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Securing the Border from Invasives: Robust Inspections Under Severe Uncertainty

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Abstract:

Two important features of agricultural quarantine inspections of shipping containers for invasive species at U.S. ports of entry are the general absence of economic considerations and the severe uncertainty that surrounds invasive species introductions. In this article, we propose and illustrate a method for determining an inspection monitoring protocol that addresses both issues. An inspection monitoring protocol is developed that is robust in maximizing the set of uncertain outcomes over which an economic performance criterion is achieved. The framework is applied to derive an alternative to Agricultural Quarantine Inspection (AQI) for shipments of fruits and vegetables as currently practiced at ports of entry in the United States.

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JEL Classification: Q18, Q57, D81

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Abstract: Two important features of agricultural quarantine inspections of shipping containers for invasive species at U.S. ports of entry are the general absence of economic considerations and the severe uncertainty that surrounds invasive species introductions. In this article, we propose and illustrate a method for determining an inspection monitoring protocol that addresses both issues. An inspection monitoring protocol is developed that is robust in maximizing the set of uncertain outcomes over which an economic performance criterion is achieved. The framework is applied to derive an alternative to Agricultural Quarantine Inspection (AQI) for shipments of fruits and vegetables as currently practiced at ports of entry in the United States.

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1. Introduction

At United States ports of entry, the contents of air, maritime, truck, and rail cargo, as well as air passenger baggage, vehicles, and mail are subject to Agricultural Quarantine Inspection (AQI) by the United States Department of Homeland Security (DHS), Customs and Border Protection officials. The purpose of AQI is to help ensure that United States agriculture is protected from accidentally or intentionally introduced pests and diseases, including the possibility of agroterrorism. In general, current practice for inspecting cargo shipments of fruits and vegetables at United States ports is based on inspecting 2% of the items in a container for the presence of pests, with some allowances for the size, contents, and origin of the container (USDA 2008a).

Although simple to apply, this inspection rule appears not to have any economic content; that is, it does not consider the costs of inspections or the losses of failing to prevent an invasive species from entering the country. Nor does it account for the severe uncertainty associated with infestations in shipping containers and the potential losses from introductions of poorly understood or surreptitiously introduced invasive species. In this paper, we propose an alternative decision criterion for determining inspection probabilities that incorporates economic considerations with particular emphasis on the severe uncertainties of pest introductions and damage.

With probability distributions over invasive species introductions and their impacts one could cast the problem of determining optimal inspection rules in the familiar terms of risk analysis. Then it would be relatively straightforward to specify inspections rules that balanced the costs of inspections against the expected benefits of preventing introductions of pests. However, this would require information that policy makers don't possess, cannot obtain at all, or cannot obtain within a timeframe that is useful. In many areas of economic decision making, including the management of invasive species, it is often difficult to measure and interpret probability distributions associated with uncertain outcomes. Consequently, concerns about the usefulness of risk assessment in the management of invasive species are evident among researchers and practitioners alike (Moffitt and Osteen 2006).

Several approaches have been developed to analyze decision making in uncertain environments. These approaches include application of the maximin, maximax, Laplace, and Hurwicz criteria (Render et al. 2009). The first two of these approaches represent polar extremes in terms of optimism and pessimism while the latter two require information similar to probabilities to be applied. Similarly, quantification of other notions related to uncertainty such

as ignorance and surprise have also required the specification of functions confined to the unit interval (Katzner 1998; Horan et al., 2002).[1]

Other decision theory research has focused on the notion of robustness in decision making under uncertainty, but without any information on probabilities. Ben-Haim (2006) has developed a new approach known as information-gap (info-gap) decision theory, which he designed for cases in which probability distributions for uncontrolled events are not available. The essence of info-gap analysis is the pursuit of decisions that are robust in the sense that, roughly speaking, they maximize the range of uncertainty in the decision environment within which the decision maker is certain to achieve a specified performance requirement. One decision is more robust than another if the range of uncertainty under which the performance requirement is met is larger. Given a performance criterion, a robust decision gives the decision maker maximum confidence that his or her performance criterion will be met.[2]

We adopt Ben-Haim's approach to the problem of determining robust inspection protocols for detecting invasive species in imported agricultural goods. In this problem, we are uncertain about the likelihood of the presence of an invasive species in the goods being inspected and the economic impact of inspection failure. Nevertheless, we seek an inspection protocol to

[1] The notion of ambiguity lies in the middle ground between risk and uncertainty. If the likelihood of uncontrolled events can be determined up to a convex set (e.g., ranges of probability values are known), then there is said to be ambiguity about the risks associated with a decision. For such cases, a decision criterion known as maxmin expected utility (Gilboa and Schmeidler 1989) suggests maximizing the minimum expected utility where the expectation is taken over the convex set.

[2] Info-gap decision theory is increasingly applied to real-world applications where probabilities or a convex set of probabilities are hard to identify but acceptable performance is not. Applications include, but are not limited to, financial risk assessment (Ben-Haim 2005), search behavior in animal foraging models (Carmel and Ben-Haim 2005), policy decisions in marine reserve design (Halpern et al. 2006), natural resource conservation decisions (Moilanen et al. 2006), inspection decisions by port authorities to detect terrorist weapons (Moffitt et al. 2005) and invasive species (Moffitt et al. 2007; Moffitt et al. 2008), the choice of environmental policies (Stranlund and Ben-Haim 2008), and engineering model-testing (Vinot et al. 2005).

maximize the set of uncertain outcomes over which the expected loss from an introduction plus the cost of inspections will not exceed a critical value.

The economic literature on invasive species is relatively recent. A bibliography of the economics of agricultural pest control covering the literature through 1980 does not contain a single reference to invasive species (Osteen et al. 1981). Some more recent studies have focused on the economics of managing invasive species once they have been introduced (e.g., White et al. 1995). From a similar perspective, Pimental et al. (2000) provide both background and an economic perspective on invasive species introductions that have occurred in the United States.

However, there is a growing literature that has focused on the prevention of invasive species introductions and preparedness for these events, rather than retrospective analyses of introductions (e.g., Perrings et al. 2000; Shogren 2000; Brown et al. 2002; Barbier and Shogren 2002; Eiswerth and van Kooten 2002; Endress 2002; Horan et al. 2002; Kaiser and Roumasset 2002; Olson and Roy 2002; Perrings et al. 2002; Settle and Shogren 2002). A portion of this literature has focused on border inspections to prevent introductions.[3] McAusland and Costello (2004) present theoretical models of international trade to consider the simultaneous choices of a tariff and inspections to prevent the entry of infested commodities. Surkov et al. (2008) focus on allocating fixed inspection resources across commodities and countries of origin to minimize the expected costs of introduced pests. They apply their model to inspections of chrysanthemum cuttings (*Dendranthema grandiflora*) imported to the Netherlands. Importantly, each of these works relies on known probability density functions, and hence, are models of risk rather than of uncertainty.

[3] Shogren (2000) provides a theoretical model of a policy maker who is charged with allocating resources to reducing the probability of an invasive species event (mitigation) and to reducing the adverse consequences of an introduction (adaptation). One could think of border inspections as part of the set of mitigation strategies, but Shogren is not explicit about this.

Moffitt et al. (2007 and 2008) examine the inspection problem with info-gap models of uncertainty. Moffitt et al. (2007) develop a robust sample size for a risk averse decision maker faced with inspecting a generic shipping problem in which a shipment may contain at most a single contaminated item. Moffitt et al. (2008) evaluate the relative robustness of alternative inspection rules for a risk neutral decision maker when the number of contaminated items can vary, but they assume that the loss when an invasive pest gets past port inspections is known. We extend this work in two important directions. First, we allow several elements of the inspection problem to be uncertain including the number of contaminated items in a shipment, the costs of inspections, and potential losses due to inspection failure. Second, we use recently available unpublished data provided by the U. S. Department of Homeland Security to illustrate the potential of our model to determine robust inspection rules.

We demonstrate the utility of our approach by comparing robust inspection rules to the AQI 2% rule. We find that optimal inspection rules provide significant increases in robustness over the AQI rule over a wide range of feasible performance criteria. Moreover, robust inspection rules suggest significantly more scrutiny of incoming shipments than the AQI rule. This suggests a reallocation of federal resources to more intense inspections and away from efforts to deal with invasives that get through the inspection process.

The rest of the paper proceeds as follows. We present the model of choosing inspection rules that are maximally robust to the uncertainty in the problem of detecting invasive species at ports. In the third section we apply the model with data about shipments that are subject to AQI, costs of inspections, and funds allocated to deal with pest introduction and outbreaks. The third section also contains our comparison of robust inspection rules to the AQI 2% rule. We conclude in the fourth section.

2. A Model of Robust Inspections for Invasive Species

Suppose that a single containerized shipment selected for inspection at a maritime port of entry contains N boxes. Inspection of n of the boxes for the presence of invasives is intended to determine whether the contents of the shipment are infested. Inspection failure is defined to mean that there is an infested box in the shipment that is not detected; hence, under this assumption, failure cannot occur if either there are no infested boxes in the shipment or if all of the boxes in the shipment are infested. To simplify the analysis of the inspection protocol, we assume that if a box is inspected the presence of an invasive will be detected. Inspection failure—an undetected entry of an invasive species—generates a loss L. The loss due to inspection failure depends on which invaders are involved, how hard the invaders are to manage following inspection failure, and what the consequences of immigration are. Because each of these elements can be highly uncertain, we regard L as highly uncertain. Additionally, a linear function, cn, gives the cost of inspection where c is a parameter reflecting a constant per box inspection cost which can depend on a number of factors and can also be regarded as uncertain.[4]

If the number of infested boxes in a container is $s > 0$, then the probability of inspection failure is given by the ratio of binomial coefficients,

$$\binom{N-s}{n} \Big/ \binom{N}{n};$$

that is, the ratio of the number of possible samples of size n which do not contain an infested box to the total number of possible samples of size n. If $s = 0$, then the probability of inspection failure is also zero as just noted.

[4] The inspection cost function need not be linear for the model development, but we assume that it is linear in our simulations in the next section. We also recognize that inspection strategies may involve significant fixed costs. These costs do not affect our analysis so we ignore them for simplicity.

The number of infested boxes in a container, if any, is uncertain, as is the potential loss from an inspection failure, and perhaps marginal inspection costs. Define the set $\mathcal{S}$ = {0, 1, 2, . . . , N} to depict the possible number of infested boxes in the container. Similarly let the set $\mathcal{L}$ = {0, 1, 2, . . .} be potential losses (in dollars) associated with inspection failure, and let the set $\mathcal{C}$ = {.01, .02, . . .} to be the possible cost in dollars of inspecting a box. In this case, an info-gap uncertainty model, $\mathcal{U}$, is a countable, non-convex set given by the power set of the cross product of $\mathcal{S}$, $\mathcal{L}$, and $\mathcal{C}$; viz.; $\mathcal{U} = \mathcal{P}(\mathcal{S} \times \mathcal{L} \times \mathcal{C})$.

For $s > 0$ and a given L and c, expected loss plus inspection cost is

$$\left[\binom{N-s}{n}\Big/\binom{N}{n}\right]L + cn.$$

If $s = 0$ given c, expected loss due to undetected entry plus inspection cost is cn. Hence, conditional on N, n, s, L, and c, expected loss due to undetected entry plus inspection cost can be expressed as

$$E\left[Cost \mid N, n, s, L, c\right] = \begin{cases} cn, \text{ if } s = 0; \\ \left[\binom{N-s}{n}\Big/\binom{N}{n}\right]L + cn, \text{ if } 0 < s \le N. \end{cases}$$

For $s > 0$ and a given L and c, the variance of loss plus inspection cost is

$$\left[\binom{N-s}{n}\Big/\binom{N}{n}\right]\left[1 - \binom{N-s}{n}\Big/\binom{N}{n}\right]L^2.$$

If $s = 0$ the variance of loss due to undetected entry plus inspection cost is 0. Hence, conditional on N, n, s, L, and c, the variance of loss due to undetected entry plus inspection cost can be expressed as

$$Var\left[Cost \mid N,n,s,L,c\right]=\begin{cases}0, \text{ if } s=0;\\ \left[\binom{N-s}{n}\Big/\binom{N}{n}\right]\left[1-\binom{N-s}{n}\Big/\binom{N}{n}\right]L^2, \text{ if } 0<s\le N.\end{cases}$$

Our objective is to provide an inspection protocol that is as applicable as AQI in addition to being most robust in meeting a performance requirement. To maintain equivalent simplicity to AQI, both conditional expected cost and the conditional variance of cost are respecified in terms of a constant percentage of items subjected to physical inspection; viz.,

[1] $$E\left[Cost \mid p,N,s,L,c\right]=\begin{cases}cr(pN), \text{ if } s=0;\\ \left[\binom{N-s}{r(pN)}\Big/\binom{N}{r(pN)}\right]L+cr(pN), \text{ if } 0<s\le N;\end{cases}$$

[2] $$Var\left[Cost \mid p,N,s,L,c\right]=\begin{cases}0, \text{ if } s=0;\\ \left[\binom{N-s}{r(pN)}\Big/\binom{N}{r(pN)}\right]\left[1-\binom{N-s}{r(pN)}\Big/\binom{N}{r(pN)}\right]L^2, \text{ if } 0<s\le N,\end{cases}$$

where p is percentage of items inspected and $r(\cdot)$ denotes rounding to the nearest integer.

We now use [1] and [2] to characterize expected costs and variance of the total annual shipments T into a country. Let $f(N)$ be the annual relative frequency of containers of size N. Annual expected loss plus inspection cost for all shipments is

[3] $$M\left(p,s,L,c\right)=\sum\nolimits_N E\left[Cost \mid p,N,s,L,c\right]\cdot f(N)\cdot T.$$

The variance of annual loss plus inspection cost is

[4] $$V\left(p,s,L,c\right)=\sum\nolimits_N Var\left[Cost \mid p,N,s,L,c\right]\cdot f(N)\cdot T^2.$$

Both $M\left(p,s,L,c\right)$ and $V\left(p,s,L,c\right)$ can be used to specify performance of a constant percentage inspection protocol like AQI. If performance is judged solely in terms of limiting expected loss from invasives plus inspection costs, then an inspection protocol is judged on its ability to satisfy $M\left(\cdot\right)\le M^*$, where M^* is predetermined. If performance is also regarded as depending on

limiting variability of expected loss plus inspection cost then an inspection protocol is judged with respect to $M(\cdot) \le M^*$ and $V(\cdot) \le V^*$, where V^* is also predetermined.

Now let us define robustness with respect to possible performance criteria. Let α be an element of $\mathcal{U} = \mathcal{P}(\mathcal{S} \times \mathcal{L} \times \mathcal{C})$, and let $\hat{\alpha}$ denote the number of elements (i.e., the cardinality) of α. Robustness, denoted $\hat{\alpha}(p)$, expresses the size of the largest set in $\mathcal{P}(\mathcal{S} \times \mathcal{L} \times \mathcal{C})$ with satisfactory performance as a function of the percentage of boxes inspected, *p*. An inspection protocol p^0 is more robust than p^1 $\left(\text{i.e., } \hat{\alpha}(p^0) > \hat{\alpha}(p^1)\right)$ in the sense that the specified performance criteria are satisfied under a larger set of possible outcomes under p^0 than under p^1. If the performance criterion is a limit M^* on expected loss from invasives plus inspection cost then

[5] $\hat{\alpha}(p) = \max|\alpha|, \text{ s.t. } M(p,s,L,c) \le M^*.$

If, in addition to $M(\cdot) \le M^*$, a limit on the variance of loss plus inspection costs is desired, then

[6] $\hat{\alpha}(p) = \max|\alpha|, \text{ s.t. } M(p,s,L,c) \le M^*,\ V(p,s,L,c) \le V^*.$

In either case, the optimal robust inspection strategy is the constant percentage of inspected containers $p^* = \arg\max \hat{\alpha}(p)$.

3. Agricultural Quarantine Inspections, Robustness, and Performance

In this section we demonstrate the utility of the model by determining robust inspection protocols with data on various aspects of U.S. port inspections for invasives in fruit and vegetable shipments. We determine robust constant percentage inspection rules for shipping containers to compare to the current AQI protocol (the 2% inspection rule).

3.1 Approach and data

For our simulations, we modify the problem so that our results will be in terms of the proportion of infested boxes instead of the number of infested boxes. This modification makes the interpretation of our results somewhat easier. Let w be the proportion of infested boxes in a shipping container, and note that the corresponding number of infested items is $s = r(wN)$, where recall that r indicates rounding to the nearest integer. Define the set $\mathcal{W}$ = {0, .01, .02, ..., 1}; that is, the set of discrete proportions in 0.01 unit increments from zero to 1. Our simulation replaces the set of potential infested items $\mathcal{S}$ in the model development with the set $\mathcal{W}$.

Our first task is to construct an estimate of the mean and variance of expected loss plus inspection costs (equations [3] and [4]), modified so that potential infestations are in percentage terms. We take $f(N)$ from the relative frequency of boxes per container in a sample of 893 shipments subject to AQI inspection at maritime ports of entry in the United States from 2004-2006 (the most recent years for which data are available). This frequency distribution is shown in Table 1. Average total shipments subject to physical inspection under AQI during this period provides an estimate for T of 496,265 shipments. See United States Department of Agriculture (2008b) for these data.

Although the model allows unit inspection costs to be uncertain, we have a reasonable point estimate for this value. Regardless of port and/or commodity, a typical inspection costs approximately $1.70 per box. This cost estimate is based on the typical time required to inspect fruit and vegetable commodities packaged in boxes and the government service pay scale in effect for inspectors during 2009. (Personal communication, Rojelio Lozano, U.S. Department of

Homeland Security). For our simulation exercise we take this inspection cost value as certain and specify the set $\mathcal{C}$ as simply $\mathcal{C}$ ={1.70}. In contrast, the set of potential losses is highly uncertain. We specify the set of potential losses as $\mathcal{L}$ = {0, 1×10^6, 2×10^6, … , 500×10^6}.

We now turn to specifying the performance criteria, M^* and V^*, in equation [6]. Recall that the specifications of M^* and V^* are choice variables for the decision maker; they are not determined from the model, so they rely on the judgments of decision makers as to what constitutes acceptable performance. We use real USDA/APHIS annual emergency program expenditures, shown in Table 2 for 1987-2008, to help specify possible performance criteria (USDA 2008c).[5] The amounts in the table are transfers from contingency funds for unforeseen pest introductions or outbreaks that threaten agricultural production. These funds are not necessarily all due to inspection failures, nor do they include all pest losses to agricultural producers, landowners, and others. Thus, there is not a one-to-one correspondence between these values and potential losses from inspection failures. However, we think they are useful because the variation in annual expenditures allow us to specify a wide range of performance criteria. Moreover, these emergency fund expenditures give us a basis for casting our results in terms of the trade off between allocating resources to inspections to prevent introductions and allocating resources to deal with the consequences of inspection failures.

We specify M^* as an estimate of variable inspection costs under AQI plus alternative levels of emergency program expenditures from the distribution given in Table 2. For variable inspection costs, the density function $f(N)$ from the data in Figure 1 combined with T = 496,265

[5] APHIS is the acronym for the USDA's Animal and Plant Health Inspection Service. We use the Producer Price Index averaged over fiscal years to convert nominal emergency funds to real values. The baseline year is 2007.

shipments gives us a mean for the annual number of boxes subject to AQI inspections of 586.306×10^6 with variance 846.593×10^{26}. These values, our estimate of variable per-box inspection costs of \$1.70 and the AQI rule of inspecting 2% of boxes in a container produces an estimated annual variable inspection cost of $\$(1.70)r(0.02\times586.306\times10^6)\approx19.934\times10^6$, with variance $\$(1.70)^2 r(0.04\times846.593\times10^{26})$.

Our analysis is conducted with six levels of M^*. The variable inspection cost estimate is the same for each level, but we use six levels of real USDA/APHIS emergency expenditures. We use the mean of the distribution in Table 2 of $\$93.813\times10^6$, as well as the upper bounds of the quintiles of the distribution; $\$24.872\times10^6$, $\$36.343\times10^6$, $\$52.089\times10^6$, $\$159.031\times10^6$, and $\$470.883\times10^6$. In addition, we also specify V^* as an additional performance criterion as in [6]. This value is set at the variance of annual inspection costs, specified above, plus the variance of the real USDA/APHIS emergency expenditures which is $\$12.786\times10^9$. The variance performance criterion is held constant as M^* varies. For all of the results reported below, the variance performance criterion does not bind.

3.2 Results

Table 3 shows the optimal robust inspection rules and levels of robustness for alternative levels of performance in terms of M^* as well as the robustness levels of the AQI 2% rule. In the table M_i^*, i = 1, …, 5, are variable inspections costs plus the top boundary of the ith quintile of the distribution of real USDA/APHIS emergency funds. M^*_{mean} is variable inspection costs plus the mean of the distribution of real USDA/APHIS emergency funds.

The last two columns of Table 3 give the robustness measures of the optimal inspection rules and the AQI rule for the various performance criteria. Recall that robustness is the

cardinality of the largest element of the power set of the cross product of $\mathcal{W}$ and $\mathcal{L}$ under which a performance criterion is met. Thus, robustness is the number of potential outcomes in terms of discrete losses from undetected infestations and infestation percentages for which the performance criterion is met. For all performance criteria analyzed (except for M^*_{AQI} which will be explained shortly), robustness under the optimal inspection rule is greater than under the AQI rule. This, of course, is by design because the optimal inspection rule maximizes robustness. It is more interesting that the optimal inspection rules are much more robust than the AQI rule; robustness under the optimal inspection rule ranges from more than 2.36 times greater than under the AQI rule for M^*_1, to nearly 4.5 times greater for M^*_4. At M^*_{mean} the optimal inspection strategy is about 4.12 times as robust as the AQI 2% inspection rule. The AQI rule, which recall is devoid of the economic and uncertainty characteristics of the problem of detecting invasive species, is simply not very robust over a wide range of reasonable levels of economic performance.

A graphical depiction of the relative robustness of the optimal inspection protocol and the AQI inspection protocol is provided in Figure 1. The robustness "curves" in the figure are derived under the assumption that the performance criterion is M^*_{mean}. The left curve collects pairs of infestation rates and potential losses (w, L) for which M^*_{mean} is met exactly under the robust optimal inspection rate of 11%. Pairs of (w, L) to the right of this curve also meet the performance requirement under this inspection rule. We can think of the curve and the area to its right as a sort of "safety zone" in the sense that the decision maker is certain that the performance requirement is satisfied for all (w, L) outcomes in this zone. The right curve in Figure 1 is the boundary of the safety zone for the M^*_{mean} performance requirement, but under the

AQI inspection rule of 2%. Given our limit on L ($500 million), it is clear that the safety zone under the optimal robust inspection rule is much larger than under the AQI rule.

In addition, the safety zone under the AQI inspection rule is a proper subset of the safety zone under the robust optimal inspection rule. This is a desirable attribute because it implies that every outcome that meets the performance criterion under the AQI inspection strategy also meets the performance criterion under the robust optimal inspection strategy. We caution the reader that this is not a general result; that is, it is possible that the robustness curves could cross for some parameters of the problem or for some other application.

Let us now return to the results in Table 3. The change in maximum robustness levels for $M_1^*,...,M_5^*$ reveals a fundamental tradeoff between robustness and performance: robustness decreases with a more stringent performance requirement (i.e., lower M^* in this application). This reflects the fact that the circumstances under which a performance criterion is met are fewer if we insist on better performance. Although not seen in Table 3 it is easy to demonstrate that robustness is zero for $M^* = 0$ indicating that a decision maker has no confidence in limiting expected costs to zero. Greater robustness only comes from tolerating higher expected costs.

The second and third columns of Table 3 reveal that the optimal inspection strategies for $M_1^*,...,M_5^*$, and M_{mean}^* involve more inspections than the AQI 2% rule. Thus, for this range of performance criteria, greater robustness is achieved by more intense inspections than under AQI. Noting that the optimal inspection rule is monotonic in the performance criteria for this application, we asked whether there is a performance criterion at which the 2% rule maximizes robustness. This performance criterion does exist and it is approximately $M_{AQI}^* \approx \$22.286\times10^6$. Given variable inspection costs of about $\$19.934\times10^6$, M_{AQI}^* allows for emergency funds of only $\$2.352\times10^6$. Note that this is lower than all of the emergency fund allocations in Table 2. This

suggests that the AQI inspection rule is optimally robust only for unrealistically low performance criteria.

The data in Table 3 also reveal important information about how robustness is achieved with inspections. For now, focus on one performance criterion, say M^*_{mean}. That optimal inspections are substantially higher than AQI inspections under this performance criterion indicates that expected losses from introductions must be significantly less to hold variable inspection costs plus expected introduction losses to M^*_{mean}. The higher inspection percentage associated with the optimal robust protocol enables detections of much lower infestations, which reduces the chance of inspection failure and the expected losses due to inspection failure. The cost saving due to preventing inspection failure more than compensates for the added inspection cost. The tradeoff between lower expected introduction losses and higher inspections costs can be dramatic. At the performance criterion M^*_{mean}, the variable costs of optimal inspections (11%) total $\$109.639\times10^6$ and expected emergency fund expenditures are only $\$4.108\times10^6$, or about 3.7% of the performance criterion. Under the 2% inspection rule with variable inspection costs of $\$19.934\times10^6$, expected emergency fund allocations are limited to $\$93.813\times10^6$ under M^*_{mean}, or about 82.5% of the performance criterion. As noted above, the former inspection strategy is much more robust than the AQI strategy. Thus, robust optimality appears to call for a shift in resources toward more inspections and away from emergency fund allocations to deal with invasive species introductions. [6]

[6] That optimal inspection rates increase with the performance criterion in Table 3 is a further reflection of how maximizing robustness calls for shifting expenditures to more inspections. We should note, however, that the relative proportions of inspection costs and expected emergency expenditures do not change monotonically as the performance criterion is increased. In general, it is worth noting that the comparative static results in Table 3 are limited to our simulation exercise and should not be taken as general results.

4. Conclusion

We have proposed a protocol for determining inspection strategies for detecting invasive species in shipments of fruits and vegetables that considers the costs of inspections and potential losses from undetected introductions, but does not rely on probability distributions that real decision makers often lack. This protocol is to choose an inspection strategy that is robust in the sense that it maximizes the set of possible outcomes under which a performance criterion is met. We use this protocol to evaluate the robustness of the current practice of inspecting 2% of items in shipping containers of fruits and vegetables at U.S. ports. For a wide range of performance criteria the 2% rule is simply not very robust to the substantial uncertainty that characterizes the problem of preventing some invasive species introductions.

Moreover, our calculations of robust optimal inspection rules suggests that a shift of resources toward more inspections and away from allocating funds to deal with invasives that get past the inspection process may be justified. Currently, agricultural inspections are funded from AQI user fees collected when international passengers and conveyances (trucks, commercial vessels, rail cars, and aircraft) enter the United States. These fees are split between DHS and USDA's Animal and Plant Health Inspection Service (APHIS), with DHS receiving about 60 percent. The U.S. Government Accountability Office (USGAO 2008) estimated that the current cost of inspecting commercial vessels is considerably less than total fees collected. Increasing the agricultural inspection rate would require that a greater proportion of AQI user fees be allocated to inspections or an increase in funding to cover the costs of the greater workload. An increase in funding could require congressional action to increase budget appropriations or identify alternative funding sources.

Our protocol for determining robust optimal inspection rules can be used to address important issues about agricultural inspections that the U.S. Government Accountability Office has raised over the years. Since the protocol can be applied to poorly understood or surreptitiously introduced organisms for which probabilities are not easily available, it can address concerns about detecting new pests and agro-terrorism threats during inspection (USGAO 2005 and 2007). By suggesting higher sampling rates than currently used under a wide range of performance criteria, the protocol can address concerns about inspection reliability raised by declining interceptions as import shipments increased (USGAO 1997, 2005, and 2007).

Although our work is motivated by detecting invasive species in fruit and vegetable shipments, this same approach is applicable to an increasingly wide range of detection problems where uncertainty is severe and effective use of scarce inspection resources is required. Useful applications of this approach likely include border inspections for smuggled contraband, general law enforcement problems, and the early detection and control of infectious diseases.

Table 1: Frequency Distribution of Boxes per Shipment Subject to AQI Inspections, United States Maritime Ports, 2004-2006.

Boxes per Shipment	Shipments	Percent
0-500	23	2.6%
500-1000	328	36.6%
1000-1500	385	42.9%
1500-2000	99	11.0%
2000-2500	34	3.8%
2500-3000	28	3.1%
Total sample shipments	897	100.0%

Source: United States Department of Agriculture (2008b)

Table 2: Total USDA/APHIS Emergency Program Funds, Plant Pests, 1987-2007*

Year	Costs (millions of 2007 dollars)	Year	Costs (millions of 2007 dollars)
1987	9.647	1998	36.343
1988	6.940	1999	52.089
1989	13.730	2000	176.562
1990	44.096	2001	250.455
1991	9.802	2002	93.523
1992	26.914	2003	97.414
1993	24.872	2004	117.779
1994	27.497	2005	232.169
1995	26.753	2006	470.883
1996	48.249	2007	159.031
1997	45.325		

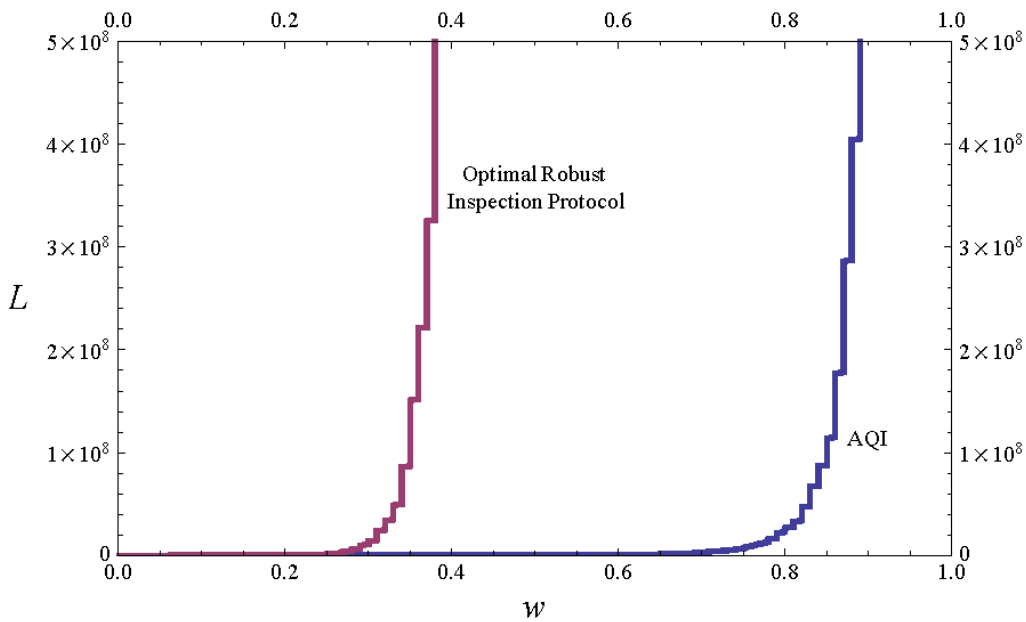
*Important pests (in order of allocated funds): citrus canker, Mediterannean fruit fly, emeral ash borer, asian longhorned beetle, karnal bunt, Pierce's disease/GWSS, sudden oak death, asian gypsy moth, grasshopper and morman cricket, potato cyst nematode, Mexican/oriental/olive/west Indian fruit flies, plum pox virus, and others.

Source: United States Department of Agriculture (2008c)

Table 3: AQI and Optimal Robust Inspection Rules

Performance Criterion (Millions$)	Percent Boxes Inspected		Robustness	
	Optimum	AQI	Optimum	AQI
$M^*_{mean} = 113.747$	11%	2%	33027	7961
$M^*_1 = 44.806$	4%	2%	15106	6394
$M^*_2 = 56.277$	5%	2%	18826	6766
$M^*_3 = 72.023$	7%	2%	24694	7173
$M^*_4 = 178.965$	16%	2%	39195	8734
$M^*_5 = 490.817$	47%	2%	47453	10484
$M^*_{AQI} \approx 22.286$	2%	2%	5063	5063

Figure 1: "Safety Zones" of Optimal Robust Inspections and AQI Inspections



References

Barbier, E. B., and J. F. Shogren. 2002. "Growth with Endogenous Risk of Biological Invasion." Paper presented at the 77th Annual Western Agricultural Economic Association International Conference, Seattle, WA.

Ben-Haim, Y. 2005. “Value at Risk with Info-Gap Uncertainty.” *Journal of Risk Finance* 6: 388 403.

Ben-Haim, Y. 2006. *Info-Gap Decision Theory: Decisions Under Severe Uncertainty*. Second Edition. Amsterdam: Academic Press.

Brown, C., L. Lynch, and D. Zilberman. 2002. "The Economics of Controlling Insect-Transmitted Plant Diseases." *American Journal of Agricultural Economics*. 84: 279-291.

Carmel, Y. and Y. Ben-Haim. 2005. Info-gap Robust-Satisficing Model of Foraging Behavior: Do Foragers Optimize or Satisfice? *American Naturalist* 166: 633-641.

Eiswerth, M. E., and G. C. van Kooten. 2002. "Uncertainty, Economics and the Spread of an Invasive Plant Species." *American Journal of Agricultural Economics* 84: 1317-1322.

Endress, L. H. 2002. "Terrorism and the Economics of Biological Invasions." Paper presented at the 77th Annual Western Agricultural Economic Association International Conference, Seattle, WA.

Gilboa, I., and D. Schmeidler. 1989. "Maxmin Expected Utility with a Non-Unique Prior." *Journal of Mathematical Economics* 18: 141-153.

Halpern, B. S., H. M. Regan, H. P. Possingham, and M. A. McCarthy. 2006. Accounting for Uncertainty in Marine Reserve Design. *Ecology Letters* 9: 2-11.

Horan, R. D., C. Perrings, F. Lupi, and E. H. Bulte. 2002. “Biological Pollution Prevention Strategies Under Ignorance: The Case of Invasive Species." *American Journal of Agricultural Economics*. 84: 1303-1310.

Kaiser, B., and J. Roumasset. 2002. "Optimal Public Control of Exotic Species: Preventing the Brown Tree Snake from Invading Hawaii." Paper presented at the 77th Annual Western Agricultural Economic Association International Conference, Seattle, WA.

Katzner, D. W. 1998. *Time, Ignorance, and Uncertainty in Economic Models*. Ann Arbor, Michigan: The University of Michigan Press.

McAusland, C. and C. Costello. 2004. “Avoiding Invasives: Trade-Related Policies for Controlling Unintentional Exotic Species Introductions.” *Journal of Environmental Economics and Management* 48: 954-977.

Moilanen, A. and B. A. Wintle. 2006. “Uncertainty Analysis Favours Selection of Spatially Aggregated Reserve Structures.” *Biological Conservation* 129: 427-434.

Moffitt, L. Joe, and Craig D. Osteen. 2006. "Prioritizing Invasive Species Threats Under Uncertainty." *Agricultural and Resource Economics Review* 35: 41-51.

Moffitt, L. J., J. K. Stranlund, and B. C. Field. 2005. “Inspections to Avert Terrorism: Robustness Under Severe Uncertainty.” *Journal of Homeland Security and Emergency Management* 2: No. 3, Article 3.

Moffitt, L. J., J. K. Stranlund, B. C. Field, and C. D. Osteen. 2007. “Robust Inspection for Invasive Species with a Limited Budget.” In A. O. Lansink, ed. *New Approaches in the Economics of Plant Health.* Amsterdam: Springer.

Moffitt, L. J., J. K. Stranlund, and C. D. Osteen. 2008. “Robust Detection Protocols for Uncertain Introductions of Invasive Species.” *Journal of Environmental Managemen*t 89: 293|299.

Olson, L., and S. Roy. 2002. "The Economics of Controlling a Stochastic Biological Invasion." *American Journal of Agricultural Economics* 84: 1311-1316.

Osteen, C. D., E. B. Bradley, and L. J. Moffitt. The Economics of Agricultural Pest Control: An Annotated Bibliography, 1960-1980. United States Department of Agriculture, Economic Research Service, Bibliographies and Literature of Agriculture Series No. 14 (January, 1981).

Perrings, C., M. Williamson, and S. Dalmazzone., eds. 2000. *The Economics of Biological Invasions*. Cheltenham, UK: Edward Elgar.

Perrings, C., M. Williamson, E. B. Barbier, D. Delfino, S. Dalmazzone, J. Shogren, P. Simmons, and A. Watkinson. "Biological Invasion Risks and the Public Good: An Economic Perspective." *Conservation Ecology* 6(2002): http://www.consecol.org/vol6/iss1/art1.

Pimental, D., L. Lach,, R. Zuniga, and D. Morrison. 2000. "Environmental and Economic Costs of Nonindigenous Species in the United States." *Bioscience* 50: 53-67.

Render, B.; R. M. Stair Jr. and M. E. Hanna. 2009. *Quantitative Analysis for Management*. Tenth edition. Pearson Education, Inc. Upper Saddle River, NJ.

Settle, C., and J. F. Shogren. 2002. "Modeling Native-Exotic Species within Yellowstone Lake." *American Journal of Agricultural Economics* 84: 1323-1328.

Shogren, J.F. 2000. "Risk Reduction Strategies Against the 'Explosive Invader." M. Perrings, M. Williamson, and S. Dalmazzone, eds. *The Economics of Biological Invasions.* Cheltenham, UK: Edward Elgar, pp. 56-69.

Stranlund, J. K. and Y. Ben-Haim. 2008. “Price-Based vs. Quantity-Based Environmental Regulation under Knightian Uncertainty: An Info-Gap Robust Satisficing Perspective.” *Journal of Environmental Management* 87, 443–449.

Surkov, I.V., A. G. J. M. Oude Lansink, O. van Kooten, and W. van der Werf. 2008. “A Model of Optimal Import Phytosanitary Inspection under Capacity Constraint.” *Agricultural Economics* 38: 363-373.

United States Department of Agriculture, Animal and Plant Health Inspection Service. 2008a. *Regulating the Importation of Fresh Fruits and Vegetables.* http://www.aphis.usda.gov/ppq/manuals/port/FV_Chapters.htm.

United States Department of Agriculture, Animal and Plant Health Inspection Service. 2008b. Unpublished Plant Protection and Quarantine-280 data.

United States Department of Agriculture, Animal and Plant Health Inspection Service. 2008c. Unpublished Agricultural Quarantine Inspection Monitoring data.

United States Government Accountability Office. 2008. *Federal User Fees: Substantive Reviews Needed to Align Port-Related Fees with the Programs They Support*. GAO-08-321, February.

United States Government Accountability Office. 2007. *Agricultural Quarantine Inspection: Management Problems May Increase Vulnerability of U.S. Agriculture to Foreign Pests and Diseases*. GAO-08-96T, October.

United States Government Accountability Office. 2005. *Homeland Security: Much Is Being Done to Protect Agriculture from a Terrorist Attack, but Important Challenges Remain*. GAO-05-214, March.

United States General Accounting Office. 1997. *Agricultural Inspection: Improvements Needed to Minimize Threat of Foreign Pests and Diseases*. GAO/RCED-97-102, May.

Vinot, P., S. Cogan, and V. Cipolla. 2005. “A Robust Model-Based Test Planning Procedure.” *Journal of Sound and Vibration* 288: 571-585.

White, J. M., P. G. Allen, L. J. Moffitt, and P. P. Kingsley. 1995. "Economics of an Areawide Program for Biological Control of the Alfalfa Weevil." *American Journal of Alternative Agriculture* 10: 173-179.