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A Model-based Approach to maximise Gross Income by Selection of Banana Planting Date

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The harvest dynamic model (SIMBA-POP) was used to choose the best planting date of a banana field in order to optimise the gross income. The proposed method takes into account the seasonal variation of the selling price of bananas. The gross income was calculated weekly by multiplying the simulated number of bunches harvested weekly by the mean weight of bunches, and by the current selling price. The weekly gross income over the simulated period was then determined. The study was carried out in Martinique (French West Indies) for climatic conditions corresponding to 50, 350, and 650 m in altitude and for different field management strategies (number of cropping cycles before replanting). The result of our simulations showed that the optimal planting month enables a 10–36% increase in income over the worst month.

1. Introduction

Export bananas (*Musa* spp., AAA group, cv. Cavendish) currently covers nearly one million hectares worldwide (FAO, 2005). Bananas are rhizomatous herbs whose terminal bud produces the inflorescence. Each plant successively produces a series of bunches, each from a lateral shoot. The sequence can be repeated for one to fifty generations or more, which means that it can be considered as perennial (Turner, 1994). The main developmental stages of banana plants include sucker appearance (which the farmer may influence by selecting the sucker early or late), growth, flowering, and harvest. Banana crops represent a collection of individual plants derived from vegetative propagules. They develop at their own rhythm and do not follow a synchronous cycle. When the stages of new sucker, flowering, and harvest occur, the population structure spreads following lognormal functions (Tixier *et al.*, 2004). Hence, at any given time, a banana crop consists of a population of individual plants at various developmental stages. The dynamics of banana bunch harvest follows peaks whose amplitudes tend to be wider over time, up to a continuous harvest after five to seven cropping cycles (*Fig. 1*). The development of bananas and the harvest dynamics depend on the climate, in particular the temperature (at least, in the case of appropriated water and mineral supply).

The date of planting strongly influences the dates of harvest peaks. Furthermore, the selling price of banana varies over time with a regular pattern; the highest prices are generally during January–April while the lowest prices are during May–November (SNM, 2005). This pattern depends mostly on other fruits grown in the importing countries (Loeillet, 2005). It is regular over years, only its amplitude varies. *Figure 2* shows the mean selling price (import price) of banana for Martinique for each month during 1999–2004 (FAO, 2005; ODM, 2005). A selling price dataset with a 'minimal variation' over the year was defined in order to test the sensitivity of the model to variations of this parameter. This 'minimal variation' data set was established by choosing for each month the value that is the closest to the annual mean value of the selling price and within the monthly variation range.

Notation

$F(t)$	number of flowering plants at step t	$N'(j,t)$	number of plants in the cohort j at step t
$H(t)$	number of harvested plants at step t	$P(t)$	selling price of banana at step t, €
$I(t)$	gross income generated at step t, €	$S(t)$	number of new suckers selected at step t
$I(n)$	cumulated gross income generated over the n simulated weeks, €	$T_{SUM}(i,t)$	heat units accumulated by the cohort i at step t, °C
i	cohort ranks for pre-flowering cohort chain	$T_{SUM}'(j,t)$	heat units accumulated by the cohort j at step t, °C
j	cohort ranks for post-flowering cohort chain	$T_d(t)$	mean temperature at step t, °C
n	number of week simulated, weeks	t	step of the model, weeks
$N(i,t)$	number of plants in the cohort i at step t	W_b	bunch weight, kg

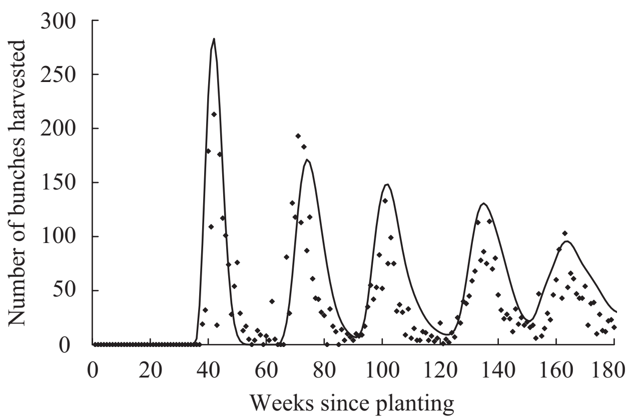

Fig. 1. Number of harvested bunches measured (◆) and simulated (▬) using the SIMBA-POP model; measurement were made in a field in Martinique at 250 m of altitude

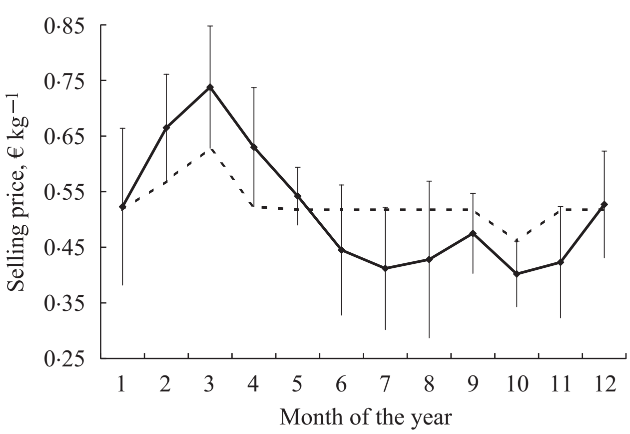

Fig. 2. Mean value (▬) with standard deviation and minimal variation value (---) of the selling price of banana (import price) for Martinique for each month of the year for the period 1999 and 2004 (SNM 2005; ODM 2005)

The strategies to manage the banana field include the choice of the planting date and the choice of the number of years of culture before destroying and replanting the field. The effect of choosing the planting date has been studied previously on the number of harvested bunches (Robinson & Nel, 1986) and on the production period (Turner & Hunt, 1987) but was never linked to the seasonal price variation and modelling tools. Empirically, the planting date is chosen so that the first or second harvest peaks to occur in the highest selling price period. This approach does not take into account the harvest dynamics in the long term. The SIMBA-POP model was developed, calibrated, and validated to forecast the harvest dynamics. A model approach presents the advantage of forecasting the harvest dynamics on a long term. This model was used to optimise the planting date of a banana field in order to maximise the gross income for Martinique (French West Indies) conditions.

2. Materials and methods

2.1. *Model description*

The model used to simulate the harvest dynamics of banana fields is the SIMBA-POP model (Tixier *et al.*, 2004). It runs with a weekly step t and its structural unit is the cohort. Each cohort represents the number of plants of the same physiological stage. Two linked chains of cohorts allow representations of the plants before flowering (pre-flowering cohort chain) and after flowering (post-flowering cohort chain). The only input data of the model is $T_d(t)$ the mean weekly temperature. Outputs include $S(t)$ the number of new suckers selected, $F(t)$ the number of flowering plants, and $H(t)$ the number of harvested plants for each step t in weeks. The passage between cohorts depends on the time, the heat

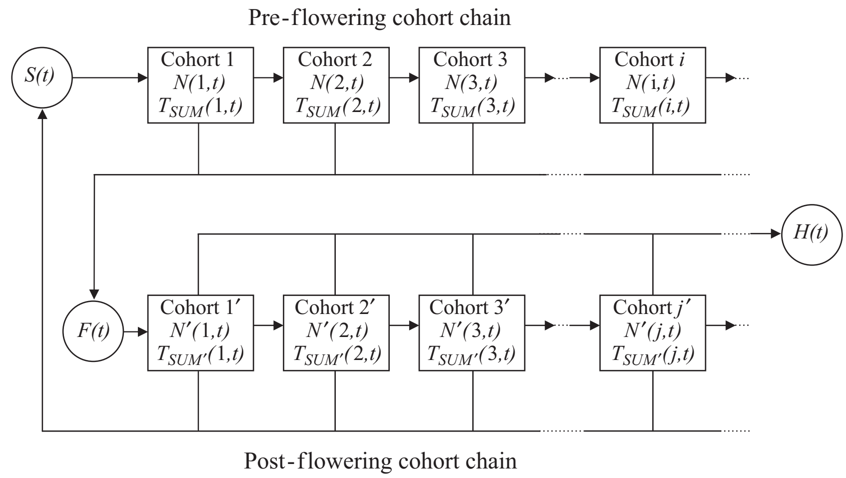

Fig. 3. Simplified structure of the SIMBA-POP model: i and j, the cohort ranks for pre-flowering and post-flowering cohort chains; $N(i, t)$ and $N'(j, t)$, the number of plants in the cohort i or j at time step t; $T_{SUM}(i, t)$ and $T_{SUM'}(j, t)$, the heat units accumulated by the cohort i or j at step t; $S(t)$, $F(t)$, and $H(t)$ the number of new suckers, the number of flowering plants, and the number of harvesting plants, respectively, at step t; arrows represent the transfer or the generation of a number of plants from one cohort to another one

unit accumulated, and the stochastic laws (flowering, sucker selection and harvest dispersions). *Figure 3* presents a simplified structure of the SIMBA-POP model. When $T_{SUM}(i,t)$ exceeds the threshold of heat unit accumulated for flowering, new flowered plants $F(t)$ are implemented in $N'(1, t)$, following a lognormal function (with a_f, b_f, c_f parameters). When $T_{SUM}'(j, t)$ exceeds the threshold of heat unit accumulated for sucker selection, new suckers $S(t)$ are implemented in $N(1, t)$, following a lognormal function (with a_s, b_s, c_s parameters). When $T_{SUM}'(j,t)$ exceeds the threshold of heat unit accumulated for harvest, plants are harvested $H(t)$. Table 1 presents the SIMBA-POP parameters used for the simulations in this paper. The banana is assumed to develop only when the temperature is over 14 °C (Ganry & Meyer, 1975; Ganry, 1980; Turner & Lahav, 1983; Turner & Hunt, 1983). Therefore, the 'heat units accumulated per day' is equal to the daily temperature minus 14.

Table 1
SIMBA-POP and yield parameters for simulations (from Tixier *et al.*, 2004 and unpublished experimental results)

Parameter	*Value*
Heat unit accumulated before first flowering, °C	1750
Heat unit accumulated before first sucker selection, °C	1950
Heat unit accumulated before first harvest, °C	900
Flowering lognormal stochastic curve parameters	
a_f, b_f, c_f	1·00; 7·00; 0·35
Sucker selection lognormal stochastic curve parameters	
a_s, b_s, c_s	1·00; 3·00; 0·28
Bunch weight W_b, kg	20
Planting density, ha^{-1}	1850

The weekly gross income $I(t)$ is calculated by multiplying the weekly number of harvested bunches $H(t)$ with the mean bunch weight W_b and with the selling price of banana in the current week $P(t)$:

$$I(t) = H(t) \times P(t) \times W_b \tag{1}$$

The cumulative gross income generated over the simulated period of n weeks $I(n)$ is calculated by summing the gross income generated on a weekly basis.

$$I(n) = \sum_{t=1}^{n} I(t) \tag{2}$$

The hypothesis of a constant bunch weight ($W_b = 20$ kg) is assumed because the potential variation of the bunch weight over time, cycle, or altitude depends on many factors. These factors do not depend on strategic choices, but depend on farming practices or agricultural constraints such as parasitism or soil properties. The result of this hypothesis is that, in this study, the bunch weight does not influence the comparison of gross profit. To clearly compare different strategies and altitude conditions, the relative gross income within the same altitude series is considered for each possible month of planting. The relative gross income for a given planting month is the ratio between the gross profit generated by this month of planting and the highest gross profit generated by a month of planting.

2.2. *Tested field management strategies*

Three field management strategies, which differed by the number of cropping cycles before replanting (one cropping cycle is equivalent to one harvesting peak) were tested. They were a short strategy (two cropping cycles) and a medium strategy (four cropping cycles), and a long-term strategy (eight cropping cycles). The simulations were for a 1-ha field with 1850 banana plants.

2.3. *Temperature data set*

The temperature data set is from Martinique at an altitude of 250 m (Atlantic coast of the island). The measurements were taken between 1994 and 2003. *Figure 4* presents the mean and the standard deviation. The 'heat units accumulated per week' is the sum of the daily heat units accumulated during the week. To calculate the temperature at other altitudes (50 and 650 m) the temperature is assumed to decrease by 0·7 °C when the elevation increases by 100 m (Albert & Spieser, 1999).

3. Results

Figure 5 shows the results of the simulations by SIMBA-POP for the two, four, and eight cropping cycles strategies. For the three strategies, the months that generated the highest gross income at the altitudes of 50, 350, and 650 m were June, May, and March, respectively.

In spite of the similitude in the optimal months determined by the model for the three tested strategies, it is noticeable that, for the three altitudes, the difference between the worst and the best month was larger for the 'two cropping cycles strategy' than for the two other strategies. The simulated difference reached 36% for the 'two cropping cycles strategy' at 650 m of altitude. For longer strategies, the difference never exceeded 20%, because as the plot ages, production is more spread over

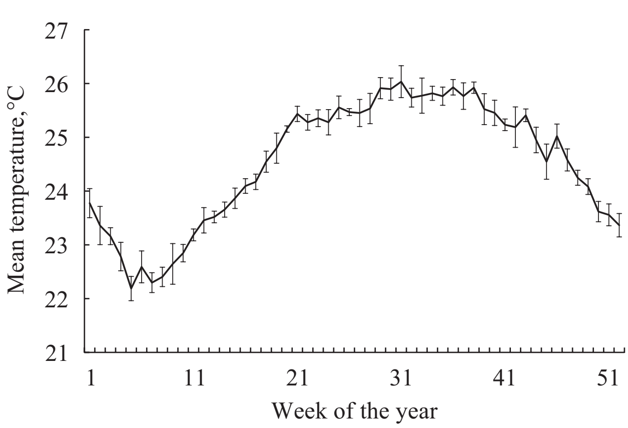

Fig. 4. Mean value and standard deviation of the weekly temperature in Martinique at 250 m of altitude (Atlantic coast of the island) between 1994 and 2003

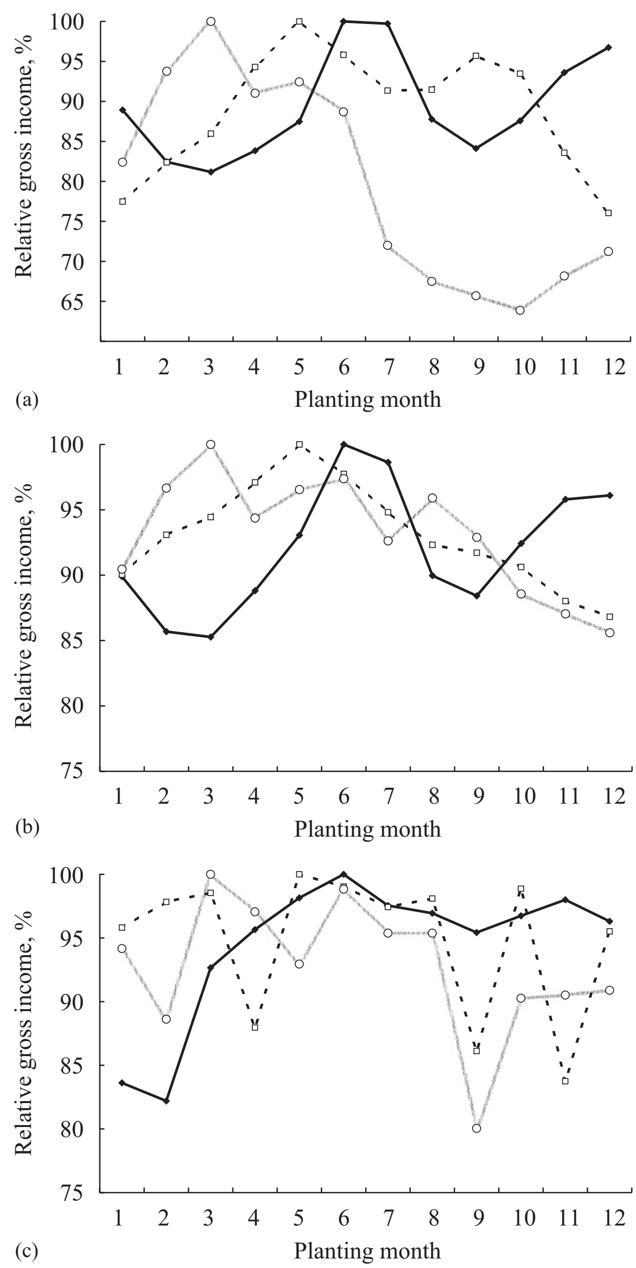

Fig. 5. Relative gross income generated at 50 m (▬), 350 m (- - -), and 650 m (▬) by a two cycles strategy (a), a four cycles strategy (b), and an eight cycles strategy (c), for every possible planting month, and for three altitudes; the relative gross income is (for every altitude series) the ratio between the gross incomes generated by the current month and the best month

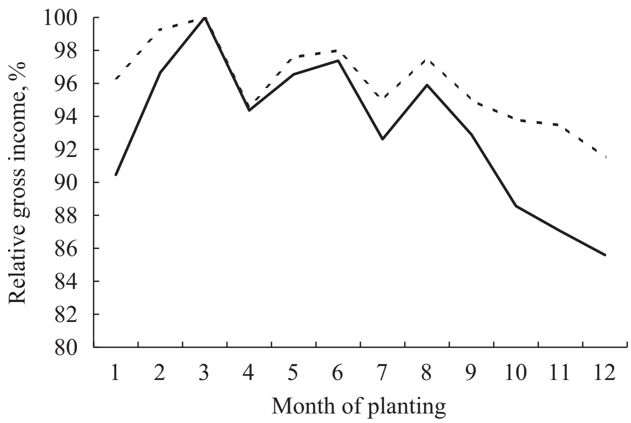

Fig. 6. Relative gross income generated at 650 m by a four cycles strategy for every possible planting month, using the mean selling price data set (——) and the minimal variation selling price data set (---); the relative gross income is the ratio between the gross incomes generated by the current month and the best month

time, and thus the effect of the price variation is weakened. The highest differences between the best and the worst month of planting were when the harvesting peaks were in harmony (resonating) with the selling price pattern. This was the case at 650 m of altitude in the 'two cropping cycles strategy'; all harvesting peaks occurred during the high-selling price period.

Figure 6 presents the results of the simulations by SIMBA-POP for a four cropping cycles strategy at an altitude of 650 m using both the mean selling price data set and the 'minimal variation' selling price data set. The difference between the worst and the best month was larger for the mean selling price data set with a 14·5% increase compared to a 8·5% increase for the 'minimal variation' data set. However, the optimal planting months are unchanged between the two scenarios.

4. Discussion

Choosing the optimal planting date causes a 36% increase in the gross income between the best and the worst month for a 'two cropping cycles strategy'. The sensitivity analysis showed that if the selling price dynamics pattern is unchanged (same maximal month) then the optimal planting months are unchanged too. Despite these results, it is important to relate the optimal months selected by SIMBA-POP to the constraints farmers face: climatic constraints like unusual climate or ploughing unavailability because of rain and farm organization constraints. The organisational constraints include the availability of labour at the date of planting and during the harvesting periods. To use labour efficiently, it may be more suitable for the harvesting peaks to be staggered across the different fields of a farm rather than only for all the fruits to require harvesting simultaneously. By predicting the harvesting peaks, SIMBA-POP permits labour to be managed more efficiently.

When there are too many constraints during the optimal planting period, it is possible to find suboptimal ones, but the gross income is slightly lower. For instance, at 50 m of altitude, for the 'two and four cropping cycles strategies', the November–December period never led to less than 94% of gross income of the best month. Yet, suboptimal planting periods do not always exist; for instance, there is no alternative period for the 650 m of altitude.

The limits of the method are mainly due to unexpected variation of the model inputs. The most fluctuating input of the model is the selling price. In case of large changes in the price pattern, the model will not be able to predict the correct optimal month for planting. Linking SIMBA-POP to a price-forecasting model as for other speculations, *e.g.* for oil (Zamani, 2004) is an interesting perspective to improve the predictive power of this method. Such models are under development for banana and will be available soon (Loeillet, personal communication).

Another possible improvement is to take into account the yield evolution over the period of the year and over cropping cycles. Such a tool exists (Tixier, 2004), it includes a high number of parameters and inputs. Furthermore, many factors, including plant parasitism or fertiliser management, influence the yield.

5. Conclusion

Our study had two main objectives. The first was to develop a method to simulate the gross income taking into account the complexity of the harvest dynamics of bananas and the seasonal variations in selling price. The second was to establish optimal planting dates for banana in the Fresh West Indies. With respect to the first objective, we developed an original method to optimise gross income, linking a plant phenology model with a price variation function. With respect to the second objective, the result of our simulations showed that the optimal planting month enables a 10–36% increase in income over the worst month. The next step will be to take into account farm level constraints such as labour availability, and to simulate variations in yield over a period of several years. Moreover, linking the harvest dynamic model (SIMBA-POP) with a price-forecasting model is a promising way to improve the predictive power of the model. This model can be generalised to other banana production areas or to any other crop subjected to complex harvest dynamics.

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