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Research article

The value of information in predicting harmful algal blooms

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A B S T R A C T

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 (HABs) 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. Our analysis revealed a prediction accuracy of a HAB occurrence of 0.65 % if additional information on zooplankton is included. We then evaluate the effect of reducing uncertainty about these indicators (e.g., through extended monitoring) on management decisions employing a VoI analysis. We find that additional information may lead to an expected welfare gain of up to 2.67 million Euro in our decision context. Our results highlight the significant potential for VoI analysis to enhance decision-making in fishery and ecosystem 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.

1. 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 (Anderson, 2009). 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, can result in paralysis and death in sea birds and lead to negative health effects for humans and other organisms (Anderson et al., 2000). These harmful algal blooms (HABs) can negatively affect water quality and pose severe economic losses for fisheries, tourism and recreation (Carias et al., 2024), and may also impair value chains in the long-term (Hoagland et al., 2002; Adams et al., 2018).

In recent years, a notable rise in the frequency of severe and unpredictable HABs has been observed in coastal waters (Anderson, 2007; Anderson et al., 2012; Gobler, 2020). Despite the significant damage caused by HABs, the mechanisms driving their sudden occurrence remain poorly understood. Accurate prediction of HABs is critical for effective management and intervention, but current understanding is limited (Lee and Lee, 2018). Therefore, enhancing predictive capabilities through advanced modelling and data collection methods is essential to mitigate the economic, environmental, and health impacts of HABs.

Various modelling approaches have been developed to better understand the dynamics of HABs and improve their prediction, leading to more effective precautionary management strategies (Chakraborty and Feudel, 2014). Alongside these efforts, continuous monitoring activities provide valuable data that contribute to a deeper understanding of

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HAB dynamics (Anderson et al., 2001). However, such monitoring is resource-intensive, involving frequent observations, water sampling, and laboratory testing (Lomax et al., 2005). Given the substantial cost of data collection, decision-makers must evaluate whether the benefits of additional information outweigh the associated costs, especially since delays in decision-making can reduce the effectiveness of management interventions. This challenge is addressed by the value of information (VoI) analysis, a decision-analytic tool that quantifies the net benefit of information gathered at a specific cost. Originating from information theory and statistical decision theory (Hirshleifer and Riley, 1979), VoI has recently been applied to areas such as conservation management (Bennett et al., 2018; Canessa et al., 2020), fisheries management (Prellezo, 2017; Haag et al., 2022), and water quality monitoring (Nygård et al., 2016; Koski et al., 2020; Luhede et al., 2024). 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, 2004). 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. VoI offers a quantitative method for assessing the expected improvement in decision-making outcomes as a result of collecting additional data, relative to the cost of that data acquisition.

This study seeks to evaluate the effect of reducing uncertainty regarding the occurrence of HABs in the German North Sea by extending monitoring efforts. Specifically, we evaluate the value of additional time-resolved data on zooplankton, a top-down control factor, to improve predictions of HABs and enable timely management interventions. Current legislation focuses primarily on nutrient reduction, particularly nitrogen, to mitigate eutrophication and HABs (Rönn et al., 2023). However, the role of zooplankton in regulating HABs is often overlooked in policy frameworks. Therefore, the objective of this study is to assess the potential improvement in management decisions by incorporating zooplankton data alongside nutrient data to enhance HAB prediction.

To do so, we develop a methodological framework to quantify the expected value of HAB predictions. We perform a VoI analysis based on numerical simulations and monitoring data from a HAB model (Chakraborty and Feudel, 2014). Our analysis quantifies the economic value of collecting additional zooplankton data and assess how reducing uncertainty impacts fishery management decisions. The results show that additional information has a positive value and imply that investing in improved predictions as an early warning system for management decisions might be worthwhile. However, the outcomes are sensitive to information quality, cost parameters and the perceived prior belief of a HAB occurrence. Ultimately, this study contributes methodologically to the VoI literature in environmental management and offers practical guidance for decision-makers in addressing HABs.

2. Methods

2.1. 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 $x \in \Omega := \{x_0, x_1\}$.[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.

Table 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	$v(a_0, x_1) = -d$	$v(a_1, x_1) = -c(a_1)$	$p_X(x_1) = p$

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. (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 (see Table 1).

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

$$\mathbb{E}_X \left[v(a^*(X), X) \right] = \mathbb{E}_X \left[\max_a v(a, X) \right] = \sum_x p_X(x) \max_a v(a, x) \,. \tag{1}$$

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. (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*:

$$\max_a \mathbb{E}_X \left[v(a, X) \right] = \max_a \sum_x v(a, x) p_X(x). \tag{2}$$

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

[1] Binary decision problems are frequently considered in VoI analysis, as they allow for an intuitive understanding of the problem (Giordano et al., 2022; Luhede et al., 2024).

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

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

$$\begin{aligned} EVPI &:= \sum_x p_X(x) \max_a v(a,x) - \max_a \left[\sum_x v(a,x) p_X(x)\right] \\ &= \mathbb{E}_X\left[\max_a v(a,x)\right] - \max_a \mathbb{E}_X\left[v(a,x)\right] \geq 0\,. \end{aligned} \tag{3}$$

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[2]

$$\begin{aligned} EVSI &:= \sum_m \left[\max_a \sum_x v(a,x) p_{X|M}(x|m)\right] p_M(m) - \max_a \sum_x v(a,x) p_X(x) \\ &= \mathbb{E}_M\left[\max_a \mathbb{E}_{x|m}\left[v(a,X)\right]\right] - \max_a \mathbb{E}_X\left[v(a,X)\right]. \end{aligned} \tag{4}$$

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 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

$$p_{X|M}(x|m) = \frac{p_{M|X}(m|x)\, p_X(x)}{p_M(m)}, \tag{5}$$

where

$$p_M(m) = \sum_x p_{M|X}(m|x) p_X(x). \tag{6}$$

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)

2.2. 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 (Eq. (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. (7b) and (7c)). Eq. (7d) describes the change in zooplankton, which is influenced by growth and linear mortality (starvation).

$$\dot{N} = k(N_{ext} - N) - g(f_1 P_1 + f_2 P_2) + r(P_1 + P_2) + \beta(h_1 + h_2)Z + \gamma\delta Z \tag{7a}$$

$$\dot{P}_1 = q\,\vartheta_1\, g f_1 P_1 - r P_1 - \sigma_1 P_1 - h_1 Z \tag{7b}$$

$$\dot{P}_2 = q\,\vartheta_2\, g f_2 P_2 - r P_2 - \sigma_2 P_2 - h_2 Z \tag{7c}$$

$$\dot{Z} = \alpha_1\, h_1 Z + \alpha_2\, h_2 Z - \delta Z. \tag{7d}$$

This minimal HAB model is convenient for our approach as it is a well-established process-oriented model developed for the study area, enabling us to explore the effect of adding information on one so far unexplored variable and the added value to the decision maker. It is suitable as it clearly explains the causal interaction of an additional control (zooplankton) on the development of a HAB. The model is carefully calibrated with regional monitoring data on zooplankton, nitrogen, and harmful and non-harmful phytoplankton (years 2015–2020) (see Fig. 1) provided by the Lower Saxony environmental agency NLWKN (Niedersächsischer Landesbetrieb für Wasserwirtschaft, Küsten- und Naturschutz), following the criteria for ecological status assessments based on the EU Water Framework Directive. A detailed description of the NPPZ model, its assumptions and a list of all parameters is given in Appendix A.1.

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

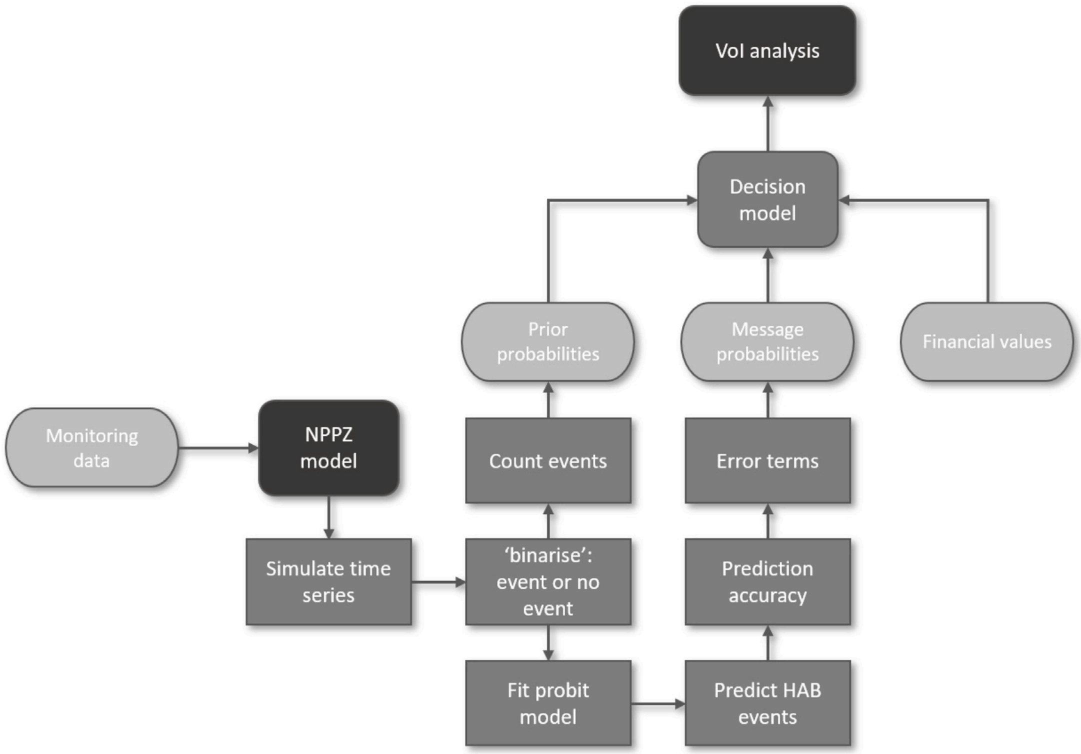

Fig. 1. Flow chart describing the methodological approach to generate the inputs for the VoI analysis. The light grey rounded shapes represent model inputs: either monitoring data or inputs retrieved from analysis or the literature. The dark grey boxes with rounded edges represent the models used. The medium grey rectangles each present a process or step.

To solve the ODE system (7), we numerically integrate it over a time range of hundred years (100×365 days); a typical result is shown in Fig. 2. Based on empirically reported HAB rates of approximately 10 per 100 years, we assume a concentration of 0.1 mg/m^3 as fixed threshold separating non-HAB years from years with a HAB event (see Section 3 for a more detailed explanation).

2.3. 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. (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. 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 predict the occurrence of a HAB and obtain probabilities of an event, i.e. to deploy our "warning system", we fit a probit regression model to the data. A probit model is typically used to estimate the probability of an event when the dependent variable is binary, as in our case $X \in \{x_0, x_1\}$ (Butryn and Fura, 2005).

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:

$$p(x_1|N) = \phi(\beta_0 + \beta_1 N) \tag{8a}$$

$$p(x_1|N, Z) = \phi(\beta_0 + \beta_1 N + \beta_2 Z), \tag{8b}$$

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 regression 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 Fig. 2). 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,

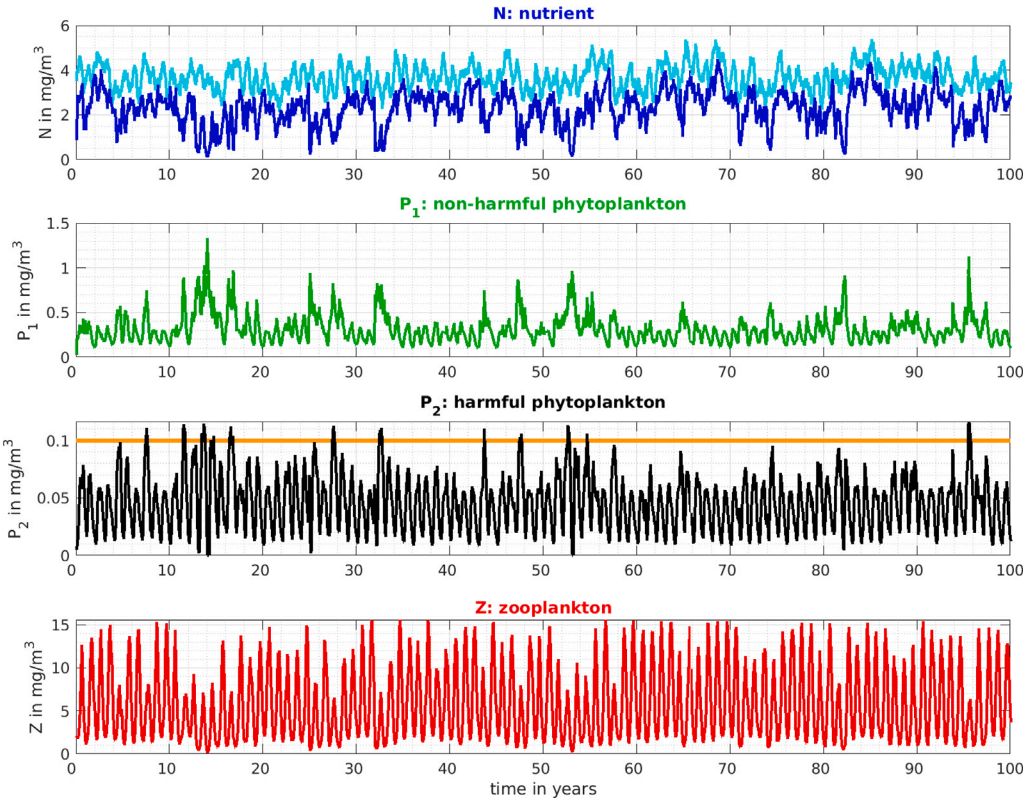

Fig. 2. Simulated time series of the NPPZ system (panels top to bottom): 1. nutrients $N(t)$ (blue) and $N_{ext(t)}$ (cyan); 2. non-harmful species $P_1(t)$; 3. harmful species $P_2(t)$ (black) together with the threshold 0.1 mg/m^3 (orange) the transgression of which defines the occurrence of a HAB; 4. zooplankton $Z(t)$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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 Fig. 6). 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 2.[3]

3. The value of information for shellfish management

3.1. 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 2024), 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 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 Fig. 2) 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 later in this article.

As described in Section 2.1, 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

[3] 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).

Table 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

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 Section 2.3). 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 2.

3.2. Results

We next calculate $EVPI$ and $EVSI$ for the problem under consideration. 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 2 we obtain from Eq. (2):

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

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 $p_X = \left(p_X(x_0), p_X(x_1)\right) = (0.89, 0.11)$, the expected payoff under perfect information (see Eq. (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. (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 2 into Eqs. (4)–(6). A corresponding step-by-step calculation of $EVSI$ is displayed in . 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.

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.

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.

We calculate $EVSI$ for different scenarios: Fig. 3 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. 3), $EVSI$ 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.

Fig. 4, 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), 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 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 Appendix A.3 for the detailed calculation.

To address the dependency on the accuracy of the information system, we calculate $EVSI$ for different combinations of Type I ('false warning') and Type II ('missed warning') errors with our initial case study values in Table 2. We display VoI in relative terms to obtain more

Table 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	$-1.75 \times 0.66 + (-3) \times 0.34 = -2.17$
$EVSI$			$-2.17 - (-3) = 0.83$	

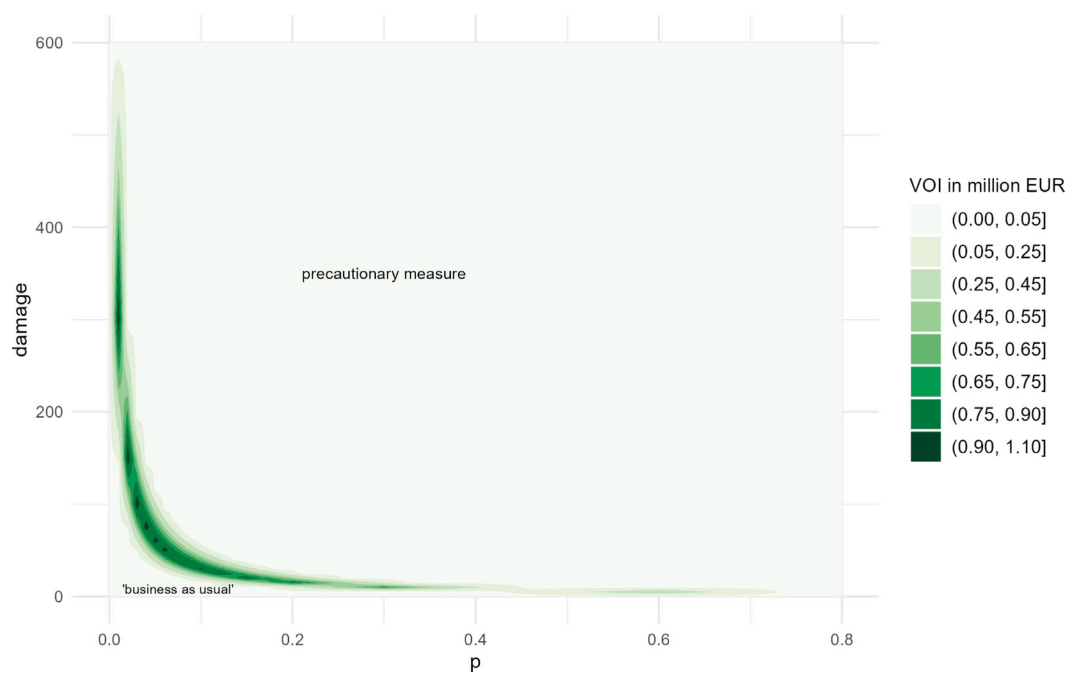

Fig. 3. VoI as a function of prior probability p of the occurrence of a HAB (x_1) and of the fixed cost of management ($c = 3$) and damage $d \in [0, 600]$.

Table 4
Summary of case distinctions. Substituting the terms of Table 2 into Eq. (4) yields: $EVSI = min\left\{dp(x_1), c\right\} - min\left\{dp(x_1, m_0)\right\} - min\left\{d[p(x_1) - p(x_1, m_0)], c(1 - p(m_0))\right\}$ Due to the three min operators we have to consider eight different cases. Details can be found in the Appendix, Appendix A.3.

Case							Findings
(a)	$c < dp(x_1)$	(α)	$c < dp(x_1, m_0)$	(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.
		(β)	$dp(x_1, m_0) < c$	(i)	$c < dp(x_1, m_1)$	$EVSI > 0$	Additional information may be worthwhile.
				(ii)	$dp(x_1, m_1) < c$	Contradiction.	
(b)	$dp(x_1) < c$	(α)	$c < dp(x_1, m_0)$	(i)	$c < dp(x_1, m_1)$	Contradiction.	
				(ii)	$dp(m_1, m_1) < c$	$EVSI > 0$	M is a contra-indicator.
		(β)	$dp(x_1, m_0) < c$	(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.

generic results and to shift the focus on the dependencies instead of absolute values. Fig. 5 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

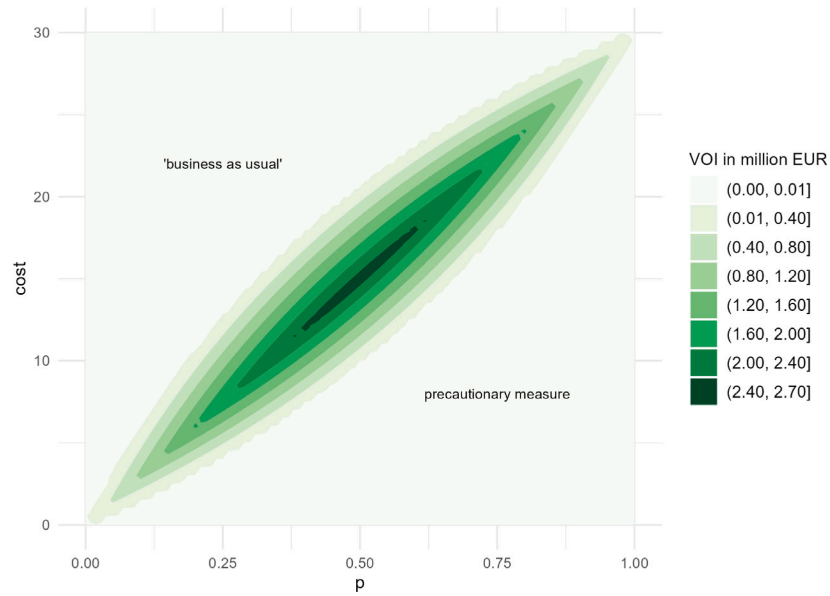

Fig. 4. $EVSI$ as a function of $p \in [0,1]$ and $c \in [0,30]$. Damage d stays fixed at 30.

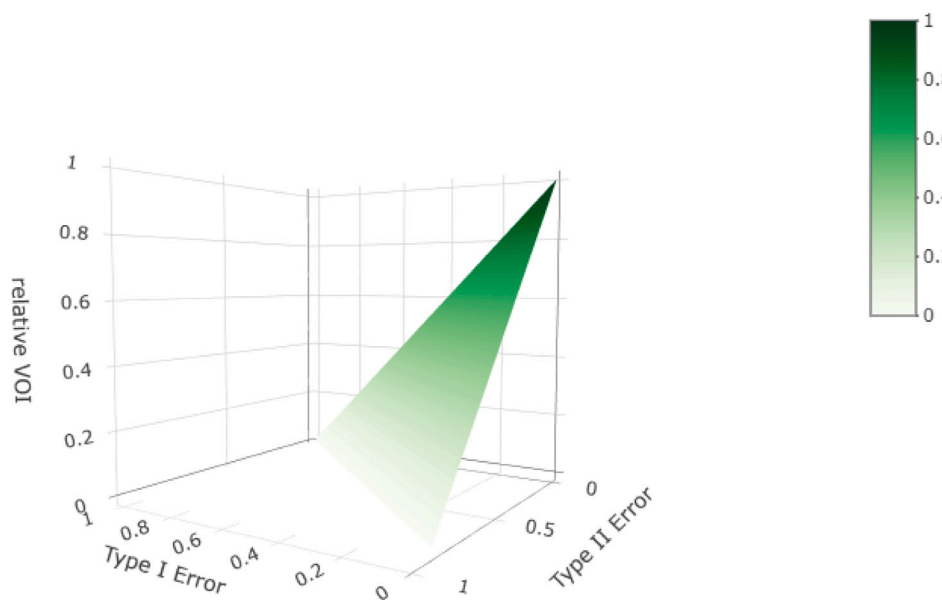

Fig. 5. The effect of the prediction accuracy on $EVSI$. $EVSI$ is calculated with the initial values, see Table 2, and the prediction accuracy is described by Type I error ('false warning') and Type II error ('missed warning'). The error terms are varied and range from 0 to 1, $EVSI$ is displayed in relative values.

decreases drastically as the Type II error increases. It decreases slightly less sharply as the Type I error increases.

4. Discussion

The objective of this study was to evaluate the effect of reducing uncertainty regarding the occurrence of HABs in the German North Sea by extending monitoring efforts. We evaluate the expected benefit of predicting HABs to improve shellfish management using value of information (VoI) analysis. Specifically, we focus on the expected benefits of acquiring additional information on zooplankton and nitrogen in predicting HABs before the event. The economic implications of HABs on shellfish fisheries underscore the importance of effective decision-making to prevent substantial damages. The results show that the value of including information on nitrogen and zooplankton yields positive values of up to 2.67 (in million Euros per year), implying that the acquisition of this information is ex ante worthwhile if the cost of data acquisition does not exceed that amount. 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 particularly 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.

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 85 000 Euros per year,[4] makes the value of additional data in our case study explicit.

Several considerations may limit the conclusions that can be drawn from this analysis. First, certain assumptions were necessitated during the modelling process. We made careful adjustments to better align the model with available data (see Appendix A.1). By carefully calibrating the model using monitoring data from the case study area, we improve its reliability. The data used for the calibration is collected following the criteria of the EU Water Framework Directive, ensuring a high-quality standard. We considered simplifications in the model to enable us to explore the effect of information and its value for the decision maker by considering an additional source of information (i.e. information on zooplankton). First, we distinguished between harmful and non-harmful phytoplankton species. In reality, the system is more complex and considering ecological communities and functional groups with more interactions would be more realistic. Second, our model only considers seasonal variability. The effect of climate variability is not included but might have an effect on the development of HABs. For example, prolonged ocean warming, marine heatwaves or changes in wind directions and precipitation patterns might alter HAB outbreaks (Gobler, 2020; Raine et al., 2010; Sinha et al., 2017; Glibert, 2020). Third, we did not include additional external environmental parameters such as salinity or pH. More comprehensive models that include the effects of plankton communities or climate variability would allow for a more realistic description and may provide more information about the state of the system (Wells et al., 2015; Ralston and Moore, 2020; Nguyen and Huynh, 2023). The simplifications to the model may influence the exact numerical value of the result and may slightly under or over-represent the actual value. However, it would not change the mechanisms of VoI and the methodological approach. If the model allows for better predictions, VoI would be higher. In comparison to the effort and cost of collecting the data for validating the model and the continuous monitoring, the value for the decision maker might not change as VoI needs to be compared to the actual cost of information acquisition. This effect could be further explored in future research.

Further, as a crucial part of our methodological approach, we set thresholds for HAB events based on peaks in the simulated time series and a literature review. These may pose limitations to the application. Lastly, one of the major challenges is finding suitable estimates for financial values. While there were no estimates on financial values available for our case study area, we obtained those values from a reported case in a neighbouring country. Although not a perfect match, the values still provide a meaningful interpretation of the scale and order of magnitude of VoI. If more local data becomes available in the future, an adjustment of the input variables could lead to more precise analysis results. We believe that despite some assumptions, our methods are valuable for gaining insights into the value of additional information for the considered decision problem. We are confident that the structure of the results as well as the order of magnitude of the resulting values provide valuable insights. We test different parameter scenarios, the results offer insights into the potential economic implications of decision-making strategies.

To account for some of the uncertainties in our decision model, we explore scenarios in which the expected damage of a HAB or the cost for management varies under a range of prior probabilities. Varying the expected damage demonstrates that additional information becomes particularly valuable when the anticipated damage is large while the probability of a HAB is low; and conversely when the damage 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. This dependence dependency of $EVSI$ on prior probability and management costs is in line with findings discussed in Giordano et al. (2022) and Luhede et al. (2024).

Our analysis shows that nitrogen alone as an indicator is not suitable as to predict HAB events, as the prediction accuracy is close to zero. However, by adding data on zooplankton the prediction accuracy increases to 65%. Even though this number may not seem especially high, the calculation of the value of this information reveals that it is still worthwhile investing up to 830k EUR in this information. We account for measuring errors or short flickering of enhanced harmful phytoplankton by varying the threshold of consecutive days of enhanced phytoplankton concentrations that are treated as a HAB event. By this, we ensured that a short exceeding of our (arbitrarily) set threshold for phytoplankton concentrations has an impact on the prediction accuracy. The accuracy of the warning system has a strong influence on VoI, as shown in the second part of the sensitivity analysis and Fig. 5, emphasising that the benefits of additional information are subject to the reliability of the information system. 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.

The high values in our analysis are not consistent with the previous literature in conservation or fisheries management, which often favours direct management over collecting additional information (e.g. Bal et al., 2018; Hanson et al., 2023; Xia et al., 2021) and VoI is relatively low. However, other cases exist where information drastically improves management outcomes (e.g Bouma et al., 2011; Costello et al., 2010; Koski et al., 2020). The exact values of VoI depend on the study's input values and are highly context-sensitive; and comparisons of values of VoI across the literature are difficult, as reporting and objectives often differ. Due to this challenge in synthesising results, to our knowledge, there has been no attempt to generalise results (Bolam et al., 2019; Holden et al., 2024). VoI analysis provides an individual assessment of the benefit of resolving uncertainty for a specific decision context, so that the results are highly sensitive to the context. The presence of uncertainty can have differing effects on management decisions and achieving objectives.

We contribute to a better understanding of VoI applications in managing HAB, which can be adjusted to other decision contexts. This study highlights the value of monitoring information to predict HAB events and provides valuable guidance for decision-making for under which circumstances investing in additional data is worthwhile to act and decide on mitigation interventions on time. From a policy maker's perspective, we can see that in our case, there is much value in considering monitoring data to improve predictions: We show that investments in monitoring multiple indicators may be welfare enhancing, which is in line with results by Dajka et al. (2022), showing that

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

multivariate assessments in local and regional ecosystem management are required for effective management concepts. Carefully selecting indicators is vital for water quality assessments (Nguyen and Huynh, 2023). The method outlined in this study provides a pathway to expand the use of VoI analyses for HAB management. The simulation of a time series combined with a probit model is a suitable technique for deriving conditional probabilities in a 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. Further, our approach can be easily adjusted to other applications and case studies.

In our study, we propose an indirect management, which does not directly manage or prevent HAB outbreaks but aims to mitigate the consequences for fisheries. Some more direct policy interventions exist, such as the prevention of HABs (Carias et al., 2024). For example, by mitigating pollutants that impact the mortality of zooplankton, which in turn may increase the probability of a HAB. However, different types of models, such as system dynamic modelling, might be needed to understand the complex interactions in water pollution (Mousavi et al., 2023). Introducing the control of pollutants as a management strategy changes the decision context and needs careful adjustments to calculate VoI.

Our study serves as a promising starting point for future research. This research could explore more scenarios, and different combinations of indicators or policy instruments, offering further guidance to decision-making and the indicator selection process. The potential for future research to make significant strides in this field is indeed hopeful and optimistic.

5. Conclusion

This article contributes to the understanding of decision-making processes and the effect of uncertainty about the occurrence of HABs 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.

CRediT authorship contribution statement

Amelie Luhede: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Jan A. Freund:** Writing – review & editing, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **Jan-Claas Dajka:** Writing – review & editing, Conceptualization. **Thorsten Upmann:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

A.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

$$g(t) = g\left[P_1(t), P_2(t)\right] = \frac{a}{1 + c\left[P_1(t) + P_2(t)\right]} \tag{9}$$

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

$$f_i(t) = f_i\left[N(t)\right] = \frac{N(t)}{e_i + N(t)} \quad \text{for} \quad i = 1, 2 \tag{11}$$

$$h_i(t) = h_i\left[P_i(t)\right] = \frac{\lambda_i P_i^2(t)}{\mu_i^2 + P_i^2(t)} \quad \text{for} \quad i = 1, 2\,. \tag{12}$$

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 (7a)–(7d) reflect the following processes:

- The term $k(N - N_{ext})$ in (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 (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 (7b) and (7c).
- The terms $-rP_1$ and $-rP_2$ in (7b)–(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 (7b)–(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 (7b)–(7c) model the grazing of phytoplankton by zooplankton which are converted with efficiency α_1 and α_2 resp. into zooplankton biomass in (7d).
- Growth of zooplankton following grazing is balancing the linear zooplankton mortality δZ in (7d).
- Through bacterial recycling a fraction γ of dead zooplankton is fed back to nutrients in (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. (10) in Appendix A.1).
- A stochastic process modelling riverine import of an essential nutrient concentration $N_{ext}(t)$ (cf. Eq. (13) in Appendix A.1).

- A stochastic process modelling slow variations of the *per capita* mortality rate δ_t (cf. Eq. (15) in Appendix A.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 (9)–(12) have the following meaning:

- The function $g[P_1(t), P_2(t)]$ in (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 $N_{ext}(t)$ is modelled as a harmonic with red noise added to it, i.e.

$$N_{ext}(t) = \left(0.9 + 0.1\cos\left[\frac{2\pi(t-92)}{365}\right] + \zeta(t)\right) \text{ g m}^{-3} \quad (13)$$

 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 $f_s = 1/\text{day}$) values ζ_t resulting from an auto-regressive process of order 1 (AR[1])

$$\zeta_t = \alpha\, \zeta_{t-1} + \epsilon_t \qquad (t = 2, 3, \ldots, \text{days}) \quad (14)$$

 with $\alpha = \mathrm{e}^{-1/(f_s \tau_c)}$ to match the empirical correlation time τ_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 $\delta(t)$ is modelled as a slowly varying random process created through interpolating the following uniformly sampled (sampling rate $f_s = 1/\text{day}$) values δ_t resulting from the recursion

$$\delta_t = \left(0.02 + 0.3\,\eta_t^2\right) \text{ day}^{-1} \quad (15)$$

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

$$\eta_t = \beta\, \eta_{t-1} + \hat{\epsilon}_t \qquad (t = 2, 3, \ldots, \text{days}) \quad (16)$$

 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 $\sigma_{\hat{\epsilon}}^2 = 5.5\times10^{-4}$.

Numerical integration was applied to the system of ODEs (7a)–(7d) with initial values: $N(0) = \frac{1}{4}N_{ext}(0)$, $P_1(0) = 0.025$ g m^{-3}, $P_2(0) = 0.005$ g m^{-3}, $Z(0) = 2$ g m^{-3} and using the following list of parameters:

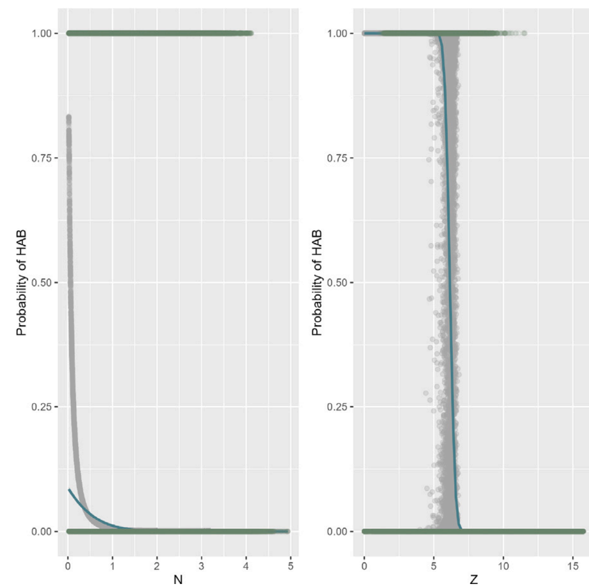

Fig. 6. Probit regression: comparison of N-model and NZ-model. The grey dots show the predicted probabilities for the occurrence of a HAB. The green dots show the actual values for a HAB (0 = no HAB, 1 = HAB). The blue line shows the trend line. We can see that for low values of Zooplankton (Z) HABs are more likely to occur based on the model.

Parameter	Value	Unit
a	1.5	day^{-1}
c	0.05	[g m^{-3}]$^{-1}$
e_1	0.1	g m^{-3}
e_2	0.1	g m^{-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	g m^{-3}
μ_2	1	g m^{-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	°C
ΔT	8	°C
t_0	212	July 31st

A.2. Figures

See Fig. 6.

A.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) yields

$$\begin{aligned}
EVSI &= \sum_m \max_a \sum_x v(a,x)p(x,m) - \max_a \sum_x v(a,x)p(x)\\
&= \max\left\{v(a_0,x_0)p(x_0,m_0) + v(a_0,x_1)p(x_1,m_0), v(a_1,x_0)p(x_0,m_0)\right.\\
&\quad \left. + +v(a_1,x_1)p(x_1,m_0)\right\}\\
&\quad + \max\left\{v(a_0,x_0)p(x_0,m_1) + v(a_0,x_1)p(x_1,m_1), v(a_1,x_0)p(x_0,m_1)\right.\\
&\quad \left. + v(a_1,x_1)p(x_1,m_1)\right\}\\
&\quad - \max\left\{p(x_0)v(a_0,x_0) + p(x_1)v(a_0,x_1), p(x_0)v(a_1,x_0)\right.\\
&\quad \left. + p(x_1)v(a_1,x_1)\right\}\\
&= \max\left\{(b-c)p(x_0,m_0) + (b-c)p(x_1,m_0), (b-d)p(x_1,m_0)\right.\\
&\quad \left. + bp(x_0,m_0)\right\}\\
&\quad + \max\left\{(b-c)p(x_0,m_1) + (b-c)p(x_1,m_1), (b-d)p(x_1,m_1)\right.\\
&\quad \left. + bp(x_0,m_1)\right\}\\
&\quad - \max\left\{(b-c)p(x_0) + (b-c)p(x_1), (b-d)p(x_1)\right.\\
&\quad \left. + bp(x_0)\right\}\\
&= \max\left\{(b-c)p(m_0), bp(m_0) - dp(x_1,m_0)\right\}\\
&\quad + \max\left\{(b-c)p(m_1), bp(m_1) - dp(x_1,m_1)\right\}\\
&\quad - \max\left\{b-c, b-dp(x_1)\right\}\\
&= bp(m_0) - \min\left\{dp(x_1,m_0), cp(m_0)\right\} + bp(m_1)\\
&\quad - \min\left\{dp(x_1,m_1), cp(m_1)\right\}\\
&\quad - b + \min\left\{dp(x_1), c\right\}\\
&= \min\left\{dp(x_1), c\right\} - \min\left\{dp(x_1,m_0), cp(m_0)\right\}\\
&\quad - \min\left\{dp(x_1,m_1), cp(m_1)\right\} \qquad (17)
\end{aligned}$$

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)

$$cp(m_0) < dp(x_1,m_0) \Leftrightarrow c < dp(x_1|m_0) \qquad (18a)$$

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

(i)

$$cp(m_1) < dp(x_1,m_1) \Leftrightarrow c < dp(x_1|m_1) \qquad (18b)$$

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 (18a) and (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)

$$dp(x_1,m_1) < cp(m_1) \Leftrightarrow dp(x_1|m_1) < c \qquad (18c)$$

Management cost is higher than the expected damage in case of a positive signal. It follows from (18c) that $EVSI = c - cp(m_0) - dp(x_1,m_1) = cp(m_1) - dp(x_1,m_1) > 0$. However, combining (18a) and (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)

$$dp(x_1,m_0) < cp(m_0) \Leftrightarrow dp(x_1|m_0) < c \qquad (18d)$$

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

(i) Eq. (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 (18d). Hence, depending on the cost of information acquisition, it may, or may not be beneficial to do so.

(ii) Eq. (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 (18c) and (18d) 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. (18a) holds, implying that the management cost is lower than the expected damage in case of a negative signal.

(i) Eq. (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 (18a) and (18b) together imply $c < dp(x_1)$, contradicting the assumption of Case (b). Hence, this case does not exist.

(ii) Eq. (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. (18a). Hence, information acquisition may be economic. However, Eqs (18a) and (18c) 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. (18d) holds, i.e., management cost is higher than the expected damage in case of a negative signal.

(i) Eq. (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. (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 (18c) and (18d) that the management cost exceeds 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.

Data availability

Data will be made available on request.

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