The Value of Earth Observation for Marine Water Quality Management

Bouma, J.A.[a], O.J.Kuik [a], H.van der Woerd[a] and A.Dekker[b]

[a] Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, De Boelelaan 1085, 1081 HV Amsterdam, the Netherlands, (jetske.bouma, onno.kuik, hans.van.der.woerd) @ivm.vu.nl
[b] CSIRO Land & Water, Canberra GPO Box 1666, ACT 2601, Australia Arnold.dekker@csiro.au

Abstract: Global Earth Observation is one of the most important sources of information for environmental resource management. With budgets for Earth Observation (EO) increasingly under pressure, it is important to be able to quantify the returns to informational investments. For this, a clear analytical framework is lacking. This paper attempts to develop and test such a framework by combining Bayesian decision theory with an empirical, expert-oriented approach. The analysis focuses on the use of EO for marine water quality management, but the methodology is applicable to other topics too. The case studies indicate that the main benefits of EO are increased spatial and temporal coverage of the existing monitoring system and generation of early warning predictions. The results suggest that the expected benefits of EO investments are positive, but that they strongly depend on the (perceived) accuracy of the information system.

Keywords: *Societal benefits of Earth Observation; Bayesian decision theory; expert elicitation; marine water quality management; coral reef management;*

1. INTRODUCTION

Information is valuable for decision-making. Although this seems a rather obvious statement, the economic value of information for decision-making is seldom addressed. This might not be a problem with sufficient investments in informational services, but explicit attention for the value of information is required if too little, or too much, investment in information is made. At present, experts argue that investment in global EO is insufficient (EC, 2007). Hence, it seems important to assess what the optimal investment level would be.

There are few studies that have attempted to estimate the value of EO information. Macauley (2006) discusses the potential benefits of EO but does not empirically assess them. Other papers use rather ad-hoc methods for assessing EO benefits, and generally lack an analytical framework (see Bouma et al. 2009 for an overview).

This paper develops an analytical framework for assessing the economic benefits of EO information, by combining Bayesian decision theory with an expert elicitation approach. Bayesian decision theory studies decision-making under uncertainty, and how information is used to update beliefs regarding uncertain parameters of the decision environment (Hirshleifer and Riley 1979). By combining Bayesian decision theory with expert elicitation, we empirically assess the influence of EO investments on decision-makers beliefs.

To quantify the benefits of EO information and test the empirical feasibility of our approach we consider two case studies: a) potentially harmful algal blooms in the North Sea and b) water quality management in the Great Barrier Reef (GBR) lagoon.

The analyses indicate that the approach used is empirically feasible and that the expected benefits of EO are positive. The benefits strongly depend, however, on the (perceived) accuracy of the information system and the current beliefs regarding uncertain parameters of the decision environment (i.e. the ‘state of the world’).

The structure of the paper is as follows. In the next section we elaborate our analytical framework. In the third section we introduce the case studies and empirical approach. In the fourth section the results are presented. The last section discusses the results and concludes.

2. METHODOLOGY

We base our analytical framework on a seminal paper by Hirshleifer and Riley (1979) regarding the value of information under uncertainty. When decision-making takes place in an uncertain environment, decision-makers have to act upon their beliefs regarding the possible ‘states of the world’. The states of the world may be something like “it will rain” or “it will remain dry” and decision-makers attach a certain probability “π_s” to each expected state of the world ($\Sigma\pi_s$=1). When the pay-off (or utility) of an action (e.g. “take an umbrella”) depends on the state of the world (“rain/dry”), decision makers are assumed to base their decision on the *expected* pay-offs of the alternative actions (the sum of pay-offs for any state of the world times its probability).

The role of information is that it gives a message “m” about the state of the world. The message is not always accurate (think of a weather forecast), but the decision-maker has an idea of the accuracy of the message, i.e., the probability of the message being right. Based on the message the decision-maker can “update” her beliefs about the state of the world and, possibly, change her decision. The value of information depends on a) the extent to which the decision-maker updates her beliefs and b) the impact this has on the expected pay-off of decision-making. A formal way of expressing the process of belief updating is reflected in the well-known Bayes’ theorem:

$$\pi_{s,m} = \Pr(s \mid m) = \frac{\Pr(m \mid s)\Pr(s)}{\Pr(m)} = \frac{q_{m,s}\pi_s}{q_m} \qquad (1)$$

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 by:

$$q_m = \sum_{s=1}^{S} q_{m,s}\pi_s \qquad (2)$$

To assess the extent to which the decision-maker uses the information to update her beliefs we need to know a) the decision-maker's prior belief and b) the perceived accuracy of the informational message. We can then estimate the impact on the expected pay-off of decision-making. For this, we compare the pay-off of the action chosen given message m (x_m) and the action that would have been chosen without additional information (x_0):

$$\Delta_m = u(x_m, \pi_{s,m}) - u(x_o, \pi_{s,m}) \qquad (3)$$

As the decision-maker does not know in advance which message the information service will produce, the expected value of the information service is the expected difference in pay-offs given the likelihoods of receiving messages m (q_m):

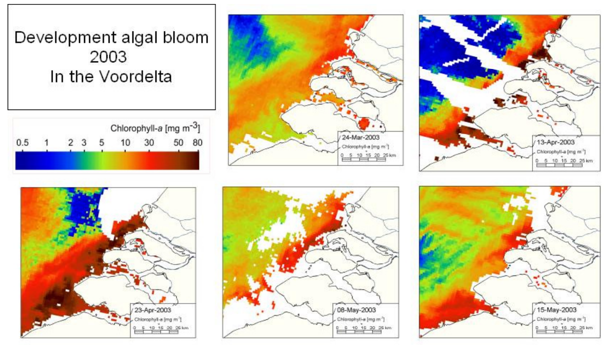
$$\Delta(\mu) = \sum_m q_m \left[u(x_m, \pi_{s,m}) - u(x_o, \pi_{s,m}) \right] \qquad (4)$$

Schimmelpfennig and Norton (2003) applied the model of Hirshleifer and Reilly (1979) to assess the value of agricultural economic research. Although their empirical application is very interesting in a number of respects (and our approach draws heavily on their work), they consulted only one decision-maker. Bouma et al. (2009) combined the Schimmelpfennig and Norton approach with a survey instrument to elicit beliefs from a larger group. Assuming that decisions on informational investments are non-strategic and consensus-based, collecting information from a larger group increases outcome robustness. In the next section we elaborate our approach.

3. EMPIRICAL APPROACH AND CASE STUDIES

As argued in the preceding paragraph, belief updating is determined by prior beliefs and the perceived accuracy of information. Information about prior beliefs can be derived from the literature or deduced from actual decision-making. Information about the perceived accuracy of the information is not readily available, and we developed a questionnaire to collect this information. In the questionnaire, we ask respondents to compare a situation with and without EO information and to express what they perceive the (remaining) uncertainty of decision-making to be. In addition, we asked questions about the perceived accuracy of EO information and the respondent's background.

Fig. 1 presents an example from the questionnaire, developed to assess the benefits of EO for predicting harmful algal blooms in the North Sea. To facilitate comparison between the present information system and the system with additional EO investment, we used EO images. In both case studies, EO was not part of the existing monitoring system yet. We sent the questionnaires to (senior) policy-makers, water managers and experts with expertise in EO and the decision-making problem concerned. The North Sea questionnaire was sent to 23 respondents of which 80% replied. Of this 80%, half answered most questions. The Great Barrier Reef questionnaire was sent to 70 respondents, of which 40% replied. Of this 40%, almost all answered most questions. In fact, the Great Barrier Reef questionnaire was sent to a smaller group of respondents with a more specialized background, because we learned from the North Sea questionnaire that those with little background in EO could not answer the questions.



1) How would you estimate the probability that with the existing monitoring system potentially harmful algal bloom is discovered in time? (%)
2) How would you estimate this probability when use is made of additional satellite observations? (%)
3) What do you believe the accuracy of the monitoring system with additional satellite observation to be? (%)

Figure 1 Example of questionnaire questions

Before presenting the results of the questionnaire, we need to know what pay-offs an updated belief about the state of the world could have. Thus, for each case study we constructed a pay-off matrix of alternative actions and possible states of the world. We assumed that pay-offs for public decision-makers would equal impacts on social welfare. We derived information about potential welfare impacts from the literature. In the following we present the two pay-off matrices.

3.1 Case study 1: Algal blooms in the North Sea

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 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 modelling (Woerd et al., 2008). 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 (or a week) ahead.

The decision-making problem is whether in a given week fishing nets should be relocated (Action x_1) or not (Action x_2). The time period considered is a week since the information system makes weekly predications and we assume decision-makers minimally need a week to relocate mussel stocks.

With regard to the prior beliefs concerning the probability of harmful algal blooms in the Dutch part of the North Sea, 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 in the Netherlands potentially harmful algal blooms are only possible during a period of 10 weeks, there is a probability of 2% per week of potentially harmful algal blooms taking place. Table 1 presents the pay-off matrix.

	Actions (x)		Priors
States (s)	x_1: Relocate nets	x_2: Do nothing	π_s
s_1: Algal bloom	-2 million euro	- 20 million euro	0.02
s_2: No bloom	- 2 million euro	0	0.98

Table 1 Pay off matrix of the North Sea case study

3.2 Case study 2: Water quality in the GBR lagoon

Declining water quality in the GBR lagoon is threatening reef quality (Brodie et al. 2008), and a major plan has been developed to improve the quality of water flowing from adjacent catchments into the lagoon. Regional targets are based on historical increases in sediment, nutrient and pesticide loads (GBRMPA 2001), as it is unclear which are the most polluting catchments. EO information is expected to reduce this uncertainty by increasing insight into the spatial and temporal variability of sediment (river plume) and nutrient (chlorophyll-a) concentrations in the GBR lagoon. This, in turn, is expected to lower the costs of implementation by allowing for a more targeted emission reduction approach.

Basically, there are two 'states of the world': s_1) there is no spatial variability in the effectiveness of emission reduction, and s_2) there is spatial variability in the effectiveness of emission reduction. Decision-makers are uncertain whether they should take action x_1) to reduce emissions across all catchments, or action x_2) to reduce emissions from selected catchments only.

We estimate the costs of the Great Barrier Reef Water Quality Action Plan to be approximately 1.1 billion USD/year. This estimate is based on per unit cost estimates of Roebeling et al. (2007). For estimating the costs of action x_2, we follow McKergow et al (2005) who argue that most of the sediment comes from two catchments and that targeting interventions to these regions is most effective. Measures to reduce nutrient emission are most effective in the wet tropical regions of the GBR (Devlin and Brodie 2005). Thus, fewer interventions would be required, and the costs of x_2 would be approximately 600 million USD/year. Finally, if interventions are targeted but there is no spatial variability, more measures are required in the selected catchments to reach the same environmental effect. Roebeling et al (2007) show that this reduces cost-effectiveness, increasing total costs to approximately 1.3 billion USD/year.

4. RESULTS

The results for the North Sea case study show that, on average, respondents expect that EO will improve marine water quality monitoring and that it will reduce uncertainty with roughly 50%. Estimates of the perceived accuracy of EO information differ among respondents, but on average respondents expect EO information to correctly predict dangerous algal bloom in 3 out of 4 cases, i.e. a type-I error of 25%. The respondents could not indicate the probability of a false alarm (type-II error), so we assumed a type-II error of 10%. For the GBR case study, the perceived type-I error was 28% and the type-II error 34%.

	Actions (x)		Priors
States (s)	x_1: Reduce N and sediment in entire catchment	x_2: Reduce N and sediment in selected catchments	π_s
s_1: No spatial variability in effectiveness of emission reduction	-1.1 billion USD	-1.3 billion USD	π_1
s_2: Spatial variability in effectiveness of emission reduction	-1.1 billion USD	-0.6 billion USD	π_2

Table 2 Pay off matrix of the Great Barrier Reef case study

Using these numbers to assess the value of EO information, we estimate the value of potentially harmful algal bloom predictions to be 74,000 euro/week. Accounting for respondent variability, the 95% sensitivity interval ranges from 34,000 to 103,000 euro/week. For the investment to be efficient, benefits should be at least 500,000 euro/year (Bouma et al. 2009). Given that algal blooms are a problem during a 10-week period, there is a 75% probability that annual benefits are sufficient to pay back costs.

In the case of water quality monitoring in the GBR lagoon the story is more complex. First of all, no EO cost data are available, so we do not know what the minimum level of benefits should be. Second, we have to assume prior beliefs based on actual decision-making. Given that decision-makers are currently choosing action x_1, reduce emissions in all catchments, the expected utility of action x_1 should exceed the expected utility of action x_2. This is the case when the probability of state 1 is 72%. Using this value and the estimated type-I and type-II errors presented earlier, the value of EO would be 52.1 million USD/year.

However, changing the prior belief estimate also changes the value of information: If we instead assume a prior belief in state 1 of 80%, the value of information reduces to 21.2 million USD/year. Although it is difficult to say what the value of prior belief should be, the analysis shows in accordance with Hirshleifer and Riley (1979) that the more convinced decision-makers are of their current policy, the lower the perceived value of EO.

Finally, the value of information is determined by its perceived accuracy. Fig 2 below illustrates this for the North Sea case study. As Fig 2 shows, algal bloom early warning information only has value if the perceived type-II error is less than 20%. Turning this argument around, by improving the accuracy of EO information its value could increase to 350,000 euro/week. In the case of water quality in the GBR lagoon, respondents indicated that they expected the accuracy of EO information to be maximally 80%. In that case, and assuming a prior belief of 70%, the value of EO could become 82 million USD/year.

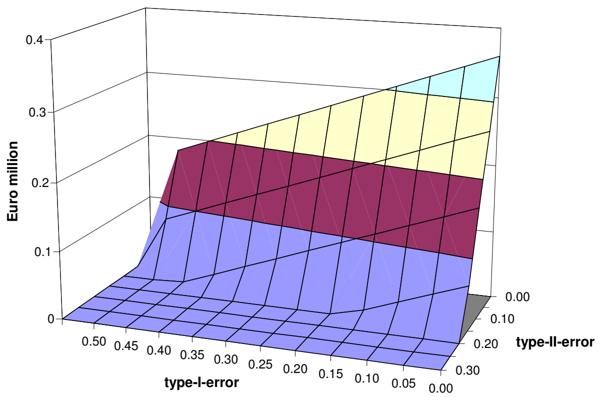


Fig 2 The value of information as a function of the type-I and type-II errors (North Sea case study)

5. DISCUSSION

We started this paper by noting that although there seems to be an increasing demand for studies estimating the value of EO information, an analytically sound and empirically feasible approach lacks. This paper has shown that a combination of Bayesian decision theory and expert elicitation can do the job, and provide insight into the perceived value of EO information and the parameters on which this value depends.

The case studies show that the method is applicable to a broad range of natural resource management problems, where uncertainties are spatial as well as temporal and where the management problems are more or less complex. Although we focused on water quality problems, we believe that its use can be extended to other core areas of EO (land, atmosphere, etc.).

The approach is promising as it links the value of information to the accuracy of the information system. This not only makes the outcomes more realistic, other studies often assuming perfect information which is hardly ever the case, but it also helps to improve the accuracy of the information system itself. Also, the combination of Bayesian decision theory and expert elicitation generates insight into decision-maker's motivations to fund EO investments, or not. If decision-makers are certain of their current policy and if they perceive the accuracy of EO information to be low, they will see little value in EO investments.

For suppliers of EO technology, our approach highlights the importance of increasing the accuracy of EO. The case studies strongly suggest that the economic pay-off of increased accuracy (in terms of a reduction in type-I and type-II errors) may be substantial.

An important challenge of the methodology is that it is difficult to construct a pay-off matrix of a management problem that is simple enough to form the basis for the subsequent computations, while still doing justice to the inevitable complexities of the real world. Also, it would be interesting to analyse the impact of decision-maker's risk-aversion levels on the value of information. The best way to address these challenges is to further apply the method to a variety of natural management decision-making problems around the world.

ACKNOWLEDGEMENTS

We would like to acknowledge the help and major inputs from Jane Waterhouse, Dave Rissik, Phinn Stuart, Chris Roelfsema and Birte Schoettker. Also, we would like to thank the respondents who participated in the surveys for their efforts and their time. The European Commission, in the framework of the GEOBENE project, funded the research.

REFERENCES

J.A. Bouma, H.van der Woerd and O.Kuik, "Assessing the value of information for water quality management in the North Sea", J of Env. Mngment 90 (2), p.p. 1280-1288, 2009

J. Brodie, J. Binney, K.Fabricius, I.Gordon, O.Hoegh-Guldberg, H.Hunter, P. O'Reagain, R.Pearson, M.Quirk, P.Thorburn, J.Waterhouse, I.Webster and S. Wilkinson, "Scientific Consensus Statement on Water Quality in the Great Barrier Reef", Brisbane, 2008

M.J. Devlin and J.Brodie, "Terrestial discharge into the Great Barrier Reef lagoon: nutrient behaviour in coastal waters", Marine Pollution Bulletin 51, p.p. 9-22, 2005

European Commission, "European Space Policy", Communication from the commission to the council and the European Parliament, COM(2007)212, Brussels, 2007.

K.E. Fabricius, "Effects of terrestrial runoff on the ecology of corals and coral reefs: review and synthesis", Marine Pollution Bulletin 50, p.p.125-146, 2005

Great Barrier Reef Marine Park Authority (GBRMPA), "The Great Barrier Reef catchment water quality action plan- a report to ministerial council on targets for pollutants loads", Townsville, 2001

J. Hirshleifer and J.G. Riley, "The analytics of uncertainty and information- an expository survey", J of economic literature 17, p.p. 1375-1421, 1979

M.K. Macauley, "The value of information: Measuring the contribution of space-derived earth science data to resource management", Space policy 22, p.p. 274—282, 2006

L. McKergow, P.Prosser, A.O.Hughes and J.Brodie, "Sources of sediment to the Great Barrier Reef World Heritage Area", Marine Pollution Bulletin 51, p.p. 200-211, 2005

L. Peperzak, "Pijpenstelen en mosselsterfte", Zoutkrant, RWS-RIKZ, Den Haag (In Dutch), may 2003.

P.C.Roebeling, M.Evan Grieken and A.J.Webster, "Environmental-economic analysis for exploration of efficient land use and land management arrangements, water quality improvement targets and incentives for best management practice adoption in the Tully-Murray catchment", research report, CSIRO, Townsville, 2007

D.E. Schimmelpfennig and G.W.Norton, "What is the value of agricultural economics research", American journal of agricultural economics 85 (1), p.p. 81-94, 2003

H.J. van der Woerd, A. Blauw, L. Peperzak, R. Pasterkamp, "A harmful algal bloom warning system for the North Sea: a combination of field data, remote sensing and computer models for algal growth and bloom transport", J. Sea Research, submitted April 2008.