 Summary attribute related to the results of VoI applications. Here, S.A. = sensitivity analysis; Revise = option to revise included; m.a. = management alternatives; data cost = cost for collecting or acquiring data/information 22

3.1 Payoff matrix for the river management problem. 34
3.2 The value of the ecological state after action a_0 or a_1 without additional information. 35
3.3 Value of perfect and imperfect information for the case of the Weser River . . 39

4.1 Matrix summarising the HAB decision problem. 55
4.2 Payoff matrix for the HAB decision problem. 64
4.3 Updating prior belief and consequences after receipt of message $M = m$ . . 65
4.4 Summary of case distinctions. Substituting the terms of Table 4.2 into Eq. (4.4) yields: $EVSI = min\,\{dp(x_1,),c\} - min\,\{dp(x_1,m_0)\} - min\,\{d[p(x_1) - p(x_1,m_0)], c(1-p(m_0)\}$ Due to the three $\min$ operators we have to consider eight different cases. Details can be found in the Appendix, Section 4.7.3. 68

Acronyms

AIC Akaike Information Criterion.

BIC Bayesian Information Criterion.

EVII Expected value of imperfect information.

EVPI Expected value of perfect information.

EVPXI Value of perfect X (partial) information.

EVSI Expected value of sample information.

EVSXI Expected value of sample X information.

FGG Weser Flussgebietsgemeinschaft Weser (River Basin District Weser).

GES Good ecological status.

HAB Harmful algal bloom.

MDP Markov Decision Process.

MLE Maximum likelihood estimators.

NLWKN Niedersächsischer Landesbetrieb für Wasserwirtschaft, Küsten- und Naturschutz (Lower Saxony Water Management, Coastal Protection and Nature Conservation Agency).

OC Optimal control.

ODE Ordinary differential equation.

POMDP Partially Observable Markov Decision Process.

PoV Posterior value.

PV Prior value.

SDP Stochastic Dynamic Programming.

VoI Value of Information.

WFD Water Framework Directive.

List of publications

Chapter 2

Luhede A, Verma P, and Upmann T. The value of information in marine conservation and management: A literature review. In Preparation.

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Eidestattliche Erklärung

Hiermit erkäre ich, Amelie Luhede, geboren am 14.05.1992 in Bremen, dass ich diese Dissertation selbstständig verfasst habe und nur die hier angegebenen Hilfsmittel und Quellen benutzt habe. Zudem versichere ich, dass diese Dissertation weder in ihrer Gesamtheit noch in Teilen einer anderen Hochschule zur Begutachtung in einem Promotionsverfahren vorliegt oder vorgelegen hat. Bis auf die angegebenen Teilpublikationen, ist diese Arbeit noch nicht veröffentlicht worden. Die Leitlinien guter wissenschaftlicher Praxis an der Carl von Ossietzky Universität Oldenburg wurden befolgt. Für dieses Promotionsvorhaben wurden keine kommerziellen Vermittlungs- oder Beratungsdienste in Anspruch genommen.

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