

MONITORING PROGRAMMES: THE FUNDAMENTAL COMPONENT OF ESTUARIES MANAGEMENT. HOW TO DESIGN ONE?

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Abstract

This article focuses on the design of a conceptual framework to design and assess environmental estuarine monitoring programmes, including the networks, to detect quality status changes in coastal areas within environmental management programmes. Monitoring is a fundamental component in any management system, and in particular in sensitive areas under strong human pressures, like estuaries. These pressures will be reflected in impacts in the ecosystem and also in responses from it. A monitoring program including the network and the indicators measured, should be designed to be able to identify the i) pressures, ii) the state and effects, and iii) the responses of human action in the estuary according to casualty chains, also the monitoring performance should

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be measured to assess the effectiveness of the monitoring program itself. Answers to these needs are studied in this article, namely in what concerns the selection and location of the monitoring stations. To evaluate the “best” monitoring design one should first clearly identify the objectives of the network and which indicators (in the sense of important variables that reflect environmental attributes) are most appropriate for the particular situation. In this work two methods for monitoring network design will be evaluated, namely i) variance-reduction based, and ii) space-filling. These two are examples of a statistically-based method, and of a random-allocation-based method. The most appropriate objective functions are used to reflect the objectives of the monitoring. In all cases the objective function models are solved with the simulated annealing meta-heuristic algorithm, implemented by the team to solve monitoring optimisation problems. Due to the amount and quality of the information available, the Sado estuary is used as a case-study to demonstrate the results of the methods and helping in the comparative analysis.

Keywords: coastal management; monitoring optimisation; environmental indicators; simulated annealing

1 Introduction

Coastal use is always associated with conflicts, exemplifying the need for management to address and mitigate the negative consequences of such conflicts and to safeguard coastal values (Moriki *et al.* [1]). In coastal zone management studies, estuaries in particular, the monitoring process is fundamental though difficult and time and cost consuming. Estuaries compared with other aquatic ecosystems have several spatial heterogeneities (Kitsiou *et al.* [2]). In any environmental management and assessment process a monitoring step should be included to both ensure that mitigation and other countermeasures are carried out and to determine the actual impacts of the action as implemented (Clark [3]).

Monitoring is a process where repetitive measurements in time and space are recorded to indicate natural variability, and changes in environmental, social and economic parameters. Measuring these changes contributes to the information base needed by managers to evaluate a plan's effectiveness. Evaluation is analysing information, some of it gained through monitoring, then comparing the results of the analysis against predetermined criteria. A well designed, ongoing monitoring program is fundamental for plan evaluation (Kay and Alder [4]). The design of an effective monitoring program depends on the plan's objectives, resources (funding and staff) and available technology. Monitoring programmes should be designed to contribute to a synthesis of information or to evaluate impacts, or analyse the complex cross-linkages between environmental quality aspects, impacts and socio-economic driving forces (RIVM [5]). It soon became evident that remote and combined stressors, while difficult to measure, also significantly alter environmental conditions. Consequently monitoring efforts began to examine ecological receptors, since they expressed the effects of

multiple and sometimes unknown stressors (Jackson *et al.* [6]). Because of the content of most stressor-response relationships, it is impossible to completely characterize all the variables, so a selected set of measurements should be made to reflect the most critical components. Such measurements, or indicators, should be included in monitoring programs to estimate trend, stressor source and magnitude of effects and lead to thresholds for management or restoration action (Fisher *et al.* [7]). The use of indicators and indices for the evaluation and assessment of the environmental status of different ecosystems is becoming a widespread procedure to analyse the various and often complex components of a system like the marine environments (Casazza *et al.* [8]). To assure that indicators serve the purpose for which they are intended and control the way they are specifically selected and developed, it is important to organize them in a consistent framework. Different methodologies are used for structuring different types of indicators and/or indices. Despite the large variety of frameworks developed so far, many of them are quite similar in their methodological approaches and most is based on causality chains. Ramos *et al.* [17] presents an overview and discussion of these frameworks.

Two common types of information used in environmental management are i) baseline information that measures the environmental conditions and status of resources before a project is commenced and ii) monitoring information that measure the changes, if any, that occurred after the project was built and operated (Clark [3]). The statistical reliability of the sampling strategy and parameters used in the baseline surveys and monitoring programs is a key factor. The technical design of monitoring networks is related to the determination of: i) monitoring sites; ii) monitoring frequencies; iii) variables to be sampled; iv) duration of sampling (the last two variables are not discussed here because they are case-specific). Most of the research results in this area have been obtained in the context of statistical procedures (Sanders *et al.* [9]); Moss [10]; IAHS [11]; Cochran [12]). These rely in the principle that there are several sources of uncertainty, due to measuring errors, inherent heterogeneities of the involved variables, and in the cases where modelling is involved, also simplifications and errors in both the modelling and numerical/analysis solution phase. McBratney *et al.* [13]), as well as many other authors after them, indicated that uncertainties are the result of lack, in quality and quantity, of information concerning the systems under study, or as a result of spatial and temporal variations of parameters. The first cause of uncertainty may be reduced by, *e.g.*, increasing the number of measurements and analysis and their accuracy. The second cause of uncertainty is much more difficult to reduce, and demand for non-exact representations of the reality. Two approaches have been used in this line: i) to model parameters as random variables with no spatial structure, resulting in monitoring plans based on random allocation and regular allocation (see, *e.g.*, Cochran [12]); ii) to model parameters as spatially distributed variables. The most popular designs of the first type are systematic random allocation, stratified random allocation, and regular designs (triangular, hexagonal, quadrangular, etc.). In an isotropic medium, the performance of these designs increases from

random allocation, to the regular designs, with stratified random in between (Chilès and Delfiner [14]). Many methods have been proposed for including physical knowledge into the design. Physical knowledge here is understood as information about the site under study, and may include statistical moments of any order, physical laws, scientific theories, and uncertainty about the observations. The more popular of these methods are the variance reduction, in the context of geostatistics, the transinformation method, in the context of statistical entropy analysis (Harmancioglu and Yevjevich [15]), and the Bayesian maximum entropy method, also from statistical entropy analysis, but much more powerful than the previous (Christakos [16]). The relative performance of methods for designing monitoring networks when reducing its dimension, with many alternative locations, requires that first an optimal allocation is determined by choosing the “best” design, i.e., the spatial allocation of the stations that is “best” in some quantitative criterion, for each method. It is in this line that the variance reduction method is evaluated against a random allocation method and their performances compared. This evaluation will help establishing the relative difference in their performance, though tested in a specific instance, and also create a benchmark analysis for methodological evaluation, within management conceptual framework.

In this work it is proposed that a conceptual framework to design and assess estuarine monitoring networks programmes be adapted from Environmental Impact Assessment follow-up. This innovative approach also includes monitoring networks (and optimisation). Due to the amount and quality of the information available, the Sado estuary is used as a case-study to demonstrate the results of the different methods and helping in the comparative analysis. A dataset of sediment data was used. Sediments have been widely used to identify sources of contamination, to measure their extent, and to long-term monitor the environmental quality of estuarine ecosystems.

2 Conceptual framework to design and assess environmental estuarine monitoring programs

Based on a rearrangement of frameworks like PSR/E (from USEPA [18]), DPSIR (RIVM, [5]; [19]) and ISO 14031 (ISO [20]), an adaptation of INDICAMP is proposed for estuarine monitoring programs (fig. 1). INDICAMP was initially developed for the post-decision monitoring programs within Environmental Impact Assessment processes (Ramos *et al.* [17]).

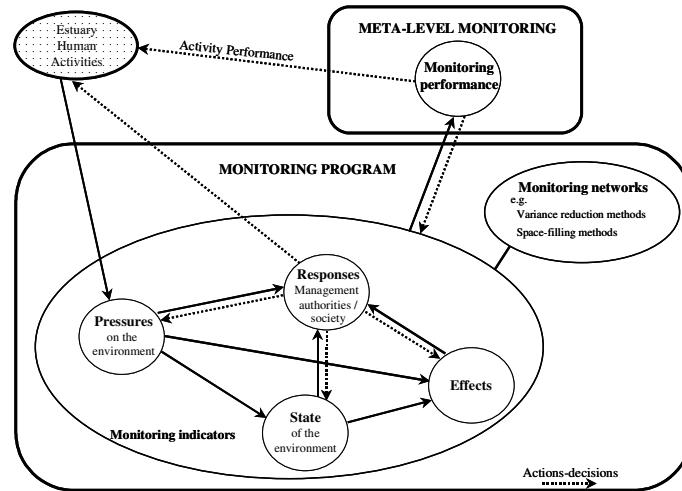


Figure 1: Environmental indicator framework to design and assess environmental monitoring programs (INDICAMP).

This framework tries to incorporate systems analysis approach, designing the main cause-effect relationships between the different categories of monitoring indicators (*pressures*, *state*, *effects* and *responses*). It also includes *monitoring performance* indicators category to assess the effectiveness of the monitoring program itself. This kind of tool could help in applying the comprehensive or targeted environmental monitoring concept used by Canter [21], i.e. the establishment of cause-effect relationships. This model shows how each human activity in the estuary produces *pressures* (like for example pollution loads or population density) on the environment, which then modifies the *state* of the environment (like for example water quality or coastal line evolution). The variation in *state* then implies *effects* or *impacts* on human health and ecosystem receptors (like for example effects on human consumption organisms quality or beach use compromise), causing estuary management authorities and society to *respond* (like for example urban and industrial waste water treatment efficiency or environmental law compliance) with various management and policy measures, such as internal procedures, information, regulations and taxes (see the dashed lines in fig. 1). The particular features of each of these categories follow the general methodology developed by (RIVM [19]). *Effects* in some way concern relationships between two or more indicators within any of the *pressures*, *state* and *responses* categories. The framework also shows that the performance of the monitoring program can be evaluated at one main stage – meta-level monitoring. At this level, *monitoring performance* indicators category (like for example monitoring reporting and communication to stakeholders or use of environmental preferable products and equipment in monitoring activities) represents the effort to conduct and implement the program, measuring also

program effectiveness. The *monitoring performance* indicators will allow the following (see the dashed lines in fig. 1): i) how appropriate the environmental and social-economic monitoring indicators are (*state, pressures, effects* and *responses* categories), leading to a review of and improvement in these components; ii) evaluation of overall monitoring activities and results, including the environmental impact of the sampling process itself, to measure how well the monitoring program is going; iii) evaluation of environmental performance activities and impact mitigation action.

The INDICAMP indicators can be measured in the different environmental component of the monitoring program (like air, water or soil) or in only one component. In the aim of this work more focus is given to the aquatic system component. For monitoring indicator selection and development, various concepts, criteria and general guidelines must also be taken into account, namely those defined by Ott [22], Barber [23], RIVM [5], Ramos [24], HMSO [25], and Jackson *et al.* [6]. The implementation of INDICAMP therefore requires the definition of a set of indicators aimed at the different parts of the framework. In this framework, monitoring indicators can be aggregated into environmental indices, to reflect the composite monitoring results of each category of the framework. The aggregation functions (mathematical or heuristic) must be selected or developed for each particular case. Since there are many different functions with several advantages and disadvantages this step must be carried out with special caution to avoid significant losses of information and assure meaningful results.

After the selection of the indicators of the INDICAMP other issues arise, where, when and in how many locations should measurements be made on the indicators of the *pressure, state* and *effects* categories. The definition of the monitoring network and the methods to accomplish it should be part of the INDICAMP framework (see fig. 1). The reliability of the data collected will affect the quality of estimates made from it and affect the decision-making process. In particular, monitoring design plays a key role in statistical inference and hence in ecological assessment (Steele, [26]). In the next chapters focus will be given to the discussion of different methods for monitoring networks design optimisation, and in their expected performance.

3 Comparison of methods for the selection and location of the monitoring stations

Before proceeding into the analysis of methods for monitoring networks optimisation, some remarks about the difference between sampling and monitoring must be introduced. Sampling is here considered the action of taking samples from a spatial (or temporal) field when the amount of information needed to design the monitoring network is scarce or unavailable. Therefore,

sampling is a prior stage in the design process. Many sampling methods have been thoroughly applied in environmental planning, namely with random, stratified random, systematic, or cluster sampling, among others (see, e.g., Cochran [12]).

Reliability of monitoring networks means that they must reproduce the correct values (precision) with the lowest variance (accuracy), and reproduce the spatial and temporal variability of the parameters under study. Usually the reliability of a monitoring network increases with the number of stations and with their relative position in space (and/or time). Common sense says that when the rate of change of parameter values change quickly in space it becomes more difficult to estimate its values, and more stations are needed. Common sense also says that in order to have a good overall picture of the spatial distribution of parameter values some stations have to be located in areas with low rate of change. Another problem arises when the budget available is limited, conditioning the total number of monitoring stations. Hence, the optimisation of a monitoring network is a problem of choosing the best locations for the monitoring stations (some small number, say, ω), given all the available possible locations, Ω . This is a combinatorial problem for which the number of possible solutions, M , is calculated by the combinatorial formula: $M = \Omega! / ((\Omega - \omega)! \omega!)$. It is easily seen that even for small values of ω and Ω the number of combinations attains very large numbers. The reliability of a monitoring network has to be evaluated in some way such that the low quality designs are discarded and the good ones are selected. Also, the evaluation must be automated because the large number of possible solutions makes manual evaluation impossible in reasonable amounts of time. Evaluation has then two steps: i) the selection of an optimisation criterion (objective function); ii) the automated procedure of evaluation. In this article two criteria are compared and a metaheuristic optimisation method called simulated annealing is used for the automated procedure. The two criteria are: i) variance reduction with statistical stratification; ii) random allocation based on a spatial metric (space-filling). These two criteria are based in different conceptual approaches, being the first a sound statistical approach that requires a large data set, geostatistical background, and is very time consuming to implement; the second is a variation of random allocation that requires no prior data, no statistical background, and is fast to implement. The results from both methods are compared and their statistical accuracy and precision are compared.

3.1 Variance reduction methods

Variance reduction methods are carried out in the context of geostatistical theory (Matheron [27]) and most frequently by interpolation with an unknown mean, i.e. by ordinary kriging. Kriging variance has been extensively used for monitoring network design. Examples can be found in the work of Bras & Rodríguez-Iturbe [28], Rouhani [29], and Nunes *et al.* [30]. These methods need

prior georeferenced data, descriptive statistical analysis, and the modelling of spatial auto-covariance functions (or, given some stationarity requirements, the variogram). At the heart of geostatistical variance reduction method used here lies the estimation error variance obtained by kriging with the method of leave-one-out (Deutsch & Journel [31]) applied to the monitoring design being evaluated. The method proceeds by: i) selecting a subset of stations, ω from the large set, Ω ; ii) obtain by kriging the estimates (and their kriging variances, if applicable) at each ω station; iii) calculate the value of the mean squared estimation error with the ω stations (or mean kriging variance); iv) select or discard the design according to the simulated annealing algorithm; v) swap one stations between the large set and the design set; v) repeat step i) through iv); vi) stop the search of new designs according to the simulated annealing algorithm and present the final solution. This method has been explained in more detail in previous works (Nunes *et al.* [30]; Caeiro *et al.* [33]).

3.2 Space-filling methods

This approach was been applied in monitoring network design by Morris & Mitchell [34] and Royle & Nychka [35], but has had very little application since then. In space-filling designs some criterion based on a metric is used to evaluate the goodness of a space covering design. The most common criteria are those that use the following criterion

$$C_{p,q}(D) = \left(\sum_{u \in C} d_p(x, D)^q \right)^{1/q} \quad (1)$$

which is an L_q average of distances between candidate stations and the design. The exponent q is usually >0 . One possible metric is

$$d_p(x, D) = \left(\sum_{u \in D} \|x - u\|^p \right)^{1/p} \quad (2)$$

where when $p < 0$, $d_p(x, D) \rightarrow 0$ as x converges to a member of D . The coverage design is the subset of ω elements in D from the Ω elements in C , $D \subset C$, that minimize the criterion $C_{p,q}(D)$. The implementation of the method is similar to that of variance reduction, but points ii) and iii) are replaced by the calculation of the criterion $C_{p,q}(D)$. It is clear here that in this criterion the only information needed is the spatial coordinates of the stations.

Simulated annealing optimisation algorithm has had many applications in water management studies and in related fields, and proved to be a good optimisation algorithm for difficult combinatorial problems. More information on the basics

of simulated annealing may be found in Kirkpatrick *et al.* [36] and Aarts & Korst [37].

4 Example application

The example case-study is in the Sado Estuary, the second largest in Portugal, with an area of approximately 24,000 ha. It is located in the West Coast of Portugal, in the area defined by the coordinates 8°42' W 38° 25' N and 8°57' W 38°32' N. The estuary comprises two channels, the Northern and the Southern, partially separated by intertidal sandbanks. Most of the water exchanged with the sea is made through the southern Channel, which reaches a depth of 25 meters, whereas in the Northern Channel the maximal depth is 10 m. The estuary is linked to the ocean by a narrow and deep channel (maximal depth of 50 m). Most of the estuary is included in the classification of Nature Reserve by Portuguese legislation, but still has an important role in the local and national economy. The estuary has, in part of its northern shores, some industries and harbours, and the city of Setúbal. Further inshore there are some mining activity, intensive farming, mostly rice fields. In the intertidal area there are also traditional saltpans and increasingly intensive fish farms. These activities may have negative impacts on water, sediment and biotic communities namely because they discharge into the estuary contaminants like heavy metals, organic compounds and nutrients (Caeiro *et al.* [38]). An environmental data management system was already developed for the estuary area, being now under development the implementation of an indicator framework to design and assess an environmental program, presented here, being the monitoring one of its most important components.

In a first extensive campaign 153 sediment locations were sampled and fine fraction (FF), organic matter (OM), and redox potential (Eh), chosen as indicators of sediment properties. These key parameters are associated with the main types and behaviour of benthic organisms, as well as with contaminant mobility/accumulation. A systematic unaligned sampling design with a grid size equal to 0.365 km² was used based on prior information on the spatial variation of sediment granulometry (fig. 2) (Caeiro *et al.* [38]). The extensive campaign was used for the delimitation of homogeneous areas within which estuarine *state* and *effects* could be monitored using less locations. These areas are also used as physical spatial components in the management system. The drawing of homogenous areas was made in 5 steps based on grouping individual sampling sites that showed similar properties while being geographically close: i) principal component (PC) extraction of the 3 sediment properties variability (FF, OM and Eh); ii) variogram model fitting to the 1st PC factor scores; iii) construction of a dissimilarity matrix; iv) cluster analysis using the complete linkage rule on the dissimilarity matrix to estimate the probability of occurrence of four selected clusters at sampled stations; v) interpolate these probabilities to unsampled

stations by indicator kriging; vi) maximum likelihood classification of these unsampled stations. Four general classes of sediment properties were obtained (1, 2, 3 and 4). These classes represent the value of an index resultant from aggregation of information (cluster analysis) and represent sediments with different organic load (fig. 2). More on this method may be found in Caeiro *et al.* ([33], [38]). All subsequent analysis uses this information.

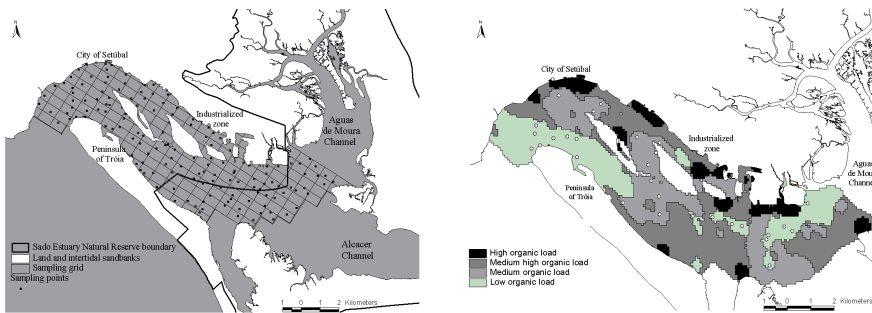


Figure 2: Sado Estuary sediment extensive sampling design and sediment classes (Caeiro *et al.* [33]).

5 Results

Indicators for each of the INDICAMP categories were selected based on the indicators criteria concept and general guidelines and estuary characteristics and data availability (see fig. 3). In the case of *Pressures* indicators located in the terrestrial zone, boundaries were drawn based on administrative limits in the Sado Estuary (e.g., watershed limits). The *state* and direct *effects* of the Estuary were mostly evaluated in the sediment and benthos compartment because sediment is the compartment where contaminants tend to accumulate first. Studying the state of the estuary mainly based on the sediment and benthos compartment also turns the methodology easier, faster and spares human and financial resources. INDICAMP tends to suggest linear relationships in estuary human activities/environmental effects. This should not, however, obstruct the view of more complex relationships between estuary pressures and environmental-impact interactions. The INDICAMP framework does not attempt to make one-to-one linkages between specific *pressures*, environmental changes and *responses*. The *state* of the environment depends on the total *effects* of multiple *pressures*. As stressed by (USEPA [18]), diagnosis of the causes of particular environmental or societal changes is usually difficult and multiple causation is the norm rather the exception. One way to deal with this complexity when designing monitoring programs is to avoid analyse unique linkages, and try to adopt an integrated approach, that relates different indicators as clusters with multiple aspects that interact with each other.

Once selected the appropriate indicators of *state* and *effects*, the location of monitoring stations has to be determined inside each homogeneous area. Hence, fourteen different monitoring network sizes (ω) were tested (Caeiro *et al.* [38]), {25,30,35,40,45,50,60,70,80,90,100,110,120,130} according to the following scheme: i) impose a number of monitoring stations (ω) to be included in the new design; ii) find the optimal allocation solution with SA; iii) increase ω and return to i).

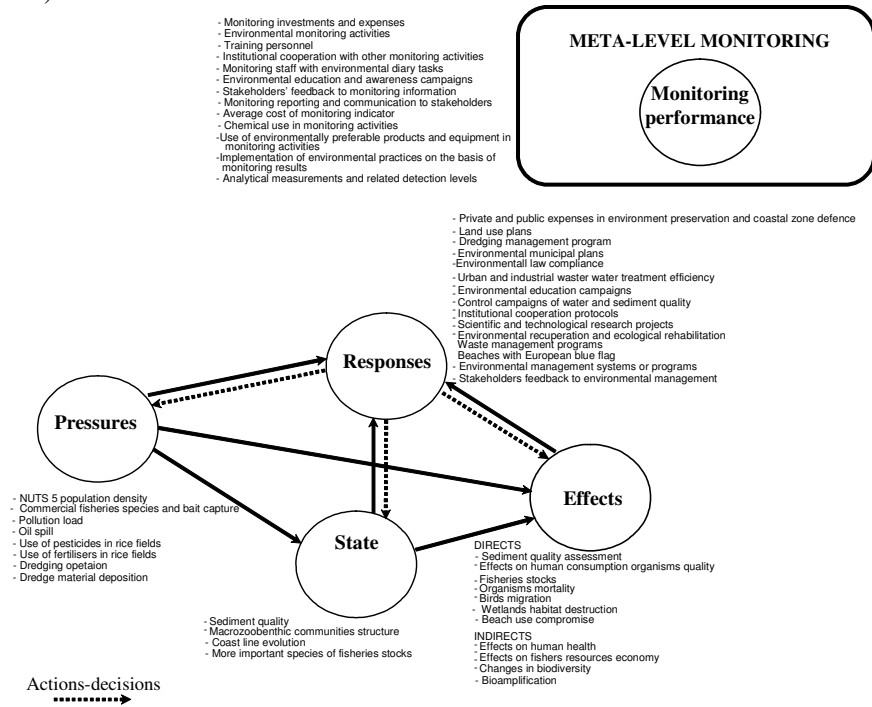


Figure 3: List of indicators selected for each INDICAMP category.

The loss in accuracy versus reduction in exploration costs as stations are removed was also performed. For that purpose a cost per sampling was computed based in previous sampling campaigns and laboratory analysis costs, considering the following criteria: i) linear distance between sampling stations; ii) constant boat velocity of 12,8 km/h; iii) 7 h of daily working period ; iv) a fixed time for sampling of 20 min; v) boat rent costs of 250 € per day ; vi) 500 € for the chemical analysis per contaminant (discount of 25 % from 20 to 50 stations, 30 % from 55 a 100 stations and 40 % from 105 to 130 stations). Fig. 4 shows the resulting gains in monitoring accuracy, as measured by the variance reduction method (objective function in the figure), and total costs of monitoring for different sizes of the monitoring design. It is clear that after the sixtieth

station the marginal gains in accuracy decrease significantly, though the monitoring costs still increase linearly. It was decided that a design with 77 stations should be chosen in order to also guarantee the placement of stations near important pollutant sources. Hence, the resulting monitoring network has an accuracy very close to one with almost twice its size, with much inferior costs, and is optimal in this context. The optimal design is shown in fig. 5. This optimal design size corresponds to 1.38 stations/km², which is within the average of sediment sample size of United States Environmental Protection Agency (USEPA) Environment Monitoring Assessment Program (EMAP) for small estuaries. The sample sizes for the different estuaries of EMAP vary from 0.11 to 4.16 stations/km² (Strobel *et al.* [39]). Such a wide interval might be related to the spatial variability of sediment parameters in each coastal zone, which is caused by differences related to geomorphological, biological and human pressures, as well as differences in the methodology used.

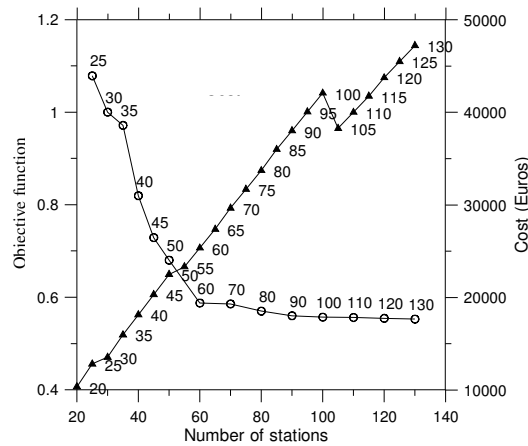


Figure 4: Measure of accuracy (objective function) versus monitoring costs for different monitoring designs sizes.

The space-filling method gives no direct indication of reliability of the monitoring network and therefore it is not necessary to evaluate different design sizes, being enough to assume, or calculate statistically the necessary size by classical methods (see, e.g. Cochran [12]). Here a monitoring network with 77 stations is used because it allows direct comparison with the variance reduction method (fig. 5). The optimisation of the monitoring design includes only the location of the stations made with the method explained before. It is clear that the designs obtained with the two methods are different, with only 36 stations belonging to both optimal designs.

A pure empirical approach is not enough to tell how well will the designs behave, that is, how reliable is one when compared to the other. In reality they both seem to cover well the area under study. To determine which is really

“best” some more calculations are needed: i) the absolute error of estimation at each station location, as a measure of local precision; ii) the mean absolute error of estimation for the entire network as a measure of global precision; iv) the mean estimation error variance as a measure of global accuracy. The first measure is represented in figs. 6 and 7, where the higher the values the larger the estimation error and the more prone to future estimation errors (when estimating future values in areas not sampled). Its clear that the absolute errors are higher with the space-filling method.

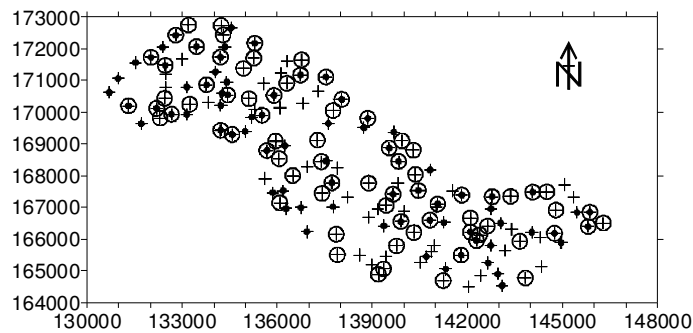


Figure 5: Original stations (in cross signs), resulting optimal monitoring network with the variance reduction method (in open circles), and optimal monitoring network with the space-filling method (in filled circles). UTM coordinates in metres.

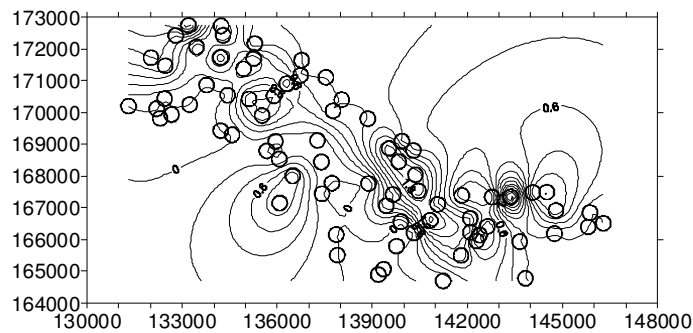


Figure 6: Interpolated absolute error of estimation for the design obtained with the variance reduction method. The optimal 77 stations design is also shown. UTM coordinates in metres.

The mean absolute errors of estimation also show this difference: 0.922 for the later and 0.584 with the variance reduction method. Therefore variance reduction

method clearly outperform the space-filling method in terms of precision. The rate between the second and first absolute estimation errors is 0.63, representing an average gain in precision of 63%. Also in terms of global accuracy the variance reduction method outperforms space-filling: the mean estimation error variance is 1.381 for space-filling and 0.798 for variance reduction. The rate between the second and first estimation error variances is 0.58, representing an average gain in accuracy of 58%.

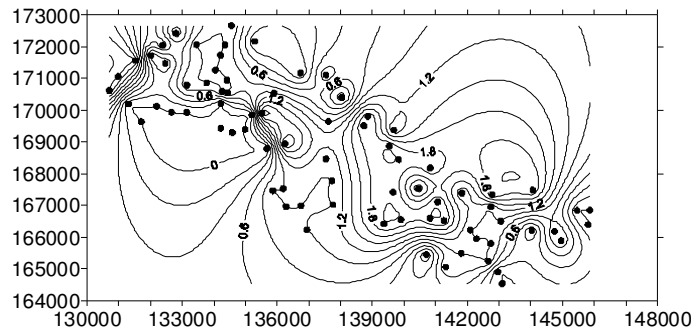


Figure 7: Interpolated absolute error of estimation for the design obtained with the space-filling method. The optimal 77 stations design is also shown. UTM coordinates in metres.

6 Conclusions

Environmental management approaches involving indicator frameworks to assess and design monitoring programs, including monitoring networks is an emerging issue in coastal areas. Moreover, the integrated framework presented in this work, in particular the assess of monitoring performance and the reliability of monitoring network designs is, in this context, innovative. In this article the environmental management programmes and the optimisation of monitoring networks were put together, serving the first as the conceptual framework under which the monitoring results must be analysed. The case-study showed examples of the indicators belonging to the different categories. Some difficulties arise in choosing the indicators for each category and in finding system interactions. Despite this, the method focus on prevention and finds simple relationships in human activities/environmental effects. Multiple causalities have also to be analysed to diagnose the causes of particular environmental or societal changes.

The work presented serves to pinpoint some drawbacks of fast, but less reliable, methods for monitoring network design, as compared to more time-consuming, but more robust methodologies. The problem still to be solved in management

programmes is the amount of resources allocated to each task, conditioning the choice for the amount of effort put in the design of data collection programs. The results presented here may help in the decision-making process by indicating the amount of gain/loss expected when choosing one method over another. Though these results clearly show that more evolved methods may give better results in terms of monitoring network designs reliability (perform better), it should be noticed that in many instances the amount of data available may make impossible to obtain the necessary statistical information required for variance reduction methods. In this cases the reliability of the monitoring network will approximate that of a random-based one, such as those obtained with space-filling. This work may serve as an indication of how far from the quality of the latter one may be.

Future works will have to deal with the comparison with other methods for monitoring network design, namely with entropy-based methods.

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