

A MULTIOBJECTIVE APPROACH FOR CROP ROTATION PLANNING

Bruno S. Miranda

FEEC/UNICAMP

Av. Albert Einstein, 400, 13083-852 Campinas, Brasil

`miranda.bsm@live.com`

Akebo Yamakami

FEEC/UNICAMP

Av. Albert Einstein, 400, 13083-852 Campinas, Brasil

`akebo@dt.fee.unicamp.br`

Priscila C. B. Rampazzo

FCA/UNICAMP

R. Pedro Zaccaria, 1300, 13484-350 Limeira, Brasil

`priscila.rampazzo@fca.unicamp.br`

ABSTRACT

Crop rotation is a powerful technique for sustainably managing fields. This paper presents a multiobjective model for the Crop Rotation Problem (CRP) based on fertilization requirements and quality attributes associated with the crops that might lead to enriching soil fertility and tillage. In this research, multiobjective approaches, such as *a priori* and *a posteriori* methods of mathematical programming, were analyzed to provide the best performance according to farmer's expectations. The distinct approach for soil attributes and cover crop's features in the proposed CRP model has enhanced sustainable ideas in the agribusiness, which can lead to minimizing the environmental impact due to the establishment of proper crop rotation. The results achieved with the proposed model are also quite valuable for long-term planning in the agribusiness.

KEYWORDS. Crop Rotation, Multiobjective Optimization, Agribusiness.

Paper topics: AG&MA - Agricultura e Meio-ambiente; OC - Otimização Combinatória; PM - Programação Matemática

1. Introduction

Technology developments have provided many improvements for agriculture and profoundly changed the human relationship with the environment [Far e Rezaei-Moghaddam, 2018]. Besides the benefits of agrarian innovations, such as positioning systems for machine control and digital image processing for crop management, there is plenty of potential for value creation along the farm's supply chain [Braun et al., 2018]. Advances in crop growth modeling and yield monitoring allied with global navigation systems have made it possible to survey crop areas with precision location, which can improve the control of soil fertility. The mapping of the fields in details and the monitoring of their current state are essential for the development of a trend referred as *precision agriculture*, which has produced massive amounts of data from the crops and the fields [Kamilaris et al., 2017].

In this context, farmers have to apply new methodologies to fully take advantage of the data achieved by the sensor technologies in the field and promote more sustainable management in the agribusiness. The crop rotation technique has become a prospect due to the benefits related to this management technique for soil quality, and optimization methods can assure efficiency in generating crop schemes and lead to reliable long-term sequences.

The main contribution of this research relies on the proposed multiobjective model for the Crop Rotation Problem (CRP), which is deeply concerned with the crop features and their impact on the crop scheme. The evaluation of some multiobjective mathematical programming methods in this paper looks forward to providing flexibility, diversity, and quality in the optimization process, which are essential attributes to reach farmers interests.

A review in the literature about the CRP is put forward in Section 2. Section 3 presents the proposed multiobjective model for the CRP. Section 4 explores methods for solving multiobjective optimization models and Section 5 evaluates their performance in optimizing the proposed CRP model, uncovering the best features and analyzing their benefits in the farmer's context. Finally, conclusion and further steps present in Section 6.

2. Previous works

Alfandari et al. [2011] proposed a Mixed-Integer Linear Programming (MIP) model for the CRP worried about the challenging agriculture in Madagascar. The banning of tavy, which is a tillage technique, where organic matter is roughly plow down and burned to prepare the soil for the next crop, led mountain farmers struggling to remain in the fields due to the reduced fertility. As yields had been declining, farmers had to clean new lands, which then increased deforest and damaged the environment. The proposed model in [Alfandari et al., 2011] aims to reduce the agrarian impact through long-term crop planning based on the minimum deforest required. Fallow periods are also included in the model.

An important mathematical definition for the CRP has been presented in [Santos et al., 2011], and it embraces spatial adjacency, crop's succession, green manure and fallow periods in the crop sequence. The proposed objective function in [Santos et al., 2011] is the maximum occupation of the fields. For solving the proposed model, the author applied the Dantzig-Wolfe decomposition and heuristic procedures. A proposed heuristic based on combining column generation and plot-to-plot heuristic provided prospect results.

Reaching production requirements for specific crops can be considered an objective or a restriction for the CRP. A mathematical model for the CRP relating specific demand for each crop is presented in [Aliano et al., 2014]. The objective function in this model represents the profitability of the solution based on the crop sequence and the allocation periods. The author acknowledges

that the CRP with demand is an NP-hard problem and presents new strategies for achieving good solutions.

Crop rotation schemes can help farmers to forecast the environmental performance of the business and optimization techniques might lead to restrain the impact generated by the production chain. A multi-stage model for farm management presents in [Brankatschk e Finkbeiner, 2015]. Besides the objective function in this research remains the profit maximization, environmental indicators based on the Life Cycle Assessment (LCA) methodology have been included in the constraint set. Optimized solutions from the model proposed in [Brankatschk e Finkbeiner, 2015] provides valuable estimations of the production, such as ozone depletion and terrestrial ecotoxicity.

Considering the significant number of reasons to establish crop rotations, a multiobjective approach seems inevitable to achieve good solutions in the agribusiness's standard. The diversity of crop sequence can be as important as profit for some farmers, the mathematical model presented in [Aliano et al., 2018] evaluates both parameters and provides equally good solutions.

3. Crop Rotation Problem

Crop rotation can be seen as a production technique, which can reduce the damage related to arthropods and microorganisms by limiting the resources available for their population [Santos et al., 2011], or a management tool, which improves business performance and leads to a long-term sustainable business [Mohler e Johnson, 2009]. The decision for planning a crop sequence takes many aspects to consider, such as market opportunities, soil characteristics, and resources (labor or equipment). Scheduling crops over long-term periods should be considered carefully and provide some stability, without compromising profits due to short-term shifts in the agribusiness [Mohler e Johnson, 2009][Clark, 2012]. The following subsections present the concepts which are deployed in the proposed objective functions and the constraint set. The nutrient budget technique considered in the model is presented in Subsection 3.1 and the cultural traits related to the cover crops and their impact in the crop rotation procedure are discussed in Subsection 3.2. The proposed mathematical model for CRP has been described in Subsection 3.

3.1. Nutrient budget

A nutrient budget measures nutrient imported to and exported from a defined system, and it represents the accounting of removed nutrients with the harvested crop and nutrient inputs from natural sources or inorganic fertilizer applications [Bassanino et al., 2011]. There are three conventional nutrient budget techniques: farm-gate, soil surface, and soil system. Agronomic ecosystems have distinct characteristics and complexity, which reflect on the accuracy of the nutrient budget technique [Watson e Atkinson, 1999] [Shober et al., 2011]. The weather can also affect the nutrient cycle and increase losses during specific periods. Soil nutrient surplus might be considered an index of sustainability in the crop field management [Shober et al., 2011] [Oenema et al., 2003].

Establishing the required amount of nutrient for each crop involves plenty of data, which should be precisely acquired in the crop field. The appealing for precision agriculture regards this concern, without regular assessment of the nutrient availability and crop requirements, any detached data relating nutrient demand seems unreasonable. Once the availability of nutrient in the soil and the proper crop requirements have been settled, establishing a soil surface nutrient budget sounds entirely appropriate. A soil surface nutrient budget accounts for all nutrients that enter the soil surface and leave the soil through crop uptake. Considering nitrogen budget, the total amount of manure or nitrogen amendment applied would be adjusted to account for ammonia volatilizing, since this amount would not enter accumulated in the soil surface, and biological nitrogen fixation. The nutrient surplus or deficit presents the total nutrient loss from the soil or soil storage variations [Bassanino et al., 2011] [Oenema et al., 2003] [Sainju, 2017].

3.2. Crops cultural traits and the crop rotation quality

Crop schemes interchanging crops from grass and legume families gradually increase soil fertility and tillage. Legume crops have outstanding performance as green manure, capturing atmospheric nitrogen and making it available for the further plants. Deep taproots in some of these crops can recycle leached nutrients in the subsoil to the upper layer. Grass crops have a fine root system, which can unleash nutrients and aggregate them into soil crumbs [Mohler e Johnson, 2009] [Loss et al., 2015].

Tilth usually describes the soil condition for proper seed germination and root growth. Soil tilth in the good state might benefit crop from improving water infiltration and aeration. Crop rotation can improve soil tilth and reduce the requirements of mechanical interventions in the crop field. Soil aggregates and the space between their structure (called pores) characterize the tilth state. On rainy and wet periods, large pores prevent oxygen deficiency, and the small ones increase water storage in the soil, which is essential during dry seasons [Mohler e Johnson, 2009].

Cover cropping has long been related to soil improvements, such as physical properties (providing ground cover and slowing down soil erosion), nitrogen availability (fixing atmospheric nitrogen into the soil) and increasing organic matter content. In general, soil quality improvements are attained through cover crop decomposition, which enriches organic matter content in the surface layer. Finally, biomass mineralization releases nutrients into absorbable ways, increasing soil fertility and reducing the consumption of amendments in the following crop [Edwards e Burney, 2005].

In this paper, soil quality has been considered in terms of the crop sequence, which evaluates the potential of soil quality improvements based on the proposed crop scheme and the cover crops selected. To evaluate the contribution of the cover crops in the crop rotation planning, rating parameters ought to be established among cover crops. Based on [Clark, 2012], eleven parameters can characterize cover crops and their benefits: 1. Total N provided by legumes; 2. Dry Matter; 3. Soil Builder (it rates the capacity of the cover crop to produce organic matter and improve tillage); 4. Erosion Fighter (it ranks how extensive and how quickly a root system develops, it also accounts the performance in holding the soil against erosion process); 5. Weed Fighter (it rates how well the cover crop out-competes weeds during its life cycle); 6. Good Grazing (it evaluates the potential as a forage); 7. Quick Growth; 8. Lasting Residue (it ranks the effectiveness of the cover crop in providing a long-lasting mulch); 9. Duration; 10. Harvest Value; 11. Cash Crop Inter-seed.

3.3. Proposed Model

The proposed mathematical embraces the concepts of soil quality, cover crop traits and nutrient budget presented in previous subsections. Decision variables and other symbols exhibited in the model are described ahead: 1. N : size of the crop set; 2. N_f : number of crop families; 3. F_p : the set of crops from the family p ; 4. M : number of periods; 5. L : number of plots; 6. $area_k$: available tillage area of each plot k (acre); 7. l_i : profitability of crop i (\$); 8. t_i : crop i production cycle, from planting date to the harvesting; 9. p_i : crop i average production per acre; 10. I_i : crop planting interval $I_{i1}, \dots, I_{in}$; 11. D_i : demand for crop i (units / M periods); 12. S_k : adjacent plots of the plot k ; 13. $F_{N_{\alpha k}}$: Nitrogen fertilizer applied in the plot k over the interval α ; 14. $F_{P_{\alpha k}}$: Phosphorus fertilizer applied in the plot k over the interval α ; 15. $F_{K_{\alpha k}}$: Potassium fertilizer applied in the plot k over the interval α ; 16. c_N, c_P, c_K : fertilization costs (\$ / unit); 17. β : sequence crop restriction factor; 18. θ : interval of fertilization balance. 19. T_{bi} : rated feature b of cover crop i ; 20. C : the set of cover crops; 21. Q_k : rotation quality rating of plot k ; 22. Q_{avg} : average rotation quality rating.

$$\max \sum_{i=1}^N \sum_{j=1}^M \sum_{k=1}^L area_k \cdot l_i \cdot p_i \cdot x_{ijk} - \sum_{\alpha \in \Omega} \sum_{k=1}^L F_{N_{\alpha k}} \cdot c_N + F_{P_{\alpha k}} \cdot c_P + F_{K_{\alpha k}} \cdot c_K \quad (1)$$

$$\max \sum_{k=1}^L Q_k - \sum_{k=1}^L |(Q_k - Q_{avg})|, \quad Q_k = \sum_{j=1}^M \sum_{i \in C} T_{bi} \cdot x_{ijk}, \quad k = 1, \dots, L \quad (2)$$

$$\text{subject to} \quad \sum_{i \in F_p} \sum_{r=0}^{t_i-1} \sum_{v \in S_k} x_{i(j-r)v} \leq L \left(1 - \sum_{i \in F_p} \sum_{r=0}^{t_i-1} x_{i(j-r)k} \right), \quad (3)$$

$$p = 1, \dots, Nf, \quad j = 1, \dots, M, \quad k = 1, \dots, L$$

$$\sum_{i \in F_p} \sum_{r=0}^{t_i+\beta} x_{i(j-r)k} \leq 1, \quad p = 1, \dots, Nf, \quad j = 1, \dots, M, \quad k = 1, \dots, L \quad (4)$$

$$\sum_{i=1}^N \sum_{r=0}^{t_i-1} x_{i(j-r)k} \leq 1, \quad j = 1, \dots, M, \quad k = 1, \dots, L \quad (5)$$

$$F_{N_{\alpha k}} - \sum_{i=1}^N \sum_{j=1+(\alpha-1) \cdot \theta}^{\alpha \cdot \theta} x_{ijk} \cdot area_k \cdot R_{N_i} \geq 0, \quad k = 1, \dots, L, \quad \alpha \in \Omega \quad (6)$$

$$F_{P_{\alpha k}} - \sum_{i=1}^N \sum_{j=1+(\alpha-1) \cdot \theta}^{\alpha \cdot \theta} x_{ijk} \cdot area_k \cdot R_{P_i} \geq 0, \quad k = 1, \dots, L, \quad \alpha \in \Omega \quad (7)$$

$$F_{K_{\alpha k}} - \sum_{i=1}^N \sum_{j=1+(\alpha-1) \cdot \theta}^{\alpha \cdot \theta} x_{ijk} \cdot area_k \cdot R_{K_i} \geq 0, \quad k = 1, \dots, L, \quad \alpha \in \Omega \quad (8)$$

$$\sum_{j=1}^M \sum_{k=1}^L area_k \cdot p_{ij} \cdot x_{ijk} \geq D_i, \quad i = 1, \dots, N \quad (9)$$

$$\sum_{k=1}^L \sum_{j \notin I_i} x_{ijk} \leq 0, \quad i = 1, \dots, N \quad (10)$$

$$x_{ijk} \in \{0, 1\}, \quad i = 1, \dots, N, \quad j = 1, \dots, M, \quad k = 1, \dots, L \quad (11)$$

$$F_{N_{\alpha k}} = \{F_{N_{\alpha k}} \in \mathbf{R}^+ \mid F_{max} \geq F_{N_{\alpha k}} \geq F_{min}\}, \quad \alpha \in \Omega, \quad k = 1, \dots, L \quad (12)$$

$$F_{P_{\alpha k}} = \{F_{P_{\alpha k}} \in \mathbf{R}^+ \mid F_{max} \geq F_{P_{\alpha k}} \geq F_{min}\}, \quad \alpha \in \Omega, \quad k = 1, \dots, L \quad (13)$$

$$F_{K_{\alpha k}} = \{F_{K_{\alpha k}} \in \mathbf{R}^+ \mid F_{max} \geq F_{K_{\alpha k}} \geq F_{min}\}, \quad \alpha \in \Omega, \quad k = 1, \dots, L \quad (14)$$

$$\Omega = \{\alpha \in \mathbf{N}^* \mid \alpha \cdot \theta \leq M, \quad \theta \in \mathbf{N}^*\} \quad (15)$$

The proposed model represents a mixed-integer programming problem. There are binary and float decision variables in this formulation. Fertilization amendments in the crop sequence are expressed by $F_{N_{\alpha k}}$, $F_{P_{\alpha k}}$ and $F_{K_{\alpha k}}$, which are float numbers, and the proper crop allocation variables x_{ijk} (binary decision variables) are stated as follows:

$$x_{ijk} = \begin{cases} 1, & \text{if the crop } i \text{ will be allocated in the period } j \text{ on the plot } k. \\ 0, & \text{case not.} \end{cases}$$

The objective function and the constraints in Eqs.1, 3, 4 and 5 are based on the researches presented in [Santos et al., 2011] and [Aliano et al., 2014]. Aside from these approaches in the literature, the proposed objective function in Eq. 1 express the profit maximization and also includes fertilization parameters, looking forward to minimizing the consumption of nutrient amendments. The second objective function in Eq. 2 presents the crop rotation quality rating, which is based on the crops cultural traits presented in Subsection 3.2.

The constraint sets in Eqs. 3, 4 and 5 hold the basic mechanisms of the CRP. The first one assures that crops from the same family will not occupy adjacent plots in the same period; the second one prevents from scheduling crops from the same family in the same area without rotating the soil or taking a fallow period, and the third one represents the spatial limitation of the plots, which assures there will not be more than one scheduled crop in a plot at a specific period. The nutrient budget concepts presented in Subsection 3.1 led to the constraint set in Eqs. 6, 7 and 8. They state that the nutrient amendments for each plot have to reach at least the crop requirements. Eq. 9 establishes the production requirements for each crop and the constraint set in Eq. 10 prevents any scheduling outside the proper seed time for each crop.

Although the objective function and the constraint set of the proposed model are straightforward, a sample solution presented in Table 1 might enlighten essential modelling features. The solution in Table 1 was generated with the optimization package called IBM ILOG CPLEX, using the weighted sum method and with balanced weights to attain equilibrium between the proposed objective functions. The plots presented in this solution are all adjacent to each other and the cultivable area of each one is: (1) Plot 1: 1.0 acre; (2) Plot 2: 1.5 acre; (3) Plot 3: 0.8 acre. The filled cells in Table 1 shows cover crops in the scheme and the cells filled with triple asterisks represents empty stages in the plot schedule (fallow periods). Each period is a two-week interval and so, the current solution scheme presents a one-year schedule.

Tabela 1: A sample solution for the proposed model.

Period	Plot 1	Plot 2	Plot 3
1	Barley (Grass) [36.7]	Bell Peppers for Fresh Market and Processing, Spring (Nightshade)	Leaf Lettuce for Fresh Market, Winter (Lettuce)
2			***
3			***
4			***
5			***
6			***
7			***
8	Tomato for Fresh Market, Summer (Nightshade)	Summer Squash for Fresh Market (Cucurbit)	Mustard, Spring (Mustard) [22.7]
9			***
10			***
11			***
12	Summer Squash for Fresh Market (Cucurbit)	***	Sorghum-sudangrass, Late Spring, Summer (Grass) [37.0]
13		***	
14		***	
15		***	
16		***	
17	***	***	***
18	Spinach for Fresh Market, Winter (Beet)	Oats, Winter Cover (Grass) [30.7]	Leaf Lettuce for Fresh Market, Fall (Lettuce)
19			
20			
21			
22			
23	Rye (Grass) [36.9]	***	Field peas, Fall (Legume) [30.0]
24		Bell Peppers for Fresh Market and Processing, Spring (Nightshade)	
Sum	73.6	48.0	89.7
Average	70.4	Total	211.2
Deviation	3.1	22.4	19.3
Total Deviation	44.8	Crop Rotation Quality Rating	166.4

The evaluation of the objective function in Eq. 2 also presents in Table 1 and is based on the information displayed in Table 2 and in Table 3. Each cover crop allocated in the solution accounts in the composition of the quality rotation index. To ensure that all the plots have an equal preference, a deviation rating appears in the objective function, which prevents undesirable disparity

among plots. These parameters are rated just for cover crops due to the particular management practices, which are far from the cash crop approach. Fertilization amendments required for this crop scheme are presented in Table 4.

Tabela 2: Rating the qualities of the cover crops in terms of soil benefits.

Vegetables	Family	Dry matter	N Scavenger	Soil Builder	Erosion Fighter	Weed Fighter
Barley	Grass	2.7	3	3	4	4
Oats, Winter Cover	Grass	2.7	3	2	3	3
Rye	Grass	2.9	4	4	4	4
Buckwheat	Buckwheat	1.3	0	2	1	1
Sorghum-sudangrass, Late Spring, Summer	Grass	4.0	4	4	4	4
Mustard, Spring	Mustard	2.7	2	3	3	3
Field peas, Fall	Legume	2.0	1	2	3	3

Tabela 3: Rating the qualities of the cover crops.

Vegetables	Family	Good Grazing	Quick Growth	Lasting Residue	Duration	Harvest Value - Forage	Harvest Value - Seed	Cash Crop Interseed
Barley	Grass	3	3	4	2	3	2	3
Oats, Winter Cover	Grass	2	4	2	1	2	2	4
Rye	Grass	2	4	4	3	1	1	3
Buckwheat	Buckwheat	3	4	0	1	0	1	3
Sorghum-sudangrass, Late Spring, Summer	Grass	2	4	3	4	4	0	0
Mustard, Spring	Mustard	2	3	1	2	0	1	0
Field peas, Fall	Legume	2	3	1	2	4	3	4

Tabela 4: Fertilization amendments required according to the crop scheme presented in Table 1

Nutrient Amendments			
	N (kg / plot / yr)	P (kg / plot / yr)	K (kg / plot / yr)
Plot 1	47.0	14.0	45.4
Plot 2	75.0	13.5	62.6
Plot 3	43.2	20.8	87.1

4. Methodology

The expression ahead represents a common model for multiobjective problems: $f_1(x)$, $f_2(x)$, $\dots$, $f_m(x)$: objective functions, which must be optimized, where $m \geq 2$; S : represents the feasible set; x : decision variable of the problem.

$$\text{minimize } F(x) = [f_1(x), f_2(x), \dots, f_m(x)] \quad (16)$$

$$\text{subject to } x \in S \quad (17)$$

The search space S is partially ordered in the sense that two arbitrary solutions are related in two possible ways: either one dominates the other or none dominates. Be x_1 e $x_2 \in S$. x_1 dominates x_2 , $F(x_1) \preceq F(x_2)$ (minimization problem), if and only if: $\forall i \in \{1, 2, \dots, m\}, f_i(x_1) \leq f_i(x_2)$ and $\exists j \in \{1, 2, \dots, m\}, f_j(x_1) < f_j(x_2)$. That is, x_1 is not worse than x_2 in any of the objectives and is better in at least one Abraham e Jain [2005]. And x is a Pareto-optimal solution if and only if x is non-dominated in relation to S , that is, no vector in the search space dominates x . In Multiobjective Optimization Problems, the expected solution is composed of a set of equilibrium points, that is, a family of solutions considered equivalent and higher than the rest of the solutions.

Solving a multiobjective problem bases on providing a set of equally reasonable solutions, therefore the Decision Maker (DM) is able to select a solution that matches the aspiration levels required by the DM [Branke et al., 2008]. There are several methods for solving multiobjective optimization problems and some of them have been analyzed in this paper to be used in the CRP, looking for approaching the most adapted with the decision maker's aspirations and the characteristics of the problem. In the *a priori* methods, the preferences of the decision maker (decision process) are defined before the resolution (optimization process). The original multiobjective problem is transformed into simpler problems, which can be solved by known methods. In the *a posteriori* methods, it is sought to generate (optimization process) the Pareto-optimal set, or part of it, so that the decision maker can choose (decision process) a compromise solution from among all available alternatives, according to some criterion or preference.

In this paper, the farmer's view represents the DM that we would like to reach. Although a minimization problem has been selected to describe the following multiobjective methods, they have been adjusted to the proposed CRP model, which is a maximization problem.

- Achievement Scalarizing Function Approach: it has been presented in [Wierzbicki, 1986]. An arbitrary vector z_{asp} holds the aspiration levels of the decision maker, which is projected on the set of Pareto Optimal (P.O.) solutions. In this approach, there is no requirement for an idealistic reference point and it does not base on metric distances.

$$\min \quad \max_{i=1, \dots, k} \frac{f_i(x) - z_i^{asp}}{z_i^{nadir} - z_i^{ideal}} \quad (18)$$

$$\text{subject to} \quad x \in \mathbf{S} \quad (19)$$

$$z_i^{ideal} = \min_{x \in \mathbf{S} | x \text{ is P.O.}} f_i(x), \quad \forall i = 1, \dots, k \quad (20)$$

$$z_i^{nadir} = \max_{x \in \mathbf{S} | x \text{ is P.O.}} f_i(x), \quad \forall i = 1, \dots, k \quad (21)$$

- The Weighted Sum Approach: it has been detailed in [Zadeh, 1963] and [Gass e Saaty, 1955]. This approach is quite intuitive and in general, many multiobjective applications have based on this technique without being fully aware.

$$\min \quad \sum_{i=1, \dots, k} w_i f_i(x) \quad (22)$$

$$\text{subject to} \quad x \in \mathbf{S} \quad (23)$$

$$w_i \geq 0 \quad (24)$$

- Goal programming: a classic approach for goal programming presents in [Charnes e Cooper, 1977].

$$\min \quad \sum_{i=1, \dots, k} w_i \delta_i(x) \quad (25)$$

$$\text{subject to} \quad f_i(x) - \delta_i \leq \bar{z} \text{ for all } i = 1, \dots, k \quad (26)$$

$$\delta_i \geq 0 \text{ for all } i = 1, \dots, k \quad (27)$$

$$w_i \geq 0 \text{ for all } i = 1, \dots, k \quad (28)$$

$$x \in \mathbf{S} \quad (29)$$

- Optimization based on boundaries: this method requires previous information from the DM, it has to select one particular objective and establish boundaries for others.

$$\min \quad f_i(x) \quad (30)$$

$$\text{subject to} \quad l_j(x) \leq f_j(x) \leq L_j, \text{ for all } j = 1, \dots, k, j \neq i \quad (31)$$

$$x \in \mathbf{S} \quad (32)$$

- ϵ -Constraint Method: this method has been introduced in [Chankong e Haimes, 1983] and [HAIMES YV et al., 1971].

$$\min \quad f_l(x) \quad (33)$$

$$\text{subject to} \quad f_j(x) \leq \epsilon_j \text{ for all } j = 1, \dots, k, j \neq l \quad (34)$$

$$x \in S \quad (35)$$

5. Discussion on Results

Considering the diversity of scenarios and specific target from each farmer, this paper provides an insight in some of the *priori* and *posteriori* methods, searching for acknowledging the benefits and the drawbacks of these methods in the optimization of the CRP. An optimization software called IBM ILOG CPLEX has been used for evaluating the proposed model. The tests in this paper have been developed in a database of 67 crops, which is build based on the information available in Clark [2012], Mohler e Johnson [2009] and USDA [2007].

Performance of the achievement scalarizing function approach has been displayed in Figure 1. Although it is a *priori* method, which usually generates a single solution from a particular set of parameters, this graphic compiles information from multiple entrances. The results from the goal programming technique have also been presented in Figure 1. Performance is close to the achievement scalarizing function approach, and it does not have to introduce the z_{nadir} and z_{ideal} , and so it requires fewer input parameters.

The solution set in Figure 2 has been attained with the weighted sum approach using a range of balanced weights. For a decision maker without a clear target in mind, this *a posteriori* method provides many solutions in a broad range. Optimization with boundaries, which gathered results are also displayed in Figure 2, can produce solutions in a broad range. Farmers might find the optimization based on boundaries method very interesting. Although they look forward to increasing their profits or even reaching the maximum feasible return, the lower boundary is well-known because it bases on the operational costs. Then, this method assures that any generated solution should at least cover their expenses.

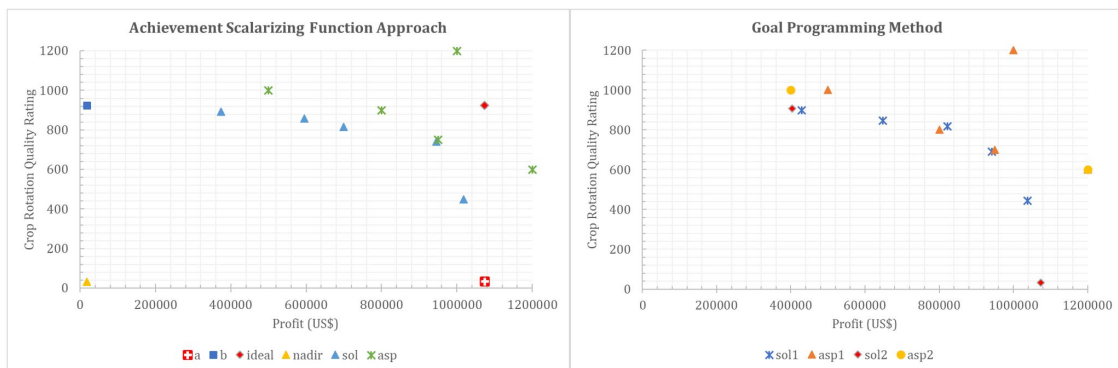


Figura 1: Graphic results attained from the optimization of the CRP using the achievement scalarizing function approach.

Figure 3 shows the solutions provide by the ϵ -constraint method. As the achievement scalarizing function, the ϵ -constraint approach requires more input data from the DM, which is not always available, and establishing the boundaries for the objectives requires expertise to avoid unfeasible problems. The achievement scalarizing function and the goal programming are powerful

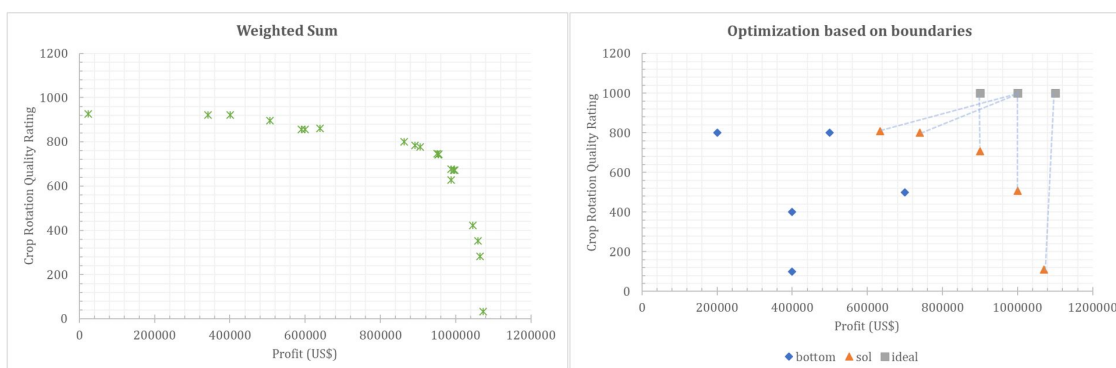


Figura 2: Applying the weighted sum in the CRP.

optimization method when the DM has already established a close target. When the aspiration range is wide, the weighted sum and the optimization based on boundaries techniques can produce large diversity in the solution set, which enhances the perception of the DM.

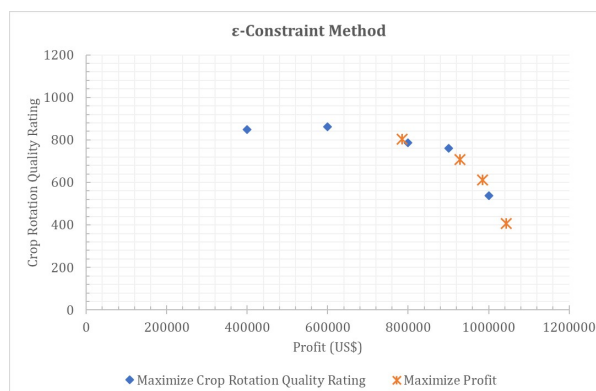


Figura 3: Optimizing the CRP with the ϵ -constraint approach.

6. Conclusions

Many real-world problems present a set of goals to be optimized. Most of the time these goals are conflicting; that is, an improvement in one goal causes deterioration in another. The proposed multiobjective model in this paper aims to approach more sustainable concepts in agribusiness management and without neglecting the profit appeal. Significant benefits for soil fertility and tillage have been analyzed and taken account of the proposed model. Although all affects of the crop scheme into the soil are hard to acknowledge precisely, the evaluating technique proposed in the quality rotation index offers a good alternative for planning long-term schedules.

The multiobjective optimization methods are fundamental for reaching quality solutions, which are solutions able to achieve the farmer's aspirations. Analyzing their performance in the CRP optimization assures the reliability of the proposed model in general applications of this problem. From the results, the selected methods manage to provide custom solutions or a broad range of solutions. Therefore, the proposed model combined with the selected optimization techniques can assist strict decision maker, who might have a small target in mind, or an indecisive one, who would like to check all the options first and later make a final decision.

The multiobjective approach for the CRP has revealed many opportunities in the agribusiness. The impact of the crop rotation technique in the crop's disease management might enrich this research and assure that all the key analysis for the crop rotation planning are considered in the mathematical model.

The proposed CRP model represents innovation in the distinctive approach for soil quality. The cover crops features related to the soil structure, which have been rarely explored in the literature as optimization problems, could also benefit many farmers, who look forward to attaining more sustainable practices.

Referências

- Abraham, A. e Jain, L. (2005). *Evolutionary Multiobjective Optimization: Theoretical Advances and Applications*, chapter Evolutionary Multiobjective Optimization, p. 1–6. Springer-Verlag, Londres, 1 edition.
- Alfandari, L., L. Lemalade, J., Nagih, A., e Plateau, G. (2011). A mip flow model for crop rotation planning in a sustainable development context. *Annals of Operations Research*, 190:149–164.
- Aliano, A., Florentino, H., e Plato, M. (2018). Metodologias de escalarizacoes para o problema de rotacao de culturas biobjetivo. *Proceeding Series of the Brazilian Society of Applied and Computational Mathematics*, 6(1).
- Aliano, A., Florentino, H., e Pato, M. (2014). Metaheuristics for a crop rotation problem. *Int. J. Metaheuristics*, 3(3).
- Bassanino, M., Sacco, D., Zavattaro, L., e Grignani, C. (2011). Nutrient balance as a sustainability indicator of different agro-environments in Italy. *Ecological Indicators*, 1(11):721–723.
- Brankatschk, G. e Finkbeiner, M. (2015). Modeling crop rotation in agricultural lcas : Challenges and potential solutions. *Agricultural Systems*, 138:66 – 76. ISSN 0308-521X. URL <http://www.sciencedirect.com/science/article/pii/S0308521X1500075X>.
- Branke, J., Deb, K., Miettinen, K., e Slowiński, R. (2008). *Multiobjective Optimization*. Springer-Verlag Berlin Heidelberg, Heidelberg, German.
- Braun, A., Colangel, E., e Steckel, T. (2018). Farming in the era of industrie 4.0. *CIRP Conference on Manufacturing Systems*, 51:979–984.
- Chankong, V. e Haimes, Y. Y. (1983). *Multiobjective Decision Making Theory and Methodology*. Elsevier Science Publishing Co., New York, NY.
- Charnes, A. e Cooper, W. (1977). Goal programming and multiple objective optimizations: Part 1. *European Journal of Operational Research*, 1(1):39 – 54. ISSN 0377-2217. URL <http://www.sciencedirect.com/science/article/pii/S0377221777810072>.
- Clark, A. (2012). *Managing cover crops profitably*. Sustainable Agriculture Research & Education (SARE) program, College Park, US, 1 edition.
- Edwards, L. e Burney, J. An overview of nutrient budgets for use in nutrient management planning. Sustainable Agriculture Research & Education (SARE) program, 2005.

- Far, S. e Rezaei-Moghaddam, K. (2018). Impacts of the precision agricultural technologies in iran: An analysis experts' perception and their determinants. *Information processing in agriculture*, 5: 173–184.
- Gass, S. e Saaty, T. (1955). The computational algorithm for the parametric objective function. volume 2, p. 39 – 45.
- HAIMES YV, Y., Lasdon, L., e WISMER DA, D. (1971). On a bicriterion formation of the problems of integrated system identification and system optimization. *IEEE Transactions on Systems, Man and Cybernetics*, SMC-1(3):296–297. ISSN 0018-9472.
- Kamilaris, A., Kartakoullis, A., e Prenafeta-Boldo, F. (2017). A review on the practice of big data analysis in agriculture. *Computers and Electronics in Agriculture*, 143:23–37.
- Loss, A., Basso, A., Oliveira, B. S., de Paula Koucher, L., de Oliveira, R. A., Kurtz, C., Lovato, P. E., Brunetto, P. C. G., e Comin, J. J. (2015). Carbono orgânico total e agregação do solo em sistema de plantio direto agroecológico e convencional de cebola. *Revista Brasileira de Ciência do Solo*, 1(39):1212–1224.
- Mohler, C. e Johnson, S. (2009). *Crop rotation on organic farms: a planning manual*. Natural Resource, Agriculture, and Engineering Service. Cooperative Extension, New York, US, 1 edition.
- Oenema, O., Kros, H., e Vries, W. (2003). Approaches and uncertainties in nutrient budgets: implications for nutrient management and environmental policies. *European Journal of Agronomy*, 1(20):3–16.
- Sainju, U. (2017). Determination of nitrogen balance in agroecosystems. *MethodsX*, 1(4):199–208.
- Santos, L., Michelon, P., Arenales, M., e Santos, H. (2011). Crop rotation scheduling with adjacency constraints. *Ann Oper Res*, 190:165–180.
- Shober, A., Hochmuth, G., e Wiese, C. An overview of nutrient budgets for use in nutrient management planning. U.S. Department of Agriculture, UF/IFAS Extension Service, University of Florida, 2011.
- USDA (2007). Vegetables usual planting and harvesting dates. <https://naldc.nal.usda.gov/download/CAT30992961/PDF>. Acessado: 2019-04-10.
- Watson, C. e Atkinson, D. (1999). Using nitrogen budgets to indicate nitrogen use efficiency and losses from whole farm systems: a comparison of three methodological approaches. *Nutrient Cycling in Agroecosystems*, 1(53):259–267.
- Wierzbicki, A. P. (1986). A methodological approach to comparing parametric characterizations of efficient solutions. In Fandel, G., Grauer, M., Kurzhanski, A., e Wierzbicki, A. P., editors, *Large-Scale Modelling and Interactive Decision Analysis*, p. 27–45, Berlin, Heidelberg. Springer Berlin Heidelberg. ISBN 978-3-662-02473-7.
- Zadeh, L. (1963). Optimality and non-scalar-valued performance criteria. *IEEE Transactions on Automatic Control*, 8(1):59–60. ISSN 0018-9286.