Economics of Surveillance: a Bioeconomic Assessment of Queensland Fruit Fly

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Contributed paper prepared for presentation at the 56th AARES annual conference, Fremantle, Western Australia, February7-10, 2012

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Abstract

Regional management of endemic pests of trade significance typically requires a surveillance system, border controls, eradication protocols and conditions for market closure and reopening. An example is the systems for managing Queensland fruit fly (Qfly) in south east Australia where the preferred approach for intensive production areas is an Area Wide Management (AWM) scheme. An AWM, such as the Greater Sunraysia PFA (GSPFA) in northern Victoria and western New South Wales, depends for its recognition amongst trade partners on an effective and credible surveillance system that identifies outbreaks rapidly, notifies exporters of trade restrictions and initiates eradication. These 'market rules' are fundamental to the economics of surveillance: they define an outbreak and thus the probability of market closure, the expected time to eradication, and consequent time to market reopening. This paper uses a spatial and dynamic bioeconomic model of Qfly infestation and spread to determine the expected optimal investment in surveillance and eradication capacity of the AWM.

Keywords

Area Wide Management, Queensland Fruit Fly, Surveillance, Market Rules

1. Introduction

Area Wide Management of Queensland fruit fly involves designating intensive horticultural production regions as pest free areas. Once established, a pest free area (PFA) status is maintained by a set of regulations and protocols that designate border controls, surveillance and eradication, termed here as ‘market rules’. The establishment of a PFA is a ‘public good’ that benefits most producers in a region. PFAs in South Australia, Victoria and New South Wales benefit producers through a price premium on export and interstate produce, reduced cost of pesticides and pest damage and reduced costs of post-harvest treatments. This paper presents a bioeconomic analysis of the surveillance, eradication and post-harvest treatment measures that underpin The Greater Sunraysia Pest Free Area (GSPFA) biosecurity system, and how the analysis is influenced by the market rules.

The GSPFA region covers approximately 2.5 million hectares across northern Victorian and western New South Wales, and was established in 1996 as a zone within the less intensively protected Fruit Fly Exclusion Zone (FFEZ). The maintenance of the Qfly free status of the GSPFA is a constant battle between, on the one hand, evolving patterns of pest invasion and, on the other, technological developments in surveillance and control method. In 2006, under new management arrangements, the GSPFA was jointly funded by Victorian and NSW governments and the three key horticultural industries, citrus, stone fruit and table grapes. The revised management methods are consistent with international Standards for Phytosanitary Measures 26 (IPSM 26 2006)

The public cost of GSPFA has meant that the scheme has been the subject of regular benefit cost analyses (BCA). The earliest BCA estimated an industry benefit for the FFEZ of up to \$14.5 million and a benefit to cost ratio (BCR) of 2.5:1 (Bateman 1991). They also indicated that most of the benefits accrued to growers and exporters. The most recent has been DPI Victoria’s (2010) BCA for the Victorian portion of the GSPFA, estimating annual benefits as \$33 million with ~75% of costs deriving from avoided post-harvest treatments of fruit for both domestic and export markets. The annual costs were \$14.4 million (PricewaterhouseCoopers 2001), of which Qfly control by DPI Victoria and producers accounted for 81% of the total (Ha *et al.* 2010, Table 13, data for Option 3). The BCR over twenty years was estimated as 2.35:1. In a separate analysis, the total costs of the fruit fly program for the DPI Victoria are given as \$4.685m per annum, of which \$2.49m is for surveillance and \$1.157m for eradication, including sterile insect (SIT) technology (Ha *et al.* 2010, Table 2). The GSPFA is supported by two key technologies. First a system of surveillance traps that: demonstrates to regulators in sensitive export markets that fruit from the region are Qfly free; identifies outbreaks quickly; and, demonstrating successful eradication following eradication. Secondly, a capacity for eradication that responds immediately to a declared outbreak.

All the BCAs of the FFEZ and PFA schemes indicated a significant return to public funds. This paper takes a different approach: instead of measuring the efficiency gains from the whole scheme this paper applies a bioeconomic model to assess the benefits of marginal changes in the intensity of surveillance. This turns out to be a particularly challenging problem as the effectiveness of the whole PFA management system rests on the ability of the surveillance system to detect otherwise unobserved pest populations.

The remainder of this paper is organized as follows. The next section describes the aspects of Qfly biology that are relevant to the economic problem. Section 4 introduces a theoretical economics model a deterministic model and then a stochastic model, discussing how market rules influence these models. Section 5 describes the data for the Sunraysia. Section 6 presents results and Section 7 concludes.

2. Queensland Fruit Fly Ecology

The Queensland fruit fly (Qfly; *Bactrocera tryoni*) is endemic to tropical and subtropical Queensland and New South Wales. Qfly was first reported as a horticultural pest in the 19th century. It is now known to have over 200 cultivated fruit and vegetable hosts. It is a risk to all of Australia's horticultural produce, but is excluded from Tasmania, Western Australia and South Australia through quarantine and eradication measures

The ecology of Qfly is well-documented, with the rate of population generation highly dependent on day degree accumulation and the availability of moisture (Yonow *et al.* 2004). Qfly populations are sensitive to sustained cold temperatures and hot dry environments. This limits the ability of Qfly to persist in much of southern Australia due to its Mediterranean to temperate climate. The exceptions are generally production and residential areas, where there is an abundance of year round food sources and moisture from irrigation. The exclusion of Qfly from these areas is economically viable as surrounding areas of pasture and grain production are unsuitable for Qfly and provide a natural geographical barrier to local population movements.

The greatest risk to the maintenance of the AWMs, such as the GSPFA, are (i) the transport into the zone of Qfly infested fruit produced from outside by human travelers; and, (ii) in the long term, climate change extending the wet summer subtropics southwards. The current rate of transport and steady expansion of endemic Qfly populations into the GSPFA is accentuated following unusually wet years. The previous literature on invasive pests overlooks weather variability and seasonality as key issues. In fact there is a tendency to treat the problem as having seasonally invariant population growth and/or dispersal (Carrasco *et al.* 2009; Cacho *et al.* 2010; Carrasco *et al.* 2010).

The economic viability of regional pest management strategies depends critically on the ecology of the pest. To establish an outbreak the pest incursion has to pass through a number of ecological filters: successful dispersal from a source population, climatic suitability of local habitat at the point of arrival, local availability of food sources, and availability of sufficient mates (an *allee* effect). These ecological filters can vary both spatially and temporally, while the sensitivity of Qfly to these filters may also vary over time. All of these filters determine the probability of an outbreak, when and where it occurs in a landscape and its severity and duration. Consequently, these filters define a heterogeneous *ecological* risk to the success of the management strategy.

3. Literature Review

A theoretical literature on pest management, often linked to empirical models has started to emerge during the 1990s, for instance (Olson & Roy 2002; Olson & Roy 2008). The focus of these studies has been on the invasion of exotic pests rather than repeated invasions of endemic pests excluded from a region. The pest is treated as a stock of a 'natural bad' to be analysed in a way equivalent to a natural resource such as a fish stock, with eradication equivalent to harvesting. Population dynamics have been extended to account for dispersion (see Kot and Schaeffer, 1996 for a review). The economic importance of dispersion is that widely spread, but sparse, pest outbreaks may have a low probability of observation and a relatively high cost of eradication. In contrast, densely populated confined outbreaks have a relatively high probability of detection and relatively low cost of eradication.

The economics of pest surveillance is a neglected topic and, to our knowledge, the only systematic treatment in relation to a biosecurity problem is that presented by Kompas and Che (2009) for Papaya fruit fly invasions. Their model is based on a dynamic, but non-spatial model of population spread associated with a time to detection.

4. Theoretical Model

The objective of AWM is to minimise expected costs in terms of control, surveillance and market access. The following sections give the surveillance costs, eradication cost function and the overall optimization problem including state equations, while discussing the influence of market rules on economic analysis.

4.1 Surveillance Cost Function

For a defined are the number of fruit fly traps deployed depends on trap density of the grid according to:

$$Q = A/\alpha^2 \tag{1}$$

where Q is the total number of trapping sites in area A spaced α metres between trap grid points. Traps are checked regularly by inspectors. The number of inspectors employed depends on the total traps monitored and the number monitored in a day. In turn the traps checked per day depends on the travel time between traps v, and the time spent at each trap β. We assume the grid is traversed efficiently. The average number of traps an inspector can check in a given period of time x:

$$x = \frac{h}{\left(\frac{\alpha}{v}\right)+\beta} \tag{2}$$

where h is the number of hours worked per inspector per period . Total inspectors L is given by:

$$L(Q,z) = \frac{z}{h}\left(\frac{Q(\alpha+\beta v)}{v}\right) \tag{3}$$

where z is the frequency of trap checking during a period. The total annual cost of surveillance activities is:

$$C_t^s(Q,z) = \gamma Q + w_I L(Q,z) \tag{4}$$

where γ is the cost of trap site maintenance per year per site; w_I the total cost per inspector including wages, transport and overheads (Florec *et al.* 2012).

4.2 Population Growth Function

Qfly control protocols are initiated in patch s when an outbreak is detected. Following Olson and Roy (2002), control depletes the population through time either until it is eradicated or no longer viable. From this relationship it is possible to specify an expected time to eradication T^e. Let $X_t(s)$ represent the size of a pest invasion at time t in patch s. The size of the pest invasion when it is discovered X^d(s) depends on how early the pest is detected, and this time to detection depends on the intensity of surveillance.

Let $a_t(s)$ represent the control undertaken at time t in patch s. Distinguishing between the uncontrolled population and the controlled population through $Y_t(s^*) = \left(X_t(s^*) - a_t(s^*)\right)$. The invasion that remains at the end of period t following control and dispersion is given by the following integro-difference equation (Kot and Schaefer, 1996):

$$Y_t(s^*) = \int G_t\left(X_t(s^*) - a_t(s^*)\right) k(s^*, s) ds$$

where $G_t(.)$ is the growth function and $k(s^*, s)$.is the probability of dispersal from s* to s. Control measured as the biomass of insects removed from a locality is given by the production function:

$$a_t(s) = f(L_t^e(s), K_t^e(s))X_t(s)$$

where $L_t^e(s)$ is the labour input and $K_t^e(s)$ is the capital input for eradication pat s. *The annual control cost* for patch s are is given by:

$$C_t^e(a_t(s), X_t(s)) = \min[\, w_L L_t^e(s) + w_K K_t^e(s): a_t(s) = f(L_t^e(s), K_t^e(s))X_t(s)] \qquad (5)$$

The expected time to eradication can be defined as the minimum time required to reduce the population at location s to a point where it is controlled.

Define a Hammerstein operator[1] as (Kot & Schaffer 1986):

$$H^j\left(y(s^*)\right) = \int G_t^j\left(y(s^*)\right) \delta(s^*, s) ds \qquad (6)$$

where j is the number of periods since arrival of the pest population. The time to detection is thus defined by:

$$T^d(s^*) = \min\left[j : \tilde{X}^d(Q) - H^j x_0 \geq 0\,\right]$$

where $\tilde{X}^d(Q)$ is the minimum population threshold for the declaration of an outbreak given the Q level of surveillance. The time to eradication from population arrival is:

$$T^e(s^*) = T^d(s^*) + t^e\left(\hat{a}(s^*)\right)$$

where $t^e(\hat{a}(s^*))$ is the duration of eradication given a fixed control protocol $\hat{a}(s^*)$ (see Florec *et al.* 2012).

4.3 Market Access Costs

A declared Qfly outbreak often results in restricted access for produce from affected patches to sensitive markets without post harvest treatment. The restriction on market access invoked by a declared pest incursion depends on the import rules applied by export markets (domestic or international) and the duration of market closure. The Qfly-free period required for the re-instatement of area-freedom status depends on the export market (see Section 4.5).

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[1] The Hammerstein operator simplifies the representation of the integrodifference equation by giving the population in patch *s* after *j* periods.

Trading partners may be separated into two categories: sensitive and non-sensitive markets. Sensitive markets require that the fruit comes from a pest free area and impose conditions to restrict market access to fruit grown when there is an outbreak. These markets may require the fruit to be disinfested while an eradication campaign is conducted, or impose a complete ban on produce grown in the infested area until it is eradicated. Non-sensitive markets are those that attach little importance to area-freedom status and accept fruit at all times. Produce can still be sent to these markets when the fly is known to be present or even when the PFA is abandoned.

In some cases, infested produce sent to markets that remain open (sensitive or non-sensitive) must be disinfested. Hence, some host produce has to be treated during both the eradication campaign and the period until PFA status is restored to the outbreak zone, through the market criteria recognised by trading partners. The total revenue losses generated by reduced market access and disinfestation treatments are then given by

$$C^m\left(T^d(s)\right) = \begin{cases} \gamma \Delta p_t q_t(s) + \gamma w_h q_t(s) & T^d(s) \leq t \leq T^e(s) \\ 0 & T^d(s) > t, t > T^e(s) \end{cases} \tag{7}$$

where $C^m\left(T^d(s)\right)$ is a cost due to a loss of market access; Δp_t is a vector of price differences between sensitive and non-sensitive markets; and, $q_t(s)$ is a vector of products by patch. The cost of market access is positive following detection and prior to eradication. Prior to detection and after eradication it is zero.

4.4 Deterministic non-spatial model

This section aims to illustrate the theory of optimal surveillance with the simplified case of one patch and a fixed frequency of inspection. Consider one patch and a production season that at most can have one outbreak of size x_0. Further assume the outbreak occurs in the first week of the season. The duration of the season is T weeks. The surveillance grid, initially, is fixed and in response to a detected outbreak there is a fixed control response $\hat{a}$. The outbreak grows according to $H^j x_0$ and once the population reaches its detection limit $\hat{X}^d$ it is detected with certainty. Following detection at T^d control commences. The importance of surveillance is that delaying the time to detection means that eradication commences with a larger outbreak and takes longer to control, giving T^e. A simplified optimization problem for a single season is given where the cost function gives the present-value of costs for the whole season. The frequency of trap inspection has been fixed at $\hat{z}$, thus the only decision variable remaining is trap density, Q :

$$Minimize\ C^T(Q) = C^e\left(\hat{a},\ X^d(Q,\hat{z})\right) + C^m\left(T^d(Q,\hat{z})\right) + C^s(Q,\hat{z}) \tag{8}$$

Subject to:

$$T^d(Q) = \min\left[j :\ \tilde{X}^d(Q) - H^j x_0 \geq 0\ \right]$$

$$T^e(Q) = T^d(Q) + t^e(\hat{a})$$

$$X_0 = x_0$$

Taking derivatives of (8) with respect to Q, the density of surveillance, yield the following first-order condition for an internal solution:

$$C_Q^s = -[C_Q^e + C_Q^m] \tag{9}$$

Optimal surveillance is defined as a point where the present value of the marginal cost of surveillance C_Q^s equals the marginal reduction in the present value of eradication costs $-C_Q^e$ plus the marginal reduction in market access costs $-C_Q^m$.

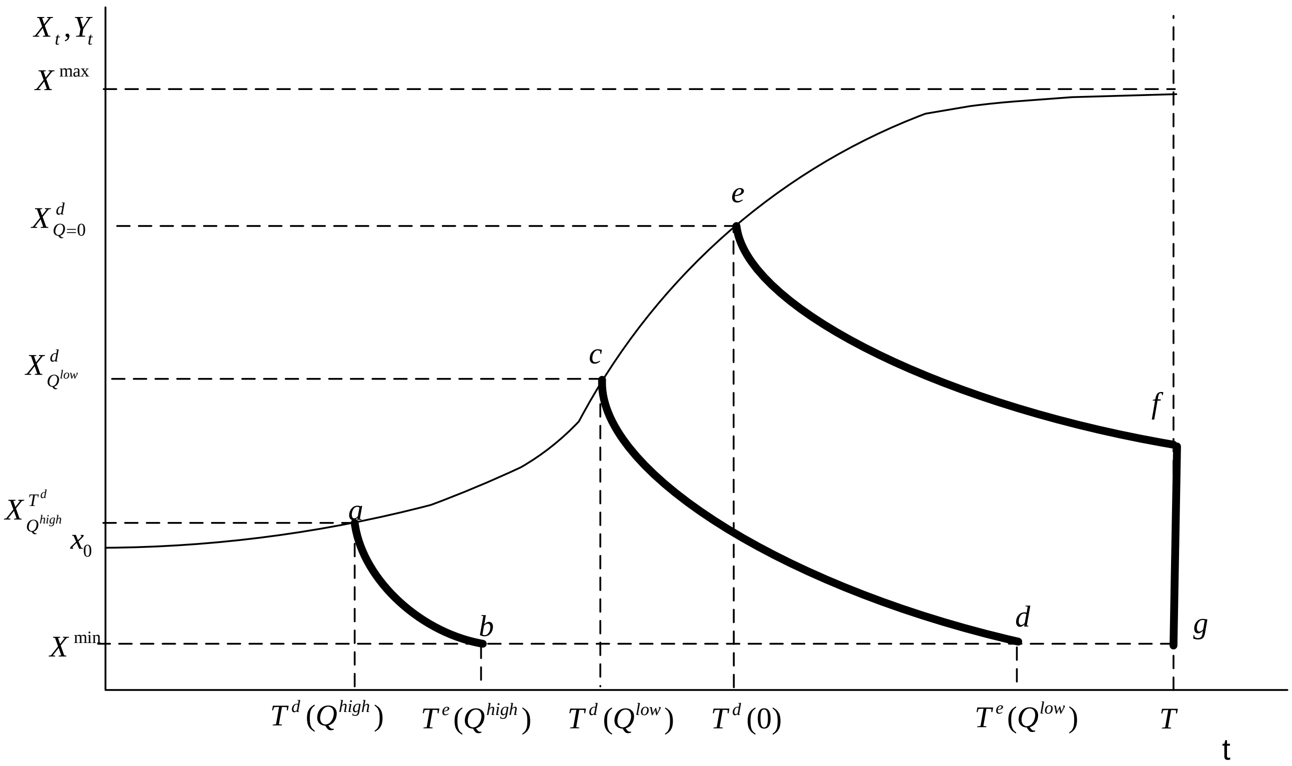

Figure 1. The Effect of Surveillance and Eradication on Population Number Following an Outbreak [after Kompas and Che 2009]

The sequence of events is illustrated in Figure 1. Assume that there is a high investment in surveillance Q^{high} leading to a relatively early detection of flies at $T^d(Q^{high})$. The pest is then controlled along the state path *ab* and when the population hits the minimum viable level X^{min} eradication is complete and markets reopen (or reopen after a delay depending on the market access protocol). A lower investment in surveillance at Q^{low} delays detection and hence eradication. If there is no surveillance then there is a natural rate of detection at $T^d(0)$. In this example, it is assumed eradication is incomplete at the end of the season, but simply there is no carry over into the next season (path *fg*).

4.5 Market Rules

Market access rules agreed to by individual trading partners are one of five types in the AWM of Qfly:

i) *Biosecurity Constraint*: the minimal level of surveillance below which no trade occurs.

ii) *Recertification Rule*: the number of generations of Qfly that must elapse before market access can be resumed following an outbreak. This is temperature driven given that Qfly phenology may be measured by accumulated day-degrees, and so will vary with location and season. Examples include: one generation and 28 days or 12 weeks, whichever is more (exports to NZ); or, three generations (citrus exports to the USA).

iii) *Areal Rule*: the size of the trade suspension zone as a radius from the declared epicentre of the outbreak. It varies with market (15 km for NZ; 80 km for Tasmania), and may be extended following further captures within the suspension zone (to 30 km from 15 km for USA).

iv) *Treatment Rule*: either no trade is permitted with the suspended area by the destination market rule, or trade is permitted with post-harvest treatment of produce. This latter option is predominately the case.

v) *Capture Rule*: the number of Qfly captures, and the pattern of how they are caught locally both spatially and temporally, that is used as the criterion to declare an outbreak. Largely, the capture rule is as described above: at least five male Qfly captured within 1 km and two weeks, or one gravid female or larvae.

As the treatment and capture rules are relatively consistent across trading partners then the first three rules are of greater current interest. The recertification and areal rules operate similarly and can increase significantly the post-harvest treatment costs, namely because the recertification rule extends the duration of a declared outbreak, occasionally into the next harvest season, while the areal rule determines the volume of production subject to suspension on average. In contrast, the biosecurity constraint determines participation in the market of trading partners: if there is no surveillance there is no AWM and no trade with those markets. Furthermore, the biosecurity constraint operates differently from the other rules in how it influences a BCA of an AWM (Figure 2).

Total revenue R^T is constant for constant produce price regardless of whether an AWM scheme is present or not. The key difference is that in the absence of an AWM scheme then trade characteristically still continues, but requires post-harvest treatment cost of all produce. Similarly, there are no surveillance or eradication costs to be incurred. Hence path *ab* describes total variable costs up to the biosecurity constraint, coincident with maximum post-harvest costs (Figure 2). Note that in the absence of a biosecurity constraint then each post-harvest treatment, eradication and surveillance costs are continuous functions of surveillance level Q, as indicated by the dashed lines. Importantly, these ‘natural’ cost functions are realised whenever the biosecurity constraint is satisfied.

Define the biosecurity constraint as Q^B. Then the optimal level of surveillance Q^* in the presence of a biosecurity constraint satisfies the following conditions:

$$
\begin{array}{lcl}
Q^* = 0 & | & C^m(0) \leq C^T(Q^B) \\
Q^* = Q^B & | & C^m_{Q^B} \leq -\left[C^s_{Q^B} + C^e_{Q^B}\right], C^m(0) > C^T(Q^B) \\
Q^* > Q^B & | & C^m_{Q^B} > -\left[C^s_{Q^B} + C^e_{Q^B}\right], C^m(0) > C^T(Q^B)
\end{array}
$$

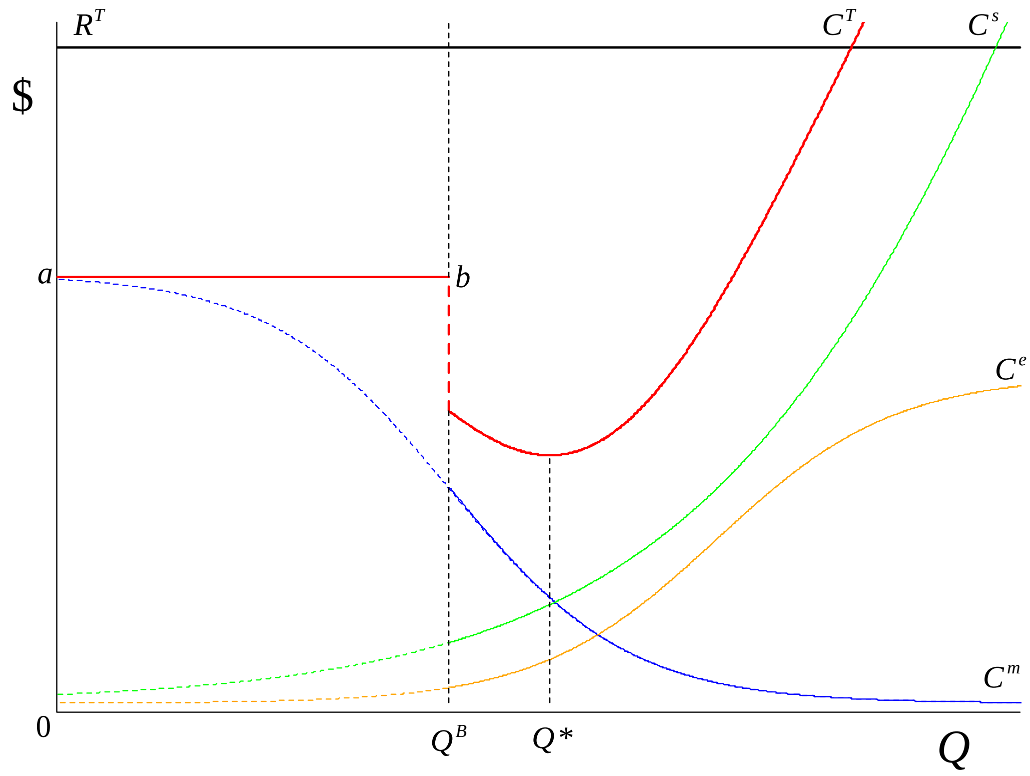

Figure 2. The Biodiversity Constraint and Optimal Surveillance

where C'_{Q^B} is the marginal cost evaluated at the budget constraint. The dependency of the component costs on Q is omitted here for simplicity, and monotonicty of the cost functions with respect to Q is assumed. The condition $Q^* = 0$ implies there is no AWM. In summary, it is optimal for the AWM manager to voluntarily undertake a level of surveillance greater than the minimal level required for AWM (i.e., the biosecurity constraint) whenever the marginal benefit of avoided post-harvest treatments is greater than the sum of the marginal costs of surveillance and eradication at the biosecurity constraint. Figure 2 illustrates the third case of a voluntary increase in surveillance.

4.6 The Stochastic Spatial-Dynamic Optimization Problem

In this section we bring together the various components of the regulator's problem and recognize that it is spatial, dynamic and stochastic. The regulator determines a level of investment to solve the following problem expected avoided cost minimization problem:

$$Minimize\ \sum_t \left[C^s(Q,z,) + \sum_s p_t^O(s)\left[C^e\left(\hat{a}, \hat{X}_d(Q,z)\right) + C^m(T^d(Q,z))\right]\delta^t\right] \tag{10a}$$

$$T^d(Q,z) = \min\left[j{:}\, Bin(H^j x_0(s), p_d) \geq r_c\right] \tag{10b}$$

$$T^e(Q,z) = T^d(Q) + t^e\left(\widehat{\mathrm{X}}^d(Q,z), \hat{a}\right) \tag{10c}$$

$$Q \geq Q^B \tag{10d}$$

where δ^t is the discount factor; p_d is the probability of detecting a Qfly within the locality of a trap; $p_t^O(s)$ is a time and location dependent probability of outbreak; and r_c is the capture rule detailing the minimum number of captures required for the declaration of an outbreak (and may involve a sum of captures in recent weeks and in neighbouring traps). The waiting times T^d and T^e are now stochastic realizations, as detection at each time point is treated as binomial trials of the current population size $X_{\mathrm{t}}(\mathrm{s}) = H^j x_0(s)$. The term $\widehat{\mathrm{X}}^d(Q,z)$ is computed as $H^{T^d(Q,z)} x_0(s)$.

In general, $p_t^O(s)$ is an ecologically determined parameter driven by climate, however it is in part defined also by the market rules. For instance, both the recertification and capture rules will alter this probability: a longer recertification period will mean that fewer outbreaks are declared as the implied long durations of outbreaks overlap and 'hide' some of the outbreaks that would have been declared for a shorter recertification period; the capture rule determines when an outbreak is declared, and hence the size of the initial population when eradication measures are begun, thereby altering consecutively $T^d(Q,z)$, X_{T^d}, $T^e(Q,z)$, C^e and C^m.

Similarly, increases in the ecologically based parameters of time to detection, time to eradication and probability outbreak will predictably lead to increased costs, but are correlated non-linearly with surveillance effort. For example, increasing surveillance may lead initially to a greater number of outbreaks being declared before plateauing to a maximum number of possible outbreaks, as the surveillance system becomes more effect in picking up those populations that would have normally self-extinguished through population *allee* effects. This is particularly the case with Qfly as 71% of captures do not involve declarations of an outbreak. By increasing surveillance the benefits of reducing the time to detection and hence post-harvest treatment costs need to be traded off against the extra costs of increasing the probability of outbreak. In fact these complex dependencies built into the model may risk non-convexities in the eradication and market cost functions of surveillance, violating the assumption of monotonicity of Section 4.5.

5. Empirical Model

The elements of (10) to be estimated include: i) costs; ii) a population growth diffusion model over local landscapes $H^j x_0(s)$; and iii) a probability of outbreak model p_t^O. Both ii) and iii) are driven by time varying climate indices. The calibration of the spatio-dynamic economic model from limited data therefore entails a number of estimation and calibration steps. The strategy employed here was to use the data available from existing Qfly trapping experiments to estimate p_t^O, and to use other readily available data on the population ecology of Qfly to infer the parameters of the growth model. An overview of how costs link to the bioeconomic model are given in Figure 3.

5.1 Definition of Landscape

The FFEZ region was represented as a pixelated landscape with 1 arcminute resolution (~1.84 km). For each pixel a number of spatial attributes were recorded: road density (m/ha); landuse (5 landuse classes); membership and distance to the PFA and FFEZ management boundaries (km); elevation (m); surface roughness (st. dev. of elevation); distance to coast (km); and number of active cuelure Lynfield traps. Temporal covariates recorded on a weekly time step were derived from daily temperature, rainfall and evaporation using the Climex model based on phenological parameters for Qfly (Sutherst *et al.* 2007).The model was applied to the 936 weeks from January 1993 to December 2010, and considers 5402 pixels where either horticultural production or residential areas are located (Figure 4).

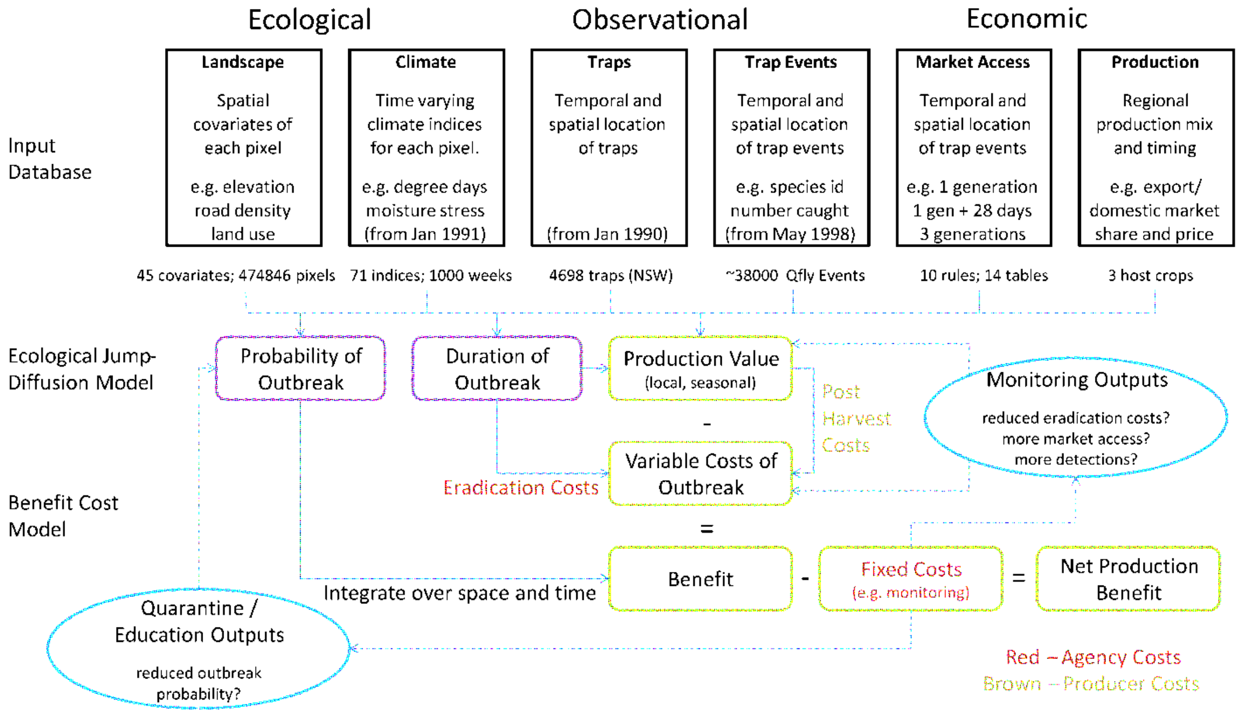

Figure 3. Flow Diagram of BCA model.

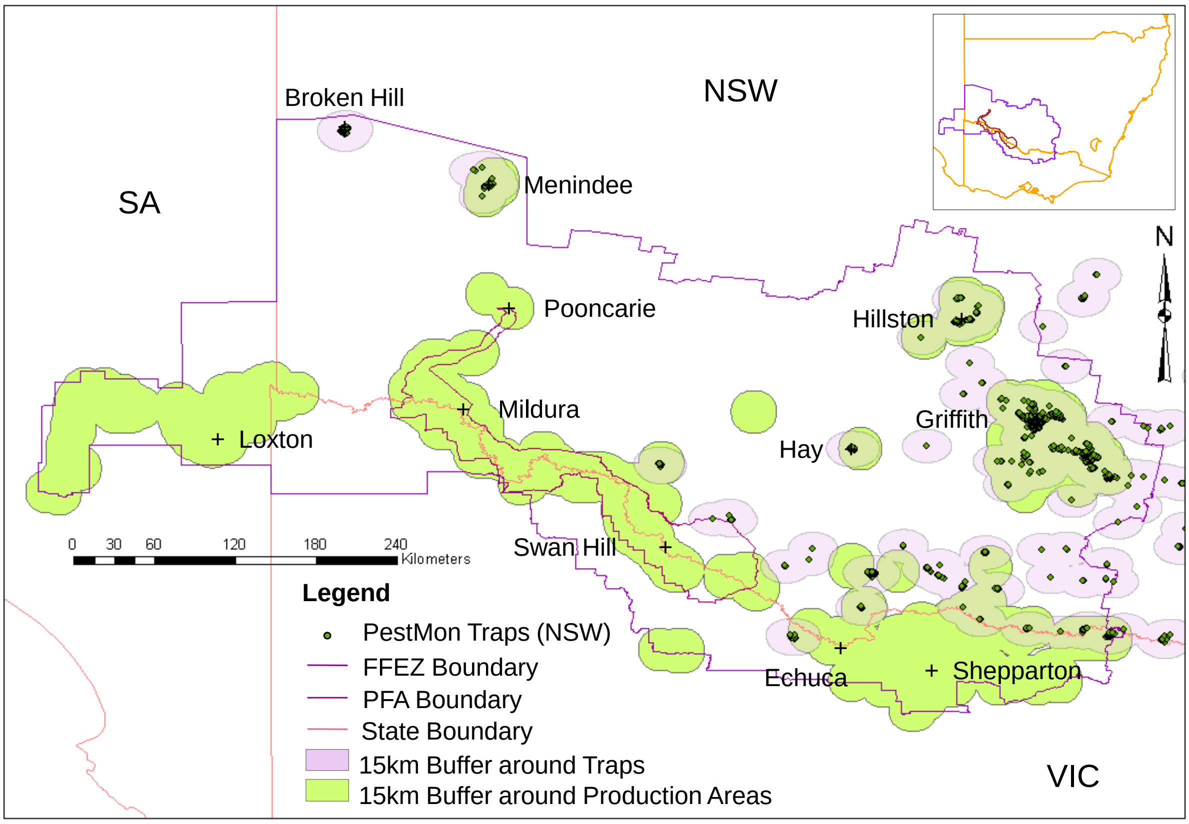

Figure 4. Map of The FFEZ Region in South Eastern Australia

5.2 Cost of Surveillance C^s

The cost of surveillance (C^s) was taken to be a function of both trapping grid density (Q) and frequency (z) of trap inspection (Figure 5). The cost surface was derived from costs for labour, trap maintenance and travel time, and is multiplied by the number of traps in the landscape. A grid cell was assigned a trap if the sum total of vine, fruit tree, other horticultural and residential land uses exceeded 0.28 of total pixel area, a threshold derived from the PestMon trap data.

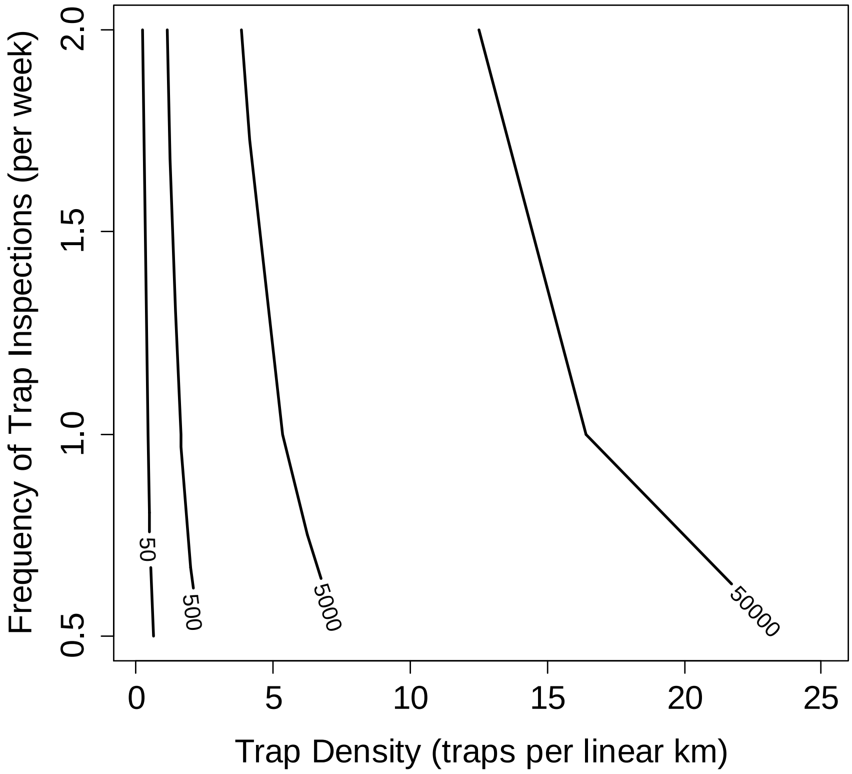

Figure 5: Surveillance Isocost Surface: Grid Density and Frequency of Trapping ($/km^2)

5.3 Probability of Outbreak $p_t^O(s)$

The study utilised the PestMon database held by Industry and Investment, NSW, recording weekly Qfly captures for 1650 permanent and temporary Cuelure traps across the NSW portion of the FFEZ. A market rule of at least five flies trapped within two weeks and 1 km was used to declare 135 outbreaks from June 1998 to December 2010. Calculation of the duration $t^e\left(\widehat{\mathrm{X}}^d(Q,z), a_t(s)\right)$ of an outbreak (eradication plus market recertification) required: i) at least one generation to lapse following the completion of a 12 week eradication period, with no Qfly caught during that time; ii) if Qfly were subsequently caught then the one generation rule was imposed again when less than five Qfly were caught; iii) if at least five Qfly were trapped then 12 weeks of eradication were imposed, followed by a reinstatement of one generation rule.

The Qfly trapping events were regressed on the spatio-temporal factors using generalised additive models (Wood, 2006). Drought stress, distance from the PFA boundary (Figure 6), and increasing density of roads and residential areas were found to be the key drivers of the probability of captures. A relative risk of outbreaks to capture events was derived from the data and then used to compute outbreak occurrence during simulation runs over the entire FFEZ.

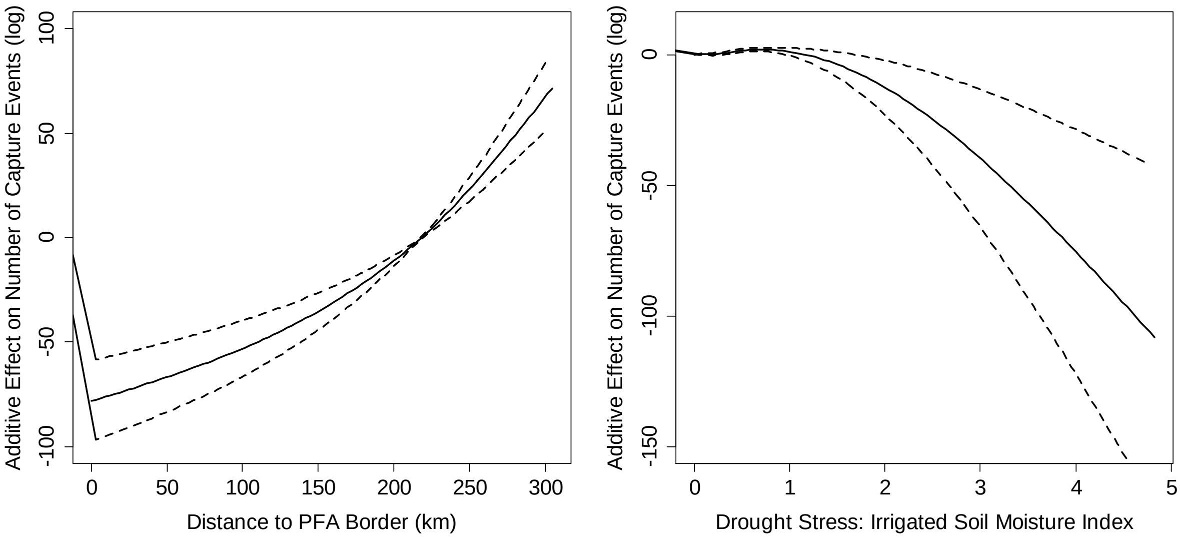

Figure 6. PFA Border and Drought Stress Effects on the Probability of Qfly Captures

5.4 Cost of Eradication C^e

The cost of eradication is a function of the duration of the outbreak, with outbreaks of longer duration more likely to require multiple eradication efforts. A single eradication effort was estimated to cost $120,546 (2010 value), and considered the cost of labour, chemical usage, and of sterile insect technology (SIT) releases following the initial two week period of chemical application. The Qfly model fixes the eradication period at 12 weeks for all outbreaks, in common with eradication practice on the ground, regardless of surveillance effort (Q, z). What varies in the model is the number of eradication efforts required during any recertification period, taken as an empirically derived stochastic function of outbreak duration. Note that outbreak duration is itself a stochastic function of the initial population captured at the time of detection (equating to the unobserved X^d), with the eradication cost incurred solely at the spatial epicentre of the declared outbreak. Hence, C^e is a function of effort (Q, z) through it's indirect dependence on X^d (e.g., X^d increases with decreasing Q, leading to greater T^e; Figure 1).

5.5 Market Costs C^m

Market costs were defined as the post-harvest costs incurred from the time of declaring an outbreak to the declaration of pest free status following satisfaction of the one generation rule, and covering all production within a 15 km radius of the outbreak. Post-harvest costs per tonne of table grapes, citrus and stone fruit were on average given as $127, $93.25 and $50, respectively, by major packing sheds in the region. These numbers differ from the $50 per tonne for each produce included in the BCA of (Ha *et al.* 2010).

The per week tonnage of production for each crop for each map pixel was computed from land use data, provided by the Bureau of Rural Services as a 1:50,000 vector map. The temporal pattern of production for each crop type is known for the region from Australian Bureau of Statistics data, as are the tonnes production per hectare per year (Figure 7). The proportion of vine crops and fruit trees (both irrigated and rain-fed for each crop type) for each pixel was computed, and fruit tree production further split into citrus and stone fruit by assigning the regional mix of production for each pixel, given that the land use map did not give that level of differentiation. Knowing the area of production for each pixel and each crop type permitted a production curve to be assigned to each pixel, with weekly post-harvest costs computed accordingly. The average proportion of each pixel's production and post-harvest costs already counted or incurred by one or more outbreaks in neighbouring pixels can be rapidly computed, using the geometry of independent intersections. Market costs are incurred for so long as the outbreak endures, and are thus dependent on the time to detection and surveillance effort $T^d(Q, z)$.

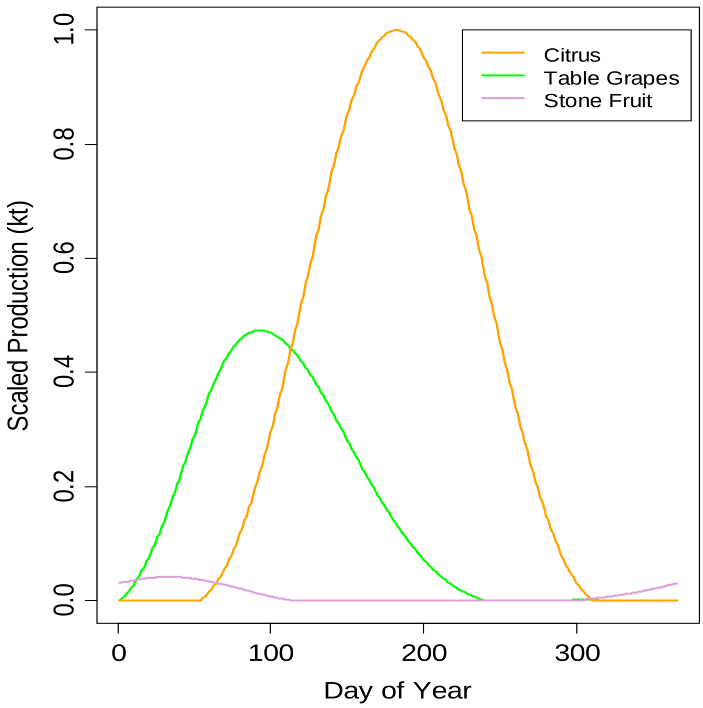

Figure 7. Time-Varying Production

5.5 Linking Surveillance Design and Benefits

Valuing the benefits of surveillance in terms of early detection required implementation of an integro-difference population model in a local raster landscape. The probability of capture, and population diffusion and growth parameters were calibrated from data presented in the existing Qfly literature (Sadler *et al.* 2011). The growth parameter was time-varying, dependent on the same Climex-derived climate indices as the probability of outbreak model, and inferred from an existing stage structured population model (Yonow *et al.* 2004). Inferring the unobserved time of population arrival and initial population number from the numbers of Qfly initially trapped when an outbreak was declared, with random locations of population arrival, required a simulated likelihood approach (Diggle & Gratton 1984). The comparison between model and data involved:

i) backward simulation of the integro-difference model from the current time period and observed captures;
ii) Defining surveillance grids of differing density and frequency of inspection, and for each grid the integro-difference model was forward simulated from each initial population and time start.
iii) The number captured at any point in time in cells containing a surveillance point followed an independent binomial distribution given by the simulated population number and probability of detection.
iv) Forward simulation was ended, and consequently the time to detection defined, when simulated captures exceeded the capture rule r_c of at least five Qfly within two weeks and one kilometer.

The benefits of monitoring could then be defined as the post-harvest costs saved through earlier detection. The number of Qfly initially captured, which correlates well with time to detection, was then used to predict the duration of outbreaks through a regression model derived from the PestMon data. In this way simulated Qfly captures provide a time-varying distribution of the duration of outbreaks dependent on prevailing climatic conditions (i.e., growth rate parameters) that, in turn, determines post-harvest costs.

6. Results

The total potential annual benefit of the PFA scheme can be valued at $39.3 million, which is the total value of post-harvest treatments within the Sunraysia region in a scenario where no outbreaks occur. Any costs are then deducted from this benefit (Table 1, Scenario 1). The variable cost of maintaining the current surveillance was estimated at $0.79 million, with $0.79 million eradication ($0.08 million standard error) and $5.4 million of incurred post-harvest costs ($4.6 million standard error), averaged over a 20 year period. Most of the variability in post-harvest costs was due variable timing of outbreaks, and hence variable durations of outbreaks, where as the mean number of outbreaks per year was relatively stable. Total net benefits were thus estimated to be $32.4 million per year of maintaining the combined FFEZ/PFA scheme as it currently stands (Table 1, Scenario 2). The total net benefits are greater than those previously reported primarily because our per unit post-harvest treatment costs are estimated to be higher than elsewhere.

If the trap density is varied in different simulation runs, but applied homogeneously across the landscape, then per pixel net benefits can be calculated. Figure 8 sums these benefits across the PFA pixels only, examining a range of trap spacings from 40 to 5000 m. Effects below 240 m trap spacings are poorly estimated, being greater than the maximum observed trap densities recorded in the PestMon database, and should be ignored. The key result is that it is optimal to surveil at the lowest possible level if undertaking surveillance over the landscape at a single rate. However, non-linear effects are evidenced in the interaction between a rapid detection and hence rapid eradication at low trap spacings (high density) and the number of outbreaks declared. Critically, non-convexity of the post-harvest treatment cost function is evidenced, with a local minimum occurring at $\sim$550 m trap spacing. In contrast, both surveillance and eradication costs decrease monotonically for trap spacings larger than 240 m.

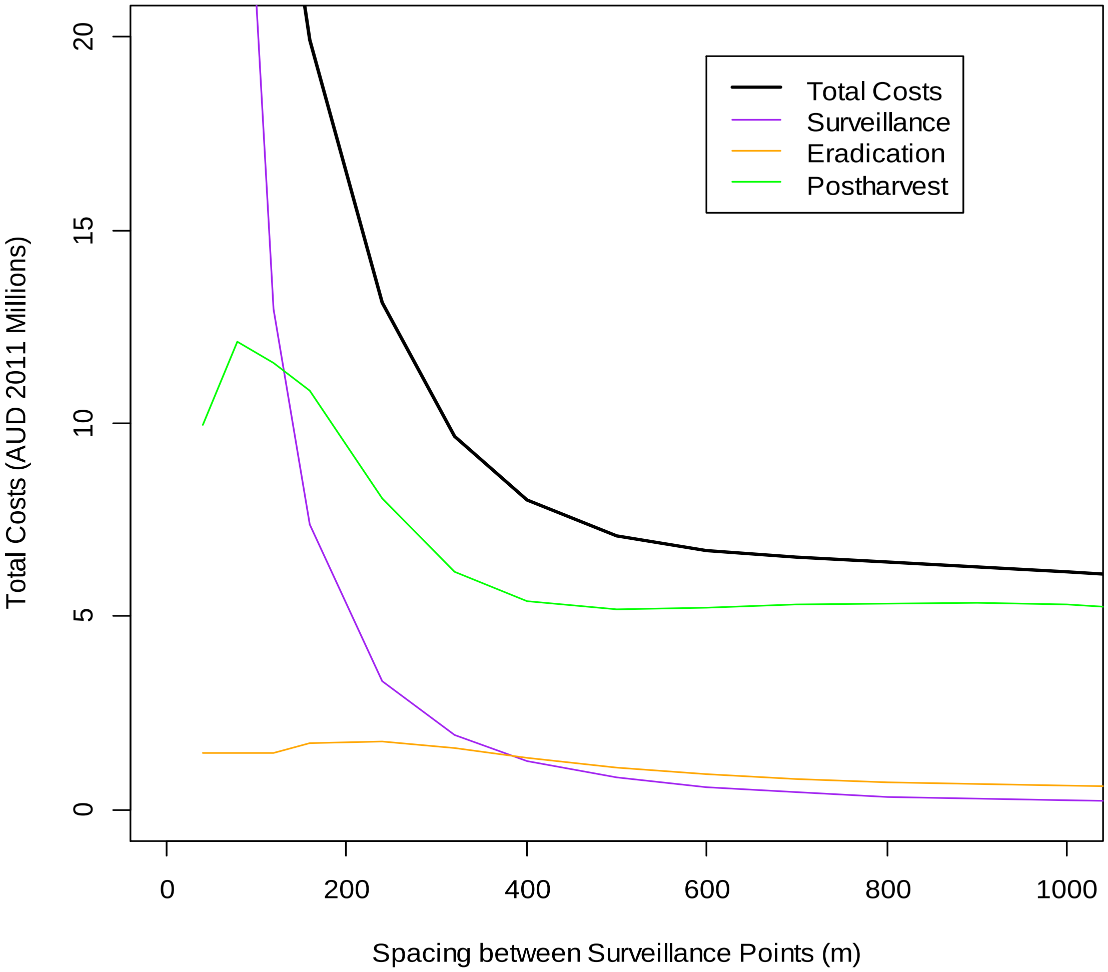

Figure 8. Total Costs of Area Wide Management with Surveillance Effort

The solution without a biosecurity constraint tends to no surveillance when the Sunraysia region is monitored at the one homogeneous surveillance rate. However, the optimal trap spacing ranges between 700 and 1000 m over the Sunraysia region, if the maximum allowable trap spacing due to market regulation is assumed to be 1000 m (i.e., the biosecurity constraint), and the optimal trap spacing allowed to vary on a per pixel basis (Figure 9). This solution has been spatially smoothed with cubic regression splines (i.e., regularized), implying that locally a near homogeneous surveillance rate is preferred, with smoothing parameter chosen through generalized cross-validation. This rate of surveillance can be readily afforded, as the net benefits of engaging in AWM over the entire region far outweigh the costs, even with the biosecurity constraint in place.

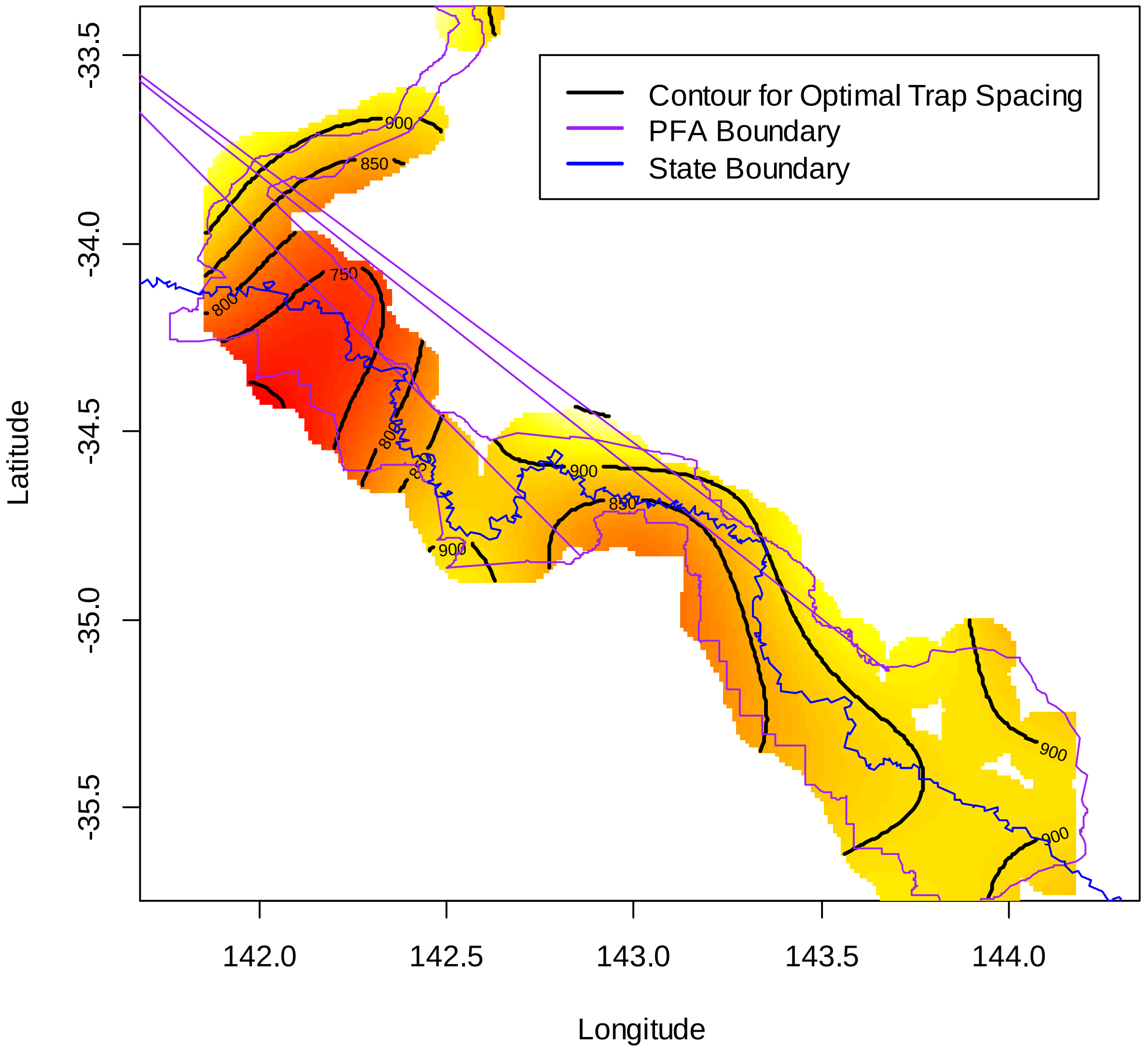

Figure 9. Spatially Optimal Surveillance Effort

While Table 1 provides a sum of costs by region (PFA or non-PFA FFEZ, NSW or Victoria), mean post-harvest costs can also be estimated for each pixel in the landscape. The result is also smoothed (i.e., regularized) and identifies a 'hotspot' in costs around the Mildura production region, corresponding to both the region of greatest production value within the PFA and the highest rates of optimal surveillance (Figure 9). Consequently, the optimal level of surveillance is predicted well by the local value of postharvest treatments (adj-$R^2 = 0.54$, p-value< 0.0001), with increased surveillance (lower trap spacings) correlating with higher production values (even if marginally).

Marginal surveillance costs and post-harvest costs are large below a 400 m trap spacing, with surveillance costs dominating post-harvest costs as the surveillance effort increases. This evidenced when post-harvest costs are increased or surveillance costs per trap are greatly reduced through a sensitivity analysis, with the 'smoothed' optimal strategy becoming increasingly heterogeneous spatially. With post-harvest costs doubled, the optimal spacing of surveillance traps can decrease to 320 m in regions of high production value (i.e., around the

Mildura 'hotspot'). This would be the scenario under market rules requiring greater time period to elapse before permitting market recertification (e.g., the three generation rule for citrus exports to the USA), or under a scenario when comparatively cheap post-harvest treatment options are lost (such as current chemical controls).

In the absence of an AWM scheme post-harvest costs are incurred on all production across the FFEZ (Table 1, Scenario 1). These annual costs are significant and total $146 million, and do not include the value of either wine grapes, dried grapes (together 85% of total grape production in the region) or juicing citrus production (50% of citrus production). The majority of these costs are borne in the non-PFA regions of the FFEZ, predominately within NSW, and hence do not feature in the BCA as they are considered the counterfactual case. While the net benefit of the current AWM strategy is $32.4 million per year (Table 1, Scenario 2) the net benefit of allowing surveillance to vary optimally across the Sunraysia PFA, while surveillance is kept to its current schedule across the remainder FFEZ, is only $0.6 million above that of Scenario 2 (Scenario 3). Immediately it can be seen that the benefits of introducing new post-harvest treatment are potentially greater than the benefits of introducing new surveillance technologies, due to the fact that post-harvest treatment costs are ubiquitously incurred over the non-PFA regions of the FFEZ. Similarly, the potential benefits of expanding the current PFA are large, given that avoided post-harvest treatment costs far outweigh surveillance and eradication costs if the current rate of outbreaks and their declared duration can be held constant. The priority of new sites for inclusion into new PFAs within the FFEZ region may be predicted reasonably well by their potentially avoided post-harvest treatment costs or production value in the first instance, and through simulation of the Qfly bioeconomic model in the second instance.

7. Summary

This paper sets out the structure of a bioeconomic model of AWM for Qfly in the GSPFA. The model is spatial and dynamic and allows for surveillance costs, eradication costs and market access costs. The purpose of this model is to estimate the returns to different aspects of AWM design, in particular the investment in surveillance, control effort, spatial extent and R&D. The approach taken is to understand the GSPFA as a bioeconomic system, thereby allowing an exploration of the current system of management and an assessment of the potential return to new developments in surveillance and control. Critically, trade agreements and market rules play an integral role in defining net benefit, and the optimal rate of surveillance across a landscape.

Acknowledgements

This work was funded by the Cooperative Research Centre for National Plant Biosecurity through Project 70100: Optimal Investment in R&D for Plant Biosecurity. Industry and Investment NSW provided key data.

Table 1. Benefit Cost Valuation of Different AWM Scenarios

			COSTS (AUD) / year[1] (000's)			
			Surveillance	Eradication	Post-harvest[2]	Total/Difference
Scenario 1: **No AWM**	**NSW**	PFA	0	0	11397	11397
		FFEZ	0	0	95765	95765
		Total	0	0	107162	107162
	VIC	PFA	0	0	27908	27908
		FFEZ	0	0	38958	38958
		Total	0	0	66866	66866
	Total	PFA	0	0	39306	39306
		FFEZ	0	0	106814	106814
		Total	0	0	146120	146120

1. Red: cost; Black: benefit
2. Post-harvest costs for regions outside of the PFA estimated using the mix of land uses within the PFA.

Scenario 2: **Current AWM Extent** **Current Monitoring**	**NSW**	PFA	38	91	9832	9704
		FFEZ	411	181	0	592
		Total	449	271	9832	9119
	VIC	PFA	188	15	24104	23901
		FFEZ	157	506	0	663
		Total	345	521	24104	23239
	Total	PFA	226	106	33937	33605
		FFEZ	568	686	0	1254
		Total	794	792	33937	32350

Red: cost; Black: benefit; calculated as net cost or benefit over 'Scenario 1: No AWM'

Scenario 3: **Current AWM Extent** **Optimal Monitoring**	**NSW**	PFA	17	~0	219	202
		FFEZ	0	~0	0	0
		Total	17	~0	219	202
	VIC	PFA	17	~0	393	409
		FFEZ	0	~0	0	0
		Total	17	~0	393	409
	Total	PFA	~0	~0	610	611
		FFEZ	0	~0	0	0
		Total	~0	~0	610	611

Red: cost; Black: benefit; calculated as net cost or benefit over 'Scenario 2: Current AWM

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