Framework for multi-criteria decision management in watershed restoration

Angel Udías, Lorenzo Galbiati, Francisco Javier Elorza, Roman Efremov, Jordi Pons and Gabriel Borras

ABSTRACT

This paper presents a hydroinformatics management tool designed to optimize the program of measures (PoM) to achieve the European Water Framework Directive (WFD) objectives in the internal Catalonian watersheds. The tool incorporates the Qual2kw water quality model to simulate the effects of the PoM used to reduce pollution pressure on the hydrologic network. It includes a Multi-Objective Evolutionary Algorithm (MOEA) to identify efficient trade-offs between PoM cost and water quality. It also uses multi-criteria visualization and statistical analysis tools as a user-friendly interface. This management tool is based on the Pressure–Impact concept, selecting the most effective combinations of sewage treatment technologies from millions of technologically admissible combinations. Moreover, the tool is oriented to guide stakeholders and water managers in their decision-making processes. Some guidelines are also given in this paper on the use of analytical relationships from the field of evolutionary multi-criteria optimization algorithms for different parameters (elitism, crossover and mutation rate, population size) to ensure that the MOEA is competently designed to navigate the criteria space of the management problem. Additionally, this paper analyzes the results of applying the management tool in the Muga watershed, whereby guaranteeing its convergence within a reasonable computational time, in order to simplify the decision-making process.

Key words | genetic algorithm, management, multi-criteria, river basin, water quality

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NOTATION

ACA	Catalan Water Agency
CEPH	Convex Edgeworth-Pareto Hull
GES	Good Ecological Status
IDM	Interactive Decision Maps
MCDSMWR	Multi-Criteria Decision Support Management in Watershed Restoration
MOEA	Multi-Objective Evolution-based Optimization Algorithm
MOSESS	Multi-criteria System of Efficient Strategy Selection
PoM	Program of Measures
RBMP	River Basin Management Plan
TOC	Total Organic Carbon
WB	Water Bodies
WFD	Water Framework Directive
WQM	Water Quality Models
WWTP	Waste Water Treatment Plant

INTRODUCTION

The Water Framework Directive (2000/60/EC, WFD) is the core of the EU water legislation, providing the foundation for long-term sustainable water management by taking due account of environmental, economic and social considerations. The main objective of the WFD is to achieve 'Good Ecological Status' (GES) for all European Water Bodies (WB) by the end of 2015. In this context, since the beginning

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of 2006, European Union member states have been developing a Program of Measures (PoM) to reduce water threats and their associated impact, to achieve the WFD's goals. Although the European Commission has published a number of guidance documents to ease the implementation of WFD (European Commission 2000, 2001, 2002), no specific methodology has been suggested to evaluate the practical efficiency of PoMs; nor is it mentioned how these combinations of measures should be selected in order to achieve the best cost-effective strategy.

Therefore, EU member states are to submit the River Basin Management Plan (RBMP), which is a document that defines a strategy to be implemented in order to satisfy year 2015s objectives. The restoration of water quality at watershed level (considering the water bodies as management units) is related to a series of objectives that should be taken into account when defining the RBMP. It is important to select a cost-effective PoM in order to reduce and, where possible, eradicate existing and future water deficits, whilst maintaining sustainable economical and social costs.

Water Quality Models (WQM) may quantify and simulate the effectiveness of PoMs in increasing water quality and quantity. Even though WQMs themselves are useful for evaluating single what-if scenarios and testing potential management alternatives, they are unable to automatically solve the multi-criteria (cost, water quality, water availability) optimization problems that involve selecting the best cost-effective PoM trade-off. Thus, linear programming (Revelle *et al.* 1968), nonlinear programming (Fujiwara *et al.* 1987) and integer programming (Bishop & Grenny 1976) have been used to solve the cost optimization river water quality management model for regional wastewater treatment. The majority of the mentioned approaches, however, only consider one or two water quality parameters and optimal decisions disregard the general state of the watershed with regard to contamination, political strategies and socioeconomic status.

In recent years, however, Multi-Objective Evolutionary Algorithms (MOEA) have been applied to obtain trade-off Pareto optimal set solutions for many multi-objective problems, with very good results in a single execution (Deb 2001). MOEAs can also be applied to many problems for which traditional mathematical programming techniques are intractable (Ritzel *et al.* 1994).

Moreover, besides the multicriteria consideration, the WFD implementation is a decision-making process related to a negotiation process, which involves several stakeholders with different interests and goals. For this reason, computer procedures for decision screening must be transparent and simple. In particular, multiple questions concerning decision-makers' subjectivity preferences should be avoided. Visualization of Pareto-efficient frontier provided by the Interactive Decision Maps (IDM) technique satisfies this requirement (Lotov *et al.* 2004).

This paper describes a new computational tool for Multi-Criteria Decision Support Management in Watershed Restoration (MCDSMWR) that has been developed to aid in water management during WFD implementation. This tool results from integrating a WQM, an MOEA and graphical analytic tools that help to solve and display complex decision-making problems. This hydroinformatics tool is able to incorporate conflicting elements such as environmental objectives and economical issues into the analysis. It also makes it possible to delineate non-dominated Pareto-optimal solutions in a number of WQM executions that are small enough to be performed on a standard PC, on a timescale that meets the requirements of the Catalan Water Agency (ACA).

Although to quantify biological, physical and chemical transformations of constituents in small Mediterranean catchments, other models (Marsili-Libelli & Giusti 2008; Mannina & Viviani 2010a, b) may be more suitable, the US Environmental Protection Agency water quality model (Qualkw2) was selected in this work to evaluate the Pareto-efficient alternatives for large-scale, yet scientifically based, hydraulic planning for the Catalonia water administration.

Several authors have already carried out cost-effective analysis of PoM prioritization (Burmistrova *et al.* 2002; Lotov *et al.* 2005; Muleta & Nicklow 2005; Galbiati *et al.* 2007), but in these earlier presentations usually one or more of the following compromises were made:

(a) The water quality model was only approximate.
(b) The problem to be resolved was a local one.
(c) Single criterion optimization was performed instead of multicriteria optimization.

In contrast, we tackle the problem from a no-compromise point of view. Note that the success of our approach was achieved thanks to several improvements on the 'standard' techniques, such as a special form of the metric for water quality measuring, which speeds up the convergence of the genetic algorithm for Pareto-frontier optimization. This made the problem capable of being solved computers in common use. The difference lies in the fact that the methodology was applied to the large-sized basins in reasonable computation time using low-cost computers. In addition, the results of using this methodological tool have made an essential contribution to the definition of the Catalan hydrological plan, which was legally enforced in 2010 (Diari Oicial de la Generalitat de Catalunya 2010). Finally, this paper presents how the MCDSMWR tool was applied in Catalonia to select the best cost-efficient PoM proposed by the ACA, in order to achieve the WFD objectives at a reasonable cost.

METHODS

The ACA WWTP program

The objective of the European Directive 91/271/EEC is to protect the environment from the adverse effects of wastewater discharges. This Directive was reinforced in 2000 by the WFD, which introduced the GES as the objective to be achieved by the end of 2015. In response to these two directives, the ACA has developed an urban and industrial wastewater treatment plant (WWTP) program (PSARU and PSARI in their Spanish acronyms) (ACA 2002, 2003). A preliminary study developed by ACA identified a number of suitable locations to build 1,300 new WWTPs in order to reduce the impact of the urban and industrial spills on all Catalan WBs.

Given the heterogeneous conditions of the Catalan rivers and their associated watersheds, and given the good level of data available, rivers were classified according to five types and ten subtypes (Munné & Prat 2004). This classification was used to determine the objectives defining the GES in the Catalan river basin district. A total of 247 water bodies (in the river category) were defined with 3,838.0 km of river network in the Catalan river basin district (an average of 15.5 km for each water body). Each WB requires a specific PoM in order to meet the WFD objectives.

Nowadays, there is a wide variety of WWTP technologies that provide different efficiency levels in the removal of water pollutants (Qasim 1999). For the PoM implementation analysis, ACA considers seven WWTP technology types, which are described in Table 1 in terms of their nutrient removal efficiency, building and operational costs. Then, in one river with n as the number of possible WWTP locations, there are 7^n different possible PoM combinations (strategies). The management solution involves finding which of these PoM combinations is efficient according to the ACA estimated conditions for the 2015 scenario.

Thus, a new MCDSMWR methodology was proposed and a hydroinformatics tool based on the methodology was developed. Both are being used in Catalonia to define the best PoM in order to reduce the threats to surface water bodies and to achieve the WFD's objectives.

Table 1 | WWTP technologies considered by ACA (Q: capacity of WWTP in m^3/d). Pollutant efficient removal and investment and operational cost. ISS: Inorganic suspended solids. ICost: Investment cost. OCost: operating cost

		Nutrient efficient removal (%)				Cost (€/m^3)	
Index	**Treatment**	**ISS**	**NH_4**	**NO_3**	**P**	**ICost**	**OCost**
X_1	Primary	50	0	0	0	Fix (222)	$-0.0001Q^{0.115}$
X_2	Secondary	90	30	0	0	$2.758Q^{-0.357}$	$4.645Q^{-0.337}$
X_3	Nitrification (60%)	95	60	0	0	$3.172Q^{-0.357}$	$5.342Q^{-0.337}$
X_4	Nitrification–denitrification 70%	95	70	70	0	$3.447Q^{-0.357}$	$5.342Q^{-0.337}$
X_5	Nitrification–denitrification 70% P removal	95	70	70	100	$3.447Q^{-0.357}$	$5.574Q^{-0.337}$
X_6	Nitrification–denitrification 85% P removal	95	85	85	100	$4.137Q^{-0.357}$	$5.574Q^{-0.337}$
X_7	Advanced	100	95	95	100	$4.413Q^{-0.357}$	$6.604Q^{-0.337}$

Mathematical problem formulation

The starting point for handling Multi-objective Optimization Problems (MOP) is to consider a set of best alternatives or solutions that represent optimal criterion trade-offs. If the scenario involves an arbitrary optimization problem with M objectives, all of which are to be maximized and are equally important, a general multi-objective problem can be formulated as follows:

$$\begin{aligned}
&\text{maximize } f_m(x), \quad m = 1, 2, \ldots, M \\
&\text{subject to: } g_j(x) \geq 0, \quad j = 1, 2, \ldots, J \\
&h_k(x) = 0, \quad k = 1, 2, \ldots, K \\
&x_i^{(L)} \leq x_i \leq x_i^{(U)} \quad i = 1, 2, \ldots, n
\end{aligned}$$

where the solution x is a vector of n decision variables: $x = (x_1, x_2, \ldots, x_n)^T$. The terms $g_j(x)$ and $h_k(x)$ are called constraint functions and $f_m(x)$ is the multi-objective function. J inequality and K equality constraints are associated with the problem. The last subsets of constraints are called variable bounds, which restrict each decision variable x_i to take a value within an interval with a lower $x_i^{(L)}$ and an upper $x_i^{(U)}$ bound. All of these constraints define the decision variable space D, or simply the decision space. In this case, a Pareto-optimal objective vector $f^* = (f_1^*, f_2^*, \ldots, f_M^*)$ is such that there is no feasible solution x' and corresponding objective vector $f' = (f_1', f_2', \ldots, f_M') = (f_1(x'), f_2(x'), \ldots, f_M(x'))$ such that $f_m^* \leq f_m'$ for each $m = 1, 2, \ldots, M$ and $f_j^* < f_j'$ for at least $1 \leq j \leq M$. In our case, the vector x represents the WWTP alternatives, which correspond to each strategy.

We use five objectives to reflect the trade-off between minimizing the total annual cost of the implemented WWTP and maximizing water quality:

$$F = [f_1, f_2, f_3, f_4, f_5] \tag{1}$$

$$\text{Min } f_1 = \sum_{i=1}^{nm} \left[\sum_{j=1}^{\text{NumWWTP}} (\text{ICost}_j + \text{OCost}_j) \right] \tag{2}$$

$$\text{Max } f_k = \text{WaterQuality}_{\text{constituen } k} \tag{3}$$

where k, $2 \leq k \leq 5$: contaminant index, nm: number of months. NumWWTP: number of WWTP, $\text{ICost}_i = f(Q_D, X_T)$: is the investment needed to build a WWTP (monthly cost with a 15-year payback period). This cost is a function of the design flow (Q_D) and the type of treatment technology applied (X_T). See Table 1. $\text{OCost}_i = f(Q_P, X_T)$: is the monthly operating cost. This cost is a function of the amount of water treated in one month (Q_P) and the type of treatment technology applied (X_T). See Table 1. $\text{WaterQuality}_{NH_4}$, $\text{WaterQuality}_{NO_3}$, $\text{WaterQuality}_{PO_4}$ and $\text{WaterQuality}_{TOC}$ are the respective concentrations (mg/l) of ammonia, nitrates, phosphates and TOC in the river water.

Due to the heterogeneity of the rivers, the concentration of the four quality criteria is usually different in each river stretch. To assess the global water quality in a basin, we need to first define a quality metric (see Equation (4)). This quality function has two different approaches, depending on whether it is measuring the achievement of the GES or its failure. Positive values of the metric mean that the WFD objectives are reached every month and for every basin stretch. A negative value means that the WFD objectives are exceeded for at least one stretch and one month. Other metrics are possible and have been analyzed (Boon et al. 1997), but we simply consider it to be a more appropriate reference for the quality limits proposed by the WFD and MOSSES efficient convergence process:

$$f_k = \begin{cases} \dfrac{\sum_{i=1}^{nm} \sum_{j=1}^{ns} (\text{LDM}_{ij}^k - \text{VI}_{ij}^k)/\text{LDM}_{ij}^k}{nm \cdot ns} & \text{if the WFD levels are met for every stretch and month} \\ -\dfrac{\sum_{i=1}^{nmi} \sum_{j=1}^{nsi(i)} (\text{LDM}_{ij}^k - \text{VI}_{ij}^k)/\text{LDM}_{ij}^k}{nm \cdot ns} & \text{otherwise} \end{cases} \tag{4}$$

where k, $2 \leq k \leq 5$: contaminant index, nm: number of months, ns: number of stretches, nml: number of months that do not meet the WFD limits, $nsl(nml)$: number of stretches that do not meet the WFD limits. This number is different for each simulation month, LDM_{ij}: concentration limit of the contaminant 'k' in stretch 'j' and month 'i', allowed by the WFD's goals, VI_{ij}: concentration of the contaminant 'k' in stretch 'j' and month 'i'.

The decision variables in this problem are the 'X_T', which is the treatment technology to be applied in each

WWTP. A discrete value with seven possibilities can be assigned to each decision variable (Table 1). In some cases, according to the physical–chemical characteristics of the stretches, a constraint for the minimum purification treatment must be added. The mathematical formulation of this constraint is the following:

$$X_T > X_{\min} \quad \forall T \quad X_T \in \{1, \ldots, 7\}$$

Solution methodology

Applying the MCDSMWR methodology to a particular catchment involves several steps, as shown in Figure 1.

The first step is to conceptualize the system (water bodies) and to define the global and local management objectives. A detailed description of the state of the water bodies is available for the current situation and there are some estimations for the 2015 forecast situation. The areas described correspond to the Catalan internal watersheds and the main management goal is to determine what will be the trade-off between water quality and cost in order to achieve it.

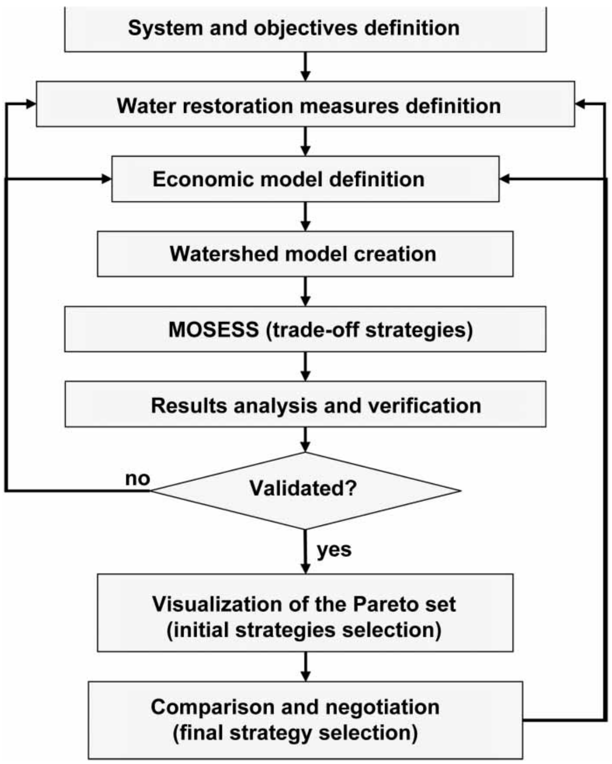

Figure 1 | Flowchart for the Multi-Criteria Decision Support Management in Watershed Restoration Methodology to ensure the achievement of the objectives.

The second step is to define the possible correctional measures for each watershed, which consists in a series of proposals (PoM) including the Catalonia urban and industrial WWTP program. This step includes deciding which is the most appropriate cleaning technology for each WWTP. The features considered by ACA for each plant type are described in Table 1.

The third step is creating economic models to determine the investment (to build a new WWTP) and the operational costs for each plant modality. Both costs depend on the specific technology implemented and the volume of water treated (Table 1). Cost models for the WWTP considered in this study are derived by historical data collected by the ACA over the last ten years. By summing up the individual cost of each WWTP for each simulated period, we are able to estimate the total cost of each PoM (strategy).

The next step is to build the watershed model according to the 'water quality model' paragraph of this paper. All the information related to catchments should be implemented in the Qual2kw model. The user's manual (Brown & Barnwell 1987) provides values and ranges for rates and constants, and some values are also available in Bowie *et al.* (1985). However, Brown & Barnwell (1987) strongly suggest that parameters should be field-measured to reduce uncertainty in the model results. Qual2kw requires an auto-calibration phase that estimates a series of coefficients which are subsequently used to simulate the present state of the river basin. The resulting characterization provides information relating to water resource quantity and quality (Pelletier *et al.* 2006).

The next step involves applying the Multi-Objective System of Efficient Strategy Selection (MOSESS) optimizer, which selects the best cost-efficient PoMs (efficient strategies) set. In many multi-objective optimization problems, knowledge about this set helps the decision-maker to choose the best alternative. The multi-objective simultaneous analysis of the global influence of all the WWTP is one of the main advantages of the proposed methodology over other approaches that perform an individual cost-effectiveness analysis of each WWTP.

Result analysis and verification step

Once the Pareto frontier is delineated it must be analyzed. However, special techniques should be used when there are more than two criteria. This is the reason why Interactive Decision Maps (IDM) have been applied (see Lotov *et al*. 2004) to simultaneously study trade-offs for up to seven criteria. IDM has been used extensively in water management issues (Burmistrova *et al*. 2002; Lotov *et al*. 2005).

MOSESS description

The main component of the MCDSMWR is the Multi-Objective System of Efficient Strategy Selection (MOSESS), which must generate the set of Pareto-optimal strategies, that is, the efficient combinations of WWTP. This algorithm is especially suitable for problems with more than two objectives and it has shown good overall performance when the fitness function evaluation has high computational requirements (Udías *et al*. 2009). A C# code was developed that links together the system's different components, as shown in Figure 2.

The MOSESS developed to optimize (select) WWTP trade-off strategies, applies binary gray encoding (Goldberg 1989) for each chromosome (optimization string). The length of each optimization string corresponds to a total number of genes, one for each facility. Each gene uses three bits to encode the seven sewage treatment levels for each plant. After decoding the chromosome, in treatment levels for each WWTP, the water quality in each reach is forecast by the WQM. The fitness value for the four quality criteria is assessed by Equation (4) and the cost criteria by Equation (2).

The initial population is generated randomly if no previous basin management information is available or, when available, this information is used to generate the initial solutions. Furthermore, each solution is evaluated according to all the decision-making criteria. At this point, the MOEA selects the solutions that are Pareto-dominant from the main population and stores them in the Pareto-front population. It also removes the solutions that are dominated by Pareto-front solutions. This process is repeated until a convergence criterion is obtained (Figure 2).

The MOSESS algorithm applies the usual procedures of selection, crossover and mutation to generate the new population. The MOSESS algorithm also introduces elitism by maintaining an external population. In each generation, the new solutions belonging to the internal population are copied to the external population when they are not Pareto-dominated by any solution for this external population. If solutions for the external population are

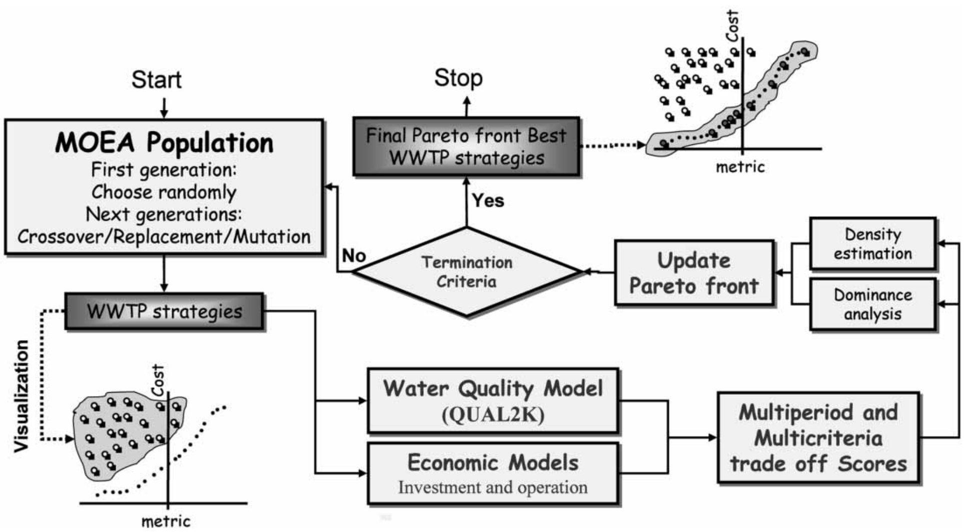

Figure 2 | Schematic layout of the MOSESS optimization procedure.

dominated by some of the new solutions, these solutions are deleted from the external population. The external elitist population is simultaneously maintained in order to preserve the best solutions found so far and to incorporate part of the information in the main population by means of the crossover. Elitism is also included in this recombination process, selecting each of the parents through a fight (tournament), between two randomly selected chromosomes from the external Pareto set (according to a density criterion) or from the population set (according to their ranking determined through a dominance criterion).

Water quality model description

Water Quality Models (WQM) seek to describe the spatial and temporal evolution of the contaminants and constituents characterizing a river flow. Many highly reliable simulation models are available today to evaluate the behavior of physical systems such as water bodies, with reasonable computational requirements (Rauch *et al.* 1998; Shanahan *et al.* 1998). We chose Qual2kw (Pelletier & Chapra 2004) as the WQM for this application because it treats all the processes to be simulated in order to assess the ACA objectives and it is a source-available code that it is easily applicable to this type of management integration. It also links with the other tools that integrate into the methodology. Qual2kw is a modernized version of the Qual2e (Brown & Barnwell 1987) model; it is a one-dimensional steady state model.

Even though the presented methodology has been applied to all Catalan internal watersheds, most of the results presented in this paper correspond to its application in the Muga Basin which was the catchment chosen by ACA to test the MCDSMWR methodology. The Muga Basin lies within the Autonomous Community of Catalonia, Spain and it flows towards the Mediterranean Sea. Muga River begins in the Pyrenees Orientals approximately 1,200 m above sea level the main channel has a length of 64.7 km; it drains a watershed of 759 km^2 (2.3% of the total area of Catalonia); it receives an annual average of 177 Hm^3 and its runoff coefficient is 0.285. Muga River has its headwaters located in mountainous areas, whereas the middle and lower parts of the watershed are subject to the Mediterranean climate, implying higher hydrological variability in these last sections.

Catalonia has a typical Mediterranean climate with dry and warm summers, mild winters and an average precipitation of 612 Hm^3 (807 mm/yr). The yearly mean daily flow of the Muga main stream outlet is 4.65 m^3/s. The base flow values from daily streamflow measures in five stations of the catchment from 2003 to 2006 were obtained from the Catalan Water Agency (available at http://www.gencat.cat/aca). Flow rate is regulated with a larger reservoir (61 million m^3) for drinking and agricultural use (ACA 2009). More details about the characteristics of the river flow can be found in Munné & Prat (2004) and Boix *et al.* (2010).

The main inputs of the WQ model are: the head water in all tributaries, point sources (urban, industrial, WWTP, etc.), water extractions and diffuse sources of pollution. The inflows for the proposed WWTPs are the urban and industrials effluents; based on information from urban and industrial discharges in the last ten years, the evolution of them has been estimated from the relation with the evolution of the population in each city and the evolution in the industrial production. The studied area includes 34 municipalities with a population of 65,756 inhabitants. Diffuse pollutants were also considered as input of the WQ model. Non-point-source pollution from agriculture constitutes a considerable contribution to the Muga river pollution. In setting up the WQ model, information about these sources was obtained through direct interview with local municipal officers (Boix *et al.* 2010).

In order to apply the Qual2kw model to a river network, the river system must be divided by river elements, which have roughly uniform hydraulic characteristics. In each cell, the model computes the major interactions between up to 16 state variables and their value for steady state and dynamic conditions. The Muga river main channel, with its 12 tributaries, has 227 km, which were divided into 54 elements with an approximate length of 5 km for these simulations (this simulation does not include catchments, spillage or reservoirs).

Twelve Qual2kw models must be built for each catchment, one for each month of the year. They all have the same geographical characteristics (geographical longitude and latitude, time zone, elevation), but each one has different meteorological characteristics (air temperature, dew point temperature, wind speed, cloud cover, shade), as well as physical–chemical and biological parameters for waste and hydraulics (morphological elements, Manning roughness coefficient, flow curve, flow).

Before applying the WQM, we need to adjust the model parameters to represent appropriately the actual behavior of the basin. Qual2kw includes a general purpose function optimization subroutine based on a genetic algorithm, PIKAIA (Charbonneau & Knapp 1995). This algorithm could automatically calibrate more than 120 parameters of the catchment. However, when a model has a large number of parameters, excessive computing time will be needed. To address this problem, before starting the model calibration processes, we perform a standard one at a time design on the 120 parameters of the catchment, which vary by one factor from the standard conditions (Daniel 1973). This is done in order to determine which parameters impose the most significant effect on model performance and therefore only include them in the calibration process. The result was to select 20 parameters that appear to be the most sensitive to the Muga models.

Monthly models were calibrated separately using the monthly data set observed from years 2003 to 2005 at three water quality control stations (Boadella D'empordà, Castelló D'empúries and Peralada). Measures of eight water quality parameters are available at each station: dissolved oxygen, suspended solids, biochemical oxygen demand, chemical oxygen demand, ammonium, nitrogen and total phosphorus. Point source pollutant loads in stream flow were prepared based on data conditions in 2006.

The validation period is based on data conditions in 2006. The 2006 simulation results for the WQM show good matches with the observed concentration in the Boadella D'empordà and Peralada stations, which are not shown here. However, for the third water quality control station, Castelló D'empúries station, the validation period results for the ammonia concentration did not show such a good matching, see Figure 3. The reason for these inferior results is that this station is very close to Figueres, the most significant pollution source in the Muga Basin, showing large differences from minimum to maximum observed values in most of the months for the calibration period. In any case the discrepancies obtained are not considered to be important for verifying the open decision methodology. The Nash–Sutcliffe model efficiency index (E_f) is used to assess the predictive power of hydrological models (Nash & Sutcliffe 1970). Figure 3 also shows a value of 0.45 for the Nash–Sutcliffe model efficiency index (E_f) value to assess calibration results obtained for the 12 monthly Muga models.

Result analysis step description

Special techniques should be used when the Pareto frontier are more than two criteria. Figure 4 shows an IDM example that visualizes the Edgewort–Pareto Hull (EPH), $H(Y)$, for three criteria, i.e. the trade-off between the cost and the ammonia and phosphate contaminants for the Llobregat watershed, by means of IDM. The contaminant criteria are assigned to the axes of the map, whereas the cost criterion is assigned to the grey scale in Figure 4. The values for the

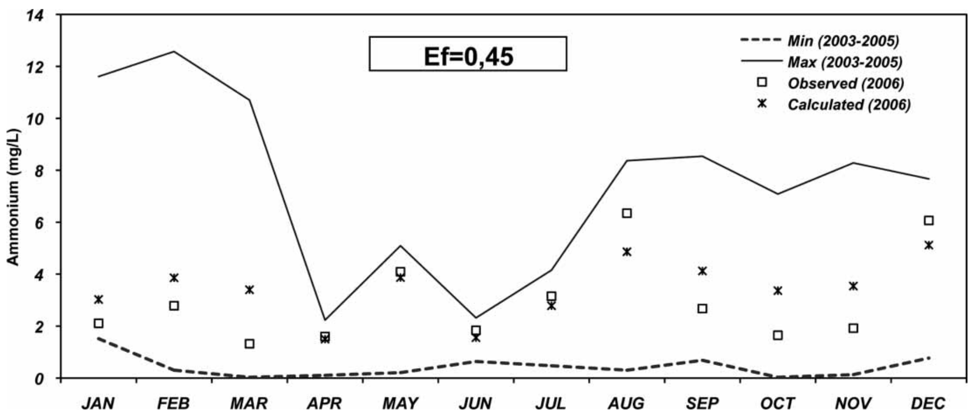

Figure 3 | Validation results for the ammonia concentration in Castelló D'empúries station, monthly averages observed data from year 2003 to 2006. E_f is the Nash–Sutcliffe efficiency statistical measure indicators for the calibration efficiency.

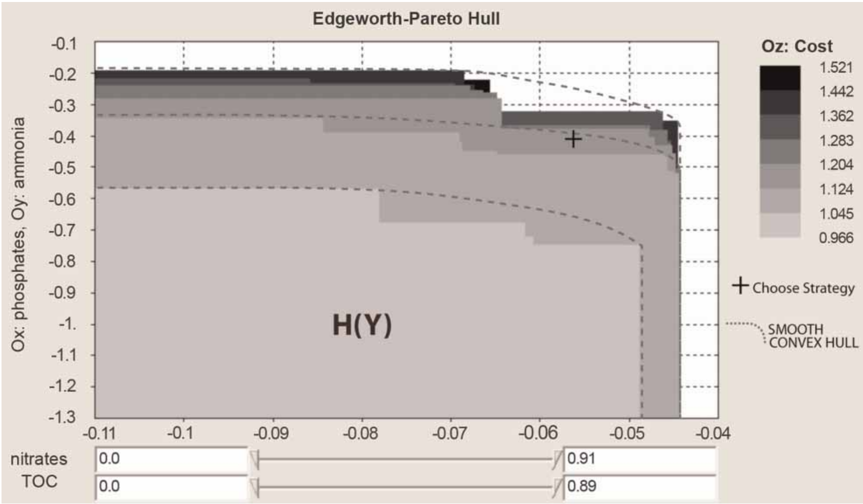

Figure 4 | IDM tool application: Visualization of the EPH decision map with the corresponding smoothed convex hull (+ chosen strategy).

rest of the quality criteria, nitrates and TOC, are set to their highest feasible values.

Another interesting concept involves constructing slices of $H(Y)$ in the plane of the criteria axis for the third criterion values corresponding to the endpoints of the intervals. We then superimpose these slices on a single screen with each slice being a specific color; the legend on the right of Figure 4 matches the color of each slide to the interval's end point that this slice was computed for. Note that a slice corresponding to a worse value for this criterion encloses the slice corresponding to a better value. This guarantees that non-dominated frontiers for these slices never intersect, even though they might touch one another.

In some cases, it may be useful to omit some data that are irrelevant to the decision-making information, namely the precise shape of the trade-off curves between the two quality criteria: ammonia and phosphates, whereby considering a decision map with 'smoothed' trade-off curves, see Figure 4. Technically, this is achieved by approximating the convex hull of $H(Y)$, see Lotov *et al*. (2004). The loss of 'noisy' information on the trade-off curves helps the decision-maker to concentrate on the essential interdependences between the different criteria.

The number of efficient strategies provided by the MOSESS when five criteria (cost, ammonia, nitrate, phosphate and TOC) are simultaneously under consideration is quite high (several hundred). By using the IDM, however, this difficult simultaneous trade-off shape analysis and comparison is quite simple for each month and catchment. The stakeholders performed a preliminary strategy selection, with the IDM visualization tools and then translated it into the 2D representation explained below.

In the 2D diagram (Figures 5 and 6), the ordinate axis represents the cost of the strategies and the abscissa axis represents the water quality for each indicator according to Equation (4). The $X = 0\%$ is exactly the WFD objective. The points falling on the left side of the graphs are strategies that do not satisfy WFD goals and the points on the right

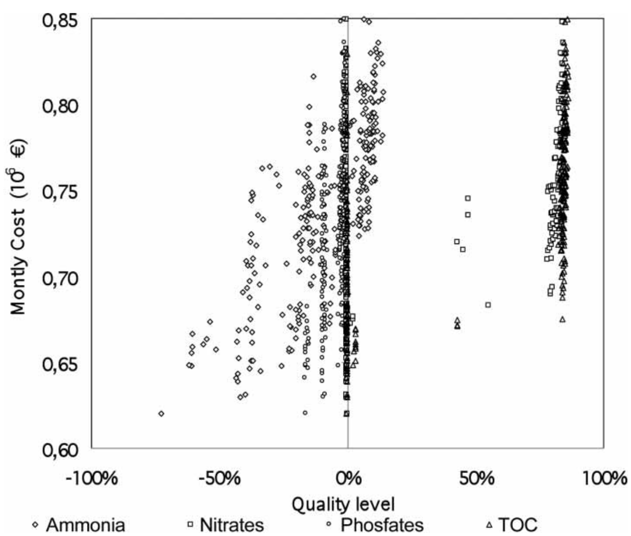

Figure 5 | Example of 2D visualization of all the Muga catchment Pareto-front strategies considering five quality criteria (cost, ammonia, nitrates, phosphates and TOC).

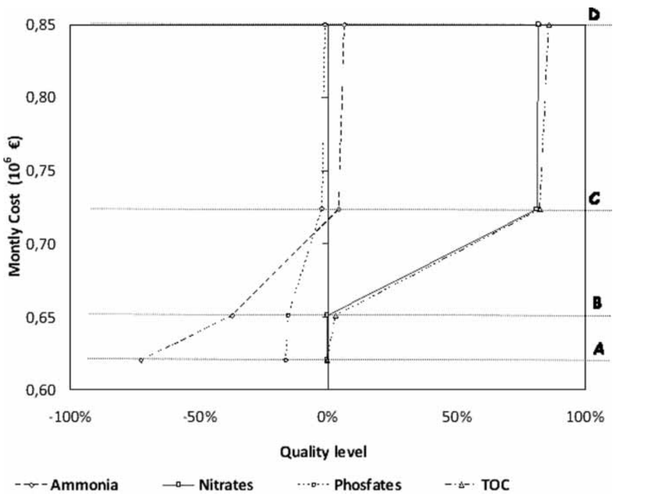

Figure 6 | Example of 2D visualization for four selected multi-criteria strategies ordered from more economical to most expensive cost: A, B, C and D. Strategy A does not fulfill any criteria; B only verifies TOC and C meets all indicators except phosphates. The D strategy, despite being more expensive, does not satisfy the phosphate objective either. In this example, it is clear that it is not worth investing in such a costly strategy as D would be, and the most reasonable strategy would be C.

side of the graphs do meet them. A positive value indicates good quality in the defined objective. Four points on the same horizontal line (one point for each water quality criteria, see Figure 6) correspond to the same strategy or combination of measures whose cost is the value in the ordinate axes. Figure 6 shows an example of the visualization of the trade-off between costs and the GES level reached by four different strategies (A, B, C and D). Each curve represents a different water quality criterion.

This 2D representation of some strategies that were previously selected through the IDM enables all the decision-makers to easily compare the effect of the different strategies. They can also discover the cost of improving each water quality criterion, as well as estimating the effects of applying purification strategies in each basin and finding out the minimum cost to achieve GES. Furthermore, this 2D representation shows whether it is possible to achieve the GES and it enables us to compare the quality levels obtained for the different contaminants, etc.

The MCDSMWR methodology is an iterative process; after the hydroinformatics tool is run the first few times, some of the correctional measures that were initially proposed usually need to be redefined. The addition of new information and/or the detection of incoherencies would also mean that part of the model would have to be modified. For example, the effluent of small towns that was not included in the initial PoM or additional water reuse facilities.

RESULTS AND DISCUSSION

Although further study regarding the analysis of scenarios should be carried out, in this work we considered that, in the 2015 scenario, only effluents (industrial and urban) changed from the 2006 scenario. From the last ten years' data about the population variations and the evolution of industrial production we forecast the values for 2015 of urban and industrial discharges. Such variations are very small in most of the Catalan catchments. Even in the Besos and Llobregat Catchments (that include the Barcelona metropolitan and industrial areas) the differences with respect to the values for 2006 are always lower than 5%. In these conditions, the calibration model (for 2006) would continue to be valid for the 2015 scenario.

For the Muga Basin optimization problem presented, ACA considers 41 WWTP locations, each with seven sewage treatment levels. Each gene uses three bits to encode these seven possible alternatives for the decision variables. Therefore, in the Muga watershed, the number of genes is 41 with a chromosome length of $41 \times 3 = 123$ bits. Thus, the number of possible strategies is $7^{41} = 4.4 \times 10^{34}$, and the goal is to find out which is the most efficient one of them, according to all the criteria.

MOSESS convergence analysis

In applying the methodology proposed, good performance of the optimization algorithm is essential, because it should find the Pareto set of strategies with minimum WQM evaluations, as each model run requires considerable computation time.

Given the fact that the optimal Pareto front in this problem is unknown, in order to compare the performance of our MOEA under different parameter settings, the 'best' non-dominated front is based on a global best front attained from all completed experiments.

In multi-objective problems, it is not as easy to compare how MOEAs perform when they converge as it is with mono-objective problems. The quality of the approximation of the Pareto front can be valued by various measures (or metrics). Among these metrics, the *S* metric or hypervolume proposed by Zitzler and Thiele has good properties concerning the outperformance relations that transfer the partial order among vectors to sets of vectors (Zitzler *et al*. 2003). The *S* metric evaluates a set of non-dominated solutions in the objective space by the hypervolume that is dominated by the set. This dominated hypervolume is given by the size of the region of the objective space (bounded by a reference point) which contains solutions which are weakly dominated by at least one of the members of the set. Tables 2–4 compare this performance in different cases by quantifying the ratio between the hypervolume of each Pareto front with the previously mentioned 'best' non-dominated front (a performance value of 1,000 is a Pareto front with the same hypervolume as the 'best' Pareto front). The 'best' non-dominated front is based on a global best front attained from all experiments after they are completed.

This scenario analyzed the effect of different population sizes, crossover rates and mutation rates on the convergence of the MOEA. The convergence of the solution is measured in terms of the number of evaluations required for *S*-metric values higher than 0.95 (for two objective executions) that was considered to be close enough to the optimal solution for this decision problem. The MOEA program is run at

Table 2 | MOEA convergence (hypervolume mean and standard deviation of five executions) for different numbers of criteria and evaluations. Two criteria: cost–ammonia. Three criteria: cost–ammonia–nitrates. Four criteria: cost–ammonia–nitrates–phosphates. Five criteria: cost–ammonia–nitrates–phosphates–TOC. January 2015 Muga catchment scenario

	Evaluations							
No. criteria	**200**	**500**	**1,000**	**2,000**	**3,000**	**4,500**	**6,000**	**10,000**
2	0.616	0.679	0.798	0.853	0.881	0.906	0.932	0.956
	0.060	0.078	0.052	0.049	0.063	0.064	0.068	0.037
3	0.611	0.651	0.668	0.749	0.770	0.876	0.835	0.842
	0.024	0.033	0.038	0.004	0.005	0.029	0.033	0.029
4	0.530	0.581	0.633	0.645	0.669	0.704	0.730	0.755
	0.042	0.047	0.033	0.030	0.039	0.003	0.020	0.028
5	0.519	0.552	0.589	0.647	0.648	0.671	0.678	0.710
	0.054	0.035	0.011	0.004	0.021	0.028	0.033	0.041

Table 3 | MOEA elitism influence (hypervolume mean and standard deviation of five executions) for different configuration. (a) Two parents selected from the internal population. (b) One parent from the internal population and the other from the external. (c) Two parents selected from the external population. (d) 25% probability of (a), 50% probability of (b) and 25% probability of (c). January 2015 Muga catchment scenario

	Evaluations							
Elitism modality	**200**	**500**	**1,000**	**2,000**	**3,000**	**4,500**	**6,000**	**10,000**
a	0.591	0.622	0.650	0.668	0.683	0.761	0.818	0.824
	0.029	0.032	0.027	0.015	0.015	0.077	0.058	0.038
b	0.544	0.610	0.656	0.715	0.900	0.950	0.969	0.997
	0.065	0.087	0.096	0.134	0.024	0.025	0.038	0.030
c	0.553	0.657	0.808	0.858	0.891	0.885	0.939	0.983
	0.071	0.106	0.027	0.018	0.034	0.054	0.058	0.049
d	0.537	0.657	0.811	0.865	0.915	0.957	0.977	0.998
	0.062	0.080	0.043	0.046	0.054	0.054	0.046	0.008

Table 4 | Comparison of the MOEA convergence efficiency for two different catchments with different number of evaluation. January 2015 scenario

Catchment		Evaluations 200	500	1,000	2,000	3,000	4,500	6,000	10,000
Muga (41 WWTP)	Mean	0.506	0.544	0.871	0.930	0.981	0.990	0.999	0.999
	St	0.060	0.078	0.052	0.049	0.063	0.064	0.068	0.037
Llobregat (217 WWTP)	Mean	0.368	0.446	0.493	0.645	0.717	0.911	0.998	0.999
	St	0.030	0.029	0.041	0.044	0.053	0.050	0.045	0.032

least five times for each combination of the crossover rate, mutation rate and population size. The results show that the best efficiency of the algorithm to approach the optimum is achieved with a small population size (five chromosomes per generation), small mutation rates (less than 5%) and a variable multi-point crossover operator, where the number of crossover points applied at each chromosome is a value close to 10 (for a chromosome length of 123 bits).

Table 2 compares the influence of the number of criteria when they are considered simultaneously. The criteria are added according to their degree of difficulty: from most (ammonium) to least (TOC). An increase in the number of criteria required more evaluations to achieve convergence. Table 3 shows the importance of elitism in the convergence process.

Table 4 compares results for the Muga scenario (41 WWTP) and the Llobregat scenario (217 WWTP). Observe that a significant increase in the size of the optimization problem only produces a slight increase in the number of evaluations required for the MOSESS to reach convergence. The genetic algorithms have proven to be more efficient and powerful when the problem size increases. In addition to making a good choice of fitness function, the other parameters of a GA (population size, mutation, crossover rate, etc.) play a very important role in GA performance. Also, a proper sewage treatment level codification, ordering cost and purification intensity from lowest to highest (see Table 1) has an effect on the computational efficiency.

Figure 7 shows the best MOSESS solution for 500 evaluations finds that the cheapest strategy that satisfactorily achieves the WFD ammonia objective costs approximately €386,000. After 6,000 evaluations, however, the same objective is achieved with a cost of €365,000, i.e. a saving of approximately 5.5%.

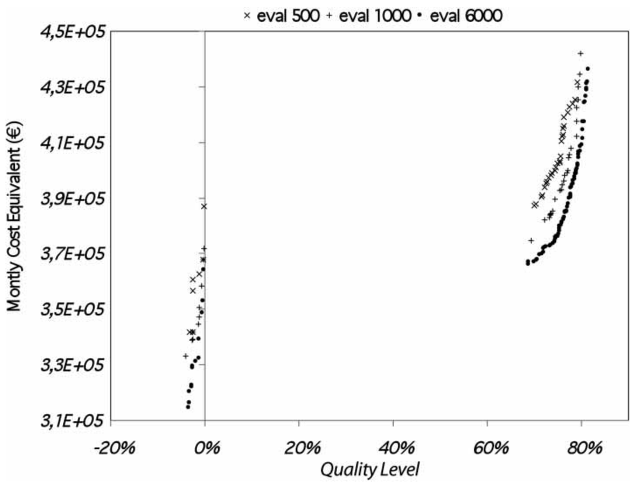

Figure 7 | Pareto fronts considering two objectives (monthly cost and ammonia quality levels) for different number of WQM evaluations (500, 1,000 and 6,000) for the January 2015 Muga scenario.

In order for the MOSESS to be applicable, the computational time required must remain within reasonable limits. This could be especially difficult in some catchments, considering that each monthly WQM execution can take more than 150 s (for the Llobregat catchment) and decisions must be taken based on the annual performance of the sewage treatment, i.e. simultaneously considering the 12 monthly models.

Starting the MOSESS search process with a set of good quality strategies, rather than applying randomly generated strategies, allows us to significantly reduce the number of WQM evaluations required to achieve the global (annual) Pareto set. The initial quality strategies for the annual optimization process are the final Pareto achieved through the execution of the MOSESS algorithm for a single monthly model. For the annual Muga scenario (12 months), Figure 8 shows slightly better convergence and distribution of the

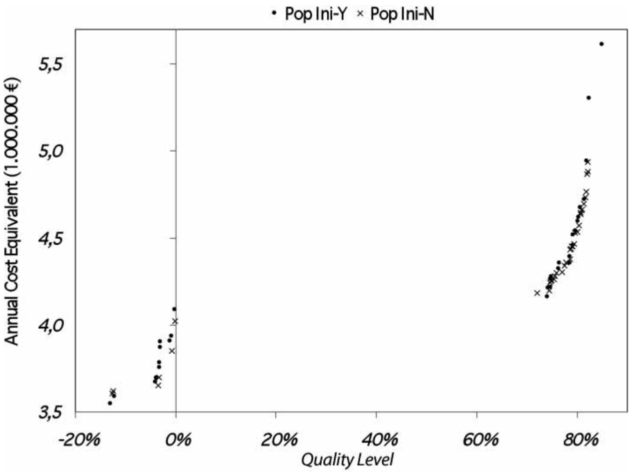

Figure 8 | Pareto fronts with two criteria (cost and ammonia) starting the MOEA with random initial population (Pop Ini-N) or with selected initial population (Pop Ini-Y) for the 2015 Muga scenario.

Pareto front when starting the search process with a select initial population. The front labeled as 'Pop Ini-N' required 48,000 monthly WQM runs (20 chromosomes for 200 generations over 12 months). The 'Pop Ini-Y' labeled front is the result of 8200 monthly WQM runs (first 20 chromosomes for 200 generations one monthly model and restart the search process with 7 chromosomes for 50 generations for 12 months).

Whenever we perform a second MOSESS run after a data change or parameter modification, based on previous initial solutions, we achieve significant computational time savings. The same trick can also reduce the computational time when we consider five criteria simultaneously, starting with a previous run that only considers two of these criteria.

Advantages of the MCDSMWR application

In a reasonably small number of WQM executions, MOSESS provides hundreds of cost-effective PoMs, which delimit the non-dominated Pareto frontier of each basin. The information on the Pareto frontier displayed by the IDM technique (Figure 4) simplifies the decision-maker's task. Each stakeholder easily identifies their region of interest on a decision map (according to their preferences).

Exploration of the Pareto frontier by means of the IDM map or 2D visualization (Figure 6) helps to understand the criterion trade-offs and to identify a preferred criterion point directly at the Pareto frontier (even with a monthly or yearly display). Furthermore, the slope of these criteria quality curves (or the Pareto-front curves) for each cost level indicates the water quality sensitivity to the water treatment actions. It shows the cost increase required to achieve a unitary water quality improvement for each strategy.

We also apply the IDM (Figure 4) to obtain neighboring strategies to one goal point in the map and compare the purification technology spatial distribution for all WWTP. In Figure 4, the goal point designated by the black cross seems to be reasonable enough from the point of view of the trade-off between the pivotal criteria: phosphates and ammonium. The alternatives located near the goal (Figure 4) are listed in Table 5. These alternatives are either subject to more careful analysis or can be filtered by another technique, possibly through 'eye filtering'. Whatever the case, IDM helps to discard most of the alternatives and to select several that do not differ much on criteria values with respect to the goal.

For one selected strategy and pollutant indicator, it is also useful to use geographical information systems (GIS) to display, or summarize, the information that is automatically generated by the developed hydroinformatics tool. Figure 9 displays the annual quality level reached for ammonia with the minimum treatment strategy for the Muga catchment and the final optimal treatment strategy selected in each WWTP location. We noted that the ammonia quality problems are restricted to reach number 50 with the selected strategy.

Table 6 compares the cost of three different strategies for the Muga and Llobregat catchments: the minimum and

Table 5 | Characteristics of the neighborhoods strategies of the chosen strategy obtained using IDM tool (Figure 4)

Your aspiration	Cost 1.2	Ammonia −0.305	Nitrates 0.9	Phosphates −0.06	TOC 0.88
Nearest points					
P1	1.1628	−0.5271	0.8999	−0.0582	0.8768
P2	1.1967	−0.2816	0.9066	−0.0642	0.8857
P3	1.2001	−0.4028	0.9032	−0.0469	0.8766
P4	1.2213	−0.5049	0.8937	−0.0581	0.8781
P5	1.3303	−0.3666	0.9021	−0.0472	0.8789
P6	1.3766	−0.3510	0.9057	−0.0443	0.8790

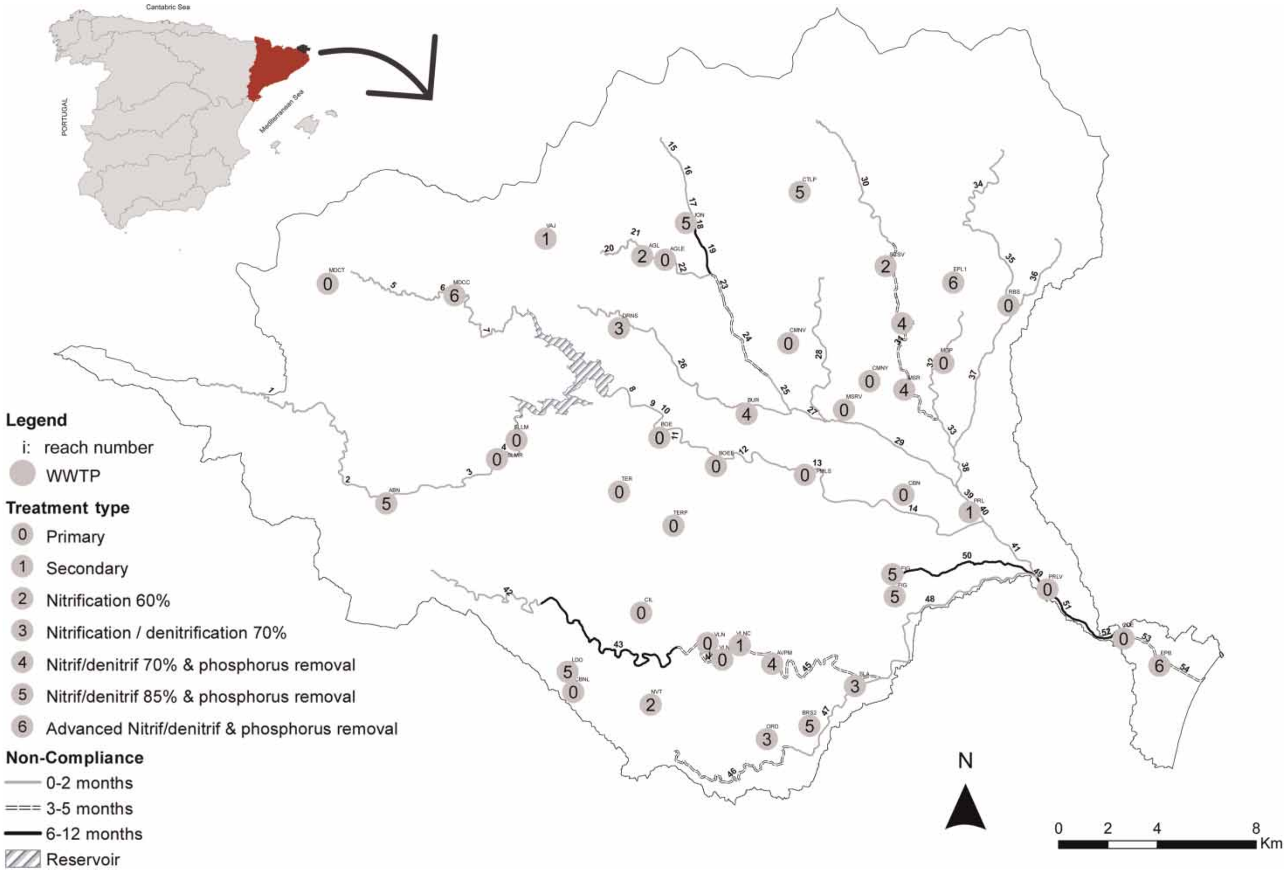

Figure 9 | Ammonium annual reach quality level map for the Muga basin for the minimum WWTP strategies and sewage treatment technology applied in each WWTP location for the final selected strategy. For the optimal strategy there only remains quality problems in reach number 50.

Table 6 | Minimal, optimal and maximal strategy cost (thousand €) for different catchments

	Cost	Strategy Min	Opt	Max
Muga	Investment	1,368	1,800	2,445
	Operation	845	1,181	2,054
Llobregat	Investment	8,857	11,023	14,586
	Operation	4,692	6,792	11,817

maximum purification technology and the optimum strategy that was finally chosen for application. We can see that the cost for the selected strategy is significantly lower than the highest one with similar quality results.

For a single criterion, it is easier to simultaneously compare strategy results for all the months and stretches through a box plot (see Figure 10). In this case, Figure 10 shows the statistical ammonium quality distribution for three different strategies. We can see the reduction in the level of contamination in stretches and months for each sewage treatment strategy.

CONCLUSIONS

This paper puts forward a new multi-criteria decision support system of water resources to find the trade-off solution for conflicting objectives in the context of the implementation of the WFD in Catalonia. In particular, an integrative Multi-Criteria Decision Support Management in Watershed Restoration methodology has been proposed to select the most efficient PoMs to reduce the pressures and associated impacts in order to achieve the WFD's objectives. Based on this methodology, a new hydroinformatics

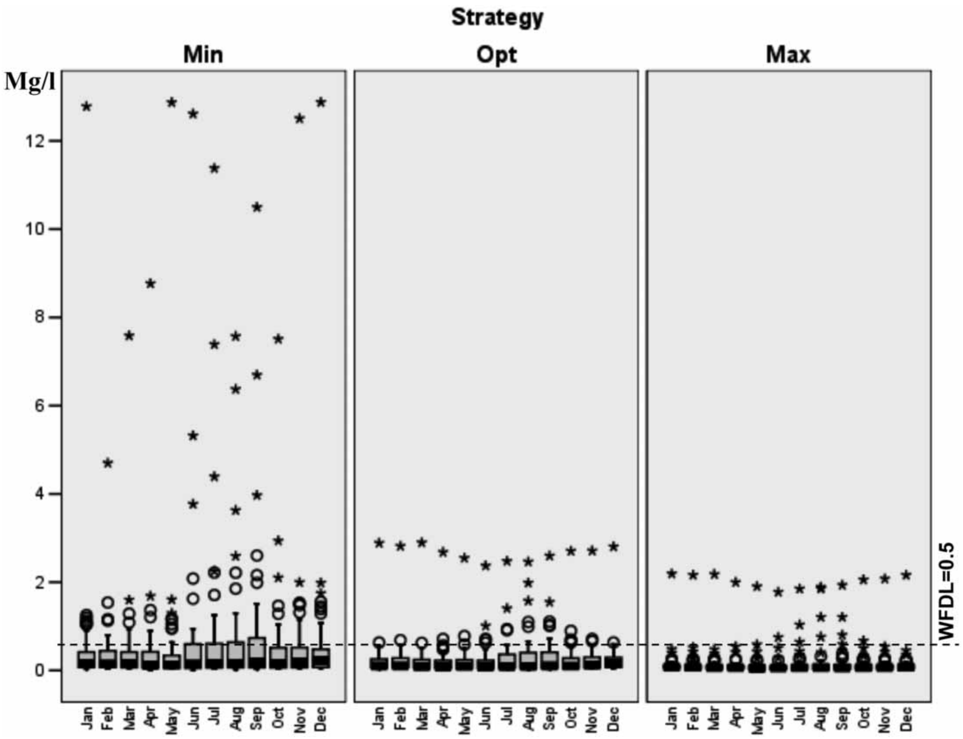

Figure 10 | Box plot example for the levels of ammonia in the stretches, depending on the month and the applied purification treatment (Min, Opt, Max) (Ter basin). Circles represent outliers further than 1.5 box lengths of 25th or 75th percentiles. The symbol (*) represents an extreme case, separated by more than three box lengths from the 75th percentile. 2015 Llobregat catchment scenario.

tool (MCDSMWR) was developed to assist in water quality management at the catchment scale.

The MCDSMWR tool presented in this paper is an effective combination of a WQM, which estimates monthly runoff and pollutant loads in the catchments, with the MOSESS algorithm, whose main component is a multicriteria genetic algorithm that is especially designed and configured to find the Pareto-optimal set of PoM (strategies). Qual2kw is the WQM used to predict the hydrologic behavior in large catchments with respect to contaminant loads by modeling the movement of various pollutants around the catchment. A range of inputs is used in the water quality simulations, including topography, climate and anthropic pressures predicted for 2015, the year in which the Water Framework Directive's objectives take effect. The MCDSMWR, complemented with the IDM for alternative selection and other user-friendly analysis tools, constitute the main core of the proposed approach.

In this paper, a case study has been carried out taking wastewater systems into account, which translates into seven different cleaning technology alternatives, which were also modeled in terms of both cost and treatment for each pollutant. Therefore, in addition to the cost criteria (operating and investment cost), four quality criteria were considered simultaneously: ammonium, nitrate, phosphate and TOC. The nonlinearity of the WQM, the integer character of the decision variables (WWTP) and the five criteria simultaneously considered, makes MOEA methods more efficient than conventional optimization methods in identifying trade-offs among multiple objectives. A major difficulty in applying the MOEA methods lies in identifying appropriate parameter settings to ensure that the decision space of the problem is effectively explored and the entire trade-off curve is identified. In this paper, we have shown information about the GA design and the best parameter values to overcome these difficulties in a practical case.

The developed methodology has been shown to be an important resource in evaluating the effectiveness of the actions that are being taken to improve water quality and to provide decision-makers with the opportunity to explore the multi-objective nature of problems, to discover trade-offs among objectives, and to make decisions given alternative solutions and to achieve PoM management outcomes for the future. The main factors intended to guarantee the system implementation success have been early end-users' involvement, development of several evolutionary prototypes, designing a specific user-friendly interface adopted for multicriteria applications and a variety of implemented models and decision support tools.

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