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Framework for Multi-Criteria Decision Management in Watershed Restoration

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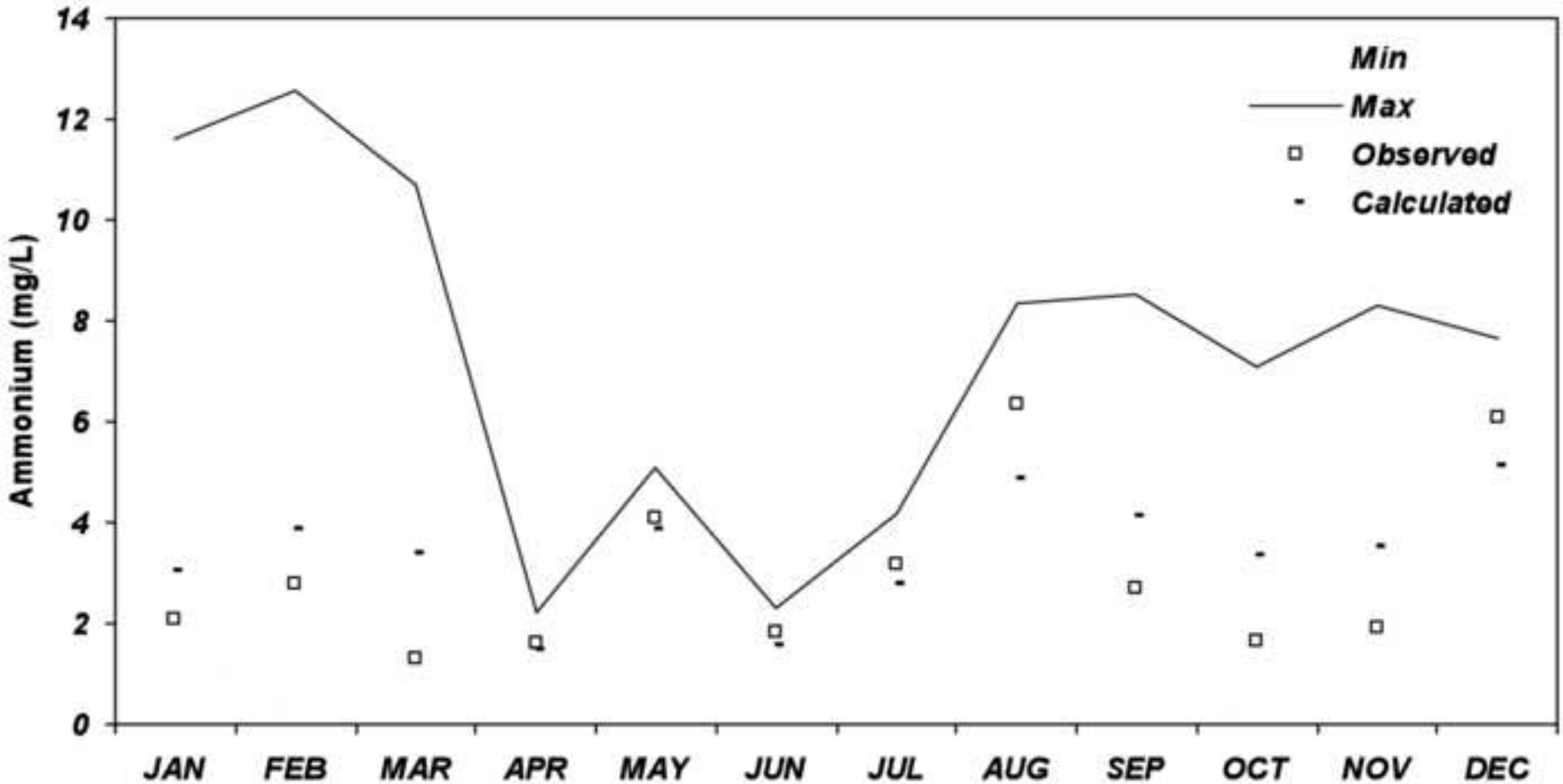

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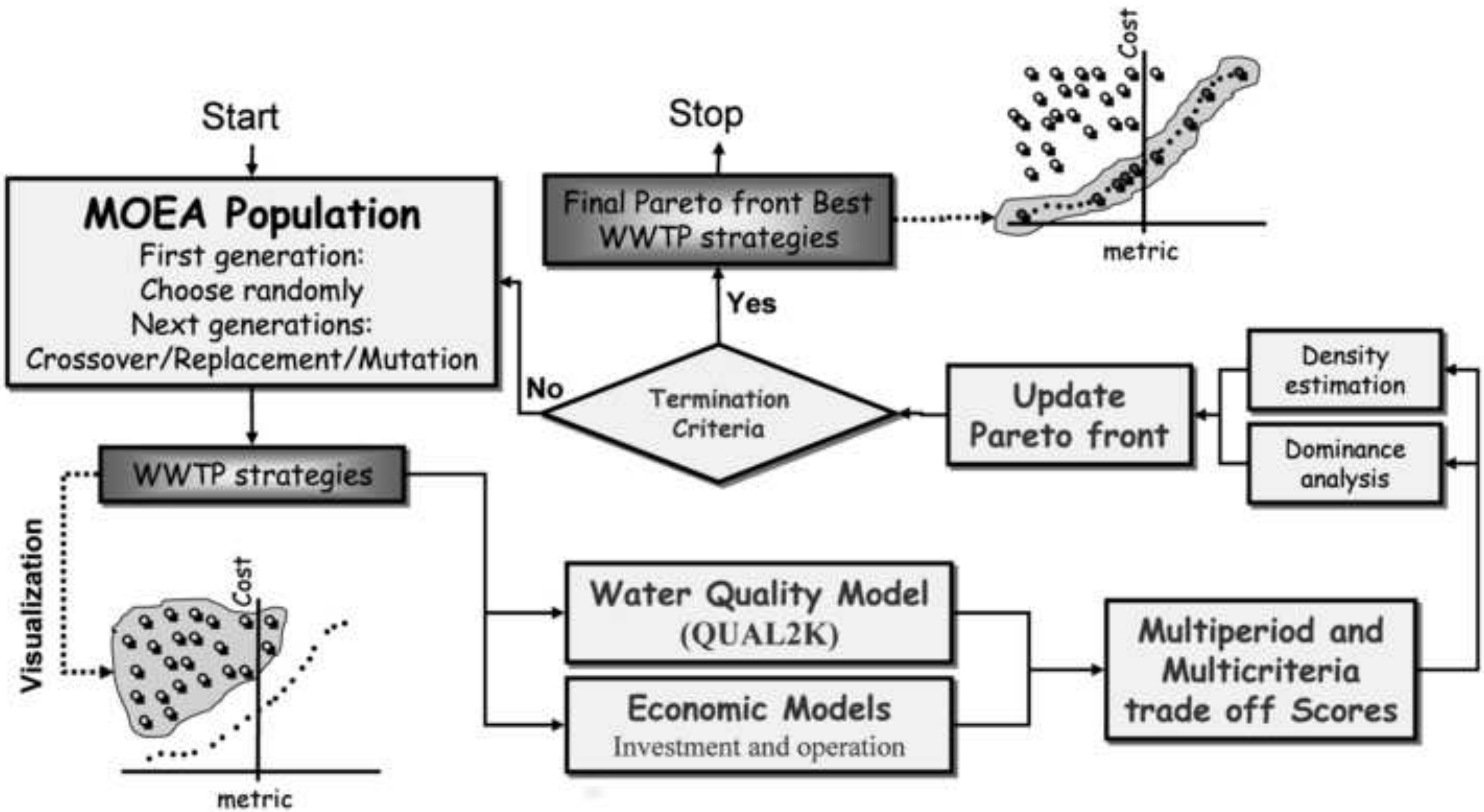

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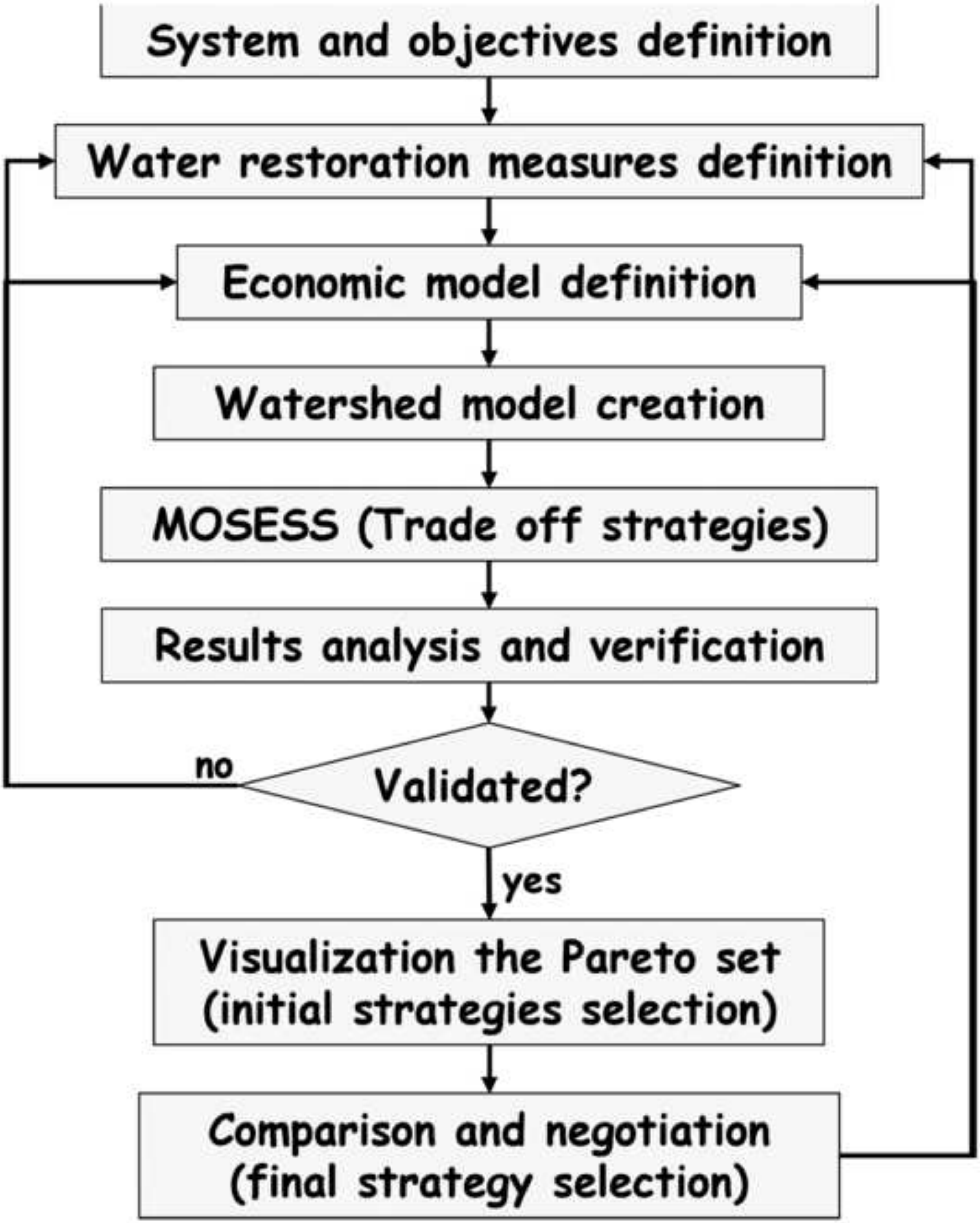

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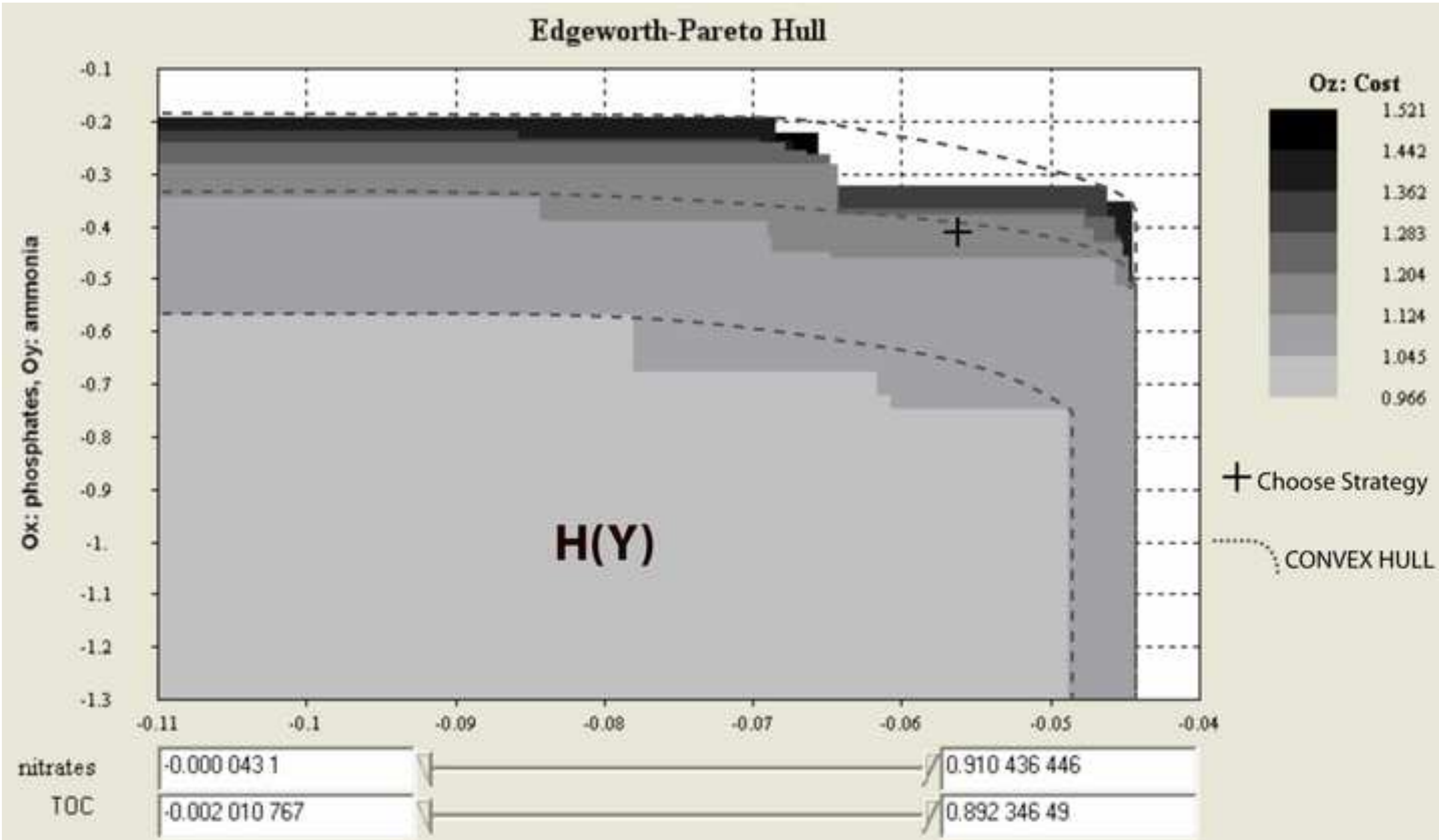

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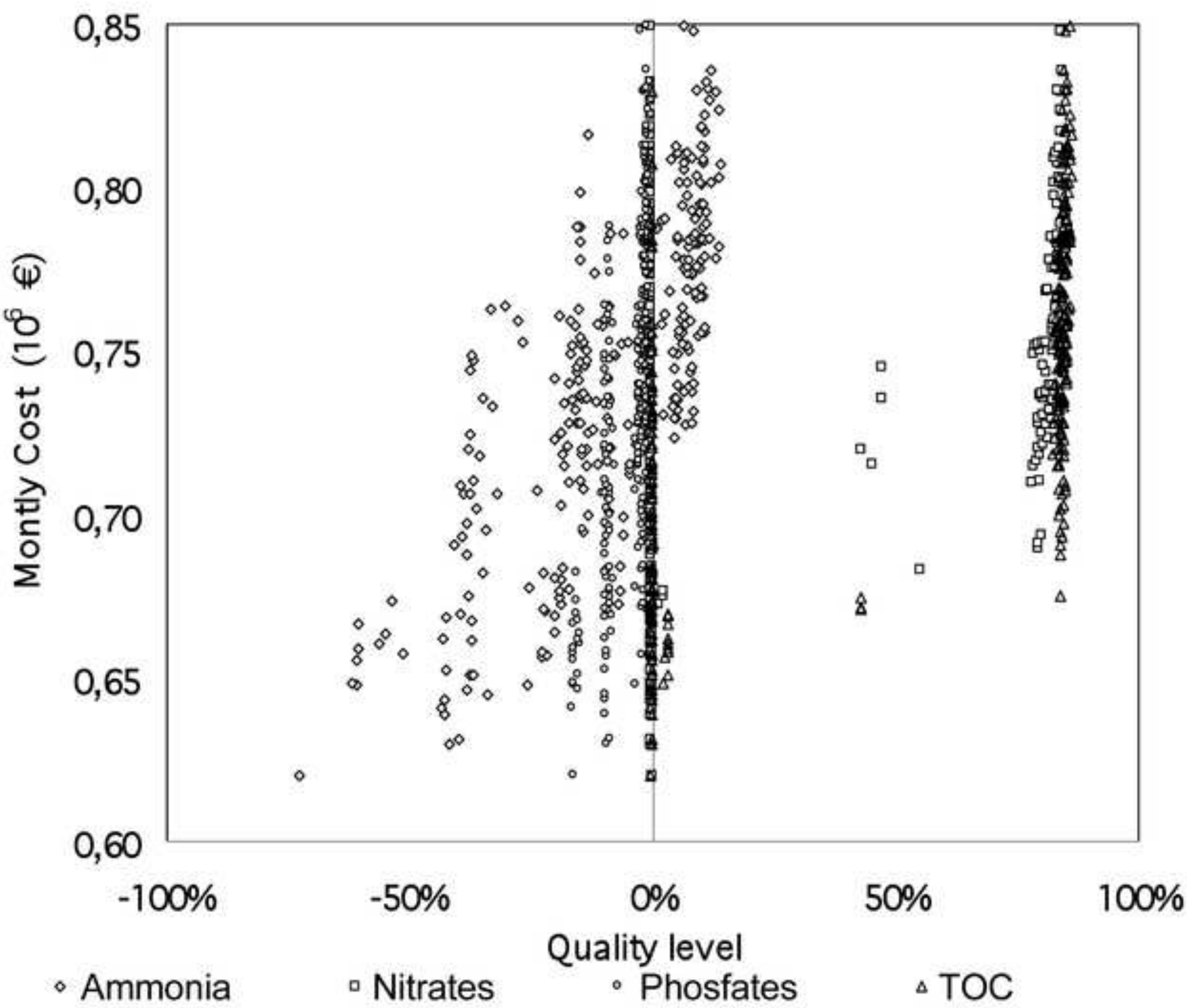

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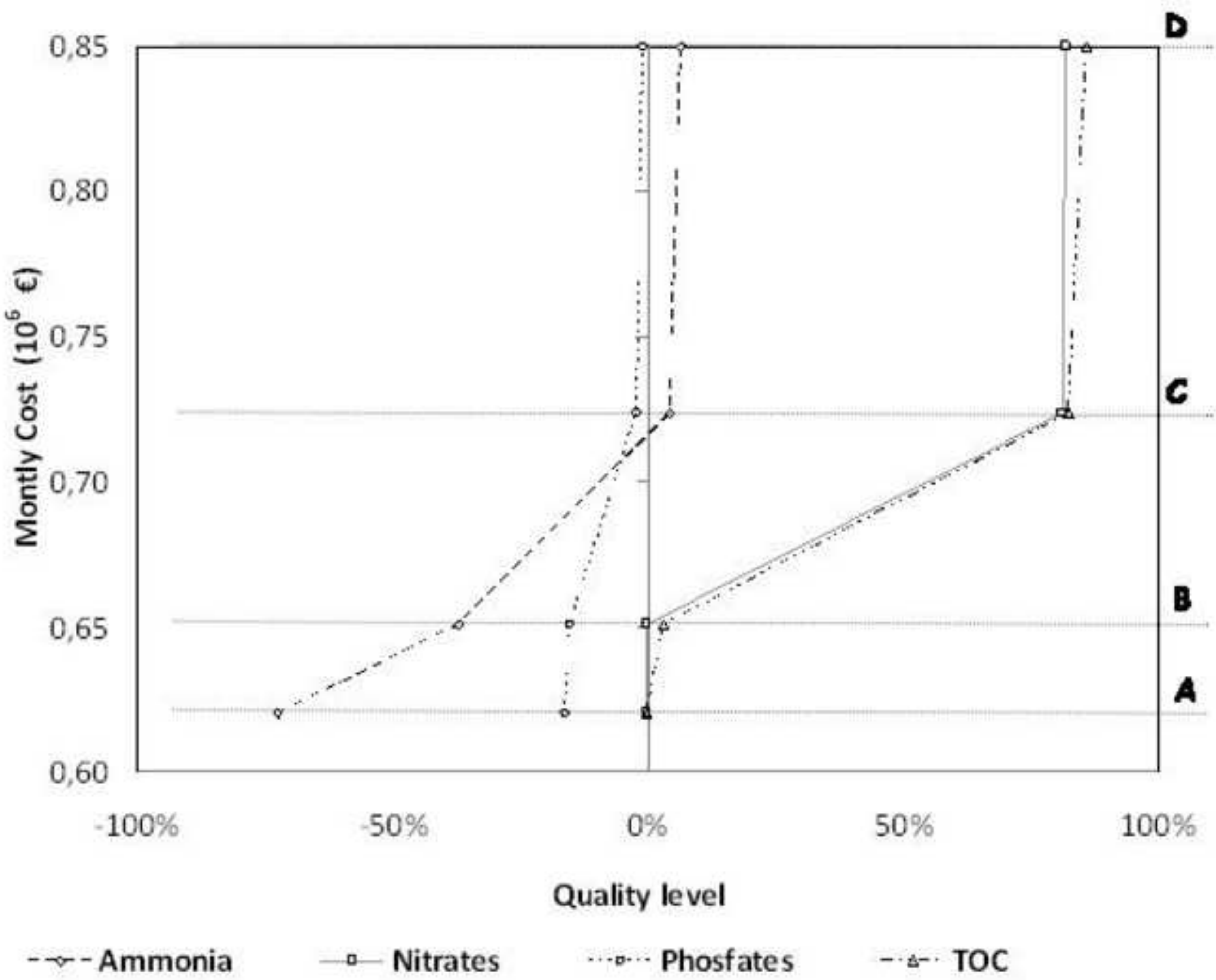

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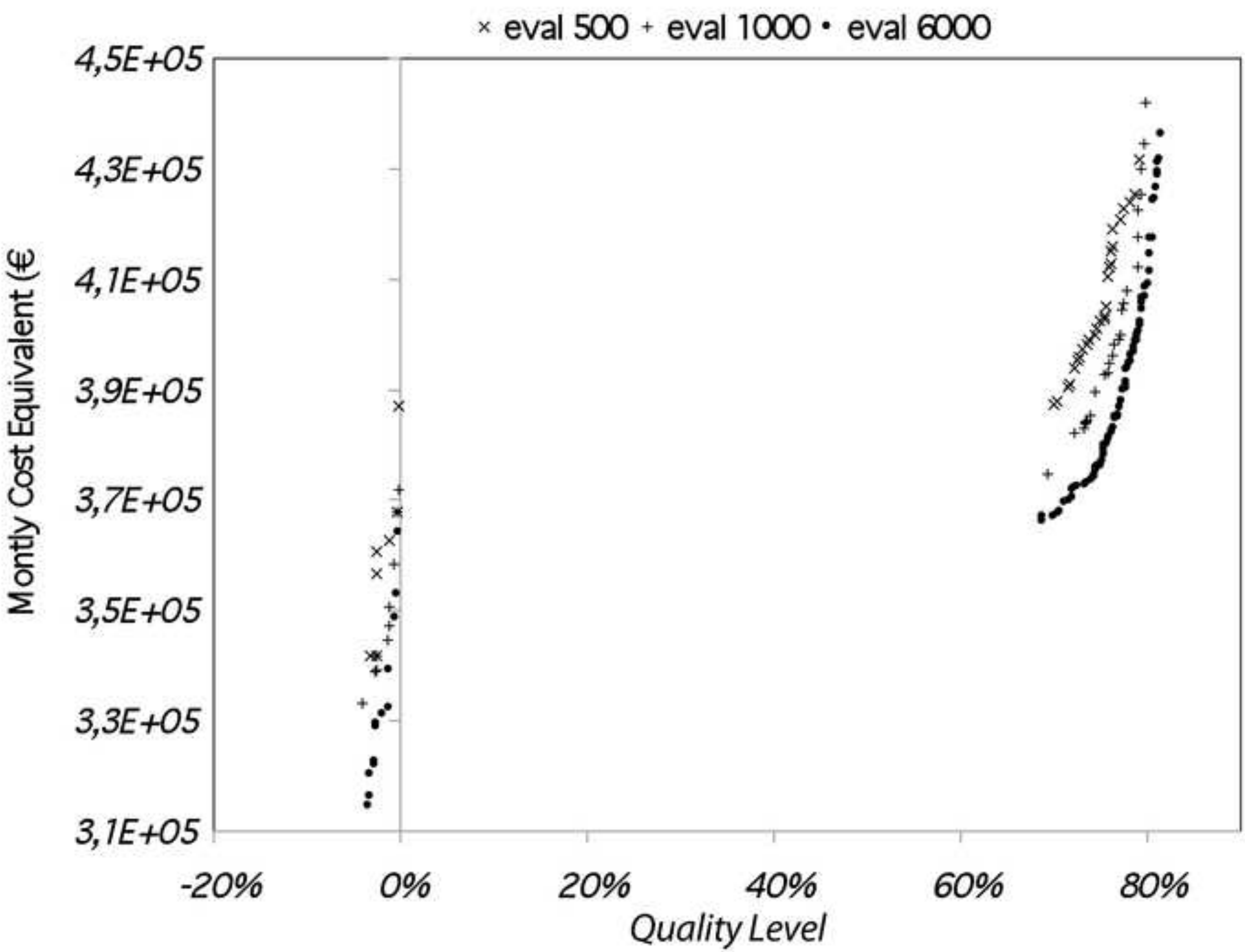

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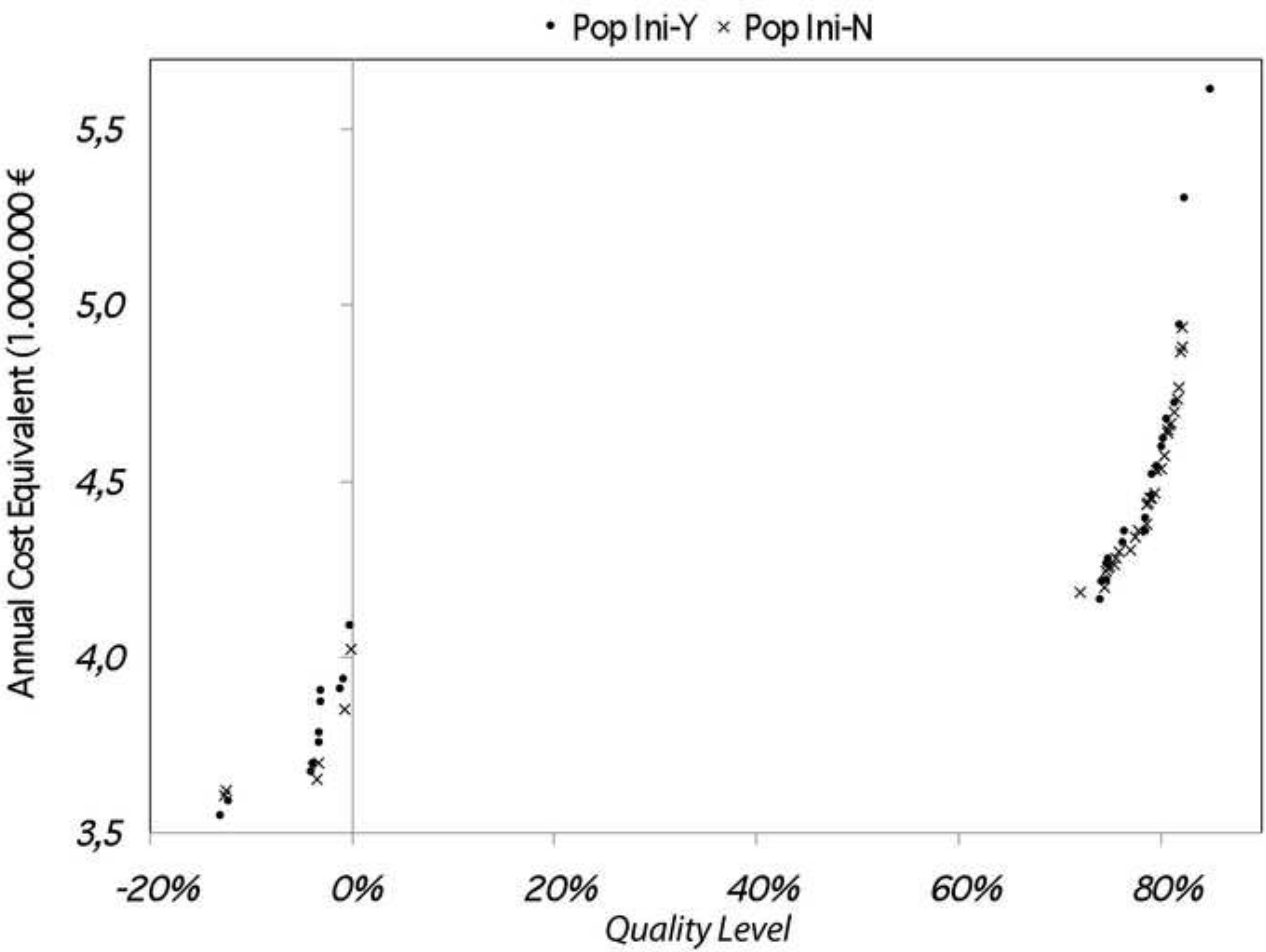

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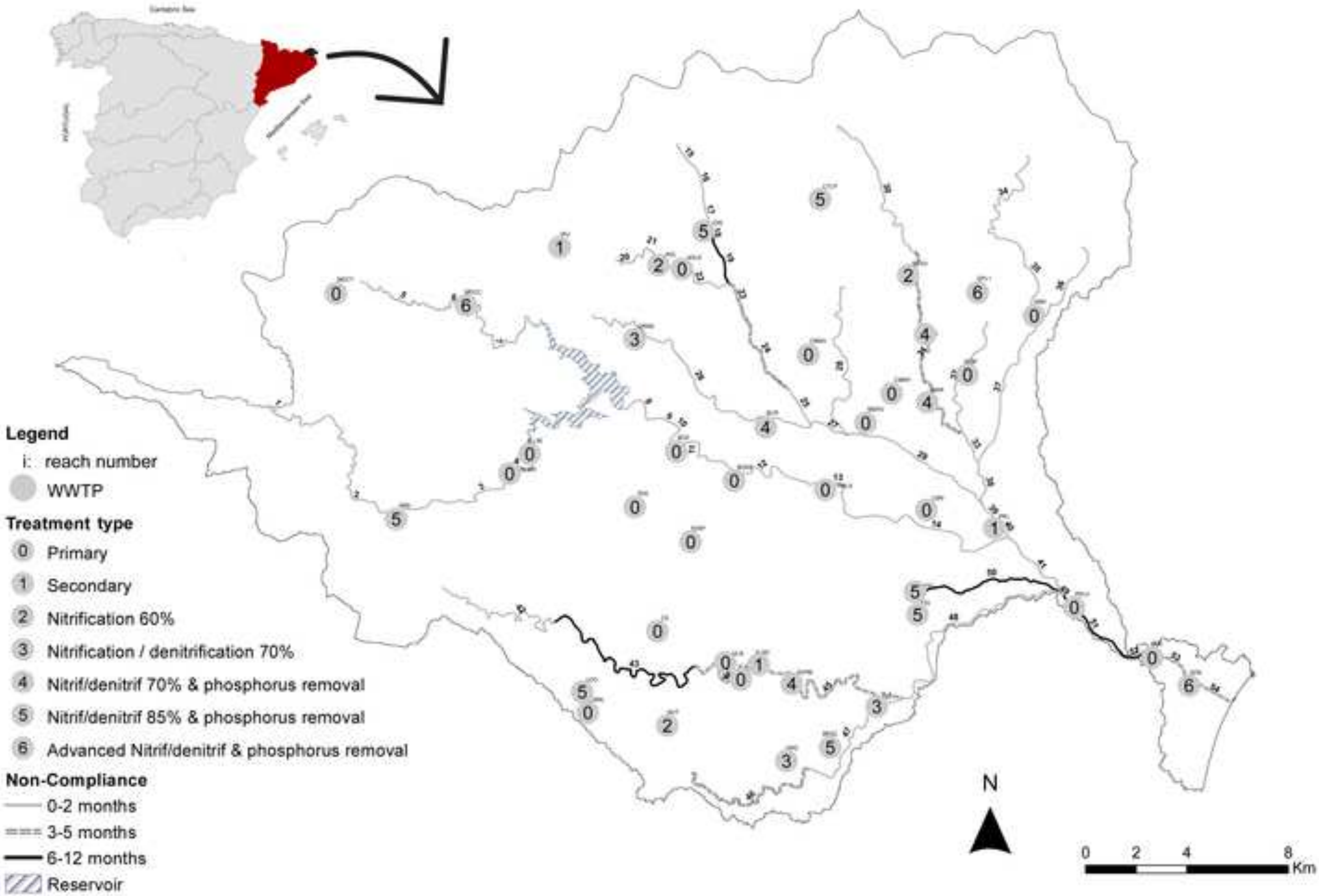

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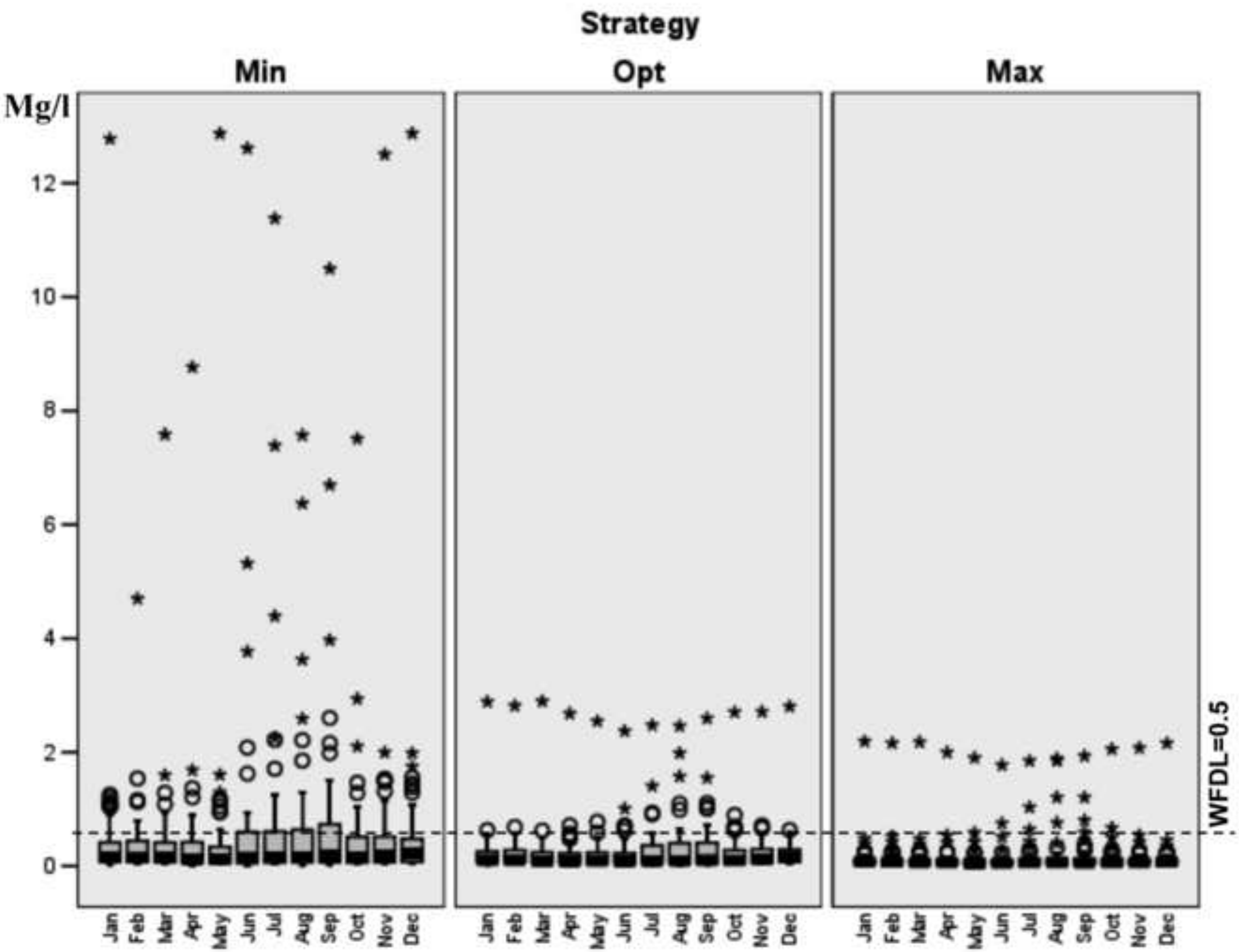

Table 1

		Nutrient Effic. Remov. (%)				Cost (€/m^3)	
index	***Treatment***	***ISS***	***NH_4***	***NO_3***	***P***	***Construct.***	***O&M***
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	$4.413Q^{-0.357}$	$6.604Q^{-0.337}$

Table 2

	Evaluations							
Npcroos	***200***	***500***	***1,000***	***2,000***	***3,000***	***4,500***	***6,000***	***10,000***
5	0.625 0.018	0.677 0.044	0.766 0.044	0.834 0.041	0.843 0.033	0.879 0.040	0.891 0.040	0.945 0.033
10	0.612 0.076	0.655 0.095	0.854 0.023	0.885 0.028	0.935 0.049	0.965 0.057	0.981 0.008	0.993 0.017
15	0.606 0.082	0.695 0.099	0.812 0.041	0.862 0.057	0.905 0.067	0.913 0.071	0.939 0.064	0.955 0.040

Table 3

	Evaluations							
Tmut	***200***	***500***	***1,000***	***2,000***	***3,000***	***4,500***	***6,000***	***10,000***
5	0.595	0.651	0.819	0.876	0.928	0.959	0.992	0.992
	0.069	0.099	0.042	0.049	0.058	0.059	0.054	0.040
15	0.582	0.653	0.788	0.836	0.845	0.867	0.885	0.918
	0.065	0.028	0.011	0.041	0.022	0.028	0.024	0.021
25	0.637	0.695	0.779	0.843	0.849	0.871	0.887	0.940
	0.019	0.054	0.060	0.049	0.049	0.037	0.038	0.021

Table 4

	Evaluations							
Pop size	***200***	***500***	***1,000***	***2,000***	***3,000***	***4,500***	***6,000***	***10,000***
5	0.535 0.060	0.571 0.065	0.828 0.048	0.874 0.056	0.931 0.084	0.970 0.069	0.986 0.078	0.986 0.041
10	0.626 0.072	0.714 0.058	0.808 0.059	0.841 0.029	0.843 0.030	0.862 0.031	0.879 0.034	0.948 0.015
20	0.650 0.018	0.750 0.056	0.817 0.015	0.894 0.026	0.914 0.063	0.915 0.072	0.925 0.064	0.963 0.055
50	0.617 0.017	0.669 0.032	0.767 0.013	0.849 0.025	0.874 0.007	0.914 0.014	0.927 0.013	0.969 0.028
100	0.620 0.015	0.621 0.024	0.762 0.061	0.812 0.075	0.856 0.061	0.905 0.067	0.945 0.078	0.932 0.034

Table 5

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

Table 6

	Evaluations							
Elitism modality	***200***	***500***	***1,000***	***2,000***	***3,000***	***4,500***	***6,000***	***10,000***
a	0,591 0,029	0,622 0,032	0,650 0,027	0,668 0,015	0,683 0,015	0,761 0,077	0,818 0,058	0,824 0,038
b	0,544 0,065	0,610 0,087	0,656 0,096	0,715 0,134	0,900 0,024	0,950 0,025	0,969 0,038	0,997 0,030
c	0,553 0,071	0,657 0,106	0,808 0,027	0,858 0,018	0,891 0,034	0,885 0,054	0,939 0,058	0,983 0,049
d	0,537 0,062	0,657 0,080	0,811 0,043	0,865 0,046	0,915 0,054	0,957 0,054	0,977 0,046	0,998 0,008

Table 7

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

Table 8

		Strategy		
	Cost	***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

Table 9

	Cost	*Ammonia*	*Nitrates*	*Phosphates*	*TOC*
Your Aspiration	***1,2***	***-0,305***	***0,9***	***-0,06***	***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

Framework for Multi-Criteria Decision Management in Watershed Restoration

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Short title: Multi-Criteria Decision Management in Watershed Restoration

ABSTRACT

This paper presents a management hydroinformatics tool designed to optimize the program of measures (PoM) to achieve the European Water Framework Directive (WFD) objectives in the inner Catalonia watersheds. The tool incorporates the Qual2k water quality model to simulate the effects of the PoM used to reduce pollution pressures on the hydrologic network. It includes a Multi-Objective Evolutionary Algorithm (MOEA) to identify efficient trade-offs between PoM cost and water quality. It uses multi-criteria visualization and statistical analysis tools as a user friendly interface. The 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.

In this paper some guidelines are also given for using analytical relations from the field of evolutionary multi-criteria optimization algorithms for different parameters (elitism, mutation rate, population size, crossover operation) to ensure that the MOEA is competently designed to navigate the criteria space of the management problem. Additionally, this paper analyzes the results of the application of the management tool in the Muga watershed, whereby guaranteeing its convergence within a reasonable computational time to simplify the decision-making process.

Keywords: Genetic algorithm, multicriteria, management, river basin, water quality

NOTATION

ACA: Catalan Water Agency

CEPH: Convex Edgeworth-Pareto Hull

EA: Evolutionary Algorithm

GES: Good Ecological Status

IDM: Interactive Decision Maps

ISS: Inorganic suspended soils

MCDSMWR: Multi-Criteria Decision Support Management in Watershed Restoration

MOEA: Multi-objective Evolution-based Optimization Algorithm

MOPs: Multi-objective Optimization Problems

MOSESS: Multi-criteria System of Efficient Strategy Selection

$Polut_{NH_4}$: is the contamination level of ammonium in water

$Polut_{NO_3}$: is the contamination level of ammonium in water

$Polut_{PO_4}$: is the contamination level of ammonium in water

$Polut_{TOC}$: is the contamination level of ammonium in water

P/I: Pressure and Impact

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 Treatments 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 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 and 2002), no specific methodology has been suggested to evaluate the practical efficiency of PoMs. Nor it is 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 meet year 2015’s objectives. The restoration of water quality at watershed level (considering the water bodies as management units) is related to a series of objectives which should be considered when defining the RBMP. It is important to select a cost-efficient PoM in order to reduce and, where possible, to eradicate existing and future water deficits, while 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 involving the selection of the best cost-effective PoM trade off. Thus, linear programming (Revelle et al. 1968), non-linear programming (Fujiwara, 1987), integer programming (Bishop & Grenny, 1976) have been used to solve the cost optimization river water quality management model for regional wastewater treatment. But the majority of the mentioned approaches only consider one or two water quality parameters and optimal decisions should be based on the general state of the watershed with regard to contaminations, political strategies and the socio-economic situation.

However, in recent years, 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 witch 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, that involves several stakeholder with different interests and goals. For this reason, computer procedures of decision screening must be transparent and simple. In particular, multiple questions concerning decision maker’s preferences must be avoided. Visualization of Pareto-efficient frontier provided by the Interactive Decision Maps (IDM) technique satisfies this requirement (Lotov, 2004).

This paper describes a new computational tool for Multi-Criteria Support Decision Management in Watershed Restoration (MCDSMWR) that has been developed to aid in water management during WFD implementation. This tool results from integrating a WQM, a MOEA, and graphical analytic tools that help to solve and display complex decision-making problems. This hydroinformatical tool is able to incorporate conflicting elements into the analysis, such as environmental objectives, economical and political issues and also makes it possible to delineate non-dominated Pareto optimal solutions from just a relatively low number of WQM executions. This kind of integrated methodology solution is becoming increasingly popular for large-scale problems of water resource management, both at watershed and regional level (Galbiati et al. 2007)(Muleta and Nicklow, 2005).

Finally, this paper presents how the MCDSMWR tool was applied in Catalonia to select the best cost-efficient PoM proposed by the Catalan Water Agency (ACA), in order to achieve the WFD objectives with a reasonable cost.

METHODS

The ACA WWTP Program

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

Given the heterogeneous conditions of the Catalan rivers and their associated watersheds, and given the good level of data availability, rivers were classified according to 5 types and 10 sub-types (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 WBs requires a specific PoM in order to meet the WFD objectives.

Nowadays there are a wide variety of WWTP technologies that provide different efficiency levels in the removal of water pollutants (Qasim, S.R., 1999). For the PoM implementation analysis, ACA considers seven WWTP technologies types, which are described in table 1 in terms of their nutrient removal efficiency and cost. Then, in one river with a number *n* of WWTP possible locations, there are 7^n different PoM possible combinations (strategies). The management solution involves finding which of these combinations are efficient.

Mathematical Problem Formulation

Starting point of 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:

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

Where the solution *x* is a vector of n decision variables: $x = (x_1, x_2, ..., x_n)^T$. 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, restricting 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 these constraints define the decision variable space D, or simply the decision space. In this case, a Pareto-optimal objective vector $f^* = (f_1^*, f_2^*, ..., f_M^*)$ is such that there does not exist any feasible solution x', and corresponding objective vector

$f' = (f_1', f_2',..., f_M') = (f_1(x'), f_2(x'),..., f_M(x'))$ such that $f_m^* \leq f_m'$ for each $m = 1, 2, ..., M$ and $f_j^* < f_j'$ for at least one $1 \leq j \leq M$.

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.

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

$$Min\ f_1 = \sum_{Nmonth=1}^{12} \left[\sum_{Nwwtp=1}^{NumWWTP} \left(ICost_{Nwwtp} + OCost_{Nwwtp} \right) \right] \tag{2}$$

$$Max\ f_2 = WaterQuality_{NH_4} \tag{3}$$

$$Max\ f_3 = WaterQuality_{NO_3} \tag{4}$$

$$Max\ f_4 = WaterQuality_{PO_4} \tag{5}$$

$$Max\ f_5 = WaterQuality_{TOC} \tag{6}$$

Where:

$ICost_{Nwwtp} = f(Q_D, X_T)$: 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.

$OCost_{Nwwtp} = f(Q_P, X_T)$: 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.

$WaterQuality_{NH_4}$: is the concentration [mg/l] of ammonia in the river water

$WaterQuality_{NO_3}$: is the concentration [mg/l] of nitrates in the river water

$WaterQuality_{PO_4}$: is the concentration [mg/l] of phosphates in the river water

$WaterQuality_{TOC}$: is the concentration [mg/l] of TOC in the river water

Due to the heterogeneity of the rivers, the concentration of the four quality criteria usually is different in each stretch of the basin. To assess the global water quality in a basin it is necessary to define a quality metric (see equation 7). 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 reach and one month. This metric is considered adequate because clearly identifies any violation of the WFD quality limits.

$$f_k = \begin{cases} \dfrac{\sum_{i=1}^{nm}\sum_{j=1}^{nr}(LDM_{ij}^k - VI_{ij}^k)/LDM_{ij}^k}{nm \bullet nr} & if\ \ the\ WFD\ levels\ are\ met\ \ for\, every\ reach\, and\ month \\ -\dfrac{\sum_{i=1}^{nmi}\sum_{j=1}^{nri}(LDM_{ij}^k - VI_{ij}^k)/LDM_{ij}^k}{nm \bullet nr} & otherwise \end{cases} \qquad (7)$$

Where:

K, 2≤ k≤ 5: contaminant index.

nm: number of months.

nr: number of stretches

nmi: number of month that exceed the WFD limits.

nri: number of stretches that exceed the WFD limits.

LDM_{ij}: concentration limit of the contaminant *"k"* in stretch *"j"* and month *"i"*, allow 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", the treatment technology to be applied in each WWTPs. A discrete value with 7 possibilities can be assigned to each decision variable. 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:

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

Water Quality Model

Water Quality Models (WQM) seek to describe the spatial and temporal evolution of contaminants and constituents characterizing a river flow. Many highly reliable simulation models are available today for estimating the behavior of physical systems such as water bodies, with reasonable computational requirements (Rauch et al. 1998) (Shanahan et al.1998). According to these references, one of the most popular river and stream water quality models are Qual2e (Brown and Barnwell, 1987). We chose Qual2kw (Pelletier, Chapra, 2004) as the WQM for this application because is a modernized version of the Qual2e model and it is easily applicable to this type of work.

The ACA chose the Muga Basin as a pilot area to test the MCDSMWR methodology. Even though the methodology was applied to all Catalan inner watersheds, most of the results presented in this paper correspond to its application in Muga basin. The Muga

Basin lies within the Autonomous Community of Catalonia, Spain and it flows into the Mediterranean Sea. It covers a surface of 759 Km^2 (2.3% of the total area of Catalonia) with a main channel of 64.7 linear km of water flow and its average annual precipitation is 612 Hm^3 (807 mm). It has a natural average annual inflow of 150 Hm^3 (this simulation does not include catchments, spillage or reservoirs). There are a total of 34 municipalities and 65,756 inhabitants in the basin.

In order to apply the Qual2k 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 channel with 12 tributaries has 227 km, which were divided for these simulations into 54 elements of approximately 5 km length.

Before the application of the WQM in the water restoration decision process, is necessary to adjust the model parameters to adequately represent 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, we perform a sensitivity analysis before the model calibration process in order to consider which parameter imposes the most effect on model performance thus include only them in the calibration process. The result was select 20 parameters seem the most sensitive for the Muga models.

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

The simulation results for the WQ model show good matches with the observed concentration in the Boadella D'empordà and Peralada stations, verification results of the model also show an overall good correspondence with observed concentrations. Figure 1 show the calibration and verification results for the ammonia concentration in Castelló D'empúries station, which is close to Figueres, the most significant pollution source in the Muga basin. This is the reason for the high difference from minimum to maximum values in most of the months and for the mismatch between the simulation and observed concentration at the end of the catchment.

MOSESS

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, 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, 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 3 bits to encode the 7 sewage treatment levels of each plant. After decoded the chromosome, in treatment levels for each WWTP, the water quality in each reach is forecasted by the Qual2k model. The fitness value for the four quality criteria is asses by equation 7 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. This information must also be included in the algorithm as an additional constraint in the search for better 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. 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 when they are not Pareto dominated by any solution of this external population. If solutions of the external population are 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 also is 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 ranking determined through a dominance criterion). Three recombination possibilities are also implemented in the algorithm: crossover of two chromosomes from the external Pareto set, crossover of two chromosomes from the previous population, and crossover of one chromosome from the previous internal population with another from the external elitist population.

Solution Methodology

In this work, a new MCDSMWR methodology has been proposed and a hydroinformatic tool, which is based on the methodology, has been 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. The application of the methodology to a particular catchment implies several steps, as shown in figure 3.

The first step is to conceptualize the system (water bodies) and to define the global and local management objectives. A detailed description of the status of the water bodies is available for the current situation and for the 2015 forecast situation. The areas described correspond to the Catalan inner watersheds and the main goal is to determine which is the tradeoff between water quality and cost to achieve it.

The second step is the definition of the possible correctional measures for each watershed which consists in a series of proposals (PoM) including the Catalonia urban and industrial WWTP program. This includes, select WWTP possible locations and decide the suitable cleaning technology for each WWTP. The features considered by ACA for each plant type are described in table 1.

The third step is the economic model definition: this includes the creation of 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 waste water treatment plants considered in this study are derived by historical data collected by the ACA over the last 10 years. By summing up the individual cost of each WWTP for each simulated period, it is possible to estimate the total cost of each PoM (strategy).

The next step is to build the watershed model according to the "water model description" paragraph of this paper. All the information related to catchments should be implemented in the Qual2k model. The user's manual (Brown and Barnwell, 1987) provides values and ranges for rates and constants and some values are also available in Bowie et al. (1985). However, Brown and Barnwell (1987) strongly suggest that parameters should be field measured to reduce uncertainty in the model results. Qual2k 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 yields information related to water resource quantity and quality (Pelletier, Chapra and Tao, 2006).

The next step involves the application of the 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 proposal methodology over other approaches that make individual cost-effectiveness analyses 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 the number of criteria is more than two. 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 7 criteria. IDM has been used extensively in water management issues (Lotov et al., 2005, Burmistrova et al., 2002).

Figure 4 shows an IDM example that visualizes the Edgewort-Pareto Hull, 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 on Figure 4. The total scale of the cost criterion is divided into several half-open intervals of equal length. The values for the rest of quality criteria: nitrates and TOC, are set to their lower positions.

Also it could be interesting construct slices of $H(Y)$ in the plane of the axis criteria for the values of the third criterion corresponding to the endpoints of the intervals. We then superimpose these slices on a single screen; each slice being of a specific color; the legend on the right of Figure 4 matches the color of each slide to the interval's end point this slice was computed for. Note that a slice corresponding to a worse value of 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.

Sometimes, it may be useful to omit some data that is irrelevant to the decision-making information, namely, the precise shape of the trade-off curves between the two quality criteria: ammonia and phosphates, 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 5 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 (fig 5 and 6), the ordinate axis represents the cost of the strategies and the abscissa axis represents the water quality of each indicator according to the equations 3 to 6. The X = 0 % is exactly the WFD objective. The points falling in the left side of the graphs are strategies that do not meet WFD goals, and the points in the right side of the graphs do meet them. 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 trade-off between costs and the GES level reached by 4 different strategies (A, B, C, and D). Each curve represents a different water quality criterion. The most economical strategy, the A strategy, not fulfilled any criteria and the B strategy only verifies the restriction with respect to TOC. Strategy C, slightly more expensive, it meets all indicators except phosphates. Since the maximum intensity sewage treatment strategy (D) not get satisfied with respect to phosphate, it is clear that it is not worth such a costly strategy as D and the most reasonable strategy would be the C.

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

The MCDSMWR methodology is an iterative process; after the hydroinformatic tool is run the first several times, some of the correctional measures that were initially proposed usually need to be redefined. New information and/or the detection of faults would also oblige part of the model to be modified.

RESULTS AND DISCUSSION

For the Muga Basin optimization problem presented, ACA considers 41 WWTP locations, each with 7 sewage treatment levels. Each gene uses 3 bits to encode these 7 possible alternatives for the decision variables. Then, in the Muga watershed, the number of genes is 41 with a chromosome length of 41x3=123 bits. Thus, the number of possible strategies is $7^{41} \approx 4.4 \times 10^{34}$, and the goal is to find the most efficient of them, according to all the criteria

MOSESS Convergence analysis

In applying the methodology described in this paper, good performance of the optimization algorithm is essential, because it should find the Pareto set of strategies with minimum WQM evaluations, since each model run requires considerable computation time. It takes 15 seconds of CPU (Intel Core II Duo 2.8 Ghz processor) for each monthly simulation of the Muga basin.

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, we take the reference of the non-dominated front that is constructed with the results from all the algorithm runs for each river basin.

In multi-objective problems, it is not as easy to compare how MOEAs perform when they converge as it is with mono-objective problems (Zitzler, 2003). In this case we use the “S” or hypervolume metric (Knowles, 2002). Tables 2 to 7 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 cells of these tables shows the results of the mean and standard deviation of the hypervolumen values, for all executions carried out for each experiment (at least five executions). This convergence analysis focuses in the GA parameters of the MOSSES algorithm.

Table 2 shows the influence of the number of points on the crossover operator. With 10 points, a very good convergence is reached with only 6,000 evaluations of the WQM. With respect to the influence of the mutation rate (table 3), low rates show also very good performance with less than 6,000 evaluations. As with steady state evolution, small population size (table 4) shows better algorithm performance with respect to both the final solution reached and the convergence achieved for the same number of evaluations.

An increase in the number of criteria required more evaluations to achieve convergence (table 5). Elitism is very important in the convergence process, table 6 shows how executions of our MOEA without elitism (all the parents are selected front the main population) exhibit poor performance.

The results shown in tables 2 to 6 correspond to MOEA executions for the same scenario in January 2015 in the Muga catchments.

Table 7 compares results for the Muga scenario (41 WWTP) and the Llobregat scenario (217 WWTP). It can be observed 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. This computational efficiency is achieved by a proper sewage treatment levels codification, ordering from lowest to highest, cost and purification intensity.

Figure 7 shows Pareto fronts corresponding to the MOSESS solutions for the January 2015 scenario in Muga, considering only two criteria (cost and ammonia) for different numbers of evaluations. The best MOSESS solution for 500 evaluations finds that the cheapest strategy that satisfactorily achieves 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 savings of approximately 5.5%.

Applicability of the MOSESS requires that the computational time required remains within reasonably limits. This could be especially hard, in some catchments, considering that each monthly execution of the WQM can take more than 150 seconds (for the Llobregat catchment) and decisions must be taken in base to the annual performance of the sewage treatments, i.e. considering simultaneously the 12 monthly models.

Starting the MOSESS search process with a set of good quality strategies, rather than applying randomly generated strategies, allow significant reduction in 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 MOSESS algorithm for a single monthly model. For the annual Muga scenario (12 months), figure 8 shows slightly better convergence and distribution of the 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 8,200 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 some 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 to find the best Pareto front considering the 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 hundred of cost-efficiency PoM, which delimitate the non-dominated Pareto frontier of each basin. The information on the Pareto frontier displayed by de IDM technique (fig 4) simplifies the decision maker's job. Each stakeholder easily identifies on a decision map his region of interest (according to his preferences) by simple click of the computer mouse.

Exploration of the Pareto frontier by means of the IDM map or 2D visualization (fig 6) helps to understand the criterion tradeoffs and to identify a preferred criterion point directly at the Pareto frontier (even with a monthly of yearly display). For example, in figure 5 and 6 can be observed that even for the most intensive sewage PoM (point D), it is impossible to achieve the WFD's objective satisfactorily for all the criteria. In this case, it would be more reasonable to select the C strategy, because spending more money does not gain better water quality results.

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 apply also the IDM (fig 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 (fig 4) are listed on Table 9. 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 alternatives and to select several that do not differ much with respect to the goal on criteria values.

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

Table 8 compares, for the Muga and Llobregat catchment, the cost of tree difference strategies: the minimum and maximum purification technology and the optimum strategy that was finally decided to apply. It can be seen as the selected strategy has a cost significantly lower than the maximum 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 fig 10). In this case, the figure 10 shows the statistical ammonium quality distribution for three different strategies: a low intensity sewage treatment strategy on the left, maximum intensity (advance for all WWTP) on the right and the strategy that decision maker finally selected in the middle. It can seen 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 tradeoff solution from conflicting objectives in the context of the implementation of the WFD in Catalonia. Particularly, 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 in this methodology a new hydroinformatic tool (MCDSMWR) was developed to assist the management of water quality at 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 specially designed and configured to find the Pareto optimal set of PoM (strategies). Qual2k 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 are used in the water quality simulations, including topography, climate and anthropic pressures predicted for the year 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, constitutes the main core of the proposed approach.

In this paper, the case study has been carried out taking into account of wastewater systems which translates into seven different cleaning technology alternatives, which also were modeled in terms of both cost and treatment for each pollutant. So in addition to the cost criteria (operating and investment cost), were considered simultaneously four quality criteria: ammonium, nitrate, phosphate and TOC. The non linearity of the WQM, the integer character of the decision variables (WWTP) and the five criteria simultaneously considered, makes MOEA methods to be more efficient than traditional optimization methods to identity tradeoff among multiple objectives. A major difficulty in applying the MOEA methods is identifying appropriate parameter settings to ensure that the decision space of the problem is effectively explored and the entire tradeoff 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 to evaluate the effectiveness of the actions which are being carried out to improve water quality and to provide decision-makers with the opportunity to explore the multi-objective nature of problems, discover tradeoffs amongst objectives, and make decisions given alternative solutions and achieving PoM management outcomes for the future. Early end users' involvement, development of several evolutionary prototypes, designing a specific user friendly interface adopted for multicriteria applications and variety of implemented models and decision support tools have been the main factors intended to guarantee the system implementation success.

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FIGURE CAPTIONS

Fig 1: Calibration and validation results for the ammonia concentration in Castelló D'empúries station, monthly averages observed data from year 2003 to 2006.

Fig 2: Schematic layout of the MOSESS optimization procedure.

Fig 3: Flow chart for the Multi Criteria Decision Support Management in Watershed Restoration Methodology to assure compliance with the European WFD in 2015.

Fig 4: Example of simple EPH decision map with the corresponding smoothed convex hull. ┼ Choose strategy.

Fig 5: Example of 2D visualization of all the Muga catchment Pareto front strategies considering 5 quality criteria (cost, ammonia, nitrates, phosphates and TOC)

Fig 6: Example of 2D visualization for four selected multi-criteria strategies (A, B, C and D).

Fig 7: Pareto fronts with two criteria (cost and ammonia) for different numbers of WQM evaluations for the one-month Muga scenario.

Fig 8: Pareto fronts with two criteria (cost and ammonia) starting the genetic algorithm with random initial population (Pop Ini-N) or with selected initial population (Pop Ini-Y) for the one month Muga scenario.

Fig 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 only remains quality problems in reach number 50.

Fig 10: Box plot for the levels of Ammonia in the stretches, depending on the month and the applied purification treatment (Min, Opt, Max) (Ter basin)

TABLE CAPTIONS

Table 1: WWTP technologies considered by ACA (Q: capacity of WWTP in m3/day)

Table 2: MOEA convergence (mean and standard deviation) for different numbers of crossover points and evaluations.

Table 3: MOEA convergence (mean and standard deviation) for different mutation rates and evaluations.

Table 4: MOEA convergence (mean and standard deviation) for different population sizes and evaluations.

Table 5: MOEA convergence (mean and standard deviation) for different numbers of objectives and evaluations.

Table 6: MOEA elitism influence (mean and standard deviation) for different configuration. a: two parents selected from the internal population; b: one parent front the internal population and other front the external; c: two parents selected from the external population ; d: 25% probability of “a”, 50% probability of “b” and 25% probability of “c”

Table 7: MOEA convergence (mean and standard deviation) for the Muga (41 WWTP) and Llobregat (217 WWTP) catchments with different numbers of evaluations.

Table 8: Minimal, optimal, and maximal strategy cost (thousand €) for different catchments.

Table 9: Characteristics of the neighborhoods strategies of the chosen strategy obtained using IDM tool (figure 4)