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Invasive Species and Biosecurity: Cost of Monitoring and Controlling Mediterranean Fruit Flies in Florida

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The growing movement of people and goods that started in the closing years of the twentieth century has increased the possibility of the accidental or intentional introduction of biohazards that can affect agricultural production in the United States. This study examines the *ex ante* decision between the deployment of monitoring devices (traps) versus the use of countermeasures to control Mediterranean fruit flies in Florida. To examine this trade-off, this study outlines a mathematical model to study the effectiveness of traps and the cost of treatment. The empirical results presented in this study indicate that additional parameterization efforts are needed.

Key Words: biohazards, conditional probability, cost of eradication, density functions

JEL Classifications: C60, Q12, Q57

This study examines the optimal combination of monitoring versus countermeasures in response to the potential introduction of biohazards into a production region. Specific issues examined include the minimum cost of controlling the Mediterranean fruit fly in Florida, including the cost of establishing, maintaining, and monitoring traps set to detect the presence of the flies, as well as the cost of controlling the flies once an infestation has been detected. In Florida, the Mediterranean fruit fly is an invasive species, the introduction of which could result in the destruction of fresh fruits and vegetables. Currently, the most likely means of introduction is by tourists carrying fresh fruit from an infected area outside the United States into Florida through a major airport (i.e., Miami, Orlando, or Tampa).

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Bayesian Decision Rule

Decisions regarding the management of biohazards are inherently dynamic and can be evaluated in a Bayesian framework. Decisions are dynamic in that actions or costs incurred in one period have an effect on costs incurred in succeeding periods. For example, additional surveillance and eradication expenditures in the early spring could reduce the cost of eradication in the late spring and early summer. The decision framework can be characterized as a Bayesian decision process in that the probability of infection is updated as new information becomes available. The decision framework then includes choosing the number of traps to set around points of entry (airports, cruise ship ports, interstate highways, etc.) to capture Mediterranean flies. If a Mediterranean fly is captured, countermeasures can be taken, such as spraying pesticides, the release of sterile male flies, or quarantine of fresh fruits and vegetables. The optimization problem then involves the choice between detection and eradication expenses. Intuitively, the more diligent the detection regimes, the smaller the population of Mediterranean flies when detection occurs, and, therefore, the less expense involved in treating the associated population by countermeasures. The economic problem results from the fact that while early detection is costly, the tendency for the pests to spread spatially makes delayed countermeasures more costly. Further, because Florida's market windows for fresh fruits and vegetables tend to be relatively short, an infestation that results in the quarantine of fresh produce could be catastrophic.

We start by defining two random variables on which the dynamic Bayesian model is conditioned. We assume that there is a true population of the biohazard (in this case Mediterranean flies) x_1. This true value then determines the probability of observing a Mediterranean fly in a trap (x_2). The random variable x_2 is a discrete variable such that $x_2 = 0$ denotes the outcome where no Mediterranean flies are observed in the trap, and $x_2 = 1$ implies that at least one Mediterranean fly has been captured in a trap. The joint probability for these random variables ($f(x_1, x_2|z)$) is, in part, determined by the number of traps set out (z). The most difficult part of this study involves the specification of the joint density function. Specifically, both the true population size of Mediterranean flies and the number of traps are hypothesized to affect the probability of detection. Neither the number of traps nor the trapping event itself, however, can be seen as causal to the overall population of Mediterranean flies.

Next, we assume that once one Mediterranean fly has been observed, countermeasures begin. Defining the cost of countermeasures as $C(x_1)$, i.e., the cost of eradication, we define the expected cost of treatment as

$$(1)\qquad E[C(x_1)|z] = \int_{\underline{x}_1}^{\overline{x}_1} [C(x_1)f(x_1, x_2 = 1|z) + 0f(x_1, x_2 = 0|z)]\, dx_1 = \int_{\underline{x}_1}^{\overline{x}} C(x_1)f(x_1, x_2 = 1|z)\, dx_1,$$

where $\underline{x_1}$ is the lower bound of the Mediterranean fly distribution, and $\overline{x_1}$ is the upper bound of the Mediterranean fly distribution. The lower bound is taken to be zero, while the upper bound is taken to be infinity. In this study, we assume that once a fly has been trapped, there is no uncertainty regarding the distribution of Mediterranean flies. This solution, however, treats the number of traps as fixed. Expanding the formulation to incorporate the number of traps yields

$$(2)\qquad E[C(x_1)|z] = \int_{\underline{x}_1}^{\overline{x}} C(x_1)f(x_1, x_2 = 1|z)\, dx_1 + p_z z,$$

where p_z is the cost of deploying and monitoring traps. Unfortunately, this specification is still incomplete because it is static. To make the problem mathematically tractable, we focus on three discrete periods within Florida's marketing season. We also assume that countermeasures are completely effective. Focusing on three periods is justified because the probability of a freeze (albeit a light freeze) reduces the likelihood of Mediterranean flies overwintering in Florida. Thus, we model the countermeasure decision using the nested formulation presented in Figure 1. Working step by step, if a Mediterranean fly is caught in the first period

$$(3)\qquad C_1 = C(x_{1,1})f(x_{1,1}, x_{2,1} = 1|z).$$

If the Mediterranean fly is caught in the second period

$$(4)\qquad C_2 = C(x_{1,2})f(x_{1,1}, x_{2,1} = 0|z) \times f(x_{1,2}, x_{2,2} = 1|z).$$

If the Mediterranean fly is caught in the last period

$$(5)\qquad C_3 = C(x_{1,3})f(x_{1,1}, x_{2,1} = 0|z) \times f(x_{1,2}, x_{2,2} = 0|z)f(x_{1,3}, x_{2,3} = 1|z).$$

Summing costs across the appropriate time periods gives

$$(6)\quad C_T = C(x_{1,1})f(x_{1,1}, x_{2,1} = 1|z) + C(x_{1,2})f(x_{1,1}, x_{2,1} = 0|z)f(x_{1,2}, x_{2,2} = 1|z + C(x_{1,3})f(x_{1,1}, x_{2,1} = 0|z)f(x_{1,2}, x_{2,2} = 0|z)f(x_{1,3}, x_{2,3} = 1|z) + p_z z.$$

Taking the expected value of total cost in Equation 6 yields

$$\begin{aligned}(7)\quad E(C_T|z) = &\int_{\underline{x}_{1,1}}^{\bar{x}_{1,1}} C(x_{1,1})f(x_{1,1}, x_{2,1} = 1|z)\, dx_{1,1} \\ &+ \int_{\underline{x}_{1,1}}^{\bar{x}_{1,1}}\int_{\underline{x}_{1,2}}^{\bar{x}_{1,2}} C(x_{1,2})f(x_{1,1}, x_{2,1} = 0|z)f(x_{1,2}, x_{2,2} = 1|z)\, dx_{1,1}\, dx_{1,2} \\ &+ \int_{\underline{x}_{1,1}}^{\bar{x}_{1,1}}\int_{\underline{x}_{1,2}}^{\bar{x}_{1,2}}\int_{\underline{x}_{1,3}}^{\bar{x}_{1,3}} C(x_{1,3})f(x_{1,1}, x_{2,1} = 0|z)f(x_{1,2}, x_{2,2} = 0|z) \\ &\qquad \times f(x_{1,3}, x_{2,3} = 1|z)\, dx_{1,1}\, dx_{1,2}\, dx_{1,3} - p_z z.\end{aligned}$$

$$x_{1,0} \rightarrow x_{1,1} \Rightarrow \begin{cases} x_{2,1} = 1 \Rightarrow C(x_{1,1}) \\ x_{2,1} = 0 \end{cases}$$

$$x_{2,1} = 0, x_{1,1} \rightarrow x_{1,2} \Rightarrow \begin{cases} x_{2,2} = 1 \Rightarrow C(x_{1,2}) \\ x_{2,2} = 0 \end{cases}$$

$$x_{2,1}x_{2,2} = 0, x_{1,2} \rightarrow x_{1,3} \Rightarrow \begin{cases} x_{2,3} = 1 \Rightarrow C(x_{1,3}) \\ x_{2,3} = 0 \end{cases}$$

Figure 1. Pest Trapping Problem

The number of traps set to detect Mediterranean flies (or any biohazard) can be determined by minimizing the expected cost in Equation 7 with respect to z. Increasing the number of traps increases the probability of detecting a Mediterranean fly if a population is present. Further, since it is more effective to treat a Mediterranean fly infestation when the number of flies is small, increasing the number of traps reduces the expected cost of treatment because countermeasures will be started early rather than later. However, the expected gains to early treatment must be weighted against the costs of additional traps.

Estimation of Marginal Probabilities

Implementation of the model presented in Equation 7 requires estimates of the joint probability of infestation and the cost of treating an infestation. We propose estimating the conditional joint distribution function using the procedure Taylor (1990) proposed to model correlated nonnormal random variables.

Taylor proposed modeling the joint probability distribution function with the product of conditional marginal distribution functions

$$(8)\quad f(x_1, x_2, \ldots, x_n) = f(x_1)f(x_2|x_1)f(x_3|x_1, x_2) \cdots f(x_n|x_1 \cdots x_{n-1}),$$

where $x_1, x_2, \ldots, x_n$ are possibly correlated random variables. In this case, we define the joint probability of a number of Mediterranean flies and catching a Mediterranean fly in a trap conditional on the number of traps set as

$$(9)\quad f(x_1, x_2|z) = f(x_1)f(x_2|x_1, z)$$

where $f(x_1)$ is marginal distribution of the number of Mediterranean flies, and $f(x_1|x_2, z)$ is the conditional probability of catching a Mediterranean fly in a trap given a population of Mediterranean flies and the number of traps set.

We follow Baker, Crowley, and Harte (1993) modeling the probability of a Mediterranean fly infestation in Florida as

$$(10)\quad r = 1 - (1 - p\Phi)^N,$$

where r is the probability of an infestation, p is the proportion of passengers arriving with high risk materials (i.e., fresh fruits or vegetables), Φ is the probability that a piece of infested material will lead to the establishment of a Mediterranean fly population, and N is the number of arrivals (Dymock 2000). Assuming that the number of survivors follows a Poisson distribution, the parameter Φ becomes

$$(11)\quad \Phi = \Psi(1 + e^{-\mu\phi} - 2e^{-\mu\phi/2}),$$

where μ is the average number of pests per infestation, ϕ is the proportion of individuals surviving to reproduce, and Ψ is the suitability of conditions for the pest (Whyte et al. 1996). Putting these two terms together, the probability of Mediterranean flies occurring in Florida becomes

$$(12)\quad f(x_1) = r = 1 - [1 - p\Psi(1 + e^{-x_1} - 2e^{-x_1/2})],$$

letting $x_1 = \mu\phi$.

Next, we model the conditional probability distribution function of catching a Mediterranean fly in a trap based on the population size and the number of traps using the hyperbolic tangent formulation proposed by Taylor (1984, 1990). As indicated by Taylor, a slight transformation of the hyperbolic tangent has a similar shape to the cumulative distribution function of a normal distribution function. Specifically, for some random variable x,

$$(13)\quad F(x) = \frac{1}{2}[1 + \tanh(x)]$$

is a valid cumulative density function with $\lim_{z\to\infty} f(x) = 0$, $\lim_{z\to\infty} f(x) = 1$, and $\partial f(x)/\partial x \geq 0\ \forall x$. Generalizing this function using a transformation function $h(x)$ yields

$$(14)\quad F(x) = \frac{1}{2}\{1 + \tanh[h(x)]\}.$$

The probability density function of x can then be derived by taking the derivative of Equation 14 with respect to x, or

$$(15)\quad f(x)= \frac{1}{2}h'(x)\mathrm{sech}^2[h(x)],$$

where $h'(x)$ denotes the partial derivative of $h(x)$ with respect to x. We then model the interaction among the number of Mediterranean flies, the number of traps, and whether a Mediterranean fly is captured in the trap using a quadratic function

$$(16)\quad \begin{aligned} h(x_1, x_2, z) &= \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 z + A_{11}x_1x_1 \\ &\quad + 2A_{12}x_1x_2 + 2A_{13}x_1z + A_{22}x_2x_2 \\ &\quad + 2A_{23}x_2z + A_{33}zz, \\ \frac{\partial H(x_1, x_2, z)}{\partial x_2} &= \alpha_2 + 2A_{12}x_1 + 2A_{22}x_2 + 2A_{23}z. \end{aligned}$$

Therefore the conditional distribution of capturing a Mediterranean fly in a trap given a population of Mediterranean flies and a number of traps is

$$(17)\quad f(x_2 | x_1, z) = \frac{1}{2}(\alpha_2 + 2A_{12}x_1 + 2A_{22}x_2 + 2A_{23}z) \times \text{sech}^2(\alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 z + A_{11}x_1x_1 + 2A_{12}x_1x_2 + 2A_{13}x_1 z + A_{22}x_2x_2 + 2A_{23}x_2 z + A_{33}zz).$$

Thus, multiplying the infestation model in Equation 12 with the conditional probability distribution of catching a Mediterranean fly given a population of Mediterranean flies in Equation 17 yields the joint distribution parameter of the expected cost function in Equation 7.

Data and Parameterization

While the joint distribution of Mediterranean flies and trapping events appears formidable, it can be estimated with available data. For example, the probability of the arrival of the biohazard is completely parameterized by the portion of passengers arriving with high-risk items (p) and a parameter relating the suitability of the environment to the infestation (Ψ). Using baggage surveys, we estimate the proportion of baggage entering the country with high-risk items to be 6.6×10^{-10} (surveys carried out by the Plant Protection and Quarantine facilities in Florida Airports between July 1993 and September 1994). Further, we approximate the suitability of the climate as 10% based on the probability of number of eggs surviving to adulthood in a mango.

Next, we estimate the parameters of the conditional distribution for the traps using experimental data. Specifically, we choose the levels of the parameters that minimize the error

$$(18)\quad \min_{\alpha, A} \sum_i \{[f(x_{2,i} = 0 | x_{1,i}, z_i) - (1 - T_i)]^2 + [f(x_{2,i} = 1 | x_{1,i}, z_i) - T_i]^2\}$$

Table 1. Least Squares Estimate of Distribution of Trap Function

Coefficients	Parameter Estimates
α_0	−3.744
α_1	0.252
α_2	1.053
α_3	0.688
A_{11}	−0.043
A_{12}	−0.021
A_{13}	−0.073
A_{22}	0.011
A_{23}	0.696
A_{33}	−0.018

$$\text{s.t.}\quad f(x_{2,i} | x_{1,i}, z_i) = \frac{1}{2}(\alpha_2 + 2A_{12}x_{1,i} + 2A_{22}x_{2,i} + 2A_{23}z_i) \times \text{sech}^2(\alpha_0 + \alpha_1 x_{1,i} + \alpha_2 x_{2,i} + \alpha_3 z_i + A_{11}x_{1,i}x_{1,i} + 2A_{12}x_{1,i}x_{2,i} + 2A_{13}x_{1,i}z_i + A_{22}x_{2,i}x_{2,i} + 2A_{23}x_{2,i}z_i + A_{33}z_iz_i)$$

$$\frac{\partial h(x_{2,i} | x_{1,i}, z_i)}{\partial x_{1,i}} = \alpha_1 + 2A_{11}x_{1,i} + 2A_{12}x_{2,i} + 2A_{13}z_i \geq 0$$

$$\frac{\partial h(x_{2,i} | x_{1,i}, z_i)}{\partial z_i} = \alpha_3 + 2A_{13}x_{1,i} + 2A_{23}x_{2,i} + 2A_{33}z_i \geq 0,$$

where T_i is the number of times that Mediterranean flies were caught in traps for a given number of traps and number of Mediterranean flies from experimental data. The last two constraints require that the trap sensitivity (i.e., the probability of catching a Mediterranean fly in a trap) be increasing with the number of Mediterranean flies in the environment and the number of traps. The parameters that minimize the sum squared error specification in Equation 18 are presented in Table 1.

Finally, we use a log-linear specification to estimate the cost of the prevention and eradication program. Specifically, the cost of prevention and eradication is specified as

Table 2. Estimated Coefficients for Cost of Prevention and Eradication

	Tampa			Miami		
Coefficients	February	June	October	February	June	October
Constant	10.329	7.072	8.774	9.626	8.803	8.235
$\ln(x_{1,t})$	0.918	1.522	0.703	0.852	1.062	0.823
$[\ln(x_{1,t})]^2$	0.012	−0.040	−0.047	0.047	−0.022	−0.005

$$(19)\quad \ln[C(x_{1,t})] = \beta_0 + (\beta_1 - 1)\ln(A) + \beta_1\ln(x_{1,t}) + \beta_2[\ln(A) + \ln(x_{1,t})]^2,$$

where $C(x_{1,t})$ denotes the eradication cost per hectare, A is the infected area in hectares, and $x_{1,t}$ is the pest population per hectare. This cost function is estimated using ordinary least squares for outbreak scenarios in Miami or Orlando in February, June, or October. The estimated cost parameters are presented in Table 2.

Results And Suggestions for Model Recalibration

The optimal trapping density for Miami and Tampa is presented in Table 3. In general, these trapping densities are far higher than the ones employed by the Animal and Plant Health Inspection Service of the United States Department of Agriculture (APHIS). Given that the model overestimates the number of traps actually deployed, the question is what characteristic of the model appears to be at fault. At the current time, the evidence suggests that our data on trap sensitivity is suspect.

Suggestions for the further refinement of the model follow two general lines. First, the Taylor approach is implicitly based on continuous random variables. Specifically, both x_1 and x_2 in the formulation are continuous random variables that can take on any real number. Thus, the first problem is that the number of Mediterranean flies must be nonnegative. The approximation error introduced by this scaling, however, is probably small. More troubling is that the catching of a Mediterranean fly in a trap is a binary event, such that if $x_2 = 0$, a Mediterranean fly has not been captured, while if $x_2 = 1$, a Mediterranean fly has been captured in the trap. Thus, the probability of capturing a Mediterranean fly is actually a Bernoulli event giving $x_2 = 0$ with probability p and $x_2 = 1$ with probability $1 - p$. To make this formulation consistent with the foregoing model, we would suggest making p a function of the level of the Mediterranean fly infestation. The formulation then becomes

$$(20)\quad f(x_1, x_2|z) = f(x_1)p(x_1, z)^{x_2}[1 - p(x_1, z)]^{1-x_2}.$$

Candidates for $p(x_1, z)$ include the logistic function

$$(21)\quad p(x_1, z) = \frac{\exp(\phi_1 x_1 + \phi_2 z)}{1 + \exp(\phi_1 x_1 + \phi_2 z)},$$

or the same transformed hyperbolic tangent function presented above

$$(22)\quad p(x_1, z) = \frac{1}{2}\{1 + \tanh[G(x_1, z)]\},$$

where $G(x_1, z)$ is a quadratic function.

The second potential difficulty involves the boundary conditions of the formulation. The large number of traps in the optimal solution presented above suggests that the optimal decision would be to forgo trapping and simply

Table 3. Optimal Trap Densities

	Optimal Trap Density	
Month	Miami	Tampa
	(# traps per hectare)	
February	322	465
June	92	82
October	184	248

initiate countermeasures. More precisely, deploying traps would simply be a costly waste of time. A similar problem occurs at the end of the time horizon. What are the implications of failing to observe a Mediterranean fly until the harvest begins? It is possible that the Mediterranean fly larvae are in the fruit, but not detected.

A third potential improvement involves increasing our understanding of the dynamics of the Mediterranean fly population. Specifically, is the logistic model presented in Equations 10 and 11 an adequate representation of the probability of the arrival of new Mediterranean flies? For example, suppose that an affected piece of fruit arrived at the airport, but none of the offspring was captured in a trap. The marginal probability of the total population of Mediterranean flies can then be expressed as $f(x_{1,1})$

$$(23) \quad f(x_{1,1}) \Rightarrow \begin{cases} f(x_{2,1} = 0 \mid x_{1,1}, z) \\ \quad \Rightarrow f(x_{1,1})f(x_{2,1} = 0 \mid x_{1,1}, z) \\ f(x_{2,1} = 1 \mid x_{1,1}, z), \end{cases}$$

where $f(x_{2,1} = 0 \mid x_{1,1}, z)$ is the probability that a Mediterranean fly was not captured given the true population of Mediterranean flies ($x_{1,1} > 0$) and number of traps, and $f(x_{2,1} = 1 \mid x_{1,1}, z)$ is the probability that a Mediterranean fly is caught in the trap under the same conditions. In the former case, the number of Mediterranean flies grows according to population dynamics in addition to the addition of new arrivals

$$(24) \quad f(x_{1,2}) = K[f(x_{1,1})f(x_{2,1} = 0 \mid x_{1,1}, z)] + r,$$

where $K(\cdot)$ represents the population dynamics.

Conclusions and Implications

In this paper, a methodology is developed to determine the optimal monitoring level for agricultural biohazards using the possibility of Mediterranean fly infestations in Florida as an example. We develop a cost minimization model that balances potential cost savings of early detection through increased surveillance against additional cost of treatment. The parameterization of the cost minimization formulation requires a probabilistic formulation of the monitoring system. We then describe our efforts to calibrate the model using ancillary data from a variety of sources, including sample data from airport monitoring and experimental data on the sensitivity of traps. In general, our preliminary results yield higher levels of monitoring than are feasible. Given these results, we propose modifications to the probabilistic formulation that may yield more viable results.

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