AESTIMUM 65, Dicembre 2014: 95-115

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Multiobjective strategies for farms, using the Dominance-based Rough Set Approach

Key words: *environmental planning; multiobjective optimization; farm management; IMO-DRSA*
Parole chiave: *pianificazione ambientale, ottimizzazione multiobiettivo, gestione aziendale*

JEL: *O21, C01*

The objective of this work is to present how the decision support method IMO-DRSA, combining the Interactive Multiobjective Optimization (IMO) with the Dominance-based Rough Set Approach (DRSA), can be efficiently applied in the agricultural sector, in order to determine optimal and sustainable planning strategies for farms. The method, elaborated by Greco, Matarazzo and Slowinski in 2008, is a novelty in the multiobjective optimization sector. Through IMO-DRSA, we found an optimal multiobjective strategy related to the farm planning of our case study, conciliating four different objectives, one of economic and three of environmental nature. Concerning some practical problems for the application of the method in the agricultural sector, availability and completeness of both environmental and economic data represented a crucial aspect. Another important point concerned the level of subjectivity intrinsic in the method.

1. Introduction

The objective of this work is to present how the decision support method IMO-DRSA, which combines the Interactive Multiobjective Optimization (IMO) with the Dominance-based Rough Set Approach (DRSA - Greco *et al.*, 2001a, 2002a), can be efficiently applied in the agricultural sector, in order to determine optimal sustainable planning strategies for farms. The method, elaborated by Greco, Matarazzo and Slowinski in 2008, is a novelty in the multiobjective optimization sector, because it follows patterns that are completely different from those used in the classical multiobjective methods. The Decision Maker (DM), by means of a simple and transparent interaction process with the analyst based on decision rules, selects the solution which expresses his preferences. At the same time, with this approach the environmental aspects connected to sustainable planning can be automatically introduced within the private management operated by the farmer.

The IMO-DRSA has been applied within a case study in the field of farm management; the final aim was to determine an optimal planning strategy for a farm, conciliating economic objectives with environmental ones. In farm management, it is fundamental to take into account multiple objectives, for reaching optimal results in terms of farm planning and managing. These objectives have to consider not only the economic aspects related to farmer profitability,

DOI: 10.13128/Aestimum-15457

but also those connected with environmental protection and sustainability[1]. Indeed, sustainability of human activities is one of the most important concerns of the European Union (Bastianoni *et al.*, 2010), and in the context of EU Agricultural Policy, farmers have to respect important fulfilment related to environment preservation and contrasting pollution. (e.g. norms related to environmental cross compliance, EU Reg. 2009 n. 73). For this reason, the decisions that a farmer has to take for the management of his farm are becoming more and more complex.

Considering this general framework, the IMO-DRSA can be rather suitable for the application in the farm management sector, for its characteristics of simplicity and transparency, in comparison with the classical optimization methods. Indeed, the classical optimization methods[2] generally require technical parameters, as weights, thresholds, trade off, that often are difficult to understand or determine for the DM (the farmer, in this context).

In the Italian scientific research context, several applications of classical multiobjective optimization in the agricultural and forestry sector have been performed, since the very beginning of '90s, after a previous long period (between '60s and '70s) in which farm planning had been essentially based on the maximization of the economic revenue of the farm, as unique objective to reach. Some examples of these kind of applications, aimed to represent in a more realistic way the complex structure of farms and thus considering multiple farmer objectives, can be found in Ciuchi and Pennacchi (1990, Weighted Goal Programming - WGP), Marangon (1992, Multiobjective Programming), Bernetti *et al.* (1992, Interactive multiobjective analysis), Bazzani (1999, meanPAD).

Several of these works considered both economic and environmental objectives, trying to reach the better compromise among them. The work of Ciuchi and Pennacchi (1990), for example, used the WGP method, in which there is a unique function, composed of multiple different objectives, that in that case were minimization of costs, minimization of soil pollution by fertilizers and pesticides, minimi-

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1 Sustainable economic development involves maximising the net benefits of economic development, subject to maintaining the services and quality of natural resources over time (Pearce *et al.*, 1988).

2 See Fishburn (1967) for the Multiple Attribute Utility Theory and Roy and Bouyssou (1993), Figueira *et al.* (2005), Brans and Mareschal (2005), Martel and Matarazzo (2005) for outranking methods; for some well known interactive multiobjective optimization methods requiring preference model parameters, see the Geoffrion-Dyer-Feinberg method Geoffrion *et al.* (1972), the method of Zionts and Wallenius – Zionts and Wallenius (1983) and the Interactive Surrogate Worth Tradeoff method – Chankong and Haimes (1978), Chankong and Haimes (1983) requiring information in terms of marginal rates of substitution, the reference point method Wierzbicki (1980), Wierzbicki (1982), Wierzbicki (1986) requiring a reference point and weights to formulate an achievement scalarizing function, the Light Beam Search method Jaszkiewicz and Slowinski (1999) requiring information in terms of weights and indifference, preference and veto thresholds, being typical parameters of ELECTRE. methods.

zation of water amount used for irrigation, minimization of labour and technical risk, in relation to a farm located in central Italy.

In the WGP, the Decision Maker must decide some "ideal targets" for each goal, and the method minimizes the difference between the ideal targets and the values reached, for the same goals, in the final optimal solution, which constitutes the best compromise among all the objectives. Moreover, the Decision Maker must decide a weight for each goal, according to his preferences. The topic of weighting is one of the critical points of this, as of other classical optimization methods, because it is difficult to determine the *ex ante* importance of each objective in relation with the others. Another limit of the method is represented by the setting of the targets: fixing a lower or higher target significantly influences the final result.

Some examples of the classical optimization methods applied in the agricultural sector at international level can be found in Bertomeu and Romero (1999), Xevi and Khan, 2005; Agrell *et al.*, 2004; Zarghaami, 2006; Brumbelow and Georgakakos, 2007; Kim *et al.*, 2007; Sahoo *et al.*, 2006.

In contrast with the classical methods, in IMO-DRSA farmers do not have to express preferences in terms of technical parameters. On the contrary, the preference model based on decision rules of IMO-DRSA "speaks the same language" of the decision maker (Greco *et al.*, 2001), representing his preferences in a logic and clear way. Through IMO-DRSA we expressed the farmer preferences by means of simple decisional rules, and we determined a strategy which conciliated a high income with low levels of nitrates lixiviation, soil erosion and water consumption. This represented the very first application of the method in this research field.

Concerning the methodological procedure, in general the IMO-DRSA complements well any multiobjective optimization method that finds the Pareto optimal set or its approximation (for a systematic introduction to multiobjective optimization, see Miettinen, 1999; for an updated state of the art of interactive multiobjective optimization see Ehrgott and Gandibleux, 2002; Ehrgott and Wiecek, 2005; Branke *et al.*, 2008; Jaszkiewicz and Branke, 2008). The method is composed of two main stages that alternate in an interactive procedure. In the first stage, a sample of solutions from the Pareto optimal set (or from its approximation) is generated. In the second stage, the DM indicates relatively good solutions in the generated sample. From this information, a preference model expressed in terms of "if ..., then ..." decision rules is induced using DRSA. These rules define some new constraints, which can be added to original constraints of the problem, cutting-off non-interesting solutions from the currently considered Pareto optimal set. A new sample of solutions is generated in the next iteration from the reduced Pareto optimal set. The interaction continues until the DM finds a satisfactory solution in the generated sample. This procedure permits a progressive exploration of the Pareto optimal set in zones that are interesting for the point of view of DM's preferences (Greco *et al.*, 2008).

Some advantages can be underlined (discussed in the final part of the work), in comparison with the classical optimization methods, both from the point of view of the input information and of the output information.

The work is structured as follows: after a brief description of DRSA and of IMO-DRSA, the case study is presented, reporting the construction of the multiobjective model for the example farm (by means of Multiobjective Programming - constraint method) and subsequently, the application of the IMO-DRSA to the model. Discussion of results and some conclusions complete the article.

2. The Method: Interactive Multiobjective Optimization guided by Dominance-based Rough Set Approach (IMO-DRSA)

2.1 Basic concepts of the DRSA

The Rough Sets theory was introduced by Pawlak (Pawlak, 1982, 1991) and it constitutes a tool to describe a set of objects, for which the available information is possibly inconsistent or ambiguous (Boggia *et al.*, 2014). The key idea of rough sets is approximation of one knowledge by another knowledge. In Classical Rough Set Approach (CRSA) (Pawlak, 1991), the knowledge to be approximated is a partition of *U* (where *U* is a finite set of objects) into classes generated by a set of decision attributes; the knowledge used for approximation is a partition of *U* into elementary sets of objects that are *indiscernible* by a set of condition attributes, that is, sets of objects having the same evaluations on these attributes. The elementary sets are seen as "granules of knowledge" used for approximation.

Given a subset of attributes $P \subseteq Q$, the indiscernibility relation with respect to P:

$$Ip = \{ (x,y) \in U \times U : \quad f(x,q) = f(y,q) \ \forall q \in P \} \tag{1}$$

represents the mathematical basis of classical rough sets theory.

In DRSA, where condition attributes are criteria and classes are preference-ordered, the knowledge to be approximated is a collection of "upward" and "downward" unions of classes and the "granules of knowledge" are sets of objects defined using dominance[3] relation instead of indiscernibility relation. This is the main difference between CRSA and DRSA (For the extended mathematical representation of the DRSA see Greco et al, 2001). The DRSA, in contrast with the classical rough sets approach, allows to consider preferences for attribute domains and for the set of decision classes thanks to the use of dominance relation. Moreover, it is important to note that CRSA enables to consider decisions which are "inconsistent", due to the limited discriminatory power of the criteria for the analysis or as a result of the hesitation of the Decision Maker (DM). Thus, in order to take

[3] The following dominance principle applies to multiple-criteria sorting problems: an object x dominating object y on all considered criteria (i.e. x having evaluations at least as good as y on all considered criteria) should also dominate y on the decision (i.e. x should be assigned to at least as good class as y). Objects satisfying the dominance principle are called consistent, and those which are violating the dominance principle are called inconsistent.

into account the preferences of the DM and the inconsistency typical of decision problems, Greco et al (1999, 2001a, 2002) proposed the DRSA as an extension of CRSA.

The sets of objects to be approximated are called upward unions and downward unions of classes, respectively:

$$Cl_t^{\geq} = \bigcup_{s \geq t} Cl_S \quad Cl_t^{\leq} = \bigcup_{s \leq t} Cl_S \quad \text{with } t=1, \dots , n; \tag{2}$$

The statement $Cl_t^{\geq} = \bigcup_{s \geq t} Cl_S$ means "x belongs to at least class Cl_t", whereas $Cl_t^{\leq} = \bigcup_{s \leq t} Cl_S$ means "x belongs to class Cl_t" at most.

We say that object x dominates object y with respect to $P \subseteq C$, denoted by $x D_P y$, if x is at least as good as y with respect to all $q \in P$. Given $P \subseteq C$ and $x \in U$, the "granules of knowledge" used for approximation in DRSA are:

- a set of objects dominating x with respect to criteria from P, called P-dominating set:

$$D^+_P(x) = \{ y \in U : y D_P x \} \tag{3}$$

- a set of objects dominated by x with respect to criteria from P, called P-dominated set:

$$D^-_P(x) = \{ y \in U : x D_P y \} \tag{4}$$

Thus, with respect to $P \subseteq C$, the set of all the objects belonging to $Cl_t^{\geq}$ without any ambiguity constitutes the P-lower approximation of $Cl_t^{\geq}$, denoted by $\underline{P}(Cl_t^{\geq})$, and the set of all objects that could belong to $Cl_t^{\geq}$ constitutes the P-upper approximation of $Cl_t^{\geq}$, denoted by $\overline{P}(Cl_t^{\geq})$:

$$\underline{P}(Cl_t^{\geq}) = \{ x \in U : D^+_P(x) \subseteq Cl_t^{\geq} \} \tag{5}$$

$$\overline{P}(Cl_t^{\geq}) = \bigcup_{x \in Cl_t^{\geq}} D^+_P(x) = \{ x \in U : D^-_P(x) \cap Cl_t^{\geq} \neq \varnothing \} \tag{6}$$

Analogously, using the P-dominated set, the P-lower approximation and P-upper approximation of $Cl_t^{\leq}$ can be defined as:

$$\underline{P}(Cl_t^{\leq}) = \{ x \in U : D^-_P(x) \subseteq Cl_t^{\leq} \} \tag{7}$$

$$\overline{P}(Cl_t^{\leq}) = \bigcup_{x \in Cl_t^{\leq}} D^-_P(x) = \{ x \in U : D^+_P(x) \cap Cl_t^{\leq} \neq \varnothing \} \tag{8}$$

The P-boundaries (P-doubtful regions) of $Cl_t^{\geq}$ and $Cl_t^{\leq}$ are defined as:

$$Bn_P(Cl_t^{\geq}) = \overline{P}(Cl_t^{\geq}) - \underline{P}(Cl_t^{\geq}) \tag{9}$$

$$Bn_P(Cl_t^{\leq}) = \overline{P}(Cl_t^{\leq}) - \underline{P}(Cl_t^{\leq}) \tag{10}$$

The dominance-based rough approximations of upward and downward unions of classes can serve to induce a generalized description of objects contained in the information table in terms of *"if..., then..."* decision rules, which can be *certain* decision rules (certain assignment of objects to "at least class Cl_t" or to "at most class Cl_s", respectively) or *approximate* (*approximate* assignment of objects to some classes between Cl_s and Cl_t , with $s<t$). Since each decision rule is a consequence relation, by a *minimal* decision rule we understand such a rule that there is no other rule with a premise of at least the same weakness and a conclusion of at least the same strength.

The syntax of the possible types of certain decision rules is the following:

a) $D_{\geq}$ decision rules, obtained from lower approximations of $Cl_t^{\geq}$:

$$if \;\; f(x, q_1) \geq r_{q1} \;\; and \;\; f(x, q_2) \geq r_{q2} \;\; and \; ... \; f(x, q_p) \geq r_{qp} \;, then \;\; x \in Cl_t^{\geq}, \tag{11}$$

where $P = \{q_1, q_2,...,q_\mathrm{p}\} \subseteq C$, $(r_{q1}, r_{q2},...,r_{qp}) \in V_{q1} \times V_{q2} \times ... \times V_{qp}$ e $t \in T$.

b) $D_{\leq}$ decision rules, obtained from lower approximations of $Cl_t^{\leq}$:

$$if \;\; f(x, q_1) \leq r_{q1} \;\; and \;\; f(x, q_2) \leq r_{q2} \;\; \text{and...} \; f(x, q_p) \leq r_{qp} \;, then \;\; x \in Cl_t^{\leq}, \tag{12}$$

where $P = \{q_1, q_2,...,q_\mathrm{p}\} \subseteq C$, $(r_{q1}, r_{q2},..., r_{qp}) \in V_{q1} \times V_{q2} \times ... \times V_{qp}$ e $t\in T$.

2.2 Basic concepts of the IMO-DRSA

Representation of preferences in terms of decision rules induced through DRSA can be fruitfully combined with an Interactive Multiobjective Optimization procedure, as proposed in Greco *et al.*, 2008. An interactive procedure is composed of two alternating stages: computation stage and decision stage. In the computation stage, a subset of Pareto optimal solutions is calculated and presented to the DM (also called user). Then, in the decision stage, the DM is criticizing the proposed solutions unless one of them is completely satisfactory. In the latter case, the procedure stops. Otherwise, the critic of the proposed solutions is used as preference information to build a preference model of the DM. This model is used to calculate a new subset of Pareto solutions, using optimal solutions in the next computation stage, with the intention to fit better the DM's preferences. In some procedures, the preference model appearing between the decision stage and the computation stage is implicit, however, it is useful when it can be explicitly shown to the DM for his or her approval.

For this, the preference model should be comprehensible and the treatment of preference information leading to the model should be intelligible for the DM. The decision rules stemming from DRSA fulfill both these requirements. The IMO-DRSA methodology is presented in the following. We assume that the interactive procedure is exploring the Pareto optimal set of a multiobjective optimization problem; however, it could also be an approximation of this set. The procedure is composed of the following steps:

- **Step 1.** Generate a representative sample of solutions from the Pareto optimal set.
- **Step 2.** Present the sample to the DM.
- **Step 3.** If the DM is satisfied with one solution from the sample, then this is the compromise solution and the procedure stops. Otherwise continue.
- **Step 4.** Ask the DM to indicate a subset of "good" solutions in the sample (exemplary decisions).
- **Step 5.** Apply DRSA to the current sample of solutions sorted into "good" and "others", in order to induce a set of ''*if..., then...*'' decision rules.
- **Step 6.** Present the obtained set of rules to the DM.
- **Step 7.** Ask the DM to select the most important decision rules in the set.
- **Step 8.** Adjoin the constraints coming from the rules selected in Step 7 to the set of constraints imposed on the Pareto optimal set, in order to update the Pareto frontier zone interesting from the point of view of DM's preferences.
- **Step 9.** Go back to Step 1.

For more details about the mathematical formulation of the method see Greco *et al.*, 2008.

2.3 Characteristics of the IMO-DRSA in comparison with classical methods

The interactive procedure presented in Section 2.2 can be analyzed from the point of view of input and output information. As to the input, the DM gives preference information by answering easy questions related to sorting of some representative solutions. Very often, in multicriteria decision analysis, in general, and in classical interactive multiobjective optimization, in particular, the preference information has to be given in terms of preference model parameters, such as importance weights, substitution rates and various thresholds. Eliciting such as information requires a significant cognitive effort on the part of the DM. It is generally acknowledged that people usually prefer to make exemplary decisions and cannot always explain them in terms of specific parameters. For this reason, the idea of inferring preference models from exemplary decisions provided by the DM is very attractive.

The output result of the analysis is the model of preferences in terms of "if..., then..." decision rules, which is used to restrict the Pareto optimal set in an iterative way, until the DM selects a satisfactory solution. This kind of preference model is very convenient for decision support, because it gives argumentation for preferences in a logical form and, therefore, it is intelligible for the DM. It "speaks DM's language" without any recourse to technical terms, like utility, tradeoffs, scalarization functions, reference points, and so on. Moreover, the DM can identify the Pareto optimal solutions supporting each particular decision rule.

All this makes that IMO-DRSA has a transparent feedback organized in a learning oriented perspective, permitting to consider this procedure as a "glass box", contrary to the "black box" typical of many classical procedures, which give a final result without any clear explanation. Decision rules provide a well understandable link between the calculation stage and the decision stage. Due to this feature, the final decision does not result from a mechanic application of a certain technical method, but rather from a mature conclusion of a decision process based on active intervention of the DM.

3. Case Study

In this part, we report the application of the IMO-DRSA within the context of the agricultural sector.

3.1. Area investigated and data used

The case study concerns a single farm, located in a rural area of Central Italy, called "Alta Valle del Tevere Umbra". In this area, which is a great hydro graphic basin served by the Montedoglio dam, irrigated agriculture has been over the time a strength point for local economy; in particular, cereals and industrial cultivations are the main products of this type of activity. Among them, tobacco still remains one of the most competitive crops to be cultivated.

Due to the type of agricultural activities and to the high amount of water, the area is relevant for the environmental point of view. The following typologies of problems can be outlined:

- Highly intensive cultivations must be avoided, especially those that cause high production of nitrates. An intensive cultivation of tobacco can lead to an excess of nitrates, with consequent lixiviation in the soil.
- An intensive use of the soil must be avoided, to prevent phenomena of erosion.
- An excessive consumption of water must be avoided. The good availability of water in the area cannot degenerate into an indiscriminate use. Water supply must not exceed the crops physiological requirement. Unfortunately, control of delivered quantities is quite absent in the area (Capone, 2008).
- The multipurpose nature of the basin has to be taken into account. The Montedoglio lake is a typical example of contemporary in-flow and out-flow uses. It provides water for agriculture and household uses, but also for ecosystems and recreational services.

Moreover, in the context of EU Environmental and Agricultural Policies, all the farmers have to respect important fulfillment related to environment preservation and contrasting pollution, according to the norms on cross compliance (EU Reg. 2009 n. 73). In particular, each farmer has to respect some "*mandatory management criteria*" (indicated in the Annex II of the UE Regulation, which refers, among others, to the Directive 86/278/CEE concerning the protection of environment and of soil, and to the Directive 91/676/CEE concerning protection of water from nitrates pollution) and to maintain "*good agronomic and environmental conditions*", reaching the main objectives of: prevention from soil erosion; protection of water from lixiviation and pollution; correct management and proper use of water resources (article n. 6 and Annex III of the same Regulation). From 2015 the new Regulation for crop compliance (EU Reg. 2013 n. 1306) will be effective, maintaining the mandatory management criteria for the same topics.

For all these reasons, conciliation among economic and environmental objectives is essential, also because mandatory, in terms of management of the single farms as in terms of territorial policies programming.

To construct the case study, several information sources have been used; the principal was the *RICA*[4] database (INEA, 2009), filtered for Umbrian Region. The farms located in the area Alta Valle del Tevere Umbra were extracted from the database, and divided into homogenous groups, according to the main typology of crops cultivated. Subsequently, we selected a single farm having tobacco as dominant cultivation; the choice of tobacco was due to its economic importance in the area. A detailed survey for this farm was performed, in order to collect specific farm data and to construct an interactive dialogue with the Decision Maker, i.e. the farmer. The characteristics of the farm were the following:

- surface: 61.79 hectares;
- agricultural usable surface (SAU): 58.96 hectares;
- irrigated surface: 30.5 hectares;
- cultivations: durum wheat (13.6 ha), common wheat (10.84 ha), maize (2.7 ha), tobacco (27.8 ha), forest (0.95 ha); set-aside and other surface (5.9 ha).

3.2. The multiobjective model for the farm

According to the concerns connected with the area and with the Environmental UE Policy Compliance explained above, we took into account 4 main objectives to be optimized. One had economic characteristics, the three others environmental ones. In particular they were:

1. Maximization of gross revenue (Max GR – euros).
2. Minimization of nitrates lixiviation (Min QLIX – kg of N/ha).
3. Minimization of soil erosion (Min QEROS – T of soil/ha).
4. Minimization of water consumption (Min QWAT – m^3 of water/ha).

The economic objective was connected with maintenance and also improvement of productivity and efficiency inside the farm, while the environmental objectives were considered in relation to the environmental problems within the territory and to the crop compliance management criteria. Indeed, farmers have to

[4] The RICA Database is elaborated by the National Institute of Agricultural Economics; it contains microeconomic data about farms, collected with a unique methodology at European level.

take into account environmental topics in order to ensure the sustainability of the territorial system in which they are involved; the internalization of environmental objectives in the model can be a solution to obtain their proper fulfillment.

Table 1 shows the economic and environmental data used for the analysis.

Table 1. Economic and environmental data used for the analysis.

Crop	Annual Gross Revenue (euro/ha)	Annual nitrates lixiviation (kgN/ha)	Annual soil erosion (T/ha)	Annual water consumption (m^3/ha)
Durum wheat	63.23	17.56	0.024	0
Comm. wheat	141.36	17.56	0.024	0
Maize	362.84	62.40	0.007	2214.60
Tobacco	2837.12	54.61	0.073	3045.11
Barley	-109.03	27.15	0.045	0
Sunflower	-281.17	35.83	0.024	0
Melon	9140.42	54.83	0.115	1112.71
Alphalpha	-158.57	10.53	0.006	2169.42

All the values in the model are referred to 1 hectare of soil, considering one year of production

According to collected data, the initial levels for the four objectives were:

- annual revenue: 82243.87 euros;
- annual nitrates lixiviation: 2115.80 kg of N;
- annual soil erosion: 2.63 t;
- annual water consumption: 90633.48 m^3.

The following elements were introduced in the model:

a) **Variables**[5]:
X_1 − Durum wheat; X_2 − Common wheat; X_3 − Maize; X_4 − Tobacco;
X_5 − Barley; X_6 − Sunflower; X_7 − Melon; X_8 − Alphalpha.

b) **Objectives functions**:
Max = GR[6]; Min QLIX; Min QEROS; Min QWAT.

c) **Restrictions**:
- Total availability of soil (corresponding to the farm agricultural usable surface).

[5] Besides the principal crops of the farm, other crops generally cultivated within the area were introduced in the model, in order to be able to hypothesize potential changes in the cultural system of the farm, in relation to the fixed objectives.

[6] Gross Revenue was calculated as the difference between the production value and the total costs of the farm (including costs about seeds, fertilizers, costs for water supply, costs for rent of equipment, costs of labour).

- Assignment of maximum 30 hectares for crop.
- Monthly necessity of labour for the strictly principal cultivation phases, for each crop.

In order to obtain the frontier of efficient solutions, the multiobjective programming – constraint method (Kuhn and Tucker, 1951) was applied (using software Lingo 8.0, 2002). The first passage of the multiobjective optimization consisted in optimizing each objective function separately determining, for each single optimization, the value of the optimized objective and the values of the other objectives. Table 2 reports the results of this passage.

The range of variation of the four objectives is reported in Table 3.

Table 2. Optimization of the objectives functions separately (by Lingo 8.0).

Single Optimization	GR (Euro)	Lixiviation (kg N)	Erosion (T)	Water (m^3)
Max Gross Revenue	156682.87	3392.74	3.14	147822.80
Min Lixiviation	0	827.19	0.88	65164.62
Min Erosion	5750.75	2123	0.38	129217.42
Min Water Quantity	0	1357.45	1.42	0

Obviously, taking into account each objective separately, the achievement of the optimal result for one of the objectives implies absolutely non optimal results for all the others (e.g. maximization of the only GR causes the highest possible values of lixiviation, erosion, and water consumption, while minimization of the only lixiviation or minimization of the only water consumption cause a null GR). Therefore, the separated optimization of the objectives clearly shows the conflict among them, in particular among the economic objective and the environmental ones.

Table 3. Range of variation of the four objectives.

Objectives	MIN	MAX
Gross Revenue (Euro)	0	156682.87
Lixiviation (kg N)	827.19	3392.74
Erosion (T)	0.38	3.14
Water Quantity (m^3)	0	147822.80

The second passage was parameterization. We performed six different parameterizations: in particular, what we made was to put the environmental objectives in form of constraints, letting them change within their variation range, while maximizing the gross revenue; subsequently, we put the gross revenue as a constraint, letting it change within its variation range, while minimizing each environmental objective separately. The progressive variation in the constraints values, within each parameterization, gave as result different values for the four objectives functions, and a different assignment in terms of surface to the crops introduced in the model.

This series of parameterization allowed us to obtain a consistent number of Paretian efficient solutions. From this set, we selected the first 20 solutions, to be subject to the DRSA, reported in Table 4. The 20 efficient solutions considerably differed in terms of objectives values and in terms of crop surfaces. The choice of the optimal solution, expecting to be a good compromise conciliating all the objectives, would have been be quite difficult without using a proper method supporting the DM; this is true especially in this case, in which the DM is a farmer, i.e. not expert in mathematical models and optimization methods.

3.3 The application of the IMO-DRSA

The DM analyzed the first 20 efficient solutions and indicated a subset of "good" solutions in the sample. The choice of good solutions clearly depended on the DM preferences in that moment. In particular, he indicated as "good" those solutions giving values for him satisfactory in terms of objectives levels (e.g. quite high gross revenue, according to his preferences, or quite low value for one of the environmental objectives). Table 4 represents in grey the procedure of preferences elicitation of the DM.

The DRSA was applied to the current sample of solutions sorted into "good" and "others" (step 5 of IMO-DRSA); therefore, the DM preferences were transformed into decision rules (Table 5). The obtained set of rules was presented to the DM, that subsequently was asked to select the most important decision rule in the set. The DM, according to his preferences, selected the rule n. 1.

The constraints coming from the rule selected (GR $\geq$ 106630.20 and QLIX $\leq$ 3066.40) were adjoined to the set of constraints imposed on the Pareto optimal set, in order to update the Pareto frontier zone interesting from the point of view of DM's preferences.

At this point, we constructed a new multiobjective model with the addition of the new constraints, and induced a new set of efficient solutions by means of another process of parameterization, analogous to the first one. The crops involved in the model were the same than before (melon and tobacco always present; durum wheat, common wheat and maize depending upon the solution considered; only in one solution introduction of barley). From the so restricted efficient frontier, 13 solutions were selected, to be presented to the DM, who indicated another time, according to his preferences, the solutions considered "good" (Table 6). The DRSA was applied to the current sample of solutions sorted into "good" and "others", in order to induce a new set of decision rules, represented in Table 7. The obtained set of rules was presented to the DM, who preferred this time the rule n. 13.

Table 4. First set of efficient solutions, and choice of the “good solutions” according to the DM preferences.

Solut.	GR	QLIX	QEROS	QWAT	Eval.	D.wheat	C.wheat	Maize	Tobacco	Barley	Sunfl.	Melon	Alphal.
1	156682.87	3392.74	3.14	147822.79		0	0	22.00	30.00	0	0	6.96	0
2	41727.26	1000.00	1.30	70324.08		0	24.25	0	0	0	0	4.71	30
3	77108.25	1400.00	2.19	16402.74		19.16	30	0	2.84	0	0	6.96	0
4	107055.78	1800.00	2.72	49278.43	good	8.36	30	0	13.64	0	0	6.96	0
5	136813.17	2200.00	3.25	82154.11	good	0	27.57	0	24.44	0	0	6.96	0
6	151365.18	2400.00	3.51	98591.95	good	0	22.17	0	29.84	0	0	6.96	0
7	24740.84	2264.83	0.60	127168.05		0	0	30	0	0	0	1.98	26.98
8	57515.52	2435.76	1.00	124047.19		0	0	30	0.50	0	0	5.35	23.12
9	86984.30	2814.15	1.60	130407.98		0	0	30	8.48	0	0	5.95	14.53
10	106630.15	3066.40	2.00	134648.50	good	0	0	30	13.80	0	0	6.34	8.81
11	126276.01	3318.66	2.40	138889.03	good	0	0	30	19.13	0	0	6.74	3.09
12	143785.71	3433.35	2.80	143493.77		0	0	27.22	24.79	0	0	6.96	0
13	46860.60	1202.81	1.82	5000.00		24.47	30	0	0	0	0	4.49	0
14	71275.78	1322.10	2.08	10000.00		21.26	30	0	0.74	0	0	6.96	0
15	98603.76	1687.11	2.57	40000.00		11.41	30	0	10.59	0	0	6.96	0
16	134906.20	2173.79	3.21	80000.00	good	0	28.27	0	23.73	0	0	6.96	0
17	151900.16	2424.45	3.51	100000.00	good	0	21.59	0.41	30	0	0	6.96	0
18	50000.00	1077.88	1.50	54858.31		1.05	30	0	0	0	0	5.39	22.52
19	140000.00	3445.27	2.70	142223.07		0	0	28.75	23.26	0	0	6.96	0
20	120000.00	1972.89	2.95	63488.28	good	3.70	30	0	18.31	0	0	6.96	0

The table shows, for each efficient solution, the values of the objective functions and the amount of surface assigned to the several crops. Solutions from 1 to 6 were selected from the results concerning parameterization of lixiviation. Solutions from 7 to 12 were selected from the results concerning parameterization of erosion. Solutions from 13 to 17 were selected from the results concerning parameterization of water quantity. Solutions from 18 to 20 were selected from the results concerning parameterization of gross revenue.

Table 5. First set of decision rules, obtained from the preferences elicitation of the DM.

1) If GR ≥ 106630.20 and QLIX ≤ 3066.40, then the solution is good. (Rule supported by solutions n. 4, 5, 6, 10, 16, 17, 20)
2) If GR ≥ 126276 and QLIX ≤ 3318.66, then the solution is good. (Rule supported by solutions n. 5, 6, 11, 16, 17)
3) If GR ≥ 106630.20 and QEROS ≤ 2, then the solution is good. (Rule supported by solutions n. 10)
4) If GR ≥ 126276 and QEROS ≤ 2.4, then the solution is good. (Rule supported by solutions n. 11)
5) If GR ≥ 106630.20 and QWAT ≤ 134648.50, then the solution is good. (Rule supported by solutions n. 4, 5, 6, 10, 16, 17, 20)
6) If GR ≥ 126276 and QWAT ≤ 138889, then the solution is good. (Rule supported by solutions n. 5, 6, 11, 16, 17)

For each rule, the solutions that support it are indicated. The DM considered the rule n.1 as the more interesting, because in his opinion it allows for a satisfactory value of gross revenue, and contemporary for a consumption of water inferior to the maximum possible value.

The selected rule was supported only by the solution n. 5; it means that this was the unique solution able to respect the restrictions proposed by the rule. Therefore, the interactive process finished with the finding of the optimal solution, i.e. the solution number 5.

4. Discussion

The optimal solution seems to be a good compromise for the conciliation of the four considered objectives. Indeed, it proposes a high gross revenue (116822.41 euros, while the maximum possible value is 156682.87), very low levels of lixiviation and water consumption with respect to the maximum possible values (1930.45 kg of N while the maximum is 3392.74, and 60000 m^3 of water while the maximum is 147822.79), and a level of erosion not very low, but however, inferior to 3 tons (2.89 tons of soil erosion, while the maximum possible is 3.14). The comparison between the values of the objectives functions in the selected solution, and the maximum possible values are reported in table 8.

Also in comparison with the initial farm situation, referring to the objectives levels, choosing the optimal solution allows to have satisfactory results; indeed, it allows to have a consistent increase of the annual revenue (from 82243.87 to 116822.41 euros), a good decrease in nitrates lixiviation (from 2115.80 to 1930.45 kg of N in one year) and in water consumption (from 90633.48 to 60000 m^3 of water in one year). The only parameter that is subject to a slight increase in the optimal solution, in comparison with the initial situation, is soil erosion, passing from 2.63

Table 6. Second set of efficient solutions, and choice of the “good solutions” according to the DM preferences.

Solut	GR	QLIX	QEROS	QWAT	Eval.	D.wheat	C.wheat	Maize	Tobacco	Barley	Sunfl.	Melon	Alphal.
1	152900.25	2626.93	3.43	110000.00		0	17.08	4.92	30	0	0	6.96	0
2	143758.95	2295.46	3.37	90000.00	good	0	24.99	0	27.01	0	0	6.96	0
3	134906.20	2173.79	3.21	80000.00	good	0	28.27	0	23.73	0	0	6.96	0
4	125931.74	2052.12	3.05	70000.00	good	1.56	30	0	20.45	0	0	6.96	0
5	116822.41	1930.45	2.89	60000.00	good	4.84	30	0	17.16	0	0	6.96	0
6	107713.08	1808.78	2.73	50000.00		8.13	30	0	13.88	0	0	6.96	0
7	122358.92	3066.40	2.40	139556.90		0	0	24.89	19.75	0	0	6.41	7.91
8	114494.54	3066.40	2.20	137102.70	good	0	0	27.45	16.78	0	0	6.37	8.36
9	106630.20	2559.95	2.20	138443.58		0	0	17.20	18.02	0	0	5.70	18.04
10	106630.20	1839.34	2.80	49527.23	good	4.49	30	0	13.72	3.79	0	6.96	0
11	106630.20	1993.93	2.60	58028.57		4.16	30	4.89	12.96	0	0	6.96	0
12	106630.20	2375.31	2.40	75796.16		0	25.80	14.12	12.08	0	0	6.96	0
13	106630.20	2772.88	2.20	94481.97		0	17.07	23.63	11.30	0	0	6.96	0

Solutions from 1 to 6 were obtained parameterizing water quantity, while maximizing gross revenue. Solutions 7 and 8 were obtained parameterizing erosion, while maximizing gross revenue. Solution 9 was obtained parameterizing erosion, while minimizing lixiviation. Solution from 10 to 13 were obtained parameterizing erosion, while minimizing water quantity.

Table 7. Second set of decision rules induced from the DM preferences model.

1) If GR ≥ 143759 and QLIX ≤ 2295.46 then the solution is good. (Rule supported by solution n. 2)
2) If GR ≥ 134906.2 and QLIX ≤ 2173.79 then the solution is good. (Rule supported by solution n. 3)
3) If GR ≥ 125931.7 and QLIX ≤ 2052.12 then the solution is good. (Rule supported by solution n. 4)
4) If GR ≥ 116822.4 and QLIX ≤ 1930.45 then the solution is good. (Rule supported by solution n. 5)
5) If GR ≥ 143759 and QEROS ≤ 3.37 then the solution is good. (Rule supported by solution n. 2)
6) If GR ≥ 134906.2 and QEROS ≤ 3.21 then the solution is good. (Rule supported by solution n. 3)
7) If GR ≥ 125931.7 and QEROS ≤ 3.05 then the solution is good. (Rule supported by solution n. 4)
8) If GR ≥ 114494.5 and QEROS ≤ 2.2 then the solution is good. (Rule supported by solution n. 8)
9) If QWAT ≤ 49527.23 then the solution is good. (Rule supported by solution n. 10)
10) If GR ≥ 143759 and QWAT ≤ 90000 then the solution is good. (Rule supported by solution n. 2)
11) If GR ≥ 134906.2 and QWAT ≤ 80000 then the solution is good. (Rule supported by solution n. 3)
12) If GR ≥ 125931.7 and QWAT ≤ 70000 then the solution is good. (Rule supported by solution n. 4)
13) If GR ≥ 116822.4 and QWAT ≤ 60000 then the solution is good. (Rule supported by solution n. 5)

The DM chose the rule n. 13, because in his opinion it allows for a very satisfactory value of gross revenue, and contemporary for a consumption of water very low with respect to the maximum possible value.

to 2.89 t per year. However, it is only a small increase in the value, clearly due to the compensation among objectives that generally occurs in order to have a good compromise solution.

In terms of trade off among the different objectives, choosing this option instead of the one that maximizes the only economic objective, the farmer renounces to an additional revenue of 40000 euros (725.5 euros/ha per year), but having at the same time a decrease in nitrates lixiviation of about 1462 kg, a decrease in the

Table 8. Comparison among values of objectives functions in the solution, and maximum possible values.

Objectives	Optimal solution	Max value
Gross Revenue (Euro)	116822.41	156682.87
Lixiviation (kg N)	1930.45	3392.74
Erosion (T)	2.89	3.14
Water Quantity (m^3)	60000	147822.80

erosion level of 0.25 tons, and a decrease in water consumption of about 87.823 m^3 of water.

Concerning the typology of crops and the related surface, the optimal solution involved 4.84 hectares of durum wheat, 30 hectares of common wheat, 17.16 hectares of tobacco, and 6.96 hectares of melon.

With respect to the real situation in the farm, the hypothesis formulated by the model proposed:

- the reduction of about 10 hectares of the surface cultivated with tobacco. Tobacco, even if is a very profitable crop, implies an important consumption of water and it has high coefficients of erosion and lixiviation (it is the crop with the highest consumption of water, the worst in terms of erosion, and the worst in terms of lixiviation after maize). For this reason, the assignment of a big surface to tobacco does not conciliate with the achievement of satisfactory values for the environmental objectives.
- The reduction of about 9 hectares of the surface cultivated with durum wheat, and the increase of about 19 hectares of the surface cultivated with common wheat. Wheat is a crop that does not imply water consumption, and with low levels of lixiviation and erosion. The preference in the model for wheat, with respect to other not irrigated crops (i.e. barley and sunflower) is due to the higher revenue obtainable through wheat, and also to the inferior coefficient of lixiviation in comparison to sunflower, and to the lower coefficients of lixiviation and erosion in comparison to barley. Wheat is also preferred to alphalpha because it has a higher revenue, and because it does not need water at all. The durum is preferred to the common variety, because of the higher revenue. The maximum possible surface (30 hectares) is entirely exploited in the model.
- The elimination of maize. Maize is the third crop in terms of economic convenience, but it needs a high quantity of water, and it has the highest coefficient of lixiviation. For this reason, it does not conciliate at all with the achievement of satisfactory values for the environmental objectives.
- The introduction of melon. Melon is in absolute the most profitable crop present in the model. Moreover, even if it needs irrigation, its consumption of water is quite low, inferior to that of tobacco. For this reason, it was introduced in the optimal solution. However, only 6.96 Hectares were introduced; this is probably

because the coefficients of lixiviation and erosion are quite high, therefore, a not big surface can be destined to melon, in order to have a right conciliation of economic and environmental objectives.

- Barley, sunflower and alphalpha did not appear in the optimal solution. Barley and sunflower are not convenient from the economic point of view; moreover, they have high coefficients of lixiviation and erosion. Alphalpha, even if has the lowest coefficients of lixiviation and erosion, is not economically convenient, and moreover, it implies a high consumption of water.

5. Conclusions

Through this work, we illustrated how the decision support method IMO-DRSA, combining the dominance based rough sets approach with multiobjective optimization, can be efficiently applied to farm management and planning, in the optic of conciliating economic purposes with environmental protection. This was the very first application of the method in this research field.

Through IMO-DRSA, we found an optimal multiobjective strategy related to the farm planning of our case study, conciliating four different objectives, one of economic and three of environmental nature. Being the economic objective obviously in conflict with the others, and being the frontier of efficient solutions very broad, the choice of the best solution, combining all the objectives, would have been difficult without an effective decision support system.

This kind of approach presented, in comparison with classical decision support methods, some strengths points that concerned both input and output information. Concerning the input, the DM gave preference information by answering easy questions related to sorting of some representative solutions. In this way, elicitation of preferences in terms of weights, substitution rates, thresholds, and so on, and the related significant cognitive effort on the part of the DM were avoided. The output result of the analysis was the model of preferences in terms of "if..., then..." decision rules, which was used to restrict the Pareto optimal set in an iterative way, until the DM selected a satisfactory solution. This kind of preference model gave argumentation for preferences in a logical form and it was intelligible for the DM, without need of recourse to any technical term. Moreover, the DM could identify the Pareto optimal solutions supporting each particular decision rule (*glass box*). Finally, the decision rules were based on ordinal properties of objective functions only, avoiding scalarization, and they could be computed in a few seconds by means of specific algorithms (Greco *et al.*, 2001b; Greco *et al.*, 2002b). The computation time grows while increasing the number of objectives, but not the number of Paretian efficient solutions.

Concerning some practical problems for the application of the method in the agricultural sector, availability and completeness of both environmental and economic data represent a crucial aspect. Environmental data are often difficult to find, while economic data are taken from past or expected farm balances, therefore, they not ever are completely realistic.

Another important point concerns the level of subjectivity intrinsic in the method. The decision maker, in this case the farmer, choices the "good solutions" in a subjective way, basing his preferences on his opinion and knowledge. Other choices, based on different opinions and made from other farmers, could lead to distinct results. Moreover, a not impartial preference towards economic objectives could be present, not considering in a proper way the environmental concerns. However, this weakness belongs to all the classical multiobjective methods, in which the DM must decide weights or thresholds in an arbitrary way.

In relation to this aspect, a mitigation of the problem could be reached inserting the use of IMO-DRSA within a consulting service for farmers; in this way choices would be made by experts of the agricultural and environmental sectors, that could guide the farmer in the decisional process.

Finally, an application at the territorial level would be interesting. In this case, more farms characterizing a territory would be involved in the process, given some objectives aimed to reach sustainable development of that territory. The results of the analysis could be used to implement territorial specific policies. The decision maker in this case would be not the single farmer, but multiple decision makers (for DRSA involving most DMs see Greco *et al.*, 2006; Greco *et al.*, 2011) would be involved, i.e. politicians commissioned to design territorial policies.

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