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Optimal spraying strategy to combat the coffee berry borer: A dynamic approach

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ABSTRACT

The coffee berry borer (CBB), *Hypothenemus hampei*, is one of the most destructive pests worldwide. In Hawaii, coffee farmers have adjusted their farm management practices to deal with CBB since its introduction in 2010. This study addresses decisions coffee farmers make to combat damage from the coffee berry borer in Hawaii. The decision to spray or not spray a biological insecticide, *Beauveria bassiana*, is modeled during a typical coffee growing season in Kona, Hawaii. If the expected damage to the crop from not spraying is greater than the cost to spray, then it is beneficial to spray in order to mitigate that damage. To estimate economic damage, a Markov-chain tracks changes in farm-level infestation levels from month-to-month based on whether the farm decides to spray or not. The Markov-chain is incorporated into a dynamic programming model to provide a decision path for spray decisions over the season that optimizes the final net-benefit for a typical farm. The developed economic model is then used as the performance standard for alternate real-world management strategies. Integrated pest management performs well but not much better than spraying on a calendar schedule, and all do better than never spraying. An IPM-calendar hybrid could improve on both alternatives.

1. Introduction

The coffee berry borer (CBB), *Hypothenemus hampei* (Ferrari 1867, Coleoptera: Curculionidae), is one of the most destructive pests to coffee worldwide, second only to coffee leaf rust, *Hemileia vastatrix* (Berk & Broome 1869, Pucciniales). In 2010, the discovery of CBB in Kona, Hawaii [1], resulted in farmers reporting up to 80–90% infestation levels of their coffee crop. More recently, bearing acreage is down 23% from the 2012–2013 season to 2017–2018 and processors rejected over 800,000 pounds of berries (ripe fruit containing the coffee bean [2]; “ripe berries” and “cherry” are used interchangeably throughout) in the 2017–2018 season. The value of utilized production is also down $19 million from $63 million in 2014–2015 to $44 million in the 2017–2018 season. Coffee farmers in Hawaii operate on small margins where costs and uncertainty in production can force farmers out of business [3,4]. With the discovery of CBB, farms are expected to shut down as costs of control increase, and production value decreases.

Integrated Pest Management (IPM) strategies provide farmers with ways to combat CBB, such as field sanitation, spraying strategies, and best practices for harvesting coffee berries and disposing of the infested coffee berries [5,6].[1] Most IPM recommendations are discrete activities that are limited in number or concentrated in a specific time period. Spraying and related activities are the only practices that occur every month throughout the year. In this study, the focus is on spraying strategies assuming that farmers follow the other recommended practices.

CBB is difficult to combat because once they enter the coffee berries, they are impervious to available insecticides and free to start the next generation. One of the main IPM recommendations is to monitor and sample the crop, then spray a biological insecticide, *Beauveria bassiana*, before CBB enter the berry. The spray kills the pest within 3–10 days and

Abbreviations: CBB, Coffee Berry Borer; DP, Dynamic Programming; IPM, Integrated Pest Management; USDA, United States Department of Agriculture.

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[1] In Hawaii, IPM strategies from other coffee producing regions were initially adapted for local recommendations [7,8], then subsequently modified for 2015, 2017, and 2020 as new information was developed.

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does not affect the taste or production of the coffee bean. However, the effectiveness is not well known for different concentrations and spray intervals, especially under varied environmental conditions. Further, the sprays and associated labor are costly, and decisions made by individual farm operators (farm-level) account for factors such as elevation, terrain, and farm size characteristics that add to the uncertainty of controlling for CBB.

To reduce the risk and uncertainty introduced by pest infestation, farmers seek reliable information that allows them to make informed decisions to mitigate the damage [9–13]. To improve farm-level information and estimate the economic impact, one approach models the behavior of the pest. Studies generally use a Markov-chain to track the temporal change in pest infestation levels during a season [14–17]. Once the pest behavior is estimated, the recursive nature of farm-level decisions is modeled in a stochastic dynamic programming framework [17–22]. The benefit of this approach is that these studies can incorporate various policy or farm management decisions to derive optimal decisions. A previous study modeled and derived monthly optimal farm-level decisions under a constant growth rate of CBB infestation [23]. However, farmers make decisions based on their previous decisions and expectations about the future. Further, CBB growth rates are not constant during the season and will vary from month-to-month. To improve upon this previous study, the variant nature of CBB infestation on a farm and the economic impact of those farm-level decisions is estimated.

In this study, a farmer's monthly decision to spray or not to spray an insecticide, and the cumulative impact on their final net-benefit is modeled. In Section 2, materials and methods outline an ideal model and how the modeling strategy is approached. Using field-level data and a Markov-chain, CBB infestation levels are modeled in each month that vary according to prior spraying decisions. Next, the farmer's expected final net-benefit is optimized using a forward-recursive dynamic programming (DP) framework. In each month, a farmer's spray decision depends on whether the cost to spray is less than the expected damage to coffee berries for the remainder of the season as a result of not spraying, where this damage is based on the CBB infestation levels from the Markov chains. Net-benefit is estimated as the difference between revenue from undamaged coffee and costs associated with CBB management. An optimal strategy is traced out using monthly spray/no spray decisions that maximize net-benefit for the entire season. In Section 3, the main results are discussed. Finally, the model in Section 4 is used to evaluate three alternate CBB spraying strategies: following IPM spray recommendations, spraying based on a calendar schedule, and to never spray.

2. Materials and methods

One of the challenging aspects of CBB is understanding the environmental factors that allow them to reproduce and how those factors impact coffee production. In Hawaii, coffee production occurs on the side of a mountain, so it is essential to factor in elevation and associated environmental effects as well as micro-climates due to differences in topography. Hawaii's unique weather patterns also vary from year-to-year and across farms – even within a farm – so determining the effects of environmental factors on coffee production and CBB is difficult. There is, however, a direct relationship between coffee berry production on the farm and CBB infestation. As coffee trees produce mature berries, CBB gain new sources of food, which allows their population to grow faster. The lack of data on this relationship and the associated environmental conditions hamper the farmer's ability to make optimal decisions. To overcome these limitations, an ideal model is discussed with its challenges and is then simplified to an operational model.

2.1. Ideal model

A model that captures coffee berry production, $Coffee_t$, is estimated in each month, t, as a function of weather, w_t, and farm-level practices, z_t.

$$Coffee_t = f(w_t, z_t)$$

Weather, w_t, takes into account many of the various environmental factors, such as rain, duration of daylight, temperature spans, and humidity, which directly affects berry production. It is also essential to account for farm-level practices, z_t, such as trimming/pruning/desuckering, and fertilizer choice and frequency of application because these decisions also affect the quality and quantity of berry production. Taking account of these factors provides the direct relationship needed to model berry growth.

Another critical component is modeling CBB population dynamics, which also carry similar relationships to berry growth. CBB prefer warmer days and ample moisture, so accounting for these in a similar setup provides a realistic idea about how CBB grow during the season.

CBB population on a farm is modeled as,

$$CBB_t = g(w_t, Coffee_t, z_t)$$

where CBB in month t is modeled as a function of weather, w_t, which accounts for the same dynamics as berry production, $Coffee_t$. CBB depend on berries that are available as food, so increases in berries imply potential increases in CBB. Farm-level practices, z_t, such as spraying and stripping berry from trees are also considered.

Next, there is a direct relationship to berry production and the CBB population, so infestation levels are modeled as a function of berry production and the CBB population,

$$InfestedAmount_t = h(Coffee_t, CBB_t)$$

The infestation amount, $InfestedAmount_t$, is tied directly to the amount of coffee berry and CBB on the farm, so how much CBB infest berries on the farm is tracked. To calculate infestation levels, divide the total infested berry by the amount of berry on the farm, $Infestation_t = InfestedAmount_t / Coffee_t$. An important point to note here is that the infestation level in each month is related to the amount of available berry on the farm (i.e., a 1% infestation level on 1000 lbs of berry versus 1% infestation level on 10,000 pounds of berry). This has implications early in the season as infestation levels appear to decrease as more berries mature, then at harvest as infestation levels increase as the amount of available berries is reduced.

Next, the different positions CBB take in the coffee berry is accounted for. The location of CBB in the coffee berry can take four positions: (1) A, the beetle has landed on the coffee berry and is beginning to eat away at the skin; (2) B, the beetle has eaten through the outer skin, but has not reached the coffee bean; (3) C, the beetle has now begun eating away at the coffee bean; and (4) D, the beetle has done significant damage to the coffee bean and has already started, or is in the process, of laying eggs [5]; see Fig. 1 for CBB positions. When CBB is in the C or D (CD) position, they are impervious to approved insecticide and are non-marketable due to the damages to the coffee bean. These positions also have a time component and vary from month-to-month as CBB attack newly formed berries. Additionally, each of these positions, $Position_{it}$, is modeled as a

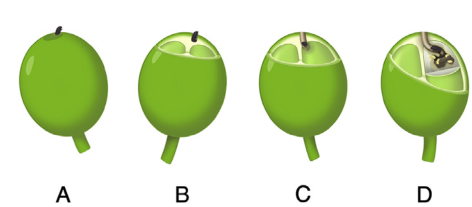

Fig. 1. CBB can take four positions in the coffee berry: (1) A, the beetle has landed on the coffee berry and is beginning to eat away at the skin; (2) B, the beetle has eaten through the outer skin, but has not reached the coffee bean; (3) C, the beetle has now begun eating away at the coffee bean; and (4) D, the beetle has done significant damage to the coffee bean and has already started, or is in the process, of laying eggs which will hatch and feed on the bean until it is completely consumed. Source: Adapted by Burt [5], from Bustillo et al. [32].

proportion of the total infestation levels on the farm. Summing across all positions provides the total infestation on the farm, $Infestation_t$.

$$Infestation_t = \sum_{i=1}^{4} Position_{it}$$

This simple model provides the percentage of the damaged crop from CBB infestation in each position. CBB infestation describes the probability of CBB being in A, B, C, D that is taken from a sample of the coffee berry. The infestation level on the farm – analogous to the farmer taking a sample – can be determined by selecting from $Coffee_t$ and CBB_t. The farmer then takes into account whether to spray or not spray based on the current infestation levels on their farm and expectations about future infestation levels.

In a previous study, the decision to spray was based on the trade-off between the expected loss in berry from not spraying versus the cost to spray is modeled [23]. If the expected loss in berry from not spraying is greater than the cost to spray, then it is beneficial to spray. This decision framework is included in the model where the expected damage in the next period is equal to the difference in the expected CD infestation next period minus the current CD infestation times the expected production in the period.

The optimal net-benefit function is defined as,

$$\text{Total NB} = \sum_{t=\text{January}}^{\text{December}} NB_t = \sum_{t=\text{January}}^{\text{December}} \left\{ \underbrace{P_t H_t (1 - D_t)}_{\text{Revenue}} \right\} - \left\{ \underbrace{c_s S_t + c_h H_t}_{\text{Cost}} \right\} \quad (1)$$

for the coffee growing season from January to December where net-benefit is defined as revenue $P_t H_t(1 - D_t)$, minus CBB control and harvest costs, $c_s S_t + c_h H_t$, where revenue equals price, P_t, times the current harvest, H_t, times the percentage of coffee that is marketable $(1 - D_t)$ where D_t represent berries that are in the CD position and non-marketable. CBB control and harvest costs are equal to the costs to spray, c_s, times decision to spray or not to spray, S_t, plus labor costs to harvest, c_h, times the current harvest, H_t. The other costs of production are assumed to be the same regardless of the decision to spray. The price of berry, P_t, is based on the infestation of CBB in the CD position (See Table 1).

2.2. Challenges and solutions

An ideal model is outlined to improve decision making on a farm; however, it is not possible to apply the ideal model due to insufficient data – records are few, and no two coffee farms are the same including different environmental conditions and management practices. By necessity, field-level data collected during May–December 2016 from farms in Kona including university research plots, and experts who have been studying the growth patterns of CBB in Hawaii is used in the present study [24]. These data account for weather and farm-level practices. By combining data and expert knowledge, a Markov-chain is estimated that models the change in the growth rate of CBB from spraying and not spraying. For simplicity, a dynamic programming model is then used to optimize the net-benefit.

To simplify the functional form for $Coffee_t$, berry production follows a logistic growth function (see Fig. 2). The logistic growth function is used

Table 1
Harvest Pricing per lbs of Coffee Cherry.

Infestation CD	Price per pound.
0–5%	\$1.80
6–10%	\$1.70
11–15%	\$1.60
16–20%	\$1.45
21–30%	\$1.20
31–40%	\$0.60
41–58%	\$0.59–0.35

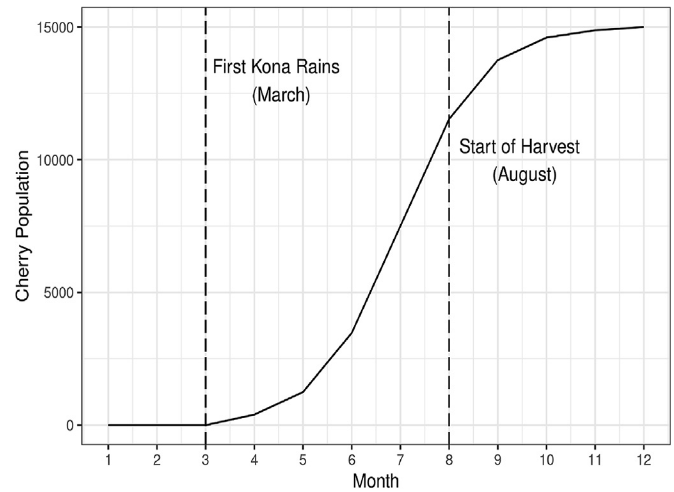

Fig. 2. The logistical growth function to estimate coffee cherry population dynamics – changes in number and size of maturing berries – from January to December.

in two ways: (1) to account for the amount of coffee berry CBB can attack each month; and (2) the amount harvested in each month. At the beginning of the season, there will be a minimal number of berries on the farm since growers have followed best management practices of strip-picking remaining coffee from the previous season. As the season continues, trees will flower, set fruit, and berries begin to mature rapidly starting in the summer. CBB population dynamics will follow berry production on the farm since berry is the food source. As more berries mature and become available, CBB will leave its host berry and infest newly formed berries. To model CBB_t, CBB population dynamics are assumed to be similar to the functional form for berry production (see below for calibrating CBB population dynamics). This simplification provides the total berry on the farm at any given month.

2.3. Infestation and Markov-chains

From the simplification of coffee production and CBB population, a Markov-chain tracks infestation levels for a farm and estimates the proportional change in each position during the season, thus allowing $Infestation_t$ to be modeled directly. The percentage of infested berries in each position at each time period is used as the basis for the farmer's decision making.

The movement between each position depends on many variables in the field, such as the maturity of the berry, and environmental factors, such as temperature. In A or B, CBB is exposed and vulnerable to insecticides. When a coffee berry is immature, CBB will remain in the AB position for extended days to weeks. Once berries mature, CBB can move from A or B to C or D position in a matter of hours, ensuring the demise of the bean.

The Markov-chain estimates the probability of CBB moving into each position and adjusts current infestation levels to reflect each month's change. For example, a sample of 100 berries from the field is collected and dissected. After dissecting the berries, 20 are in the AB position and 10 are in the CD position. Next month, another 100 dissected berries show 15 are in the AB position and 15 are in the CD position. From the first month to the next month 5 berries have moved from the AB position into the CD position. Therefore, 5% of the berries will move from AB to the CD position. This behavior can be modeled using a Markov-chain to identify the changes for each position (state) in each month as well as the percentages in each position. Further, Markov-chains allow changes between months to be variant (e.g., change from AB to CD will be different from March to April than April to May).

Two separate Markov-chains are employed to portray the decision to spray or not to spray. When a farmer decides to spray, more CBB in the AB position is killed so there is a lower probability of CBB eventually moving into the CD position than if the farmer decides not to spray. Each month will have a different level of change and the infestation levels are adjusted based on the decision to spray or not to spray.

Formally, a time-inhomogeneous Markov-chain is defined as,

$$\mathbb{P}(X_t = x_t | X_{t-1} = x_{t-1}, X_{t-2} = x_{t-2}, \ldots, X_0 = x_0) = \mathbb{P}(X_t = x_t | X_{t-1} = x_{t-1})$$

where the probability, $\mathbb{P}$, of a stochastic process, X, in month t is equal to x_t conditional on the previous month's stochastic process, X_{t-1}, which is equal to x_{t-1} in the previous month until $t = 0$. The intuition here is that the current state is based on the previous month's infestation level until the state returns to the beginning, t_0. Therefore, at X_0 initial values are estimated to start the stochastic process through t. In terms of infestation levels, the stochastic processes, X_t, are the different positions of CBB and the path throughout a growing season's $t = 0, \ldots, T$. Initial values are estimated as,

$$V_0 = [\, v_{1,0} \quad v_{2,0} \quad v_{3,0} \quad v_{4,0} \,]$$

where vector V_t contains four elements (probability in each state that sum to 100%):

(1) $v_{1t} = NI$: % not infested or those berries with no holes,
(2) $v_{2t} = ABL$: those berries with a hole and have live CBB in the AB position,
(3) $v_{3t} = ABD$: those berries with a hole and have dead or missing CBB, and
(4) $v_{4t} = CD$: berries with a hole and have CBB in the CD position.

$$V_0 = [\, NI_0 \quad ABL_0 \quad ABD_0 \quad CD_0 \,]$$

Next, two sets of transition matrices are defined for spraying (SP_t) and not spraying (NSP_t) where each matrix defines a probability for each month, t, with event probabilities, a_{ijt} and b_{ijt}, in the probability space. Formally, the transition matrices are defined as,

$$SP_t = \begin{bmatrix} a_{11t} & a_{12t} & a_{13t} & a_{14t} \\ 0 & a_{22t} & a_{23t} & a_{24t} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} NSP_t = \begin{bmatrix} b_{11t} & b_{12t} & b_{13t} & b_{14t} \\ 0 & b_{22t} & b_{23t} & b_{24t} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

For SP_t, the movement from state i to state j in a_{ijt} is the probability that the current state, or infestation level, will transition to a different state in a_{ijt}. For example, NI to ABL is defined as a_{11t} to a_{12t}, from ABL to ABD is a_{22t} to a_{23t}, and ABL to CD is a_{22t} to a_{24t}. Once a berry is damaged in CD it cannot be undone, therefore, a_{33t} and a_{44t} are defined as one in the matrices. Zeros in the matrices prevent impossible movements, such as CBB that are in AB position and dead moving to CD, or CBB in CD position undoing the damage and moving back to AB. The no spraying matrix elements determine the same position movements at SP_t, although, probabilities between movements may be higher due to not spraying.

To track the current levels of infestation, vector V_t is defined as,

$$V_t = [\, NI_t \quad ABL_t \quad ABD_t \quad CD_t \,]$$

where each position of CBB is defined as an element in each month t. The choice to spray is a binary decision (zero or one), S_t, equal to one if the farmer decides to spray and zero if the farmer decides not to spray. Therefore, to estimate the current infestation, given a choice decision, the vector, V_t, is equal to,

$$V_t = V_{t-1} \cdot [S_t \cdot SP_t] + V_{t-1} \cdot [(1 - S_t) \cdot NSP_t]$$

To find berry in the CD position, damage, D_t, is the fourth element of the vector V_t,

$$D_t = CD_t$$

To demonstrate how this Markov-chain works, a simple matrix algebra example for month one is estimated as,

$$V_1 = V_0 \cdot [S_1 \cdot SP_1] + V_0 \cdot [(1 - S_1) \cdot NSP_1]$$
$$D_1 = CD_1$$

where a vector, V_0, is equal to the initial infestation levels of each position of CBB, times the choice to spray ($S_1 = 1$) or not spray ($S_1 = 0$) using the transition matrices defined above. The current non-marketable berry is equal to the element in the vector where $D_1 = CD_1$. For month two, the current infestation levels are equal to,

$$V_2 = V_1 \cdot [S_2 \cdot SP_2] + V_1 \cdot [(1 - S_2) \cdot NSP_2]$$
$$D_2 = CD_2$$

where a vector of infestation levels, V_2, in month two uses the previous infestation levels, V_1, to estimate current levels based on the decision to spray or not spray utilizing the transition matrices in month two. The vector V_t can then be multiplied by harvest amount to get the quantities of berry that are NI, ABL, ABD (all acceptable in the market) and CD (damaged and not marketable, in the model).

2.4. Data and calibration

To calibrate the Markov matrices, it would be best to identify two identical farms in the same location where one sprayed all year round and the other did not. A comparison of the two farms would provide the growth rate difference resulting from the primary decision to spray. Unfortunately, and as previously noted, the data not available are observations on infestation levels from January to May and information for a farm that never sprays. To overcome these limitations, expected initial infestations levels are interpolated based on what field-level experts suggest; that is, a higher initial level with no spraying. The infestation percentages should be higher in the early part of the year because of fewer berries on the tree then slowly decline with flowering and as berries form and mature faster than CBB reproduce. We then utilized field-level data from our research plots at the UH-CTAHR Kona Research Station and data collected from 25 farms from May to December ([24, 25], Luis Artistizábal and Suzanne Shriner, personal communication). Each farm provided results from sampling cherry on their farm in each month and the various positions CBB were in. Combining the interpolated data with observed field-level data provides a complete season of infestation levels for a typical farm in Kona, Hawaii.

The procedure to calibrate the Markov-chains uses a maximum likelihood estimator and the likely probability of moving between each state given the data.[2] The data used to calibrate the Markov-chains is a combination of interpolated data and field-level estimates from January–December. The calibration technique produces two sets of Markov-chain transition matrices (decision to spray and to not spray) for the twelve months in a growing season that includes the four positions, NI, ABL, ABD, and CD (see Fig. 3). The transition matrices provide estimates of infestation levels in each month based on whether a farmer decides to spray or not and track those levels through time. These estimates are used in the dynamic model to derive optimal farm-level decision making.

2.5. Dynamic programming

In this section, a dynamic programming economic model is developed where the optimal strategy for a farmer is the set of monthly spray decisions that maximize the net-benefit over the entire growing season. Available berries are also accounted for through a logistic growth

[2] The markovchain package was used to calibrate the Markov-chain matrices [26].

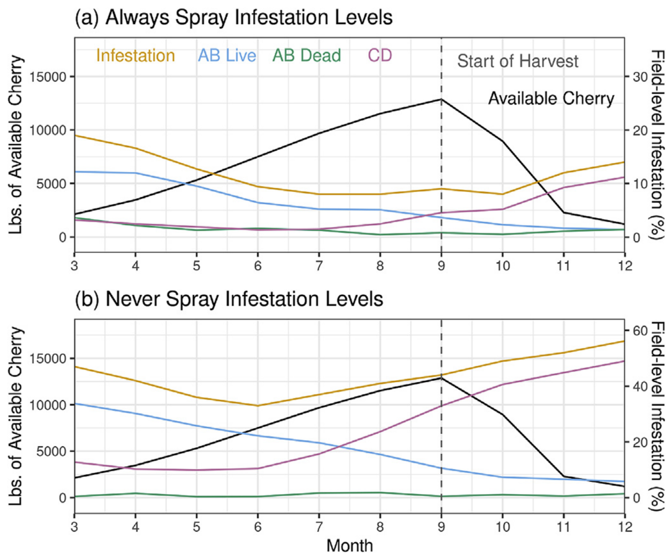

Fig. 3. Data used to calibrate Markov-chains for tracking CBB positions and infestation levels for (a) Always Spray Infestation Levels and (b) Never Spray Infestation Levels. Data was generated from field-level observations for 2016 coffee growing season and expert knowledge. Available cherry represents cherry that is available on the farm and is ready for harvest.

function and then optimize the harvesting of berries during a month of harvest. One advantage of using dynamic programming to address the optimal strategy for a coffee farmer is that it fits nicely into decisions farmers make every month. The real strength of the dynamic programming model is that it can use the Markov-chains to determine a set of monthly decision strategies based on the impact of previous decisions while also accounting for expected subsequent infestation levels. As a result, an entire season of decisions is modeled and optimal spraying strategies are extracted.

To determine available ripe berries to harvest it is important to account for the transition from flowering, to immature and mature green berries, ripe berries (cherry), and overripe berries (raisins); however, this introduces complexity beyond the scope of this study due to limitations in data. For simplification, cherry growth follows a logistic growth function, G_t that provides available cherry to harvest,

$$G(K, r, t) = \frac{K}{1 + e^{-rt}}$$

where K is the total expected cherry on the farm at the end of the season, r, is the growth rate of cherries, and t is the time component.

Available cherry is then harvested on the farm and assumed that there is a proportion of total cherry, $\rho(c)$, harvested in September, October, November, and December (32%, 48%, 12%, 8%, and 0% for all other months). H_t is defined as percentages that are infested in each position and price based on CD infestation level.[3] On a farm, as the amount of harvested cherry increases, available ripe coffee cherry declines. To account for this, the amount harvested, H_t is subtracted from current available cherry G_t. The amount harvested in each month equals,

$$H_t = \rho(c) \cdot K$$

To estimate the damage to harvested cherries from CBB, the results from the Markov-chain above are used. The proportion of CBB in the CD position is defined as $D_t = CD_t$. To calculate the total amount of harvested cherry in the CD position, the current CD infestation level is multiplied by the current amount harvested, H_t.

The objective function optimizes net-benefit which is defined as the revenue generated from cherry crop minus any costs (see equation (1)). The revenue includes reduction due to economic damages from CBB and costs include spraying and harvesting. The economic damage from CBB in the CD position, $D_t = CD_t$, is obtained from the vector that tracks infestation levels, V_t. This result is utilized to account for damages to revenue. Spraying costs are included if the decision to spray is made. Harvesting costs include a labor rate applied to the amount harvested.

A dynamic programming model is derived to utilize all components discussed above. Formally, a value function, $f()$, in month one is equal to the net-benefit in period one, NB_1, given harvest, H_1, and current levels of infestation, V_1,

$$f_1^* = NB_1(H_1, V_1)$$

moving forward to month two carries with it the optimal results from previous month one, f_1^*, which includes total harvested, H_1, and infestation levels based on the decision to spray or not to spray, V_1. Month two is defined as,

$$f_2^* = \max_{NB}\left\{NB_2; \beta\left(NB_2(H_2, V_2) + f_1^*\right)\right\}$$

where the net-benefit is maximized for month two, NB_2, with a discount factor, β, plus the optimal net-benefit from month one, f_1^*. The dynamic nature of the model includes the previous optimal value function and optimization in the current month; thus, the Bellman equation can be written as,

$$f_t^* = \max_{NB}\left\{NB_t; \beta\left(NB_t(H_t, V_t) + f_{t-1}^*\right)\right\}$$

where the optimal function in month t is defined as f_t^*, which maximizes the current month, t, plus previous optimal value function, f_{t-1}^* is given a discount factor β.

An important feature of this model is that the variant nature of infestation levels is captured between months and base the decision to spray on whether the damage to berries from not spraying is higher than the cost to spray. By optimizing the net-benefit given the level of infestation, V_t, and expected changes in CD_{t+1}, the results are compared in the next month to determine this decision. Finally, the optimal decision path is derived for a coffee growing season.

3. Results

The provided economic model utilizes parameters in Table 2 which describe a typical farm in Kona with two acres of coffee farmland and a projected yield of 7500 pounds of berries per acre. Farm labor per hour equals $15 and harvest labor is $0.50 per pound of berries. If the farm decides to spray, a single spray occurs per month with a total cost of $214.[4] The farm is assumed to have followed best practices so had low initial infestation levels at the beginning of the season as follows: 5.5% AB live, 2.5% AB dead or missing, 3% CD, and 89% NI.

The results of the economic model are presented in Table 3 and Fig. 4. The optimal spray schedule is to not spray during January–May, spray from June–November, and not spray in December. In the resulting CBB levels in each month (Table 4), the initial decreases in the various infestation percentages during the first half of the year reflect the growth in the number of mature berries relative to CBB as described previously. Once the coffee berries are sufficiently mature, CD levels increase until reaching 9.23% in December. Again, this level is based on the available

[3] At the mill, a sample of harvested cherry is collected, dissected, and CBB position infestation levels are calculated to price the harvest. This behavior is modeled in the DP set up to provide a realistic scenario for coffee farms.

[4] Total costs include insecticide costs ($140) plus labor costs ($30) plus water ($20) plus surfactant for *Beauveria bassiana* ($24) equals $214.

Table 2
Model parameters for a typical farm in Kona, Hawaii.

Parameter	Unit	Estimate
Acres	Acres	2
Projected Cherry	Lbs. per acre	7500
Farm Labor	Dollars per hour	$15
Spray Labor	Hours per acre	1
Harvest Labor	Dollars per lbs.	$0.50
Pesticide	Quart per acre	1
Pesticide Costs	Dollars per quart	$70.35
Water	Gallons per acre	100
Water Cost	Dollars per 1 k gallons	$1.00
Surfactant	Ounces per acre	45
Surfactant Costs	Dollars per quare	$8

cherry on the farm and does not represent the total CD infestation over the season, which is 3.7%.

The damage to the crop as a result of the spray schedule totals 560 pounds of berries (Table 3). Due to increases in CD infestation levels, price decreases from $1.80 to $1.70 per pound of berries from October to November. The projected total loss in revenue from coffee cherry damage is $984.20 and the total net-benefit is $17916.

These results suggest that if best practices are followed to ensure a low initial infestation level then spraying in the early part of the season is not justified given the combination of few available berries and low pest pressure. When mature berries start to increase (around May or June) then it is beneficial to spray. Spraying is not necessary for December when there is not enough crop remaining and a short period of time until harvest.

4. Discussion

Research on coffee production and CBB management in Hawaii is challenged by the heterogeneity of farming operations that result from the diverse environmental conditions, compounded by different management practices including shade or open field production, coffee varieties used and planting densities, degree of mechanization, and usage of different cultivation and pest control techniques. An overview of previous research [27] describes studies that have typically involved observations from no more than 10–15 farms.

The provided economic model uses an alternate approach that expands on previous modeling work [23]. This approach focuses on a hypothetical operation with characteristics of a typical coffee farm, and predicts the results if that farm had engaged in various spray management programs. The farm makes spray decisions that maximizes a net-benefit function given CBB infestation levels in previous months and based on expected damage from not spraying versus spraying. In a given period, if the expected damage for the remainder of the season from not spraying is higher than the cost to spray, then it is beneficial to spray. Since the same farm is involved with different programs, all other environmental and management factors are unchanged.

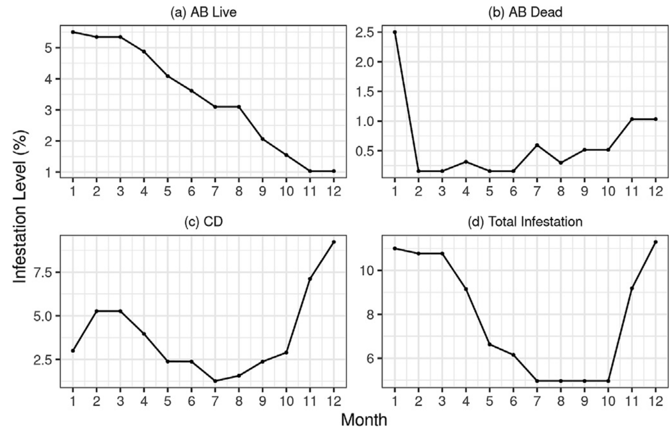

Fig. 4. CBB infestation levels from the economic model results from January through December for (a) AB Live, (b) AB Dead, (c) CD, and (d) Total Infestation. The overall infestation levels are magnified by the availability of mature berries between seasons, then reflect the impact of treatment. AB Live decreases and low levels of infestation are reflected in low AB Dead levels. CD reflects the initial high percentage, decreases as damaged beans are harvested, then builds from mid year with cumulative damage to remaining beans.

Table 4
Field-level infestation results from economic model.

Month	Spray Decision	AB Live (%)	AB Dead (%)	CD (%)	Infested (%)
Jan	No Spray	5.5	2.5	3	11
Feb	No Spray	5.34	0.16	5.27	11
Mar	No Spray	5.34	0.16	5.27	11
Apr	No Spray	4.87	0.31	3.96	9
May	No Spray	4.09	0.16	2.38	7
Jun	Spray	3.61	0.16	2.38	6
Jul	Spray	3.1	0.59	1.27	5
Aug	Spray	3.1	0.3	1.57	5
Sep	Spray	2.07	0.52	2.38	5
Oct	Spray	1.55	0.52	2.9	5
Nov	Spray	1.03	1.03	7.12	9
Dec	No Spray	1.03	1.03	9.23	11

With perfect information, the ideal economic model defines the optimal spray strategy that will result in the largest possible net benefit. However, this theoretical strategy is not practiced in the field because farmers do not have sufficient information about the future. Three simplified strategies are identified that farmers could use: choosing from the spray decisions outlined in the CBB integrated pest management program (Fig. 5) or "IPM Choice", spraying based on a calendar schedule "Always Spray", and "Never Spray."

Each strategy relies on different assumptions and costs. The economic model assumes perfect information about future infestation levels; thus

Table 3
Field-level economic model results for a typical farm.

Month	Spray Decision	Harvested Cherry (lbs.)	Harvested Damage (lbs.)	Harvested Cost	Cherry Price	Net-benefit	Net-benefit (Cum. Sum)
Jan	No Spray	0	0	$0	$1.80	$0	$0
Feb	No Spray	0	0	$0	$1.80	$0	$0
Mar	No Spray	0	0	$0	$1.80	$0	$0
Apr	No Spray	0	0	$0	$1.80	$0	$0
May	No Spray	0	0	$0	$1.80	$0	$0
Jun	Spray	0	0	$0	$1.80	$-214	$-214
Jul	Spray	0	0	$0	$1.80	$-214	$-428
Aug	Spray	0	0	$0	$1.80	$-214	$-642
Sep	Spray	4800	114	$2400	$1.80	$6026	$5384
Oct	Spray	7200	208	$3600	$1.80	$9146	$14,530
Nov	Spray	1800	128	$900	$1.70	$1946	$16,476
Dec	No Spray	1200	110	$600	$1.70	$1440	$17,916

% A/B Alive

% infestation 0	1%	2%	3%	4%	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%	55%	60%	65%	70%	75%
1%	0.01	0.02	0.03	0.04	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75
2%	0.02	0.04	0.06	0.08	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5
3%	0.03	0.06	0.09	0.12	0.15	0.3	0.45	0.6	0.75	0.9	1.05	1.2	1.35	1.5	1.65	1.8	1.95	2.1	2.25
4%	0.04	0.08	0.12	0.16	0.2	0.4	0.6	0.8	1	1.2	1.4	1.6	1.8	2	2.2	2.4	2.6	2.8	3
5%	0.05	0.1	0.15	0.2	0.25	0.5	0.75	1	1.25	1.5	1.75	2	2.25	2.5	2.75	3	3.25	3.5	3.75
10%	0.1	0.2	0.3	0.4	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5
15%	0.15	0.3	0.45	0.6	0.75	1.5	2.25	3	3.75	4.5	5.25	6	6.75	7.5	8.25	9	9.75	10.5	11.25
20%	0.2	0.4	0.6	0.8	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
25%	0.25	0.5	0.75	1	1.25	2.5	3.75	5	6.25	7.5	8.75	10	11.25	12.5	13.75	15	16.25	17.5	18.75
30%	0.3	0.6	0.9	1.2	1.5	3	4.5	6	7.5	9	10.5	12	13.5	15	16.5	18	19.5	21	22.5
35%	0.35	0.7	1.05	1.4	1.75	3.5	5.25	7	8.75	10.5	12.25	14	15.75	17.5	19.25	21	22.75	24.5	26.25
40%	0.4	0.8	1.2	1.6	2	4	6	8	10	12	14	16	18	20	22	24	26	28	30
45%	0.45	0.9	1.35	1.8	2.25	4.5	6.75	9	11.25	13.5	15.75	18	20.25	22.5	24.75	27	29.25	31.5	33.75
50%	0.5	1	1.5	2	2.5	5	7.5	10	12.5	15	17.5	20	22.5	25	27.5	30	32.5	35	37.5

=0-0.99 – Spraying not recommended; will cost more than the expected value of coffee saved from CBB
=1-1.99-Consider spraying, especially early in the season
=2-4.99 – Especially early in the season, this is a critical level to start spraying to avoid economic loss.
=5-9.99 – You are starting to lose money due to CBB damage. Losses will be greater if you don't spray.
=10-19.99 – You are losing money due to CBB damage, but you may still want to spray.
=>20 – Processors may reject your harvest. The value of your harvest may not cover picking cost, so consider focusing on your next crop (i.e. strip pick, stump prune)

Fig. 5. IPM recommendations based on dissected AB infestation and total infestation levels (Kawabata et al., 2020).

monitoring/sampling are not needed. The optimal spraying strategy from the economic model is the best a farmer can do. The IPM Choice strategy requires monitoring/sampling in each month, so the associated costs of 2-labor hours per acre ($30) are included. When a farm decides to spray regardless of information or sampling/monitoring results, they incur only costs to spray. This strategy of spraying on a schedule can be considered a mechanism to cope with inadequate information. A farm that decides to spray is compared against a farm that decides never to spray. Each strategy is then examined to evaluate their performance, with results in Table 5 and Figs. 6 and 7.

Table 5 lists the monthly spray decisions for different strategies. Always Spray and IPM Choice are the same until the last two months, while for the economic model, the decisions are to spray for six months and not spray for six months. The resulting infestation levels are presented in Fig. 7. All strategies followed the same IPM recommendations, so start the year at the same levels. There is little difference in AB Live throughout the year. For AB Dead, with Always Spray and IPM Choice there are higher levels earlier in the year due to the spraying. CD levels are paramount, as they reflect the actual damage to the crop. For CD and overall infestation, all strategies have similar patterns until midseason, then the levels for No Spray infestation start increasing as the berries mature. The largest differences among the strategies other than No Spray occur at the very end of the season.

Similar patterns are reflected in the results provided in Fig. 6. The quantities of marketable cherry, or berries that are free from CD damage at the mill, are highest for Always Spray (14512 pounds), followed by nearly identical Economic Model (14438 pounds) and IPM Choice (14437 pounds), and then Never Spray (10984 pounds). The corresponding percentages of the total crop that are damaged are Always Spray (3.3%), Economic Model and IPM Choice (both 3.7%), and Never Spray (26.8%). The final CD infestation level when deciding to always spray is lowest (8.76%), followed by the economic model (9.23%), IPM choice (14.97%), and Never Spray (40.99%). As expected by the growing CBB population and the diminishing quantity of coffee remaining to be harvested, the final CD levels are higher than the level for the entire crop. These rates along with the final CD levels reflect the similarities among strategies.

Finally, in terms of net-benefit, the economic model performs best ($17916) followed by Always Spray ($16632), IPM Choice ($16340), and Never Spray ($5524). The difference in net-benefit between Economic Model and Always Spraying is $1284, which suggests that if the costs to collect the data for use in the economic model are higher than $1284, then it would make sense to instead always spray each month. The difference between Always Spraying and IPM Choice is $292 so even a relatively small savings in the time needed to sample and monitor could have an impact on grower use of IPM Choice [28–30]. For Never Spray, the marketable cherry is more than two-thirds of the Economic Model, yet the net-benefit is less than a third because of both the percentage of infested harvest and the subsequent lower price for the cherry on the sliding scale (Table 1).

Table 5
Spray decisions for alternative spraying strategies.

Month	Never Spray	Always Spray	IPM Choice	Economic Model
Jan	No	Spray	Spray	No
Feb	No	Spray	Spray	No
Mar	No	Spray	Spray	No
Apr	No	Spray	Spray	No
May	No	Spray	Spray	No
Jun	No	Spray	Spray	Spray
Jul	No	Spray	Spray	Spray
Aug	No	Spray	Spray	Spray
Sep	No	Spray	Spray	Spray
Oct	No	Spray	Spray	Spray
Nov	No	Spray	No	Spray
Dec	No	Spray	No	No

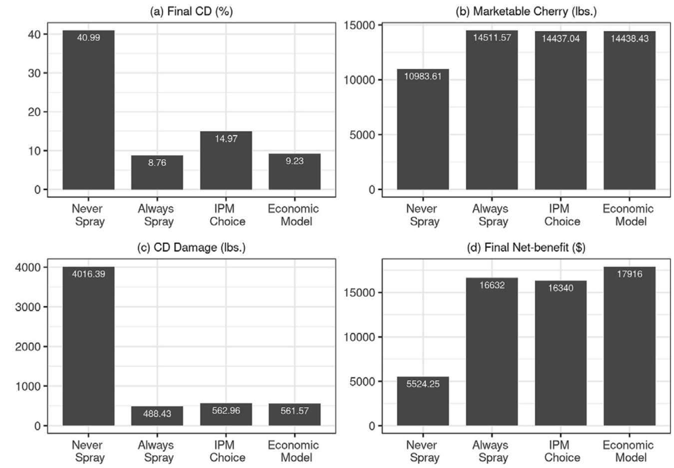

Fig. 6. Results for a typical farm from the Economic Model, IPM Choice, Always Spray, and Never Spray for (a) Final CD (%), (b) Marketable Cherry (lbs.), (c) CD Damaged (lbs) cherry, and (d) Final Net-benefit ($). Never spraying results in very high damage levels as measured by Final CD % and Damage. The Marketable Cherry is similar with treatments, but the cost and timing of those treatments result in a wider range of Net-benefits. This can be substantial with more acreage. The Economic Model is the profit maximizing best case.

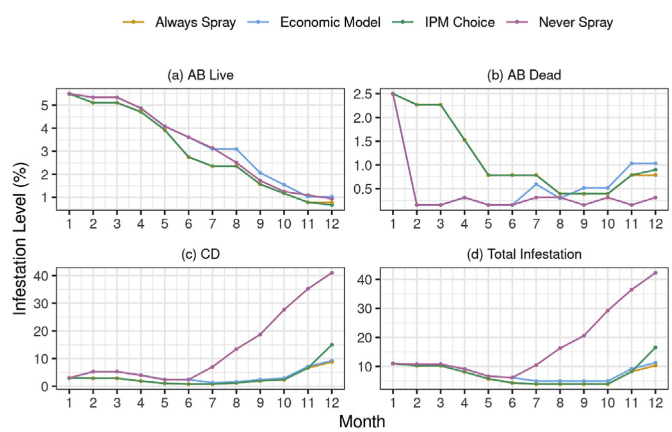

Fig. 7. CBB infestation levels for the Economic Model, IPM Choice, Always Spray, and Never Spray. CBB Infestation levels are reported from January through December. This expands on Fig. 4 to show all models. Never spraying has the most pronounced differences, whereas the spray treatments are similar (except for AB dead). The differences arise in the costs of the treatments.

Compared to the Economic Model, Always Spray and IPM Choice have higher or comparable quantities of marketable berries but they also have higher costs so have lower net-benefits that are $1284 and $1576 less, respectively. Both alternatives have excess cost from spraying in the early portion of the year where doing so has low impact; there are few berries to infest and low initial levels of CBB, so spraying has little effect on CBB levels. In addition, IPM Choice has the additional cost of monitoring and sampling in each month.

The only other published Hawaii research compared threshold based (comparable to IPM Choice but with more restrictive conditions to trigger an application) and calendar-based spray strategies [31]. That study found that growers following threshold guidelines applied roughly half as many applications (4–5 versus 7–11 sprays over the year), with the fewer sprays concentrated early in the season as berries matured. Yields between strategies were similar and there were no significant differences in total defects so authors concluded that threshold spray programs cost less than half as much, measured as a percentage of gross yield. However, the costs of the monitoring and sampling in order to make the spray decisions were not included. Doing so would narrow the difference in cost between the two strategies, so overall these results agree with the findings of the current study.

These results verify that spraying is necessary to maintain profitability while managing CBB. Results suggest that IPM Choice and Always Spray strategies are reasonable alternatives to the economic model, given that farmers are unlikely to have perfect information. Further, a combination of the two might improve their performance, in particular, the reduction or elimination of spraying when doing so has little benefit. Since the IPM recommendations appear to trigger spraying too early, one possibility is raising the spray threshold, i.e. spray at higher infestation and AB alive levels. Then, since monitoring and sampling are less costly than spraying, the farmer might use the new threshold only until spraying is triggered, then spray on a set schedule until the majority of the coffee has been harvested.

5. Conclusion

Understanding CBB infestation levels are critical to determining economic damages and improving farm-level decision making for CBB management. This study uses all available information and expert knowledge to calibrate a Markov-chain that tracks monthly changes in infestation levels based on the decision to spray or not spray in each month of the coffee growing season. These estimates are incorporated into a forward-recursive dynamic programming model that determines the optimal decision path for monthly spraying decisions based on the trade-off between the cost to spray and expected damage in the remainder of the season from not spraying.

The results suggest it is best not to spray in January–May, then spray from June–November before stopping at the end of the season. For a typical farm in Kona, this decision path results in losses to CBB of 3.7% of the season's crop, a final CD infestation level of 9.4%, and the total net-benefit of $17916.

The economic model is then compared against alternative strategies of IPM Choice, Always Spray, and Never Spray. Results verify the importance of spraying and indicate that the three strategies that incorporate spraying have relatively similar results. The results suggest that management strategies might be improved by combining current IPM spraying recommendations with a calendar-based strategy.

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