2022-09-01

Optimization model to support sustainable crop planning for reducing unfairness among farmers

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http://hdl.handle.net/10026.1/19490

1 **Collaborative Models to Define Sustainable Crop Planning Reducing**

2 **the Unfairness among Farmers in an Uncertain Context**

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

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

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37 business model, channels are characterized to be more direct (fewer intermediary

38 actors). The value chain proposes value to the customer by looking at previous concepts

39 and, at the same time, reducing the unfairness among farmers through a better

40 distribution of costs and benefits according to the farmer's key resources. In this

41 business model, it is very important to balance supply and demand in order to reduce

42 waste in every farmer and the unmet demand. To achieve this balance, it is necessary to

43 consider the demand during the crop planning decision-making process, which is the

44 core of farming system management. Crop planning consists in choosing the crops to be

45 planted, their acreage and their allocation to the farmland (Dury et al., 2012). Crop

46 planning decisions will determine future harvest and flow of crops along the chain, and

47 therefore their supply. However, it is not possible to reach a perfect balance between

48 demand and supply given the impact of uncertainty on both elements. These sources of

49 uncertainty inherent to the agri-food sector jointly with others negatively impact on the

50 agri-food supply chain's performance and sustainability (Esteso et al. 2018).

51   Another aspect that leads to this imbalance is that crop planning decisions are

52 usually made independently by each farmer once per season. This way of making

53 decisions usually contributes to the overproduction of the crops that were more

54 profitable on last season, leading to the drop down of prices and the production of

55 wastes. On the opposite, this produces scarcity in the supply of crops that appeared to be

56 less profitable on last season when compared to their demand, leading to the increase of

57 their prices. Collaboration mechanisms can be used when making the crop planning

58 decisions to better balance supply and demand, reducing waste and unmet demand, and

59 to protect the supply chain against the negative impact of uncertainty (Esteso et al.

60 2018). Zaraté et al. (2019) conclude that research on coordination issues in agricultural

61 SCs is in its early development. Besides Handayati et al. (2015) state in their review that

62 studies on supply chain coordination in agri-food sector with a particular focus on

63 small-scale farmers is very scarce. One collaboration mechanism applicable to the crop

64 planning problem is the decision synchronization that consists in jointly making

65 planning and operational decisions for all farms (Simatupang and Sridharan, 2005) in a

66 centralized manner.

67 To the best of our knowledge, there are no model-based computerized tools

68 to support the crop planning decisions in this new business model. It seems obvious that

69 models for crop planning should consider the demand of crops to balance supply and

70 demand, however few papers do it. In addition, most of these papers only model

71 decisions related to the crop planning such as the selection of crops to plant, the

72 definition of the area or plots allocated to each crop and decisions about the resources

73 needed to plant and cultivate the planted areas such as the irrigation, labouring, and the

74 use of fertilizers.

75 However, to balance supply and demand it is necessary to take into account

76 more operative decisions. However, few papers as well as this paper take into account

77 additional more operative decisions such as the harvest, transport and sale of crops in

78 order to anticipate the balance between supply and demand at markets (Ahumada et al.,

79 2012; Ahumada and Villalobos, 2011a, 2011b; Flores et al., 2019; Flores and

80 Villalobos, 2018; Mason and Villalobos, 2015; Najafabadi et al., 2019; Nguyen et al.,

81 2019). In the particular case of transport decisions, analysed models do not take into

82 account neither the capacity of vehicles nor the minimum cargo to be filled in order to

83 use a vehicle, which determines the quantity of vehicles necessary to transport crops

84 and limits the quantity of crops to be transported ready to satisfy demand. This paper

85 models all these aspects, filling the gap identified in literature.

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86   Most models for crop planning considering the demand of crops such as the

87   proposed by Cid-Garcia and Ibarra-Rojas (2019) and Ren et al. (2019) assume that all

88   demand should be met, allowing, and not penalizing the overproduction of crops and

89   assume that all production is sold. However, few papers model what happens when

90   an imbalance between supply and demand occurs, such as the generation of

91   waste in cases of overproduction (Hasuike et al., 2018; Mason and Villalobos, 2015) or

92   unmet demand in cases of underproduction (Albornoz et al., 2020; Darby-Dowman et

93   al., 2000; dos Santos et al., 2010; Flores and Villalobos, 2018; Forrester et al., 2018;

94   Hasuike et al., 2018; Mason and Villalobos, 2015; Nguyen et al., 2019; Villa et al.,

95   2019). Furthermore, waste is also generated due to the limited shelf-life of crops that

96   has been modelled in few models (Ahumada and Villalobos, 2011a, 2011b). None of

97   the papers allowing the crops overproduction implements mechanisms to reduce wastes

98   generated along the chain by the excess of product and its perishable nature. With this

99   objective this paper, that models the over and underproduction of crops due to the

100   uncertainty in both supply and demand, proposes to settle the excess of supply at each

101   period in order to reduce the quantity of generated waste and promote the sale of fresh

102   products.

103   Given the perishability of crops and the impact that the allocated land area and

104   planting period of crops have on harvesting, and consequently, in the future available

105   supply, it is also important to take into account the multi-period nature of the problem

106   when addressing the harvesting and distribution decisions jointly with the cropping plan

107   ones to satisfy the also seasonal market demand. This aspect is even more crucial when

108   limited capacity of resources per period exist for implementing more operative

109   decisions being necessary to efficiently plan their use.

110   All the above papers propose centralized models to support the aforementioned

111   decision-making processes. Although centralized decision making process is proved to

112   provide the best results for the entire agri-food supply chain (Stadtler, 2009), obtained

113   solution would be difficult to implement in a real agri-food supply chain unless all lands

114   belong to the same farmer since centralized decision making produces inequalities

115   among the supply chain members (Ertogral and Wu, 2000) leading to the unwillingness

116   of farms to collaborate. Because of this, analysed models could not be used to solve the

117   crop planning problem in the new business model where the reduction of the unfairness

118   among farmers is essential.

119   Besides, analysed models mainly optimize economic aspects, leaving out the

120   environmental and social aspects of sustainability which is another fundamental

121   characteristic of this new business model. However, some of the analysed models

122   optimize objectives related to more than one aspect of sustainability. For example,

123   Adekanmbi and Olugbara (2015) who maximize the supply chain profits (economic)

124   while minimizing the land use (environmental). Najafabadi et al. (2019)

125   consider the three aspects of sustainability by maximizing the supply chain profits

126   (economic) while minimizing the water consumption, and the use of fertilizers and

127   pesticides (environmental) and maximizing employment and food safety (social). The

128   rest of the models to support crop planning problem analysed in this section only

129   optimized economic objectives. It is remarkable that none of these models considered

130   the reduction of wastes and unfairness among farms as objectives while

131   these aspects are fundamental for the Sustainable Development Goals (SDG) set by the

132   United Nations (2019) and for the new business model also aligned with the Common

133   Agricultural Policy (CAP) Objectives.

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134   Finally, few existing models to support the crop planning while considering

135 demand of crops take into consideration the uncertain nature of factors related to the

136 agri-food sector. In this case, Darby-Dowman et al. (2000) model the uncertainty of the

137 plants yield stochastically while Ahumada et al. (2012) additionally

138 consider the stochastic nature of market prices. On their part, Najafabadi et al. (2019)

139 consider that the resources needed per crop are uncertain and modelled them by using

140 fuzzy sets. This paper models the uncertainty on the yield of plants, demand of crops,

141 and market and settlement prices by using fuzzy set theory since it is appropriate for

142 cases in which uncertainty is associated with vagueness, ambiguity, imprecision and/or

143 lack of information on a particular element of the problem at hand (Alemany et al.,

144 2015) which is our case.

145   Therefore, to the authors' knowledge, there is a gap in literature as regards

146 models for supporting the crop planning decisions in this new business model for

147 achieving a sustainable supply chain. The objective of the paper is to cover this gap by

148 developing a computerized tool based on a novel **U**ncertain **M**ulti-**O**bjective

149 Centralized mathematical programming model for the **S**ustainable **C**rop **P**lanning

150 **P**roblem, dubbed as UMO-SCPP hereunder. The UMO-SCPP model seeks to balance

151 the supply and demand of crops in an agri-food supply chain composed by farmers and

152 retailers without intermediaries and considers different characteristics of the business

153 model that to the best of authors' knowledge have not been previously modelled in

154 literature.

155   Main novelties of the proposed mathematical programming model are: i)

156 modelling of the new business model itself, ii) inclusion of collaboration among

157 stakeholders of the same SC stage, iii) anticipation of more operative decisions such as

158 harvest, transport, and sales decisions when defining the crop planning, iv) modelling of

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159 the distribution of cargo into vehicles, v) consider the possibility of settling the

160 oversupply of crops in the same period of their harvest to guarantee the freshness of

161 crops and to reduce generated waste and supply chain losses, vi) modelling of multi-

162 objective approach considering the three aspects of sustainability by means not only

163 maximizing profits (economical objective) but also minimizing waste (environmental

164 objective,) and minimizing the economic unfairness among farmers for implementing

165 the collaborative approach (social objective), and vii) inclusion of inherent agri-food

166 supply chain uncertainty by fuzzy modelling of parameters related to the yield, demand

167 and prices of crops.

168 The UMO-SCPP model is validated with realistic data from an Argentinean case

169 study for two scenarios. Results show that it is possible to find solutions where the level

170 of unfairness among farmers and waste generated are improved by slightly decreasing

171 the total profit. Therefore, with this proposal we are contributing to increase the

172 sustainability of the agri-food supply chains in its three dimensions simultaneously.

173 The rest of the paper is aligned to the research methodology and is structured as

174 follows. The fuzzy multi-objective MILP model to address the problem under study and

175 the resolution methodology used to solve it are exposed in Section 2. Results are

176 analysed and discussed in section 3. Finally, conclusions and future research

177 lines are drawn in Section 4.

2 Materials and Methods

179 This section first explains the assumptions under which the crop planning problem is

180 solved for the new business model, followed by the fuzzy multi-objective mathematical

181 programming model to support crop planning decisions. Finally, the CPM-EES-U

182 model is transformed into an equivalent crisp model to facilitate its resolution.

> **Commented [SL1]:** What is this? Give full name before use the short name.

183 *2.1 Crop planning in the new business model*

184 The business model under study is characterized by the lack of intermediaries between

185 farms and retailers. Therefore, an agri-food supply chain composed by a set of farms

186 and retailers directly linked that produce and commercialize multiple crops with limited

187 shelf-life is considered (Figure 1).

188 Figure 1. Supply chain configuration and main activities.

189
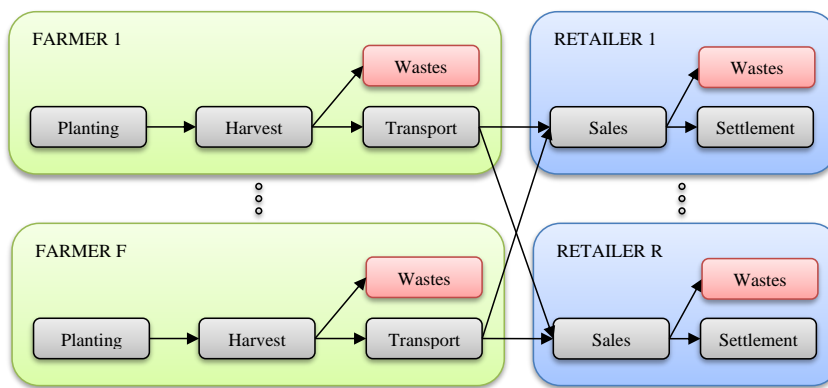
190   Farmers are responsible for farming activities (planting, cultivation, and harvest)

191 and for the transport of crops to retailers, where crops are sold to end consumers. Each

192 farm disposes of one farming location with a limited planting area. Farmers define the

193 area to plant with each crop per period, considering that a minimum area needs to be

194 planted per selected crop and period due to technical reasons. The yield of plants

195 depends on the crop, and its planting and harvest date. All crop matured at plant needs

196 to be harvested in the same period. The transport of crops is made by trucks in a way

197 that a minimum percentage of the cargo quantity needs to be loaded to use one truck.

198   The business model also seeks to serve customers with very fresh products. To

199 do this, the considered supply chain transport and selling the products on the same

200 period of their harvest, being not allowed to store products from one period to the

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201 following. So, crops harvested and not transported to retailers on the same period will

202 be wasted in the farm level. On the other hand, all the crops that arrive to the retailer

203 and are not sold in the same period will also be wasted. To reduce the wastes generated

204 along the chain, this business model allows to settle a part of the oversupply of crops

205 limited by a percentage of the demand with a reduced price. Finally, a minimum service

206 level service is ensured for all crops in all retailers.

207 *2.2 Fuzzy mathematical programming model formulation*

208 The nomenclature used to formulate the UMO-SCPP model is exposed in Table 1,

209 where uncertain parameters are identified by the symbol $\sim$. The uncertain parameters

210 are modelled with Fuzzy Set Theory since it has proved their validity for the uncertainty

211 associated with vagueness, imprecision, inexact statements, incomplete, lack of

212 information and/or unobtainable information on a particular element (Mundi et al.,

213 2016). This model considers that the sales and settlement prices, as well as the crop

214 yields, and demands are uncertain parameters since their values cannot be known in

215 advance.

216 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.

217   The triple bottom line is modelled with three objectives that combined through

218   the weighted sum method (Marler and Arora, 2010) conform a single objective function

219   (1). The objectives are scaled by dividing their values between the maximum value that

220   they can acquire. These maximum values are obtained by executing the model

221   maximizing only one objective (Z_{EC}, Z_{ENV}, or Z_{SOC}).

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

222   The economic objective (Z_{EC}) maximizes the supply chain profits (2). The first

223   term represents the sales obtained by demanded crops and settled crops. The rest of

224   terms are related to the costs for planting, cultivation and harvest, transport of crops and

225   penalizations for unmet demand. Since market and settlement prices for each crop,

226   retailer and period are not known in advance to the crop planning decision and fluctuate

227   as a consequence of the balance between supply and demand among other factors, these

228   parameters are considered uncertain in this model.

$$Z_{EC} = \sum_r \sum_c \sum_t (\widetilde{sp}_{rct} \cdot S_{rct} + \widetilde{gp}_{rct} \cdot G_{rct} - bc_{rc} \cdot B_{rct}) - \sum_l \sum_c \sum_{p \in P_c} pc_c \cdot A_{lcp} \tag{2}$$

$$- \sum_l \sum_r \sum_c \sum_t tc_{lrc} \cdot T_{lrct} - \sum_l \sum_r \sum_t cc \cdot N_{lrt}$$

11

229   The environmental objective minimizes wastes along the chain (3). Wastes can

230   be generated at the farming location by crops not distributed to the following stages of

231   the supply chains, and at retailers when there is an oversupply of crops that cannot be

232   finally be settled.

$$Z_{ENV} = \sum_c \sum_t \left(\sum_r W_{rct} + \sum_l WL_{lct} \right) \tag{3}$$

233   The social objective minimizes the economic unfairness among farmers (4),

234   calculated as the absolute difference between the overall profit per area for farming

235   locations and the profit per area per each farming location. This objective is one of the

236   main novelties of this model. The non-linearity of this objective is solved by replacing it

237   with (5-7) where PR (8) and PL_l (9) are the overall profit for farming locations and the

238   profit per each farming location l, respectively. Profits at the farm level are calculated as

239   the difference between the sale of crops to retailers and costs related to the planting and

240   transport of crops. The selling price for each crop at this level is also modelled as an

241   uncertain parameter as it cannot be known in advance given its dependence to several

242   factors such as the market prices.

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

$$Z_{SOC} = \sum_l D_l \tag{5}$$

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

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

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

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

12

243   The UMO-SCPP model is subjected to the following constraints. The area

244   allocated to each crop in all periods cannot exceed the total area of each farm (10).

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

245   In case a crop is planted, the minimum planted area is limited due to technical

246   reasons (11). In addition, no more area than the corresponding to the farmer can be

247   planted with the same crop.

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

248   Mature crops at plants are necessarily harvested (12) and transported to markets

249   or wasted in this same period due to the limited shelf-life of crops (13). The yield of

250   plants is considered as an uncertain parameter in this model since it is dependent of

251   uncontrollable factors such as the weather, soil properties among others.

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

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

252   To correctly calculate the wastes produced at the farm level it is necessary to

253   take into account the limited availability of transport, aspect that have not been

254   previously modelled in other models. Therefore, a minimum quantity of crops needs to

255   be transported in order to use one truck, and the transported quantity cannot exceed the

256   capacity of trucks (14).

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

257   All crops transported to retailers need to be sold or wasted in the same period of

258   their transport since the business model under study does not allow to store perishable

259   crops from one period to the following. With this, costs related to the workforce and

260   facilities needed to the cold storage of perishable crops at retailers is eliminated. In

261   addition, in order to reduce the quantity of wastes generated at markets, it is allowed to

262 settle crops in cases in which supply excess demand, which is a novelty of this model.

263 Therefore, crops that arrive to markets are necessarily sold, settled, or wasted in the

264 same period due to the limited shelf-life of crops and the business model implemented

265 (15).

$$\sum_l T_{lrct} = S_{rct} + G_{rct} + W_{rct} \qquad \forall r, c, t \qquad (15)$$

266 A minimum service level needs to be guaranteed when meeting demand (16).

267 This ensures that a part of the demand fixed by the decision makers will be necessarily

268 met for each crop in each retailer. The demand for each crop is also modelled as an

269 uncertain parameter since it cannot be known in advance to the period of sales.

$$\sum_t S_{rct} \geq \sum_t sl_c \cdot \tilde{d}_{rct} \qquad \forall r, c \qquad (16)$$

270 In addition, in cases in which demand is higher than the supply, a part of the

271 demand can be lost. So, the sum of sales and unmet demand for each crop, period and

272 retailer should be equal to the demand of such crop. Thus, the unmet demand can only

273 be produced in cases in which demand excess supply (18).

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

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

274 On the other hand, the demand for settled crops is limited by a percentage of the

275 demand (19). The settlement of crops is only allowed in this business model in cases in

276 which there is an oversupply of crops.

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

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

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

14

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)

$$Z_{EC} = \sum_r \sum_c \sum_t \left(\frac{sp_{rct}^1 + 2 \cdot sp_{rct}^2 + sp_{rct}^3}{4} \cdot S_{rct} + \frac{gp_{rct}^1 + 2 \cdot gp_{rct}^2 + gp_{rct}^3}{4} \cdot G_{rct} \right. \tag{21}$$

$$\left. - bc_{rc} \cdot B_{rct} \right) - \sum_l \sum_c \sum_p pc_c \cdot A_{lcp} - \sum_l \sum_r \sum_c \sum_t tc_{lrc} \cdot T_{lrct}$$

$$- \sum_l \sum_r \sum_t cc \cdot N_{lrt}$$

$$PR = \sum_l \left(\sum_r \sum_c \sum_t \left(\frac{op_{rct}^1 + op_{rct}^2 + op_{rct}^2 + op_{rct}^3}{4} - tc_{lrc} \right) \cdot T_{lrct} - \sum_c \sum_p pc_c \cdot A_{lcp} \right. \tag{22}$$

$$\left. - \sum_r \sum_t cc \cdot N_{lrt} \right)$$

$$PL_l = \sum_r \sum_c \sum_t \left(\frac{op_{rct}^1 + op_{rct}^2 + op_{rct}^2 + op_{rct}^3}{4} - tc_{lrc} \right) \cdot T_{lrct} - \sum_c \sum_p pc_c \cdot A_{lcp} \tag{23}$$

$$- \sum_r \sum_t cc \cdot N_{lrt} \qquad \forall l$$

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

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

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

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

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

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

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

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™ 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.

16

302   In the considered case study, a set of farms located in the region of La Plata

303 define the weekly crop planning for three varieties of tomato for the next year. All

304 varieties share the same planting/harvest calendar (Figure 2). Demand and prices are

305 extracted from the Buenos Aires Central Market webpage. The rest of data is gathered

306 from interviews with Argentinean farming experts from the Universidad de La Plata.

307 All data can be found at https://cigip.webs.upv.es/docs/CropPlanningData.ods. In case

308 of fuzzy parameters, obtained data is used as the most possible values for their

309 membership functions while the lower and upper bounds are obtained by varying these

310 central values by 10%.

311 Figure 2. Planting/Harvest calendar.

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

🟧 Planting 🟩 Harvest

312
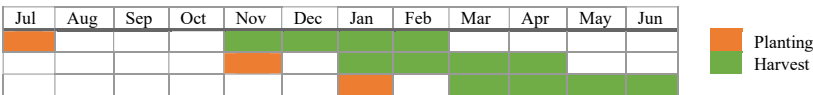
313   The weights assigned to each objective differentiate between their importance

314 (Song and Kang, 2016). When defining the weights assigned to the objectives that

315 compose the global objective function, decision makers hardly know their preferences

316 and how to quantify them (Mavrotas, 2009). The Analytic Hierarchy Process (AHP)

317 (Saaty, 1990) facilitates this task by obtaining the relative importance of elements, in

318 this case the objectives, from a subjective comparison of their importance. For that, a

319 paired comparison of the objectives is done by using the scale proposed by Saaty (1990)

320 that gives higher values to most relevant elements. The weight to be assigned to each

321 objective is then calculated by dividing the sum of values assigned to each objective by

322 the sum of all values of the comparison matrix. The comparison matrix and the obtained

323 weight distribution for this case study are shown in Table 4.

324 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

325   The UMO-SCPP model is solved for 11 α-cuts representing the degree of

326   feasibility of the solution and for the weights' distribution extracted from the AHP

327   (TBL scenario). The model is also solved by assigning all the weight to the economic

328   objective (economic scenario) to extract managerial insights from the comparation of

329   results. Solutions obtained for the triple bottom line indicators (supply chain profits,

330   wastes and unfairness among farms) by both scenarios are shown in Figures 3 to 5

331   where the blue line correspond to the economic scenario where all weight is assigned to

332   the supply chain profit and the orange line correspond to the TBL scenario that assigns

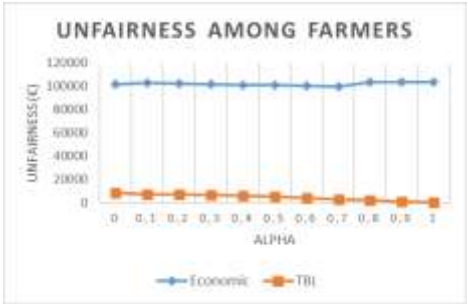333   weights to the three objectives of the global objective function.

334   Figure 3. Results – Supply chain profits.

335

336   Figure 4. Results – Wastes.

337

18

338   Figure 5. Results – Unfairness among farmers.

339

340   From results obtained for the economic scenario, it is extracted that it obtains the

341   best profits for the entire supply chain in all α-cuts. However, wastes associated with

342   these profits are high and make up over 52% of the total harvest. In addition, the total

343   profits obtained at the agricultural level are only distributed among the 30% of the

344   farmers so that some farmers obtain losses (up to -22000 €/ha) while others obtain great

345   profits (up to 25000 €/ha). This generates a great perception of unfairness among

346   farmers, preventing them from collaborating and abiding the planning obtained with the

347   centralized model.

348   On the other hand, the TBL scenario that represents the new business model

349   arising in the agri-food sector obtains lower profits to the economic scenario. However,

350   this scenario shows improvements in terms of wastes and economic unfairness among

351   farmers. In the case of wastes, these can account for 30% of the total harvest, which

352   despite representing a high percentage shows a significant improvement with respect to

353   the economic scenario. In this case, the profits at the agricultural level are distributed

354   among all farmers, obtaining a minimum of 55 €/ha and a maximum of 2400 €/ha.

355   Therefore, the feeling of fairness among farms is greatly benefited in the TBL scenario

356   with respect to the economic scenario, making farmers more participatory and willing to

357   implement the obtained planning.

19

358   Therefore, it is extracted from the comparison between the results obtained by

359   both scenarios that the environmental and social aspects of sustainability can be highly

360   improved in exchange for a slight decrease in the economic results. For example, by

361   considering the proposed multi-objective approach, reducing the obtained profits at the

362   economic scenario in an 8 to 9% leads to the reduction of the quantity of crops wasted (-

363   47% in average with regard to the economic scenario) and of the economic unfairness

364   among farmers (-95% in average with regard the economic scenario). In addition, the

365   reduction on the economic unfairness among farmers encourages them to comply with

366   decisions made in a centralized way, avoiding the unwillingness to collaborate that is

367   usually related to the centralization of the decision-making process.

368   The values obtained for the models' objectives per α-cut get worse for both

369   scenarios as the degree of feasibility (α) of the solution increases. This is because the

370   constraints with fuzzy parameters are more flexible when the feasibility degree decreases.

371   Therefore, a balance between the satisfaction of the value obtained for each objective and

372   the degree of feasibility of the solution should be made by decision makers in order to select

373   the solution to be finally implemented in the real agri-food supply chain (Esteso et al.,

374   2018b).

375   The solved model counted with 6,724 constraints and 6,181 variables from

376   which 5,415 were continuous, 520 were integer and 246 were binary variables. Optimal

377   solutions were found for all α scenarios with an average resolution time of 1.27 seconds.

378   **4   Conclusions**

379   A multi-objective model called UMO-SCPP to centrally define the crop planning for an

380   agri-food supply chain under uncertain context is designed for a new business model.

381   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

21

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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