Multi-criteria evolutionary algorithm optimization in horticulture crop management

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Abstract:

Climate variability requires adaptive production systems in agriculture often resulting in significant irreversible investments. Cultivar replacement programs in horticulture orchards that substitute older varieties for more heat- and drought-resilient varieties have enterprise values that are highly sensitive to the timing of such investments. Farm-level replacement programs are subject to multiple constraints around debt serviceability, operating costs, the replacement cycle and the rate of degradation of the existing orchard. The maximization of enterprise value subject to multiple constraints can be reduced to a multi-objective optimization problem. Over long horizons this optimization process generates a very-large solution space. Using a multi-objective evolutionary algorithm we examine uncertainties around climatic effects and the timing of investments for horticultural operations and derive the optimal times to adapt using cultivar replacement techniques. We find that naive switching decisions using traditional valuation methods are found to be suboptimal and can initiate poor decisions, potentially undermining adaptation efforts. We further show that opposing economic and climatic conditions can adversely impact enterprise value based on mistiming the investment decision. Application of the GA solver is demonstrated using a vector-based GIS to a farm where individual portions of an orchard are subject to varying rates of production, degradation and age.

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Key words: Genetic algorithm, cultivar replacement, macadamia, optimization, net present value, climate change

Introduction

Agricultural operations evolve and adapt to the prevailing climate. Many operate in locations vulnerable to climate impacts, particularly to variations in temperature and rainfall for non-irrigated horticultural orchards, which have a direct and substantial effect on production. Cultivar replacement for orchards are conducted with a certain degree of regret derived from uncertainty around future cost-benefit trade-offs. Decisions relating to the replacement of cultivars in orchards with higher-yielding heat/humidity-resistant breeds are irreversible and therefore costly if the decision to switch is mistimed. Choosing the optimal point at which to adapt is thus made difficult by the effect of climate uncertainty and variability on decision thresholds. A simple replacement cycle appraised using trial and error methods based on net present value (NPV) may ignore subtle changes in timing that maximise value to the grower and which fully accounts for the cost of irreversible decisions.

In practice growers have the flexibility to respond to both shifting environmental conditions and horticultural produce prices in two important ways. First, they can choose to switch a proportion of their orchard at discrete points in time to more appropriate cultivars when the rate of degradation of the existing orchard increases. Second, they can choose to delay the replacing of cultivars if economic conditions to do so are unfavourable. A grower can then maintain a baseline level of income from the existing orchard coupled with the upside of investment returns from gradual cultivar replacement. The challenge is to evaluate the optimal rate of replacement given a range of economic and environmental conditions.

We adopt a modified genetic algorithm (GA) approach to solve the multi-objective problem of estimating the optimal times for replacing cultivars for an average-sized macadamia orchard. Genetic or evolutionary algorithms are a population-based stochastic optimization method that uses the principles of natural selection and genetic inheritance to iteratively improve the solution for an objective function by selection, recombination and mutation. This approach has been applied in agricultural systems to analyse crop-rotation and crop selection (Mayer et al., 2001; Sarker and Ray, 2009) but there has been limited analysis around the timing of investments in horticultural operations.

We model the optimal switching profile for macadamia growers in four distinct geographical locations to compare the critical decision points for crop transfer in response to altered climatic conditions. We show that the decision to switch cultivars is highly sensitive to operating costs, expected prices and the rate of orchard degradation. The analysis shows that if prices are anticipated to rise in the absence of orchard degradation then the optimal time of replacement extends beyond 25-30 years. However as the rate of orchard degradation accelerates the optimal time to commence cultivar replacement diminishes rapidly and may result in an optimal investment time that has already expired. Such adaptation cycles may extend beyond the climatic cycle and cause distress on existing cultivars which may impact future production. We use this approach in an application to a local farm setting using vector-based GIS techniques to demonstrate that the replacement cycle can be further refined given detailed data at each point in an orchard.

Macadamia production

Macadamia nut is native to Australia but was only commercially developed after Hawaiian growers successfully developed an industry following the tree's introduction to the islands as a windbreak for sugarcane plantations. Most ecological modelling suggests that climate change will significantly alter the volume and quality of macadamia nut production in Hawaii, Southern California, Australia and South Africa, where the bulk of the global production of this nut variety is concentrated (Reid, 2002). Mature macadamia production systems dependent on older cultivars are at the extreme of individual species' latitudinal range and are being affected by climate-induced variation in both temperature and rainfall. Climate cycles affect the timing of phenology, the initiation of flowering pollination vectors and the maturation of fruit. Since both onset of flowering and maturation of fruit are known to be determined by climatic parameters it is predicted that elevated temperatures and decreased rainfall at specific times of the year will reduce the reproductive capacity of certain macadamia cultivars (Rickards and Howden, 2012).

Similar to other tree nut crops, macadamias experience production in the fourth or fifth year after planting and fully mature after around 12 years. Yields vary with location, season, variety and grower expertise but typical farms consist of around 300 trees per hectare with peak yields at maturity of 3.5-4 tonnes of nut in shell (NIS) per hectare. Prices are paid at a benchmark level of 33% sound kernel recovery, 3.5% maximum unsound kernel recovery and 10% moisture content which have ranged from US$1.50/kg to US$4.50/kg NIS over the past 20 years.

The enterprise value of an agricultural operation is comprised of the present value of expected future returns plus the value of future investment opportunities. A farm that maintains the flexibility to alter production in the future will be worth more than an identical farm that cannot. Traditional NPV analysis assumes that investments are reversible and the current decision is a now or never opportunity (Dixit and Pindyck, 1994; Carey and Zilberman, 2002).

The transitional years during which a grower waits for newly grafted or planted cultivars to mature are irreversible. Forgone revenue cannot be recovered and the grower does not receive the salvage value of spent capital from another source during the transition. The grower does, however, have a choice as to when to switch cultivars as well as how much of the existing orchard can be switched at each future point in time. The level of a grower's perception of uncertainty about future price premiums will largely dictate the duration of the delay of an investment.

The conversion from older to newer cultivars can be represented as a series of investment outlays at specific times on a portion of the farm while maintaining some minimum level of production from the existing orchard to maintain income for the grower. An initial outlay of K_1 may be followed by subsequent outlays of $K_2, K_3, \ldots, K_n$ at random times which generate cash flows upon reaching maturity.

Methodology

Genetic algorithms (GA) have been applied to a broad range of learning and optimization problems since their inception by Holland (1962; 1975). They are a population-based improvement heuristic approach where an initial random solution is improved using an evolutionary search process. GAs search for an optimal solution by simulating processes of evolutionary development of a population of candidate solutions. Feasible candidate solutions are represented as individuals in a population. The improvement heuristic does not necessarily need to operate directly on the objective function but can operate through a chromosome representation of the problem as a proxy. We adopt this approach because the solution space for investment phase problems at multiple dates (from 30 to 50 years) and using multiple inputs (up to 20 cost and yield inputs) is extremely large and forms a complex fitness surface.

In a comparative study of methods for large-scale environmental optimization problems, Mayer et al. (2001) conclude that so-called heuristic methods (e.g., genetic algorithms and simulated annealing) outperform more classical methods (e.g., non-linear programming). They have been used in an array of agricultural problems. For instance, Mayer et al. (1999; 2001) successfully used genetic algorithms for a single objective beef production model. A range of agricultural planning problems also extended this reasoning towards multi-objective models (Joubert et al., 2007; Francisco and Ali, 2006; Raju and Kumar, 1999; Mainuddin et al., 1997). A limitation of these studies was that each problem was solved as a single objective model using conventional goal programming or compromise programming methods.

When problems cannot be constructed to be dependent on single objective solution then the GA approach offers an option for optimizing multiple objectives simultaneously. A comprehensive multi-objective evolutionary algorithm used by deVoil et al. (2006) solved a crop choice and sowing problem. Sarkar and Ray (2009) introduced a bi-objective linear crop-planning model and adapted it as a nonlinear optimization program to demonstrate the use of alternate forms of constrains in solving crop-planning problems. We extend this research by offering a multi-objective orchard cultivar replacement process that uses the replacement cycle process variable through time as the objective function subject to multiple embedded constraints. The aim of multiple-objective optimisation formulation is to derive a set of Pareto optimal solutions under a range of economic conditions. The Pareto solutions for each scenario are non-dominated in the sense that no other solution results yield a better result. The algorithm chooses a solution from the set of non-dominated solutions based on a decision strategy.

The first objective function we use in this formulation is to maximise total gross margin from both the existing orchard and replacement cultivars including the investment expense at each replacement time over a sufficiently long horizon:

$$\text{Maximize } N_1 = \sum_{i=1}^{T}(R_i - C_i)_{1-\alpha} e^{-ri-d} + \sum_{j=i}^{T}\left(R_j - C_j\right)_{k,\alpha} e^{-rj} - \sum_{k=1}^{z}\sum_{j=1}^{T} I_{k,\alpha}, \qquad (1)$$

where R_i and C_i represent annual revenues and operating costs respectively for the existing orchard for *i=1,…,T*, R_j and C_j represent annual revenues and operating costs respectively for the replacement orchard *k: k=1,2…,z* for *j=i,…T, r* is the constant discount rate, *d* is the rate of degradation of the existing orchard, α is the portion of the orchard switched to newer cultivars and I_k represents the investment cost at each discrete point *k* for *j=i,…T* for a total of *z* investments.

The second objective is to minimize total working capital required:

$$\text{Minimize } N_2 = \sum_{i=1}^{T}\sum_{i\in j} V_{ij,1-\alpha} + \sum_{i=1}^{T}\sum_{i\in j} V_{ij,\alpha(k)}, \qquad (2)$$

where V_{ij} represents the variable cost associated with harvesting in the existing orchard and harvesting in the replacement orchard (costs will differ due to tree age, height, fertiliser and pest control needs). No harvest costs are incurred if no production is available.

The main constraint we apply is for cumulative gross farm income to exceed a minimum threshold Q_n so that a grower to maintain a minimum income over the cultivar replacement cycle:

$$N_3: \sum_{i=t}^{t+n} (R_i - C_i)_{1-\alpha} e^{-ri-d} + \sum_{j=i}^{t+n} \left(R_j - C_j\right)_{k,\alpha} e^{-rj} \geq Q_n \tag{3}$$

where *n* is a cycle of sufficient length to ensure smoothed income exceeds a minimum level. The second constraint is that the number of cultivar replacement cycles, if any, will define the proportion that is replaced at each investment point. Therefore if three discrete investment periods are deemed optimal then exactly one-third of the orchard is replaced at each so that the full orchard is replaced over the long cycle. If no replacements are deemed optimal then the orchard is left untouched. Other standard constraints include the total land available for production and/or conversion must not exceed the total available, demand for produce is not limited by exogenous factors and is reflected in farm gate prices, and decision variables must be strictly positive or zero. We assume the land has an infinite life, macadamia cultivars have long lives and depreciated equipment is restored by replacement so the depreciation necessary to maintain the investment is added to operating costs.

The genetic algorithm (GA) randomly generates a population of 'individuals' tuned to the investment decision point at each year as well as codifying each of the resource constraints. The 'genes' of each individual indicate whether to replace a portion of the orchard (binary operators assigned to a year over a 50-year horizon), subject to the constraints, fixed and variable costs, also represented as binary operators as an additional string of genes. The evaluation phase of the GA ranks all individuals in the population.

A replacement rate of 50 per cent in the selection phase is used to allow new individuals to enter the population to replace lower ranked individuals. The reproduction phase introduces new individuals as offspring created using genetic operators to randomly selected feasible individuals. For recombination we use a two-point cross-over $c_1 \in \left[0, \frac{c_{max}}{2}\right]$ and $c_2 \in \left[\frac{c_{max}}{2}, c_{max}\right]$ where c_{max} is the minimum gene span of both parent individuals. The mutation operator ensures the solution space is fully explored by switching random genes in the new genetic material created by each parent. A minimum mutation rate of 1/(chromosome length + 1) was used in the GA to limit the population size and iteration cycles to a reasonable level.

The fitness evaluation method employs the ratio of the total gross margin for each solution to the total gross margin when no investment in cultivar replacement is conducted. That is, the fitness operator is:

$$\frac{\sum_{i=1}^{T}(R_i - C_i)_{1-\alpha} e^{-ri-d} + \sum_{j=i}^{T}\left(R_j - C_j\right)_{k,\alpha} e^{-rj} - \sum_{k=1}^{z}\sum_{j=1}^{T} I_{k,\alpha}}{\sum_{i=1}^{T}(R_i - C_i)e^{-ri-d}}, \tag{4}$$

where the numerator is a repeat of the first objective function N_1 and the denominator is the net present value of the orchard without a cultivar replacement process. The fitness function is used to rank individuals and in the absence of a stop criterion the reproduction process repeats. The stop criterion is set as less than 1 per cent improvement in the value of the fitness function over ten iterations of the GA solver.

When the stop criterion is reached the set of individuals with the highest ranking represent the Pareto-optimal front. A solution $x^* \in F$ is termed Pareto optimal if there does not exist another $x \in F$, such that $f_i(x) \leq f_i(x^*)$ for all *i=1, . . . ,k* objectives and $f_j(x) \leq f_j(x^*)$ for at least one *j* where *F* represents the feasible space (i.e., regions where all constraints are satisfied) and $f_j(x)$ represents the *j*th objective corresponding to strategy x. If the solution space is limited to X solutions instead of the entire feasible and infeasible space, the set of solutions are termed as non-dominated solutions. In practice all solutions cannot be evaluated exhaustively, so the goal of multi-objective optimization is to arrive at a set of non-dominated solutions that are sufficiently close to the set of Pareto solutions. Diversity among these set of solutions helps ensure the process is selecting individual strategies from a wider set of solution alternatives (Sarker and Ray, 2009).

Solving constrained optimization problems using evolutionary algorithms has a number of well-known issues. First, solving multi-modal problems that have many local solutions in a feasible region can undermine convergence to the ‘global’ solution. Second, solutions to problems with equality constraints are often inadequate since they generally convert such constraints into relaxed inequality constraints which does not guarantee a feasible solution. Third, the stability and efficiency of the search process is not consistently high and the quality of the search process within the GA may not fully overcome the effect of randomness exploited for the purposes of the search.

To address these problems which will arise due to the structure of this GA, we apply the ε-constrained method to the solution set-up (Coello, 1999; Deb, 2000). We introduce a constraint violation function $\phi(x)$ to indicate by how much a search point x violates the constraints, defined as:

$$\begin{cases} \phi(x) = 0 \ (x \in F) \\ \phi(x) > 0 \ (x \notin F) \end{cases}. \tag{5}$$

The ε-level comparison is defined as an order relation on the set of $\big(f(x), \phi(x)\big)$. The ε-level comparisons are defined by a lexicographic order where $\phi(x)$ precedes $f(x)$ because the feasibility of x is more important than the minimization or maximization of $f(x)$. An optimization problem solved by the ε-constrained method (i.e., ordinary comparisons are replaced with ε-level comparisons $N \leq \varepsilon$ is defined as

$$(N \leq \varepsilon)\ minimize_{\leq\varepsilon}\ f(x), \tag{6}$$

where $minimize_{\leq\varepsilon}$ represents the minimization operator based on the ε-level comparison $\leq \varepsilon$. A problem N_ε is defined such that the constraint of *N*, that is $\phi(x) = 0\ (x \in F)$ is relaxed and replaced with $\phi(x) \leq 0\ (x \in F)$ such that

$$(N^\varepsilon)\ minimize\ f(x) \text{ subject to } \phi(x) \leq 0\ (x \in F). \tag{7}$$

A constrained optimization problem N_0 can be transformed into an equivalent unconstrained optimization problem $N_{\leq 0}$ using ε-level comparisons. If ε-level comparisons are incorporated into our existing unconstrained optimization method (Equations 1 and 2) then the constrained optimization problems (Equations 1 to 3) can be more reliably solved. An optimal solution of N_0 can be obtained using the ε-constrained method by converging ε to 0 in a similar way of increasing a penalty coefficient to infinity using an arbitrary penalty function method (Joines and Houck, 1994).

A summary of the ε-constrained genetic algorithm (GA) process is provided in Algorithm 1.

Algorithm 1. Genetic algorithm process

Generate the initial population of random solutions
for 1 to the number of iterations **do**
    Assess feasibility: feasible individuals are placed in the mating pool
    Assess the quality of the chromosomes, based on the fitness function
    Transfer the elite individuals into the next generation
    repeat
        Roulette wheel selection: allocate probabilities of selection based on quality of each individual in the mating pool
        Crossover: fill the next generation by two offspring of two randomly selected parents from the mating pool
    until the new generation is filled
    Mutation: randomly change some of the genes with small probability (not for the last run)
    if the best individual in this generation is better than the best one recorded so far **then**
        Make it the best individual
    end if
end for
end
Output the best individual and the gross margin ratio

The following arguments were applied to the genetic algorithm:

- *strMin*: Each gene corresponds to the weight of an asset in the portfolio (a vector of 0's).
- *strMax*: Vector of 1's.
- *pSize*: Population size is set equal to 1000.
- *iter*: Number of iterations is 100.
- *mutChance*: Chance of mutation is lower limited to 1/(chromosome length + 1).
- *elite*: Number of chromosomes carried over to the next generation is 50% of population size.

For each GA simulation the same random number generator seed was used so that the initial population for each scenario was identical. GA simulations were conducted for a range of constant farm-gate prices. The practical limitation of there being no exact algorithm to obtain a near-optimal solution for this model requires multiple solutions to test for convergence of the fitness function.

Results

The algorithm was run on a laptop with an IntelR CoreTM i7-4600U CPU @ 2.10 GHz 2.70 GHz processor, with 16 GB RAM and 64-bit operating system under Windows 10. Coding language R was used to implement the solver. The trial dataset included four geographic locations with varying input costs to demonstrate the feasibility of the approach. The cost input assumptions are provided in Table 1.

	Hawaii	California	Australia	Southern Africa
Orchard size (trees)	6000	6000	6000	6000
Operating costs (/ha)	\$3,000	\$2,800	\$3,500	\$1,600
Harvest costs (/ha)	\$1,425	\$1,350	\$1,500	\$550
Average area (ha)	20	20	20	20
Average yield (kg/tree)	12	12	12	12
Yield degradation (p.a.)	2%	2%	2%	2%
New cultivar costs (/tree)	\$14	\$18	\$20	\$8
Time to initial harvest (years)	7	7	7	7
Time to full maturity (years)	12	12	12	12

Table 1. Cost profile, yields and other inputs for each location.

We set the minimum income threshold Q_n to a gross margin of US\$5,000/ha averaged over a 5-year cycle. Convergence in the GA process and profit ratio results was confirmed via a solver performance function that assessed average and best evaluation values for each iteration of the process. Results for two GA solver processes are provided in Figures 1a and 1b for different orchard degradation rates of 0 per cent and 4 per cent as an illustration.

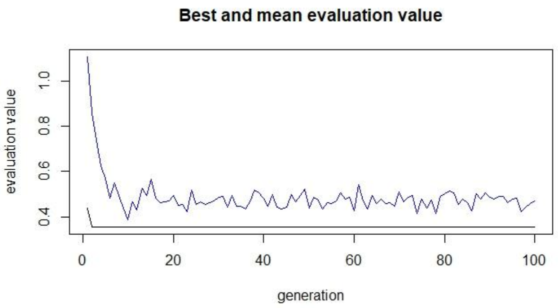

Figure 1a. GA solver convergence for a Hawaiian grower (initial net margin = \$10,180/ha, 0% p.a. orchard degradation, 25% yield increase using new cultivars.

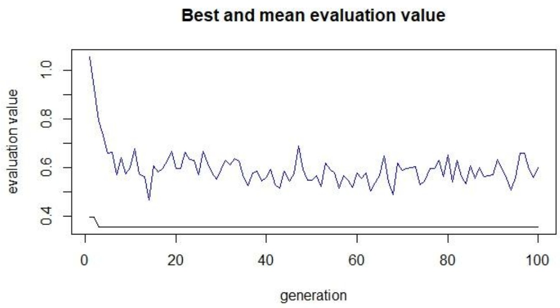

Figure 1b. GA solver convergence for a Hawaiian grower (initial net margin = \$10,180/ha, 4% p.a. orchard degradation, 25% yield increase using new cultivars

Given the transition to newer cultivars is irreversible the investments made up to a certain point in time represent a grower's commitment to the transition. We first consider the optimal transition process for a range of farm gate prices (held constant over the life of the orchard) for different annual rates of degradation with initial farm-gate prices earning growers a healthy gross margin of $11,880/ha, which represents a net return on assets of around 21 per cent for a Hawaiian grower. Figures 2a-2d consists of four panels, each representing the optimal investment points highlighted by black squares over a 35-year horizon for a range of farm-gate prices at 0, 2, 4 and 6 per cent annual degradation rate of the existing orchard. As prices increase (ascending on the y-axis) the preference is for replacement actions to occur earlier and less frequently, for each fixed annual rate of degradation. When the annual rate of degradation approaches around 6 per cent the enterprise value of the existing orchard declines very rapidly. The optimal replacement rate suggested by the GA compresses the investment frequency so that to maximize enterprise value, a grower should conduct several parallel investments within the first 7 years to avoid compounding diminishing production volumes after that point. The rate of degradation of the existing orchard is therefore a key variable for growers to monitor as they weigh up cultivar replacement activities.

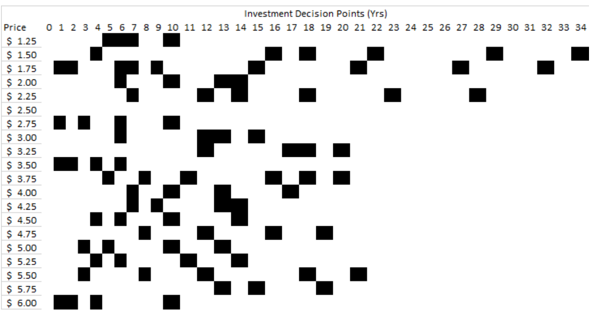

Figure 2a: Investment times for replacement cultivars for a Hawaiian grower (initial net margin = $10,180/ha, 0% p.a. orchard degradation, 25% yield increase using new cultivars). Black pixels indicate which parcel has been replaced.

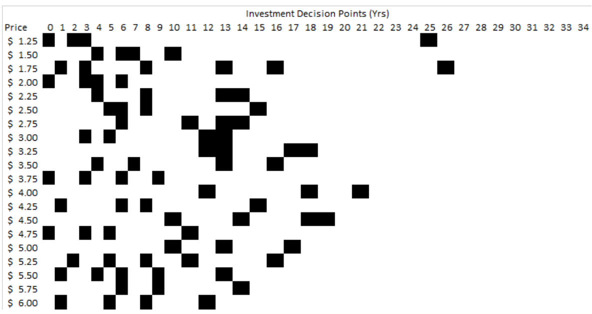

Figure 2b: Investment times for replacement cultivars for a Hawaiian grower (initial net margin = $10,180/ha, 2% p.a. orchard degradation, 25% yield increase using new cultivars). Black pixels indicate which parcel has been replaced.

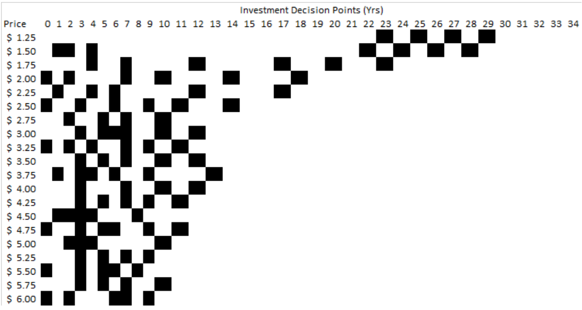

Figure 2c: Investment times for replacement cultivars for a Hawaiian grower (initial net margin = $10,180/ha, 4% p.a. orchard degradation, 25% yield increase using new cultivars). Black pixels indicate which parcel has been replaced.

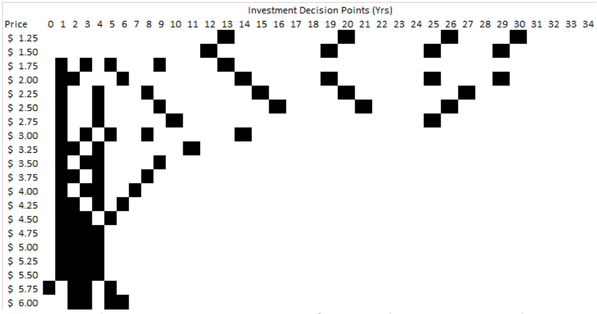

Figure 2d: Investment times for replacement cultivars for a Hawaiian grower (initial net margin = $10,180/ha, 6% p.a. orchard degradation, 25% yield increase using new cultivars). Black pixels indicate which parcel has been replaced.

At very low prices (i.e., less than the Hawaiian grower breakeven price of US$1.85/kg NIS) the GA derives a preference for several staggered investments later in time regardless of the rate of degradation experienced by the existing orchard. This is due to the fact that in the absence of any investment in replacement cultivars the grower's breakeven price is at this level and the grower becomes indifferent between replacing the orchard or not. The resulting investment cycle therefore represents a loss minimization tactic initiated and confirmed by the GA.

We examined the investment cycle profiles for each of the four locations referred to in Table 1. For a given rate of existing orchard degradation, the optimal sequence appears to be for fewer but larger investments to replace cultivars for the higher margin locations (S. Africa and Hawaii) while more frequent and lower investments are optimal for lower margin locations (California and Australia). These profiles have been excluded for brevity but are available from the author on request.

The profiles reveal insights into the characteristics of long-lived horticulture orchards. All else being equal, the greater the number of stages in the transition process the lower the initial investment and the smaller the time between subsequent investments. However the time to initial production and full maturity for newer cultivars remains relatively fixed at 7 and 12 years respectively so there is a natural limit to the most effective transition rate. Too many parallel investments within the 7 to 12-year maturity period sacrifices income from the existing orchard and is an inferior investment option to the decision to replace cultivars fewer times but in larger portions. This presents the greatest value impact when the number of transitions is 2 (half the orchard is under transition for 7 years) and 6 (33 percent of the orchard remains in transition for several years at a time).

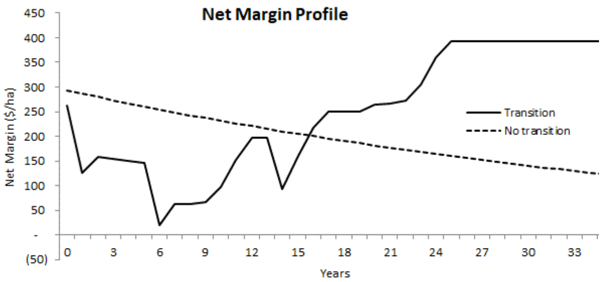

Figure 3a. Cash profile for invest vs. no invest decision using optimal GA solver investment cycle times for a Hawaiian grower (initial net margin = $10,180/ha, 2% p.a. orchard degradation, 25% yield increase using new cultivars, constant price=$4.00/kg).

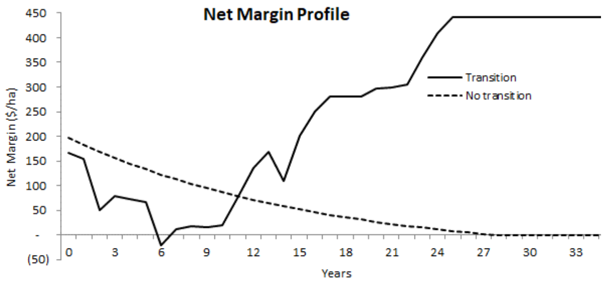

Figure 3b. Cash profile for invest vs. no invest decision using optimal GA solver investment cycle times for a Hawaiian grower (initial net margin = $10,180/ha, 6% p.a. orchard degradation, 25% yield increase using new cultivars, constant price=$4.00/kg)

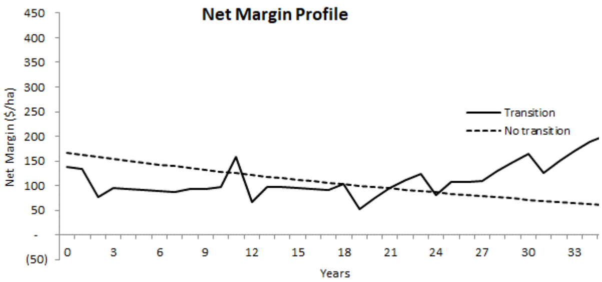

Figure 3c. Cash profile for invest vs. no invest decision using optimal GA solver investment cycle times for a Hawaiian grower (initial net margin = $10,180/ha, 2% p.a. orchard degradation, 25% yield increase using new cultivars, constant price=$2.00/kg).

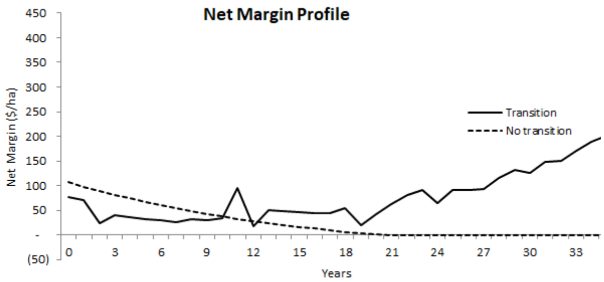

Figure 3d. Cash profile for invest vs. no invest decision using optimal GA solver investment cycle times for a Hawaiian grower (initial net margin = $10,180/ha, 6% p.a. orchard degradation, 25% yield increase using new cultivars, constant price=$2.00/kg).

As the rate of degradation increases, the need to transition to newer cultivars becomes greater, especially for Hawaii, California and particularly Australia where gross margins are much leaner. The imperative to switch cultivars at an accelerated pace becomes greater and the grower's option value increases dramatically. This can be highlighted using cash flow profiles that compares replacement strategies against a baseline strategy of no replacement (i.e., an annual cash flow profile of the profit ratio defined in Equation 4). Figures 3a and 3b illustrate the cash flow profiles over 35 years for a Hawaiian grower implementing an optimal replacement strategy assuming a 2 per cent and 6 per cent annual degradation rate respectively. If, over the course of the replacement process within 10-

15 years the rate of degradation accelerates to 6 per cent, then the cash flow profile of the existing orchard diminishes to zero (after 27 years) while the replacement strategy profile greatly improves. Growers who engage in an optimal replacement program under modest degradation rates suffer from low and even negative gross margins until degradation rates increase. While low and sometimes negative margins early in the investment cycle imply low enterprise value, examining the cash flow profiles over a 35-year horizon demonstrates that much of the improved enterprise value will be derived from higher expected gross margins from the replacement cultivars. This outcome is even more acute in a low price environment illustrated in Figures 3c and 3d. For a price of US$2/kg NIS, which is near to the break-even level for many growers, the gross margin from the existing orchard declines to zero after around 18 years. In the absence of a replacement program that commenced well before this time in accordance with the optimal strategy implied in Figures 2b and 2d, the value of abandoning the orchard outstrips its enterprise value.

Macadamia prices are volatile and expectations of constant prices is unrealistic. The flexibility for growers to invest in cultivar replacement is directly related to the instability of gross margins through time caused by price variability and the rate of orchard degradation. A grower presuming that high current prices translates to an increase in enterprise value as justification for delaying investment under the assumption of modest orchard degradation may suffer a significant decline in total enterprise value if the degradation assumption grossly underestimates the realized rate.

Figures 4a to 4d provide boxplot results of profit ratio sensitivities to the discount rate, new cultivar yields, annual degradation rates of existing cultivars and new cultivar costs for growers in four locations at the optimal transition rate at each respective location. The variability of profit ratios using optimized cultivar replacement strategies for each grower location were examined using 10,000 Monte Carlo historical simulations of price, cost and production yield.

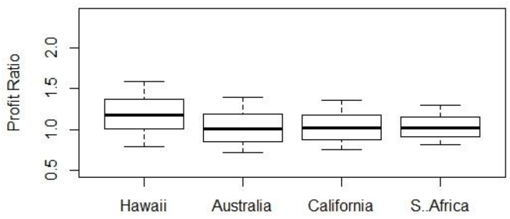

Figure 4a. Profit ratio sensitivity to the discount rate *r* for growers in Hawaii, Australia, California and S. Africa using optimal GA solver investment cycle times for each grower type (initial net margin = $10,180/ha, 2% p.a. orchard degradation, 25% yield increase using new cultivars).

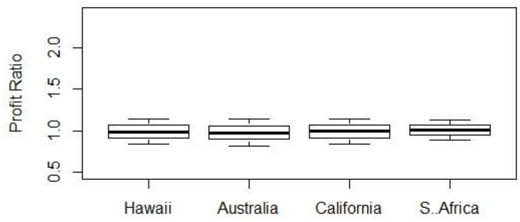

Figure 4b. Profit ratio sensitivity to the new cultivar yield for growers in Hawaii, Australia, California and S. Africa using optimal GA solver investment cycle times for each grower type (initial net margin = $10,180/ha, 2% p.a. orchard degradation, 25% yield increase using new cultivars).

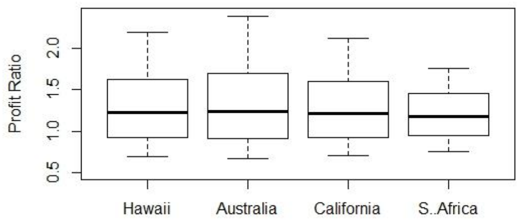

Figure 4c. Profit ratio sensitivity to the annual rate of degradation of the existing orchard for growers in Hawaii, Australia, California and S. Africa using optimal GA solver investment cycle times for each grower type (initial net margin = $10,180/ha, 2% p.a. orchard degradation, 25% yield increase using new cultivars).

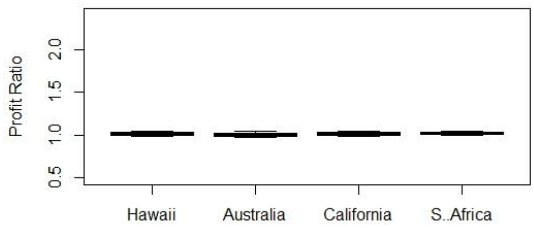

Figure 4d. Profit ratio sensitivity to new cultivar costs for growers in Hawaii, Australia, California and S. Africa using optimal GA solver investment cycle times for each grower type (initial net margin = $10,180/ha, 2% p.a. orchard degradation, 25% yield increase using new cultivars).

As expected from the conclusions drawn in the previous analysis, profit ratio sensitivity is highest for varying annual orchard degradation rates (Figure 4c) and is particularly significant for low margin production locations (Hawaii, Australia, California). The discount rate used as a proxy for a grower's cost of capital also affects profit ratios (Figure 4a) in much the same proportions as degradation rates. Variability in the profit ratio observed from variations in the realized yield of new cultivars and the capital costs of replacement and relatively minor (Figures 4b and 4d respectively).

The key results from the GA solver in descending order of impact on enterprise value are summarised as follows:

- increases in the rate of degradation of the existing orchard and enhancements in yield from newer cultivars accelerates the investment sequence frequency;
- increased prices should motivate earlier investments in cultivar replacement;
- higher costs of capital shifts the optimal replacement cycle to occur earlier however the replacement frequency remains relatively stable; and
- increased uncertainty in underlying cost and yield assumptions increases the enterprise value inherent in the decision to invest in cultivar replacement.

The key problem confronting growers is that high prices coupled with modest rates of degradation of the existing orchard intuitively returns a higher enterprise value which inhibits investment in cultivar replacement. If degradation rates accelerate in the future beyond initial expectations, it may be too late for the grower to recover and it becomes optimal for the grower to exit the industry. This potential circumstance faces many growers across the four locations we examined with the possible exception of Southern Africa, where growers have experienced price growth for the past ten years. If orchard degradation rates accelerate beyond expectations, growers may never catch up on forgone revenue and it becomes suboptimal to continue.

Application

To demonstrate the applicability of this approach to individual orchards we maximize the objective function subject to added constraints as defined using the ε-constrained GA solver in a local setting, where individual portions of an orchard are subject to varying rates of degradation and age, as is common in many horticultural settings. Tourino et al. (2003) demonstrated the application of a combined region-growing algorithm and a simulated annealing optimisation routine in a raster-based geographic information system (GIS) for solving a land partitioning problem. A limitation of their approach is the evaluation of the objective function being evaluated for only two independent domains however a main strength is the capacity to dynamically adjust parcel layouts. Like GA solvers, the use of simulated annealing does not guarantee a global optimum solution but is known to be a relatively robust and efficient optimization method. For our solution we modify the GA along similar lines to the simulated annealing method in Tourino et al. (2003). We adapt the solver to a vector-based GIS to solve a revised multi-objective optimisation problem subject to some added constraints while keeping parcel or block sizes fixed.

The objective is to identify land parcels to be replaced with new cultivars subject to the constraints previously discussed governing replacement cost, income and orchard degradation rates. Deb (2000) distinguishes between hard and soft constraints; hard constraint cannot be violated without making the solution infeasible while soft constraints allow a range of variation within which a solution is feasible (e.g., by specifying a maximum variation). As specified in the earlier GA, the ε-constrained multi-objective problem with pre-defined constraints can be reduced to a set of solutions that are optimal through trade-offs between each of the objectives and constraints. Graphically, the optimal solutions continue to lie on the Pareto-optimal front.

To formulate the objective function for reduction to a GA, a sample farm is represented by an individual who evolves during the optimisation process. The farm is divided into parcels representing chromosomes where each chromosome encodes the characteristics related to size, degradation rate and age. Each chromosome is split into blocks that have a core gene defined by its identifier and when combined into a parcel and then a farm, these individuals comprise a 'population.' We construct the GA to have a hierarchical vector-based structure where individuals-chromosomes-genes represent a solution for the farm, land parcels and blocks respectively. The genetic process used above has been modified as follows: initially, a population of 39 blocks (200 trees per subsection) is constructed and apportioned by general orchard characteristics (by parcel) and assigned an identification number (1 to 39). Each block of the four parcels is assigned an identifier which is codified in the objective function chromosome and used as a reference for the replace/don't replace decision at the start of each year over a 35-year horizon. The added constraints to the original GA solver include an upper age limit of 60 years for each block $A_{i,p}$ of trees (because degradation rates known to greatly accelerate beyond 60 years) and once a block commences an investment transition to new cultivars it ceases to be available for replacement. The added constraints are thus

$$N_4 : A_{i,p} \leq 60;\ \ p \in \{1, \dots, 39\}; i \in \{1, \dots, 35\}, \tag{8}$$

$$N_5 : \mathrm{I}_{A(i,p)}\{x\} := \begin{cases} 1\ if\ x \in I_{k,\alpha} A_{i,p} \\ 0\ if\ x \notin I_{k,\alpha} A_{i,p} \end{cases}, \tag{9}$$

where $\mathrm{I}_{A(i,p)}\{x\}$ represents an indicator function that prevents investing in $I_{k,\alpha}$ block $A_{i,p}$ if an investment in that block has already occurred.

We use average harvest volumes for each parcel-block based on the cultivar varieties planted in that location. We use an average-sized (20ha) macadamia orchard from Australia as an example, where gross margins are somewhat lean and a range of tree varieties are present. The fitness operator remains equivalent to Equation (4) measured as the ratio of the net present value for each GA solution to the net present value where no investment in cultivar replacement is conducted.

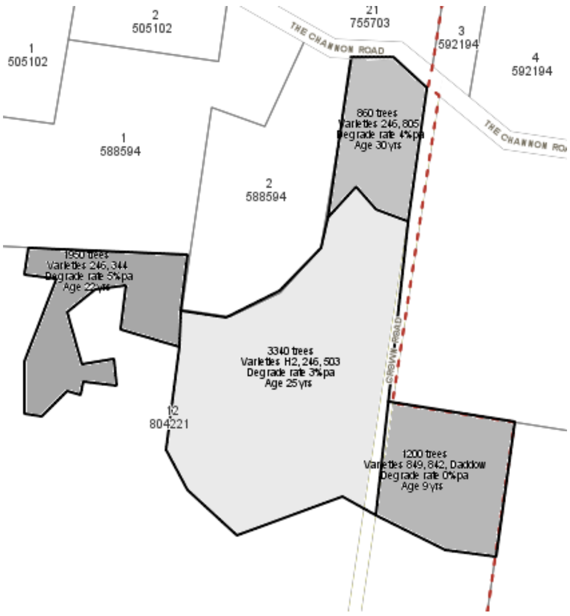

Figure 5a. Plan view of Australian 20ha orchard consisting of 7800 trees categorised into 4 main parcels defined by variety mix, degradation rate and age.

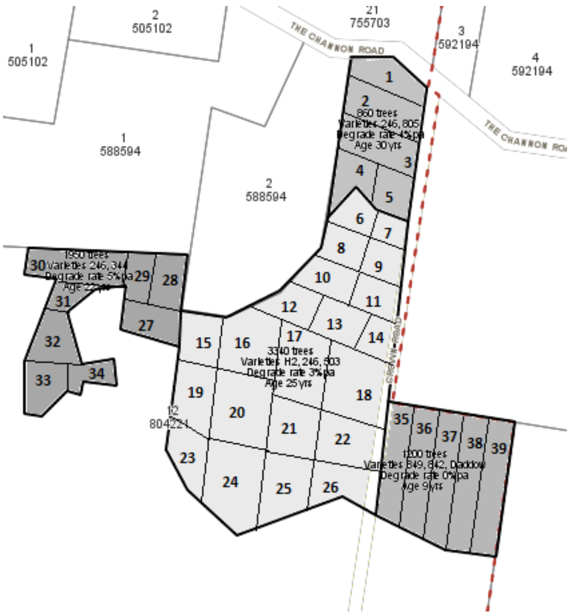

Figure 5b. Plan view of Australian 20ha orchard consisting of 7800 trees categorised into 39 subsections defined by variety mix, degradation rate and age.

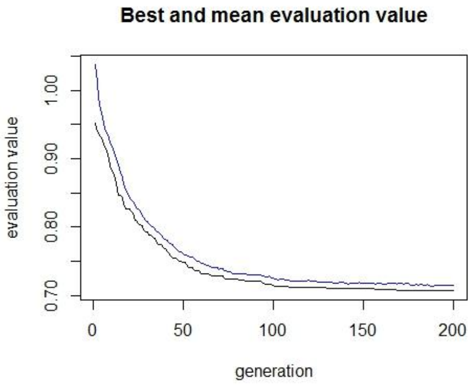

Figure 5c. GA solver convergence for an Australian grower (initial net margin = $7,600/ha, variable orchard degradation, 25% yield increase using new cultivars).

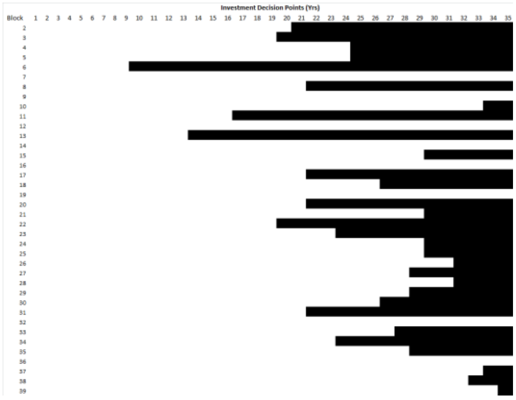

Figure 5d. Investment profile for the optimal replacement cycle for an Australian grower (initial net margin = $7,600/ha (US$3.00/kg NIS), variable orchard degradation, 25% yield increase using new cultivars). Black lines indicate which of the 39 blocks has been replaced.

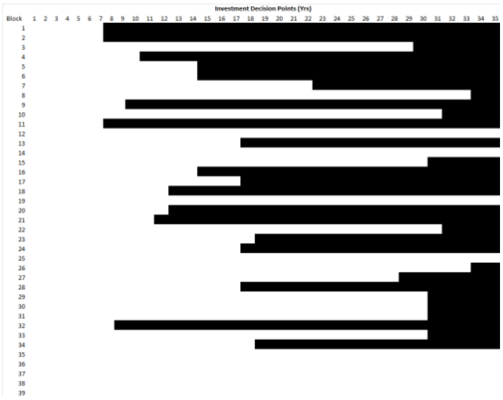

Figure 5e. Investment profile for the optimal replacement cycle for an Australian grower (initial net margin = $2,770/ha (US$1.85/kg NIS), variable orchard degradation, 25% yield increase using new cultivars). Black lines indicate which of the 39 blocks has been replaced.

Figure 5f. Investment profile for the optimal replacement cycle for an Australian grower (initial net margin = $13,900/ha (US$4.50/kg NIS), variable orchard degradation, 25% yield increase using new cultivars). Black lines indicate which of the 39 blocks has been replaced.

Figure 5a illustrates a GIS plan view of the orchard along with variety, age and degradation rates for each parcel while Figure 5b provides an illustration of the arbitrary assignment of 200-tree blocks within each parcel.

Assuming yield enhancements of 25 per cent for newer cultivars and a discount rate of 7.5 per cent the rate of convergence of the GA solver is provided in Figure 5c for a price level of US$3/kg NIS. The number of iterations required to derive an optimal solution is substantially higher for the arbitrary assignment of blocks within larger parcels subject to variations in mix, degradation and age relative to the optimal replacement rate solution arrived at above. The added constraints and volume of computations requires an increase in GA solver population as well as iterations needed to achieve solution convergence. Block by block data of production volume, degradation rate, harvest cost, etc. could be achieved through this method without suffering from added computation time.

The optimal replacement program assuming a price of US$3/kg NIS is provided in Figure 5d. The black line indicates when each of the 39 blocks undergoes replacement. By construction, replacement is conducted only once during the 35-year horizon. Figures 5e and 5f depict the optimal replacement profile assuming a price of US$1.85/kg and US$4.50/kg NIS respectively. In a low price environment (Figure 5e) the incentive to replace the orchard with higher yielding cultivars overrides the cost of investment however the critical investment points occur later in time. The parts of the orchard with higher rates of degradation are selected for replacement first (blocks 1 to 5, and 27 to 34), although this preference is sometimes displaced by the need to replace other blocks within the orchard before the life of the trees reaches 60 years (subsections 6 to 26). For high price environments the incentive to replace the orchard with higher yielding cultivars overrides the loss associated with zero revenue in blocks waiting to mature. Replacement decisions and therefore costs are incurred almost immediately in many parts of the degrading orchard in an effort to recover income and increase enterprise value as rapidly as possible.

While these results appear obvious there are several points worth noting. First, the intensive block replacement program decision under the mid- and high-price environment replaces cultivars in several blocks from different parcels simultaneously. This was found to be optimal rather than working sequentially through each block in order of the rate of degradation. This solution provided by the GA method is due to the minimum income constraint represented in Equation (3). If positive operating income is not needed to service debt and living expenses for a grower then the optimal replacement program may accelerate and result in a different investment sequence. Grower constraints are thus an important consideration in farm management applications.

Second, there is a degree of randomness in the sequence adopted under the optimal solution between different prices. This implies that the order of replacement is less important to the value of the enterprise than the actual timing of cultivar replacement for each block, especially when similar rates of degradation between parcels are observed. Better defined and more detailed data for the rate of degradation and production volume for each block would yield a more refined outcome. The advent of precision agriculture techniques in the near future in providing low-level data will provide opportunities to derive decision recommendations that contribute more directly to enterprise value.

Finally, these results depend entirely on assuming retrospective data is representative of future production. Dynamically incorporating forecasted production, price and degradation data based on real-time data monitoring coupled with data projections would lend greater credence to the replace/don't replace decision for each block. Indeed, the size and shape of blocks could be dynamically adjusted along with the investment decision process. An extension to the land replacement identification process would be to avoid arbitrary block sizes and permit a random population of individuals to be created using, for instance, Thiessen polygons to divide the 2D Euclidean space into a number of blocks equal to the optimal number of replacement cycles. Adjusting the GA solver to meet this need would require additional computation time through added but more flexible soft constraints, and would be achievable using the solver construction described above.

Concluding remarks

We have shown that the dual decision to (1) switch cultivars, and (2) selecting a proportion of an orchard to switch, is a strong function of expected price and a weak function of operating costs. The analysis shows that the optimal replacement rate is a strong function of price and orchard degradation. Generally, it is not optimal for more than one-fifth of an average orchard to be switched in any 5 to 7-year period. This means that the adaptation cycle for macadamia farmers may extend to a long horizon of 35 years which could lie beyond the climatic cycle and cause distress on existing cultivars, impacting total production. The GA approach offers insight into the sensitivities growers face regarding input assumptions and shows that optimal cycle times do not significantly vary by location. In the absence of switching to newer cultivars in an optimal way as discussed in this analysis, the confluence of high prices and high rates of degradation will have significant adverse impacts on the value of macadamia production in the years ahead. This effect will be felt most acutely in lower margin locations. More detailed data on soil quality, harvest volume, degradation and tree age at an appropriately granular level could be integrated with the GA solver to better define the optimal replacement sequence for an entire orchard.

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