Universal Journal of Operations and Management
https://ojs.wiserpub.com/index.php/UJOM/

Research Article

A Decision-Analytic, Simulation-Based Model for Plantation Management Under Uncertainty in a Competitive Environment

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Received: 13 October 2022; **Revised:** 18 November 2022; **Accepted:** 18 December 2022

Abstract: This work takes a decision-analytic approach to develop a prescriptive model for three essential plantation management decisions: the size of the cultivated area, the method of cultivation, and the price at which the produce will be sold. These decisions are key to plantation performance and are made difficult by uncertainty and the fact that they are neither made simultaneously nor at the same informational state, aspects that the presented approach explicitly includes. The model is developed by addressing the management of a hypothetical plantation. Decision trees are used to represent the structure of the problem, and simulation is employed to calculate the plantation's expected sales given the market conditions. The simulation relies on a customer preference model that fulfills Keeney's Value-Focused Thinking (VFT) requirements for a proper value representation. The results are presented as recommendations for planted areas and cultivation methods, while the implemented selling price depends on the conditions observed at harvest (market and produce characteristics). According to the results, the presented approach is successful in guiding plantation management decisions and may be useful in increasing plantation competitiveness.

***Keywords*:** decision analysis, plantation management, uncertainty

1. Introduction

The management of farms dedicated to growing and marketing edible products is a process hindered by multiple uncertainties. Some decisions that must be taken more or less immediately (for example, the extension of the area to be planted, the type of plant sown, and the method of cultivation) have consequences that will be observed after a considerable wait. Because of this, these decisions are affected by a great deal of uncertainty: the uncertainties inherent to plant development (i.e., the yield of the land and the quality of the product depend on unpredictable factors like rainfall and humidity) are compounded by the uncertainties related to what market conditions (i.e., competing products and demand) will be like at the time the product is to be sold. In contrast, the decision about the produce sale price is made after harvesting, once the quality and quantity of the product are known and the qualities and prices of competing merchandise have been observed. At said time, however, uncertainties related to competitors' inventories and total product demand would still be unresolved.

Due to the difficulty in producing a formal mathematical model capturing the peculiarities of the problem, plantation managers tend to use cost-benefit analyses that exclude uncertainty, wasting information that, when duly codified and structured, can be used for the decision. The present work puts forward a model for plantation management,

DOI: https://doi.org/10.37256/ujom.2120232000

addressing the decisions of planted land extension, cultivation method, and produce sale price. The model is developed from a decision analysis perspective, being that this is a discipline aiming to help with complex decision-making (Howard, 1996; Howard & Abbas, 2016).

On the state of the art, while the main objective of plantation managers is to maximize profit, there are several reported approaches intending to introduce other objectives in their decision-making: sustainability and conservation considerations are included in the optimization models of Zerger et al. (2011), Kocjančič et al. (2018), Topping et al. (2019), and Mwambo et al. (2020); nutritional improvements brought about by auto consumption farms are considered by Ahmed et al. (2000); Barton et al. (2016) applied Bayesian networks in a model including ecological impacts in choosing tree species for reforestation; Prato and Herath (2007) included technical considerations in distributing harvested rainfall for crop irrigation. Nikoloski et al. (2017) used a multicriteria optimization model solved with DEXI software to assess the feasibility of changing a livestock farm into a plantation; Punantapong (2016) used the Analytical Hierarchy Process to ponder agro-industrial investments decisions; and Hosseinzade et al. (2017) used the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) approach to design crop watering controllers. Other multicriteria approaches are shown by Yin et al. (2018) for locating the site of an aquaculture facility and by Rocchi et al. (2019) for managing a chicken breeding installation. Finally, the usage of global positioning systems and multicriteria optimization models for managing a Kenyan community in an ecologically friendly manner is presented by Agrell et al. (2004), regarding land selection for farm placement by Romano et al. (2015), and for planning rainwater harvesting facilities by Jha et al. (2014) and Toosi et al. (2020).

Applications of decision analysis for planning livestock health interventions are shown by Parsons et al. (1986) and Silva et al. (2018) for vaccinating pigs, and by Oltenacu et al. (1990) and Dorshorst et al. (2006) for supervising cow pregnancies and preventing tuberculosis, respectively. The usage of mathematical programming for farm planning and design is shown by Lien (2003) and Plà et al. (2004); for operating plantations of biodiesel-producing crops by Shastri et al. (2011); for calendarizing soil fertilization by Monjardino et al. (2015); and for scheduling sowing and harvest when frosts are likely by Põldaru and Roots (2014) and when product spoilage is possible by Widodo et al. (2006). Finally, the recent availability of low-cost remote sensing devices has spurred research efforts into exploring the usage of real-time, digitally transmitted information in supporting plantation management. Applications can be found relative to fertilizer scheduling (Colaço et al., 2021), poultry farm monitoring (Bumanis et al., 2022), plantation yield prediction (Kouadio et al., 2021), machinery cost estimation (Mattetti et al., 2022), and the usage of mobile-phone technology (Ahikiriza et al., 2022).

While several of the mentioned research papers deal with agro-industrial management decision-making, they consider that the relevant decisions are made simultaneously and with identical information, thus stating and solving multiobjective optimization problems involving several variables. But, as mentioned before, in plantation management, the decisions are neither simultaneous nor based on the same information state (i.e., the selling price is decided knowing elements that were uncertain when the planted area was set). This difference should be accounted for when modeling the decision.

This manuscript contributes to the field of plantation management research by presenting a mathematical model that accurately captures the problem uncertainties as well as the different timing and information states of the decisions. A decision-analytic perspective is taken for model development, ensuring that the resulting recommendations fulfill the axioms of rational decision-making (Resnik, 1987). The decision structure, as given by the timing of decisions and uncertainties, is neatly represented in a decision tree. An additional distinct contribution in this manuscript is the prediction of plantation sales through simulation, based on a client preference model relying on Value-Focused Thinking (VFT) concepts (Keeney, 1992). The next section describes the proposed methodology, followed by sections showing the results, providing discussion, and drawing conclusions.

2. Methodology

The following sections describe the proposed approach by presenting a prototype plantation management problem.

2.1 *Case study description*

The deciding entity is a farmer who sows an extension of land A (area units) with seeds of a certain marketable species, using cultivation method m. A "cultivation method" comprehends the utilization of a technique or tool allowing greater control of crop growth and modifying the land yield, such as using fertilizers, providing irrigation instead of relying on rainfall for watering, installing nurseries, etc. The amount of produce harvested by the farmer Q_{F0} (mass units) is given by a yield γ (mass/unit area) that depends on the method of cultivation $\gamma(m)$,

$$Q_{F0} = A \times \gamma(m) \tag{1}$$

Several uncontrollable factors (e.g., rainfall, sunlight, and humidity) cause the relationship between the cultivation method and yield to be stochastic, with a conditional probability distribution $P(\gamma|m)$. It is also assumed that the harvested product's quality, "q_F," can be assigned a numerical value indicating the degree to which the product possesses characteristics valued by the buyer. If such a metric is not available, an attribute can be constructed in terms of product color, size, firmness, and so on (Hubbard, 2014). With a probability distribution $P(q_F|m)$, the probability of different levels of q_F depends on the cultivation method.

After harvest, the farmer decides the sale price of his product, p_F ($/unit mass), already knowing its quantity and quality. His sales depend on the customer's preference for price and quality and on other competing products present in the market. This work puts forward a model for the customer's preferences, described in the following section. It is assumed that the market is composed of three competing products: the farmer's and those offered by two competitors named A and B.

2.2 *Customer preference model*

The customer preference model is developed using Keneey's VFT, which has been used elsewhere to analyze agro-industrial decisions (Chew-Hernández et al., 2019). At a given time, the product available in the market consists of Q_F (mass units) of the farmer's product and Q_A and Q_B (mass units) from competitors A and B, respectively. The respective qualities of the farmer's and competitors' products are called q_F, q_A, and q_B, while their prices are, respectively, p_F, p_A, and p_B ($/unit mass). This is illustrated in Figure 1.

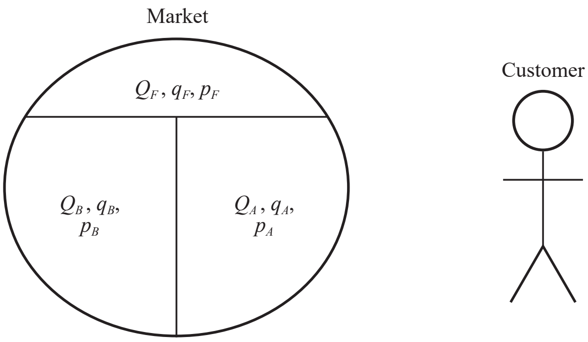

Figure 1. Market composition and customer

Let Q_D (mass units) be the product quantity that a customer intends to buy. The customer's set of options O includes those competing products (either the farmer's [F] or those of competitor A [A] or B [B]) of which there is enough inventory to fulfill his requirements.

$$O = \{i \epsilon O | Q_i \geq Q_D\} = F, A \text{ or } B \quad (2)$$

The customer's preference for option i is given by an additive utility function $U(i)$,

$$U(i) = k_P \times U_P(i) + k_q \times U_q(i) \quad (3)$$

Where functions U_P and U_q are linear functions of the price and quality of option i, j refers to a member of the set of options O,

$$U_q(i) = \frac{q_i - \min_{j \in O}\{q_j\}}{\max_{j \in O}\{q_j\} - \min_{j \in O}\{q_j\}} \quad (4)$$

$$U_p(i) = \frac{\max_{j \in O}\{p_j\} - p_i}{\max_{j \in O}\{p_j\} - \min_{j \in O}\{p_j\}} \quad (5)$$

The weights k_P and k_q add up to one and reflect the perceived importance of price and quality to the customer. According to VFT, a proper preference representation requires that the numerical values of the weights consider what the balanced traits are and how much they vary between options; if a trait varies a lot, its importance in the evaluation grows. To capture this behavior, the size of the price and quality variation between the options is calculated,

$$\Delta P = \max_{j \in O}\{p_j\} - \min_{j \in O}\{p_j\} \quad (6)$$

$$\Delta q = \max_{j \in O}\{q_j\} - \min_{j \in O}\{q_j\} \quad (7)$$

The threshold values of ΔP, called ΔP_L and ΔP_M, are established in such a way that an indicator variable, "size of the price change" ($T_{\Delta P}$), takes the value "Low" if $\Delta P < \Delta P_L$, "Medium" if $\Delta P_L < \Delta P < \Delta P_M$ and "High" if $\Delta P_M < \Delta P$. Similarly, thresholds of Δq are established, such that the variable "size of the variation in quality" $T_{\Delta q}$ is set to "Low" if $\Delta q < \Delta q_L$, "Medium" if $\Delta q_L < \Delta q < \Delta q_M$ and "High" if $\Delta q_M < \Delta q$. Based on values of $T_{\Delta P}$ and $T_{\Delta q}$, an average value of k_P, $\hat{k}_P$, is set. Table 1 shows an example of what the values of $\hat{k}_P$ can be. Nevertheless, when modeling a real-life problem, such values can be adjusted to reflect what is known about consumers' preferences.

Table 1. Values of $\hat{k}_P$ for combinations of $T_{\Delta P}$ and $T_{\Delta q}$

Value of $T_{\Delta P}$	Value of $T_{\Delta q}$	$\hat{k}_P$
High	High	0.5
	Medium	0.7
	Low	0.9
Medium	High	0.3
	Medium	0.5
	Low	0.7
Low	High	0.1
	Medium	0.3
	Low	0.5

To consider the variability in customer preferences, $\hat{k}_P$ is set as the mean of a normal probability distribution, with a 0.05 standard deviation. The weight k_q is calculated as $1 - k_P$.

2.3 *Simulation model*

Process simulation was used to calculate the farmer's sales S_F (mass units) for a total market demand D (mass units) and the farmer's and competitors' initial inventories of, respectively, Q_{F0}, Q_{A0}, and Q_{B0} (mass units) of product with respective qualities and prices of q_F, q_A, q_B, p_F, p_A, and p_B.

Customers show up at the market according to an exponentially distributed time between arrivals with a mean λ (time units), with each customer requiring a uniformly distributed quantity Q_D of product. As explained in Section 2.2, the customer determines his options based on the available quantities of products, evaluates the utility function U for each option according to their price and quality, and selects the option producing the highest U value. The selected product inventory is decreased by Q_D before the next customer arrives. Customers continue to arrive as long as the sum of their demands Q_D is less than the total market demand D. The farmer's sales S_F is the sum of the demands of all customers who selected his production, and his income is the products of S_F and the selling price p_F.

2.4 *Decision structure*

The farmer's decisions and uncertainties are structured using a decision tree (Figure 2). To be able to use this representation, it is assumed that each variable (decision or uncertainty) can take one of a finite set of discrete levels. In Figure 2, these levels are differentiated by superscripts, with the notation Nx indicating the number of levels used in the discretization of variable x (i.e., the area A must be one of the NA discrete values A^1, A^2, ..., A^{NA}). In decision trees, decisions are shown as squares, while uncertainties are shown as circles. Squares and circles are collectively known as "nodes." The lines that emanate from a decision denote its alternatives, while those stemming from an uncertainty represent the possible outcomes and their probabilities.

Decision trees are read from left to right: if an uncertainty (circle) lies to the right of a decision (square), it means that the decision is made without knowing the outcome of the uncertainty. Conversely, a decision is made knowing the outcomes of the uncertainty nodes appearing to its left. The consequences are placed at the tips of the tree branches. These represent the result arising if the alternatives chosen and the results of the uncertain events are those shown by the lines in the path from the root node (the first node of the tree, starting from the left) to the relevant branch tip. The trees are solved from right to left, calculating the expected value of uncertainty nodes and selecting the alternative leading to the node with the highest expected value for decision nodes.

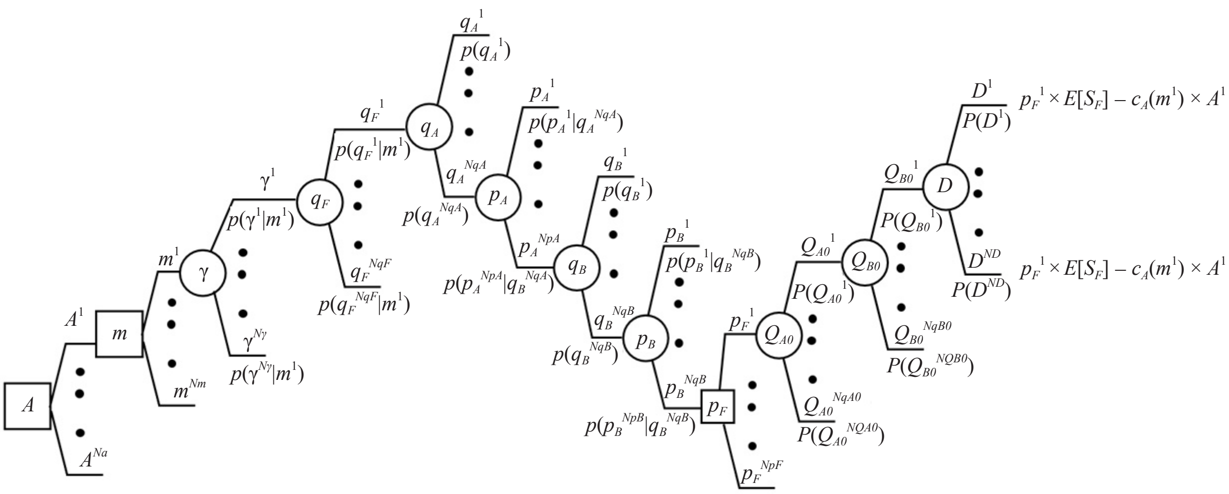

Figure 2. Farmer's decision tree

According to Figure 2, when deciding the area of A and cultivation method m, the farmer has beliefs about the yields and qualities that can be achieved by the available cultivation methods, and these can be stated as conditional probabilities $P(\gamma|m)$ and $P(q_F|m)$. Relative to the market condition at harvest time, he has some knowledge of the possible competitors' product quality, their asking price for a given quality, and their inventories, and such knowledge can be coded as probabilities $P(q_A)$ and $P(q_B)$, conditional probabilities $P(p_A|q_A)$ and $P(p_B|q_B)$, and probabilities $P(Q_{A0})$ and $P(Q_{B0})$. Additionally, a probability distribution $P(D)$ of the size of total demand can be elicited.

From the tree, it is seen that when the farmer decides his selling price, p_F, he knows the results of the plant growth process (the value of γ and q_F) and the qualities and prices of competing products (q_A, q_B, and p_A, p_B), but he will still be uncertain about Q_{A0}, Q_{B0}, and D.

The farmer's profit P_F (\$) is his income, given by his expected sales at his selling price ($p_F \times E[S_F]$), minus his investment, which is the product of the planted area and a unitary cost c_A (\$/unit area) that varies with the cultivation method ($P_F = p_F \times E[S_F] - c_A(m) \times A$). The farmer's expected sales $E[S_F]$ for a given tree branch tip are calculated by running the simulation model (Section 2.3) with the values of Q_{F0} (where $Q_{F0} = A \times \gamma$), q_F, q_A, p_A, q_B, p_B, p_F, Q_{A0}, Q_{B0}, and D associated to the lines that make up the path going from the root node to the relevant branch. As the simulation has stochastic elements, it is replicated several times and the results are averaged to obtain the expected value of S_F, $E[S_F]$. For example, in Figure 2, the value of $E[S_F]$ shown at the top right corner is calculated by simulating with $Q_{F0} = A^1 \times \gamma^1$, $q_F = q_F^{\ 1}$, $q_A = q_A^{\ NqA}$, $p_A = p_A^{\ NpA}$, $q_B = q_B^{\ NqB}$, $p_B = p_B^{\ NpB}$, $p_F = p_F^{\ 1}$, $Q_{A0} = Q_{A0}^{\ 1}$, $Q_{B0} = Q_{B0}^{\ 1}$, and $D = D^1$, while the value of $E[S_F]$ for the tip shown at the center-right side of Figure 2 is calculated with the same values, exception made of demand, which takes the value $D = D^{ND}$. Solving the decision tree provides the recommended cultivated area A and method m, while the recommended sale price depends on the observed conditions after harvest.

3. Results

This section shows the results of applying the approach to a concrete, albeit hypothetical, situation. The model results are produced through the following steps:

a. Numerical values for the model parameters and probability distributions should be obtained. The information needed to solve the model comprises the technical and market-related parameters presented in Sections 3.1 and 3.2. It should be noted that the numerical values shown in these sections do not come from a real-life situation but are provided to present numerical results. However, if a real situation is being examined, relevant values can be elicited and substituted into the corresponding variables.
b. The farmer's profit for the alternatives and outcomes (i.e., the results of the uncertainties) on the line path going from the root node (node A in Figure 2) to each tree branch tip is calculated using the preference and simulation models detailed in Sections 2.2 and 2.3.
c. Once all profits are substituted in their relevant tips, the tree is solved from right to left (i.e., it starts by calculating the expected profit of node "D" in Figure 2). The expected profit of an uncertainty node is the expected value of the profit of the lines emanating from it, while the expected profit of a decision node is that of its alternative with the greatest expected profit.
d. Once the procedure outlined in (c) reaches the root node, the recommended area A can be read by noticing the alternative of this node that leads to node m with the highest expected profit. From the said node, the recommended method m is read from its alternative leading to the node γ with the highest expected value.
e. The last decision, the selling price p_F, will be read from the portion of the tree stemming from the selected values of A and m, but only once the results of the uncertainties between nodes m and nodes p_F are known. So, when solving the model, only the recommendations of A and m can be known immediately, but the price must wait until harvest, as more information will be known by then.

Point (e) highlights an important innovation between the presented approach and previously reported ones in solving multivariable optimization models of farm management decisions (e.g., Agrell et al., 2004; Toosi et al., 2020), as the latter do not consider that some decisions are to be made later when some uncertainties are already resolved. Additionally, the usage of preference modeling (point b) to estimate the plantation profit through simulation was not considered in previous research.

3.1 *Technical parameters*

There are three types of planting methods under consideration (m^i, i = 1, 2, and 3) with associated costs shown in Table 2.

Table 2. Cultivation methods

Cultivation method	Cost c_A (\$/area unit)
m^1 = Plain, without irrigation	5
m^2 = With irrigation and fertilizers	10
m^3 = With irrigation, fertilizers, and nurseries	15

The cultivation method affects the perspective of different values of land yield γ^j (j = 1, 2, and 3) and the quality of the harvested product q_F^j (j = 1, 2, and 3) as shown in Tables 3 and 4, where probabilities $P(\gamma^i|m^j)$ and $P(q_F^i|m^j)$ are displayed.

Table 3. Yield probability distribution conditional on cultivation method $P(\gamma^i|m^j)$

Yield (mass/unit area)	Cultivation method		
	m^1	m^2	m^3
$\gamma^1 = 0.5$	0.7	0.2	0.1
$\gamma^2 = 1$	0.2	0.5	0.2
$\gamma^3 = 1.5$	0.1	0.3	0.7

Table 4. Harvested product quality probability distribution given cultivation method $P(q_F^i|m^j)$

Quality	Cultivation method		
	m^1	m^2	m^3
$q_F^1 = 0.2$	0.7	0.2	0.1
$q_F^2 = 0.5$	0.2	0.5	0.2
$q_F^3 = 0.8$	0.1	0.3	0.7

3.2 *Market characteristics*

The probability distributions of the demand D and the competitors' product qualities and inventories are shown in Tables 5 to 9.

Table 5. Probability distribution of total demand $P(D^i)$

Demand (mass units)	$P(D^i)$
$D^1 = 250$	0.333
$D^2 = 500$	0.333
$D^3 = 750$	0.334

Table 6. Probability distribution of competitor A's product quality $P(q_A^i)$

Quality	$P(q_A^i)$
$q_A^1 = 0.2$	0.333
$q_A^2 = 0.5$	0.333
$q_A^3 = 0.8$	0.334

Table 7. Probability distribution of competitor B's product quality $P(q_B^i)$

Quality	$P(q_B^i)$
$q_B^1 = 0.2$	0.333
$q_B^2 = 0.5$	0.333
$q_B^3 = 0.8$	0.334

Table 8. Probability distribution of competitor A's initial inventory $P(Q_{A0}^i)$

Amount of product (mass units)	$P(Q_{A0}^i)$
$Q_{A0}^1 = 50$	0.333
$Q_{A0}^2 = 250$	0.333
$Q_{A0}^3 = 450$	0.334

Table 9. Probability distribution of competitor B's initial inventory $P(Q_{B0}^i)$

Amount of product (mass units)	$P(Q_{B0}^i)$
$Q_{B0}^{\mathbf{1}} = 50$	0.333
$Q_{B0}^{\mathbf{2}} = 250$	0.333
$Q_{B0}^{\mathbf{3}} = 450$	0.334

The probability distribution of the price presented by competitors depends on the quality of the product they show, which is indicated in Tables 10 and 11.

Table 10. Probability distribution of competitor A's product price given its quality $P(p_A^i|q_A^j)$

Price ($/mass units)	Competitor A's product quality q_A^j		
	$q_A^1 = 0.2$	$q_A^2 = 0.5$	$q_A^3 = 0.8$
$p_A^1 = 10$	0.7	0.2	0.1
$p_A^2 = 15$	0.2	0.5	0.2
$p_A^3 = 20$	0.1	0.3	0.7

Table 11. Probability distribution of competitor B's product price given its quality $P(p_B^i|q_B^j)$

Price ($/mass units)	Competitor B's product quality q_B^j		
	$q_B^1 = 0.2$	$q_B^2 = 0.5$	$q_B^3 = 0.8$
$p_B^1 = 10$	0.7	0.2	0.1
$p_B^2 = 15$	0.2	0.5	0.2
$p_B^3 = 20$	0.1	0.3	0.7

The farmer's selling price p_F is constricted to be either 10, 15, or 20 ($/mass units). The simulations for determining the farmer's sales were run with a customer's interarrival time exponentially distributed with a mean of 20 time units and a customer's individual demand distributed uniformly between 10 and 20 mass units. $E[S_F]$ was taken as the average of 100 simulation replications.

3.3 *Recommended planted area and cultivation method*

Figure 3 shows the farmer's expected profit $E[P_F]$ and recommended cultivation method versus cultivated area. For small area values, it is recommended to use the m^3 method, while m^1 is for large area values. The m^2 method is only recommended for a narrow slit of A values between 190 and 200 area units. The maximum $E[P_F]$ occurs when an extension of 150 area units is sown using the most sophisticated method m^3, resulting in an expected profit of $ 535.40. So, the recommended cultivated area and method are, respectively, 150 area units and m^3.

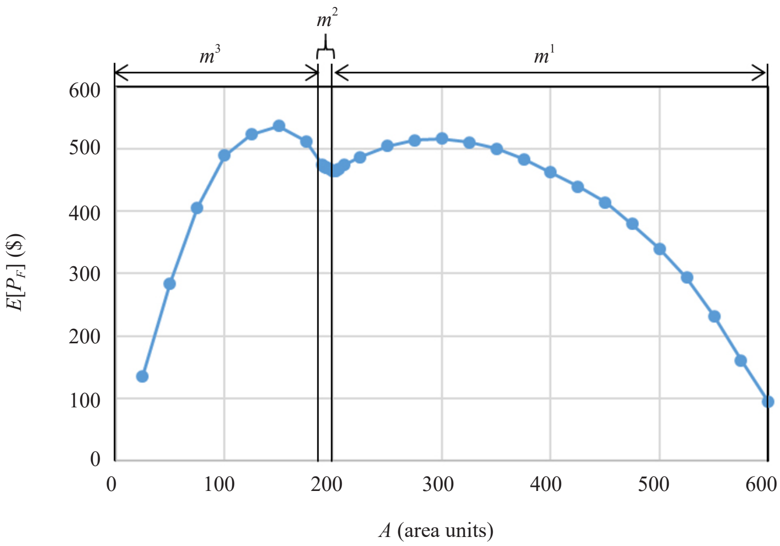

Figure 3. Farmer's expected profit and recommended cultivation method versus A

The probability distribution for P_F ranges produced by the recommended A and m, is shown in Figure 4. Overall, there is a probability of around 32% of incurring a loss (a negative P_F value). However, among possible losses, moderate ones are more likely to happen than big ones.

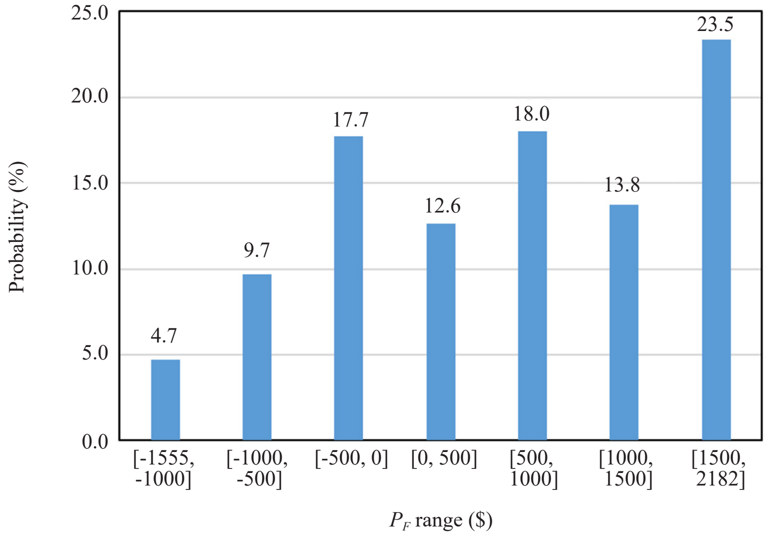

Figure 4. Probabilities for ranges of farmer's profit for recommended A and m

Figure 5 shows the profit cumulative probability distribution, $F(P_F)$, for the recommended cultivation area and method, conditional on the quality of the harvested product. It is observed that the probability of incurring losses given that the harvested product is of low or medium quality ($q_F = 0.2$ or 0.5) is high, at around 85% and 62%, respectively. However, the recommended cultivation method is the most sophisticated one m^3 (Table 2), and this method is believed unlikely to result in qualities $q_F = 0.2$ or $q_F = 0.5$, according to the data of Table 4 that was used as input to the model.

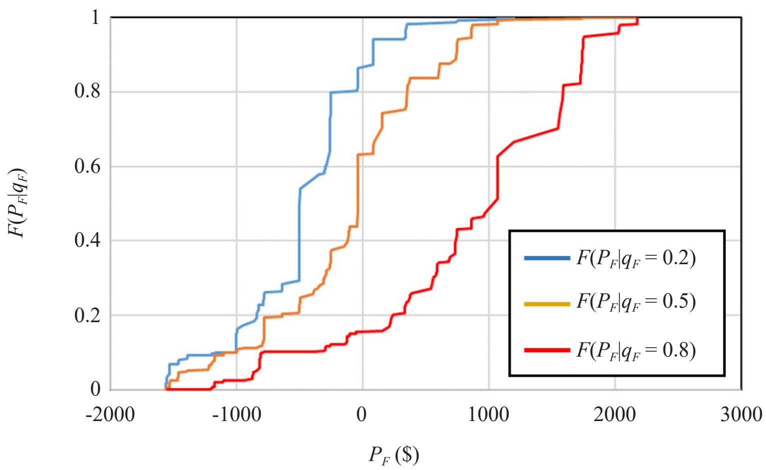

Figure 5. P_F cumulative probability distributions are given crop quality for recommended A and m

3.4 *Recommendation of farmer's selling price*

After implementing the recommended planted area and cultivation method and once the crop has been harvested, the farmer decides the produce's selling price (p_F). Thus, p_F is determined with knowledge of the yield (γ) and quality of the harvested product (q_F) and the qualities and prices of the competitors' product (q_A, p_A, q_B, and p_B). For the recommended planted area of 150 area units and cultivation method m^3, the farmer's selling price for the possible scenarios of γ, q_F, q_A, p_A, q_B, and p_B is shown in Tables 12 to 14. According to the input data in Section 3.2, competitors A and B are equivalent, thus not all possible combinations of q_A, p_A, q_B, and p_B need to be listed, as, for example, scenarios where $p_A = 10$ and $p_B = 15$ produce the same results as those where $p_A = 15$ and $p_B = 10$.

In Tables 12 to 14, a color identifies the recommended p_F for each scenario, with the corresponding expected farmer's profit shown. For example, if the farmer's harvested product quality q_F is 0.2 and competitor A presents a product of quality 0.2 at \$ 10 and competitor B presents a product of quality 0.5 at \$ 20 ($q_A = 0.2$, $p_A = 10$, $q_B = 0.5$, $p_B = 20$), the farmer should sell at a price of $p_F =$ \$ 15 (as indicated by the color of the relevant cell in Table 12), resulting in an expected loss of \$ 207.

When the p_F recommendation changes with the observed land yield (γ), the table cell is divided into halves and a value of γ is written in one half-cell. This means that the value of p_F coded by the half-cell color should be used for the stated γ value, while the p_F recommendation given by the other half-cell color applies to the complementary values of γ. For example, if $q_F = 0.2$, $q_A = q_B = 0.2$, $p_A = 10$, and $p_B = 15$, the relevant cell of Table 12 shows that a p_F of \$ 10 is recommended if the yield is γ^3 and a p_F of \$ 15 if the yield is either γ^1 or γ^2. If a table cell is not divided, it is understood that the recommended value of p_F is the same regardless of what γ is.

In Tables 12 to 14, the price presented by competitors (p_A and p_B) grows from left to right and the quality of their product (q_A and q_B) from top to bottom. Three possible competitors' behaviors can be defined concerning the combination of their product quality and price: "underpricing" means that their price is low relative to the quality of their product (e.g., when they place a high-quality product $q_A = 0.8$ at a low price $p_A = 10$); "overpricing" means that their price is high for their product quality (e.g., if $q_A = 0.2$ and $p_A = 20$) and "pricing fairly" implies that their price harmonizes with their offered quality (e.g., for example, $q_A = 0.2$ and $p_A = 10$; $q_A = 0.5$ and $p_A = 15$ or $q_A = 0.8$ and $p_A = 20$). In Tables 12 to 14, the underpricing behavior grows moving closer to the lower left corner, while overpricing increases as one approaches the upper right corner. Fairly priced competitors' products lie on a diagonal that goes from the upper left corner to the lower right corner of the tables.

From Tables 12 to 14, it is noted that the farmer's expected profit decreases with the underpricing behavior of competitors and increases if they tend to overprice their products, as the latter makes the farmer's product more competitive. According to the input data in Section 3.2, competitors are perceived as more likely to price fairly than to present an overpriced or underpriced product. If the quality of the farmer's harvested product turns out to be low ($q_F = 0.2$), in almost all cases where the competitors present an underpriced or reasonably priced product, a farmer's loss is expected (Table 12). If the competing products are underpriced, the expected loss is around \$ 700, which remains unchanged if the competitor's product quality improves. This happens because, as his low-quality harvest forbids him to compete against a high-quality, low-price competitor's product, the farmer's best bet is hoping that competing inventories are small and leave some market demand uncovered, to which he can sell his product at a high price (\$ 20). If competitors present a reasonably priced or overpriced product, the farmer should lower his price (to \$ 10 or \$ 15) to compensate for his low quality and increase sales, minimizing losses and making a profit if the competitors greatly overprice their product.

Table 12. Farmer's product selling price (p_F) if harvested quality q_F is 0.2

$p_F = 10$, $p_F = 15$, $p_F = 20$

		$p_A = 10$			$p_A = 15$		$p_A = 20$
q_A	q_B	$p_B = 10$	$p_B = 15$	$p_B = 20$	$p_B = 15$	$p_B = 20$	$p_B = 20$
$q_A = 0.2$	$q_B = 0.2$	-1148 γ^3, -497	γ^3, -250 -1009	73.1	70	377	835
	$q_B = 0.5$	-703	-500	-207	γ^3, -35 -1002	387	625
	$q_B = 0.8$	-704	-703	-703	-507	γ^3, -252 -1009	65
$q_A = 0.5$	$q_B = 0.5$	-703	-703	-0.04	-332	-204	623
	$q_B = 0.8$	-705	-704	-704	-702	-500	-206
$q_A = 0.8$	$q_B = 0.8$	-704	-704	-703	-703	-705	-565

The farmer's recommended selling prices if the quality of his product is intermediate (q_F = 0.5) are shown below (Table 13). Compared to the case of q_F = 0.2 (Table 12), there are more cases for which responding to underpriced competing products with prices of \$ 15 or \$ 10 is recommended, but these scenarios still result in a loss. The recommendation to compete against overpriced products is to set a price of \$ 15 or \$ 20 depending on the qualities and prices of competitors, with a price of \$ 15 being recommended against competing products of high quality (i.e., one of the competitors' product qualities is greater than or equal to 0.5 and the other is 0.8) so as to compensate the farmer's quality of 0.5 with a lower price.

Table 13. Farmer's product selling price (p_F) if harvested quality q_F is 0.5

p_F = 10, p_F = 15, p_F = 20

			p_A = 10		p_A = 15		p_A = 20
q_A	q_B	p_B = 10	p_B = 15	p_B = 20	p_B = 15	p_B = 20	p_B = 20
q_A = 0.2	q_B = 0.2	-332	-206	474	624	γ^1, -1103 823	1583
	q_B = 0.5	-491	γ^1, -1463 -201	63.9	379	626	1262
	q_B = 0.8	-704	γ^1, -1554 -602	-333	-206	72.6	476
q_A = 0.5	q_B = 0.5	γ^3, -499 -1137	γ^3, -257 -1001	66	72	382	836
	q_B = 0.8	-703	-705	γ^3, -247 -1009	γ^3, -255 -1013	-92	377
q_A = 0.8	q_B = 0.8	-703	-709	-517	-561	γ^1, -1455 -254	283

Finally, Table 14 shows the farmer's recommended price when the quality of his harvest is 0.8. This quality allows him to request the highest price (\$ 20) in all cases of overpriced competitors' products and in most cases of competing products that are priced fairly. When land yield is high $\gamma = \gamma^3$, a farmer's price of \$ 15 is recommended when one of the competitors' product quality is 0.8 and the other is either 0.2 or 0.5. When competitors' products are underpriced the farmer's prices are prescribed to be \$ 15 or \$ 10 to remain competitive.

Table 14. Farmer's product selling price (p_F) if harvested quality q_F is 0.8

p_F = 10, p_F = 15, p_F = 20

			p_A = 10		p_A = 15		p_A = 20
q_A	q_B	p_B = 10	p_B = 15	p_B = 20	p_B = 15	p_B = 20	p_B = 20
q_A = 0.2	q_B = 0.2	1120	1244	1253	1583	1582	1583
	q_B = 0.5	552	1116	1257	1480	1584	1584
	q_B = 0.8	61.9	382	γ^3, 1070 -130	474	1256	1257
q_A = 0.5	q_B = 0.5	275	372	476	1143	1262	1584
	q_B = 0.8	γ^3, -256 -1011	-91.12	γ^3, 390 -594	380	γ^3, 1080 -140	1246
q_A = 0.8	q_B = 0.8	γ^3, -503 -1143	γ^3, -254 -1011	59	79	375	835

4. Discussion

Section 3.3 shows that the recommended values of the sown area and cultivation method are, respectively, 150 area units and method m^3. Once these have been implemented, the selling price to use depends on the results of the plant's growth, mainly the quality of the crop, and on the prices and qualities of competing products (Section 3.4). Previously reported approaches to the mathematical modeling of farm management calculate the recommended values for all decision variables simultaneously. However, such an approach is incorrect, as in the plantation problem, some decisions are made later than others and with more information. So, the method put forward here corresponds more closely to the real nature of the problem. It should be stressed that the results of Sections 3.3 and 3.4 are for the model input described in Sections 3.1 and 3.2, and for a different problem, the recommendations should differ.

As is natural when recommending courses of action for uncertain situations, implementing the prescribed alternatives does not guarantee that a loss will not be incurred (Figures 4 and 5). This is the consequence of the demand and competitors' behavior relative to their quality and stock sizes being highly uncertain with flat probability distributions (Tables 5 to 9). However, the scenarios for which losses are observed are associated with low qualities of the harvested product, and, according to the input data, getting such qualities is unlikely when using the chosen cultivation method. Nevertheless, before implementing the recommended decisions, Figures 4 and 5 should be discussed with the plantation manager to see if he finds the risk acceptable. In case the resulting risk of a loss is deemed unacceptable, a utility function penalizing losses can be used to convert profit into utility units, and the decision tree of Figure 2 is solved with utilities at its branch tips. The recommendations so obtained would result in a diminished risk of incurring losses.

5. Conclusion

As plantations face several uncertainties that critically impact their profitability, their management has been the subject of multiple research efforts. This work adds to these by presenting a plantation management prescriptive model that includes technical and market-related uncertainties and captures the decisions' timing and information state. The approach takes a decision analysis perspective, uses a decision tree to represent the decision structure, and a customer preference model and simulation to estimate the plantation sales given the competitive environment.

Results of the model are provided for a hypothetical case study, showing the recommended area and cultivation method, and the selling price contingent on the prevalent scenario when the product is marketed. The decision model captures the decision structure, and the results are plausible given the characteristics of the test case treated. However, the approach presented here still lacks the validation of being applied to a real-life situation, in which issues that cannot be foreseen when working on hypothetical problems (e.g., difficulties in eliciting farmer knowledge to use in the model, social or environmental considerations, etc.) may prove important. An obvious avenue of future work is the application of the model to a practical scenario, which is currently being worked on by analyzing the growth of hibiscus flowers at a small local plantation.

Conflict of interest

The authors declare that they have no competing interests.

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