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DETECTION CAPACITY, INFORMATION GAPS AND THE DESIGN OF SURVEILLANCE PROGRAMS FOR INVASIVE FOREST PESTS

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Abstract

Integrated pest risk maps and their underlying assessments provide broad guidance for establishing surveillance programs for invasive species, but they rarely account for knowledge gaps regarding the pest of interest or how these can be reduced. In this study we demonstrate how the somewhat competing notions of robustness to uncertainty and potential knowledge gains could be used in prioritizing large-scale surveillance activities. We illustrate this approach with the example of an invasive pest recently detected in North America, *Sirex noctilio* Fabricius. First, we formulate existing knowledge about the pest into a stochastic model and use the model to estimate the expected utility of surveillance efforts across the landscape. The expected utility accounts for the distribution, abundance and susceptibility of the host resource as well as the value of timely *S. noctilio* detections. Next, we make use of the info-gap decision theory framework to explore two alternative pest surveillance strategies. The first strategy aims for timely, certain detections and attempts to maximize the robustness to uncertainty about *S. noctilio* behavior; the second strategy aims to maximize the potential knowledge gain about the pest via unanticipated (i.e., opportune) detections. The results include a set of spatial outputs for each strategy that can be used independently to prioritize surveillance efforts. However, we demonstrate an alternative approach in which these outputs are combined via the Pareto ranking technique into a single priority map that outlines the survey regions with the best trade-offs between both surveillance strategies.

Keywords:

Info-gap, *Sirex noctilio*, robustness, opportuneness, invasion model, spatial simulation, Pareto frontier, multi-criteria ranking

1. INTRODUCTION

Non-indigenous invasive species are a universally recognized problem, causing significant environmental changes (Clavero and Garcia-Berthou 2006; Mack et al. 2000; Meyerson and Reaser 2003; Strayer et al. 2006) and large-scale economic damages (Perrings et al. 2002; Pimentel et al. 2001, 2005) worldwide. Most introductions of new species have been attributed to global trade (Costello and McAusland 2003; Jenkins 1996; Levine and D'Antonio 2003; Perrings et al. 2005), with some proportion of these new species becoming established, invasive pests (Williamson and Fitter 1996). However, the flow of potential pests into novel geographic areas via trade (or any other pathway) cannot be stopped completely by existing phytosanitary standards (e.g., the World Trade Organization Agreement on the Application of Sanitary and Phytosanitary Measures, FAO-IPPC 2005; Margolis et al. 2005) or biosecurity procedures (e.g., Cook and Fraser 2008; Reaser et al. 2008; Waugh 2009), so post-border surveillance for non-indigenous species remains a critical task. For example, in 2007 the United States Department of Agriculture (USDA) allocated $US 1.2 billion for management of invasive species, with approximately 22% directed for early detection and rapid response activities (NISC 2007). A considerable portion of such costs is spent on large-scale pest surveillance programs (Tobin 2008).

An effective post-border surveillance program for a new invasive organism should ideally achieve two main goals. First, the program should facilitate sufficiently rapid detection of emerging outbreaks so that relevant agencies can implement appropriate response measures. Another important but less acknowledged objective is that the program should reduce the impact of uncertainties about the target pest's behavior in its new environment based on observations accumulated through time. The intensity and spatial pattern of a pest surveillance program is usually determined by various factors such as the distribution of hosts, possible pathways of the pest's introduction and spread (Kenis et al. 2009; Hulme 2009; Hulme et al. 2008), anticipated economic and environmental consequences, and the public response to invasion (Frankel 2008; Poland and McCullough 2006).

Consider a hypothetical scenario where a regulatory agency is mandated to organize a large-scale surveillance program in response to the recent introduction of a new pest, despite knowing little about its behavior and the level of threat it presents to an identified group of hosts. To help in this effort, the agency employs an invasion risk model that is parameterized using whatever information is available about the pest. The model forecasts the expansion of the pest from a few currently known locations to a set of sites i within a region of interest, each of which is assigned a probability, p_i, and corresponding standard deviation, $\sigma(p_i)$, that it will be invaded within a time period, t_{max}. If the behavior of the pest happens to be well known (i.e., $\sigma(p_i)$ values are generally low compared to p_i), then the most logical configuration for a network of survey locations would emphasize sites with high p_i values or at the anticipated front of the invasion at t_{max}. However, when knowledge about the pest is scarce, two strategies can be considered. One effective strategy to reduce uncertainty would be a survey configuration that prioritizes sites with the highest $\sigma(p_i)$ values (Yemshanov et al. 2010). However, a different perspective is possible: If knowledge is scarce, then any unanticipated finds of the pest at locations perceived as "safe" (i.e., having low p_i) would also be considered successes, since they will enhance knowledge of the pest's behavior in its new environment. In short, the design of an effective survey network can be perceived as a trade-off between these two strategies, where the appropriate choice depends on the amount of information available about the pest.

1.1. Species of Concern.

In this study, we focus on a non-indigenous forest pest (*Sirex noctilio* Fabricius) that was recently discovered in eastern North America and has subsequently expanded its range. Most sub-boreal and temperate regions in eastern North America are believed to be climatically suitable for the species (Carnegie et al. 2006), and it is considered a serious threat to pine (*Pinus* spp.) forests throughout this region (Borchert et al. 2007; Corley et al. 2007; Haugen 2006). Most quantitative knowledge about its ecology is based on experiences in the Southern Hemisphere, where *S. noctilio* is a pest attacking plantations of introduced pines. There is still vast uncertainty regarding the insect's behavior in North America, yet there is a need to devise a monitoring program in order to ascertain the scope of the invasion and the actual ecological/economic impact on pine forest and craft an appropriate response strategy.

1.2. Study Concept.

The basic concept of the analysis is as follows. We first use a spatial stochastic simulation model that formulates our assumptions (along with their corresponding uncertainties) about the pest's behavior in our region of interest. The model projects the dynamic spread of the pest through the landscape as a two-dimensional map. Based on the stochastic maps of the invasion, we estimate the outcome of survey efforts as a time lag between the pest's arrival at a given map location and its first detection. This information is then used to calculate the expected utility of a survey effort at that map location. The utility values account for both the benefits of timely detections and the abundance of susceptible host.

Finally, we use the info-gap decision theory framework (Ben-Haim 2006) to explore the two surveillance strategies alluded to earlier: (1) maximizing the chance of sufficiently rapid detections given the uncertainties about the pest's behavior, and (2) maximizing the network's potential to reduce uncertainties about the pest via unanticipated finds. While we are uncertain about the likelihood that the pest is present at any given location and the odds of its detection, we seek a survey pattern that maximizes the range of uncertainty over which the expected benefits of successful detection will nevertheless be gained. Compared to surveillance allocations that are based on maximization of the detection rate or cost minimization criteria, our approach focuses on the potential knowledge gaps about the pest and thus generates survey designs that are less influenced by risk preferences or biases that often exist in expert-driven prescriptions (Ouchi 2004).

Briefly, info-gap theory formulates the problem of uncertainty in terms of a gap between what is known and what has to be known in order to make reliable assessments. Compared to other decision methods that maximize the potential utility of the outcome by exhaustively exploiting the best-estimated data and models, the info-gap approach focuses on the robustness of an acceptable outcome to errors in those data and models (Ben-Haim 2006). Info-gap analysis has been applied previously to the topic of invasive species management, for example in developing robust inspection protocols at ports of entry (Moffitt et al. 2008). Furthermore, our analysis is conceptually similar to the study of Davidovitch et al. (2009), who applied info-gap decision theory to compare two surveillance strategies for the coastal brown ant (*Pheidole megacephala*) on Barrow

Island, Australia. However, our study differs from Davidovitch et al. (2009) in two ways. First, we apply info-gap analysis in a geographic setting (i.e., we evaluate different spatial configurations of potential survey areas, rather than the broad proportional relationship of surveillance system components). Secondly, we focus on prioritizing the surveillance efforts by exploring the trade-offs between surveillance strategies that maximize robustness to uncertainties and / or focus on opportunistic, unanticipated finds.

2. METHODS.

2.1. Modeling Invasion.

We used a spatial stochastic model to simulate *S. noctilio* invasion in eastern North America. The model portrays invasion as a discrete spatial process (Fuentes and Kuperman 1999) within a specific forecast horizon, t_{max} (30 years in this study). On a 1-year time step, *S. noctilio* populations spread from currently infested locations or from potential new entry points (e.g., marine ports). *S. noctilio* has a broad bioclimatic tolerance and the potential to establish across the entire range of pine forests in eastern North America (Carnegie et al. 2006). The likelihood that *S. noctilio* will successfully establish in newly invaded locales depends on the geographic distribution, susceptibility and abundance of hosts as well as the distance to already existing infestations. An established *S. noctilio* population is expected to damage the local host resource. The model has been described in detail in Yemshanov et al. (2009a, b) and Koch et al. (2009), so here we highlight only the relevant model parameters as well as updates that were necessary for this particular study.

Briefly, the simulations started from a map of known *S. noctilio* infestations in southern Ontario, New York, and Pennsylvania (APHIS 2007; De Groot et al. 2006). We recognize that the current map of known infestations may not reflect all (i.e., undetected) infestations, therefore we considered the entire area within the perimeter defined by the outermost infestation points to be infested with a viable *S. noctilio* population. We also modeled the pest's potential for future entry into eastern North America as a function of the value of imported commodities (Costello and McAusland 2003; Levine and D'Antonio 2003). Here we used a "high-risk" scenario, described in Yemshanov et al. (2009b), that assumed international phytosanitary standards for all wood packaging and raw wood materials (FAO-IPPC 2005) would have a relatively modest impact on entry probabilities. For each port, we estimated a local probability of entry, $W_{x(t)}$, from the volumes of received shipments of commodities capable of harboring *S. noctilio* (FHTET 2007a). In addition to the marine ports, we incorporated the probabilities of accidental introductions of the pest at urban areas and industrial sites (where the human-assisted movement of wood commodities is very likely). For eastern North America, the total introduction potential at these "inland" sites was assumed to be 0.02 per year (at least one entry over 50 years). This potential was subsequently apportioned into local probabilities of entry based on urban population size. Note that human-assisted entries of invasive organisms at urban areas represent a significant knowledge gap (McNeely 2001) and our assumption here represents only a coarse depiction of inland entry potential.

At each time step, successful entries and existing infestations were used to simulate spread of the pest in eastern North America with a travelling wave model (Sharov and Liebhold 1998). The population spread was estimated as dependent on the probability of colonization in the nearest adjacent map location, p_0, and the distance, d, from the nearest known infested location, constrained by the maximum distance, d_{max}, at which new locations may be successfully invaded (50 km). In successfully invaded locations, the maximum annual *S. noctilio* population size and the total damage to host was constrained by a carrying capacity (see Yemshanov et al. (2009b) and Koch et al. (2009) for details).

The establishment of *S. noctilio* populations depended on abundance and susceptibility of hosts (pines). The susceptibility, s_v, sets the probability for *S. noctilio* to establish new populations and was modeled as a species-specific function of pine age constrained by a susceptibility maximum, s_{max}. Based on USDA Forest Service ratings (FHTET 2007b), eastern North American pine species were divided into two groups, with $s_{max} = 0.95$ for species considered to have "very high" or "high" susceptibility and $s_{max} = 0.5$ for species considered to have "low" or "medium" susceptibility. The model also required tracking the geographical distribution and abundance of pine forests and their growth over time. Maps of pine composition and age were derived from the National Forest Inventory for Canada (Gillis 2001) and the USDA Forest Service Forest Inventory and Analysis database (USDA FS 2007). The growth of the pine resource and the amount of host surviving after *S. noctilio* infestation were modeled via growth rate curves, $g_{j(t)}$, defined separately for the US (Dixon 2008) and Canada (Ung et al. 2009); see other model details in Yemshanov et al. (2009b) and a sensitivity analysis of model parameters in Koch et al. (2009).

2.2. Modeling Detections and Their Lag Times.

For the second step of our analysis, we used the maps of stochastic spread patterns generated with the invasion model to simulate detections and estimated expected mean lag times between the arrival of *S. noctilio* and its first "find" at locations of interest over the forecast time period, t_{max}. For each potential survey location i (i.e., a map cell in the study area), the model recorded the time of the pest's initial arrival. Then, for each annual time step starting with the year of arrival, we simulated survey effort as a uniform random event, with a probability of successful detection, p_t. We assumed the surveys were undertaken on an annual basis. The p_t characterized the efficiency of the traps and lures used in the surveys, which is typically very poor for new pests when population levels remain low (Crooks 2005; Mehta et al. 2007; Venette et al. 2002). The lag time, χ_i, was then calculated as the difference between the time of the pest's arrival at location i and its first successful detection, and varied between 0 for immediate detections and $t_{\max}$ when the survey effort failed to detect an invasion.

2.3. Expected Utility of a Survey Effort.

We used maps of χ_i values (generated for each independent model run) to calculate the expected utility of survey efforts. We considered detections with zero lag time at sites with abundant host as the most desired survey outcomes. Davidovitch et al. (2009) also related survey success to the probability of detection within a designated period of time, however we used the actual lag time between the pest's arrival and its first successful "find" as our performance metric.

Let v_i be the per hectare amount of host at survey location i (i.e., a map cell) and c_i its per-cubic meter value. The spatial resolution (5x5-km) for our analysis is roughly equivalent to the typical one-year dispersal range of the bulk of a *S. noctilio* population (which has been estimated to be within a radius of <3 km – see Haugen 2006). For simplicity, we assumed individual survey locations did not overlap, that is:

$$\sum_{i}^{I} v_i \leq V_{total} \qquad [1]$$

where I is the total number of map cells (potential survey locations) and V_{total} is the total amount of the host resource across the study area landscape. Given this assumption, when a survey detected the presence of *S. noctilio* at a location i, the potential utility was represented as follows:

$$C_i = v_i\, s_v \delta(\chi_i) \quad [2]$$

where v_i is the amount of susceptible host resource at location i, s_v is the susceptibility of this host resource to an outbreak ($s_v \in [0;1]$) and $\delta(\chi_i)$ is a function that calculates the benefit that can be expected given delayed detection. Notably, if detection is substantially delayed or fails completely (i.e., as χ_i approaches t_{max}), then C_i approaches zero. The patterns and timing of the pest's expansion, the χ_i values, and the amount and degree of susceptibility of the host resource all varied geographically, thus changing the value of C_i across the study landscape.

We estimated the benefit that can be expected from delayed or failed detections as a logistic function, $\delta(\chi_i)$, of the time lag χ_i between the pest's arrival at a location and its first detection:

$$\delta(\chi_i) = 1 - \frac{1}{1 + e^{-(\varpi(\chi_i - 3.78\varpi^{-1.065}))}} \quad [3]$$

where ϖ is a shape parameter in the logistic equation, $\varpi \in [0; 1]$. Note that Equation 3 uses just this one parameter to define how quickly the invader can expand its population to a level that precludes cost-effective management activities (Fig. 1). The logistic shape of the function and the coefficients were fitted from expert estimates based on previous experience with *S. noctilio* in the Southern Hemisphere and estimated $\varpi \approx 0.5$ (D.Haugen, pers. comm., see Yemshanov 2009a).

2.4. Maximizing the Survey's Robustness to Uncertainties and/or Capacity to Gain Knowledge via Unanticipated Finds.

As the last step in our analysis, we use the information gap (info-gap hereafter) concepts of robustness and opportuneness (Ben-Haim 2006) to find the geographic distribution of potential survey areas that best addresses two competing objectives. First, we seek to identify the maximum level of uncertainties in the invasion model which still allow reliable detection of the pest. If the tolerable level is large then the model outputs are robust to uncertainty and vice versa. Second, we seek the least level of uncertainty about the pest's behavior that must be tolerated to enable the possibility of a very successful survey. The "success" is represented in our case by reliable detections which occur within a sufficiently short time after the invasion so these detections translate into knowledge about the current extent of invasion. If the level of uncertainty which is necessary for success is low, then the opportunity for success in excess of the anticipation is high.

Our approach stems from previous work assessing the robustness of pest risk maps to uncertainties (Yemshanov et al. 2010), as well as studies of optimal reserve design by Moilanen and Wintle (2006) and Moilanen et al. (2006). Basically, info-gap analysis requires very limited prior knowledge about the structure of uncertainty in the system being modeled; rather, it assumes an unknown and unbounded horizon of uncertainty (Ben-Haim 2006). Typically, the info-gap framework includes three components: a "process" model, a performance requirement, and a model for uncertainty. The process model is a formalized representation of the system of interest that incorporates the elements considered to be most important (Ben-Haim 2006; Regan et al. 2005). Here, we use the previously described spatial invasion model as our "process model". Each model scenario is associated with a vector of X model parameters and assumptions, $X_u \in (x_1, x_2, \ldots, x_u)$. In this study, the vector X_u includes several invasion model parameters previously identified as having a high impact on the pest's risk predictions (see Koch et al. (2009) for details): the local entry potential at marine ports and inland locations ($W_{x(t)}$); the local probability of colonization (p_0); the maximum distance at which a new colony may become established ($d_{\max}$); the total amount of host resource available at a given location ($g_{j(t)}$), represented by a map of host distribution across the landscape; and the susceptibility of the host resource (s_v). The vector also includes the detection probability (p_t) as well as the shape parameter (ϖ) that translates the detection lag time into the expected utility value (see Eq. 3).

In an info-gap framework, the process model outcomes are used to calculate an expected utility metric, $C_i(x)$, which in our case is the expected utility of survey effort at a given location i using given parameter values x, as described in Eq. 2. The utility metric is evaluated in terms of a performance requirement, which usually assesses the metric value against a certain threshold value:

$$C_i(x) \geq C_{\min} \qquad [4]$$

thus requiring the expected utility to be equal to or above the critical threshold, $C_{\min}$. The $C_{\min}$ value depends on the amount of host under threat, the detection lag time and also the detection probability, p_t. We interpret $C_{\min}$ as a minimum utility value at which a survey effort can be considered a "success".

The info-gap uncertainty model describes what is unknown about the process model parameters or functional relationships that comprise the vector X_u. The initial (or nominal, in Ben-Haim (2006)) parameter values, $\bar{x}_u$, are usually based on the best knowledge presently available about the pest and the efficacy of the detection mechanisms (e.g., traps or lures) used in the survey. However, since such knowledge is typically scarce, it is impossible to exactly specify whether the initial parameter values are true or how much they may deviate from their true values. We depict this supposition with the uncertainty model, which assumes that any parameter x_u may deviate by an unknown fraction, *a,* or less from its nominal $\bar{x}_u$ value, (also referred to as the horizon of uncertainty). For this study we employ a simple, uniform model of uncertainty, $H(a)$, that contains a family of nested intervals for each $a > 0$:

$$H(a) = \left\{ X_u : \frac{|x_u - \bar{x}_u|}{\bar{x}_u} \le a, x_u \ge 0, u = 1,\ldots,U \right\} \qquad [5]$$

where each x_u element of the vector X_u deviates from its nominal values by a proportion a or less:

$$\bar{x}_u - \bar{x}_u a \le x_u \le \bar{x}_u + \bar{x}_u a \qquad [6]$$

Since the value of a is unknown, we use a set of nested intervals (a_1, a_2, …) ranging from 0 to 1.0. The upper limit of a represents a typical scenario with the severe knowledge gaps about the pest (i.e., model parameters could vary by up to ±100%).

2.5. Robustness and Opportuneness of a Survey Effort.

Uncertainty in the invasion process model decreases confidence in the ability to detect the pest in locations where it is expected to be found, but at the same time, increases the chance of unanticipated detections which enhance our knowledge about the pest's behavior in a new environment. These two aspects are captured by the *robustness* and *opportuneness* functions. For each potential survey location *i*, we define its robustness, $\hat{\alpha}(x)$, as the maximum value of the uncertainty horizon a that guarantees the expected utility $C_i(x)$ of a survey effort to be no less than the critical threshold C_α:

$$\hat{\alpha}(x) = \max\left\{a : \left(\min_{x \in H_i(a)} C_i(x)\right) \geq C_\alpha\right\} \qquad [7]$$

Locations with unexpected finds of the pest may also have relatively high $C_i(x)$ values. Our second objective is to exploit this fact, essentially by finding the lowest level of uncertainty that must be tolerated in order to enable the possibility of unanticipated detections (surprises). For each potential survey location i, we define its opportuneness, $\hat{\beta}(x)$, as the minimum value of the uncertainty horizon a that enables (but does not guarantee) the possibility of detection with the expected utility $C_i(x)$ exceeding the minimum threshold C_β:

$$\hat{\beta}(x) = \min\left\{a : \left(\max_{x \in H_i(a)} C_i(x)\right) \geq C_\beta\right\} \qquad [8]$$

Essentially this describes the possibility of detecting the pest significantly earlier than it might be expected under the robust-satisfying conditions and also gaining useful knowledge about the pest's behavior. In summary, the C_α and C_β thresholds are the equivalents of the $C_{\min}$ value in Eq.4. Although C_α and C_β can be treated as independent variables (depending on a decision maker's aspirations), in this study they were set to similar values to simplify comparison of $\hat{\alpha}(x)$ and $\hat{\beta}(x)$.

The inner minimum in Eq.7 is the inverse of the robustness function. That is, a plot of the inner minimum vs. a is the same as a plot of C_α vs. $\hat{\alpha}(x)$. Likewise, the inner maximum in Eq.8 is the inverse of the opportuneness. We actually evaluate $\hat{\alpha}(x)$ and $\hat{\beta}(x)$ by evaluating their inverses. These inverses can be found by sampling the info-gap model of uncertainty, $H(a)$, at horizons of uncertainty a, $a = 0, \ldots, 1$, to obtain a unique set of parameter values $x_{(m)}$ and calculate the expected utility $C_i(x_{(m)})$ for M independent realizations, $m = 1,\ldots,M$. Specifically, we sampled $H(a)$ by selecting values for the invasion model parameters $x_{(m)}$ from a random uniform distribution around their nominal values, $\bar{x}_u$, defined by $\pm a$ (see Eq. 6).

The minimum and maximum values of $C_i(x_{(m)})$ for a given uncertainty horizon a represent estimates of the inverses of $\hat{\alpha}(x)$ and $\hat{\beta}(x)$, respectively, and were found by recalculating $C_i(x_{(m)})$ M times until the values of min $C_i(x_{(m)})$ and max $C_i(x_{(m)})$ were stabilized:

$$\left[\underset{x_m \in H(a)}{x_m} \overset{Nreps}{\Rightarrow} \delta(\chi_i), v_i, s_i \Rightarrow C_i(x_{(m)}) \right]_{m=1,\ldots,M} \overset{Mreps}{\Rightarrow} \begin{array}{l} \min\limits_m C_i(x_{(m)}) \approx \alpha(x) \\ \max\limits_m C_i(x_{(m)}) \approx \beta(x) \end{array} \qquad [9]$$

Eq. 9 describes a numerical approximation of $\hat{\alpha}(x)$ and $\hat{\beta}(x)$ that requires $M \times N$ individual model replications, where each of the M replications includes the N independent model simulations necessary to generate the maps of $C_i(x_{(m)})$ and stabilize their spatial configuration. Consistent with the "high-risk" scenario described in Yemshanov et al. (2009a), N was set to 300 replications. The minimum value of M replications required to stabilize the robustness and opportuneness functions was estimated using the convergence metrics described in Yemshanov et al. (2010). In all cases, the robustness and opportuneness maps started to stabilize after ~250 replications, so M was set to 500. To make the processing time reasonable, we estimated only the critical utility levels, C_α and C_β, that yielded the robustness and opportuneness values $\hat{\alpha}(x)$ and $\hat{\beta}(x) =$ 0, 0.3, 0.5 and 0.7 (instead of estimating the whole shape of $\hat{\alpha}(x)$

and $\hat{\beta}(x)$). Overall, the scenarios required approximately 1.2 million individual model simulations.

As a result, each potential survey location (map cell) was characterized by values of C_α and C_β for each horizon of uncertainty, a = 0, 0.3, 0.5 and 0.7. The C_α values represent the critical utilities necessary for adequately robust outcomes, while the C_β values represent windfall utility constituting better-than-anticipated outcomes (i.e., surprising detections). Based on the shape of the functions, C_α vs. a and C_β vs. a, it was possible to outline the geographic areas where surveys will be more (or less) rewarding in detecting and / or reducing uncertainties about the pest.

2.6. Prioritizing Survey Efforts.

From our perspective, a survey location which is both robust and opportune is preferable to one which is not. Or, given two locations which have comparable robustness but one is more opportune, the latter is preferred. Thus, the most rewarding survey strategy would not only promote robust detections but would simultaneously maximize the opportunity for unanticipated finds of a pest (i.e., maximizing $\hat{\alpha}(x)$ and minimizing $\hat{\beta}(x)$ for given expectations of C_α and C_β).

In this study, robustness and opportuneness at any survey location were represented by two sets of C_α and C_β values for each horizon of uncertainty, a = 0, 0.3, 0.5 and 0.7. Hence, we used a multi-criteria ranking technique to aggregate these values to a single ordinal rank that identifies the most rewarding survey sites.

Multi-criteria analysis employs various approaches such as multi-attribute utility theory (Keeney and Raiffa 1976), the analytic hierarchy process (Saaty 1980), various outranking methods (Doumpos and Zopounidis 2002; Roy 1996) and compensatory methods that use weighted averaging (Belton and Stewart, 2002; Løken 2007; Steele et al. 2009). Most of these techniques, however, require prior knowledge regarding the relevance of, or relationships between, the individual criteria (Steele et al. 2009). In our case, such knowledge about the relevance of individual C_α and C_β values was unavailable, therefore we opted to use a multi-criteria aggregation based on Pareto dominance.

Suppose $\mathcal{N}$ points need to be ordered in K dimensions. In our case, K is a criteria space equal to the total number of C_α and C_β values; $K = 4$ in the scenario that used the C_α values only (the "robust finds") and $K = 8$ in the scenario using both C_α and C_β (both "robust" and "opportune" finds). A Pareto front is formed by points whose performance with respect to one criterion cannot be improved without sacrificing performance with respect to at least one other criterion, a condition known as Pareto optimality (Pareto 1971). For a set of $\mathcal{N}$ points in a K-dimensional criteria space, the Pareto front is usually defined by the subset of the total population of points, $\mathcal{N}'$, that is non-dominated by the rest of the population ($\mathcal{N} - \mathcal{N}'$). In a K-dimensional space, a point S_1 dominates another point S_0 when:

$$S_{1k} \geq S_{0k} \ \forall \ k = 1, \ldots, K \text{ and } S_{1k} > S_{0k} \text{ for some } k \qquad [10]$$

Fig. 2 illustrates the Pareto concept using a two-dimensional example (i.e., with $K = 2$).

We used a Pareto ranking algorithm described in Goldberg (1989). The technique first finds non-dominated elements of the population $\mathcal{N}'$, assigns them rank 1 and then removes them from the population temporarily. Next, a new non-dominated subset in the rest of the population is assigned rank 2, and so forth. As a result, each element of the population is assigned a Pareto rank. Fig. 2 shows an example of aggregated risk ranks that have been derived from the subsequent Pareto frontiers. Since, in our case, each element of the population $\aleph$ is represented by a map cell, their ranks can be mapped in geographical space. Importantly, all points comprising each Pareto front are non-dominant to each other and thus offer the best performance in terms of the trade-offs between all criteria in K.

Note that the location of the Pareto frontier depends on the relative arrangement of individual data points and usually requires normalization of data with skewed, irregular or clustered distributions. To ensure the sparseness and uniformity of the data along each criteria dimension k, we applied a ranking normalization outlined by Godfrey et al. (2007), and then rescaled the final ranks to a 0-1 range so the highest ranks (demarcating high-priority survey areas) received values close to 1 and the lowest ranks close to 0.

3. RESULTS.

3.1. Probability of Invasion and Expected Utility of a Survey Effort.

Figs. 3A and 3B show the risk and output uncertainty maps generated for the initial scenario (i.e., using the nominal parameter values $\bar{x}$). Fig. 3A depicts, for each map cell, the estimated probability, $p_j(\bar{x})$, that *S. noctilio* will establish a viable population over the period $t_{\max}$, while in Fig. 3B the uncertainty of this estimate is represented by the standard deviation, $\sigma_j(\bar{x})$. As expected, the probability of invasion is close to 1 in areas with sufficient host near the existing infestations in the northeastern U.S. and southern Ontario. The probability declines to low levels ($p_j < 0.4$) for areas beyond the primary invasion front predicted over the period $t_{\max}$. Alternatively, the output uncertainty estimates are highest near this expected invasion front.

Fig. 4 shows the expected utility values (C_α and C_β) that are achievable for given levels of robustness and opportuneness $\hat{\alpha}(x)$ and $\hat{\beta}(x)$ equal to the uncertainty horizons a = 0, 0.3, 0.5 and 0.7. Generally, values of $a \leq 0.3$ indicate fairly good knowledge about the pest, while values of $a \geq 0.5$ suggest severe knowledge gaps.

For all of the tested scenarios, robust-satisfying and opportune survey strategies exhibit distinct geographic patterns of variation in utility values. These differences are relatively small when knowledge about the pest is good (i.e., $a = 0$; Figs. 4A, 4B) but become significant in the presence of knowledge gaps ($a = 0.7$; Figs. 4E, 4F).

In the absence of uncertainties ($a = 0$), the geographical variation in utility values, for both robustness and opportuneness, approaches the pattern of $\sigma_j(x)$ (Figs. 4A, 4B); most notably, the highest utility values are observed in the areas near the anticipated front of invasion (i.e., areas where $\sigma_j(x)$ peaks under this nominal scenario, Fig. 3B).

When the uncertainties are moderate ($a = 0.3$; Figs. 4C, 4D), it appears that robust-satisfying surveys would best be constrained to regions where the estimated risk of *S. noctilio* invasion, $p_j(x)$, is relatively high. Preferred regions include areas of pine forest in boreal Canada, the US Northeast and the US Upper Midwest near the presently known range of *S. noctilio*; despite somewhat lower expected utility and estimated invasion risk, coastal areas in the southeastern US, which are close to marine ports of entry (i.e., potential sources of new introductions) and contain abundant pine forests, may also be appropriate (Fig. 4C).

As knowledge about the pest decreases, the area that allows for confident (robust-satisfying) surveillance decreases dramatically and is basically limited to map locations where *S. noctilio* can be expected to build a large population over a short time horizon

(Fig. 4E). However, knowledge gaps appear to increase the proportion of the study area where opportune finds are likely beneficial (i.e., exhibit high utility, Fig. 4F). The impact of knowledge gaps on the geographical distribution of opportune finds is minor, and is primarily manifested as a more uniform distribution of the expected utility values across the entire study area (Fig. 4F vs. Fig. 4B). Because the estimated position of the main invasion front is less certain in this case, it is preferable to undertake a more spatially uniform sampling of a larger area, albeit as intensely as possible (Fig. 4F). Compared to robust-satisfying finds, the distribution of opportune finds is mostly shaped by host presence and does not appear to be influenced by the distance from the locations currently invaded by *S. noctilio*, i.e., the current invasion front (Fig. 4F).

3.2. Ranking Survey Priorities.

Fig. 5 presents integrated Pareto ranks based on the robustness function (represented by the C_α criteria) and Fig. 6 shows the scenarios using both robustness and opportuneness (C_α as well as C_β criteria). Each figure includes maps for two scenarios with the detection accuracies $p_t = 0.02$ and 0.1.

3.2.1. Robust-Satisfying Strategy

As perhaps expected, the robust-satisfying strategy prioritizes surveys in the regions where the estimated risk of invasion is high and the variability in this estimate is low (see Fig. 3A and 3B, respectively). The geographic position of high-priority survey areas (i.e., rank > 0.95 in Fig. 5) is highly sensitive to the extent of knowledge about *S. noctilio*. When uncertainties are severe, high-priority survey areas are quite limited in number and extent (Figs. 5C, 5D). Moreover, when the detection rate is low and knowledge about the pest is poor (Fig. 5C), high-priority survey areas can only be found in close proximity to currently invaded sites with abundant host. The scenarios (Figs. 5B, 5D) with higher detection accuracies ($p_t = 0.1$) also indicate medium-level (rank > 0.6) priority areas along the southeastern US coast, although these areas are restricted in extent when knowledge is poor (Fig. 5D).

Table 1 reports the area and land percentage covered by the highest and lowest 5% of the survey ranks. Higher detection accuracy increases the area of high-priority surveys, especially when knowledge gaps are present. This change is most evident in the southeastern US (Table 1).

When knowledge about the pest is good (i.e., $a \leq 0.3$), the highest-ranked survey areas include the location of the anticipated invasion front (Figs. 5A, 5B). Changing the detection accuracy in this case does not significantly impact the geographic location of high-priority survey areas (see ranks above 0.95 in Figs. 5A, 5B). However, in the scenario with good knowledge but poor detection accuracy ($p_t = 0.02$, Fig. 5A), areas beyond the anticipated invasion front have been assigned relatively low ranks. This suggests that poor capacity for detecting the pest may undercut the potential value of detailed knowledge about its spread behavior. Furthermore, this emphasizes the point that a robust-satisfying strategy is not appropriate for delimiting the full extent of an invasion (i.e., including isolated infestations beyond the main front).

3.2.2. Ranking based on both strategies

Fig. 6 presents survey rankings based jointly on robust-satisfying and opportune strategies. The highest ranks in these scenarios represent the best trade-offs between both strategies. When knowledge about the pest is good ($a \leq 0.3$), the highest survey ranks (>

0.95) are found in the coastal pine forests of North and South Carolina, Georgia and Virginia (Figs. 6A, 6B). Another survey hotspot is located in northern Michigan and north-central Ontario. These geographic regions encompass locations that are probably within the range of *S. noctilio* expansion over a 30-year time horizon, yet just beyond the main invasion front. Notably, a difference in detection accuracy does not seem to have a significant impact on the ranking pattern given good knowledge about the pest (Fig. 6A vs. Fig. 6B).

It is further worth noting that when the level of knowledge and the detection accuracy are both good, the rankings based jointly on robust and opportune strategies are similar to those based only on a robust-satisfying strategy (Fig. 5B vs. Fig. 6B). Otherwise, the robust-only and jointly robust/opportune strategies diverge, most dramatically so when knowledge gaps are severe (Figs. 5C, 5D vs. Figs. 6C, 6D). Under a joint strategy, the distribution of highest survey ranks when $a > 0.3$ is fairly uniform across much of the pine forest region of the southeastern US (Figs. 6C, 6D). However, the emphasis on the southern pine region is more pronounced in the scenario assuming poor detection accuracy (Fig. 6C); when the detection accuracy improves (Fig. 6D), the distribution of survey ranks becomes somewhat more evenly distributed across the entire study area. Compared to the scenario using $p_t = 0.02$, the $p_t = 0.1$ scenario assigned 9-18% lower ranks to most of the regions with abundant pine resources.

Under a robust-satisfying strategy, severe knowledge gaps decrease the total map area assigned the highest surveillance ranks (Table 1). However, under a joint strategy, the area of highest ranks in the southeastern US actually increases. Furthermore, knowledge gaps about the pest also decrease the total area where surveys are considered to be unfeasible (i.e., assigned the lowest ranks) under a joint survey strategy. For eastern

North America this area accounts for approximately 15.3-16.2% (for p_t = 0.02 and 0.1, respectively) in the scenarios assuming good knowledge about the pest and declines to 12.3-12.7% in the scenarios with severe knowledge gaps (Table 1).

4. DISCUSSION.

Making decisions in the presence of severe uncertainties is commonly considered an inevitable part of risk mapping for new invasive organisms (Andersen et al. 2004, Baker et al. 2005, Venette et al. 2010). Pest risk assessments attempt to fill knowledge gaps, but their creation – and subsequently their value – often depends on information from other, geographically (and to some degree ecologically) distinct regions where the pest is known to exist. In our study, we demonstrate a practical approach of embedding the uncertainties in a pest risk mapping process and using the results in subsequent planning of pest surveillance activities. Our methodology also proposes an expected utility metric that is based on detection lag time and therefore could be more useful in supporting regulatory and quarantine decisions compared to more common probabilistic estimates of risk.

The results reveal the impacts of two major sources of uncertainty on the delineation of survey priorities across a study area: the capacity to detect a pest when it has arrived at a suitable site (represented here as detection accuracy, p_t) and the uncertainties about the pest's behavior in a novel environment (formulated here as the uncertainty model $H(a)$ and the uncertainty horizon a). Higher detection accuracy, like the availability of more detailed knowledge, generally decreases the proportion of the study area where surveys should be a high priority. In fact, improving the capacity to detect the pest may be as advantageous as reducing uncertainties about the pest's expansion through the landscape. This is an important consideration because it justifies the allocation of considerable resources towards improving the accuracy of capture and detection methods for new invasive organisms. Moreover, poor detection capacity diminishes the utility of surveillance efforts and therefore undercuts the benefits from gaining new knowledge about the spread and extent of invasion.

4.1. Importance of Inclusion of both Robustness and Opportuneness.

We believe that it is important to evaluate pest survey designs in terms of both opportuneness and robustness. When knowledge about the pest is poor, it is optimal to maximize the potential survey area and make the survey pattern more geographically uniform across this area, constrained only by the presence-absence of a susceptible host. Alternatively, more detailed knowledge about the pest typically translates to a smaller area where surveys should be considered a high priority. As expected, knowledge gaps cause a balance shift with respect to the relative importance of robust-satisfying and opportune survey strategies. Our results suggest that a robust-satisfying strategy becomes increasingly relevant when knowledge about a new pest improves or the accuracy of detecting the pest increases (i.e., $a \rightarrow 0$ or $p_t \rightarrow 1$). However, when knowledge about the pest is poor (i.e., $a > 0.3$), a vast majority of the high-ranked survey locations can be attributed to the "opportune" strategy. This is similar to the finding of Davidovitch et al. (2009) that survey strategies relying on incidental detections have a better chance of detecting the pest within a critical period of time.

When the robustness function is applied alone (like in many other info-gap analyses; – see Moilanen et al. 2006; Regan et al. 2005), it may lead to overly pessimistic estimates by maximizing the avoidance of severe uncertainties and overlooking the benefits of unexpected finds. In our case, the robust-satisfying conditions held for only a relatively small fraction of the survey locations close to already infested sites and thus precluded the possibility of detecting any dramatic departures from the anticipated progress of the invasion. Therefore, we believe that a more appropriate survey strategy is not to guarantee early detection *per se*, but rather to explore ambient geographic and temporal uncertainty regarding the pest of interest, under the assumption that any detections that may arise from the unknown variation will substantially contribute to the overall long-term success of the survey effort.

This study did not consider the potential impacts of cost constraints on surveillance priorities. Adding budget constraints and costs of conducting the surveys may change the allocation of high-priority sites, however this type of analysis would require more detailed spatial data on road access and travel costs to the potential survey sites, as well as costs of installing and servicing traps and total survey budgets. Such information may also be dependent on land ownership and administrative jurisdictions. Hence, an incorporation of cost constraints may be a more appropriate focus for regionalized, local studies.

4.2. Technical Issues and Future Work.

The study involved computationally intensive simulations, so the number of scenarios and the spatial resolution of the maps of survey priorities were restricted to fit our available processing capacity. While we used a relatively simple invasion model (essentially a two-dimensional discrete implementation of the traveling wave model described by Sharov and Liebhold (1998)), we used Monte Carlo simulations to apply the model of uncertainty $H(a)$ and perform the info-gap analysis. This required sampling an

X-dimensional model parameter space for uncertainty (see Eqs. 5 and 6). Thus, the necessary computing time is a noteworthy constraint on spatial applications of the approach.

The discrete nature of the technique used to calculate robustness and opportuneness represents another potential issue. In order to reduce the processing time, we calculated the expected utility thresholds C_α and C_β for a given value of the robustness and oppportuneness functions $\hat{\alpha}(x)$ and $\hat{\beta}(x)$. Basically, we sampled the value of the robustness and opportuneness functions at four points, $a = 0$, 0.3, 0.5 and 0.7, instead of estimating the functions' shapes over the entire interval [0; 1]. While this greatly reduced the amount of calculations, we recognize that this technique may lose some fine-scale details about the shape of the robustness and opportuneness functions and how these may change depending on the scenario assumptions. We believe that a more rigorous (but computationally more demanding) approach would be to generate additional points to estimate the shape of $\hat{\alpha}(x)$ and $\hat{\beta}(x)$ and fit them with a functional equation, such that each map cell would be assigned a functional form of $\hat{\alpha}(x)$ and $\hat{\beta}(x)$. While this could provide a better analytical foundation for characterizing robustness and opportuneness, it would necessitate an extra processing step to fit sampled points to a functional equation. This would also make the results of the Pareto aggregation less dependent on the number of sampling points of $\hat{\alpha}(x)$ and $\hat{\beta}(x)$ and more consistent across different scenarios and geographical examples (because the aggregation would be applied to the function coefficients instead of sampled values of $\hat{\alpha}(x)$ and $\hat{\beta}(x)$).

One issue that we did not consider in this study is the dynamic capacity to change the surveillance strategy in response to successful (or failed) detections. Clearly, adding a decision making component that analyses the structure of uncertainty from the most recent surveys and then adaptively changes the detection strategy would be a challenging task in a geographic context. First, the local structure of uncertainty would have to be estimated across a geographic space in a dynamic fashion. (This would require application of various learning algorithms, such as Kalman filtration, in a spatial setting.) Once the local structure of uncertainty was identified, the next step would be to find an optimal strategy to adjust the surveys. This step could be accomplished using spatial optimization techniques (Hof and Bevers 1998). Finally, the surveillance decision model would have to be adjusted for a decision maker's particular risk preferences. These modifications will be a focus of our future work.

5. CONCLUSIONS.

Decision support tools can be very useful in managing and estimating uncertainties associated with emerging threats, especially when knowledge about a new invader is vague and/or sparse. The methodology presented here provides a consistent way of incorporating severe uncertainties into pest surveillance program design, and enables decision makers to explore a wide range of choices in the presence of severe knowledge gaps about the new invasive threat. Essentially, the approach capitalizes on the capacity of the pest survey network to explore ambient uncertainty about the pest, and identifies the geographic areas where detections of the pest that are not anticipated by current knowledge will be the most rewarding. Importantly, the concept used here is fairly generic and can be applied when knowledge about the invasive organism is severely limited. This makes the methodology a good alternative to expert-based decisions in planning early-warning surveillance efforts since it avoids personal biases and risk aversions.

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Tables:

Table 1. Land area (thousands km^2) and the percentage of the total area (%) allocated with the highest and lowest survey priority (the highest and lowest 5% of the aggregated Pareto ranks).

Knowledge about pest's behavior (a)	Detection accuracy, p_t	Risk rank (rescaled to [0;1])	Survey strategies (scenarios): Robust-satisfying only				Robust-satisfying and opportune			
			East. Can.*	N.E. U.S.	S.E. U.S.	East. N.A.	East. Can.	N.E. U.S.	S.E. U.S.	East. N.A.
Good ($a \leq 0.3$)	0.02	>0.95 (highest)	7.7 (4.4)	2.4 (0.7)	3.1 (1.1)	13.2 (1.7)	3.6 (2.0)	1.3 (0.4)	33.8 (12.3)	38.7 (5.0)
		<0.05 (lowest)	113.3 (64.9)	261.8 (79.5)	176.3 (63.9)	551.5 (70.7)	49.9 (28.6)	68.7 (20.9)	7.6 (2.8)	126.3 (16.2)
	0.1	>0.95 (highest)	8.3 (4.8)	3.6 (1.1)	9.4 (3.4)	21.3 (2.7)	2.5 (1.5)	2.0 (0.6)	34.8 (12.6)	39.3 (5.0)
		<0.05 (lowest)	101.5 (58.1)	231.2 (70.2)	131.9 (47.8)	464.6 (59.6)	47.6 (27.3)	64.4 (19.5)	7.1 (2.6)	119.1 (15.3)
Poor ($a > 0.3$)	0.02	>0.95 (highest)	0.9 (0.5)	0.0 (0.0)	0.0 (0.0)	1.0 (0.1)	1.1 (0.7)	0.3 (0.1)	43.0 (15.6)	44.4 (5.7)
		<0.05 (lowest)	162.8 (93.2)	310.7 (94.3)	275.7 (99.9)	749.2 (96.1)	48.2 (27.6)	44.1 (13.4)	7.0 (2.5)	99.3 (12.7)
	0.1	>0.95 (highest)	1.7 (1.0)	2.1 (0.6)	0.6 (0.2)	4.2 (0.5)	0.9 (0.5)	0.2 (0.1)	39.7 (14.4)	40.8 (5.2)
		<0.05 (lowest)	159.5 (91.3)	298.3 (90.6)	254.0 (89.1)	711.8 (91.3)	47.7 (27.3)	41.0 (12.5)	7.0 (2.6)	95.8 (12.3)

* Geographic regions:
East. Can – eastern Canada;
N.E. U.S. – northeastern US;
S.E. U.S. – southeastern US;
East N.A. – eastern North America.

Figure captions:

Fig.1. Utility of a survey effort as a function of the detection lag time, $\delta(\chi_i)$.

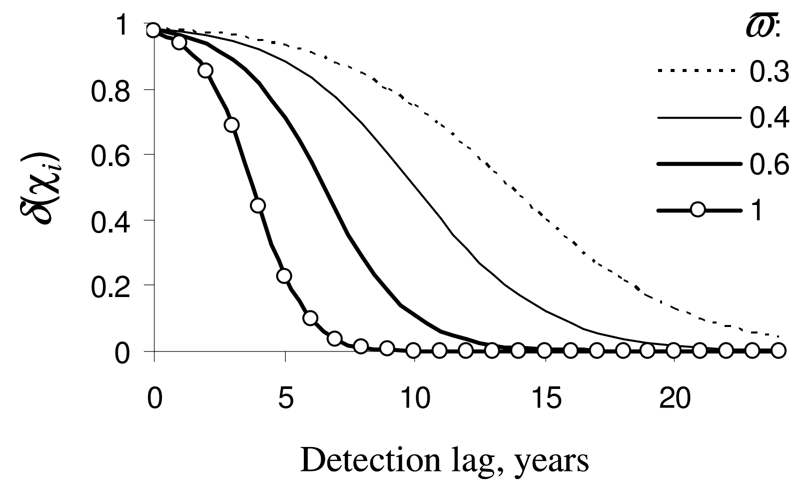
Fig.2. Multi-criteria ranking based on the Pareto dominance.

Fig.3. Classified maps of *S. noctilio* invasion risk and the uncertainty of risk estimates for the scenario using the nominal parameter values, $\bar{x}$: A) probability of invasion, $p_j(\bar{x})$; B) standard deviation of p_j estimates, $\sigma_j(\bar{x})$.

Fig.4. Expected utility values, C_α and C_β, for the scenarios assuming pest detection accuracy $p_t = 0.1$. The horizon of uncertainty: A,B) 0; C,D) 0.3; E,F) 0.7.

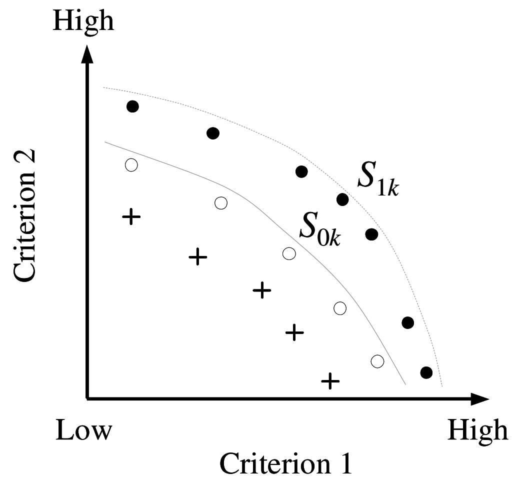
Fig.5. Survey priority ranks based on the robust-satisfying strategy. Highest ranks denote higher survey priorities and vice versa. The scenarios: A) $p_t = 0.02$, $a \leq 0.3$ (good knowledge about the pest, poor detection accuracy); B) $p_t = 0.1$, $a \leq 0.3$ (good knowledge about the pest, good detection accuracy); C) $p_t = 0.02$, $a > 0.3$ (severe knowledge gaps, poor detection accuracy); D) $p_t = 0.1$, $a > 0.3$ (severe knowledge gaps, good detection accuracy).

Fig.6. Survey priority ranks based on both the robust-satisfying and opportune strategies. Highest ranks denote higher survey priorities and vice versa. The scenarios: A) $p_t = 0.02$, $a \leq 0.3$ (good knowledge about the pest, poor detection accuracy); B) $p_t = 0.1$, $a \leq 0.3$ (good knowledge about the pest, good detection accuracy); C) $p_t = 0.02$, $a > 0.3$ (severe knowledge gaps, poor detection accuracy); D) $p_t = 0.1$, $a > 0.3$ (severe knowledge gaps, good detection accuracy).



ϖ:
0.3
0.4
0.6
1
$\delta(\chi_i)$
0
0.2
0.4
0.6
0.8
1
0
5
10
15
20
Detection lag, years

Fig.1.



- Pareto frontier 1

- Pareto frontier 2

Ranks based on the Pareto dominance

● - Rank 1 (dominates ranks 2 and 3)

○ - Rank 2 (dominates rank 3, dominated by rank 1)

+ - Rank 3 (dominated by ranks 1 and 2)

Fig.2.

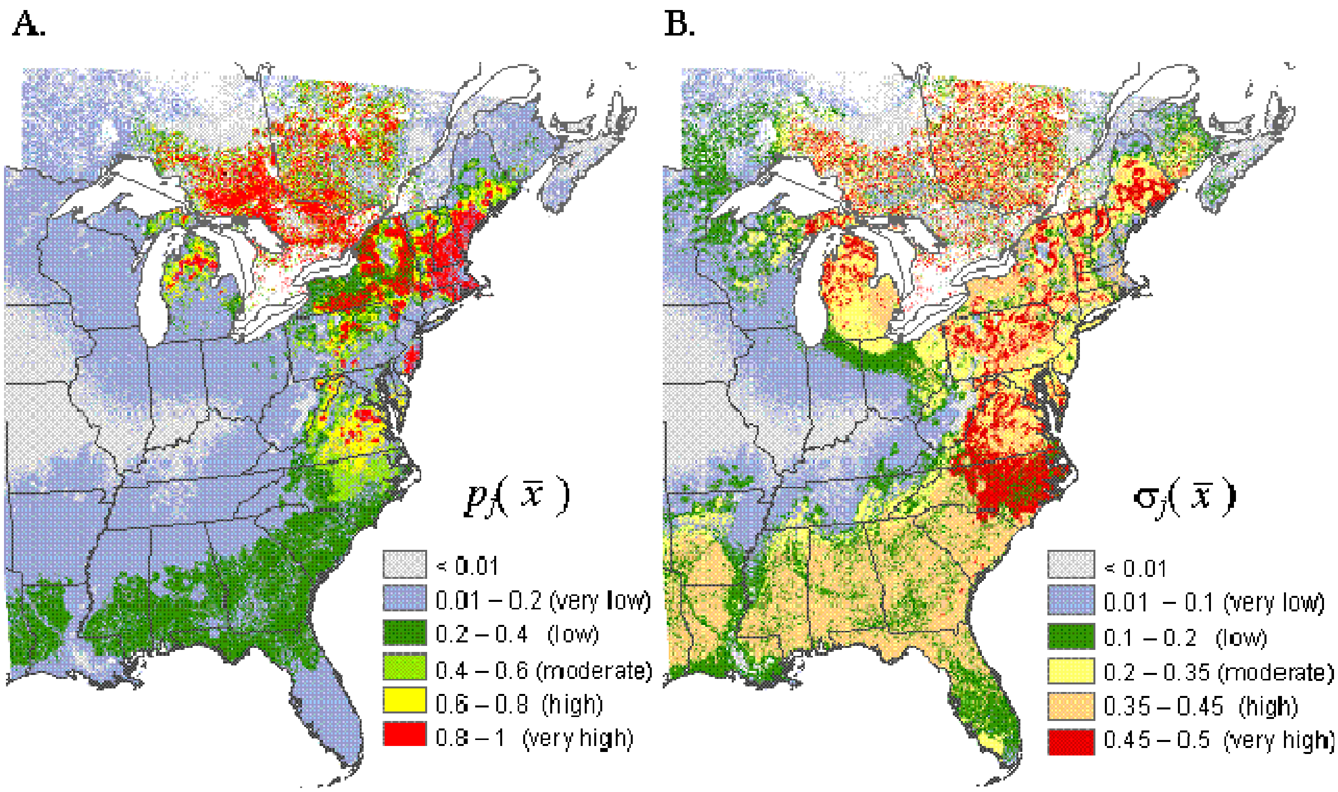

A.
B.
$p_j(\bar{x})$
< 0.01
0.01 – 0.2 (very low)
0.2 – 0.4 (low)
0.4 – 0.6 (moderate)
0.6 – 0.8 (high)
0.8 – 1 (very high)
$\sigma_j(\bar{x})$
< 0.01
0.01 – 0.1 (very low)
0.1 – 0.2 (low)
0.2 – 0.35 (moderate)
0.35 – 0.45 (high)
0.45 – 0.5 (very high)

Fig.3

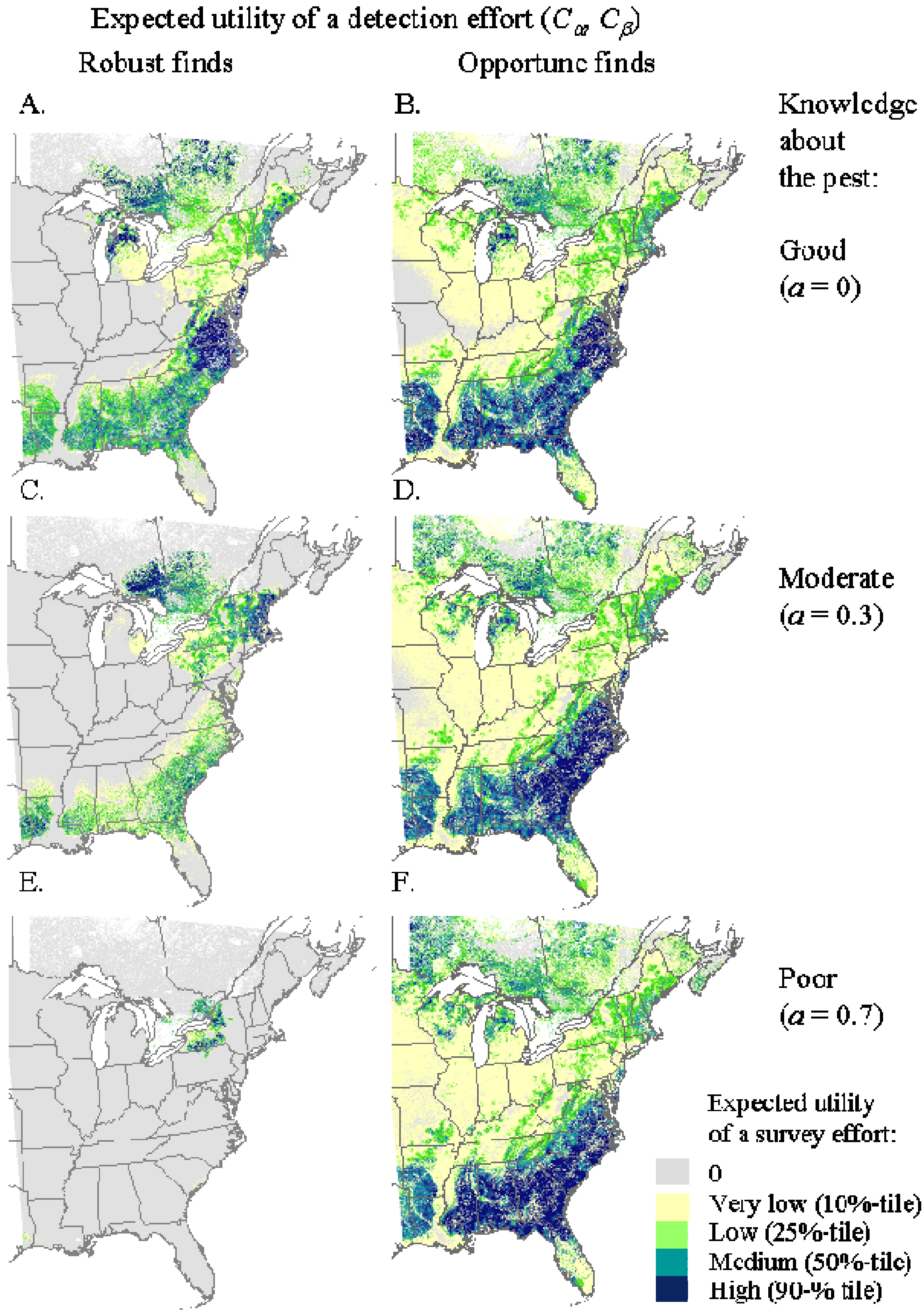
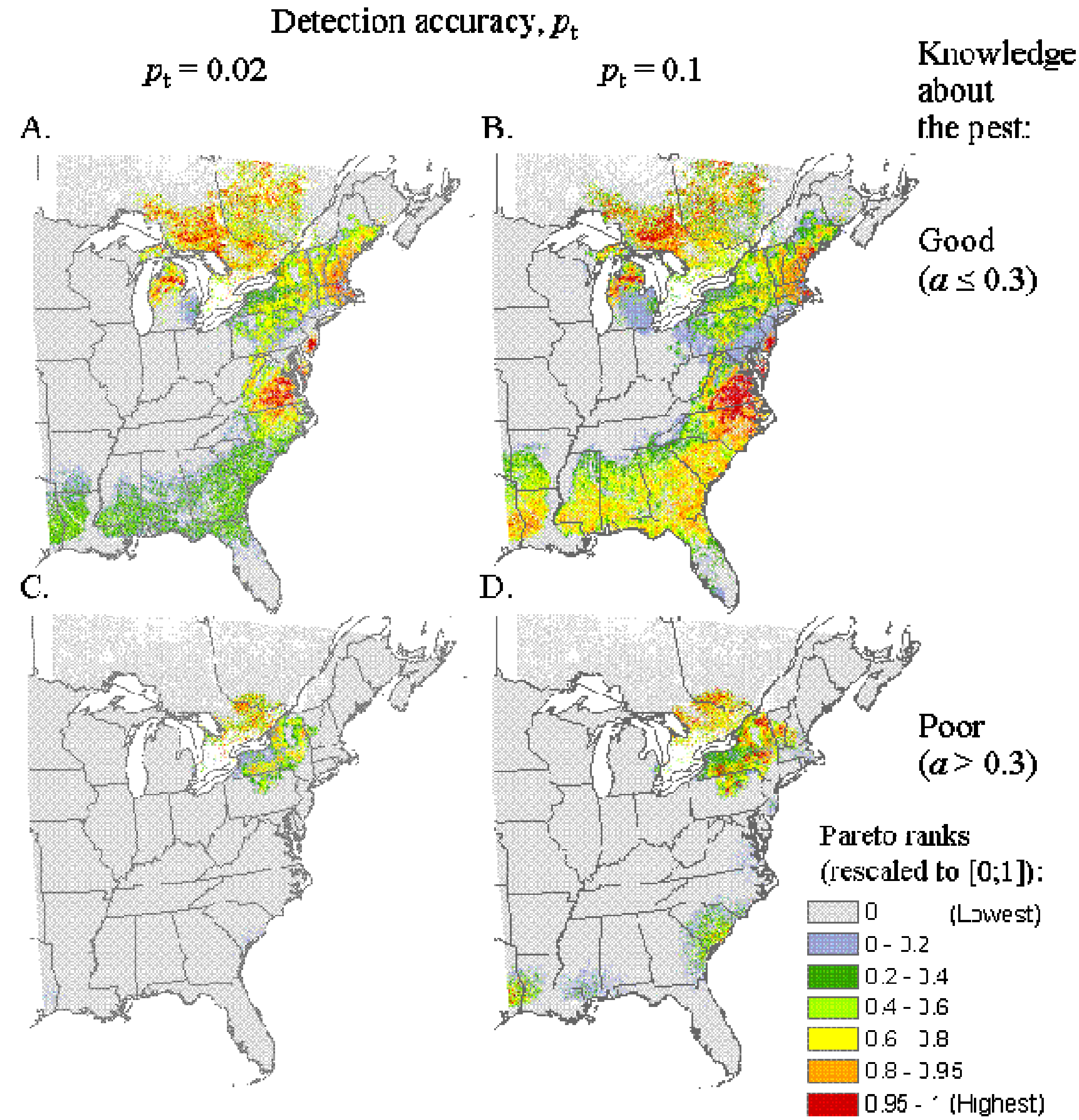
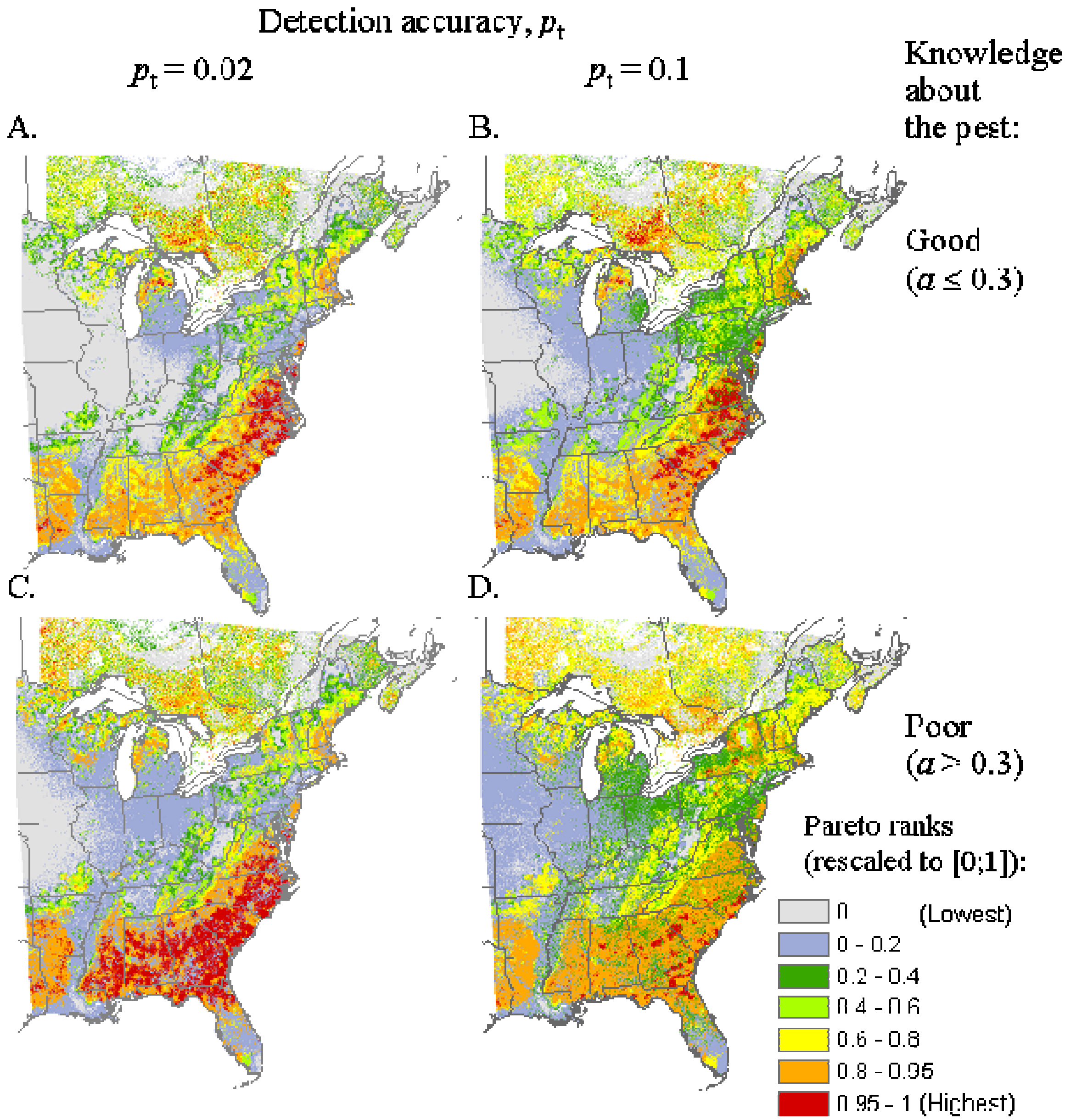

Expected utility of a detection effort (C_α, C_β)
Robust finds
Opportune finds
A.
B.
Knowledge about the pest:
Good ($a = 0$)
C.
D.
Moderate ($a = 0.3$)
E.
F.
Poor ($a = 0.7$)
Expected utility of a survey effort:
0
Very low (10%-tile)
Low (25%-tile)
Medium (50%-tile)
High (90-% tile)

Fig.4.



Detection accuracy, p_t
$p_t = 0.02$
$p_t = 0.1$
Knowledge about the pest:
A.
B.
Good ($a \leq 0.3$)
C.
D.
Poor ($a > 0.3$)
Pareto ranks (rescaled to [0;1]):
0 (Lowest)
0 - 0.2
0.2 - 0.4
0.4 - 0.6
0.6 0.8
0.8 - 0.95
0.95 - 1 (Highest)

Fig.5.



Detection accuracy, p_t
$p_t = 0.02$
$p_t = 0.1$
Knowledge about the pest:
A.
B.
Good ($a \leq 0.3$)
C.
D.
Poor ($a > 0.3$)
Pareto ranks (rescaled to [0;1]):
0 (Lowest)
0 - 0.2
0.2 - 0.4
0.4 - 0.6
0.6 - 0.8
0.8 - 0.95
0.95 - 1 (Highest)

Fig.6.