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Collaborative Models to Define Sustainable Crop Planning Reducing the Unfairness among Farmers in an Uncertain Context

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Inherent uncertainty surrounding the agri-food sector negatively impacts the supply chain’s (SC) sustainability and performance. A main consequence of this uncertainty is the imbalance between supply and demand with volatility in prices and high quantities of waste and unmet demand. Usually, farmers are the most affected by the negative impact of uncertainty. To improve their competitive position, it is necessary to implement new business models that encourage the collaboration among farms, try to reduce the number of intermediaries between farms and markets, reduce the activities related to the management of perishable crops and their associated costs, and enable mechanisms to sell the oversupply of crops such as their settlement. In this paper, a novel multi-objective model is proposed to support the crop planning under uncertainty for the proposed business model. Three objectives aligned with the triple bottom lines are considered: SC profit maximization (economic), waste minimization (environmental) and unfairness minimization (social). The last objective reduces the unwillingness of farms to cooperate with the crop planning. The model is solved with the weighted sum method and compared to an equivalent model considering only economic objectives, concluding that environmental and social aspects can be highly improved by little decreasing profits.

Keywords: sustainability; collaboration; crop planning; unfairness; fuzzy multi-objective model

1 Introduction

A new business model is arising in the agri-food sector that seeks to serve customers that appreciate freshness and quality of products and are aware of sustainability. In this business model, channels are characterized to be more direct (fewer intermediary actors). The value chain proposes value to the customer by looking at previous concepts and, at the same time, reducing the unfairness among farmers through ~~a~~ better distribution of costs and benefits according to the farmer's key resources. In this business model, it is very important to balance supply and demand in order to reduce waste in every farm~~er~~ and the unmet demand. To achieve this balance, it is necessary to consider the demand during the crop planning decision-making process, which is the core of farming system management. Crop planning consists in choosing the crops to be planted, their acreage and their allocation to the farmland (Dury et al., 2012). Crop planning decisions will determine future harvest and flow of crops along the chain, and therefore their supply. However, it is not possible to reach a perfect balance between demand and supply given the impact of uncertainty on both elements. These sources of uncertainty inherent to the agri-food sector jointly with others negatively impact on the agri-food supply chain's performance and sustainability (Esteso et al. 2018).

Another aspect that leads to this imbalance is that crop planning decisions are usually made independently by each farmer once per season. This way of making decisions usually contributes to the overproduction of the crops that were more profitable on last season, leading to the drop down of prices and the production of wastes. On the opposite, this produces scarcity in the supply of crops that appeared to be less profitable on last season when compared to their demand, leading to the increase of their prices. Collaboration mechanisms can be used when making the crop planning decisions to better balance supply and demand, reducing waste and unmet demand, and to protect the supply chain against the negative impact of uncertainty (Esteso et al. 2018). Zaraté et al. (2019) conclude that research on coordination issues in agricultural SCs is in its early development. Besides Handayati et al. (2015) state in their review that studies on supply chain coordination in agri-food sector with a particular focus on small-scale farmers is very scarce. One collaboration mechanism applicable to the crop planning problem is the decision synchronization that consists in jointly making planning and operational decisions for all farms (Simatupang and Sridharan, 2005) in a centralized manner.

To the best of our knowledge, there are no model-based computerized tools to support the crop planning decisions in this new business model. It seems obvious that models for crop planning should consider the demand of crops to balance supply and demand, however few papers do it. In addition, most of these papers only model decisions related to the crop planning such as the selection of crops to plant, the definition of the area or plots allocated to each crop and decisions about the resources needed to plant and cultivate the planted areas such as the irrigation, labouring, and the use of fertilizers.

However, to balance supply and demand it is necessary to take into account more operative decisions. However, few papers as well as this paper take into account additional more operative decisions such as the harvest, transport and sale of crops in order to anticipate the balance between supply and demand at markets (Ahumada et al., 2012; Ahumada and Villalobos, 2011a, 2011b; Flores et al., 2019; Flores and Villalobos, 2018; Mason and Villalobos, 2015; Najafabadi et al., 2019; Nguyen et al., 2019). In the particular case of transport decisions, analysed models do not take into account neither the capacity of vehicles nor the minimum cargo to be filled in order to use a vehicle, which determines the quantity of vehicles necessary to transport crops and limits the quantity of crops to be transported ready to satisfy demand. This paper models all these aspects, filling the gap identified in literature.

Most models for crop planning considering the demand of crops such as the proposed by Cid-Garcia and Ibarra-Rojas (2019) and Ren et al. (2019) assume that all demand should be met, allowing, and not penalizing the overproduction of crops and assume that all production is sold. However, few papers model what happens when an imbalance between supply and demand occurs, such as the generation of waste in cases of overproduction (Hasuike et al., 2018; Mason and Villalobos, 2015) or unmet demand in cases of underproduction (Albornoz et al., 2020; Darby-Dowman et al., 2000; dos Santos et al., 2010; Flores and Villalobos, 2018; Forrester et al., 2018; Hasuike et al., 2018; Mason and Villalobos, 2015; Nguyen et al., 2019; Villa et al., 2019). Furthermore, waste is also generated due to the limited shelf-life of crops that has been modelled in few models (Ahumada and Villalobos, 2011a, 2011b). None of the papers allowing the crops overproduction implements mechanisms to reduce wastes generated along the chain by the excess of product and its perishable nature. With this objective this paper, that models the over and underproduction of crops due to the uncertainty in both supply and demand, proposes to settle the excess of supply at each period in order to reduce the quantity of generated waste and promote the sale of fresh products.

Given the perishability of crops and the impact that the allocated land area and planting period of crops have on harvesting, and consequently, in the future available supply, it is also important to take into account the multi-period nature of the problem when addressing the harvesting and distribution decisions jointly with the cropping plan ones to satisfy the also seasonal market demand. This aspect is even more crucial when limited capacity of resources per period exist for implementing more operative decisions being necessary to efficiently plan their use.

All the above papers propose centralized models to support the aforementioned decision-making processes. Although centralized decision making process is proved to provide the best results for the entire agri-food supply chain (Stadtler, 2009), obtained solution would be difficult to implement in a real agri-food supply chain unless all lands belong to the same farmer since centralized decision making produces inequalities among the supply chain members (Ertogral and Wu, 2000) leading to the unwillingness of farms to collaborate. Because of this, analysed models could not be used to solve the crop planning problem in the new business model where the reduction of the unfairness among farmers is essential.

Besides, analysed models mainly optimize economic aspects, leaving out the environmental and social aspects of sustainability which is another fundamental characteristic of this new business model. However, some of the analysed models optimize objectives related to more than one aspect of sustainability. For example, Adekanmbi and Olugbara (2015) who maximize the supply chain profits (economic) while minimizing the land use (environmental). Najafabadi et al. (2019) consider the three aspects of sustainability by maximizing the supply chain profits (economic) while minimizing the water consumption, and the use of fertilizers and pesticides (environmental) and maximizing employment and food safety (social). The rest of the models to support crop planning problem analysed in this section only optimized economic objectives. It is remarkable that none of these models considered the reduction of wastes and unfairness among farms as objectives while these aspects are fundamental for the Sustainable Development Goals (SDG) set by the United Nations (2019) and for the new business model also aligned with the Common Agricultural Policy (CAP) Objectives.

Finally, few existing models to support the crop planning while considering demand of crops take into consideration the uncertain nature of factors related to the agri-food sector. In this case, Darby-Dowman et al. (2000) model the uncertainty of the plants yield stochastically while Ahumada et al. (2012) additionally consider the stochastic nature of market prices. On their part, Najafabadi et al. (2019) consider that the resources needed per crop are uncertain and modelled them by using fuzzy sets. This paper models the uncertainty on the yield of plants, demand of crops, and market and settlement prices by using fuzzy set theory since it is appropriate for cases in which uncertainty is associated with vagueness, ambiguity, imprecision and/or lack of information on a particular element of the problem at hand (Alemany et al., 2015) which is our case.

Therefore, to the authors' knowledge, there is a gap in literature as regards models for supporting the crop planning decisions in this new business model for achieving a sustainable supply chain. The objective of the paper is to cover this gap by developing a computerized tool based on a novel **U**ncertain **M**ulti-**O**bjective Centralized mathematical programming model for the **S**ustainable **C**rop **P**lanning **P**roblem, dubbed as UMO-SCPP hereunder. The UMO-SCPP model seeks to balance the supply and demand of crops in an agri-food supply chain composed by farmers and retailers without intermediaries and considers different characteristics of the business model that to the best of authors' knowledge have not been previously modelled in literature.

Main novelties of the proposed mathematical programming model are: i) modelling of the new business model itself, ii) inclusion of collaboration among stakeholders of the same SC stage, iii) anticipation of more operative decisions such as harvest, transport, and sales decisions when defining the crop planning, iv) modelling of the distribution of cargo into vehicles, v) consider the possibility of settling the oversupply of crops in the same period of their harvest to guarantee the freshness of crops and to reduce generated waste and supply chain losses, vi) modelling of multi-objective approach considering the three aspects of sustainability by means not only maximizing profits (economical objective) but also minimizing waste (environmental objective,) and minimizing the economic unfairness among farmers for implementing the collaborative approach (social objective), and vii) inclusion of inherent agri-food supply chain uncertainty by fuzzy modelling of parameters related to the yield, demand and prices of crops.

The UMO-SCPP model is validated with realistic data from an Argentinean case study for two scenarios. Results show that it is possible to find solutions where the level of unfairness among farmers and waste generated are improved by slightly decreasing the total profit. Therefore, with this proposal we are contributing to increase the sustainability of the agri-food supply chains in its three dimensions simultaneously.

The rest of the paper is aligned to the research methodology and is structured as follows. The fuzzy multi-objective MILP model to address the problem under study and the resolution methodology used to solve it are exposed in Section 2. Results are analysed and discussed in section 3. Finally, conclusions and future research lines are drawn in Section 4.

2 Materials and Methods

This section first explains the assumptions under which the crop planning problem is solved for the new business model, followed by the fuzzy multi-objective mathematical programming model to support crop planning decisions. Finally, the CPM-EES-U model is transformed into an equivalent crisp model to facilitate its resolution.

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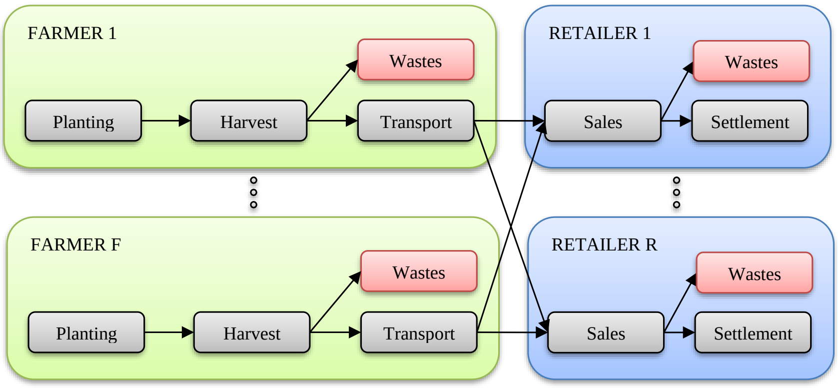
2.1 Crop planning in the new business model

The business model under study is characterized by the lack of intermediaries between farms and retailers. Therefore, an agri-food supply chain composed by a set of farms and retailers directly linked that produce and commercialize multiple crops with limited shelf-life is considered (Figure 1).

Figure 1. Supply chain configuration and main activities.



Farmers are responsible for farming activities (planting, cultivation, and harvest) and for the transport of crops to retailers, where crops are sold to end consumers. Each farm disposes of one farming location with a limited planting area. Farmers define the area to plant with each crop per period, considering that a minimum area needs to be planted per selected crop and period due to technical reasons. The yield of plants depends on the crop, and its planting and harvest date. All crop matured at plant needs to be harvested in the same period. The transport of crops is made by trucks in a way that a minimum percentage of the cargo quantity needs to be loaded to use one truck.

The business model also seeks to serve customers with very fresh products. To do this, the considered supply chain transport and selling the products on the same period of their harvest, being not allowed to store products from one period to the following. So, crops harvested and not transported to retailers on the same period will be wasted in the farm level. On the other hand, all the crops that arrive to the retailer and are not sold in the same period will also be wasted. To reduce the wastes generated along the chain, this business model allows to settle a part of the oversupply of crops limited by a percentage of the demand with a reduced price. Finally, a minimum service level service is ensured for all crops in all retailers.

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2.2 Fuzzy mathematical programming model formulation

The nomenclature used to formulate the UMO-SCPP model is exposed in Table 1, where uncertain parameters are identified by the symbol $\sim$. The uncertain parameters are modelled with Fuzzy Set Theory since it has proved their validity for the uncertainty associated with vagueness, imprecision, inexact statements, incomplete, lack of information and/or unobtainable information on a particular element (Mundi et al., 2016). This model considers that the sales and settlement prices, as well as the crop yields, and demands are uncertain parameters since their values cannot be known in advance.

Table 1. Nomenclature for the UMO-SCPP model.

Indexes	
c	Crops
p	Planting periods
t	Time periods
l	Farming locations
r	Retailers
Set of indexes	
P_c	Set of periods p in which crop c can be planted.
PT_{cp}	Set of periods t in which crop c planted in period p can be harvested.
Parameters	
ap_l	Available area for planting in location l.
am_c	Minimum area to be planted with crop c when it is decided to plant it (technical reasons).
$\tilde{y}_{cpt}$	Yield of crop c planted at p and harvested at t.
$\tilde{d}_{rct}$	End consumers' demand of crop c at retailer r at period t.
$\tilde{e}_{rct}$	Excess of demand of crop c that can be sold at retailer r at a settlement price.
$\widetilde{sp}_{rct}$	Market price of crop c at retailer r at period t.
$\widetilde{op}_{rct}$	Selling price of one kg of crop c at retailer r at period t.
$\widetilde{gp}_{rct}$	Settlement price of one kg of crop c at retailer r at period t.
bc_{rct}	Penalty cost for not meeting one kg of crop c demand at retailer r at period t.

pc_c	Planting, cultivation and harvest cost for one plant of crop c.
tc_{lrc}	Cost of transporting one kg of crop c from location l to retailer r.
sl_c	Minimum service level for each crop c.
cc	Fix cost of using one truck.
cap	Capacity of one truck in kilograms.
mc	Minimum percentage of the truck capacity that should be filled to be used.
Variables	
A_{lcp}	Area planted in location l with crop c at planting period p.
H_{lct}	Quantity of crop c harvested at location l in period t.
WL_{lct}	Quantity of crop c wasted at location l at period t after its harvest.
T_{lrct}	Quantity of crop c transported from location l to retailer r in period t.
N_{lrt}	Number of trucks required to transport crops from location l to retailer r in period t.
W_{rct}	Quantity of crop c wasted at retailer r at period t.
S_{rct}	Quantity of crop c sold at retailer r at period t.
B_{rct}	Unmet demand of crop c at retailer r at period t.
G_{rct}	Quantity of crop c settled at retailer r at period t.
D_l	Difference between the region and location l profit per area (absolute value).
YP_{lcp}	Binary variable with value equal to one when location l plant crop c at period p, and zero otherwise.
Y_{rct}	Binary variable that takes value equal to one when demand of crop c at period t and retailer r is higher than supply, and zero otherwise.

The triple bottom line is modelled with three objectives that combined through the weighted sum method (Marler and Arora, 2010) conform a single objective function (1). The objectives are scaled by dividing their values between the maximum value that they can acquire. These maximum values are obtained by executing the model maximizing only one objective (Z_{EC}, Z_{ENV}, or Z_{SOC}).

$$Max\ Z = w_{EC} \cdot \frac{Z_{EC}}{Z_{EC_{max}}} - w_{ENV} \cdot \frac{Z_{ENV}}{Z_{ENV_{max}}} - w_{SOC} \cdot \frac{Z_{SOC}}{Z_{SOC_{max}}} \tag{1}$$

The economic objective (Z_{EC}) maximizes the supply chain profits (2). The first term represents the sales obtained by demanded crops and settled crops. The rest of terms are related to the costs for planting, cultivation and harvest, transport of crops and penalizations for unmet demand. Since market and settlement prices for each crop, retailer and period are not known in advance to the crop planning decision and fluctuate as a consequence of the balance between supply and demand among other factors, these parameters are considered uncertain in this model.

$$Z_{EC} = \sum_{r}\sum_{c}\sum_{t}(\widetilde{sp}_{rct} \cdot S_{rct} + \widetilde{gp}_{rct} \cdot G_{rct} - bc_{rc} \cdot B_{rct}) - \sum_{l}\sum_{c}\sum_{p \in P_c} pc_c \cdot A_{lcp} \\ - \sum_{l}\sum_{r}\sum_{c}\sum_{t} tc_{lrc} \cdot T_{lrct} - \sum_{l}\sum_{r}\sum_{t} cc \cdot N_{lrt} \tag{2}$$

The environmental objective minimizes wastes along the chain (3). Wastes can be generated at the farming location by crops not distributed to the following stages of the supply chains, and at retailers when there is an oversupply of crops that cannot be finally be settled.

$$Z_{ENV} = \sum_{c}\sum_{t}\left(\sum_{r} W_{rct} + \sum_{l} WL_{lct}\right) \tag{3}$$

The social objective minimizes the economic unfairness among farmers (4), calculated as the absolute difference between the overall profit per area for farming locations and the profit per area per each farming location. This objective is one of the main novelties of this model. The non-linearity of this objective is solved by replacing it with (5-7) where PR (8) and PL_l (9) are the overall profit for farming locations and the profit per each farming location l, respectively. Profits at the farm level are calculated as the difference between the sale of crops to retailers and costs related to the planting and transport of crops. The selling price for each crop at this level is also modelled as an uncertain parameter as it cannot be known in advance given its dependence to several factors such as the market prices.

$$Z_{SOC} = \sum_{l}\left|\frac{PL_l}{ap_l} - \frac{PR}{\sum_l ap_l}\right| \tag{4}$$

$$Z_{SOC} = \sum_{l} D_l \tag{5}$$

$$D_l \geq \frac{PL_l}{ap_l} - \frac{PR}{\sum_l ap_l} \qquad \forall l \tag{6}$$

$$D_l \geq \frac{PR}{\sum_l ap_l} - \frac{PL_l}{ap_l} \qquad \forall l \tag{7}$$

$$PR = \sum_{l}\left(\sum_{r}\sum_{c}\sum_{t}(\widetilde{op}_{rct} - tc_{lrc}) \cdot T_{lrct} - \sum_{c}\sum_{p\in P_c} pc_c \cdot A_{lcp} - \sum_{r}\sum_{t} cc \cdot N_{lrt}\right) \tag{8}$$

$$PL_l = \sum_{r}\sum_{c}\sum_{t}(\widetilde{op}_{rct} - tc_{lrc}) \cdot T_{lrct} - \sum_{c}\sum_{p\in P_c} pc_c \cdot A_{lcp} - \sum_{r}\sum_{t} cc \cdot N_{lrt} \qquad \forall l \tag{9}$$

The UMO-SCPP model is subjected to the following constraints. The area allocated to each crop in all periods cannot exceed the total area of each farm (10).

$$\sum_{c}\sum_{p\in P_c} A_{lcp} \leq ap_l \qquad \forall l \tag{10}$$

In case a crop is planted, the minimum planted area is limited due to technical reasons (11). In addition, no more area than the corresponding to the farmer can be planted with the same crop.

$$amin_c \cdot YP_{lcp} \leq A_{lcp} \leq ap_l \cdot YP_{lcp} \qquad \forall l, c, p \in P_c \tag{11}$$

Mature crops at plants are necessarily harvested (12) and transported to markets or wasted in this same period due to the limited shelf-life of crops (13). The yield of plants is considered as an uncertain parameter in this model since it is dependent of uncontrollable factors such as the weather, soil properties among others.

$$\sum_{p\in P_c} \tilde{y}_{cpt} \cdot A_{lcp} = H_{lct} \qquad \forall l, c, t \tag{12}$$

$$H_{lct} = WL_{lct} + \sum_{r} T_{lrct} \qquad \forall l, c, t \tag{13}$$

To correctly calculate the wastes produced at the farm level it is necessary to take into account the limited availability of transport, aspect that have not been previously modelled in other models. Therefore, a minimum quantity of crops needs to be transported in order to use one truck, and the transported quantity cannot exceed the capacity of trucks (14).

$$cap \cdot mc \cdot N_{lt} \leq \sum_{c} T_{lct} \leq cap \cdot N_{lt} \qquad \forall l, t \tag{14}$$

All crops transported to retailers need to be sold or wasted in the same period of their transport since the business model under study does not allow to store perishable crops from one period to the following. With this, costs related to the workforce and facilities needed to the cold storage of perishable crops at retailers is eliminated. In addition, in order to reduce the quantity of wastes generated at markets, it is allowed to settle crops in cases in which supply excess demand, which is a novelty of this model. Therefore, crops that arrive to markets are necessarily sold, settled, or wasted in the same period due to the limited shelf-life of crops and the business model implemented (15).

$$\sum_{l} T_{lrct} = S_{rct} + G_{rct} + W_{rct} \qquad \forall r, c, t \tag{15}$$

A minimum service level needs to be guaranteed when meeting demand (16). This ensures that a part of the demand fixed by the decision makers will be necessarily met for each crop in each retailer. The demand for each crop is also modelled as an uncertain parameter since it cannot be known in advance to the period of sales.

$$\sum_{t} S_{rct} \geq \sum_{t} sl_c \cdot \tilde{d}_{rct} \qquad \forall r, c \tag{16}$$

In addition, in cases in which demand is higher than the supply, a part of the demand can be lost. So, the sum of sales and unmet demand for each crop, period and retailer should be equal to the demand of such crop. Thus, the unmet demand can only be produced in cases in which demand excess supply (18).

$$S_{rct} + B_{rct} = \tilde{d}_{rct} \qquad \forall r, c, t \tag{17}$$

$$B_{rct} \leq \tilde{d}_{rct} \cdot Y_{rct} \qquad \forall r, c, t \tag{18}$$

On the other hand, the demand for settled crops is limited by a percentage of the demand (19). The settlement of crops is only allowed in this business model in cases in which there is an oversupply of crops.

$$G_{rct} \leq \tilde{e}_{rct} \cdot \tilde{d}_{rct} \cdot Y_{rct} \qquad \forall r, c, t \tag{19}$$

Finally, the nature of decision variables is defined (20).

$$\begin{array}{ll} A_{lcp}, H_{lct}, WL_{lct}, T_{lct}, W_{ct}, S_{ct}, B_{ct}, G_{ct}, D_l, PR, PL_l & CONTINUOUS, \\ N_{lt} & INTEGER \\ YP_{lcp} & BINARY \end{array} \tag{20}$$

2.3 Solution Method

The methodology proposed by Jiménez et al. (2007) to transform a fuzzy model into an equivalent crisp model is used in this paper. We refer readers to the original paper (Jiménez et al., 2007) for more information about this method. In this paper, it is assumed that fuzzy parameters ($\tilde{a}$) are characterized by triangular membership functions ($\tilde{a} = (a^1, a^2, a^3)$) that represent the most pessimistic, possible and optimistic values for the uncertain parameters (Mula et al. 2010), what is in concordance with the problem under study. The auxiliary crisp model is formulated as follows where parameter α represents the degree of feasibility for each solution and ranges between 0 and 1, being 1 the value related to the highest degree of feasibility of a solution:

$$Max\ Z = w_{EC} \cdot \frac{Z_{EC}}{Z_{EC_{max}}} - w_{ENV} \cdot \frac{Z_{ENV}}{Z_{ENV_{max}}} - w_{SOC} \cdot \frac{Z_{SOC}}{Z_{SOC_{max}}} \tag{1}$$

Subject to:

(3)-(7), (10), (11), (13)-(15), (20)

$$\begin{aligned} Z_{EC} = \sum_r \sum_c \sum_t \Bigg(& \frac{sp^1_{rct} + 2 \cdot sp^2_{rct} + sp^3_{rct}}{4} \cdot S_{rct} + \frac{gp^1_{rct} + 2 \cdot gp^2_{rct} + gp^3_{rct}}{4} \cdot G_{rct} \\ & - bc_{rc} \cdot B_{rct} \Bigg) - \sum_l \sum_c \sum_p pc_c \cdot A_{lcp} - \sum_l \sum_r \sum_c \sum_t tc_{lrc} \cdot T_{lrct} \\ & - \sum_l \sum_r \sum_t cc \cdot N_{lrt} \end{aligned} \tag{21}$$

$$\begin{aligned} PR = \sum_l \Bigg(& \sum_r \sum_c \sum_t \left(\frac{op^1_{rct} + op^2_{rct} + op^2_{rct} + op^3_{rct}}{4} - tc_{lrc} \right) \cdot T_{lrct} - \sum_c \sum_p pc_c \cdot A_{lcp} \\ & - \sum_r \sum_t cc \cdot N_{lrt} \Bigg) \end{aligned} \tag{22}$$

$$\begin{aligned} PL_l = \sum_r \sum_c \sum_t & \left(\frac{op^1_{rct} + op^2_{rct} + op^2_{rct} + op^3_{rct}}{4} - tc_{lrc} \right) \cdot T_{lrct} - \sum_c \sum_p pc_c \cdot A_{lcp} \\ & - \sum_r \sum_t cc \cdot N_{lrt} \qquad \forall l \end{aligned} \tag{23}$$

$$\sum_{p\in P_c}\left[\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{y_{cpt}^{1}+y_{cpt}^{2}}{2}\right)+\left(\frac{\alpha}{2}\right)\cdot\left(\frac{y_{cpt}^{2}+y_{cpt}^{3}}{2}\right)\right]\cdot A_{lcp}-H_{lct}\leq 0 \qquad \forall l,c,t \tag{24}$$

$$\sum_{p\in P_c}\left[\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{y_{cpt}^{2}+y_{cpt}^{3}}{2}\right)+\left(\frac{\alpha}{2}\right)\cdot\left(\frac{y_{cpt}^{1}+y_{cpt}^{2}}{2}\right)\right]\cdot A_{lcp}-H_{lct}\geq 0 \qquad \forall l,c,t \tag{25}$$

$$\sum_{t}S_{rct}\geq\sum_{t}\left[\alpha\cdot\frac{d_{rct}^{2}+d_{rct}^{3}}{2}+(1-\alpha)\cdot\frac{d_{rct}^{1}+d_{rct}^{2}}{2}\right]\cdot sl_c \qquad \forall r,c \tag{26}$$

$$S_{rct}+B_{rct}\leq\left(\frac{\alpha}{2}\right)\cdot\left(\frac{d_{rct}^{1}+d_{rct}^{2}}{2}\right)+\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{d_{rct}^{2}+d_{rct}^{3}}{2}\right) \qquad \forall r,c,t \tag{27}$$

$$S_{rct}+B_{rct}\geq\left(\frac{\alpha}{2}\right)\cdot\left(\frac{d_{rct}^{2}+d_{rct}^{3}}{2}\right)+\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{d_{rct}^{1}+d_{rct}^{2}}{2}\right) \qquad \forall r,c,t \tag{28}$$

$$B_{rct}\leq\left[\alpha\cdot\frac{d_{rct}^{1}+d_{rct}^{2}}{2}+(1-\alpha)\cdot\frac{d_{rct}^{2}+d_{rct}^{3}}{2}\right]\cdot Y_{rct} \qquad \forall r,c,t \tag{29}$$

$$G_{rct}\leq\left[\alpha\cdot\frac{e_{rct}^{1}+e_{rct}^{2}}{2}+(1-\alpha)\cdot\frac{e_{rct}^{2}+e_{rct}^{3}}{2}\right]\cdot\left[\alpha\cdot\frac{d_{rct}^{1}+d_{rct}^{2}}{2}+(1-\alpha)\cdot\frac{d_{rct}^{2}+d_{rct}^{3}}{2}\right]\cdot Y_{rct} \qquad \forall r,c,t \tag{30}$$

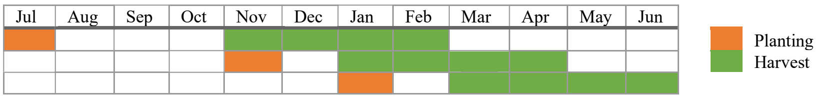
3 Computational experiments: Application to the Argentinean case study

The UMO-SCPP model was implemented in MPL® 5.0.8 and solved by using the solver Gurobi^{TM} 8.1.1 in a computer with an Intel® Xeon® CPU E5-1620 v2(C) @3.70GHz processor, with an installed capacity of 35GB and a 64-bits operating system. Microsoft Access Database was used to store input data and obtained results.

The UMO-SCPP model is solved for an Argentinean case study in which the determination of the final sales price for agricultural products depends on diverse factors such as the production, commercialization and consumption structure, the power of the actors implied in the price fixing, and the balance between supply and demand. Thus, the Argentinean government is implementing national policies prioritizing familiar farming, promoting direct commercialization channels, and boosting sales at major markets so that supply and demand at commercialization link have a greater level of concentration enabling farmers to not only be price takers.

In the considered case study, a set of farms located in the region of La Plata define the weekly crop planning for three varieties of tomato for the next year. All varieties share the same planting/harvest calendar (Figure 2). Demand and prices are extracted from the Buenos Aires Central Market webpage. The rest of data is gathered from interviews with Argentinean farming experts from the Universidad de La Plata. All data can be found at https://cigip.webs.upv.es/docs/CropPlanningData.ods. In case of fuzzy parameters, obtained data is used as the most possible values for their membership functions while the lower and upper bounds are obtained by varying these central values by 10%.

Figure 2. Planting/Harvest calendar.



Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
🟧				🟩	🟩	🟩	🟩				
				🟧		🟩	🟩	🟩	🟩		
						🟧		🟩	🟩	🟩	🟩

🟧 Planting
🟩 Harvest

The weights assigned to each objective differentiate between their importance (Song and Kang, 2016). When defining the weights assigned to the objectives that compose the global objective function, decision makers hardly know their preferences and how to quantify them (Mavrotas, 2009). The Analytic Hierarchy Process (AHP) (Saaty, 1990) facilitates this task by obtaining the relative importance of elements, in this case the objectives, from a subjective comparison of their importance. For that, a paired comparison of the objectives is done by using the scale proposed by Saaty (1990) that gives higher values to most relevant elements. The weight to be assigned to each objective is then calculated by dividing the sum of values assigned to each objective by the sum of all values of the comparison matrix. The comparison matrix and the obtained weight distribution for this case study are shown in Table 4.

Table 4. Pairwise comparison matrix

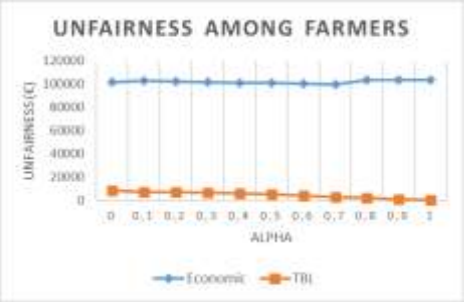
	Z_{EC}	Z_{ENV}	Z_{SOC}	w_f
Z_{EC}	1	5	5	0.66
Z_{ENV}	1/5	1	1/3	0.09
Z_{SOC}	1/5	3	1	0.25

The UMO-SCPP model is solved for 11 α-cuts representing the degree of feasibility of the solution and for the weights' distribution extracted from the AHP (TBL scenario). The model is also solved by assigning all the weight to the economic objective (economic scenario) to extract managerial insights from the comparation of results. Solutions obtained for the triple bottom line indicators (supply chain profits, wastes and unfairness among farms) by both scenarios are shown in Figures 3 to 5 where the blue line correspond to the economic scenario where all weight is assigned to the supply chain profit and the orange line correspond to the TBL scenario that assigns weights to the three objectives of the global objective function.

Figure 3. Results – Supply chain profits.

Figure 4. Results – Wastes.

Figure 5. Results – Unfairness among farmers.



From results obtained for the economic scenario, it is extracted that it obtains the best profits for the entire supply chain in all α-cuts. However, wastes associated with these profits are high and make up over 52% of the total harvest. In addition, the total profits obtained at the agricultural level are only distributed among the 30% of the farmers so that some farmers obtain losses (up to -22000 €/ha) while others obtain great profits (up to 25000 €/ha). This generates a great perception of unfairness among farmers, preventing them from collaborating and abiding the planning obtained with the centralized model.

On the other hand, the TBL scenario that represents the new business model arising in the agri-food sector obtains lower profits to the economic scenario. However, this scenario shows improvements in terms of wastes and economic unfairness among farmers. In the case of wastes, these can account for 30% of the total harvest, which despite representing a high percentage shows a significant improvement with respect to the economic scenario. In this case, the profits at the agricultural level are distributed among all farmers, obtaining a minimum of 55 €/ha and a maximum of 2400 €/ha. Therefore, the feeling of fairness among farms is greatly benefited in the TBL scenario with respect to the economic scenario, making farmers more participatory and willing to implement the obtained planning.

Therefore, it is extracted from the comparison between the results obtained by both scenarios that the environmental and social aspects of sustainability can be highly improved in exchange for a slight decrease in the economic results. For example, by considering the proposed multi-objective approach, reducing the obtained profits at the economic scenario in an 8 to 9% leads to the reduction of the quantity of crops wasted (-47% in average with regard to the economic scenario) and of the economic unfairness among farmers (-95% in average with regard the economic scenario). In addition, the reduction on the economic unfairness among farmers encourages them to comply with decisions made in a centralized way, avoiding the unwillingness to collaborate that is usually related to the centralization of the decision-making process.

The values obtained for the models' objectives per α-cut get worse for both scenarios as the degree of feasibility (α) of the solution increases. This is because the constraints with fuzzy parameters are more flexible when the feasibility degree decreases. Therefore, a balance between the satisfaction of the value obtained for each objective and the degree of feasibility of the solution should be made by decision makers in order to select the solution to be finally implemented in the real agri-food supply chain (Esteso et al., 2018b).

The solved model counted with 6,724 constraints and 6,181 variables from which 5,415 were continuous, 520 were integer and 246 were binary variables. Optimal solutions were found for all α scenarios with an average resolution time of 1.27 seconds.

4 Conclusions

A multi-objective model called UMO-SCPP to centrally define the crop planning for an agri-food supply chain under uncertain context is designed for a new business model. The UMO-SCPP model optimizes three objectives aligned to the triple bottom line. A single objective is constructed by applying the weighted sum method and the weights distribution is defined with the AHP (TBL scenario) or by assigning all weight to economic objective (economic scenario).

After analysing mathematical programming models to support crop planning while considering the crops demand, it was found that main novelties of this proposal are: i) modelling of a new business model, ii) collaboration among stakeholders of the same SC stage, iii) joint modelling of crop planning, harvest, transport and sales decisions, iv) modelling of the distribution of cargo into vehicles, v) settlement of overproduction to reduce wastes, supply chain losses and to ensure the freshness of sold crops, vi) multi-objective approach considering the three aspects of sustainability, vii) minimization of wastes as an environmental objective, viii) minimization of economic unfairness among farmers as a social objective, and ix) fuzzy modelling of parameters related to the yield, demand and prices of crops.

Results show that optimizing environmental and social aspects of sustainability leads to crop planning with economic results similar to the obtained by only optimizing the economic objective. In addition, such solutions highly reduce the quantity of wastes along the supply chain, and the economic unfairness among the actors of the agri-food supply chain. Thus, the proposed model and its results contribute to the following Sustainable Development Goals (SDGs) from the United Nations: 2) Zero Hunger, 10) Reduced Inequalities, 12) Responsible consumption and production, and 17) Partnerships for the goals from the United Nations.

The multi-objective approach considered in this paper based on the weighted sum method has some limitations for the implementation of results in the real agri-food supply chain. This results from the fact that the distribution of weights to objectives depends on the subjectivity of decision makers. In addition, the obtained solution can only be the optimum for the defined weights distribution. To solve this, the UMO-SCPP model could be solved in the future with the ε-constraint method to obtain a set of non-dominated solutions not influenced by the subjectivity of decision makers when defining the distribution of weights among objectives. In this case, a method to choose the most satisfactory solution for the supply chain should be defined.

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