Predicting the Benefits of Banana Bunchy Top Virus Eradication in Australia

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Abstract

Benefit cost analysis is a tried and tested analytical framework that can clearly communicate likely net changes in social welfare from investment decisions to diverse stakeholder audiences. However, in a plant biosecurity context, it is often difficult to predict policy benefits over time due to complex biophysical interactions between invasive species and their hosts. In this paper, we demonstrate how benefit cost analysis remains highly relevant to biosecurity decision-makers using the example of a plant pathogen targeted for eradication from banana growing regions of Australia, banana bunchy top virus. We develop a partial budgeting approach using a stratified diffusion spread model to simulate the likely benefits of eradication to the banana industry over time relative to a status quo policy. Using Monte Carlo simulation to generate a range of possible future incursion scenarios, we predict that

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eradicating the disease will generate $12.5-23.6 million increased annual revenue for the banana industry. To reduce these benefits to zero would require a bunchy top re-establishment event three years in every four. Sensitivity analysis indicates that eradication benefits can be greatly improved through improvements in disease surveillance and incursion response.

Key Words: Biosecurity; benefit cost analysis; invasive alien species

Introduction

Comprehensive bioeconomic decision support frameworks are increasingly needed to assist policy makers in managing plant biosecurity risks. Benefit cost analysis is a highly effective means of communicating expected net returns from investment decisions to diverse groups of stakeholders. For biosecurity economists, it can provide a valuable means to convey a raft of technical economic and scientific information via metrics that are easily absorbed by risk managers. In this paper, we demonstrate this important property using the example of the Banana Bunchy Top Virus (BBTV) in Australia, which is currently being considered for eradication.

Bananas are an important crop throughout the world, particularly in developing counties where their importance as a food crop is only surpassed by rice, wheat and maize [1-3]. More than 120 countries produce bananas, with world production estimated to be in excess of 100 million tonnes [2]. Australia contributes less than 0.5 per cent of global production [2], but banana cultivations makes a sizeable contribution to regional economies across northern Australia. In 2010, the States of Queensland, New South Wales, the Northern Territory and Western Australia produced a combined total of 301 450 tonnes of bananas with a gross value of $492.2 million [4].

All modern cultivars of banana have evolved from intra-specific and inter-specific crosses of the two wild diploid species *Musa acuminata* and *Musa balbisiana* [3,5]. Selection of high-yielding *Musa* clones and current cultural practices in large-scale monoculture plantations has given rise to the occurrence of a wide range of pests and diseases [3,6], of which BBTV is one of the most economically important causing plant deformities, stunted growth and reduced fruit set [7]. The virus is principally transmitted by the banana aphid (*Pentalonia nigronervosa*), as well as through infected plant suckers and other plant tissues used in banana propagation [8,9].

BBTV has been present in eastern Australia since the early 1900s. Its severity was clearly demonstrated in the 1920s when approximately 90 per cent of the Queensland and New South Wales banana crops were destroyed [10]. This prompted State government initiatives to contain BBTV through controls on the movement of planting materials from affected areas, which led to a gradual recovery of the banana industry. In 1993, a Banana Plant Health Improvement Project was initiated by the industry aimed at eradicating BBTV from Australia [11]. However, despite achieving substantial reductions in the prevalence of the virus to outright eradication was not achieved.

In this paper, we re-visit this eradication policy and use computer-simulated economic impact scenarios to determine the likely net benefits of BBTV eradication if it were to be achieved. We use a partial budgeting approach in conjunction with a stratified diffusion model to estimate BBTV prevalence and control responses under a status quo and an eradication scenario over time. We then compare these scenarios and calculate a likely financial return to the banana industry from investing in eradication.

Methods

We assume that the current incidence of BBTV is eliminated from Australia and concentrate on events that might subsequently transpire. As such, we treat eradication of future incursions as an investment alternative to a 'status quo' approach with respect to BBTV management. We assume that the Australian banana industry is represented by a single planning body determining appropriate biosecurity investment strategies. Predicted investment paths are defined as a function of expected yield and input cost changes (and hence profitability) from investing in BBTV eradication relative to a status quo approach. We make the assumption that the planning body will choose to invest in BBTV eradication in region (i.e. State or Territory) *i* in time step (i.e. year) *t* if it is expected to reduce grower losses by a greater amount than additional costs. The dichotomous adoption variable, α_t, which takes on the value of 1 if the central planner invests in eradication across *n* regions in year *t* and 0 otherwise, is defined as:

$$\alpha_t = \begin{Bmatrix} 1 \text{ if } \sum_{i=1}^{n} d_{it} \geq \sum_{i=1}^{n} c_{it} \\ 0 \text{ if } \sum_{i=1}^{n} d_{it} < \sum_{i=1}^{n} c_{it} \end{Bmatrix} \quad (1)$$

where d_{it} is the total difference in predicted cost increments induced by BBTV between the eradication and status quo policy options in region *i* in time *t*, and c_{it} is the total cost of implementing an eradication strategy in region *i* in time *t*. We focus on the estimation of $\sum_{i=1}^{n} d_{it}$ to determine how large $\sum_{i=1}^{n} c_{it}$ would need to be before α_t assumes a value of 0.

The current pre-border biosecurity strategy for addressing the threat of exotic banana pathogens includes the use of strict phytosanitary measures on traded bananas, which lower the probability of BBTV re-entering after eradication via trade routes. Indeed, these measures are so strict that they effectively mean prominent banana exporting countries such as the Philippines cannot land product in Australia at a sufficiently low price to be competitive on the domestic market for fresh bananas. Post-border biosecurity measures include monitoring through disease surveillance, robust detection and rapid response to incursions.

If, as a result of these post-border measures, a BBTV incursion is detected early enough, there may be a strong likelihood of eradication through plant removal and destruction. Hence, the value of d_t is influenced by eradication costs and probability of eradication success. This probability of success is assumed to decline negative exponentially at a rate of $e^{1.5A_{it}}$, where A_{it} is the area infected with BBTV in region *i* year *t* weighted by the probability of infection and density of infection. If an outbreak is not detected early enough, a longer term management strategy is required to minimise BBTV impacts using insect control technologies and lethal chemical treatments for infected plants.

Algebraically, we expressed d_t as:

$$d_{it} = \left\{ \begin{array}{l} E_{it}A_{it} \text{ if } A_{it} \leq A_{it}^{\text{erad}} \\ Y_{it}P_tT_{it}A_{it} + V_{it}A_{it} \text{ if } A_{it} > A_{it}^{\text{erad}} \end{array} \right\} \quad (2)$$

where: E_{it} is the cost of eradication per hectare in region *i* in year *t*; A_{it}, as stated above, is the area infected with BBTV in region *i* year *t* weighted by the probability of infection and density of infection; A_{it}^{erad} is the maximum technically feasible area of eradication in region *i* in year *t*; Y_{it} is the mean change in yield resulting from the control of insect vectors and treatment of infected trees in region *i* in year *t*; P_t is the prevailing domestic price for bananas in year *t*; and V_{it} is the increase in variable cost of production per hectare induced by BBTV on-plantation management methods in region *i* in year *t*.

A_{it} is inclusive of BBTV re-entry and establishment probabilities (denoted p^{ent} and p^{est}, respectively), and therefore represents the area predicted to be in need of additional management effort (i.e. beyond normal plantation management activities) due to BBTV infection in region *i* in year *t*. A Markov chain process, described in Hinchy and Fisher [12], is used to change p^{ent} and p^{est} over time according to a vector of transitional probabilities. These transitional probabilities describe the likelihood of moving from one virus state to another. p^{ent} and p^{est} are combined to form a probability of invasion, p_i:

$$p_i = p^{\text{ent}} \times p^{\text{est}} \text{ where } 0 < p_i < 1. \quad (3)$$

To describe the movement of BBTV post-establishment in multiple regions we use a stratified diffusion model combining both short and long distance dispersal processes [13]. It is derived from the reaction diffusion models originally developed by Fisher [14] which have been shown to provide a reasonable approximation of the spread of a diverse range of organisms [15-19]. These models assert that an invasion diffusing from a point source will eventually reach a constant asymptotic radial spread rate of $2\sqrt{r_i D_{ij}}$ in all directions, where r_i describes a growth factor for BBTV per year in region *i* (assumed constant over all infected sites) and D_{ij} is a diffusion coefficient for an infected site *j* in region *i* (assumed constant over time) [19-22]. Hence, we assume that the original infection (i.e. the first of a probable series of sites, *j*) takes place in a homogenous environment in region *i* and expands by a diffusive process such that area infected at time *t*, a_{ijt}, can be predicted by:

$$a_{ijt} = p_i\left[\pi\left(2t\sqrt{r_i D_{ij}}\right)^2\right] = p_i\left(4D_{ij}\pi r_i t^2\right). \quad (4)$$

For practical purposes, an estimate of D_{ij} can be derived from the mean dispersal distance ($\bar{\delta}_{ij}$) of the pathogen at an infection site, where $D_{ij} = \frac{2\left(\bar{\delta}_{ij}\right)^2}{\pi t}$ [23-25]. $\bar{\delta}_{ij}$ is the site-specific average distance (in metres) over which dispersal events leading to infection occur. By assuming D_{ij} is constant across all sites *j* we ignore demographic stochasticity and consequent non-uniform invasion [24].

The density of BBTV infection within a_{ijt} influences the control measures required to counter the effects of infection, and thus partially determines the value of A_{it}. We assume that in each site *j* in region *i* affected, the infection density, N_{ijt}, grows over time period *t* following a logistic growth curve until the carrying capacity of the environment, K_{ij}, is reached:

$$N_{ijt} = \frac{K_{ij} N_{ij}^{\min} e^{r_i t}}{K_{ij} + N_{ij}^{\min}(e^{r_i t} - 1)}. \quad (5)$$

Here, $N_{ij}^{\min}$ is the size of the original influx at site *j* in region *i* and r_i is the intrinsic rate of density increase in region *i* (assumed to be the same as the intrinsic rate of population increase) [24].

In addition to a_{ijt} and N_{ijt}, the size of A_{it} depends on the number of nascent foci (see Moody and Mack [26] – these are *satellite* infection sites) in year *t*, s_{it}, which can take on a maximum value of $s_i^{\max}$ in any year. These sites result from events external to the outbreak itself, such as weather phenomena, animal or human behaviour, which periodically jump the expanding infection beyond the infection front [24]. We use a logistic equation to generate changes in s_{it} as an outbreak continues:

$$s_{it} = \frac{s_i^{\max} s_i^{\min} e^{\mu_i t}}{s_i^{\max} + s_i^{\min}(e^{\mu_i t} - 1)} \tag{6}$$

where μ_i is the intrinsic rate of new foci generation in region *i* (assumed constant over time) and $s_i^{\min}$ is the minimum number of satellite sites generated in region *i*.

Given equations (4)-(6), we can express A_{it} as:

$$A_{it} = \sum_{j=1}^{m} \left(a_{ijt} N_{ijt}\right)^{s_{it}} \text{ where } 0 \le A_{it} \le A_i^{\max} . \tag{7}$$

The total benefit to the central planner of adopting an eradication policy for BBTV in year *t*, B_t^{BBTV}, can be expressed as:

$$B_t^{\text{BBTV}} = \sum_{i=1}^{n} d_{it} \alpha_t . \tag{8}$$

In the following section we estimate $\sum_{i=1}^{n} d_{it}$ using multiple BBTV re-entry and spread scenarios for Australia's banana growing regions over a 30 year period. These include grower areas of coastal Queensland, the north coast of New South Wales, parts of Western Australia and the Northern Territory (i.e. $n = 4$) (see Table 1). Where there is uncertainty surrounding parameter values, they are specified within the model as distributions and a Latin hypercube sampling algorithm used to sample from each distribution. In each of 10 000 model iterations one value is sampled from the cumulative distribution function so that sampled parameter values are weighted according to their probability of occurrence. The model calculations are then performed using this set of parameters.

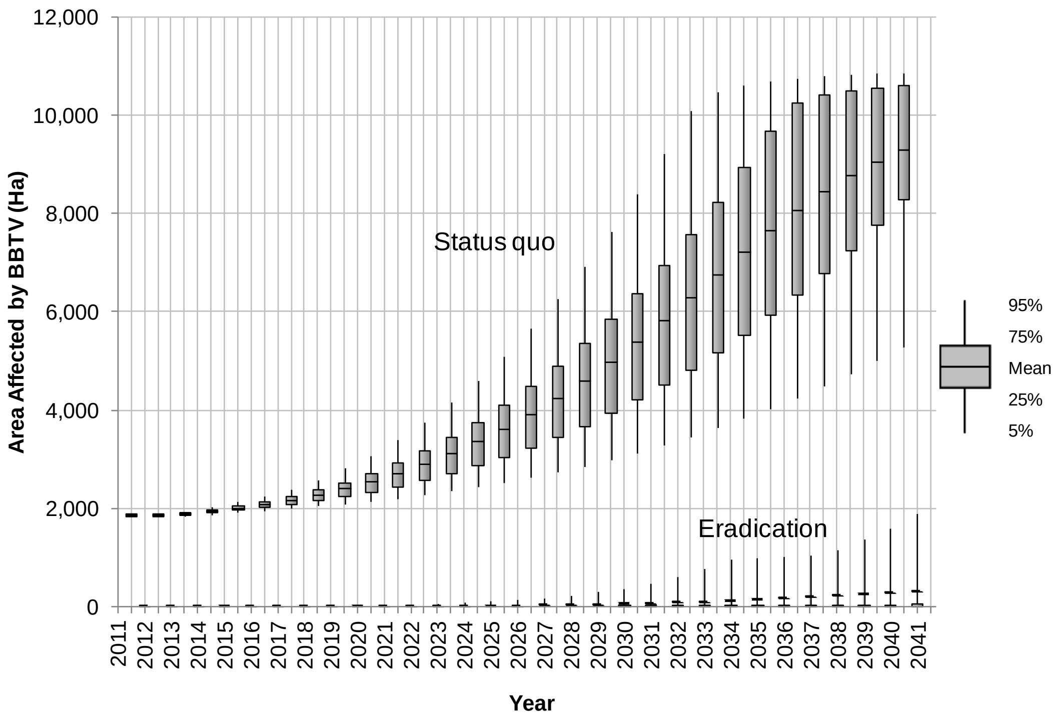
Table 1 provides banana production information for each region used in the analysis. It also contains region-specific BBTV (re-)entry and (re-)establishment probabilities. Given the continued stringent SPS measures against imported bananas, the probability of entry in new areas beyond the historical distribution of BBTV (i.e. Northern Territory and Western Australia) is regarded as very low: within the range 1.0×10^{-3} to 5.0×10^{-2} [27]. In areas where the virus has been present (i.e. Queensland and New South Wales), the likelihood of re-entry was arbitrarily assumed to be low: within the range of 5.0×10^{-2} to 0.3. The probability of establishment upon entry was assumed to be moderate in all regions: within the range of 0.3 to 0.7 [27].

A list of all other the model parameter distributions appears in Table 2. Note that *i*, *j* and *t* subscripts are omitted in Tables 1 and 2 since, with the exception of p^{ent} and insecticide and application cost, parameter specification does not change over spatial or temporal ranges. Table notes provide details where a spatial variation is assumed.

Results

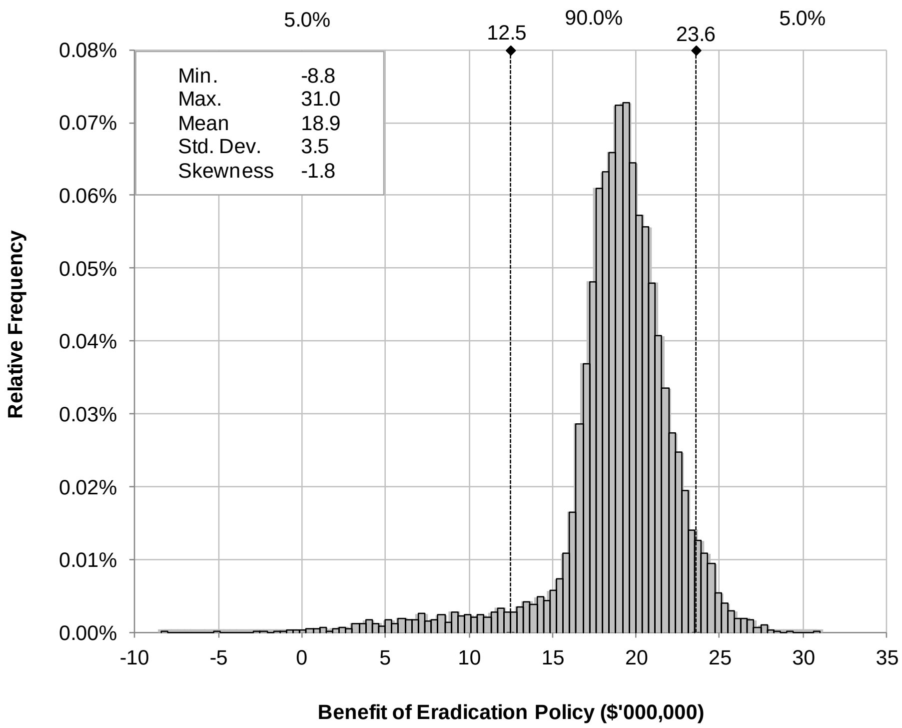
Despite eradication being assumed to have been achieved at the outset of the analysis, our assumptions are such that re-establishment is likely to occur at some point or multiple points over the estimation period. The model simulates these re-establishment events as a Poisson process where BBTV successfully re-establishes in Queensland and New South Wales on an average of one year in six, and in Western Australia and the Northern Territory one year in 50. Therefore, the resultant expected spread area values under the eradication and status quo scenarios calculated from the 10 000 iterations of the model are positive. However, as Figure 1 reveals, the extent of expected spread under an eradication policy is substantially below that of a status quo policy. These projections have been aggregated across all production regions to produce Figure 1.

Figure 1. Likely spread of BBTV over time with and without an eradication policy



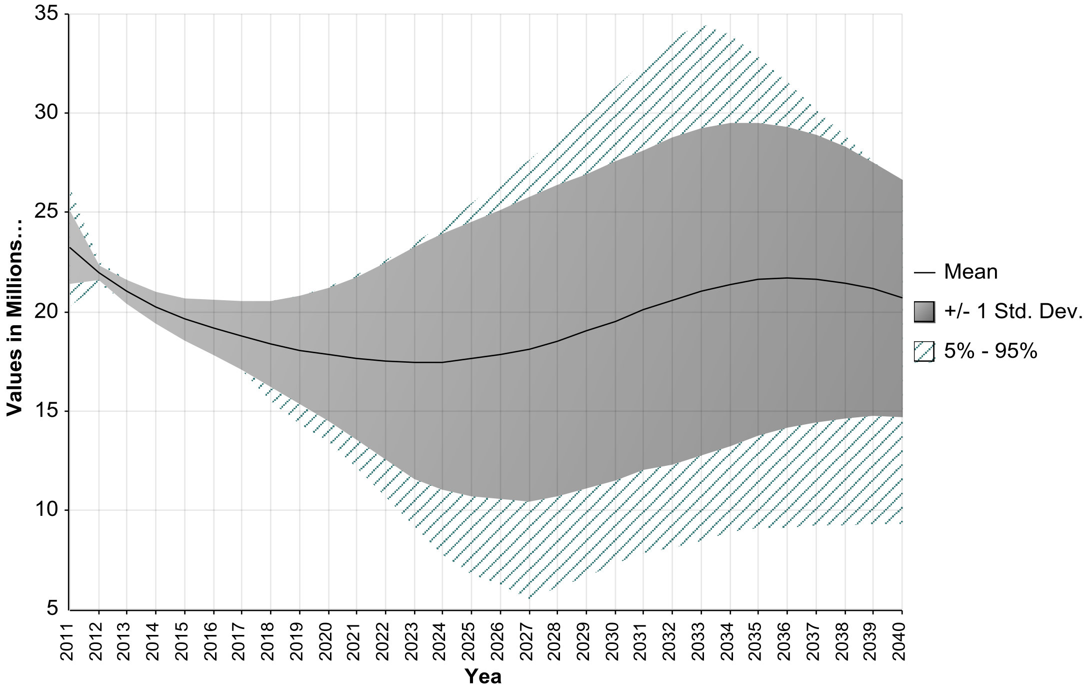
The present value of average benefits accruing from a BBTV eradication policy is estimated by the model to average \$18.9 million per year over 20 years across banana producing regions (i.e. $\sum_{i=1}^{n} d_{it} = \$1.89 \times 10^7$). Recall from equations (1) and (8), this represents the threshold level of $\sum_{i=1}^{n} c_{it}$ beyond which the central planning body will choose not to invest in eradication as an alternative to a status quo strategy (i.e. $\alpha_t = 0$). The standard deviation of the distribution of average annual biosecurity benefits is \$3.5 million and skewness -1.8 (i.e. the distribution is skewed left such that the left tail is long compared to the right tail).

Figure 2. Expected annual benefit of BBTV eradication over 20 years.



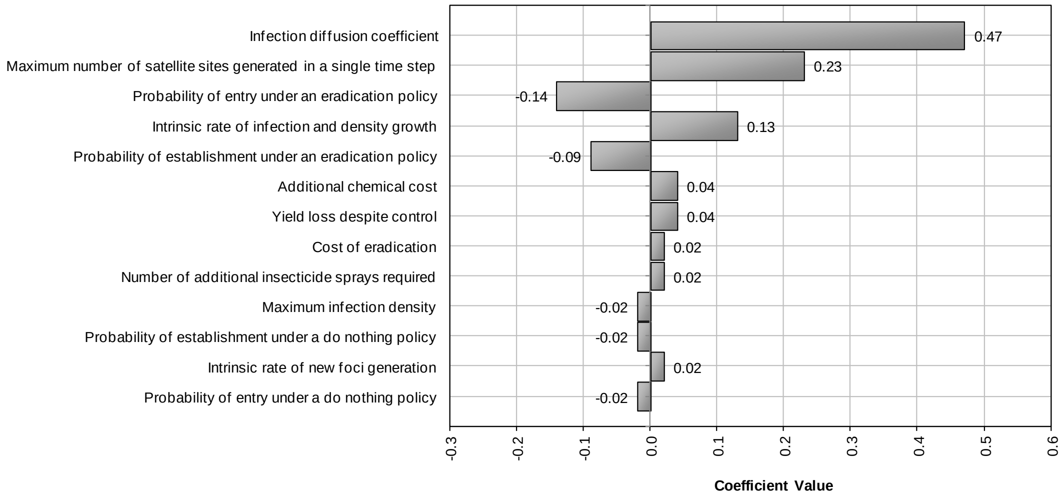
Given current average banana yields, our estimated value of $\sum_{i=1}^{n} d_{it}$ is equivalent to an annual increase in national banana production harvest volume of 11.6 million tonnes per year. While Figure 2 shows benefits over a 20-year period, Figure 3 illustrates how these annual eradication benefits are expected to change over time as the expected difference in BBTV prevalence between the eradication and status quo scenarios increases the further into the future we project. Here, the mean benefit of BBTV eradication predicted by the model is plotted ± 1 standard deviation and 5 per cent and 95 per cent confidence bounds. All projected benefits are discounted at 5 per cent per annum.

Figure 3. Expected annual benefit of BBTV eradication over time.



In view of the uncertainty surrounding many of the parameters used to describe the BBTV (re)infection and spread process, the sensitivity of the change in expected eradication benefits to the key assumptions of the model must be tested. Parameters were sampled from a uniform distribution with a maximum (minimum) of +50 per cent (-50 per cent) of the original values entered in to the model using Monte Carlo simulation. The Spearman's rank correlation coefficients relating the sampled model parameter values and the change in $\sum_{i=1}^{n} d_{it}$ were then calculated. The results are presented in Figure 4.

Figure 4. Sensitivity analysis.



The sensitivity tests indicate that the model is highly responsive to changes in five of the parameters listed in Tables 1 and 2 (13 of which are shown in Figure 4). These parameters and their correlation with predicted $\sum_{i=1}^{n} d_{it}$ are the infection diffusion coefficient (0.47), the maximum number of satellite sites generated in a single time step (0.23), the probability of entry under an eradication policy (-0.14), the intrinsic rate of infection and density growth (0.13) and the probability of establishment under an eradication policy (-0.09).

To indicate how high the probability of BBTV entry and establishment under an eradication strategy must be to produce a result where the central planner is indifferent between the eradication and status quo options (i.e. $\sum_{i=1}^{n} d_{it} = \$0$) requires the model to be aggregated across all States and Territories. If we consider the sum of all banana growing areas in Australia as one susceptible host block, the probability of BBTV entry and establishment under an eradication strategy that would lead to expected costs in both policy scenarios to be equivalent is approximately 0.75. This requires a re-entry and establishment event to occur in three of every five years post-eradication.

Discussion

Our results are indicative of the potentially large benefits of investing in eradication for BBTV. Based on the model outlined in the Methods section, it is shown in the Results section that eradicating the virus is likely to produce a net benefit over time provided the annual costs of doing so do not exceed $18.9 million.

The sensitivity analysis reveals a high sensitivity of this result to changes in several biological parameters that can be influenced by post-border biosecurity policies. Indeed, four of the five most sensitive model parameters fall into this category, including the infection diffusion coefficient, the maximum number of satellite sites generated in a single time step, the intrinsic rate of infection and density growth and the probability of establishment under an eradication policy. Policies that encourage crop monitoring and disclosure of detection information could have the effect of lowering each of these parameters, thus increasing the likely returns to an eradication policy over time.

The cost of achieving BBTV eradication is not known, but the eradication of the fungal pathogen black Sigatoka (*Mycosphaerella fijiensis* (Morelet)) from north Queensland between 2001 and 2003 provides at least some indication of what the possible BBTV eradication cost might be. *M. fijiensis* was detected in 2001 in the Tully area, the major banana-growing region of Australia. Although past detections of the fungus in far north Queensland were eradicated with similar tactics to those we have suggested for BBTV eradication (i.e. removal of infected plants followed by burial and burning), a programme of intensive de-leafing was employed to remove the majority of inoculum from plants in the Tully outbreak [28,29]. This was followed by intensive fungicide treatment applied to plants weekly in rotation for a period of 6 months after de-leafing. In total, the eradication cost A$17 million [29].

If this figure can be considered broadly representative of a relatively small scale eradication program, let us hypothetically assume that the eradication of BBTV might involve a cost more than three times this amount. Even if eradication costs are as high as $60 million and it takes a full five years to remove the virus completely, our results indicate that returns to the industry would be highly favourable. A benefit cost analysis performed using our estimated value would produce a benefit cost ratio of 1.6:1.0 (i.e. every $1.00 spent on eradicating the disease returns $1.60 worth of benefit to the industry). It is possible, indeed likely, that eradication of BBTV can be achieved at substantially lower cost. If this is the case and eradication is achieved, the returns on investment will be higher.

Future extension of the model developed in this analysis could include the consideration of flow-on effects of BBTV to the regional and national economies using a general equilibrium model [30]. While the importance of potential costs of non-market (e.g. environmental costs due to the use of pesticides) and indirect market impacts (e.g. reduced purchases of inputs after an industry is affected by an invasive species) of BBTV are acknowledged, they have not been included in the model due to high levels of uncertainty in the data. If the environmental costs of the use of, for instance, pesticides to control BBTV insect vectors were to be included, the benefits of eradication over time would probably increase. On the other hand, the use of more complex biophysical modelling of susceptibility and resilience to infection [e.g. 31] may indicate less substantive damage attributable to BBTV. Using a general equilibrium model or using an ecosystems approach may improve the investigative power of the analysis, but would impose a cost in terms of the increased need for information to run the models effectively.

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Table 1. Australian banana production statistics by region

Producer	Area (ha) [a]	Production volume (MT) [a]	Average yield (T/ha) [a]	Value produced ($'000,000) [a]	Probability of entry, p^{ent}
Queensland	10,083	279.09	27.68	448.3	Uniform(0.3,0.7)
New South Wales	1,057	10.75	10.17	17.7	Uniform(0.3,0.7)
Western Australia	200	5.64	28.19	15.1	Uniform(1.0×10^{-6}, 1.0×10^{-3})
Northern Territory	203	5.98	29.46	11.1	Uniform(1.0×10^{-6}, 1.0×10^{-3})

[a] ABS [4].

Table 2. Model parameters.

Parameters	Status quo
Probability of establishment, p^{est}. [a]	2.6×10^{-4} to 1.3×10^{-1}
Detection probability.	Binomial(1.0, 0.6)
Probability of successful eradication in a single time step given an infected area, A.	$e^{1.5\times A}$
Population diffusion coefficient, D (m^2/yr). [a,b]	Pert(0,2.5×10^3, 5.0×10^3)
Minimum area infected immediately upon entry, A^{min} (m^2).	1.0×10^3
Maximum area infected, A^{max} (m^2). [c]	1.2×10^8
Intrinsic rate of infection and density increase, r(yr^{-1}). [a]	Pert(0.10,0.15,0.20)
Minimum infection density, N^{min} (#/m^2).	1.0×10^{-4}
Maximum infection density, K (#/m^2). [a]	Pert(100,550,1000)
Minimum number of satellite sites generated in a single time step, S^{min} (#).	1.0
Maximum number of satellite sites generated in a single time step, S^{max} (#). [a]	Pert(10,5,10)
Intrinsic rate of new foci generation per unit area of infection, μ (#/m^2). [a]	Pert(1.0×10^{-6},3.0×10^{-6},5.0×10^{-6})
Discount rate (%).	5.0
Supply elasticity. [d]	Uniform(0.2,0.8)
Demand elasticity. [d]	Uniform(-1.1,-1.0)
Prevailing market price for bananas in the first time step ($/T). [c]	1,900
Maximum area considered for eradication (ha).	400
Cost of eradication, E ($/ha). [e]	Pert(1.0×10^4,1.5×10^4,2.0×10^4)
Increased insecticide and application cost ($/ha). [f]	130
Yield reduction despite control, Y (%).	Pert(0.0,2.5,5.0)

[a] Specified with reference to Cook [27] and Waage et al. [32] using distributions defined in Biosecurity Australia [33]; [b] Derived from Sapoukhina et al. [34]; [c] ABS [4], Note 1ha = 10 000m^2 ; [d] Ulubasoglu et al. [35]; [e] Assumes zero compensation following banana plant removal, average density of planting of 2 000 stems/ha and removal, transport, destruction and chemical costs amounting to $20 per tree. This is inclusive of labour (team of three at $50/hr per person), bulldozing equipment ($100/hr at 20 hours per hectare), truck hire ($75/hr), incendiaries ($60/ha for green waste) and creation of a circular chemical buffer zone approximately 5 hectares in diameter around previously infected sites. Chemical used is assumed to be dithane (applied at a rate of 3kg/ha or $25/ha) and oil (applied at 3L/ha or $10/ha) at fortnightly intervals rotated with propiconazole (applied at a rate of 0.3L/ha or $5/ha). Assume 2 additional dithane treatments are required and 4 propiconazole treatments (and therefore 6 additional oil treatments), each taking 1 hour per hectare to apply; [f] Assumes: (i) labour costs of $50/ha (i.e. 1 application × 1hr/ha × $50/hr); (ii) 75mL of chemical solution is used per banana plant per treatment costing $10 per litre (e.g. dimethoate diluted to 75mL/100L (DAWA, 2000)) (i.e. approx. $15/ha); and (iii) two additional chemical treatments will provide sufficient suppression of banana aphid.