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Assessing the value of information for water quality management in the North Sea

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ABSTRACT

Global Earth Observation (GEO) is one of the most important sources of information for environmental resource management and disaster prevention. With budgets for GEO increasingly under pressure, it is becoming important to be able to quantify the returns to informational investments. For this, a clear analytical framework is lacking. By combining Bayesian decision theory with an empirical, stakeholder-oriented approach, this paper attempts to develop such a framework.

The analysis focuses on the use of satellite observations for Dutch water quality management in the North Sea. Dutch water quality management currently relies on information from '*in situ*' measurements but is considering extending and deepening its information base with satellite observations. To estimate returns to additional investments in satellite observation, we analyze the added value of an extended monitoring system for the management of eutrophication, potentially harmful algal blooms and suspended sediment and turbidity in the North Sea. First, we develop a model to make the potential contribution of information to welfare explicit. Second, we use this model to develop a questionnaire and interpret the results.

The results indicate that the expected welfare impact of investing in satellite observation is positive, but that outcomes strongly depend on the accuracy of the information system and the range of informational benefits perceived.

1. Introduction

Information is important for decision-making. Although this seems a rather obvious statement, the value of information for decision-making is seldom addressed. This might not be a problem when sufficient investments in informational services are made, but explicit attention for the value of information is required if too little, or too much, investments in information are made. In the case of Global Earth Observation (GEO), governments and supra-national organizations like the European Space Agency (ESA) and the American National Aeronautics and Space Administration (NASA) have substantially invested in GEO over a long period of time (Peeters and Jolly, 2004). Recently, however, budgets for GEO investment have come under pressure and GEO experts argue that, currently, insufficient investments in GEO are being made (EC, 2007).

GEO information basically involves all observational information concerning the state of the world, including satellite observations and '*in situ*' information. This paper specifically focuses on the added value of satellite-based information.

Generally, satellite-based information extends the geographical and temporal coverage of the information system and supports the development of early warning systems to prevent disasters and avoid damage resulting from, example forest fires, droughts and floods (GEOSS, 2004). Also, it can generate new observations that were not available before. To assess the economic, social and environmental benefits of GEO information, the European commission funded the 3-year GeoBene project (www.geo-bene.eu). This paper presents one of the case studies of this project, an assessment of the economic benefits of satellite-based information for water-quality management in the North Sea.

There are few studies that have actually estimated the value of GEO information. Macauley (2006) and Williamson et al. (2002) discuss the potential benefits of GEO information but do not empirically evaluate any effects. Other papers use rather ad-hoc methods for assessing specific benefits of GEO information, without a more general framework to systematically evaluate effects (see, for example, Isik et al., 2005; Trigg and Roy, 2007; Lybbert et al., 2006; Chen et al., 2004; Kalluri et al., 2003; Kaiser and Pulsipher, 2004). A study that tries to make a comprehensive assessment of the benefits of GEO information is a study commissioned by the ESA to PriceWaterhouseCoopers (PWC, 2006). This study uses stakeholder consultation and expert judgment to evaluate GEO benefits, and concludes that the potential benefits of additional investments in GEO information are large.

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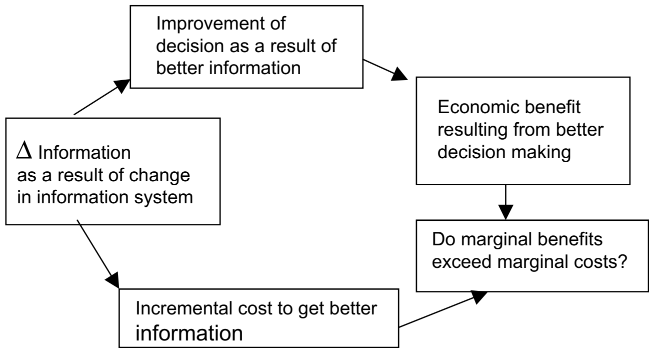

Fig. 1. Assessing the value of information (after Fritz et al., in press).

The problem with the PWC study is, however, that again, an analytical framework is lacking and that the variation in judgments is not represented well. This is crucial for the robustness of stakeholder consultation studies, especially when the uncertainty of the estimates is large (Morgan et al., 2001).

The objective of this paper is to develop a methodologically sound and empirically feasible approach to measuring the economic benefits of GEO information. To focus the analysis we consider the case of Dutch water quality management in the North Sea. At present, water quality in the North Sea is monitored through '*in situ*' measurements. Extending this system with satellite observations would increase the temporal and geographical coverage of water quality monitoring in the North Sea. In addition, it would allow for the development of an early warning system to prevent damages from excessive algal blooms (see the review by Stumpf and Tomlinson, 2005). Also, investing in satellite observation could make a more systematic monitoring of turbidity possible, which could help enforce environmental regulations regarding sea-water clarity around economic activities (construction, sand mining) in the North Sea.

To evaluate the benefits of satellite observation for Dutch water quality management we use an empirical, stakeholder-oriented approach. We develop a methodological framework, based on Bayesian decision theory, evaluating the role of information in the context of decision making under conditions of uncertainty. Based on the work of Schimmelpfennig and Norton (2003) and Morgan et al. (2001) we develop a questionnaire to estimate how investments in satellite-based information are expected to reduce the uncertainty of water quality decision-making. To test the methodology, we select a range of stakeholders involved in water quality management, including experts, policy makers and representatives of interest groups.

The results indicate that the framework of Bayesian decision theory is suitable for assessing the value of information, if respondents have some experience with the use of satellite-based information. In the case of Dutch water quality management, the expected welfare impacts of investments in satellite observation are positive, but outcomes are sensitive to the perceived accuracy of the information system and the range of informational benefits perceived.

In Section 2 we elaborate the conceptual framework and the empirical approach. We then introduce the case study, the use of satellite observations for water quality management in the North Sea. In Section 4 we present the results and in Sections 5 and 6 we discuss the results and conclude.

2. Methods

2.1. Conceptual framework

Assessing the economic value of information basically involves two steps: First, the contribution that information makes to decision-making has to be made explicit. Second, the contribution of better decision making to welfare has to be assessed (Fig. 1).

With regard to the first step, it is important to realize that information can only improve decision-making if decision-making is uncertain. If decision-makers are completely certain about the outcomes of their decision-making, then additional information will have no influence and, hence, will have no significant welfare impact. An exception is when additional information increases the efficiency of the information system. In this case, the incremental costs of additional information are really benefits, for example, when total monitoring costs are reduced.

In the next two paragraphs we elaborate the conceptual framework for assessing the value of information, using the economic literature on decision-making under uncertainty. In this literature, the contribution of information to decision-making and the contribution of decision-making to welfare are jointly addressed. The potential impact of informational investments on monitoring costs is not further elaborated. However, when considering the welfare impacts of investments in Dutch water quality monitoring, both the costs and benefits of the investment will be addressed.

2.1.1. Decision making under uncertainty

In their seminal paper on the economics of information, Hirshleifer and Riley (1979) provide a theoretical framework for analyzing the role of information when decision-makers are uncertain about 'the state of the world' (event uncertainty). In a certain world, economic theory predicts that a rational decision-maker will choose the action with the highest utility. If outcomes are uncertain, decision-makers base their decisions on the *expected* utility of the outcomes instead. This expected utility depends on the perceived probability of the different 'states of the world', or the expected probability that a certain outcome will be reached[1].

Table 1 presents the decision problem for two potential actions ($x = 1,2$) and two possible states of the world ($s = 1,2$). As Hirshleifer and Riley (1979) express it: the decision-maker chooses among *actions*, while Nature may be metaphorically said to choose among *states*. The consequences (or outcomes), $c_{x,s}$, of the actions, differ depending on the 'state of the world'.

Formally, the expected utility of action x can be expressed as,

$$u(x, \pi_s) \equiv \pi_1 v(c_{x1}) + .. + \pi_s v(c_{xs}) \equiv \sum_{s=1}^{S} \pi_s v(c_{xs}) \tag{1}$$

with π_s the perceived probability of state s, c_{xs} the consequence (or outcome) associated with action x in state s, v the utility of the outcome of the actions given the different states of the world, and S the number of possible states of the world.

Without information about the probability of alternative 'states of the world', a decision-maker must act upon his own (prior) beliefs. If the decision-maker is very uncertain about 'the states of the world' and these states have a large impact on the consequences of alternative actions, it might be a good idea to seek additional information about the likelihoods of the potential 'states of the world' before taking action. Whether a decision-maker is willing to invest in acquiring information will, depend on the extent to which information is expected to reduce the uncertainty of his or her decision-making. It is important to note here that the decision-maker is taken to be a private actor. When discussing water quality management, this is, clearly, not the case. Still, the

[1] We consider expected utilities, and not expected values, since decision-makers might have variable risk preferences. Although in the case study we only consider expected values, the methodological framework should be general enough to include risk preferences in the analysis as well.

Table 1
Decision making under uncertainty

		States		
		$s = 1$	$s = 2$	Utility of the acts
Actions	$x = 1$	c_{11}	c_{12}	u_1
	$x = 2$	c_{21}	c_{22}	u_2
	Beliefs as to the state	π_1	π_2	

theoretical framework of Hirshleifer and Riley (1979) is applicable, if we assume that the (public) decision-maker maximizes social, instead of individual, returns. We will come back to this assumption when elaborating our empirical approach.

2.1.2. The value of information

Using the framework developed by Hirshleifer and Riley (1979) requires a couple of steps. First, the impact of an informational message on decision-making needs to be assessed. This depends on the extent to which the decision-maker uses the information to update his beliefs regarding the 'state of the world'. A formal way of expressing the process of belief updating is reflected in the well-known Bayes theorem[2]:

$$\pi_{s,m} = \Pr(s|m) = \frac{\Pr(m|s)\Pr(s)}{\Pr(m)} = \frac{q_{m,s}\pi_s}{q_m} \tag{2}$$

with $\pi_{s,m}$ the posterior probability, or the updated belief, π_s the prior probability, or the belief before the additional information, $q_{m,s}$ the conditional probability of receiving message m given state s (the likelihood of receiving message m given state s), and q_m the unconditional probability of receiving informational message m. The unconditional probability of receiving message m is related to the conditional probabilities (of receiving message m in state s) by:

$$q_m = \sum_{s=1}^{S} q_{m,s}\pi_s \tag{3}$$

hence, whether an informational message succeeds in making decision-makers change their belief function depends upon the decision-makers prior belief regarding the possible 'states of the world' and the perceived accuracy of the informational message, or the likelihood of receiving message m given state s.

Subsequently, with the 'updated beliefs' the decision-maker might choose a different action than what he would have chosen with his prior beliefs. The 'value' of message m is simply the difference between the utilities of the actions that is chosen given message m (x_m) and the action that would have been chosen without additional information (x_0):

$$\Delta_m = u(x_m, \pi_{s,m}) - u(x_0, \pi_{s,m}) \tag{4}$$

Then, since we do not know in advance which message the information service will produce, the expected value of the information is the expected difference in utilities of actions given the likelihoods of receiving messages m (q_m):

$$\Delta(\mu) = E(\Delta_m) = \sum_m q_m \left[u(x_m, \pi_{s,m}) - u(x_o, \pi_{s,m})\right] \tag{5}$$

$\Delta(\mu)$ is the expected utility of the new information, and can thus be used as an indicator of the value of this information, or the decision-maker's maximum willingness to pay. A rational decision-maker would invest in informational services if his or her willingness to pay (reflecting the societal willingness-to-pay) exceeds the cost of purchase.

In fact, there are three factors that determine the value of information (Hirshleifer and Riley, 1979). First, it depends on the confidence decision-makers have in their beliefs. The more confident the decision-maker is about his expectation regarding the possible state of the world, or the tighter the decision-makers' probability distribution function, the less likely the decision-maker is to invest in information or change his beliefs. Second, it depends on the extent to which the decision-maker expects the information to be true. As in statistical significance testing, an informational message can be false in two ways: the message can incorrectly reject the 'true' state, and it can fail to reject the 'false' state. In decision theory, the former error is called a Type I error and the latter error is called a Type II error. If the perceived errors are large, the value of the information will, clearly, be less. Third, it depends upon the content of the information: the more surprising the informational message, or the larger the difference with the existing belief, the greater the likelihood that the prior belief will be updated (Hirshleifer and Riley, 1979; Lybbert et al., 2006).

2.1.3. Assessing the value of GEO information

Although Bayes' rule has been widely applied in theoretical work analyzing decision-making under conditions of uncertainty (see, for example, Yokota and Thompson (2004)) few studies have actually tried to empirically estimate the prior and posterior probabilities involved. One of the few studies that have attempted to empirically estimate prior and posterior probabilities is the study by Schimmelpfennig and Norton (2003). To evaluate the value of agricultural economics research, Schimmelpfennig and Norton asked senior policy makers about their perceptions of the payoffs, measured in terms of economic surplus estimates, $v(c_{xs})$, prior probabilities, π_s, and the likelihoods of new research producing "true" messages, $q_{m,s}$. On the basis of this information, they were able to calculate the value of agricultural economics research in a number of case studies, such as a crop insurance program and a food safety program.

This paper builds on the approach of Schimmelpfennig and Norton, using stakeholder consultation to estimate the extent to which decision-makers actually use GEO information to update their beliefs. In Section 2.2 we further elaborate our approach.

2.2. The empirical approach

Although Schimmelpfennig and Norton (2003) suggest that it is sufficient to consult one or two key decision-makers to estimate prior and posterior belief functions, there are two reasons why we believe that it is important to consult a wider range. First, public decision-making often involves more than one actor and by capturing the perceptions of several key actors a more representative estimate of the value of information can be made[3]. Second, given the large uncertainties surrounding the estimation of the value of information, involving a larger number of respondents might help increase the robustness of the results. Hence, in line with the broader literature on stakeholder elicitation (see, for example, Morgan et al., 2001) we decided to consult a wider range of stakeholders and use the variance of the respondents' answers to analyze the robustness of our results.

[2] There is actually more work on Bayesian decision theory in environmental management, even if few of those deal with the value of information directly (see, for example, Ellison, 1996; Varis and Kuikka, 1999).

[3] Schimmelpfennig and Norton (2003) suggest that if decision-making is strategic, or if more than one decision-making center is involved, explicit attention should be paid to the political weight of the different decision-making centers. In the case of Dutch water quality management, decision-making is strongly consensus-based. Hence, we do not explicitly account for the political weight of the different decision-making centers but instead assume that in the decision-making process the views and interests of the different actors are accounted for.

For the stakeholder consultation, we developed a questionnaire based on Bayesian decision theory. The main aim of the questionnaire was to elicit stakeholder perceptions regarding the impact of satellite observations on the effectiveness of water quality monitoring in the North Sea. We asked respondents to evaluate three cases: the value of GEO information for the management of (a) potentially harmful algal blooms, (b) eutrophication and (c) seawater turbidity and suspended sediments. We asked respondents to compare the existing information system of mainly '*in situ*' measurements with a situation in which use is made of additional satellite observations as well, illustrating the examples with images and explanatory text (see Fig. 2).

We asked respondents to quantify their answers when estimating the extent to which they expected satellite-based information would reduce the uncertainty of decision-making. In addition, we asked some qualitative questions about the perceived value of information, the occurrence of certain events and the extent to which respondents expected that the demand for satellite observation information would increase due to, for example, the future implementation of the European Marine Strategy or other expected developments and trends.

We tried to get a representative spread of decision-makers and experts concerned with marine water quality management in the North Sea. In the total number of 23 respondents, we included 8 policy makers, 7 water managers, 4 researchers and 4 representatives of interest groups. Respondents were selected on the basis of their expertise and experience with water quality monitoring in the North Sea. In addition, we tried to get representatives from each of the parties involved in Dutch water quality management. Also, we suggested in the e-mail accompanying the questionnaire that respondents were free to forward the questionnaire to their colleagues or other potential candidates.

By consulting a wide range of stakeholders, we hoped to not only gain insight into the distribution of answers, but to test the empirical feasibility of the methodological framework as well. Better understanding of the factors determining whether decision-makers can quantify the contribution of information can help further develop the empirical approach. Clearly, with a population of only 23 subjects, it is impossible to reach statistically robust results, but given the research objective, it seemed important to test the empirical feasibility of the approach as well.

We tested the questionnaire internally and externally by having two senior decision-makers answer the questions beforehand. Before sending the questionnaire off, we contacted all selected respondents to explain the project and ask for their collaboration. We promised respondents that their answers would be dealt with anonymously and that we would share the results. Of the 23 questionnaires we distributed, we received 19 copies back (83%). Of these 19 responses, 14 answered the full questionnaire while 5 left most of the questions blank. Only 10 respondents (52%) responded to most questions quantitatively. Before we analyze the results, in Section 3 we first introduce the case study.

3. Description of the case study

The North Sea is one of the world's major shelf seas and one of the major fish-producing ecosystems in the world. The marine ecosystems in the Dutch part of the North Sea are under intense anthropogenic pressure from fishing, nitrogen input (from air and rivers), recreational use and habitat loss. The main problem is eutrophication, or an excess of nutrients in the marine ecosystem (Vermaat et al., 2004). Eutrophication results in changes in the marine ecosystem, causing biological, chemical and physical changes in the structure of flora and fauna. In addition, and probably as a result of eutrophication, the intensity and frequency of excessive growth of micro-algae has increased over the last decennia (Cadée and Hegeman, 2002; Glibert et al., 2005). These algal blooms can result in the release of substances that are toxic

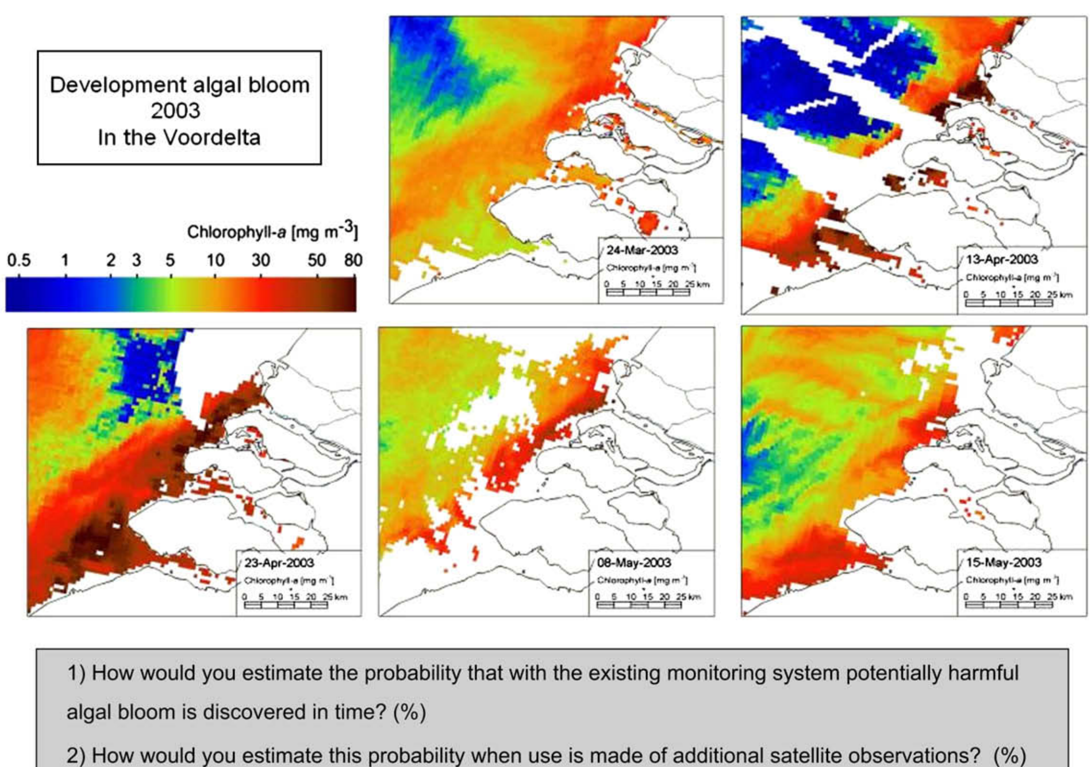

Fig. 2. Example of questionnaire questions.

both to man and to other marine life. When these blooms decay, it may cause benthic anoxia, leading to the seabed being devoid of much of its life (EEA, 2003). One of the most important economic damages resulting from excessive algal blooms is loss of shellfish production and dying fish.

To inform water managers and policy makers about the spread and intensity of eutrophication and to warn about the possibility of potentially harmful algal blooms, the Dutch Ministry of Transport and Public Works maintains a monitoring programme at 19 marine stations in the Dutch part of the North Sea (www.waterbase.nl) taking bi-weekly water samples. At present, the ministry is considering extending this system of water quality monitoring with satellite observations regarding chlorophyll-a concentrations and suspended sediment (Roberti and Zeeberg, 2007). Chlorophyll-a is the main light-harvesting pigment of algae and is therefore a proxy for the algal biomass. Suspended sediment is the main source of turbidity, which determines to a large extent the underwater light climate in the North Sea (RIKZ, 2002).

To contribute to the discussion regarding the use of satellite observations for water quality monitoring in the North Sea, we initially wanted to consider three case studies; eutrophication, excessive algal blooms and suspended matter. However, since we could only make an estimate of the economic pay-offs associated with an early warning system for excessive algal blooms, we had to concentrate on this one case study instead.

In the case of eutrophication, estimating economic pay-offs was difficult because more than 85% of the nutrients come from poorly controllable sources, like historical stocks of phosphates and nitrates and atmospheric deposition. Hence, better information about the geographical and temporal spread of chlorophyll-a hardly allows for better-targeted interventions [4]. Similarly, the economic pay-off associated with improved monitoring of seawater clarity and turbidity was difficult to assess. Not only do large uncertainties exist as to the impact of suspended sediments on ecosystem functioning, it is unclear to what extent information about suspended sediments can be used to improve seawater clarity and avoid damages in the long run (Pasterkamp and Vermaat, 2004).

Fortunately, there are clear pay-offs associated with the prevention of economic damages resulting from excessive algal blooms. In 2001, excessive algal blooms caused a loss of approximately 20 million euro to the Dutch mussel cultivation sector (Peperzak, 2003). If early warning information would have been available, this loss could have been avoided by preventively relocating mussel cultivation plots at 10% of the damage costs (Woerd et al., 2005). In fact, in 2006 an early warning system became operational for the near-real time early detection and forecasting of algal blooms in Dutch coastal waters, using a combination of field data, satellite observations and hydrodynamic- and biological modeling (Woerd et al., 2005, submitted for publication). The system can detect rapid rises in chlorophyll-a levels during bloom formation. On the basis of these observations a transport model makes predictions about the transport of the bloom, 5 days ahead. In case of a perfect system, this would allow the mussel farmer sufficient time to take adaptive measures.

Also, we estimated the impact of GEO information on water quality monitoring costs. Generally, it is expected that satellite observation can substantially reduce monitoring costs (Roberti and Zeeberg, 2007). In the case of eutrophication, Hakvoort (2006) estimates a cost reduction of approximately 40%, or 2 million euro per year. In this estimate, the capital costs of satellite observation are not included. When also accounting for the capital costs of satellite observation, annual costs are approximately 2.5 million per year (personal communication of Dutch aeronautics and space institute, NIVR). Based on these crude estimates, the prevention of economic damage from excessive algal blooms would need to generate an annual benefit of at least 500,000 euro to make GEO investments economically efficient. This figure does not include the operational costs of developing and maintaining an early warning system, but from a (confidential) cost-benefit analysis carried out in the development phase of the algal blooms early warning service, we know that the operational costs are comparatively small, i.e. less than 10% (Woerd et al., 2005).

4. Results

4.1. The value of GEO information

The main results of the questionnaire are presented in Table 2.

The results show that, on average, respondents expect that satellite observations will improve water quality monitoring in the North Sea. The expected improvement is largest in the case of suspended sediments and the related turbidity, because the present monitoring system only covers certain locations, and gives very limited insight into the distribution of seawater clarity in the North Sea (RIKZ, 2002). For eutrophication the opposite holds, with well-functioning water monitoring system in place and good insight in the relation between the sources and effects (see, however, McQuatters-Gollop et al., 2007). In the case of potentially harmful algal blooms, currently no early warning system exists, but information about chlorophyll-a levels can be used to help predict excessive algal blooms.

Interestingly, the range of answers is especially large for the present monitoring of excessive algal blooms and the potential satellite-based monitoring of suspended sediment. This can be explained by the fact that: (a) opinions differ as to the need for an early warning system regarding algal blooms[5] and (b) the fact that the idea of having a satellite-based information system for the monitoring of suspended sediment remains relatively unexplored. In fact, several respondents indicated not being very confident about their answers regarding the monitoring of suspended sediment as they knew relatively little about this technique.

Still, the range in answers is substantial and the number of those able to quantify their answers relatively low (10 out of 19). If we divide respondents on the basis of their (self-reported) expertise and professional affiliation, we end up with four respondent groups (4–6 persons per group): (1) policy makers-general, (2) policy makers-experts (3) researchers and (4) water managers, practical. Interestingly, in the last group respondents were not able to quantify any answers. The main explanation for this seems to be that these respondents indicated knowing little about satellite-based information and having difficulties to quantitatively assess the contribution of information to decision-making.

In Fig. 3 we present the results of the first three groups[6]. Since the results indicated that four respondents might have strategically answered the questionnaire, we present two results per group: with and without the outliers (= strategic responses). Outliers were

[4] Considering the uncertainties that exist with regard to the main drivers of eutrophication, in the longer run this situation might change. For example, there is an ongoing debate about the relative importance of seawater temperature versus nutrient inflow (see, for example, McQuatters-Gollop et al., 2007). If this changes the understanding of eutrophication processes, it could change the value of observational information regarding chlorophyll-a. At present, measures like the removal of saturated soils might be an option, but the costs of these measures are such that they are generally not considered being economically feasible.

[5] For example, local fishermen suggested that they can actually see excessive algal blooms coming by looking at the sea. However, this reaction seems at least partly inspired by strategic reasoning, as fishermen do not want to contribute to the costs (they do want the government to compensate their losses, however).

[6] And, obviously, we only present figures of the respondents that were able to quantify their answers.

Table 2
The added value of satellite observations for water quality monitoring in the North Sea

	Eutrophication ($n = 13$)		Potentially harmful algal blooms ($n = 10$)		Suspended sediments ($n = 10$)	
	Present (%)	Present + GEO (%)	Present (%)	Present + GEO (%)	Present (%)	Present + GEO (%)
Average expectation of water quality being well monitored[a]	63	75	50	73	26	69
Range in answers	50–100	80–100	10–90	50–100	10–50	20–90

[a] Median values are, respectively, 60% and 80%, 50% and 73% and 25% and 70%.

defined on the basis of their professional affiliation: in the first two groups, two respondents seemed to strategically underestimate the contribution of satellite-based information, because of their strong affiliation with the current monitoring system. In the expert group, the two representatives of interest groups seemed to have overestimated the benefits for strategic reasons as well.

Interestingly, general policy makers seem to expect most from investments in satellite observation, whereas the water managers responsible for water quality monitoring judge the remaining uncertainties to be relatively high. Experts are most optimistic about the uncertainties associated with the information system, but they regard the added value of satellite observations to be relatively small. Ideally, the answers of the different respondents would be weighted for their impact on water quality decision-making. Roughly speaking, water policy makers are most likely to play a decisive role in investment-related decision-making, whereas the role of outside experts is likely to be small. However, since we don't have information to weight respondent perceptions, we take the average values, as reported in Table 2, to reflect the expected likelihood that satellite observations accurately predict harmful algal blooms on time, the perceived likelihood being on average 75% (the Type I error is therefore 25%).

In addition to the likelihood that the information system is accurate in predicting potentially harmful algal blooms, we also need to know the probability that the system predicts excessive algal blooms when the threat of economic damage is nil (Type II error). Unfortunately, questions asking respondents about the perceived Type II accuracy of the monitoring system were hardly answered. Hence, we had to assume a Type II error on the basis of expert judgment instead. We assume the accuracy of the early warning system to be 90%, reflecting a 10% probability (= Type II error) that predictions in satellite observations near bloom detection threshold levels are too high (Woerd et al., 2005). Since the system has only been operational for a limited amount of time, a more robust estimate of the Type II error can, at present, not be made. Hence, we will explicitly account for different Type II errors when assessing the robustness of our results.

Now, to assess the value of early warning information, we assume a decision-making process in which the water quality manager decides weekly whether to relocate the fishing nets (Action $x1$) or to do nothing (Action $x2$). The time period considered is a week since the information system makes bi-weekly predications and as soon as a bloom is observed, within 24 h of the actual satellite overpass, hydrodynamic models can predict algal bloom transport 5 days ahead. Also, we assume decision-makers minimally need a week to relocate mussel stocks (see also Songhui et al., 2000 and Fernández et al., 2003). In the questionnaire, respondents unanimously indicated that they expected that potentially harmful algal blooms, like the one in 2001, would take place every 5 years. Since potentially harmful algal blooms are only possible during a period of 10 weeks, or 2 months, a year, there is a perceived probability of 2% per week of potentially harmful algal blooms taking place (Reid et al., 1990). Hence, the prior expected probability of potentially harmful algal blooms is estimated to be 2%. In Table 3 we illustrate the decision-making problem using the framework of Bayesian decision theory.

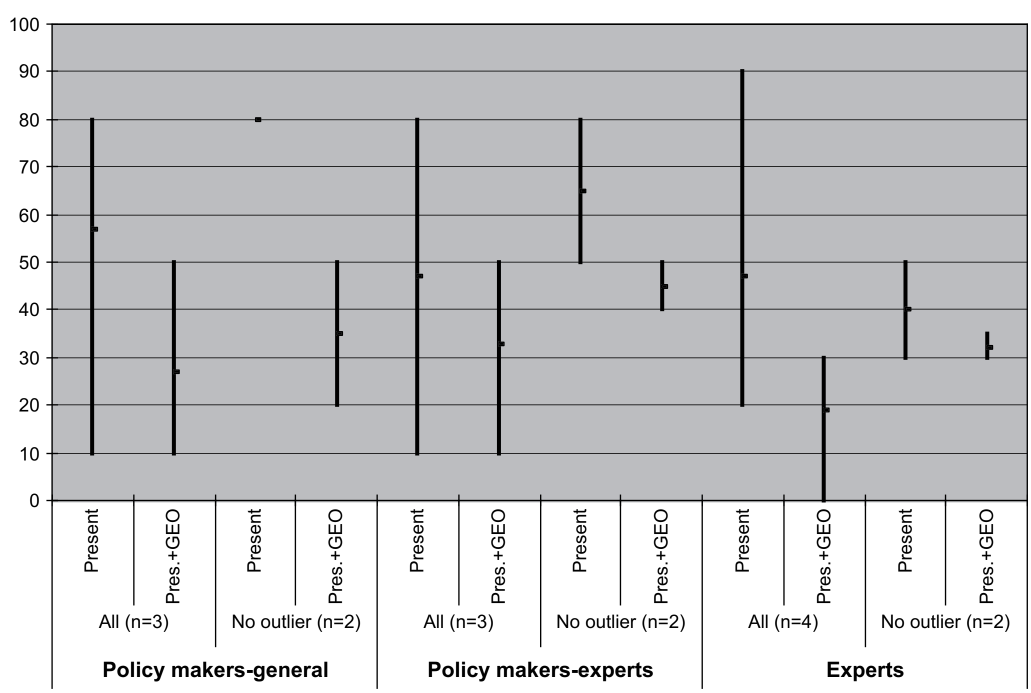

Fig. 3. Perceived uncertainties in the monitoring of potentially harmful algal blooms.

Table 3
The decision-making matrix for assessing the value of information

States (s)	Actions (x) (in million euro/week)*		Priors (π_s)	Likelihoods ($q_{m,s}$)		Joint probabilities ($\pi_s q_{m,s}$)	
	$x1$: relocate fishing nets	$x2$: do nothing	π_s	$m1$: "Danger!"	$m2$: "No panic"	$m1$	$m2$
S1: harmful algal bloom	−2	−20	0.02	0.75	0.25	0.015	0.005
S2: non-harmful algal bloom	−2	0	0.98	0.10	0.90	0.098	0.882
$u(x, \pi_s) = \Sigma\pi_s c_{xs}$	−2	−0.4		Message probability ($q_m = \Sigma q_{m,s}\pi_s$)		0.113	0.887
$u(x_0, \pi_s) = \text{ma} \times u(x, \pi_s)$		−0.4		Posteriors ($\pi_{s,m} = q_{m,s}\pi_s/q_m$)	$s1$	0.133	0.006
					$s2$	0.867	0.994
				Expected surplus $u(x, \pi_{s,m}) = \Sigma\pi_{s,m}c_{xs}$	$x1$	−2.000	−2.000
					$x2$	−2.655	−0.113
				$u(x_m, \pi_{s,m}) = \max u(x, \pi_{s,m})$		−2.000	−0.113
				$\Delta(\mu) = \Sigma q_m[u(x_m, \pi_{s,m}) - u(x_0, \pi_{s,m})]$		0.074	

*Source: Peperzak (2003) and Woerd et al. (2005).

Table 3 shows that without the early warning system, a rational water quality manager would do nothing because the expected utility of Action $x2$ (−€0.4) is greater than that of Action $x1$ (−€2.0). With the information system in place, the water quality manager can update his prior beliefs regarding the probabilities of potentially harmful algal blooms according to Eq. (2). (see also the posteriors in Table 3). With these updated beliefs, the rational water quality manager will now relocate fishing nets (Action $x1$) when the information system predicts potentially harmful algal blooms ("danger!"; $u(x1) = -2 > u(x2) = -2.655$) and will do nothing when the information system gives no warning ("No panic"; $u(x1) = -2 < u(x2) = -0.113$)). The value of the information system ($\Delta(\mu)$) can now be calculated with Eq. (5).

As the results in Table 3 show, the value of information ($\Delta(\mu)$) is estimated to be €0.074 million (or €74,000) per week. Since the costs of the new information system are only €50,000[7] per week, the benefits of investing in satellite observations exceed costs by almost €24,000 per week suggesting a social rate of return of 48%. Clearly, with large uncertainties surrounding the likelihood estimates, the robustness of these results needs to be assessed. This will be the subject of the next paragraph.

4.2. Robustness of the results

There are two factors that are likely to significantly influence our results. First, our estimate of the probability that the information system would wrongly predict potentially harmful algal blooms (Type II error) is based on expert judgment. The expert consulted indicated that little is known about Type II errors and that the actual uncertainties might be higher. If we assume, for example, that the probability of a Type II error is 20%, then the value of information becomes nil. In fact, given a Type I error of 25%, once the probability that Type II error exceeds 13%, the value of information becomes nil. Fig. 4 presents the value of information as a function of Type I and Type II errors, ranging from 50% to 0% and from 30% to 0%, respectively. The x-axis (the base) depicts Type I errors, the y-axis (depth) depicts Type II errors and the z-axis (height) depicts the value of information in euro million. Completely accurate information (zero errors) would have a value of €0.37 million. The value of information decreases sharply as Type II errors increase and it also decreases (but somewhat less sharply) as Type I errors increase. In our central estimate, with a Type I error of 25% and a Type II error of 10%, the value of information is €0.074 million.

[7] The costs per week (€50,000) are calculated as annual costs (€500,000) divided by 10 weeks of potential algal bloom. Again, the operational costs of the early warning system are not included, but they are relatively low.

Second, considering the variance in respondent answers, the results might change too. Accounting for the range in respondent perceptions the 95% confidence interval for the value of information ranges from 34,000 to 103,000 euro a week. Given that the estimate of satellite observations reducing existing monitoring costs with 2 million euro per year is expected to overestimate the actual benefits, the benchmark of 50,000 euro per week is probably the lower bound. Given the variance in responses, the expected probability that this benchmark is reached is approximately 75%. Hence, there is a 75% probability that investments in satellite observation are welfare enhancing in the case of Dutch water quality management in the North Sea. Still, if the Type II accuracy of information is less than 90%, this is no longer the case.

5. Discussion

The results of the analysis indicate that in the case of Dutch water quality management there is a 75% probability that investments in additional satellite observation are welfare enhancing. However, the results strongly depend on whether the accuracy of the information system is sufficiently high. Most studies assessing the value of information do not pay attention to the accuracy of the information system or the Type-I and Type-II errors involved. This basically means that these studies cannot present a robust estimate of the value of information, since the accuracy of the evaluated information system might be relatively low. Also, paying attention

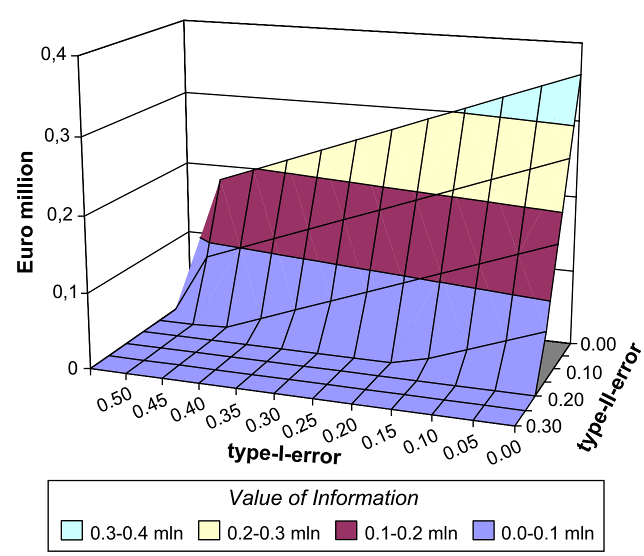

Fig. 4. The value of information as a function of the sizes of Type I and Type II errors.

to the perceived accuracy of the information system provides important information for information system developers, who tend to pay little attention to the impact false predictions might have. By making the economic value of improving information system accuracy explicit, investments in system improvement can be better targeted and returns to investment can be improved.

In addition, this paper has shown that Bayesian decision theory offers a suitable framework for assessing the economic value of information. By combining Bayesian decision theory with stakeholder consultation, it becomes possible to evaluate the added value of informational investments. However, the analysis also indicated that using Bayesian decision theory requires a high level of expertise and awareness of the respondents: respondents with little background in satellite-based information systems were not able to answer questions in a quantitative way.

This is actually an important outcome, since it indicates that the value of information depends on awareness levels as well. The wide range in respondent answers also indicates that the uncertainties surrounding the estimates are large. Apart from differences in understanding the potential of satellite-based observation systems, respondents differ in their understanding of the potential uses of satellite-based observations as well. Clearly, observations that help a complex model reduce the uncertainty of its predictions have a higher economic value than observations for which no scientific models yet exist. This also became apparent from the case study analysis, respondents being less able to estimate the added value of turbidity monitoring since the potential uses of these kinds of observations are still largely unclear. All in all, the large uncertainties surrounding value of information estimates and the fact that estimates also depend on awareness levels seem to underline the importance of including several decision-makers in the consultation. Although this might not make it possible to present statistically robust estimate of the value of information, accounting for the variance in respondent answers does allow for a more robust representation of results.

Finally, there are two factors that have not been explicitly addressed in this paper, but that might require further elaboration in the work to come. First, there are several psychological reasons why people might not use (new) information to update their beliefs (Rabin, 1998). Although by consulting experts the biases resulting from such non-rational behavior might be somewhat reduced, further research is needed to assess the potential impact of these effects. Second, in the analysis of this paper we did not explicitly account for political factors, assuming that the consensus-oriented approach of Dutch water management would include the perceptions of all stakeholders in the final decision made. However, one respondent remarked that the department responsible for the monitoring of water quality in the North Sea is not responsible for damages caused to the mussel sector and that, hence, water quality managers have no incentive to invest in early warning systems at all. This is a good example of how the organization of resource management and information access matters in assessing the value of information. It is also an indication that the value of information generated is only a potential value and that the actual value will depend upon political factors as well.

6. Conclusion

We started this paper by noting that although there seems to be an increasing demand for studies estimating the value of information, a theoretically sound and empirically feasible approach seem to be lacking. This paper has shown that a combination of Bayesian decision theory and expert consultation can offer a suitable approach. The approach seems especially promising as it links the value of information to the accuracy of the information system. This is important because this: (a) increases outcome robustness and (b) provides information that can help improve the accuracy of the information system itself.

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