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Decision support for diffuse pollution management

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ABSTRACT

The effort to manage diffuse pollution at the catchment scale is an ongoing challenge that needs to take into account trade-offs between environmental and economic objectives. Best Management Practices (BMPs) are gaining ground as a means to address the problem, but their application (and impact) is highly dependant on the characteristics of the crops and of the land in which they are to be applied. In this paper, we demonstrate a new methodology and associated decision support tool that suggests the optimal location for placing BMPs to minimise diffuse surface water pollution at the catchment scale, by determining the trade-off among economic and multiple environmental objectives. The decision support tool consists of a non-point source (NPS) pollution estimator, the SWAT (Soil and Water Assessment Tool) model, a genetic algorithm (GA), which serves as the optimisation engine for the selection and placement of BMPs across the agricultural land of the catchment, and of an empirical economic function for the estimation of the mean annual cost of BMP implementation. In the proposed decision support tool, SWAT was run a number of times equal to the number of tested BMPs, to predict nitrates nitrogen (N-NO3) and total phosphorus (TP) losses from all the agricultural Hydrologic Response Units (HRUs) and possible BMPs implemented on them. The results were then saved in a database which was subsequently used for the optimisation process. Fifty different BMPs, including sole or combined changes in livestock, crop, soil and nutrient application management in alfalfa, corn and pastureland fields, were evaluated in the reported application of the tool in a catchment in Greece, by solving a three-objective optimisation process (cost, TP and N-NO3). The relevant two-dimensional trade-off curves of cost-TP, cost-N-NO3 and N-NO3–TP are presented and discussed. The strictest environmental target, expressed as a 45% reduction of TP at the catchment outlet, which also resulted in a 25% reduction of the annual N-NO3 yield was met at an affordable annual cost of 25 €/person by establishing an optimal combination of BMPs. The methodology could be used to assist in a more cost-effective implementation of environmental legislation.

Software availability

The Decision Support Tool was developed in the Laboratory of Hydrology and Water Resources Management of NTUA and can be provided to interested parties following communication with the authors of this paper.

1. Introduction

The Water Framework Directive (WFD, Directive, 2000/60/EC), the Nitrates Directive (Council Directive 91/676/EEC) and the agri-environmental issues raised within the EU's Common Agricultural Policy (CAP) require cost-effective pollution abatement measures, including the implementation of agricultural Best Management Practices (BMPs) at the catchment scale, to lower Nitrogen (N) and Phosphorus (P) pollution in European water bodies. The coordination of these measures at the catchment scale also form part of the interventions that should be included in integrated River Basin Management Plans (RBMPs) to assist in improving Good Ecological Status (WFD, Directive, 2000/60/EC).

Farming practices such as conventional tillage, chemical fertilisation and manure application to fields, high livestock stocking rates and over-grazing have all been identified as potential pressures deteriorating water quality in agricultural catchments (Cherry et al., 2008). In order to optimise both the reduction of the Non-Point Source (NPS) pollution arising from those sources and the decrease of implementation cost of mitigation strategies, there is a need to be able to identify optimal locations for BMPs across the landscape, in such a way that maximises their effectiveness while minimising

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their cost. Usually, an acceptable compromise is expected when the most effective BMPs are assigned to the locations of the catchment that act as major sources of NPS pollution, due to, for example, climate, land use, soil and topography. Furthermore, BMPs effectiveness also depends on the degree to which control of each separate nutrient element is desired, as different BMPs are better at reducing specific types of pollutants than others (Jha et al., 2009).

This makes the placement of BMPs at the catchment scale a multi-objective problem, with a significant number of possible combinations, especially for large catchments. For addressing this problem the following elements are required from a Decision Support System (Panagopoulos, 2010): (a) a robust NPS estimator, usually a process-based model, which can adequately represent the effect of several types of BMPs, at all locations within the catchment on the parameters of interest (usually TP, sediments and N-NO3), (b) an economic model or an economic function that can adequately represent the cost of implementing different BMPs at various locations and (c) an optimisation algorithm, that can provide an efficient method of searching through an extensive, non-linear and non-continuous solution space, such as evolutionary algorithms (Makropoulos and Butler, 2005; Schwefel, 2000). Multi-objective evolutionary algorithms are capable of treating several objectives separately and develop a global Pareto-optimal front (Tan et al., 2002), subsequently used by decision makers to explore trade-offs between (pareto) optimal solutions, in a transparent way that can potentially take into account specific local circumstance and priorities.

Within such a decision support framework one could choose from a variety of hydrological-based models operating at the catchment scale, which can assist decision making for diffuse pollution management (Yang and Wang, 2009). Informed decisions for catchment management can also be supported by modeling frameworks that combine point and semi-distributed catchment models into a user friendly interface (Vigiak et al., 2011) and in some cases also include environmental predictions and economic values into a single hydro-economic tool (Kragt et al., 2011). In any case, and despite improvements in support tools, a strong cooperation between modelers, field researchers and decision makers is needed in order to overcome problems related to monitoring data limitations, scaling issues and natural process representation that still exist (Bende-Michl et al., 2011).

In this work, the SWAT (Soil and Water Assessment Tool) model (Arnold et al., 1998), probably the most widely known process-based distributed modeling tool, was used to reproduce various physical and biogeochemical processes in the catchment, identify critical NPS areas and explicitly represent BMPs implementation on them (e.g., Barlund et al., 2007; Cools et al., 2011; Panagopoulos et al., 2011a; 2011b; Santhi et al., 2006; Turpin et al., 2005). SWAT is considered a robust, interdisciplinary tool that has been extensively applied in Europe, USA and the rest of the world, alone or combined with other tools (e.g., Gassman et al., 2007). Moreover, there are numerous studies that have combined SWAT with the other two components to optimise selection and placement of BMPs in agricultural catchments (e.g., Arabi et al., 2006; Bekele and Nicklow, 2005; Gitau et al., 2004, 2006; Jha et al., 2009; Maringanti et al., 2009; Muleta and Nicklow, 2002, 2005; Rabotyagov et al., 2010; Veith et al., 2003, 2004). All of these methodologies, exclusively developed and tested in the USA, used a genetic algorithm (GA) as the search technique (Goldberg, 1989; Holland, 1975), and a simple economic component based on local data in order to improve management schemes across the total area of agricultural catchments.

Although SWAT has been widely used in Europe, no such methodology of agricultural land management at the catchment scale has been proposed in the European literature. Decision support for river basin management with respect to nutrient pollution has, however, received extensive attention in Europe through the development of a number of DSS, such as for example, the Elbe-DSS (Graf et al., 2009), the MULINO DSS (*m*DSS), described in Fassio et al. (2005), Giupponi (2007) and Mysiak et al. (2005), the FLUMAGIS DSS (Volk et al., 2007, 2008) as well as the computerised and integrated framework SEAMLESS-IF (Ittersum et al., 2008), which can assess alternative agricultural and agro-environmental policies and technologies across a range of scales. These DSS have, however, been intensive with respect to physical and socio-economic data needs and usually required advanced user skills to be successfully adjusted in various spatial scales and situations. Most of them have been better operated at the regional scale or in large-scale watersheds rather than in medium-sized catchments, and generally employed multi-criteria decision rules which through subsequent phases of normalisation and weighting derived a single overall performance score for every option (e.g., Fassio et al., 2005). Explicitly multi-objective evolutionary optimisation was not usually part of these frameworks.

Moreover, there is always room for improvement and further development of the USA-developed SWAT-GA methodologies mentioned above. For instance, four of them (Gitau et al., 2004, 2006; Veith et al., 2003, 2004) did not address the issue of multi-objective optimisation and did not provide the trade-off curve between competing objectives. In contrast, three other studies (Bekele and Nicklow, 2005; Muleta and Nicklow, 2002, 2005) provided a trade-off curve, but only between cost and sediment loads, so they did not examine a high range of BMP types with respect to N and P reduction. Arabi et al. (2006) provided, on the other hand, a trade-off curve, but the environmental objective represented a weighted load reduction of all pollutants. Even in this case, reduction of each separate nutrient was not explicitly identified. Notable exceptions are the works of Jha et al. (2009) and Rabotyagov et al. (2010), who simultaneously minimised three criteria, providing the trade-off curve between the two different nutrients as well. A limitation of these studies however, was that the NPS estimator (SWAT) was executed each time the optimisation procedure evaluated a solution, leading to a computationally demanding process.

Maringanti et al. (2009) on the other hand, have conducted multi-objective optimisation and have substituted the dynamic linkage between SWAT and the optimisation algorithm by a BMP database that serves as the real-time NPS load estimator and cost data provider. This led to a significant acceleration of the process and this concept is central to the work developed in our paper. However, Maringanti et al. (2009) tested a single BMP type for rice and three BMP types, along with their combinations, for soybean cultivation. Hence, they did not explore the usefulness of such an approach when testing a large variety of BMPs including nutrient application, crop, soil and livestock management measures at the same time, which was the main purpose of the work presented in this paper. To achieve this purpose we developed an efficient and user friendly decision support tool, for determining optimal placement of agricultural BMPs and the trade-offs between multiple objectives in order to cost-effectively control diffuse pollution at the catchment scale.

2. Methods and tools

The two major components of the proposed decision support tool (Genetic Algorithms, and the model SWAT) are briefly presented next.

2.1. Genetic algorithms (GAs) and the MATLAB-GA toolbox

The past 20 years have seen an extensive growth in the development and application of flexible and powerful evolutionary algorithms (EAs) and genetic algorithms (GAs) in particular, for solving environmental and water resources problems (Nicklow et al., 2010) due to their ability to solve non-linear, nonconvex, multimodal, and discrete problems for which deterministic search techniques incur difficulties. For multi-objective optimisation in particular, where the solution is a multi-dimensional front (the pareto front), GAs have been developed that apart from the convergence to the optimal front, also ensure the conservation of an adequate spread of solutions on that front (usually based on a metric of their distance from each other). One of the most popular, robust, efficient and fast multi-objective GAs is the *Nondominated Sorted Genetic Algorithm* (NSGA-II), developed by Deb and colleagues (Deb, 1999; Deb, 2001; Deb et al., 2002).

In this work, a controlled, elitist GA, that is a variant of NSGA-II, as coded in the MATLAB R2007b GA toolbox, was used to drive the optimisation process. The controlled elitism always favors individuals with a better fitness value (rank). As the algorithm progresses, it maintains population diversity for convergence to an optimal Pareto front by using the options 'ParetoFraction' and 'DistanceFunction'. The first limits the number of individuals on the Pareto front (elite members) and the second is an embedded crowding distance function that helps to maintain their diversity by favoring individuals that are relatively far from each other, while this diversity is either calculated in function (phenotype) or in the design space (genotype), (MATLAB, 2010).

The algorithm follows the traditional GA steps for optimising a problem. It begins by creating a random or user-defined initial population. It then creates a sequence of new populations by performing individual ranking, selection, crossover and mutation. There are several options in the toolbox for running these processes, whose selection is a heuristic problem based on trial and error. More details for the genetic operators and parameters of the MATLAB-GA can be found in the user guide of the algorithm (MATLAB, 2010).

2.2. SWAT model description

The Soil and Water Assessment Tool (SWAT) is a river basin model developed by the U.S.D.A. Agricultural Research Service (Arnold et al., 1998). The present study used SWAT2005 version and ArcView Geographic Information System interface (AVSWAT-X), an upgrade of AVSWAT (Di Luzio et al., 2004). SWAT divides the watershed into subbasins and subsequently into Hydrologic Response Units (HRUs), which represent the different combinations of land use and soil types in each subbasin. The processes associated with water and sediment movement, crop growth and nutrient cycling are modelled at the HRU scale. Sediment yields are estimated for each HRU with the Modified Universal Soil Loss Equation (MUSLE) (Williams, 1975), which incorporates empirical expressions of the impact that soil attributes, land cover types, topography and support practices have on erosion. Surface runoff volumes for each HRU are simulated using the SCS curve number (CN) method (USDA, Soil Conservation Service, 1972), while peak runoff rate predictions are made through modification of the rational method (Neitsch et al., 2005a).

SWAT divides N and P in the soil into two parts, each associated with organic and inorganic N and P transport and transformations, and simulates their cycles, which are associated with simulated management practices taking place in each HRU. Planting, harvesting, tillage passes, irrigation, grazing and nutrient applications can be simulated for each crop or livestock system at specific dates. Fertilisation can be applied on a continuous basis or automatically according to crop nutrient stress. These management operations are more explicitly defined in each HRU by specific management parameters (e.g., tillage depth, N and P contents, amount of fertiliser, manure types etc.). Thus, when alternative management practices are considered in a SWAT study, changes in the aforementioned parameters can be implemented, providing significant degrees of freedom in the choice of practice or practices and the location of application. For practices such as contour farming or strip-cropping, indirect changes to specific parameters that represent cultivation patterns are required (Arabi et al., 2008). Filter strip trapping of sediment and nutrient load, on the other hand, is based solely on filter width (Neitsch et al., 2005a).

SWAT outputs are calculated at the subbasin level on a daily basis and are summarised on a monthly and annual basis. At the HRU scale, the model calculates sediments exported from the edge of fields in t/ha and nutrients (mineral and organic forms) in kg/ha. Nitrates nitrogen (N-NO3) is the major component of the mineral-N load, while the modeler can also estimate total N (TN) and total P (TP) loads by summing loads of different N and P species (Neitsch et al., 2005b).

3. Methodology

The Decision Support Tool (DST) was comprised of five components (Panagopoulos, 2010) (Fig. 1): a) the BMPs that were developed according to the catchment management needs, b) an empirical economic component, which calculated the cost of their implementation, c) the SWAT model, which evaluated the catchment baseline, the environmental effectiveness of the BMPs, and estimated the crop yield to inform the economic component, d) a BMP Database that stored nutrient losses and costs for all HRUs and BMPs, and e) a MATLAB-GA, which served as the optimisation engine for the selection and placement of BMPs in the agricultural land in order to optimise both environmental and economic objectives. As the efficiency of agricultural practices depends on location and site specific circumstance, including climate, soils and types of crops and livestock, the developed methodology and proposed tools are presented next, directly associated to the study area to facilitate understanding and link to the reality on the ground.

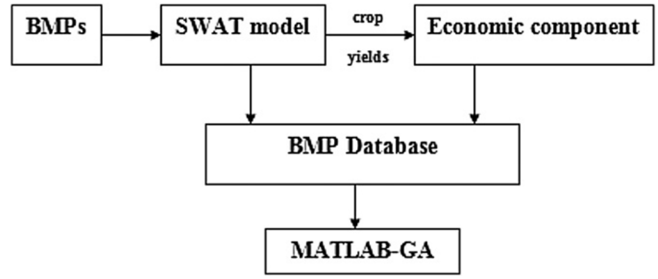

Fig. 1. A schematic representation of the Decision Support Tool.

3.1. Study area

The wider Arachtos catchment (2000 km^2) is located in the western part of Greece and drains to the Amvrakikos gulf, a semi-closed marine area of 405 km^2 connected to the Ionian Sea to the West through a narrow natural channel (Fig. 2a). During the last 3 decades, the downstream part of the catchment has been influenced by the operation of a dam with significant trapping of sediments. The dam was constructed 20 km upstream of the estuary for hydropower production, and serves as flood protection for the town of Arta. The reservoir provides water for irrigation of neighbouring agricultural land and has become a biotope for several species of fish fauna. Moreover, both the reservoir and the upstream rivers offer plenty of recreational opportunities. On the other hand, due to sediment supply reduction in the coastal areas, the lowest part of the river mouth has significantly retreated, while, due to significant erosion phenomena in the catchment, the reservoir useful storage capacity is rapidly reduced (Georgiou and Mimikou, 2006; Panagopoulos et al., 2008).

Eutrophication phenomena are particularly undesirable in the reservoir as well as in the estuary, which is a habitat for endangered species, protected by the Ramsar Convention (Kotti et al., 2005). However, such phenomena have been observed indicating that the water quality of the Arachtos river should be improved, with nutrient concentrations ideally lying below permissible thresholds. According to the national classification system for small and medium-sized Greek rivers (Skoulikidis et al., 2006), 'Good' water quality status corresponds to maximum concentrations of 0.60 mg/l for N-NO3 and 0.165 mg/l for TP, while 'High' status corresponds to 0.22 mg/l N-NO3 and 0.125 mg/l TP. Measurements upstream of the reservoir have however indicated that river concentrations are greater than the high status thresholds, indicating that the Arachtos main river and its tributaries is of 'moderate' or even worse water quality status. It is thus necessary to preserve river water quality at the highest possible level in order to ensure its Good Ecological Status by 2015, as required by the WFD.

The study area consists of the upstream part of the Arachtos catchment that drains through a maximum stream length of 50 km through the Plaka outlet (Fig. 2b). The rivers of the 940 km^2 upstream catchment area have not been subject to human intervention, while point sources are limited and nutrient pollutants arise mainly from diffuse sources. An additional criterion for choosing this outlet for analysis in this study was that the Plaka river station is the only location with available measurements of

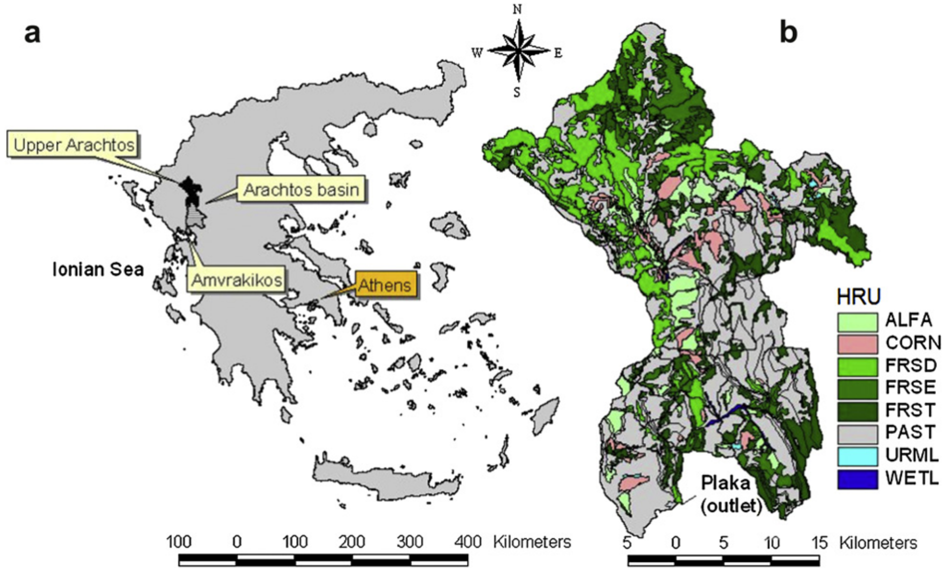

Fig. 2. The upper Arachtos catchment. Note: Fig. 2a shows the location of the study area within Greece, while Fig. 2b depicts the HRUs in the catchment based on the land cover classes, which correspond to alfalfa (ALFA), corn (CORN), deciduous forest (FRSD), evergreen forest (FRSE), mixed forest (FRST), pasture (PAST), low density urban land (URML) and water (WETL).

flows, sediments and water quality, allowing for a reliable calibration of the model (Panagopoulos et al., 2011b; 2011c).

The climate in the study area is of Mediterranean type with a mean annual temperature of 15 °C and a rainfall depth of 1500 mm, while the catchment is characterized by a very high slope gradient (slopes up to 30% and elevations between 248 and 2400). The mean annual flow at the outlet is 37 m^3/s and the sediment yield is 1.4 Mt/y. Impermeable flysch deposits cover the northern part of the catchment, while flysch and karstic systems of limestones are interchanged in the central and lower parts. Some alluvial deposits also exist in the catchment area (Panagopoulos et al., 2008). Natural pasture covers 45% of the area serving as grazing land for animals. The main crops cultivated for satisfying livestock nutrition needs are corn and alfalfa that cover 12% of the catchment area (Fig. 2b). Current management practices can be summarized as follows: corn is fertilised with 300 kgN/ha/y and 33 kgP/ha/y, while a deep soil tillage operation follows harvest at the end of September. Alfalfa is cultivated in a 5-year rotation scheme, receiving 22 kgN/ha only in the first year and 45 kgP/ha in February of each following year. Nitrogen and Phosphorus emissions in pastureland arise from 3000 cattle, 100 000 sheep and 2 million broilers (Eurostat, 2000). In the wider mountainous landscape of the Epirus RBD, where the study area is situated, farmers still follow their old customs, being adherent to the traditional agricultural ways of frequent and extensive grazing (Zervas, 1998), which is allowed for cattle and sheep from April to October. During the remaining months of the year (wet period) manure is applied according to a continuous time scheme with a 7-day interval, representing the periodical spread of manure after its collection in enclosing areas. As for poultry manure, the above scheme is considered as standard practice for the whole year (Panagopoulos et al., 2011b; 2011c).

3.2. The SWAT Arachtos representation of the baseline

SWAT requires spatial data representing the Digital Elevation Model (DEM), the land cover and the soil map of the catchment. In the present study, topography was represented by a 50 × 50 m DEM. In the Arachtos catchment, detailed soil information was not available; a geological map (1:50 000) provided by the National Institution of Geology and Mineral Exploration (http://www.igme.gr) was used instead. The three geological types (Fig. 3b) were associated with soil class permeability, with flysch considered impermeable (Ksat = 10 mm/h), alluvial semipermeable, and limestone permeable (Ksat = 150 mm/h). Additional soil parameter values governing surface runoff generation, were defined during calibration by keeping the relative hydrological behaviour between soils close to reality (Panagopoulos et al., 2011b; 2011c). The CORINE Land Cover CLC 1:100.000 vector map of 2000 (EEA-ETC/TE, 2002) and data of the national FSS (Eurostat, 2000) regarding crops allocation per administrative unit, were used to represent land use. Current management practices per land use type were considered homogeneous across the catchment. After dividing the catchment into 27 subbasins, each one representing approximately 4% of the catchment area (Fig. 3a), the combination of subbasins, land use types and geological types resulted in 259 HRUs, consisting of 23 corn (CORN), 29 alfalfa (ALFA), 61 pastureland (PAST) and 146 HRUs of forest, urban and water landuse types (Fig. 2b). The average corn and alfalfa HRU areas were 190 and 210 ha respectively, while pastureland was represented by fields of 600 ha on average. In the present study, any HRU comprised several actual fields. This division can be considered appropriate for common BMP implementation at all fields of the same land cover type that belong to a particular village or small town.

Daily time series of rainfall were available from 8 raingauges (Fig. 3a). Calibration and validation of water discharge and sediment loads were conducted on a monthly basis for long periods within 1964–2002 at the Plaka and at the Tsimovo monitoring stations (Fig. 3a). For nutrient data, only sparse measurements of N-NO3 and TP concentrations were available and hence a comparison of seasonal or annual values was made to make sure that model outputs were close to observations. A detailed description of the Arachtos model parameterization and calibration procedures can be found in Panagopoulos et al. (2011b, 2011c).

The baseline scenario, representing business-as usual for the catchment was modeled in SWAT. As an example, for the most recent 5-year period of the simulation (2001–2005), the model calculated a mean annual flow of 36.7 m^3/s and a mean annual

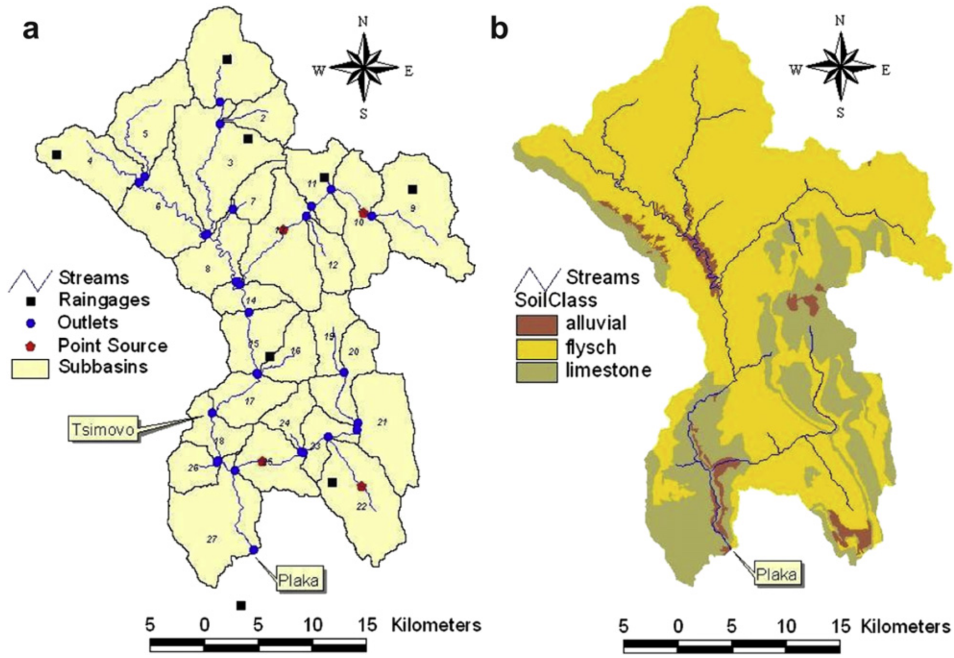

Fig. 3. Subbasins and monitoring points (a) and soil types (b) in the Arachtos catchment.

evapotranspiration of 486 mm, while the mean annual precipitation was 1550 mm. Under conventional practices, soil losses from all HRUs entering streams were estimated at 1390 Kt/y, while the mean annual river sediment yield at the outlet was 1320 Kt/y. Nitrates nitrogen (N-NO3) river loads were calculated by SWAT equal to 769 t/y, while TP loads equal to 263 t/y. The aforementioned values, if expressed in annual loads per ha of catchment area, are equal to 14 t/ha of sediments, 8 kg/ha of N-NO3 and 2.8 kg/ha of TP. The mean annual concentrations of N-NO3 and TP at the outlet without in-stream processes active in SWAT were calculated as 0.65 and 0.22 mg/l respectively. Agricultural diffuse losses were responsible for more than 80% of both N and P losses, with corn being the land use type resulting in the highest sediment and nutrient losses (Panagopoulos et al., 2011b, 2011c).

3.3. BMPs development, SWAT representation and implementation cost

A series of BMPs appropriate to the catchment characteristics of Arachtos were proposed, covering a representative range of interventions, including crop, soil, nutrient application and livestock management. These BMPs have not yet been put into practice in the study area, so the investigation of the possible effects of their implementation and up-scaling on water quality is of significant interest as it could inform cost-effective programmes of measures that will be required during RBMP development. Specifically, the following types of BMPs were examined:

- Establishment of 5 m-wide filter strips on corn, alfalfa and pastureland.
- Reduction of chemical fertilisation to corn and alfalfa: For alfalfa, this BMP was applied by completely removing N from fertilisation and by reducing P by 50%. For corn, a 30% reduction in both N and P rates was applied.
- One month delay in timing of chemical fertilisation to corn and alfalfa.
- Contour farming cultivation of corn.
- No-tillage cultivation of corn.
- A 30% reduction in sheep and poultry numbers in pasture.
- Storage of poultry manure for 3 months and spreading to fields only during the dry season: When at least three-month storage of manure before spreading to fields is adopted, gaseous losses of ammonia, nitrous oxide and immobilisation of N occur, which reduce the quantity of mineral-N available for loss by leaching or in surface runoff. A reduction of 15% in N was considered to occur. This method has no effect on P (Cuttle et al., 2007).
- Reduction of the sheep grazing period along with manure storage: Grazing was reduced by two months, when their breeding was assumed to take place indoors. The collected manure was stored and then spread in fields on a weekly basis and only during the dry period.

A summary of the key information related to the selected BMPs is presented in Table 1. A short description of how each BMP operates in reducing diffuse pollution is given in the 4th column (COST Action 869, 2006; Cuttle et al., 2007; Schoumans et al., 2011), while in the next, the SWAT representation of each BMP is described.

The costs presented in Table 1, were calculated as the additional costs needed to implement a specific BMP compared to the baseline. BMP costs included capital and maintenance costs for a 5-year period of BMP operation, as well as loss of incomes arising by its implementation. The latter represented possible losses of corn and alfalfa yields from each HRU as well as revenue losses from the reduction in livestock numbers. Cost estimation of the aforementioned BMPs was undertaken mainly by taking into consideration two recent studies conducted by the National Agricultural Research Foundation (NAGREF) of Greece regarding alfalfa cultivation and sheep-breeding (Tzouramani et al., 2008a, 2008b). For filter strips reported annual cost rates from Cuttle et al. (2007) were also used for comparison to our approximations. For calculating the costs of grazing season reduction and manure storage, published values from the inventory of measures developed in the UK (Cuttle et al., 2007) were also taken into account.

All prices were estimated with reference to 2007, when both NAGREF studies were conducted and should thus be considered

Table 1
List of agricultural BMPs selected for the analysis of the Arachtos catchment.

Land use	BMP	BMP description	BMP rationale	HOW implemented in SWAT	COST Additional cost − income[a]
CORN	C1	Timing of chemical fertilisation	Reducing the risk of nutrient transport	29/4 instead of 29/3	No COST
	C2	Fertiliser reduction	Reducing N and P inputs to soil	−30% N and P	−0.19 €/kg fert 20-10-00 −0.245 €/kg fert 33-00-00 0.17 €/kg yield lost
	C3	Contour Farming	Reducing surface runoff and erosion	$P_{USLE} = 0.9$ $CN_{new} = CN - 3$ (Arabi et al., 2006)	10 €/ha (more labour, fuel) 0.17 €/kg yield lost
	C4	No-tillage	Reduce soil erosion, N mineralisation and P mobilisation	Tillage removal	- 40 €/ha (less labour, fuel) 0.17 €/kg yield lost
	C5	Filter strips	Delay runoff Trap sediments and nutrients	5 m strip width	50 €/ha (seeds, labour, fuel)
ALFALFA	A1	Timing of chemical fertilisation	Reducing the risk of nutrient transport	15/3 instead of 15/2	No COST
	A2	Fertiliser reduction	Reducing N and P inputs to soil	−100% N, −50% P	−0.17 €/kg fert 11-52-00 and 00-15-00 0.17 €/kg yield lost
	A3	Filter strips	Delay runoff Trap sediments and nutrients	5 m strip width	50 €/ha (seeds, labour, fuel)
PASTURE	P1	Poultry numbers reduction	Reducing N and P inputs to soil	−30% manure deposition	Broilers (0.35 €/animal)
	P2	Storage of poultry manure and application only in the dry season	Reducing manure N content Reducing the risk of transport	15% reduction in manure N content Application from April to September Double the manure application rate	Broilers (0.15 €/animal) (more labour, fuel)
	P3	Sheep numbers reduction	Reducing N and P inputs to soil	−30% manure deposition	Sheep (3.56 €/animal)
	P4	Reduce sheep grazing season by 2 months. Manure storage and spread during the dry season	Reducing N and P inputs to soil Reducing manure N content Reducing the risk of transport	Sheep grazing 150 days: 1May-30 Sep Store manure of the non-grazing period and deposition during: 1 May–30 Sep with 30% N content reduction and 40% increase in the application rate	Sheep (3.5 €/animal) (more labour, fuel)
	P5	Filter strips	Delay runoff Trap sediments and nutrients	5 m strip width	50 €/ha (seeds, labour, fuel)

[a] Positive values in the last column indicate additional cost of BMP implementation compared to conventional practice. Negative values indicate additional farmers' income arising from BMP implementation.

highly reliable. Other estimations related to fuel and labour costs, although sensitive to assumptions (Schou et al., 2006), were calculated with common unit values for the different BMPs in the study area and hence provided a solid basis for relative comparisons, even if absolute values had a degree of uncertainty. Specifically, labour costs were calculated based on average hours needed to undertake the establishment of a BMP and they were then multiplied by a constant hourly labour rate of €8. Similarly, fuel costs were calculated based on the number of machinery operations needed and the length of time required to undertake them considering a constant rate for diesel (0.92 €/l). Both rates presented above were the averages within typical narrow ranges met in 2007 at the national level; hence, possible small deviations were not able to affect the ranking of different BMPs with respect to their total cost of implementation. On the whole, it is suggested that the economic estimates used in this work, given the usual economic data limitations, should be considered reliable and representative for examining the relative magnitude of mean annual costs between different BMPs and locations. More details on the estimation of the cost of each BMP can be found in Panagopoulos (2010) and Panagopoulos et al. (2011c).

All BMPs selected for each land use type in Table 1 were compatible with each other. For example, the five BMPs suggested as suitable for corn could be combined with each other (C1 + C2, C1 + C2 + C3 etc.) thus giving rise to composite practices, whose cost of implementation could be obtained as the sum of the costs of the separate actions. Thus, for corn the total number of composite BMPs that could be applied was 31:

$$CORN_{BMPs} = \binom{5}{1} + \binom{5}{2} + \binom{5}{3} + \binom{5}{4} + \binom{5}{5} = 31 \quad (1)$$

When the baseline (non-BMP) practice of corn cultivation was also included in the set, the total number of practices under consideration for all areas with corn fields reached 32. Similarly, the number of BMPs applicable to alfalfa was 8. Finally, not all combinations were considered feasible for pasture, thus 10 BMPs were selected for inclusion to the optimisation scheme. Fifty different BMPs were finally selected and are numbered sequentially in Table 2.

3.4. Development of the BMP database

The BMP database, developed for use with the BMP decision support tool, stored losses of mean annual sediments, N-NO3 and TP, as well as the respective calculated costs arising from the implementation of each BMP to all HRUs.

Table 2
List of BMPs combinations selected for corn, alfalfa and pastureland HRUs of the Arachtos catchment.

BMP number	BMP	Land use	BMP Number	BMP	Land use	BMP number	BMP	Land use
1	baseline	CORN	18	C1 & C2 & C4	CORN	35	A2	ALFA
2	C1	CORN	19	C1 & C2 & C5	CORN	36	A3	ALFA
3	C2	CORN	20	C1 & C3 & C4	CORN	37	A1 & A2	ALFA
4	C3	CORN	21	C1 & C3 & C5	CORN	38	A1 & A3	ALFA
5	C4	CORN	22	C1 & C4 & C5	CORN	39	A2 & A3	ALFA
6	C5	CORN	23	C2 & C3 & C4	CORN	40	A1 & A2 & A3	ALFA
7	C1 & C2	CORN	24	C2 & C3 & C5	CORN	41	baseline	PAST
8	C1 & C3	CORN	25	C2 & C4 & C5	CORN	42	P1	PAST
9	C1 & C4	CORN	26	C3 & C4 & C5	CORN	43	P2	PAST
10	C1 & C5	CORN	27	C1 & C2 & C3 & C4	CORN	44	P3	PAST
11	C2 & C3	CORN	28	C1 & C2 & C3 & C5	CORN	45	P4	PAST
12	C2 & C4	CORN	29	C1 & C2 & C4 & C5	CORN	46	P5	PAST
13	C2 & C5	CORN	30	C1 & C3 & C4 & C5	CORN	47	P1 & P3	PAST
14	C3 & C4	CORN	31	C2 & C3 & C4 & C5	CORN	48	P2 & P4	PAST
15	C3 & C5	CORN	32	C1 & C2 & C3 & C4 & C5	CORN	49	P1 & P3 & P5	PAST
16	C4 & C5	CORN	33	baseline	ALFA	50	P2 & P4 & P5	PAST
17	C1 & C2 & C3	CORN	34	A1	ALFA	51[a]	NO BMP	OTHER

[a] The 51st option was incorporated to facilitate the expression of no interventions in non-agricultural areas.

The database consisted of tables that contained information concerning the environmental or cost variables (in this case four tables for four variables: TP, N-NO3, sediments and cost) for each HRU. Rows, in these tables represented the HRUs of the catchment and columns represented the loads and costs that resulted after each BMP has been implemented in the specific HRU. In the case of the Arachtos catchment each Table contained 259 × 51 cells, whereby 259 was the number of HRUs in the catchment and 51 was the number of BMPs totally tested (Table 2). The 51st was not actually a BMP but was incorporated to facilitate the expression of no interventions in non-agricultural areas.

The procedure for creating the BMP database was simple and completely automated (Fig. 4). A set of scripts in MATLAB found and opened the input 'mgt' files used by SWAT to identify practices within each HRU. It recognised landuse and soil information and set the values which were required to represent each BMP. For example, in order to assess the introduction of filter strips in corn HRUs, the script related to BMP no. 6 in Table 2 was executed, recognised all 'mgt' files with corn as their land use type and set the filter strip value to 5 m instead of 0. SWAT was then run for 5 years (2001–2005) thus simulating mean annual loads that would have been produced from all HRUs during this period, if a BMP was applied.

After each run, the mean annual pollutant losses from each HRU and the mean annual crop yields were obtained, as well as the respective cost estimates for each BMP implementation, which were automatically stored in the BMP database. The database contained total actual losses of pollutants from each HRU and BMP (as opposed to differences in pollutant losses or percentage changes from the baseline). Pollutant loads and costs referred to the total for each HRU. These could have been expressed in specific load (per hectare) but it was decided to include the required transformation in the optimisation problem in order to obtain a direct estimate of the total annual loads and costs produced by each BMP combination.

3.5. Multi-objective optimisation

A single-objective optimisation (in this case: minimisation) for the sum of loads or costs would attempt to locate the BMP that minimises pollutant losses or cost for each HRU (one from each row of the matrix) and to aggregate at the catchment level. Such a minimisation problem in the case, for example, of TP can be formulated as follows:

$$\min \sum_{i=1}^{259} \mathrm{TP}(i,j), \quad \mathrm{TP}_{(\mathrm{HRUs,BMPs})} = \begin{bmatrix} a_{1,1} & \cdots & \cdots & a_{1,51} \\ a_{2,1} & \cdots & \cdots & a_{2,51} \\ \cdot & \cdots & \cdots & \cdot \\ a_{i,1} & \cdot\cdot & a_{i,j} \cdot\cdot & a_{i,51} \\ \cdot & \cdots & \cdots & \cdot \\ \cdot & \cdots & \cdots & \cdot \\ a_{259,1} & \cdots & \cdots & a_{259,51} \end{bmatrix} \quad (2)$$

where $a_{i,j}$, is the element of the matrix, which corresponds to TP losses from the i_{th} HRU when the j_{th} BMP was implemented.

The problem solution for the single objective is straightforward. However, when two or more conflicting objectives are included in the optimisation problem, for instance, when TP, N-NO3 losses and cost are all objective functions for minimisation, the BMP combination that minimises one objective does not necessarily minimise another. Thus Eq. (2) was extended to include two more objectives: N-NO3 and Cost, and the optimisation problem addressed in the Decision Support Tool (DST) became:

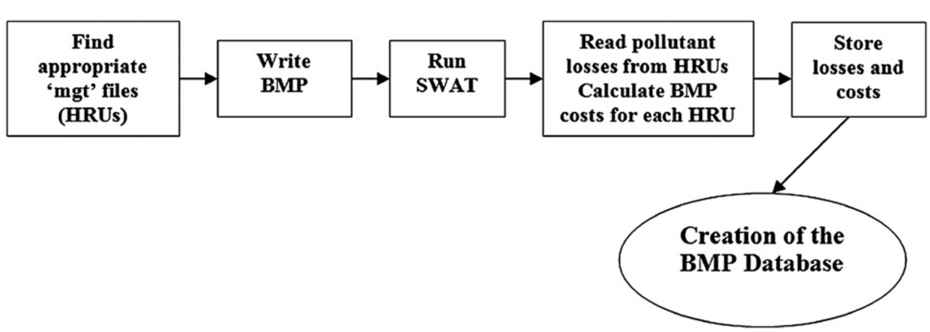

Fig. 4. Populating the BMP database.

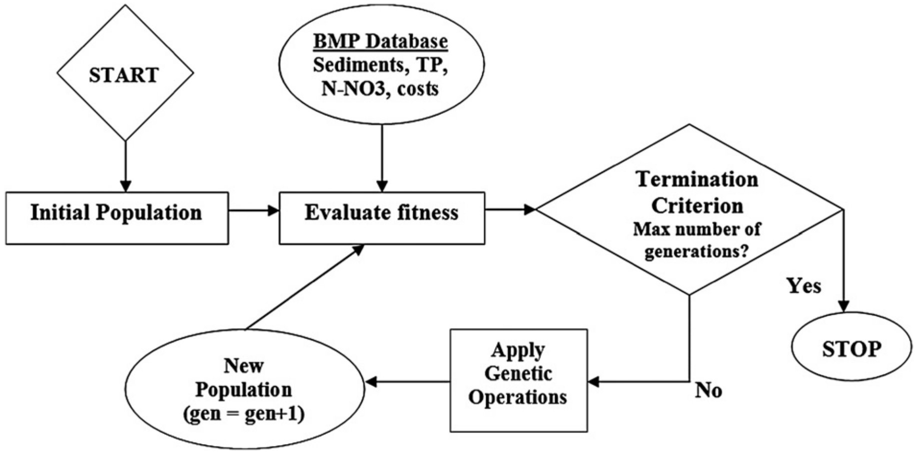

Fig. 5. The multi-objective optimisation process for BMP selection and placement.

$$\min\left[\sum_{i=1}^{259}\mathrm{TP}(i,j)\wedge\sum_{i=1}^{259}\mathrm{N{-}NO3}(i,j)\wedge\sum_{i=1}^{259}\mathrm{Cost}(i,j)\right] \quad (3)$$

The multi-objective optimisation process is depicted in Fig. 5.

The optimisation process started with the initialization of a population either randomly, by the GA or by the user. Each individual of the population consisted of genes equal to the number of decision variables (in this case equal to the number of HRUs in the catchment). The values of genes of an individual formed the genotype, while their real representation (phenotype), represented a combination of BMPs in the HRUs of the Arachtos catchment. A real integer coding was selected to represent this problem, thus the genes of each individual were expressed by integer values between 1 and 51, representing the 51 alternative BMP options reconsidered in this work (Table 2). The representation of one hypothetical individual (chromosome), which represented a complete, composite solution for the entire catchment, is shown in Fig. 6.

To ensure that the algorithm created only valid solutions (individuals), a set of lower and upper bounds (LB and UB) was also defined so that the GA was driven to select values from the first 32 columns of the BMP Database for corn HRUs, from the following 8 for alfalfa and the next 10 for pastureland. For non-agricultural HRUs the GA was constrained to choose values only from the last (51st) column so that it would not delay by selecting between equal values stored in all the 51 columns. Although no BMPs were implemented in these HRUs, such a definition was necessary in the programming structure which had as objective functions the minimisation of the total nutrient loads from the catchment. The selection of the 51st column could facilitate the expression of no intervention in those areas with a clear distinction from possible no interventions in agricultural areas (BMP 1, 33 and 41). Bound constrains in each x_i chromosome gene (HRU) were therefore the only mathematical constraints of the optimisation problem and are expressed as follows:

$$1\le x_i^{\mathrm{CORN}}\le 32,\quad 33\le x_i^{\mathrm{ALFA}}\le 40,\quad 41\le x_i^{\mathrm{PAST}}\le 50,\quad 51\le x_i^{\mathrm{OTHER}}\le 51 \quad (4)$$

Once appropriately formulated, the individuals of the population were evaluated according to the fitness functions, which were the sum of pollutant losses and costs from all HRUs provided by the BMP Database (Fig. 5), which in this case acted as a lookup table, instead of running SWAT. The algorithm tried to minimise all possible user defined criteria through an iterative process of population evolution. After the evaluation of the population, the algorithm compared the generation number with a maximum generation counter, defined as the termination criterion. If the current generation number was equal to the maximum, the algorithm stopped, otherwise the population was undergone selection and genetic operations (crossover, mutation) in order to form a new population for the next generation. The higher the population size and the number of maximum generations, the better the convergence to the optimal Pareto front, but the higher the computation time of the process.

A three-criterion optimisation is presented here, including the minimisation of N-NO3 and TP loads to surface waters and the total costs of BMPs implementation in the Arachtos catchment. As mentioned in 3.1, both N-NO3 and TP river concentrations at the baseline scenario have been found to exceed the upper limits of ‘Good’ water quality status. Especially for P, the deviation of the baseline annual concentration (0.22 mg/l) from the maximum permissible value (0.165 mg/l), corresponding to ‘Good’ water quality status, was almost 25%, while a much smaller deviation was found for N-NO3, equal to 8% (0.65 mg/l at the baseline instead of 0.60 mg/l which was the lowest desirable target). Even for N-NO3, however, a much greater reduction than 8% is preferred in order to guarantee a good ecological status of the river with respect to the level of this nutrient. Both nutrient minimisation objectives were

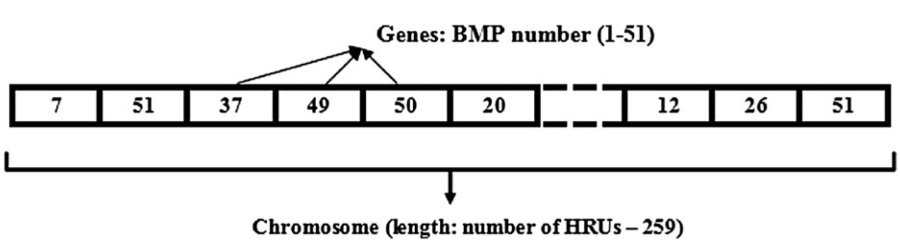

Fig. 6. A chromosome representing a complete BMP scheme in the Arachtos catchment (a composite management solution for the entire catchment).

expected to be conflicting with cost, while a (less) conflicting relationship between the reduction magnitudes of the two nutrients, caused by BMPs, was also expected.

3.6. Selected GA functions and parameters

To optimise the selection and placement of BMPs, a set of appropriate GA parameters was required in order to guarantee the convergence to the optimal front within reasonable time. Although a detailed sensitivity analysis of the MATLAB-GA parameter sets is beyond the scope of this paper, a quick reference to our selections regarding the genetic operations and the GA parameters is included:

- The use of the "Rank" function for scaling individuals was found as the most effective. This function scales the raw scores based on the rank of each individual instead of its score. The rank of an individual is its position in the sorted scores, thus the rank of the most fit individual is 1, the next most fit is 2, and so on (MATLAB 2010). Selection of individuals was then performed by tournament selection, which selected two or more players (individuals) at random and then the best individual out of that set was considered to be a parent. This selection method is generally suggested for multi-objective optimisation problems (MATLAB, 2010; Makropoulos and Butler, 2005; Nicklow et al., 2010).
- Scattered crossover was selected as the preferred crossover method. A random binary vector was created and the algorithm combined the genes of the first parent, corresponding to the places where the binary vector was a 1 and the genes of the second, corresponding to the places where the vector was a 0 (MATLAB, 2010).
- A crossover probability of 0.8 was set in our optimisation problem after a quick sensitivity analysis with a small number of population size and maximum generations.
- Finally, a Gaussian mutation was selected and as the mutation function embedded in MATLAB is adjusted to variables of type 'double', a new mutation function for integers was written. With this mutation option, the amount of mutation was proportional to the standard deviation of a Gaussian distribution and decreased at each new iteration proportionally to the user defined preferences. In this study, the amount of mutation was defined to decrease by 75% at the last generation.
- In terms of size of population and maximum number of generations, the Pareto front was found to improve considerably when population increased. Even after a relatively small number of generations (e.g., 1000), the Pareto front tended to approach a near optima with high population sizes (500 or 700). As was to be expected, a large number of sets of population and generation values led to acceptable Pareto fronts. A compromise with respect to efficiency and computation time was made and a population of 250 with a total maximum number of generations equal to 40 000 was selected for the specific problem of the three-criterion optimisation. A Pareto fraction equal to 0.4 was selected to limit the number of solutions in the first Pareto front to 100.

4. Results and discussion

4.1. Evolution of trade-off frontiers between cost and nutrient loads

The optimal trade-off frontiers of cost-TP and cost-N-NO3 produced after the termination of the three-objective optimisation are shown in Fig. 7 along with their evolution during the optimisation process. As can be clearly observed, both total nutrient losses from HRUs were found to significantly decrease from the baseline starting even from the first generations as most of the BMPs included in the random initial population were actually effective in reducing pollutants. Both TP and N-NO3 were significantly reduced from the baseline after a few generations, as the most important HRUs and BMPs in reducing pollutants seemed to have been already found. These (important) HRUs were usually the largest by size, whose greater contribution to the total loads had been readily identified. The most promising BMPs were filter strips and fertilisation reduction.

The algorithm then continued to find better solutions but with a slower convergence rate. After 5000 generations the algorithm had identified some additional combinations of BMPs selection and placement, which most probably included the combination of the best BMPs with not so efficient ones, such as the timing of fertiliser application, the storage of manure and the corn contour farming in more extended areas in the catchment. During the first 5000 generations the frontiers had also lengthened to the side of negative cost, meaning that the algorithm had clearly identified BMPs such as alfalfa fertilisation reduction and no-tillage cultivation of corn, which had been proved to increase income (Panagopoulos et al., 2011c). However, the frontier was still far from the optimal, which could be concluded from the minimum loads, which were 457 000 kg for N-NO3 and 102 000 kg for TP. The minimum cost was also identified in the BMP Database at −500 000 €, representing the maximum increase in the farmers net income. This implied that there were possible BMP combinations in the catchment which did not cost at all and could in fact even ensure an income increase for the agricultural population. Finally, the

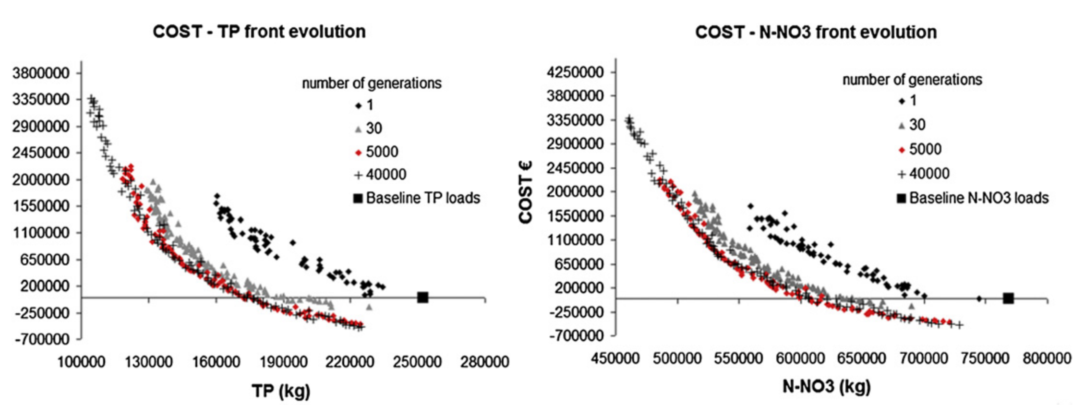

Fig. 7. Evolution of Cost-TP and Cost-N-NO3 fronts during the optimisation process (fronts at 1, 30, 5000 and the maximum 40,000 generations are depicted).

algorithm converged slowly and identified more BMP combinations between 5000 and 40 000 generations, providing an acceptable approximation of the true fronts. A closer observation of the front's evolution indicated that the algorithm converged at around 20 000 generations.

The total time needed for the termination of the optimisation was 5 h and 30 min on an Intel(R) Core(TM)2 CPU@ 2.13 GHz and 4 GB RAM, thus the algorithm spent approximately 0.002 s/evaluation (250 × 40 000 evaluations). If this process had been conducted with a dynamic link to SWAT, an average of 20 s per SWAT run (evaluation) would have been needed and the optimisation problem would have become impractical to solve. The use of the BMP Database as a lookup table resulted in a 10^4 times faster optimisation process, permitting a large number of generations and a better search of the solution space. The database can be populated for any catchment if appropriate cost data exist with minimal customisation.

The BMP database contained pollutant values for the outlet of each HRU and did not include calculations of pollutant propagation downstream (e.g., at the outlet of the whole catchment). Clearly the sum of the values at the HRU level did not necessarily coincide with pollutant yields at the catchment outlet, due to in-stream processes. This means that what the DST attempted to minimise, was in fact the pollutant losses from the HRUs, rather than the concentration of pollutants out of the outlet of the catchment. Apart from the obvious advantage of this approach in terms of computational speed, it can be suggested that this objective is better suited for agricultural catchments than the more usually attempted objective of the downstream node, as the objective of Good Ecological Status, implies moving the point of interest from the outlet upsteam, to all river segments of the catchment. This is because in the former case, what is being minimised is pollution across the catchment, while in the latter, the influence of in-stream processes (incl. differences in flows and hence dilution) may hide the effect of pollution from parts of the catchment. Thus, a considerable reduction in nutrient levels at the outlet may not be indicative of the reductions in pollutant achieved in upstream areas.

By using the BMP database in this study we sought to minimise environmental pollution across the whole upstream Arachtos catchment, where water quality of tributary rivers might have also been of concern. In the particular case of Arachthos, however, in-stream nutrient processes should not be considered significant at an annual basis. The reason is the limited hydrographic network development due to the small area and narrow shape of the catchment, combined with severe rainfall events that result in fast hydrological responses (small residence time). Both small areas of watercourses and quick river response limit the extent of in-stream biogeochemical processes (Behrendt and Opitz, 2000; Kronvang et al., 1999). Given the fact that loads from point sources in the catchment are insignificant, it can be assumed that annual nutrient loads at the outlet are closely correlated to total nutrient diffuse losses from fields entering rivers and streams. It is therefore suggested that by minimising pollutant losses from HRUs we can also minimise pollutant yields at the outlet of the upstream Arachtos catchment.

Clearly, if the problem of interest contained features or structures (such as dams) that would imply a significantly different nutrient removal efficiency this approach would need to be modified to account for such process – for example by running model evaluations for the pareto front – as discussed below.

4.2. Detection of solutions on the optimal trade-off fronts

In order to examine optimal solutions, cost-TP, cost-N-NO3 and N-NO3–TP optimal fronts are shown separately in Fig. 8. To translate the solution to nutrient concentration levels at the outlet, the 100 pareto set solutions proposed by the GA were imported into SWAT and the model was executed 100 times to calculate the mean annual (2001–2005) concentrations at the outlet (Plaka river site – see Fig. 2b).

These trade-off schemes provided information on 100 different BMP combinations, which resulted in various costs and nutrient concentrations. Solution 1 (Fig. 8) indicated with a green rectangle, allowed to reduce TP to 0.125 mg/l (Fig. 8a), the upper limit of the "High" water quality status class (Skoulikidis et al., 2006). This application management solution achieved a 45% TP reduction from the baseline at a cost of approximately 500 000 €, providing a possibly acceptable compromise between conflicting objectives. On the other hand, the same solution identified in the cost-N-NO3 space (Fig. 8b), reduced N-NO3 concentration to 0.49 mg/l, and thus achieved a reduction of 25% as compared to the baseline. In fact, this level of reduction can also be considered significant as the resulting concentration lay below the upper limit of the "Good" water quality status set by Skoulikidis et al. (2006) at 0.60 mg/l.

Another interesting point on the fronts is solution no 2, indicated with a red triangle (Fig. 8a and b). This was first identified in the cost-N-NO3 space in order to marginally achieve the aforementioned upper limit of N-NO3 concentration (0.6 mg/l). In the Arachtos catchment, an 8% reduction from the baseline was enough to achieve this goal. It was interesting, however, that this reduction could be delivered by a BMP combination that actually increased the farmers' income. A net additional income of 400 000 € for farmers at the catchment level was expected through this solution, which mainly consisted of chemical fertilisation reduction in alfalfa HRUs, having no impact on yields (Panagopoulos et al., 2011c). The same solution on the cost-TP front (Fig. 8a) caused a reduction in concentration to 0.187 mg/l, 14% lower than the baseline. Although this was not adequate to reach environmental targets with respect to TP (set at 0.165 mg/l, corresponding to a 'Good' quality class (Skoulikidis et al., 2006)), it was indicative that this improvement (0.022 mg/l TP) could actually be achieved with an increase in the farmers' income.

The two solutions discussed above revealed that TP and N-NO3 did not exhibit conflicting behaviour. The exact relationship between N-NO3 and TP reduction magnitudes for the full range of objective function values could be obtained by representing their trade-off curve (Rabotyagov et al., 2010). Graph (c) of Fig. 8 revealed that the reduction of one nutrient caused a reduction of the other; however, a significant difference in the magnitude of these reductions was observed by implementing various BMP combinations across the catchment, with TP being reduced more drastically than N-NO3. For instance, the maximum reduction of 60% for TP corresponded to a 40% N-NO3 maximum reduction from the baseline, while a moderate reduction of 30% for TP resulted approximately to a 20% for N-NO3. The relationship between the two nutrient reduction rates was almost linear with TP systematically decreasing by approximately 50% more than N-NO3 from the baseline when a BMP allocation scheme was selected from the optimal front. This more drastic reduction of TP was a reasonable outcome as the BMPs investigated had a greater impact on P. Filter strips, for example, were more effective in reducing pollutants transported via surface pathways (such as P) than pollutants transported via subsurface pathways (such as N-NO3). As another example, fertilisation reduction to alfalfa resulted to P reduction in every year of its 5-year growth cycle, while N reduction was lower, as this practice affected N quantities only on the first and single year of its application. This synergistic behaviour, attributed to the nature of the majority of BMPs selected and/or designed for this study, is considered to be an important finding that can facilitate policy

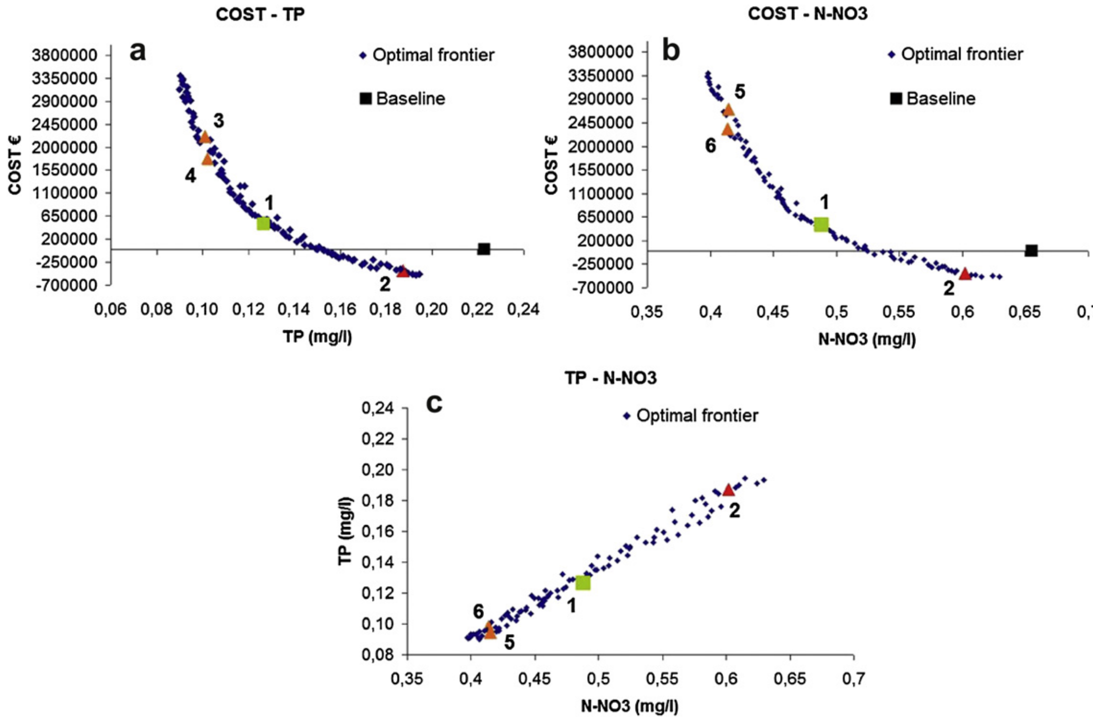

Fig. 8. Optimal trade-off frontiers produced from the three-criterion optimisation. Notes: Graph (a) represents the optimal front on the cost-TP space, graph (b) on the cost-N-NO3 space and graph (c) on the N-NO3–TP concentration space. Solution 1 (green rectangle) achieves TP concentration reduction of almost 45% and N-NO3 reduction of 25% from the baseline, while solution 2 (red triangle) achieves reductions of 14% and 8% for the two nutrients. Solutions 3–4 & 5–6 (orange triangles) correspond to similar cost and effectiveness, but maybe represent significantly different BMP allocations across the catchment. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

makers in controlling the reduction level of two pollutants at the same time.

Other important solutions on the fronts presented in Fig. 8a and b are those that were concentrated close to the *x* axis, thus those which resulted in environmental improvements at little or no cost. As demonstrated, there were several management schemes that could considerably reduce TP and N-NO3 with BMP combinations across the catchment with zero cost. The minimum concentrations that could be achieved by these "zero net cost solutions" were 0.15 mg/l TP and 0.53 mg/l N-NO3 and corresponded to a combination of expensive and profitable BMPs. For example, they included the implementation of no-tillage BMPs in corn fields and chemical fertilisation reduction in alfalfa fields, along with other more efficient and expensive BMPs (e.g., filter strips) in these fields and in a limited number of pastureland HRUs, which in combination resulted in a close-to-zero cost for the whole catchment.

Clearly this cost aggregation at the catchment level, obscured the issues of limitations arising from the cost allocation across the catchment. In the previous case for example, a zero total cost solution would correspond to loss of revenue for some farmers and to additional benefits for others. The study area is occupied by almost 4000–5000 families (18 000 inhabitants), scattered in villages and small towns, a representative situation of the agricultural population in any Greek province. These communities were geographically represented in SWAT by groups of neighboring HRUs of several land cover types. The HRUs corresponded to groups of smaller individual fields, so each HRU corresponded to a number of real fields of the same crop, belonging to different farmers of the same community and treated in the same way.

The majority of the agricultural families within the catchment hold livestock and cultivate corn and alfalfa to cover animal nutrition needs. Thus, a combined management solution suggesting, for example, profitable BMPs in one land cover type (alfalfa or corn) and expensive BMPs in either the same or another land cover type (pasture) resulted to small economic discrepancies between different agricultural communities and different farmers within the catchment. It is suggested therefore, that by implementing such a combined management scheme, the majority of farmers would incur both gains and losses at the same time through the implementation of the portfolio of profitable and expensive BMPs respectively in their lands, and that these distributions of gains and losses would be evenly distributed throughout the area.

On the other hand, a recent study has shown that heterogeneity in the catchment at the level of the individual farm is crucial for achieving an acceptable/optimal total abatement cost (Doole, 2010), by arguing that differences in production levels per farm (crop yields, animal productivity) can drive the management decisions towards the most cost-effective pollution reduction level. In our work, lack of data prevented an analysis at such detailed level, however, the heterogeneity in farmers' profits was not considered high, while the catchment is too small to influence market prices among different communities; hence the influence of heterogeneity at the very local level, albeit interesting, was considered less important.

If a significant amount of economic resources was available for river basin management, other solutions would be more preferable from the Pareto front. For instance, solutions 3 and 4 in the cost-TP space represent combinations of BMP implementation, which decreased TP concentrations by more than 50% (0.10 instead of 0.22 mg/l). Similarly, solutions 5 and 6 caused a significant reduction in N-NO3 concentrations equal to 35% (0.42 instead of 0.65 mg/l). These schemes included BMP combinations which simultaneously incorporated many different unique BMPs in each land use type, which maximised the environmental effectiveness. Such solutions included the combined application of nutrient, crop and soil management operation for corn, while manure and livestock management along with the establishment of filter strips for pastureland. The cost of implementing these practices increased to close to 3M€.

Assuming that farmers have partial financial participation when such a plan is implemented, the situation is more complicated and it is essential that socio-economic factors be taken into consideration before reaching a decision. Significant management alterations related mainly to livestock numbers and to the grazing period length in the whole catchment or in specific parts may disturb their way of living and may hence conflict with existing socio-economic constraints. The analysis provides the opportunity to take these constraints into consideration by analysing neighboring solutions within the Pareto front, which result in similar overall targets but which may differ in the corresponding BMP allocation schemes. Both sets of solutions (3&4 in Fig. 8a and 5&6 in b) represented BMP combinations of very high effectiveness in reducing pollutants, differing slightly in their total cost of implementation, but with a (potentially significant) difference in the spatial allocation of BMPs in the catchment. This implies that further examination by the decision makers would be required to identify suitable (and perhaps equitable) management schemes and reach an acceptable solution, considering local factors as well as potential schemes to re-allocate costs and benefits, including for example but not restricted to state subsidies to promote good practices.

4.3. Solution mapping

All solutions from the optimal Pareto front can be depicted in maps demonstrating the BMP selection and placement in the Arachtos catchment for each solution. For example, solution 1 of Fig. 8, which allowed for a decrease of TP concentrations to 0.125 mg/l, is presented in Fig. 9.

For alfalfa fields (green background) the solution suggested chemical fertilisation reduction (BMP 35), combined with a delay in the timing of application in some fields (BMP 37) or more extensively with the establishment of filter strips (BMP 39). There was, however, one field in the Northern part of the catchment where all three possible alfalfa BMPs were combined (BMP 40).

For corn (pink background), the solution favoured BMPs that mostly included the establishment of filter strips along with a series of alternative additional BMPs (BMP 13, 15, 22, 26, 28, 29, 30). This happened because filter strips were more efficient in reducing the significant TP losses from corn fields via sediment or direct trapping. However, fertilisation reduction was not included in most of these combined BMPs and as can be seen in Fig. 9, it was not chosen by the algorithm in any of the larger corn HRUs of the Northern part of the catchment, where the combined BMPs 14, 15, 26 and 30 were mostly preferred. On the other hand, this BMP was implemented in the large corn HRU located in the southwestern end of the catchment (BMP 29). By identifying this HRU in Fig. 9 in combination with the soil map of Fig. 3b, it can be observed that corn was growing on the most permeable soil there (limestone). As

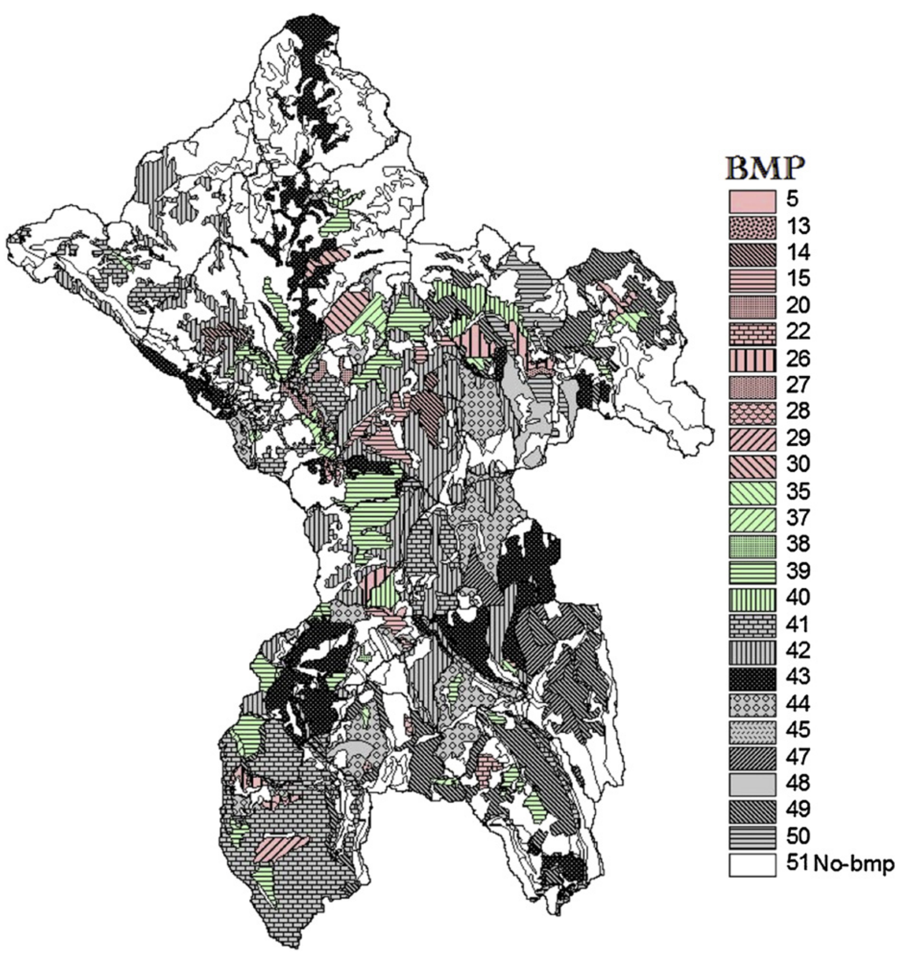

Fig. 9. BMP allocation of solution no.1 in the Arachtos catchment (TP: 0.125 mg/l, N-NO3: 0.49 mg/l).

corn was very sensitive to fertiliser nutrition, the algorithm seemed to prefer including fertilisation reduction in this area, where soil properties did not favour nutrient movement with surface runoff. Therefore, nutrient surpluses on the ground were not significantly reduced and yields were not particularly influenced by the practice. In this way, the algorithm increased the efficiency in reducing pollutants, by slightly increasing the total cost.

For pastureland (grey background), a wide range of possible BMPs was applied across the catchment. However, it is of great interest that a number of large pastureland HRUs, such as the one in the downstream most part of the catchment, was not managed at all (BMP41). Again, we can assume that the algorithm found this compromise solution by preferring not to apply BMPs in a large part of pastureland in the South, where permeable soils caused lower pollutant losses, therefore, their mitigation was less cost-effective than in the North. On the other hand, poultry and sheep reduction (BMP 42 and BMP 44), along with the establishment of filter strips (BMP 49) were favoured by the algorithm in the majority of pastureland HRUs.

In this optimisation problem, sediments were not included explicitly as an objective although a number of BMPs did actually have a significant effect on sediments as well. For solution no. 1 (Fig. 9) for example, sediment losses from all HRUs were 20% less compared to the baseline. However, the optimisation algorithm was not fine-tuned to prioritise sediment reducing practices. BMPs that included filter strips would reduce significantly sediments as well.

It has to be noted here that the effectiveness of filter strips in trapping sediments (and attached pollutants) is in practice influenced by many factors such as flow characteristics, sediment size, vegetation type as well as the location of the strips in the field (Gumiere et al., 2010). SWAT estimates a standard 59% reduction efficiency for pollutants transported with surface runoff (sediments, most of P constituents and a significant proportion of the total N-NO3), on the basis of a "standard" 5 m-wide strip, ignoring these crucial factors. This should be considered a limitation that probably resulted in an overestimation of the efficiency of filter strips, contrary to all other BMPs of the study, which were considered to be much more accurately simulated by the model.

In terms of costs, solution no.1 had a cost of implementation of nearly 500 000 €, which approximately corresponded to 25 €/inhabitant/year and using a similar rationale as in the zero-cost solution discussed above, it can be assumed that this cost was almost uniformly distributed among farmers. When comparing the results of the optimisation process with the business-as usual BMP selection and placement approach, e.g., Panagopoulos et al. (2011c), the optimisation process identified solutions that achieved environmental targets at a much lower cost. As Panagopoulos et al. (2011c) report, they selected 8 BMP combinations, previously tested in the Arachtos catchment on the basis of engineering judgment. Only one of these selected BMP implementations managed to reduce TP to the desirable levels but with a fivefold cost of implementation, as it included the establishment of filter strips to all HRUs. The decision support tool on the other hand, enabled the consideration of spatial variation across multiple variables and, through evaluation of numerous different scenarios, met the same water quality goal with much lower costs of implementation.

5. Conclusions and future research

The decision support tool presented in this paper by creating a lookup table (the BMP database) informed by the NPS estimator (SWAT model) significantly accelerated the optimisation process. This can permit the testing of a large number of BMPs even in large catchments with hundreds of unique hydrological locations. The tool was tested in the Arachtos catchment of Western Greece and trade-off curves of cost-TP, cost-N-NO3 and N-NO3–TP were developed using a multi-objective GA.

The three-criterion optimisation framework presented addressed the importance of analysing solutions that reflected the reduction of more than one pollutant at the same time. This can assist the decision-making process by supporting the analysis of the impact of multiple combinations of BMPs in the catchment. Policy-makers and stakeholders can explicitly see the trade-offs between cost and nutrient reductions and examine spatial patterns or impose additional local constraints.

The strictest TP concentration target in the catchment was met by establishing a combination of BMPs at an affordable annual cost of 25 €/inhabitant, which also resulted in significant N-NO3 reductions as compared to the baseline. In the Arachtos catchment, an acceptable compromise between economic and environmental criteria could be the combination of filter strips in corn and in selected pastureland fields with the fertilisation reduction in alfalfa fields, which would not conflict with socio-economic criteria, mainly related to livestock management.

Further programming adjustments in the tool are currently under way to make the application of the methodology more user friendly and increase its transferability to other catchments. Even in this version, however, the tool offers opportunities for exploring BMP scenarios for river basin management and can assist in the development and implementation of cost-effective RBMPs in Europe.

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