Journal of Environmental Management 150 (2015) 367–377

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Managing outbreaks of invasive species — A new method to prioritize preemptive quarantine efforts across large geographic regions

J.R. Withrow [a], [*], E.L. Smith [b], [1], F.H. Koch [c], D. Yemshanov [d]

[a] *Softec Solutions, Inc., Contractor for the USDA-FS FHTET, NRRC Bldg. A Ste 331, 2150 Centre Avenue, Fort Collins, CO 80526, USA*
[b] *USDA-FS Forest Health Technology Enterprise Team, NRRC Bldg. A Ste 331, 2150 Centre Avenue, Fort Collins, CO 80526, USA*
[c] *Research Ecologist, USDA Forest Service, Southern Research Station, Eastern Forest Environmental Threat Assessment Center, 3041 Cornwallis Road, Research Triangle Park, NC 27709, USA*
[d] *Natural Resources Canada, Canadian Forest Service, Great Lakes Forestry Centre, 1219 Queen Street East, Sault Ste. Marie, ON P6A 2E5, Canada*

ARTICLE INFO

Article history:
Received 18 October 2013
Received in revised form
22 October 2014
Accepted 4 November 2014
Available online 3 January 2015

Keywords:
Emerald ash borer
Risk assessment
Cost-benefit analysis
Quarantine
Pest management
Invasive species

ABSTRACT

In pest risk assessment it is frequently necessary to make time-critical decisions regarding management of expanding pest populations. When an invasive pest outbreak is expanding rapidly, preemptive quarantine of areas that are under imminent threat of infestation is one of only a few available management tools that can be implemented quickly to help control the expansion. The preemptive quarantine of locations that surround an infested area also acts as a safeguard to counteract the risk of failed detections of the pest in field surveys. In this paper, we present a method that assesses the suitability of preemptive quarantine measures at the level of small geographical subdivisions (U.S. counties). The cost of a preemptive quarantine in a given county is weighed against the protective benefit of delaying the spread of an outbreak to other neighboring counties. We demonstrate the approach with a decision support model that estimates the suitability of preemptive quarantine across multiple counties that surround areas infested with the emerald ash borer (Agrilus planipennis Fairmaire (EAB), Coleoptera: Buprestidae), an emerging major threat to ash tree species (*Fraxinus* spp.) in North America. The model identifies the U.S. counties where the installation of preemptive quarantine would most effectively slow the spread of EAB populations and reduce risk to high-value areas.

1. Introduction

Management of large-scale outbreaks of invasive exotic species relies on timely detections to minimize the effects of initially undetected spread and impact. Unfortunately, detection efforts for such species can be imperfect, especially in instances of low-density pest populations (Marshall et al., 2009). This results in uncertainties in the detection of new populations. Such is consistent with many other aspects of invasive species management, which tend to involve risk analyses under uncertainty (Bartell and Nair, 2003; Burgman et al., 1999; Caley et al., 2006). Consequently, there is a pressing need, both internationally and domestically, for the development of scientifically sound risk assessment methods under conditions where the supply of empirical data is below demand (Andersen et al., 2004; Justo-Hanani et al., 2010).

Quarantines implemented along and around establishment zones and dispersal pathways have been recognized as effective tools that help to address the typical lack of knowledge about new invaders and the common inability to detect them in a timely fashion (Hennessey, 2004). The implementation of quarantine depends on some understanding of a species' key spread vectors and geographic factors that may contribute to the successful movement of the pest through the landscape. Human-mediated spread has been recognized as an important vector for many forest and agricultural pests (Shigesada and Kawasaki, 1997), hence any action that limits the human activities that cause the movement of invasive organisms over distances beyond the species' natural spread range could, in theory, increase the amount of time available for early detection and the development of an appropriate mitigation strategy. Furthermore, if the ability to detect a pest in the early stages of invasion is limited, it is quite possible that populations could already be established in areas deemed uninfested (i.e.,

---

[*] Corresponding author. Tel.: +1 970 295 5865; fax: +1 970 295 5815.
E-mail addresses: johnwithrow@fs.fed.us (J.R. Withrow), elsmith@fs.fed.us (E.L. Smith), fhkoch@fs.fed.us (F.H. Koch), dyemshan@nrcan.gc.ca (D. Yemshanov).
[1] Tel.: +1 970 295 5841.

http://dx.doi.org/10.1016/j.jenvman.2014.11.001
0301-4797/© 2014 Elsevier Ltd. All rights reserved.

where the pest survey did not yield positive finds). In such cases, a preemptive quarantine in the regions adjacent to areas with positive detections of a pest of interest is believed to be one of the few available management options that could potentially help slow the pest's expansion and protect locations with high-value host resources (Lodge et al., 2006).

Imposing a quarantine is a costly action. Quarantines disrupt economic activities in the affected areas and impose additional local costs related to monitoring, shipping restrictions, and preventative treatments (e.g., USDA APHIS, 2010). In addition, costs are also experienced on the federal level. The United States Department of Agriculture (USDA), for example, in 2007 allocated $1.2 billion USD towards the management of invasive species, with approximately 22% directed towards early detection, rapid response, and preemptive measures (NISC, 2007). Thus, minimizing the potential costs of quarantine is always a concern, and a preemptive quarantine should only be imposed when it is sufficiently advantageous to do so. Several techniques have been proposed to estimate the suitability of a quarantine action as a measure to slow the spread of invasive pests (Sharov and Liebhold, 1998; Soliman et al., 2010), with risk and threat analyses among the most widely used. Risk and threat analyses usually involve the assessment of various consequences of a quarantine action, direct assessment of the factors that influence the spread of an outbreak (such as the abundance of a susceptible host species, proximity to already infested sites, anticipated spread rate of an outbreak), as well as potential costs associated with imposing a regulatory action (Venette et al., 2010). Several studies have applied cost-benefit calculations to estimate the suitability of strict regulatory measures (Cooke and MacDonell, 2008; Mehta et al., 2010; Maguire, 2004) to mitigate the likelihood of severe pest outbreaks, however these assessments are difficult to implement at the level of fine-scale geographical subdivisions (U.S. counties) due to a lack of geographically explicit data about the size and spatial allocation of economic activities that may be associated with the pest of interest.

When considering the imposition of a preemptive quarantine in regions surrounding the area already infested by a pest, the simplest approach is to prioritize regions based on the relative impact of a particular quarantine action on the local spread rate of the pest. These analyses may be guided by maps that depict the likelihood of pest arrival (or another risk metric) in the area of interest (Yemshanov et al., 2009; Venette et al., 2010). In this study, we undertake a somewhat different approach and consider not only the suitability of quarantine in a given geographical county but also the expected benefits of imposing the quarantine in the neighboring counties that surround the county of interest. We consider the spread of an invasive pest as a gradual geographic dispersal process, and estimate the capacity of a preemptive quarantine to block the potential spread pathways of the pest to other geographic domains. By adding the evaluation of potential benefits to other geographic counties, we essentially evaluate the ability of the quarantine action undertaken at a given locale to help slow the spread at a broader geographic scale. This total benefit is weighted against the cost of conceding the loss of host within the newly quarantined county. Using this cost-benefit analysis, we estimate an optimal quarantine allocation across multiple counties that surround the infested area, and we assign to each county (i.e., a potential candidate for preemptive quarantine) a quarantine priority rank.

1.1. Species of interest

This study assesses the priorities of a preemptive quarantine for the exotic invasive emerald ash borer (*Agrilus planipennis* Fairmaire (EAB), Coleoptera: Buprestidae), a major pest of all ash tree species (*Fraxinus* spp.) in North America (Jendek, 1994; Poland and McCullough, 2006). The first EAB population was discovered in the city of Detroit in the summer of 2002, and the pest has since spread throughout much of the eastern United States and eastern Canada (Poland and McCullough, 2006). A primarily semivoltine buprestid (Siegert et al., 2010), adult EAB females lay eggs on the exterior of the bark. Larvae hatch and bore into the phloem, where they develop through four larval instars. The larvae excise serpentine galleries through the phloem and score the outer xylem, resulting in an eventually lethal girdling of the tree (Cappaert et al., 2005). These factors, combined with the lack of coevolved host resistance and a diverse natural enemy complex, make EAB a significant threat to ash resources throughout North America. Ash constitutes approximately 7% of saw timber in the eastern United States, with a stumpage value estimated at $25 billion. In addition, with ash being one of the most prolific of all urban tree genera, potential costs of removing urban ash trees throughout the United States have been estimated to be as much as $20-60 billion, in addition to replacement costs (Raupp et al., 2006; Cappaert et al., 2005; Snydor et al., 2007).

Currently, no reliable methods of early EAB detection have been developed. The effective geographic range of trap lures is unknown at this time, and external symptoms on ash trees become apparent only after the local population density has increased to a degree by which time beetles have already dispersed (Herms and McCullough, 2014). Efforts have focused on the development of optimized sampling (e.g., Coulston et al., 2008) and trap characteristics (e.g., Marshall, 2009, 2010). The long-distance dispersal of EAB is often assisted by the movement of infested materials, such as firewood, nursery stock and logs (Tobin et al., 2010; Cappaert et al., 2005). For this reason, the management of EAB has relied heavily on the regulation of the movement of EAB-associated materials by way of quarantine measures on such materials at the county level (USDA APHIS, 2011).

1.2. Study objectives

In this study, we demonstrate how one can implement a cost-benefit suitability analysis for preemptive quarantine, using EAB as an example. We estimate the suitability of imposing a preemptive quarantine for EAB at the level of U.S. counties. For each county we consider the amount of susceptible host resource (ash) under risk of infestation, as well as the potential risk of infestation to neighboring counties if an outbreak were to be established in said county. Formally, we define the additional risk of infestation to the surrounding counties as the product of the total value of the susceptible host in surrounding counties and the probability that the pest population will spread to the neighboring counties. The latter component is depicted via an omnidirectional dispersal kernel that estimates the likelihood of spread across geographic space as a function of distance.

2. Methods

2.1. Model of pest invasion spread

Consider a landscape consisting of m small territorial subdivisions (e.g., U.S. counties). Each county can be characterized as infested or uninfested with a given pest, i.e.:

$$\delta_i = \begin{cases} 0 & \text{if county } i \text{ is uninfested} \\ 1 & \text{if county } i \text{ is infested} \end{cases} \tag{1}$$

where $i \in \{1 \ldots m\}$. It is important to note here that the above variable describes specifically what counties are *known* to be infested and those that are not. In some cases detection is imperfect, and hence such knowledge is equally imperfect, so in equations to follow we also describe the probability that an “uninfested” county ($\delta_i = 0$) is actually infested but not known to be infested.

Let H_i define the hazard if a given county i is infested with EAB, which is assumed to be dependent on the amount of available host in the county. (We note, however, that the hazard estimate may also include other aspects, such as harvestable portion of stands, the value of ecological services, and other factors.) For all counties, the hazard value can be estimated as $(1-\delta_i)H_i$ with the portion in parentheses limiting such hazard to counties not already known to be infested. With risk being herein defined as probability multiplied by hazard, the risk of infestation can then be estimated as $P_i(1-\delta_i)H_i$ where P_i is the probability that county i is infested. Since county i may receive the pest from multiple infested counties, the total risk of infestation, P_i, can be estimated as the sum of independent pest arrival probabilities from all surrounding infested counties. We estimated the probability of pest arrival as a function of distance from the nearest infested county, as represented by a Gaussian dispersal kernel. A Gaussian kernel describes the simplest spatial diffusion process among a multitude of kernel types proposed to characterize spread in ecological invasions (Kot et al., 1996; Iverson et al., 2010; Mercader et al., 2009; Neubert and Parker, 2004; Pitt et al., 2009). For an infested county of origin, j, that is not under quarantine, we define the probability of human-assisted spread to county i as:

$$P_i = \sum_{j=1, j\neq i}^{m} \frac{a\delta_j}{\sigma\sqrt{2\pi}} e^{-\frac{d_{ij}^2}{\sigma^2}} = a\theta_i \tag{2}$$

and if the county of origin is under quarantine, then the probability of spread takes the same form with modified parameters:

$$\tilde{P}_i = \sum_{j=1, j\neq i}^{m} \frac{\tilde{a}\delta_j}{\tilde{\sigma}\sqrt{2\pi}} e^{-\frac{d_{ij}^2}{\tilde{\sigma}^2}} = \tilde{a}\tilde{\theta}_i \tag{3}$$

where for each equation a and σ (and $\tilde{a}$ and $\tilde{\sigma}$) denote the standard parameters of the Gaussian kernel – the amplitude and the standard dispersal distance (Kot et al., 1996; Banks, 1994) and d_{ij} is the Euclidean distance between the centroids of counties i and j. Here the term “amplitude”, hereafter referred to as “invasion amplitude”, has units describing the number of expected new infested counties expressed as a proportion of existing infested counties (e.g., for a 10% growth in infested counties, invasion amplitude has a value of 0.1).

We also make a simplifying assumption that quarantine affects only the amplitude of the dispersal kernel (i.e., the parameter $\tilde{a}$ in equation [3]) but does not change the standard dispersal distance (i.e., $\sigma = \tilde{\sigma}$). With this assumption, the probabilities of pest arrival with and without quarantine can be related via the ratio of kernel amplitude values:

$$\tilde{P}_i = \frac{\tilde{a}}{a}P_i \quad \tilde{\theta}_i = \theta_i \tag{4}$$

This allows us to use the ratio between the kernel amplitude values to adjust the probability of pest arrival under quarantine conditions as well as to define the proportional reduction of human-mediated dispersal via quarantine, $\tilde{\omega}$, as:

$$\tilde{\omega} = 1 - \frac{\tilde{a}}{a} \tag{5}$$

In addition to human-assisted spread, the pest can also spread by natural biological means. We used a similar Gaussian kernel to define the probability of pest dispersal by biological means:

$$\hat{P}_i = \sum_{j=1, j\neq i}^{m} \frac{\hat{a}\delta_j}{\hat{\sigma}\sqrt{2\pi}} e^{-\frac{d_{ij}^2}{\hat{\sigma}^2}} = \hat{a}\hat{\theta}_i \tag{6}$$

Here, we denote the parameters related to biological spread with a hat notation (“^”). For many invasive pests established in North America, natural biological spread represents a relatively small component of the total spread potential and the majority of long-distance introductions can be attributed to human activities (Neubert and Caswell, 2000; Koch et al., 2009). Notably, quarantine actions are generally focused on stopping the human activities which may cause the long-distance spread of pests. Therefore, we have made a simplifying assumption that the quarantine would have no impact on the natural biological spread component.

Using our simplified notation at the end of equations (3), (4), and (6), we define the following:

$$I_i = \left(1 - \tilde{a}\theta_i\right)\left(1 - \hat{a}\hat{\theta}_i\right) \tag{7}$$

as the combined probability that county i *has not* been infested by individuals dispersed from any known infested county by either natural or anthropogenic means. Its complement $(1-I_i)$ then is the probability that the county has been infested by either means by individuals from at least one known infested county.

Stated differently, the expression $(1-I_i)$ denotes the probability that a given county believed to be uninfested $\delta_i = 0$ is actually infested, but unknowingly so. We can then subsequently define the risk that such an unknowingly infested county i now imposes on all other counties through anthropogenic means:

$$\varphi_i = \sum_{j=1, j\neq i}^{m} (1-\delta_j)H_j \frac{a}{\sigma\sqrt{2\pi}} e^{-\frac{d_{ij}^2}{\sigma^2}} \tag{8}$$

as well as the reduction of such risk via quarantine:

$$\varphi_i - \tilde{\varphi}_i = \left(1 - \frac{\tilde{a}}{a}\right)\varphi_i \tag{9}$$

2.1.1. *The cost-benefit analysis: estimating the suitability of preemptive quarantine*

For each uninfested county, we estimated the suitability of preemptive quarantine in terms of the individual contribution of a given county's quarantine to the added protection of the nearby counties. This required estimating, for each county i, the potential decrease of the probabilities of EAB movement to the adjacent counties via the quarantine.

Using the notation defined above, we estimated the cost of preemptive quarantine action as:

$$C_i = (1-\delta_i)H_i I_i \tag{10}$$

or the product of the host value H_i of the non-quarantined ($\delta_i = 0$) county and the probability that the county is not already infested I_i (i.e., the value of the county multiplied by the probability that the quarantine is unnecessary). Similarly, the benefit of such quarantine can be written as:

$$B_i = (1-\delta_i)(1-I_i)\tilde{\omega}\varphi_i \tag{11}$$

or the probability that an unquarantined county ($\delta_i = 0$) is actually infested $(1-I_i)$ multiplied by the benefit to surrounding counties via quarantine. The suitability of a preemptive quarantine at county i can then be estimated as the difference between the benefits of protecting the host resource in the surrounding counties and the cost of imposing the quarantine at county i:

$$Q_i = B_i - C_i = (1-\delta_i)[(1-I_i)\tilde{\omega}\varphi_i - H_iI_i] \tag{12}$$

The value of the suitability metric Q_i can then be used to support quarantine decisions. Positive values ($Q_i > 0$) imply that imposing a preemptive quarantine at the county i is suitable, while negative values ($Q_i < 0$) suggest it is not suitable. In addition, the relative values of Q_i can be used to rank multiple territorial counties across large heterogeneous landscapes and prioritize them for quarantine.

2.2. Model parameterization

Table 1 lists a summary of the model parameters defined in the previous equations. We used data from the USDA Animal and Plant Health Inspection Service (APHIS) EAB survey (USDA/APHIS/PPQ IPHIS) to list counties infested with EAB for each year since 2002 and estimate the pest‘s capacity to spread via biological and human-assisted means. Information from the Canadian National Forest Inventory (Gillis et al., 2005) was also included in the model, albeit only for simulation, not parameterization. Fig. 1 displays the total number of EAB infested counties for each year. We used a nonlinear regression in R (R Development Core Team, 2011) to fit the data and estimate an annual rate of EAB expansion. Based on fitted estimates, we set the amplitude parameters for human-mediated and natural spread of the pest, a and $\hat{a}$ (see Table 1), to 30% per year.

The parameter for natural biological standard dispersal distance,$\hat{\sigma}$, of EAB was set to 5 km (Table 1). This estimate, though consistent with Taylor et al. (2007), implies a somewhat greater dispersal rate than the 800 m dispersal distance that was found by Siegert et al. (2010), but is much more conservative than the 10–20 km distances employed by Kovacs et al. (2010), which is understandable since the latter study modeled natural and anthropogenic dispersal together.

The distance parameter σ for human-assisted spread (Table 1) was estimated from a county-based analysis. Fig. 2 shows a histogram of distances between the centroids of known EAB infested counties in 2002 and centroids from counties newly infested in 2003. From this histogram the anthropogenic standard dispersal distance was estimated as approximately 100 km.

The model also required estimating the efficacy of quarantine. Since available literature did not provide quantitative evidence of the efficacy of regulatory actions implemented for EAB in the past, we assumed that quarantine would reduce the rate of human-assisted dispersal by half (Table 1) but also tested a range of efficacy values from 0 to 100%. Although Mumford (2002) lists multiple regulatory successes that imply high values of quarantine efficacy, little direct information exists on estimating this quantity, which unfortunately will be illustrated in the Sensitivity Analysis as being a parameter to which the results are highly sensitive.

Table 1
List of model parameters, showing amplitude and dispersal distances of natural and anthropogenic dispersal as well as efficacy of quarantine and values of host in each county.

Parameter	Description
a	Amplitude of human-aided dispersal in the absence of quarantine (expected proportional increase of infested counties in the following year)
$\tilde{\omega}$	Efficacy of quarantine (0 being “no effect” to 1 being a “full effect”)
$\hat{a}$	Amplitude of natural dispersal (expected proportional increase in infested counties in the following year)
σ	Standard dispersal distance of human-aided dispersal (km)
$\hat{\sigma}$	Standard dispersal distance of natural dispersal (km)
$H_i \forall i \in \{1\ldots m\}$	Host (hazard) value for each county i (unitless)

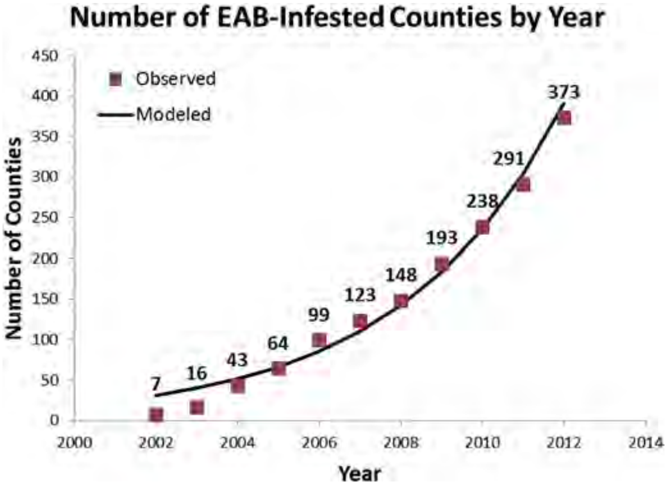


Fig. 1. The number of U.S. counties infested with emerald ash borer (*Agrilus planipennis* Fairmaire) over time. Observed values were from APHIS EAB survey (USDA/APHIS/PPQ IPHIS); modeled estimate (bold line) shows an exponential curve fit.

Quarantine efficacy may prove to be the most challenging to quantify, since the influence of regulatory measures in preventing subsequent establishments may be difficult to detect given a myriad of potentially confounding factors (host availability, site accessibility, etc.) that may influence the same. In addition, estimation of this quantity is further complicated by the multitude of quarantine techniques available, the multiple time frames in which efficacy can be defined, and the complex ways in which efficacy can be influenced by the spatial allocation of resources between high-risk and low-risk areas (Mumford, 2002). As a quick measure of the appropriateness of the preemptive quarantine, the proportional difference in number of newly infested counties inside and outside the quarantine were compared using a binomial distribution (Ott, 1993).

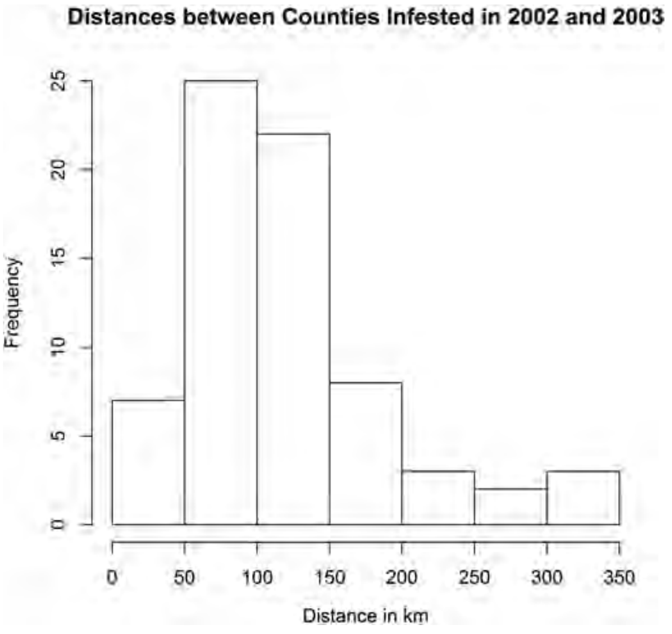


Fig. 2. Histogram of distances between the centroids of newly infested counties in 2002 and centroids of counties newly infested in 2003. From this histogram the standard anthropogenic dispersal distance was estimated to be 100 km.

Table 2
List of modifications made to non-host parameters in sensitivity analyses, expressed as percentage departures from baseline values.

Parameter modification	a, $\hat{a}$	$\tilde{\omega}$	σ	$\hat{\sigma}$
+100%	0.600	1.000	200,000	10,000
+50%	0.450	0.750	150,000	7,500
+25%	0.375	0.625	125,000	6,250
+15%	0.345	0.575	115,000	5,750
Baseline value	**0.300**	**0.500**	**100,000**	**5,000**
−15%	0.255	0.425	85,000	4,250
−25%	0.225	0.375	75,000	3,750
−50%	0.150	0.250	50,000	2,500
−100%	0.000	0.000	1*	1*

2.3. *Sensitivity analysis*

Sensitivity analyses can be used to systematically and comprehensively test the effect of changes in model parameters (Starfield and Bleloch, 1991) and can reveal a hierarchy of parameter importance in the model, thus providing insights into model structure and properties. No single, universally accepted procedure for sensitivity analysis of multi-parameter models has been developed (McCarthy et al., 1995; Frey and Patil, 2002; Greenland, 2001), but a common approach to sensitivity analysis is to explore the effects of changing parameters, one at a time, on a target output variable (Henderson-Sellers and Henderson-Sellers, 1996; Swartzman and Kaluzny, 1987). We recalculated the model results with the parameters changed by fixed percentages (e.g., ±10%, one parameter at a time). We tested all parameters displayed in Table 1, with the caveat that the amplitudes of unregulated anthropogenic and natural dispersal, a and $\hat{a}$, were consistently maintained as equal to each other. With the exception of the host parameters, we evaluated changes in the model outputs based on alterations of the individual parameters at four levels, ±15%, ±25%, ±50% and ±100% (Table 2).

3. Results

Sensitivity results are displayed in Figs. 3–5, where each map illustrates the change in Q_i model output (Q suitability change, or "QS Change") in response to the modification of a single model parameter while holding all others constant. The maps use a consistent color scheme and scale to illustrate the different degrees of impact that changes in one parameter can have in comparison to changes in a different parameter. An increase in invasion amplitude by 50% (Fig. 3A) increases the probability of infestation to the counties near to those already infested, thereby causing an increase in suitability of imposing the quarantine (areas in blue). The impact of a reduction of invasion amplitude by 50% is close to the precise opposite (Fig. 3B). An increase in the efficacy of the quarantine has the same impact on quarantine suitability for counties outside the quarantine zone (Fig. 4), since an increase in the quarantine efficacy makes such quarantine efforts more potentially beneficial.

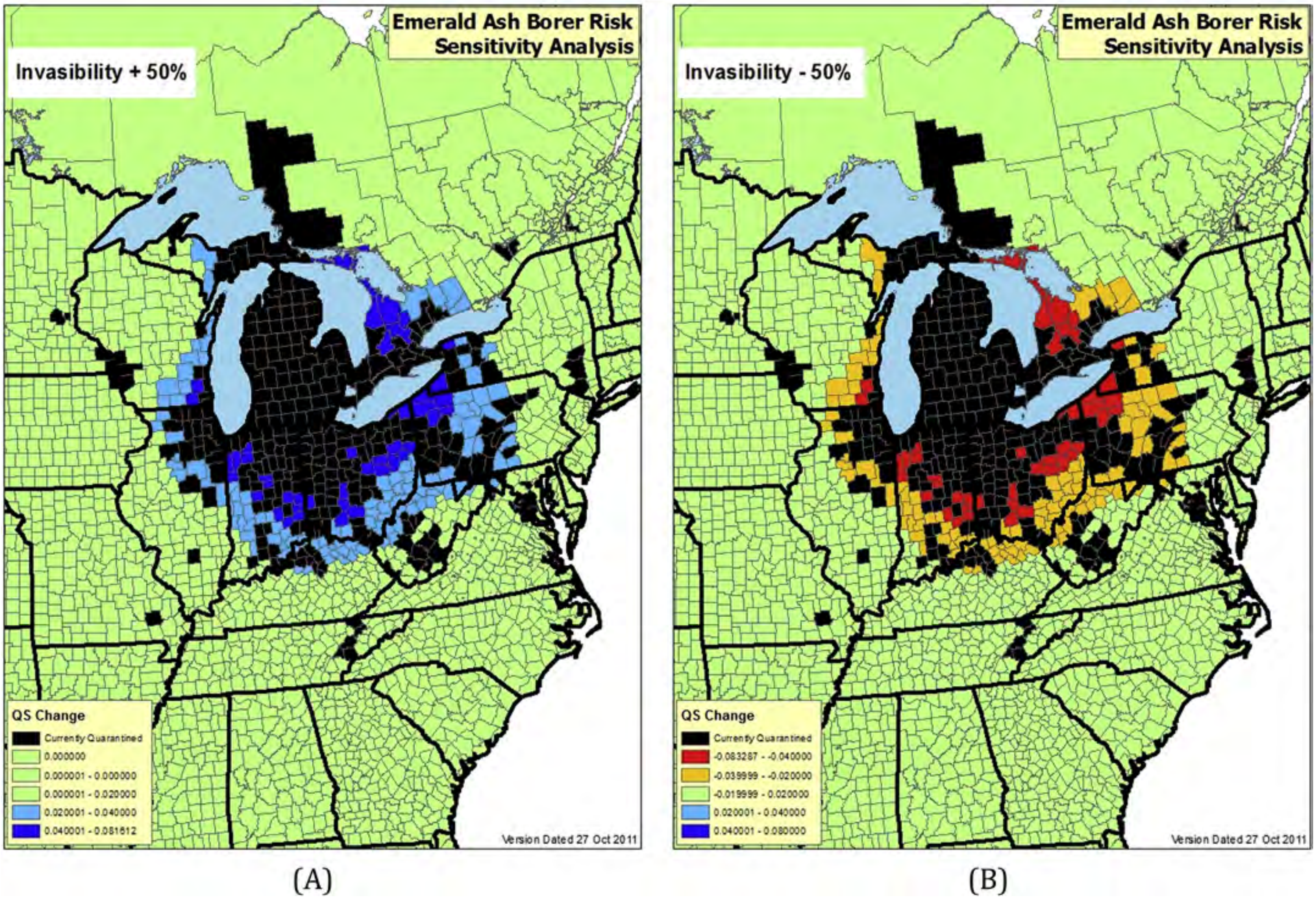


Fig. 3. Changes in Q_i model results for each county in response to a 50% increase (A) and a 50% decrease (B) in the invasion amplitude parameters (a and $\hat{a}$).

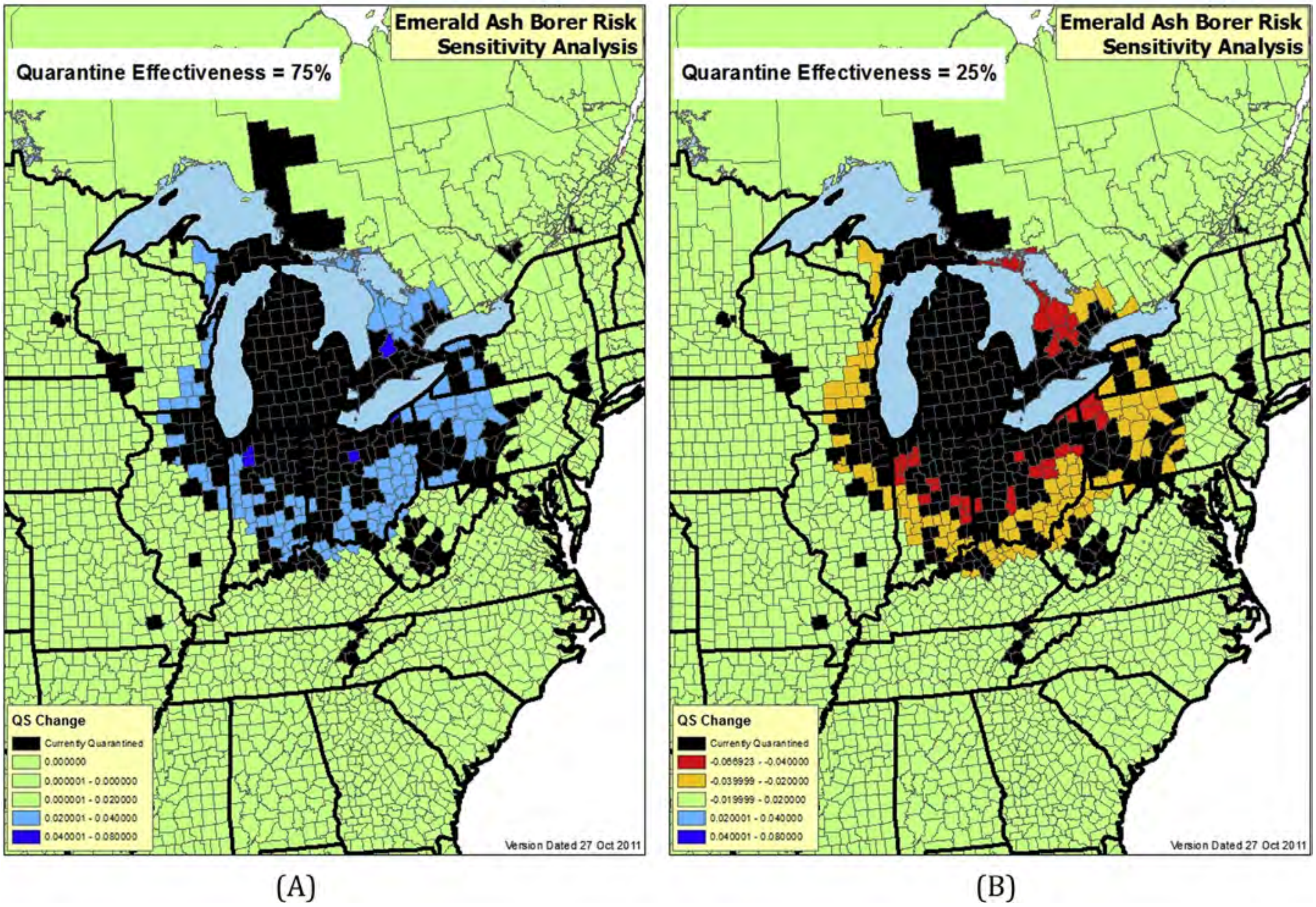


Fig. 4. Changes in Q_i model results for each county in response to a 50% increase (A) and decrease (B) in efficacy of quarantine ($\tilde{\omega}$).

Similar alterations of the human-assisted standard dispersal distance values (σ) produce results that are highly dependent upon the county's distance to the nearest infested locations (Fig. 5). An increase of human-assisted dispersal distance results in higher quarantine suitability for counties relatively distant from known infestations (Fig. 5A). This shows up especially in northeastern Wisconsin, which receives an increased probability of infestation from three geographic sources: the upper peninsula of Michigan, the greater Chicago area and northeastern Illinois, and the Mississippi River valley in the vicinity of the city of Dubuque, in northwestern Iowa. Decreases in anthropogenic spread distances increase the suitability of counties near to infested ones, at the expense of more remote counties (Fig. 5B).

The sensitivity of the outputs to the changes in host parameters was then investigated. Describing the total possible ash losses could be attempted in multiple ways. With ash being a prolific species in the eastern United States, total county area could serve as a proportional estimator. More directly, ash at risk could be estimated using the USDA Forest Inventory and Analysis (FIA) data, an ongoing systematic, plot-based inventory of non-urban forested areas (Lund and Thomas, 1989; USDA Forest Service, 2006). Third, with ash being a common urban tree species, county population could conceivably serve as a proportional proxy variable for the presence of ash. Hence, four scenarios were employed. For the baseline scenario (results to follow in Fig. 7) we assumed that host amounts for all counties were equal ($H_i = 1$). Such is the assumption for all baseline model runs. Next, we employed three alternative scenarios (Fig. 6) which assumed that (A) the host values are proportional to the county area, (B) the values of H_i are proportional to total county population, and (C) the total host value is proportional to the county's total basal area of ash estimated via a spatial interpolation of information from the FIA database (Krist et al., 2010). In particular parts (B) and (C) display drastic departures from the baseline results, where strong increases in suitability are observed in blue for low-value areas in an effort to protect the high-value areas in red, which in part (B) are counties of high population and in part (C) are counties of high non-urban ash basal area.

Fig. 7 presents the map of the quarantine suitability ranks for the scenario that uses the baseline parameter values. As anticipated, the areas where the preemptive quarantine would be most feasible are in close proximity to the existing EAB infestations throughout the eastern U.S. Fig. 7 also shows the boundary (blue outline) of an existing preemptive sampling restriction area previously implemented by USDA APHIS in 2011. This boundary includes all but eastern Pennsylvania and most of West Virginia. Notably, in these two states the existing boundary is approximated by the boundary between moderate (yellow) and high (orange) values of modeled quarantine suitability ranks. The modeled ranks, therefore, provided the prescriptive feedback of extending this existing boundary of future sampling restriction to include all areas of high and very high quarantine suitability ranks (marked in orange and red). Hence, although the model results describe suitability for preemptive quarantine, in this instance it was used for the similar purpose of determining which locations to exclude from future sampling efforts

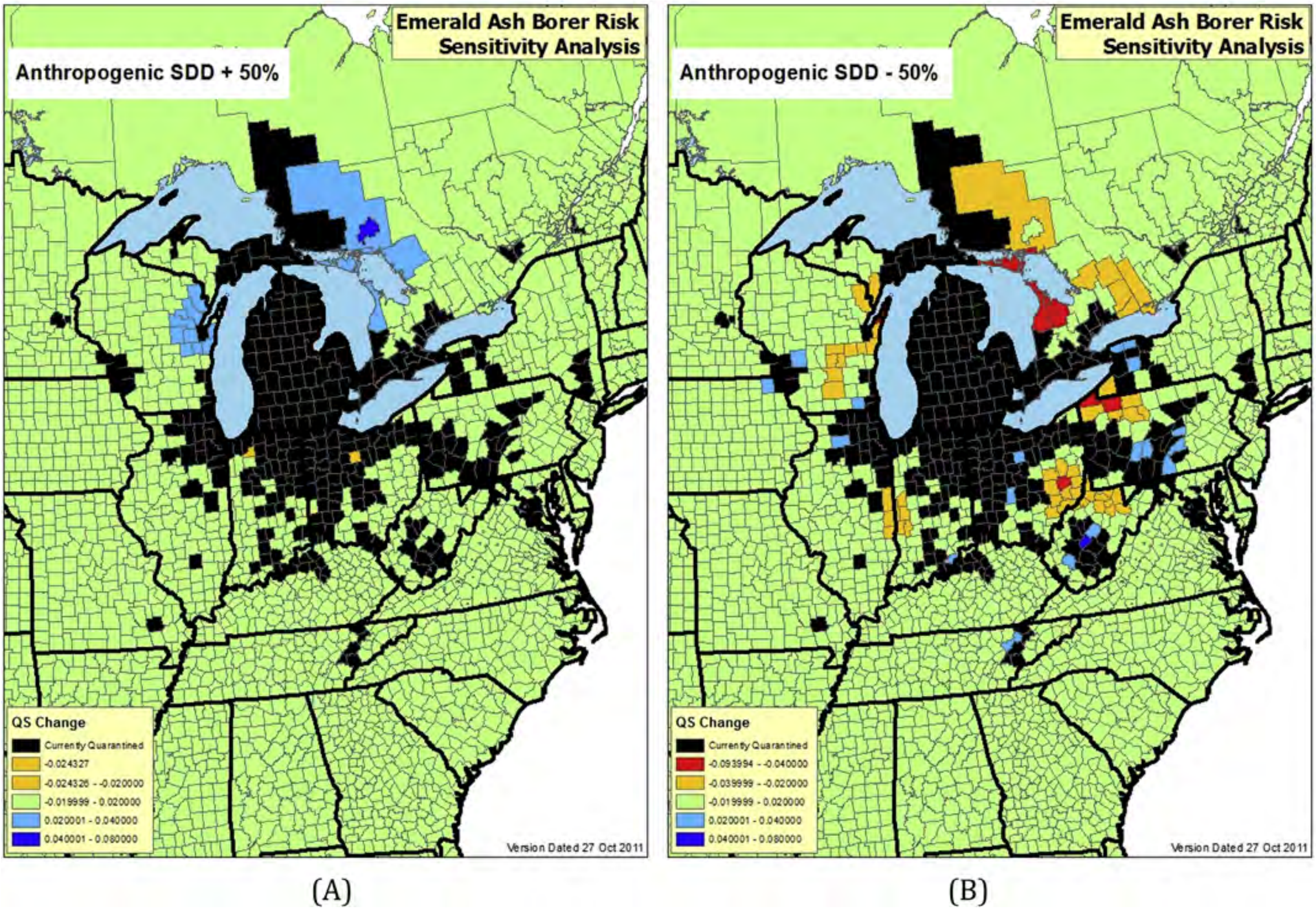


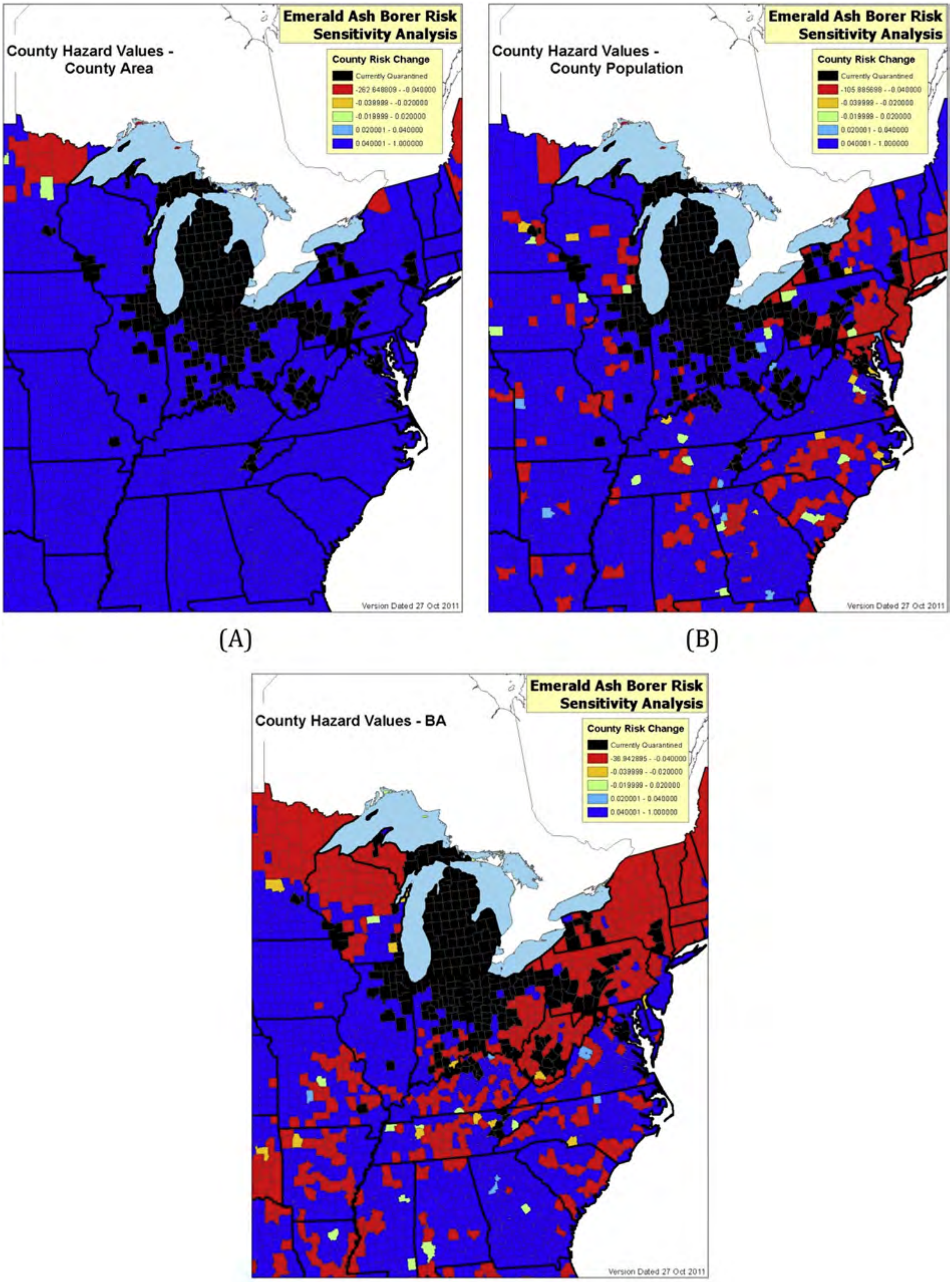
Fig. 5. Changes in Q_i model results for each county in response to a 50% increase (A) and decrease (B) in the standard human-mediated dispersal distance parameter (σ).

for EAB detection. Table 3 shows the number of counties inside and outside of this sampling exclusion zone along with the number of counties found to be infested in the following year. Even with sampling efforts within the exclusion zone only coming from auxiliary sources, the proportion of newly discovered infested counties within the exclusion zone was found to be significantly higher ($\chi^2 = 204.3086, df = 1, P < 0.0001$) than the proportion of newly discovered infested counties outside the zone.

As suggested by the model, the new area of future sampling restriction would extend throughout all of Michigan except the western portions of the Upper Peninsula, all of eastern and southern Wisconsin, all of northern and northeastern Illinois, all but extreme southwestern Indiana, all of Ohio, northern Kentucky, northern Virginia, western Maryland and New York, and all but southern West Virginia and eastern Pennsylvania. The area would now affect multiple new areas of public land, including Hoosier National Forest (IN), Wayne National Forest (OH), Monongahela National Forest (WV), the Allegheny National Forest (PA) and northern portions of Daniel Boone National Forest (KY). Some new urban forests affected by the new quarantine boundary would include Madison (WI), Terra Haute (IN), Ashland (KY), Canton (OH), Jamestown (NY), Niagara Falls (NY), Huntington (WV), Parkersburg (WV), Morgantown (WV), and Winchester (VA).

4. Discussion

In a decision-making context a preemptive quarantine often represents one of few available options that can be employed within an overall preventative management strategy to slow rapidly expanding outbreaks of invasions when little is known about the organism of concern. Such efforts conceivably reduce overall risks to a larger geographic area and potentially allow for more time for effective detection and mitigation efforts to develop (Krushelnycky et al., 2004). In this paper, we propose a simple yet analytically tractable model to estimate the suitability of preemptive quarantine in a geographically explicit environment. Our model incorporates two key spatially explicit management considerations: the choice of protecting the host resource in a *given* county and the option of protecting the host resources in *surrounding* counties by placing the given location under quarantine. In this model formulation we have used a fairly simple premise that the capacity of the quarantine in one county to prevent (or delay) the subsequent infestation of other (nearby or distant) regions should be perceived as an important decision factor when considering the imposition of regulatory action. This factor was regularly neglected in prior EAB surveys and decisions to regulate areas were mostly based on proximity to detected infestations and the amount of susceptible host resource in the local vicinity (Iverson, 2010; Mercader et al., 2011). Notably, the capacity of a preemptive quarantine to influence the expansion rate of an outbreak has been acknowledged in the context of controlling the spread of infectious disease (Day, 2004). In our model scenarios, the introduction of geographically explicit parameters (such as spatially varying amounts of host resources, Fig. 6) helps better understand the capacity of the preemptive quarantine to slow the spread of pest invasions in a spatially heterogeneous environment.



(A) (B)

(C)

Fig. 6. Changes in Q_i model results for each county in response to different approaches to estimating the relative value of each U.S. county, where the value is made proportional to (A) county area, (B) county population, and (C) total ash basal area.

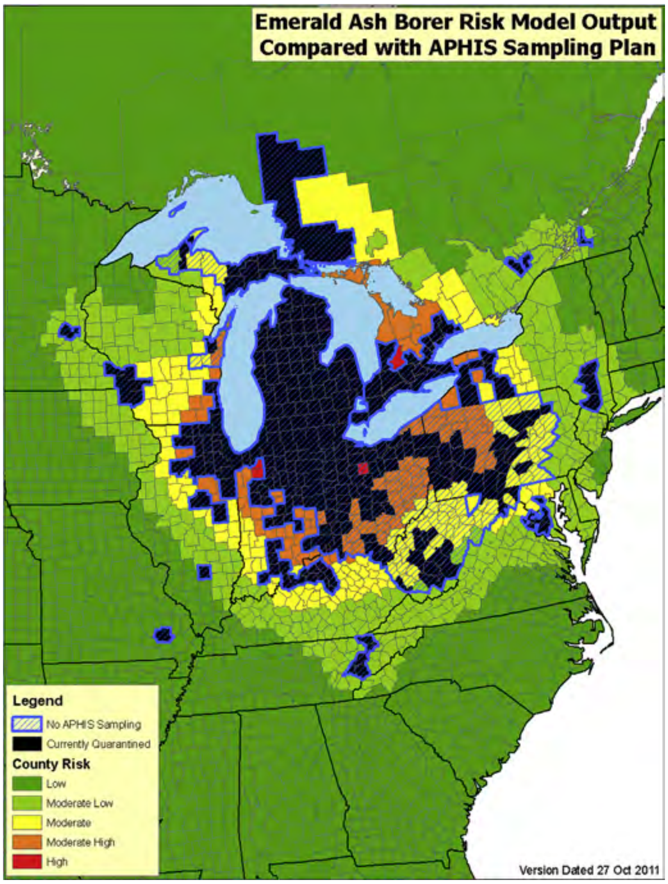


Fig. 7. Suitability (Q_i) of preemptive quarantine for emerald ash borer at the end of 2011 displayed as interpretive categories. The boundary of the preemptive sampling restriction area previously planned by USDA APHIS is shown in blue.

It should be noted that recent experiences with managing the expansion of EAB in the U.S. and Canada provide a wide (and somewhat controversial) range of opinions regarding the estimated efficacy of preemptive quarantine actions for EAB. Our model provides an analytical tool that could help identify critical thresholds of quarantine efficacy for particular pest management scenarios and better understand how this may influence the overall spread rate of an expanding pest population.

The approach presented here has a traditional foundation, relying on two simple dispersal models, accounting for local variation of the susceptible host resources, and using recent surveys of the invasive organism of interest. Notably, the model accommodates time-critical updates of new detections, which is an important consideration for practical management of invasive pest outbreaks. Our approach permits us to individually decouple and evaluate key assumptions about the ecology of an invasive organism from assumptions concerning management (quarantine efficacy) and also from effects resulting from the spatial arrangement of host and quarantine. In addition, determining which model parameter contributes the most to the quarantine suitability value helps identify where knowledge refinements about the pest's behavior may be most urgently needed. Among the model parameters, the model outputs were most sensitive to the changes in human-assisted invasion amplitude, quarantine efficacy, and knowledge of host value and location. Changes in the dispersal parameters had less impact on the model outputs.

Table 3
Number of newly infested counties inside and outside the restricted sampling area ($\chi^2 = 204.3086, df = 1, P < 0.0001$).

	Not in sampling restriction area	In sampling restriction area
No new detection	2770	240
New detection occurred	37	45

Another advance of the methodology presented here is the development of a geographically explicit metric for quantifying the suitability of the preemptive quarantine effort. The study illustrates how this metric (Q_i) can be used to compare different locations across large geographical regions and identify the spatial domains where the suitability metric is the most (or least) sensitive to known parameters about the pest of concern. Moreover, our method may be applicable at the level of smaller spatial counties in cases where information about the infestation, the amount of host and/or local economic factors that cause a human-assisted spread of the pest is available.

The study had several limitations. First, the analysis uses a simplistic dispersal kernel to estimate the spread of the pest population. Ideally, the dispersal process should be modeled as realistically as possible; however our capacity to depict the spread process is often limited by a lack of knowledge about the invasive organism of interest (especially for newly detected invaders). Different shapes of dispersal kernels can be further explored (such as leptokurtic kernels – Andow et al., 1990), however their parameterization can be challenging due to a lack of data about the historical rate of species' spread. In addition, in the case of human-mediated dispersal, one should also consider the replacement of the kernel approach with a network–based methodology that would display spread in a pathway-centric form along different artificial transportation corridors and spread vectors (Koch and Smith, 2010). Second, we only used the total amount of host resource to estimate the potential risk of infestation. More complex metrics may include more in-depth assessments of host quality, economic value, or degree of anticipated losses to market access that would more accurately describe the potential losses associated with an outbreak. Performing this adaptation of the model to include a more complex bioeconomic risk metric should be a straightforward task and can be applied to pests other than EAB. The model's strong sensitivity to the depiction of host resource compels future efforts with this model to accurately describe such county-based risk metrics.

Another important aspect that has been partially omitted from the results presented here is the notion of detection efficiency. For simplicity, our study assumed a perfect detection efficiency so that the probability of detecting the species (if present at a given location) is 1. Technically, our model can be further modified to accommodate an imperfect detection efficiency. Poor detection of the pest can be modeled via a detection efficiency parameter, ε ($0 \le \varepsilon < 1$), which then can be applied to the probability of species presence. In the present model framework surveys undertaken with poor detection efficiencies would result in higher invasion amplitude values (for example, if the detection efficiency in our baseline scenario is to be set to 0.1, then the dispersal amplitude values, a and $\hat{a}$, would increase from 0.3 to 3.0). Hence, uncertainties in detection efficiency propagate to increased uncertainty in the amplitude parameters. Since the sensitivity analysis indicated the model results to be highly sensitive to the dispersal amplitude parameters, the estimation of proper detection efficiency values becomes a critical part of the model parameterization process.

The study also did not explore spatial variabilities in quarantine efficacy or pest dispersal parameters. Possible geographic refinements of the dispersal model could include adding spatial parameters linked to certain types of landscape features (such as terrain, road network or settlements). Technically, our approach can be modified to account for the geographic variation of key model parameters, although this would require development of a more complex spatially dependent model that could track these parameters in a geographical domain. This will be a topic of future work.

The model has been implemented in an ESRI ArcGIS geographic information system (GIS) environment (Ormsby et al., 2001) and represents a simple, efficient, and expandable decision support tool for spatially explicit decision-making in response to expanding exotic pest invasions. We anticipate a typical use of the model as a time-critical rapid assessment tool. The underlying data assumptions and model results could be quickly updated in response to newly discovered locations as well as improved knowledge about an organism's behavior in its new environment, resulting in an objective, data-driven approach applying principles of adaptive management to the spread of exotic pests. Although the model principles are applicable to any expanding exotic pest, its application would be most appropriate to instances where preemptive quarantine would be an option under consideration due to the existence of one or more of the following:

1. The pest in question attacks a high-value host,
2. Most of the high-value host has yet to be attacked (i.e., the preemptive quarantine has a benefit of protecting unattacked high-value host),
3. The region of unattacked host is divisible into multiple geographic units of management (i.e., quarantining a portion of the unattacked host is an option),
4. Detection efforts of the pest have limited or unknown efficacy (i.e., the probability of undetected presence of the pest in a given geographic unit is considerable), and
5. Effective quarantine of such a pest to within one or more geographic units is a viable possibility (i.e., quarantine is a viable option and has some efficacy).

With the above qualifications in mind, the most advantageous use of the current model may be in the early phases of introduction of a newly discovered exotic pest, when most of the host stands are believed to be unaffected, but effective detection strategies have yet to be developed. Examples of such pests may include *Sirex noctilio* (Stone and Coops, 2004), *Ips typographus* (Wermelinger, 2004), and *Anaplophora glabripennis* (USDA APHIS, 2013). In regards to more advanced cases of exotic invasion such as European gypsy moth (*Lymantria dispar dispar*), efforts such as the “Slow the Spread” initiative (USDA Forest Service, 2007) display an alternative methodology of reducing the spread rate of a visible infestation front by way of intensive sampling in areas immediately ahead of the front. With the above five requirements in mind, this intensive sampling reduces the likelihood of undetected introduction (Requirement 4) and is applied to a forest pest that is far beyond the initial stage of invasion (Requirement 2). Hence, this methodology describes a different situation of detection and management, and illustrates further the applicability of the present work to instances of early invasion and poor detection capability.

For the reader's reference a copy of the model ArcGIS python code is available as a supplementary data file.

5. Conclusions

In this paper, we have described a methodology to assess the suitability of preemptive quarantine at the level of multiple small geographic subdivisions. A model presented here presents an analytic decision-support tool for the allocation of preemptive quarantine areas in one or more spatial subdivisions aimed to protect the rest of the uninfested landscape from a spatially dispersing exotic pest. The model compares the cost associated with imposing the quarantine at a given spatial subdivision with an estimated benefit in reducing the risk of infestation to other subdivisions in a landscape. Overall, the model facilitates a rapid data-driven decision support tool, and simple yet intuitive model formulations provide insights into which ecological and socioeconomic processes could potentially play the most important roles in the ongoing expansion of an outbreak.

Acknowledgments

We are very grateful to Marla Downing of USDA-FHTET and Paul Chaloux of USDA-APHIS for their continued support of this project. This project was funded under USDA-FS Task Order AG-7604-D-09-0541.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2014.11.001.

References

Andersen, M.C., Adams, H., Hope, B., Powell, M., 2004. Risk assessment for invasive species. Risk Anal. 24 (4), 787–793.
Andow, D.A., Kareiva, P.M., Levin, S.A., Okubo, A., 1990. Spread of invading organisms. Landsc. Ecol. 4, 177–188.
Banks, R.B., 1994. Growth and Diffusion Phenomena: Mathematical Frameworks and Applications. Springer-Verlag, 464 pp.
Bartell, S.M., Nair, S.K., 2003. Establishment risks for invasive species. Risk Anal. 24 (4), 833–845.
Burgman, M.A., Keith, D.A., Walshe, T.V., 1999. Uncertainty in comparative risk analysis for threatened Australian plant species. Risk Anal. 19 (4), 585–598.
Caley, P., Lonsdale, W.M., Pheloung, P.C., 2006. Quantifying uncertainty in predictions of invasiveness. Biol. Invasions 8, 277–286.
Cappaert, D., McCullough, D.G., Poland, T.M., Siegert, N.W., 2005. Emerald ash borer in North America: a research and regulatory challenge. Am. Entomol. 51 (3), 152–165.
Cooke, R.M., MacDonell, M., 2008. Regulating under uncertainty: newsboy for exposure limits. Risk Anal. 28 (3), 577–587.
Coulston, J.W., Koch, F.H., Smith, W.D., Sapio, F.J., 2008. Invasive forest pest surveillance: survey development and reliability. Can. J. For. Res. 38, 2422–2433.
Day, T., 2004. Predicting quarantine failure rates. Emerg. Infect. Dis. 10 (3), 487–488.
Frey, H.C., Patil, S.R., 2002. Identification and review of sensitivity analysis methods. Risk Anal. 22 (3), 553–578.
Gillis, M.D., Omule, A.Y., Brierley, T., 2005. Monitoring Canada's forests: the national forest inventory. For. Chron. 81 (2), 214–221.
Greenland, S., 2001. Sensitivity analysis, Monte Carlo risk analysis, and Bayesian uncertainty assessment. Risk Anal. 21 (4), 579–583.
Henderson-Sellers, B., Henderson-Sellers, A., 1996. Sensitivity evaluation of environmental models using fractional factorial experimentation. Ecol. Model. 86 (2–3), 291–295.
Hennessey, M.K., 2004. Quarantine pathway pest risk analysis at the APHIS plant epidemiology and risk analysis laboratory. Weed Technol. 18 (suppl. 1), 1484–1485.
Herms, D.A., McCullough, D.G., 2014. Emerald ash borer invasion of North America: history, biology, ecology, impacts, and management. Annu. Rev. Entomol. 59, 13–30.
Iverson, L.R., Prasad, A., Bossenbroek, J., Sydnor, D., Schwartz, M.W., 2010. Modeling potential movements of the emerald ash borer: the model framework. In: Pye, J.M., Rauscher, H.M., Sands, Y., Lee, D.C., Beatty, J.S., tech (Eds.), Advances in Threat Assessment and their Application to Forest and Rangeland Management. Gen. Tech. Rep. PNW-GTR-802, vol. 1. U.S. Department of Agriculture, Forest Service, Pacific Northwest and Southern Research Stations, Portland, OR, pp. 581–597, 708 pp.
Jendek, E., 1994. Studies in the east Palaearctic species of the genus *Agrilus* Dahl, 1823 (Coleoptera: Buprestidae). Part I. Entomol. Probl. 25 (1), 9–24.
Justo-Hanani, R., Dayan, T., Tal, A., 2010. The role of regulatory decision-making on non-indigenous species introductions. Biol. Invasions 12, 2815–2824.
Koch, F.H., Yemshanov, D., McKenney, D.W., Smith, W.D., 2009. Evaluating critical uncertainty thresholds in a spatial model of forest pest invasion risk. Risk Anal. 29, 1227–1241.
Koch, F.H., Smith, W.D., 2010. Representing human-mediated pathways in forest pest risk mapping. In: Pye, J.M., Rauscher, H.M., Sands, Y., Lee, D.C., Beatty, J.S., tech (Eds.), Advances in Threat Assessment and their Application to Forest and

Rangeland Management. Gen. Tech. Rep. PNW-GTR-802, vol. 1. U.S. Department of Agriculture, Forest Service, Pacific Northwest and Southern Research Stations, Portland, OR, pp. 421–443, 708 pp.

Kot, M., Lewis, M.A., van den Driessche, P., 1996. Dispersal data and the spread of invading organisms. Ecology 77 (7), 2027–2042.

Kovacs, K.F., Haight, R.G., McCullough, D.G., Mercader, R.J., Siegert, N.W., Liebhold, A.M., 2010. Cost of potential emerald ash borer damage in U.S. communities, 2009–2019. Ecol. Econ. 69, 569–578.

Krist Jr., F.J., Sapio, F.J., Tkacz, B.M., 2010. A multicriteria framework for producing local, regional, and national insect and disease risk maps. In: Pye, J.M., Rauscher, H.M., Sands, Y., Lee, D.C., Beatty, J.S., tech (Eds.), Advances in Threat Assessment and their Application to Forest and Rangeland Management. Gen. Tech. Rep. PNW-GTR-802U.S. Department of Agriculture, Forest Service, Pacific Northwest and Southern Research Stations, Portland, OR, pp. 621–636.

Krushelnycky, P.D., Loope, L.L., Joe, S.M., 2004. Limiting spread of a unicolonial invasive insect and characterization of seasonal patterns of range expansion. Biol. Invasions 6, 47–57.

Lodge, D.M., Williams, S., MacIsaac, H.J., Hayes, K.R., Leung, B., Reichard, S., Mack, R.N., Moyle, P.B., Smith, M., Andow, D.A., Carlton, J.T., McMichael, A., 2006. Biological invasions: recommendations for U.S. policy and management. Ecol. Appl. 16 (6), 2035–2054.

Lund, H.G., Thomas, C.E., 1989. A Primer on Stand and Forest Inventory Designs. Washington, DC: USDA Forest Service General Technical Report GTR-WO-54, 96pp.

Maguire, L.A., 2004. What can decision analysis do for invasive species management? Risk Anal. 24 (4), 859–868.

Marshall, J.M., Storer, A.J., Fraser, I., Beachy, J.A., Mastro, V.C., 2009. Effectiveness of differing trap types for the detection of emerald ash borer (Coleoptera: Buprestidae). Environ. Entomol. 38 (4), 1226–1234.

Marshall, J.M., Storer, A.A., Fraser, I., Mastro, V.C., 2010. Efficacy of trap and lure types for detection of *Agrilus planipennis* (Col., Buprestidae) at low density. J. Appl. Entomol. 134, 296–302.

McCarthy, M.A., Burgman, M.A., Ferson, S., 1995. Sensitivity analysis for models of population viability. Biol. Conserv. 73 (2), 93–100.

Mehta, S.V., Haight, R.G., Homans, F.R., 2010. Decision-making under risk in invasive species management: risk management theory and applications. In: Pye, J.M., Rauscher, H.M., Sands, Y., Lee, D.C., Beatty, J.S., tech (Eds.), Advances in Threat Assessment and their Application to Forest and Rangeland Management. Gen. Tech. Rep. PNW-GTR-802, vol. 1. U.S. Department of Agriculture, Forest Service, Pacific Northwest and Southern Research Stations, Portland, OR, pp. 445–468, 708 pp.

Mercader, R.J., Siegert, N.W., Liebhold, A.M., McCullough, D.G., 2009. Dispersal of the emerald ash borer, *Agrilus planipennis*, in newly-colonized sites. Agr. For. Entomol. 11, 421–424.

Mercader, R.J., Siegert, N.W., Liebhold, A.M., McCullough, D.G., 2011. Influence of foraging behavior and host spatial distribution on the localized spread of the emerald ash borer, *Agrilus planipennis*. Popul. Ecol. 53, 271–285.

Mumford, J.D., 2002. Economic issues related to quarantine in international trade. Eur. Rev. Agric. Econ. 29 (3), 329–348.

Neubert, M.G., Caswell, H., 2000. Demography and dispersal: calculation and sensitivity analysis of invasion speed for structured populations. Ecology 81 (6), 1613–1628.

Neubert, M.G., Parker, I.M., 2004. Projecting rates of spread for invasive species. Risk Anal. 24 (4), 817–831.

NISC (National Invasive Species Council), 2007. Fact Sheet: National Invasive Species Council Fiscal Year 2007 Interagency Invasive Species Performance Budget, Online Source: National Invasive Species Council. Available from: http://www.invasivespecies.gov/global/org_collab_budget/organizational_budget_performance_based_budget.html.

Ormsby, T.E., Napoleon, R.B., Groessl, C., Feaster, L., 2001. Getting to Know ArcGIS Desktop: Basics of ArcView, ArcEditor, and ArcInfo. ESRI, Inc., Redlands, CA, 541 pp.

Ott, R.L., 1993. An Introduction to Statistical Methods and Data Analysis, fourth ed. Duxbury Press, Belmont, CA.

Pitt, J.P.W., Worner, S.P., Suarez, A.V., 2009. Predicting Argentine ant spread over the heterogeneous landscape using a spatially explicit stochastic model. Ecol. Appl. 19 (5), 1176–1186.

Poland, T.M., McCullough, D.G., 2006. Emerald ash borer: invasion of the urban forest and the threat to North America's ash resource. J. Forest. 104 (3), 118–124.

R Development Core Team, 2011. R: a Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL. http://www.R-project.org/.

Raupp, M.J., Cumming, A.B., Raupp, E.C., 2006. Street tree diversity in eastern North America and its potential for tree loss to exotic borers. Arboric. Urban For 32 (6), 297–304.

Sharov, A.A., Liebhold, A.M., 1998. Model of slowing the spread of gypsy moth (Lepidoptera: Lymantriidae) with a barrier zone. Ecol. Appl. 8, 1170–1179.

Shigesada, N., Kawasaki, K., 1997. Biological Invasions: Theory and Practice. Oxford Univ. Press, New York, 218 pp.

Siegert, N.W., McCullough, D.G., Williams, D.W., Fraser, I., Poland, T.M., Pierce, S.J., 2010. Dispersal of *Agrilus planipennis* (Coleoptera: Buprestidae) from discrete epicenters in two outlier sites. Environ. Entomol. 39 (2), 253–265.

Soliman, T., Mourits, M.C.M., Oude Lansink, A.G.J.M., van der Werf, W., 2010. Economic impact assessment in pest risk analysis. Crop Prot. 29, 517–524.

Starfield, A.M., Bleloch, A.L., 1991. Building Models for Conservation and Wildlife Management. Burgess Press, Minneapolis, MN.

Stone, C., Coops, N.C., 2004. Assessment and monitoring of damage from insects in Australian eucalypt forests and commercial plantations. Aust. J. Entomol. 43, 283–292.

Swartzman, G.L., Kaluzny, S.P., 1987. Ecological Simulation Primer. Macmillan, New York, NY.

Sydnor, T.D., Bumgardner, M., Todd, A., 2007. The potential economic impacts of emerald ash borer (*Agrilus planipennis*) on Ohio, U.S., communities. Arboric. Urban Forest. 33 (1), 48–54.

Taylor, R.A.J., Poland, T.M., Bauer, L.S., Windell, K.N., Kautz, J.L., 2007. Emerald ash borer flight estimates revised. In: Mastro, V., Lance, D., Reardon, R., Parra, G., [comps.] (Eds.), Proceedings, Emerald Ash Borer and Asian Longhorned Beetle Research and Technology Development Meeting, 29 October – 2 November 2006, Cincinnati, OH. FHTET-2007-04. USDA Forest Health Technology Enterprise Team, Morgantown, WV, pp. 10–12.

Tobin, P.C., Diss-Torrance, A., Blackburn, L.M., Brown, B.D., 2010. What does 'local' firewood buy you? Managing the risk of invasive species introduction. J. Econ. Entomol. 103 (5), 1569–1576.

USDA APHIS, 2010. Initial Regulatory Flexibility Analysis, Interim Rule, Emerald Ash Borer, Additional Counties in Kentucky, Michigan, Minnesota, New York, Pennsylvania, and Wisconsin; the Entire State of West Virginia 09-098-1. USDA Animal and Plant Health Inspection Service. April 2010.

USDA APHIS, 2011. Emerald Ash Borer Program Manual, *Agrilus planipennis* (Fairmaire) USDA APHIS PPQ Emergency and Domestic Programs Emergency Planning, Riverdale, Maryland.

USDA APHIS, 2013. Asian Longhorned Beetle Cooperative Eradication Program in Clermont County, Ohio. Revised Environmental Assessment, Riverdale, Maryland. May 2013.

USDA/APHIS/PPQ Integrated Plant Health Inspection System (IPHIS). Deployed starting in 2010, IPHIS supports USDA/APHIS in its mission to manage plant health emergencies that occur in the United States.

USDA Forest Service, 2006. The Forest Inventory and Analysis Database: Database Description and Users Guide Version 2.1. National Forest Inventory and Analysis Program, St. Paul, MN, 197 pp.

USDA Forest Service, 2007. Slow the Spread: a National Program to Manage the Gypsy Moth, Gen. Tech. Rep. NRS-6. Department of Agriculture, Forest Service, Northern Research Station, Newtown Square, PA: U.S., 109 pp.

Venette, R.C., Kriticos, D.J., Magarey, R.D., Koch, F.H., Baker, R.H.A., Worner, S.P., Gómez Raboteaux, N.N., McKenney, D.W., Dobesberger, E.J., Yemshanov, D., De Barro, P.J., Hutchinson, W.D., Fowler, G., Kalaris, T.M., Pedlar, J., 2010. Pest risk maps for invasive alien species: a roadmap for improvement. BioScience 60 (5), 349–362.

Wermelinger, B., 2004. Ecology and management of the spruce bark beetle *Ips typographus* – a review of recent research. For. Ecol. Manag. 202, 67–82.

Yemshanov, D., McKenney, D.W., Pedlar, J.H., Koch, F.H., Cook, D., 2009. Towards an integrated approach to modeling the risks and impacts of invasive forest species. Environ. Rev. 17, 163–178.