Diversity and Distributions, (Diversity Distrib.) (2012) **18**, 33–46

A dominance-based approach to map risks of ecological invasions in the presence of severe uncertainty

Denys Yemshanov[1]*, Frank H. Koch[2†], D. Barry Lyons[1], Mark Ducey[3] and Klaus Koehler[4]

[1]*Natural Resources Canada, Canadian Forest Service, Great Lakes Forestry Centre, 1219 Queen Street East, Sault Ste. Marie, ON P6A 2E5, Canada,* [2]*Department of Forestry and Environmental Resources, North Carolina State University, 3041 Cornwallis Road, Research Triangle Park, NC 27709, USA,* [3]*Department of Natural Resources and the Environment, University of New Hampshire, 114 James Hall, Durham, NH 03824, USA,* [4]*Canadian Food Inspection Agency, 59 Camelot Drive, Ottawa, ON K1A 0Y9, Canada*

*Correspondence: Denys Yemshanov, 1219 Queen Street East, Sault Ste. Marie, ON P6A 2E5, Canada.
E-mail: dyemshan@nrcan.gc.ca

†Current address: USDA Forest Service, Southern Research Station, Eastern Forest Environmental Threat Assessment Center, 3041 Cornwallis Road, Research Triangle Park, NC 27709, USA.

ABSTRACT

Aim Uncertainty has been widely recognized as one of the most critical issues in predicting the expansion of ecological invasions. The uncertainty associated with the introduction and spread of invasive organisms influences how pest management decision makers respond to expanding incursions. We present a model-based approach to map risk of ecological invasions that combines two potentially conflicting goals: (1) estimating the likelihood of a new organism being established at a given locale and (2) quantifying the uncertainty of that prediction.

Location Eastern and central Canada.

Methods Our methodology focuses on the potential for long-distance, human-assisted spread of invasive organisms. First, we used a spatial simulation model to generate distributions of plausible invasion outcomes over a target geographical region. We then used second-degree stochastic dominance (SSD) criteria to rank all geographical locations in the target region based on these distributions. We applied the approach to analyze pathways of human-assisted spread (i.e., with commercially transported goods) of the emerald ash borer (EAB) (*Agrilus planipennis* Fairmaire), a major pest of ash trees in North America.

Results The projected potential of the pest to establish at remote locations is significantly shaped by the amount of epistemic uncertainty in the model-based forecasts. The estimates based on the SSD ranking identified major 'crossroads' through which the movement of the EAB with commercial transport is most likely to occur. The system of major expressways in Ontario and Quebec was confirmed as the primary gateway of the pest's expansion throughout the Canadian landscape.

Main conclusions Overall, the new approach generates more realistic predictions of long-distance introductions than models that do not account for severe uncertainties and thus can help design more effective pest surveillance programmes. The modelling technique is generic and can be applied to assess other environmental phenomena when the level of epistemic uncertainty is high.

Keywords

***Agrilus planipennis*, epistemic uncertainty, human-assisted spread, invasive species, pathway model, stochastic dominance.**

INTRODUCTION

Invasive alien species cause significant impacts in agriculture, forestry and the environment, with worldwide economic losses estimated at US $ 1.4 trillion annually, or roughly 5% of the current global economy (Pimentel *et al.*, 2001) and likely to increase in the near future (Perrings *et al.*, 2005; Westphal *et al.*, 2008). In recent decades, quantitative models have become increasingly popular for assessing risks associated with invasive alien organisms (Andersen *et al.*, 2004a; b; Foxcroft

DOI: 10.1111/j.1472-4642.2011.00848.x
http://wileyonlinelibrary.com/journal/ddi

et al., 2007; Venette *et al.*, 2010). Prioritization of geographical locations facing the threat of possible invasion by a non-native organism is often called 'risk mapping' (Koch *et al.*, 2009; Yemshanov *et al.*, 2009; Venette *et al.*, 2010; Magarey *et al.*, 2011). The entire geographical area of concern is usually divided into a set of small sub-units so each individual unit can be ranked by the potential for the invasive organism of interest to become established and cause a measurable impact. Taken together, these individual units constitute a 'risk map' that is the spatial realization of an underlying model of the pest's anticipated expansion in a new landscape.

Unfortunately, public calls for action when an invasive organism is newly detected in a given region seldom allow enough time to acquire the data necessary to characterize the regional risk well. As a result, quantitative models used to assess risk are rarely precise, and outputs are usually limited to a coarse characterization of establishment and/or impact potential (Andersen *et al.*, 2004b; Baker *et al.*, 2005; Simberloff, 2005). Perhaps more importantly, such pest risk assessments include considerable uncertainty that is rarely quantified (Andrews *et al.*, 2004; Koch *et al.*, 2009). This is particularly true for geographically explicit risk estimates like pest risk maps (e.g., US Department of Agriculture, Forest Health Technology Enterprise Team (FHTET), 2007a,b; Pitt *et al.*, 2009; Venette *et al.*, 2010).

The omission of uncertainty has serious implications when risk maps are used to support decision making. Uncertainty inevitably changes the interpretation of risk estimates because most decision makers in pest management and regulation are fundamentally risk averse. If uncertainty is not addressed in a risk map then a decision maker is forced to rely on his or her subjective perceptions of the uncertainty. This is problematic: Behavioural research indicates that humans, including experts, tend to underestimate uncertainty by a considerable margin (Kahneman *et al.*, 1982). Thus, when uncertainty is assessed subjectively, the consequences for risk assessments can be as substantial as when uncertainty is omitted (Morgan & Henrion, 1990; Gigerenzer, 2002), especially if knowledge about the invasive organism in question is poor.

Systematic characterization of uncertainty is complicated by the fact that there are different definitions of the types as well as the potential sources of uncertainty (Elith *et al.*, 2002; Regan *et al.*, 2002; Walker *et al.*, 2003; Baudrit *et al.*, 2007; Refsgaard *et al.*, 2007). In general terms, uncertainty may be categorized as stochastic (associated with natural variability) or epistemic (derived from incomplete knowledge about the organism of interest). Stochastic uncertainty is irreducible but may be represented in a formal manner, while epistemic uncertainty can in theory be reduced through additional research or data (Elith *et al.*, 2002; Refsgaard *et al.*, 2007). While several techniques have been proposed to quantify uncertainty, such as sensitivity analysis (Swartzman & Kaluzny, 1987; Henderson-Sellers & Henderson-Sellers, 1996), ensemble prediction systems (Worner & Gevrey, 2006; Demeritt *et al.*, 2007) and multiple model comparisons (Hartley *et al.*, 2006), directly incorporating uncertainty into risk maps remains a challenging task.

Aggregating risk and uncertainty

For this study, we consider a risk assessment of ecological invasion performed in a geographical domain using a stochastic model that is based on uncertain knowledge about an invasive organism of interest. A small number of previous pest risk mapping efforts (e.g., Rafoss, 2003; Cook *et al.*, 2007; Pitt *et al.*, 2009; Yemshanov *et al.*, 2009) have used stochastic simulations to predict the pattern of expansion of an invasive organism across a particular region of concern. A key feature of this approach is that the results from repeated simulations may be presented as a distribution of plausible invasion outcomes for each geographical location in the region of interest. In turn, the locations may be comparatively evaluated based on two aspects of their outcome distributions: the central tendency (defined in this case by the mean), which serves as an estimate of the invasion 'risk', and the variation (i.e., the variance) in the distribution, which serves as a basic measure of the uncertainty in the risk estimate. While a stochastic simulation approach thus quantifies uncertainty, it does not directly incorporate this uncertainty into the risk estimate. One way to resolve this is to plot all of the individual locations as a point cloud in a two-dimensional space of their expected risk (i.e., distribution mean) and uncertainty (i.e., variance) values. The points, and corresponding geographical locations, in the outermost layer of this cloud (i.e., a mean-variance frontier) have the worst possible combinations of risk and uncertainty. This approach has been used widely in economic literature (Markowitz, 1952; Arrow, 1971) but can only be applied to normally distributed data and therefore has limited practical use (as data sets often fail the test for normality).

METHODS

Risk mapping as a portfolio valuation problem

The concepts of risk and uncertainty, as outlined earlier in the ecological invasion context, can be thought of as analogous to the concepts of 'return' and 'volatility' of financial assets in economic literature (Arrow, 1971). In recent years, these concepts have been used widely to address uncertainty in investment decision making (Levy & Markowitz, 1979; Levy, 1998; Götze *et al.*, 2008) and other disciplines, such as evaluation of farm community programmes (Kramer & Pope, 1981), crop production choices (Lee *et al.*, 1987), best irrigation practices (Harris & Mapp, 1986) and testing for risk aversion (Levy & Levy, 2001).

In this article, we adapt classical return-volatility criteria for portfolio valuation to map the risk of invasion by a species under uncertain conditions, such as might result from limited knowledge about the behaviour of an invader. We interpret the probability (or risk) of invasion as analogous to the term 'net return' in financial literature, and the variation in this probability as analogous to 'volatility'. Essentially, the process of mapping invasion risk can be envisioned as akin to finding an optimal investment strategy (see Sharpe, 1964; Elton &

Gruber, 1995) that yields the highest possible returns while incorporating the tradeoffs between net return and volatility. The problem of allocating high- and low-risk locations in a geographical setting can thus be treated as equivalent to a financial portfolio allocation problem that is solved by finding the most efficient set (from an investor's perspective) of portfolio segments in the total investment pool based on their expected net returns of financial assets and their volatilities. Our analysis adopts this 'most efficient set' concept and proceeds as follows. We first use a stochastic model of invasion to estimate distributions of plausible invasion outcomes for each geographical location of interest, i ($i \in 1,\ldots, N$), in our study area. We then treat these N locations as individual 'portfolios'. Similarly to the task of allocating the investment-efficient set of portfolios with the best tradeoffs between the net returns and their volatility, we find a subset N of 'portfolios' among N locations in the map that has the greatest risks in terms of both projected invasion risk and its uncertainty. We apply stochastic dominance criteria to find this 'efficient' subset N.

Stochastic dominance

The stochastic dominance concept (SD henceforth) is a form of stochastic ordering that refers to a set of relations between a pair of distributions. The concept has been widely used to compare distributions of portfolio returns and to differentiate efficient and inefficient sets of investments in financial economics (Hadar & Russel, 1969; Hanoch & Levy, 1969; Rothschild & Stiglitz, 1970; Whitemore, 1970). SD shares many similarities with majorization theory in statistics, which deals with partial ordering of vectors (Levy, 1992). Fundamentally, any rational decision maker will prefer a hypothetical portfolio x_1 to an alternative portfolio x_2 whenever x_1 has stochastic dominance over x_2 (Fishburn & Vickson, 1978; Levy, 1998). Notably, stochastic dominance is perceived to be superior to the aforementioned mean-variance frontier approach for investment selection, in particular because it uses the entire cumulative distribution of expected returns rather than just the first two moments of the distribution (Gandhi & Saunders, 1981).

The SD rule compares two distributions in terms of their cumulative distribution functions, or cumulative distribution functions (CDFs) (Levy, 1998). For a given variable x, the value of its CDF at y is the probability that x should be no greater than y. In our pest risk mapping context, we compare two geographical locations, f and g. At each location, the multitude of plausible outcomes of invasion (in our case, the results from all individual runs of the stochastic invasion model) is described by the distribution, $f(x)$ or $g(x)$, of a variable x over an interval $[a;b]$ (Fig. 1a). In our study, x denotes the annual rate of the introduction of an invasive organism estimated for a given location in each model run, which varies from 0 to 1 (i.e., the ϕ_i value; see equation S5 in Appendix S1).

To test for stochastic dominance, we represent the distributions of x at f and g by their respective CDFs, $F(x) = \int_a^x f(x)\mathrm{d}x$ and $G(x) = \int_a^x g(x)\mathrm{d}x$. Formally, location f dominates g by the first-degree stochastic dominance rule (FSD) if

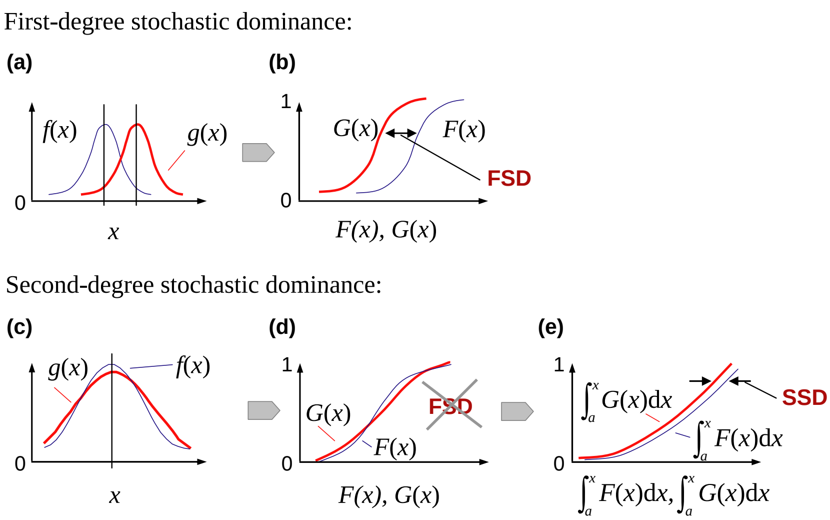

Figure 1 Comparing two distributions using the first-degree and second-degree stochastic dominance rules: (a) example distributions, $f(x)$ and $g(x)$, of invasion outcomes at two corresponding map locations, f and g; (b) the CDFs, $F(x)$ and $G(x)$, of $f(x)$ and $g(x)$ in Fig. 1(a). 'First-degree stochastic dominance rule (FSD)' indicates the first-degree stochastic dominance conditions are satisfied (i.e., $G(x)$ and $F(x)$ do not cross each other); (c) two additional example distributions of invasion outcomes at f and g. In this case, $f(x)$ and $g(x)$ have similar mean values; (d) the CDFs, $F(x)$ and $G(x)$, of $f(x)$ and $g(x)$ in Fig. 1(c). The crossed 'FSD' sign denotes that first-degree stochastic dominance conditions fail (i.e., $F(x)$ and $G(x)$ cross each other); (e) the integrals, $\int_a^x F(x)\mathrm{d}x$ and $\int_a^x G(x)\mathrm{d}x$, of the CDFs in Fig. 1(d). 'SSD' indicates the second-degree stochastic dominance conditions are met (i.e., $\int_a^x F(x)\mathrm{d}x$ and $\int_a^x G(x)\mathrm{d}x$ do not cross each other).

$$G(x) - F(x) \geq 0 \text{ for all } x, \text{ and}$$
$$G(x) - F(x) > 0 \text{ for at least one } x. \quad (1)$$

In short, the FSD rule implies that the CDFs of *f* and *g* do not cross each other (Fig. 1b) and *f* has a higher probability of reaching a given value of *x* than *g* does at any percentile point. The test for FSD also supposes that a decision maker will always prefer the 'higher-value' choice (Levy, 1998) at any realization of *x* (i.e., will place greater management priority on a location with higher likelihood of pest invasion than a location with lower likelihood).

In many practical situations, differences between the distributions of *f* and *g* can be subtle. For example, they may have very close mean values (as shown in Fig. 1c) such that $G(x)$ and $F(x)$ cross each other (Fig. 1d) and the FSD conditions are not met. Second-degree stochastic dominance (SSD) provides more selective delineation by comparing the integrals of the CDFs $F(x)$ and $G(x)$:

$$\int_a^x F(x)\mathrm{d}x \text{ and } \int_a^x G(x)\mathrm{d}x.$$

Location *f* dominates the alternative *g* by SSD if

$$\int_a^x [G(x) - F(x)]dx \geq 0 \text{ for all } x, \text{ and}$$
$$\int_a^x [G(x) - F(x)]dx > 0 \text{ for at least one } x. \quad (2)$$

Similarly to FSD, the SSD condition implies that the integrals of the CDFs $F(x)$ and $G(x)$ do not cross (Fig. 1e). For both FSD and SSD, because $G(x)$ and $F(x)$ represent the entire distributions of the introduction rates of an invasive organism at locations *f* and *g*, uncertainty in the predicted invasion outcomes at these sites is incorporated into the comparison process. Furthermore, SSD also adds the assumption that the decision maker is risk averse (i.e., given two choices with the same expected mean level of outcome, the more certain choice is always preferred, see Levy (1998) for discussion). For this reason, we applied the SSD rule for this study. Higher-order stochastic dominance criteria have also been developed (Whitemore, 1970; Ng, 2000), but their interpretation from a decision-making perspective is less straightforward.

The test for stochastic dominance is a pairwise comparison with three possible outcomes: *f* dominates *g*, *g* dominates *f*, and *g* and *f* are 'non-dominant' to each other (i.e., the test for dominance fails in both directions). Like most financial applications of the SD concept (Porter *et al.*, 1973; Porter, 1978; Post, 2003), our risk mapping study analyzed a large set of elements (a map consisting of *N* locations in our case) and hence required undertaking multiple pairwise SSD tests. The objective of the multiple pairwise comparisons was to delineate a subset N_1 from the total set *N* where each of its elements dominates (according to the SSD rule; see equation 2) any element in the rest of the set, N–N_1. Conversely, no element in N_1 could be dominated by an element in N–N_1 based on the SSD rule. Also, within that subset N_1, all elements were 'non-dominant' to each other, such that the dominance conditions (equation 2) could not be satisfied between any pair of them. The subset N_1 is often called a 'non-dominated' or 'efficient' set in asset allocation literature (Porter *et al.*, 1973; Fishburn & Vickson, 1978; Porter, 1978; Post & Versijp, 2007).

Once the first non-dominated subset N_1 was found, it was assigned the highest rank 1 and removed from set *N* temporarily. Next, a second non-dominated subset, N_2, was determined from the rest of the map, N–N_1, assigned a rank of 2, and temporarily removed, and so forth (Fig. 2). The process was repeated until no non-dominated set was found, or in other words, when every location in the map had been assigned a rank based on the SSD rule. Essentially, this technique followed Goldberg's (1989) ranking algorithm for finding nested non-dominated sets. The method is conceptually similar to the ranking algorithm described in Yemshanov *et al.* (2010).

Operationally, the algorithm was implemented in three steps. Prior to ranking, each map location was assigned a unique identifier (Fig. 2). Next, we calculated the CDF integrals for each location based on its distribution of projected invasion rates, generated through multiple realizations of an invasion model (described later). After the ranking was complete, the final ranks were then referenced back to the original geographical locations and plotted as a map of risk ranks defined by the SSD rule (Fig. 2). To compare different scenarios, we inverted and rescaled the ordinal risk ranks 1,…, *Z* to a 0–1 range, so the highest-risk ranks were close to 1 and the lowest risks were close to 0.

Species of interest

We applied an approach based on stochastic dominance to assess the expansion of the emerald ash borer (EAB), *Agrilus planipennis* Fairmaire (Coleoptera: Buprestidae), a forest insect native to Asia but discovered near Detroit, Michigan and Windsor, Ontario in 2002. It has since spread to 14 additional US states and another Canadian province (Fig. 3). The EAB is a major threat to North American ash trees (*Fraxinus* spp.), as all are susceptible to EAB attack. The pest has already caused significant damage in eastern North America, particularly in urban forests (Poland & McCullough, 2006; Kovacs *et al.*, 2010). The natural spread capability of EAB (i.e., the typical flight distance of mated females, who are the strongest fliers) is ≈3 km (Taylor *et al.*, 2010); the majority of longer-distance introductions of new populations have been caused by human transport (Haack *et al.*, 2002; Kovacs *et al.*, 2010), with commercial and passenger vehicles moving materials infested with EAB (such as logs, firewood, nursery stock or related material). The existing capacity to detect EAB is still relatively poor, such that new detections usually indicate the presence of already established populations (de Groot *et al.*, 2008). Despite significant investment in EAB management efforts – $32 million by USDA-APHIS alone in 2008 (Kovacs *et al.*, 2010) – timely detection of outlying EAB infestations remains extremely difficult.

Recent analyses of EAB control options have demonstrated the value in forecasting the long-distance spread of EAB as a

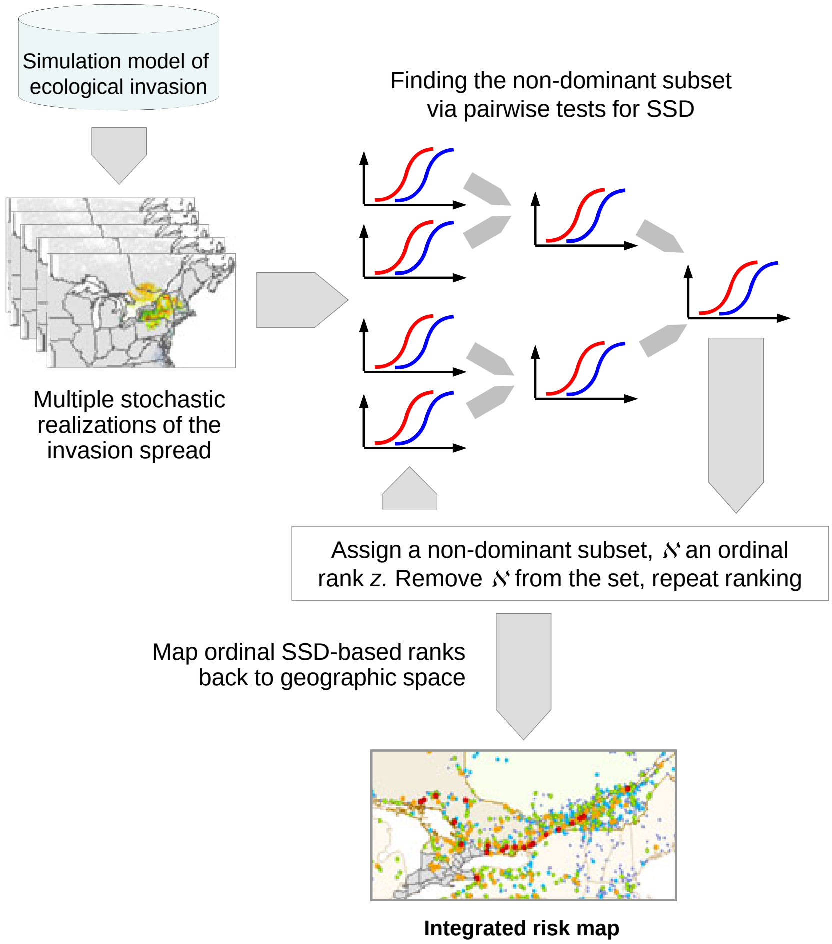

Figure 2 Mapping invasion risks with the SSD rule.

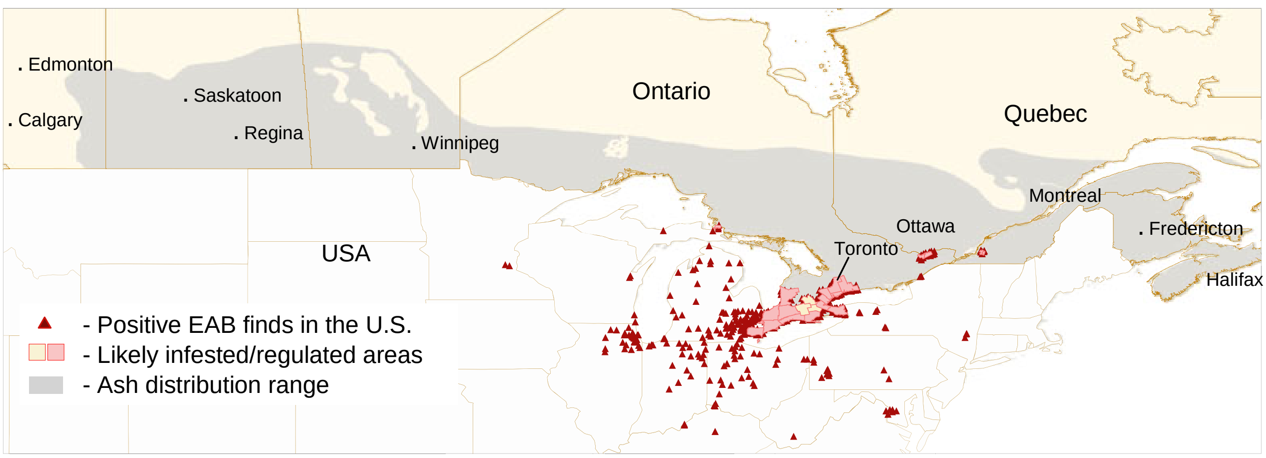

Figure 3 Geographical distribution of the emerald ash borer (as per February 2011). The map is centered on Canadian locations and does not show positive detections of the pest in the USA, south of Illinois–West Virginia.

way to promote time-critical detections beyond the main invasion front (Kovacs *et al.*, 2010). Although long-distance dispersal has been recognized as a key contributor to the rates at which invasions expand, this aspect remains the most uncertain and difficult characteristic of invasions to estimate adequately (Neubert & Caswell, 2000; Koch *et al.*, 2009; Melbourne & Hastings, 2009). This study quantifies, in a spatially explicit fashion, the long-distance spread of EAB via commercial transportation corridors. The geographical domain of our analysis was primarily defined by the native range of ash species in eastern North America (Little, 1971) (Fig. 3). (As explained in the next section, we only report the results for Canada, so the US ash range is not shown in Fig. 3.) Ash species have also been commonly planted as ornamental trees in urban and rural municipalities (Poland & McCullough, 2006); therefore, we included in the study major municipalities in Saskatchewan and Alberta that fall west of the primary ash distribution range.

Model of human-assisted EAB spread via freight transport

Many geographical dispersal models have relatively poor capacity to predict long-distance spread (Andow *et al.*, 1990; Buchan & Padilla, 1999; Neubert & Caswell, 2000); therefore, a pathway-based, vector model type was chosen for this study. Recent models by Muirhead *et al.* (2006) and Prasad *et al.* (2010) combined both short-range natural dispersal and human-assisted long-range dispersal of EAB, while another model of EAB spread (BenDor *et al.*, 2006) only dealt with the former mode. Our study focuses exclusively on long-distance movement of EAB populations with commercial freight transportation and does not address aspects of EAB's biological (i.e., local) spread.

We developed a pathway-based model of EAB spread by commercial freight transport through an extensive (i.e., national-scale) road network. Our primary data were a roadside survey database maintained by Transport Canada (TC). The database stores summaries of individual freight routes collected during a 2005–2007 roadside survey at truck weigh stations across Canada. A full description of the database and the pathway model can be found in Appendix S1; here, we provide a brief summary.

The movement of commodities and cargoes commonly associated with forest invasive pests has been recognized as a viable predictor of the human-mediated spread of invasive organisms (Koch *et al.*, 2011). We used the tonnages of forest-pest-associated commodities reported in the roadside survey database to build a pathway matrix where each element defined the probability of the pest being moved with commercial transports from a given location i to another location j (equations S1–S4, Appendix S1). The pathway matrix stored the probabilities of EAB transmission, p_{ij}, for each pair of locations i, j in the transportation network and included ≈5000 major municipalities and rural settlements in Canada and the USA.

We then used the pathway matrix to simulate movements of the pest through the transportation network with commercial freight transports from previously infested areas (i.e., from network locations proximal to known EAB populations) to all other locations in the transportation network. The model was initialized with the distribution of known EAB populations in Canada and the USA (US Department of Agriculture, Animal and Plant Health Inspection Service (APHIS), 2011a) as of February 2011. We first identified all potential nodes in the pathway matrix that were near sites infested with EAB. A forest stand can progress from all healthy trees to all dead ash trees in about six years (Knight *et al.*, 2010). However, lightly infested trees can remain asymptomatic for several years (Cappaert *et al.*, 2005). Consequently, many infestations establish and expand for several years prior to their detection. Thus, we assumed that a viable EAB population would exist at nodes within 10 km of sites with positive EAB finds (which roughly corresponds to 3–4 years of biological spread).

Based on the stochastic simulations, each location (a network node i) outside of likely infested or regulated areas (see Fig. 3) was characterized by a distribution, $G_i(\phi_i)$, of the potential rates of EAB transmission to that location. We then used the SSD rule to rank the CDFs of the $G_i(\phi_i)$ through pairwise comparisons (see Stochastic Dominance section) and thus characterize the relative risk levels of all of these locations from the perspective of a risk-averse decision maker.

RESULTS

EAB transmission rates

Figure 4 shows the EAB transmission rates (ϕ_i) calculated for particular geographical locations outside the likely infested/regulated areas of Canada. The data generally emphasize one of Canada's major transportation arteries as a key pathway of EAB transmission: the Highway 401 corridor, which runs from the Detroit (MI)–Windsor (ON) area to the Montreal (QC) area (Highway 401 becomes Autoroute 20 in Quebec). One location, Niagara Falls (ON), has a transmission rate above 0.1 year^{-1}, with the vast majority exhibiting low annual rates of EAB transmission ($\phi_i < 0.01$ year^{-1}). Most of the EAB infestation potential is allocated to locations in eastern Canada (Fig. 4a). Correspondingly, western Canada (Fig. 4b) displays extremely low potential for EAB to be introduced (and subsequently established) by commercial truck transport of pest-associated freight. This is unsurprising, because very low probabilities are typical for rare long-distance spread events (Nathan *et al.*, 2003); more importantly, most of the transmission rates show a considerable degree of variation that exceeds their estimated values by an order of magnitude. In Fig. 5, the geographical distribution of the locations exhibiting high variance in their transmission rate values closely follows two major transportation arteries in Ontario and Quebec: the aforementioned Highway 401 corridor between Toronto and Montreal, and Highways 400-17 and 11 running north from Toronto to Parry Sound (ON) and North Bay (ON) (Fig. 5a). Four locations in western Canada (Fig. 5b) show a relatively high variance, including the cities of Calgary (AB) and Winnipeg (MB) as well as two USA–Canada border crossings in Manitoba and Saskatchewan (where the introduction of EAB from US locations is predicted to be more likely than elsewhere in these provinces).

Assessing risks of human-assisted EAB introductions with the SSD rule

Figure 6 shows the map of EAB risk rankings calculated for individual locations using the SSD rule. Generally, the

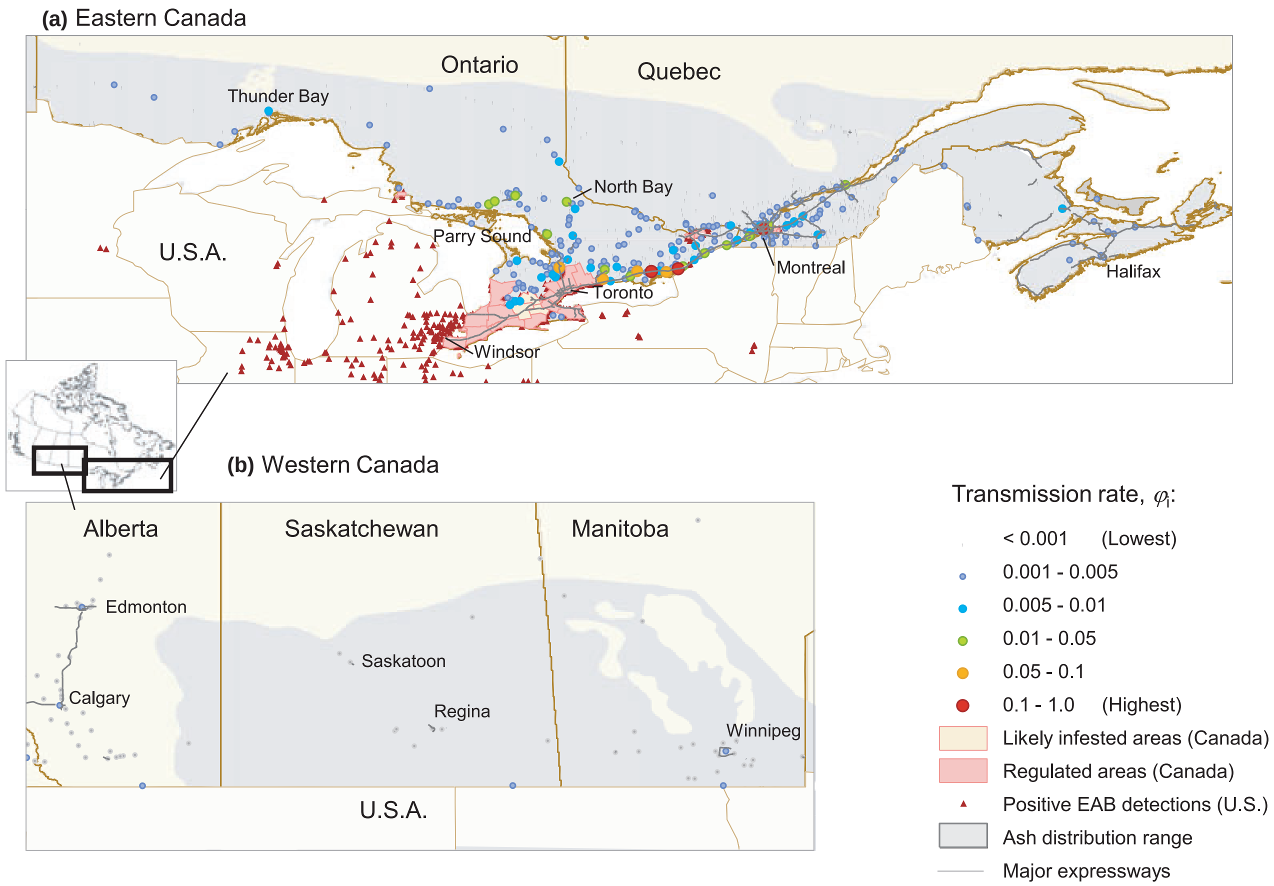

Figure 4 Estimated EAB transmission rates for major Canadian municipalities.

geographical pattern of risk ranks follows the map of the variance of ϕ_i (Fig. 5), although there are some notable differences; for example, a continuous line of locations with moderately high (0.75–0.95) risk rankings can be seen along Highway 11 between Toronto and North Bay (ON) (Fig. 6a). Despite general similarities to the geographical pattern of variance presented in Fig. 6, the highest-risk (> 0.95) locations based on the SSD rule delineate the critical EAB transmission corridors more precisely: Highway 400 north of Toronto and Highway 401 between Toronto and Montreal. Most locations in the top 5% of risk ranks are along the Highway 401 corridor between Toronto and Montreal. Other high-risk locations are found along the Trans-Canada Highway near Barrie (ON) and Parry Sound (ON).

With respect to western Canada, most locations have risk ranks below 0.5, although a few municipalities, such as Edmonton (AB) and Saskatoon (SK), have moderate (0.5–0.75) rankings. The handful of locations with moderately high (0.75–0.95) risk ranks in western Canada are the same as those emphasized in the map of the variance of ϕ_i (Fig. 6b): the cities of Calgary (AB) and Winnipeg (MB), plus the two major Canada–USA border crossings in Manitoba and Saskatchewan. Notably, the SSD ranks track the variance so closely because, as a defining characteristic of each location's CDF, the variance figured prominently in the overall assignment of risk during this analysis.

Table 1 lists the locations with the highest (> 0.9) SSD-based risk rankings, together with their associated transmission rates, ϕ_i. Given somewhat limited capacity to validate the pathway model (in our case by calibrating the model by recent records of EAB spread along Highway 401, the main vector of EAB expansion in Ontario), the ϕ_i values should be considered as approximate estimates. Notably, the transmission rates for the highest-risk locations show a higher degree of variation (i.e., between 0.01 and 0.14) than is observable in their SSD-based risk ranks. Indeed, many locations from this list of top risk ranks have relatively low transmission rates. Compared with the SSD-based ranks (Fig. 6), the transmission probability values alone (Fig. 4) were not sufficient to identify sets of locations comprising key EAB transmission corridors. In short, because the SSD-based risk ranking incorporates uncertainties via explicit consideration of each location's entire distribution of risks (in the form of CDF integrals), a considerably larger number of points are ranked as high risk despite having moderate ϕ_i values. The SSD-based ranks also better agree with recent field experience regarding the potential pattern of EAB spread in southern Ontario and Quebec, with frequent detections along the Highway 401 corridor

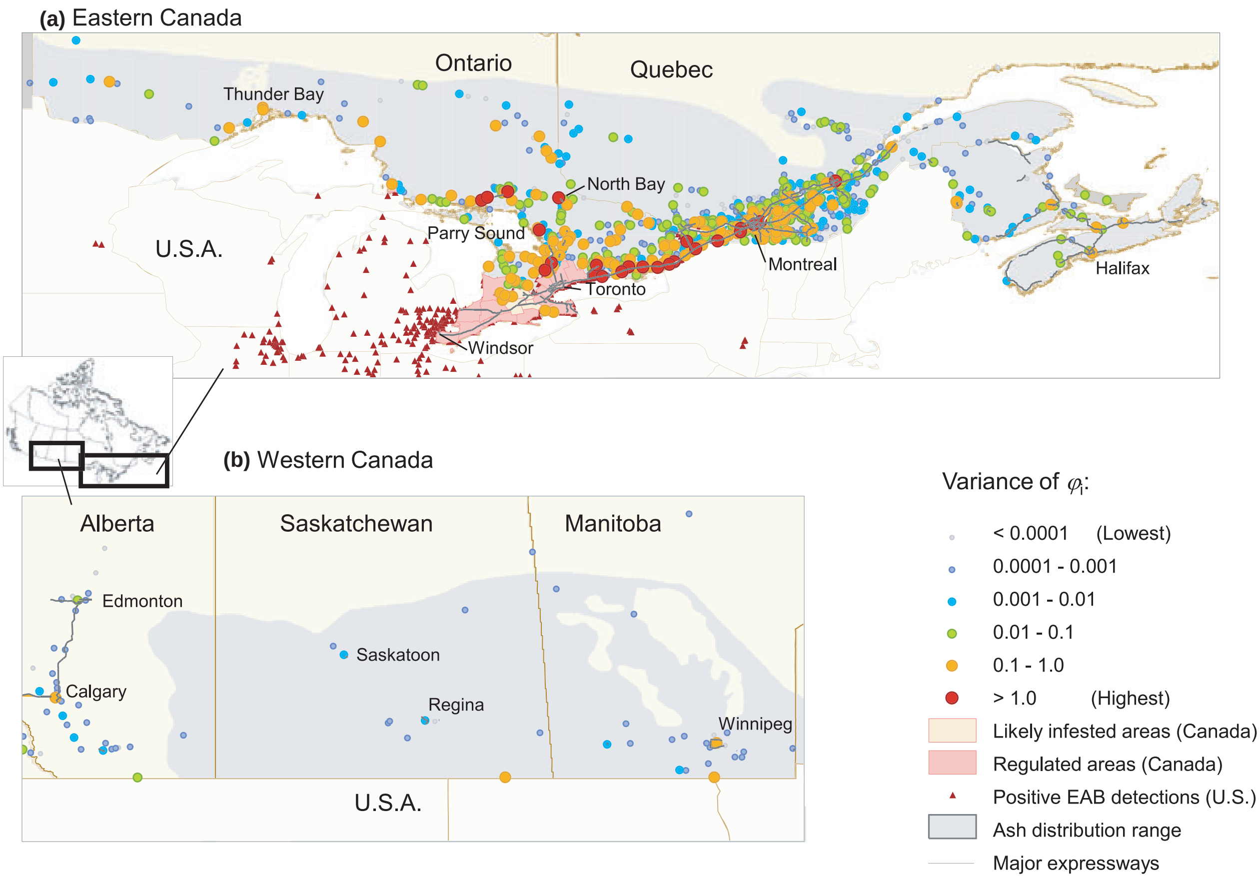

Figure 5 Variance of EAB transmission rates for major Canadian municipalities.

(E. Bullas-Appleton, CFIA, pers. comm.). Furthermore, a delineation of generally higher risk ranks for a geographically broader set of locations agrees well with the principle of extensive geographical coverage of detection surveys that has been adopted by the USDA EAB monitoring programme for the USA (US Department of Agriculture, Animal and Plant Health Inspection Service (APHIS), 2011b).

DISCUSSION

Decisions about the management of invasive species frequently occur under circumstances of limited knowledge about an invader and its likely impact in its new environment. When risk estimates are based on poor knowledge, a risk analyst may be unable to provide accurate probabilistic estimates and often ends up, at best, with model-based summaries based on simple distribution moments (such as the mean establishment rate and possibly the variance). The stochastic dominance rule is theoretically superior to methods based on distribution moments because it considers the entire distribution of invasion outcomes (in a CDF form) and is based on minimally restrictive assumptions regarding a decision maker's risk perceptions (Porter *et al.*, 1973; Meyer *et al.*, 2005). SD is effectively nonparametric and does not need the specification of a decision maker's utility function (i.e., defining a numerical 'utility' value for every possible outcome a decision maker may face) or the probability distribution functional form (Kuosmanen, 2001). Caulfield (1988) compared the stochastic dominance and mean-variance approaches for forestry applications and concluded that the SD concept is more useful as a screening technique for making decisions under risk. Hildebrandt & Knoke (2011) similarly concluded that SD should be seen as a method to separate high-risk alternatives.

The stochastic dominance approach also helps address the issue of uncertainties in model-based forecasts by directly linking these uncertainties with a decision maker's preferences. For example, a higher level of variation in the underlying $G(x)$ [and $F(x)$] distributions may increase the size of each non-dominant set (N) extracted iteratively from the full set of geographical locations (N) and therefore coarsen the ranking classification based on the SSD rule (equation 2). In practical terms, when the uncertainty of an underlying distribution [$G_i(\phi_i)$ in this study] is higher, more elements will be assigned a higher SSD rank than might be expected given their mean values. We believe that this tendency of the SSD rule to delineate larger subsets when the level of variation increases positively demonstrates the sensitivity of the risk rankings to the extent of uncertainty in the underlying risk model outputs, thus representing another advantage over methods based on the distribution moments alone.

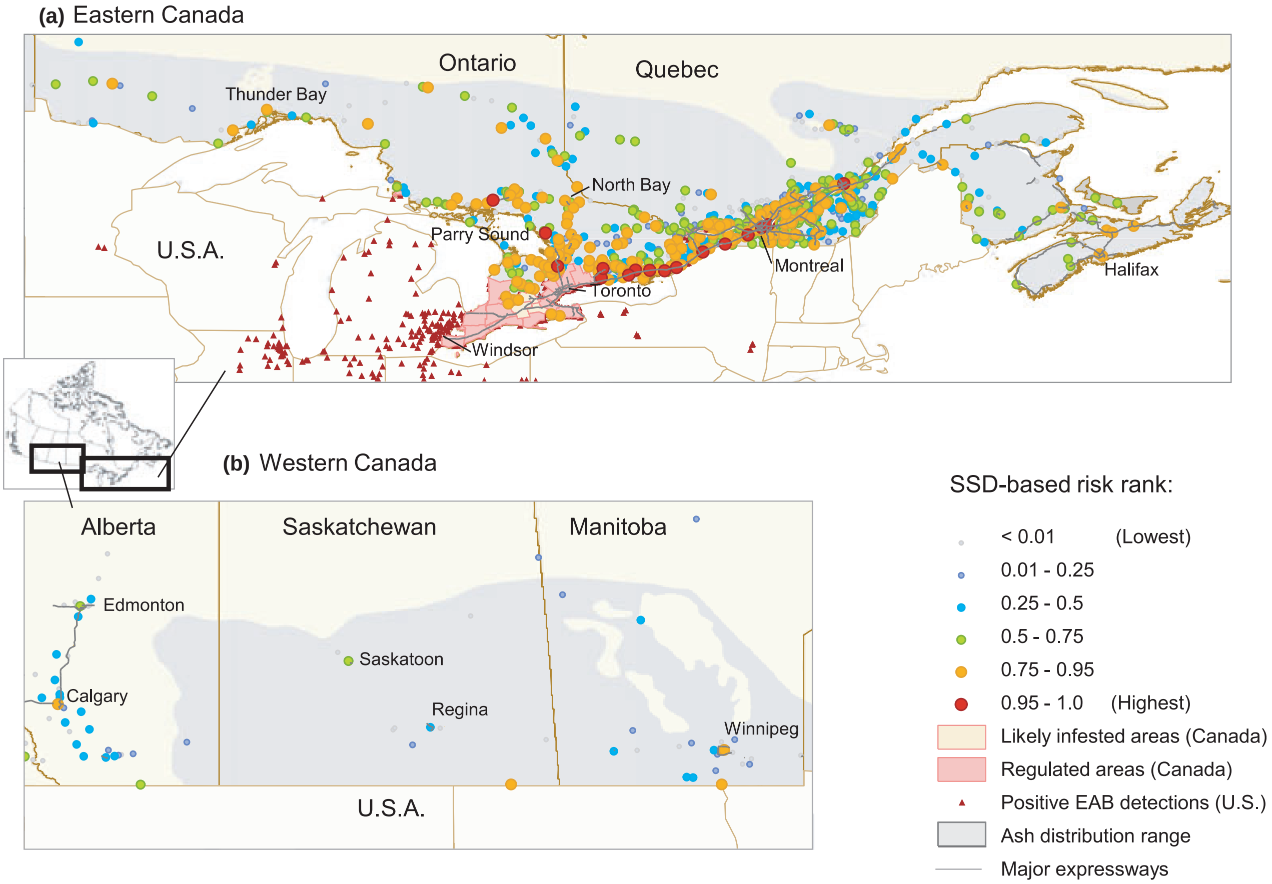

Figure 6 Risk of EAB long-distance spread, via commercial freight transportation, for major Canadian municipalities based on the SSD rule.

The capacity of the SSD concept to account for uncertainty (via explicit comparison of the CDF integrals) also improves the utility of stochastic invasion models as decision support tools. In our study, the approach provided better stratification of the long-distance spread pathways of the EAB. The risk ranking based on the SSD rule was sufficient to delineate the system of primary expressways in Ontario and Quebec as a principal means of EAB spread through these provinces. More importantly, the incorporation of uncertainty in the SSD risk rankings of individual locations emphasized places that would be relatively low risk if looking only at the average transmission rates. This aspect is critical; because it highlights distant population nuclei that would likely not be predicted if uncertainty was omitted, the SSD approach better facilitates timely and targeted detections of a pest beyond the main invasion front, thus helping to reduce surveillance costs and, potentially, slowing the spread of the pest over long distances.

Given the complexity of the pathway model and associated SSD ranking algorithm, a couple of performance aspects warrant further investigation. The first aspect is how well the probabilistic pathway model recreates the information stored in the pathway matrix and underlying roadside survey data. An analysis of their correspondence (Fig. S1, Appendix S1) shows reasonably good fit ($R^2 = 0.92$). This is not surprising given that the underlying transportation data were represented by relatively simple and short routes. The prediction accuracy of the pathway model would likely be lower if the individual pathway routes were more complex and included topological features not well captured by our first-order pathway matrix (such as branches and loops); fortunately, this was not the case.

The second issue is how changes in the transportation network's topology might affect the risk rankings based on the SSD rule. For example, removing a portion of the network's nodes would change the flows of commodities through the remaining nodes. Changes in the transportation network's topology could also affect the redistribution of the variance of the transmission rates throughout the remaining nodes (which would cause subsequent changes in the SSD rankings). Because the configuration of the transportation network is based on geographical features and the locations of major settlements in North America, these changes cannot be predicted analytically but instead would require further numeric tests under a set of realistic scenarios (i.e., a sort of customized sensitivity/uncertainty analysis). This will be a focus of future work.

Table 1 List of geographical locations in eastern Canada with the highest SSD risk ranks above 0.9.

Province	Nearby location	SSD risk rank [0;1]	Transmission rate, ϕ_i, year^{-1} [0;1]
Quebec	Montreal	1.0 (highest)	0.14
Ontario	Gananoque	1.0	0.14
Ontario	Napanee	1.0	0.12
Ontario	Kingston	0.99	0.06
Ontario	Port hope	0.99	0.06
Ontario	Belleville	0.99	0.05
Ontario	Barrie	0.98	0.06
Ontario	Cardinal	0.98	0.03
Quebec	Les Cedres	0.97	0.04
Ontario	Peterborough	0.97	0.04
Ontario	Cornwall	0.97	0.03
Ontario	Trenton	0.97	0.02
Ontario	Nairn Centre	0.95	0.03
Ontario	Parry Sound	0.95	0.03
Quebec	Quebec City	0.95	0.03
Quebec	Boucherville	0.95	0.02
Ontario	Sudbury	0.94	0.03
Ontario	Lansdowne	0.94	0.02
Ontario	North Bay	0.94	0.02
Quebec	Vaudreuil Dorion	0.94	0.01
Ontario	Espanola (Hwy 17)	0.93	0.02
Ontario	Alliston	0.93	0.02
Ontario	Cobourg	0.93	0.01
Ontario	Kemptville	0.93	0.01
Ontario	Chisholm	0.92	0.01
Ontario	Lindsay	0.92	0.01
Ontario	Brockville	0.92	0.01
New Brunswick	Moncton	0.92	0.01
Ontario	Orillia	0.92	0.01

Technical considerations

The SD ranking technique is generic and can be applied in conjunction with many other types of stochastic ecological models and model ensembles when the level of epistemic uncertainty is high. For example, the approach can be applied to various spatial dispersal models that generate a distribution of maps of an organism's invasion or colonization potential. While this study demonstrates the SD technique using a point-based dataset (i.e., the nodes of the transportation network), the algorithm can just as easily be applied to a collection of raster maps (where the individual map cells are ranked according to the SSD rules). Operationally, the model accepts raster spatial datasets that are generated by common GIS systems.

The SD approach does have shortcomings. The algorithm requires undertaking pairwise tests for stochastic dominance and has a computational complexity on the order of $ZN(N-1)/2$ (where Z is the total number of ranks and N is the number of geographical locations). This limits the application of the method to relatively moderate-resolution maps. As a practical matter, it also precludes the use of SD criteria that are higher than second-order (Porter *et al.*, 1973). Higher-order SD criteria, such as 3rd and 4th-degree SD (Leshno & Levy, 2002; Post, 2003; Post & Versijp, 2007), provide means for generating more selective risk rankings; however, interpreting their restrictive assumptions about decision makers' preferences is quite difficult (and the analyses would require even more computing power).

In some cases, the SD criteria may not be strict enough to outline a sufficiently small subset. We believe that this is not an issue when mapping risks of invasive alien species, because in this context, a decision maker is typically focused on outlining relatively broad planning regions for determining how and where to respond to an outbreak. Furthermore, the ordinal nature of non-dominant risk ranks delineated by the SSD rule also makes them a useful prioritization metric.

Porter (1978) found that the size of the efficient set delineated by the SD rule is an increasing function of the number of data points used to estimate the cumulative probability function. This issue can be addressed by applying a percentile approach (Levy, 1998) that uses a fixed number of percentile points to build the CDF when testing for stochastic dominance. Another critical point is that SD rules can only be used for pairwise comparison and hence provide only a partial ranking of a given global set. If one were interested in comparing alternative risk rankings, this would require an extra step of remapping the final ranks to a common scale. The simplest direct approach to derive a common ranking scale for multiple datasets is to combine data points from all sets into a single superset that includes representative samples from all alternative scenarios and then assign the ranks with respect to all possible distributions that can be found in the alternative scenarios. We believe this addresses a major criticism of methods based on partial ranking: an inability to generate a common ranking space.

CONCLUSIONS

In this study, we have demonstrated an application of the stochastic dominance concept to assess and map risks associated with ecological invasions. We believe that the approach is a major step forward in model-based assessments of ecological risks and distributions of invasive organisms because it provides a simple way to incorporate uncertainty into the final risk estimates and communicate both risk and uncertainty in a single decision support product. In our study of assessing the human-assisted spread of EAB in Canada, the approach helped to confirm major expressway corridors as a major vector of human-mediated spread in Ontario and Quebec. The SSD rule appears to be sufficient to delineate major geographical areas of concern and has good potential for prioritizing risks of invasive species introductions under severe uncertainty.

ACKNOWLEDGEMENTS

The authors extend their gratitude and thanks to Kirsty Wilson and Marty Siltanen (Natural Resources Canada, Canadian Forest Service) for technical support and diligence with preparing the Canadian roadside database and helping undertake the pathway modelling study; Marcel Dawson, Julia Dunlop and Annie Baxter (Canadian Food Inspection Agency) for help with acquiring the Canadian roadside database. The participation of Denys Yemshanov was supported by an interdepartmental NRCan – CFIA Forest Invasive Alien Species initiative. The participation of Frank Koch was supported by Research Joint Venture Agreement #10-JV-11330146-064 between the USDA Forest Service, Southern Research Station, Asheville, NC and North Carolina State University. The participation of Mark Ducey was supported by the Agriculture and Food Research Initiative Competitive Grants Program Grant No. 2010-85605-20584 from the National Institute of Food and Agriculture.

REFERENCES

Andersen, M.C., Adams, H., Hope, B. & Powell, M. (2004a) Risk assessment for invasive species. *Risk Analysis*, **24**, 787–793.

Andersen, M.C., Adams, H., Hope, B. & Powell, M. (2004b) Risk analysis for invasive species: general framework and research needs. *Risk Analysis*, **24**, 893–900.

Andow, D.A., Kareiva, P.M., Levin, S.A. & Okubo, A. (1990) Spread of invading organisms. *Landscape Ecology*, **4**, 177–188.

Andrews, C.J., Hassenzahl, D.M. & Johnson, B.B. (2004) Accommodating uncertainty in comparative risk. *Risk Analysis*, **24**, 1323–1335.

Arrow, K.J. (1971) *Essays in the theory of risk bearing*. Markham, Chicago.

Baker, R., Cannon, R., Bartlett, P. & Barker, I. (2005) Novel strategies for assessing and managing the risks posed by invasive alien species to global crop production and biodiversity. *Annals of Applied Biology*, **146**, 177–191.

Baudrit, C., Couso, I. & Dubois, D. (2007) Joint propagation of probability and possibility in risk analysis: towards a formal framework. *International Journal of Approximate Reasoning*, **45**, 82–105.

BenDor, T.K., Metcalf, S.S., Fontenot, L.E., Sangunett, B. & Hannon, B. (2006) Modeling the spread of the emerald ash borer. *Ecological Modelling*, **197**, 221–236.

Buchan, L.A.J. & Padilla, D.K. (1999) Estimating the probability of long-distance overland dispersal of invading aquatic species. *Ecological Applications*, **9**, 254–265.

Cappaert, D., McCullough, D.G., Poland, T.M. & Siegert, N.W. /forenames> (2005) Emerald ash borer in North America: a research and regulatory challenge. *American Entomologist*, **51**, 152–165.

Caulfield, J.P. (1988) A stochastic efficiency approach for determining the economic rotation of a forest stand. *Forest Science*, **34**, 441–457.

Cook, D.C., Thomas, M.B., Cunningham, S.A., Anderson, D.L. & De Barro, P.J. (2007) Predicting the economic impact of an invasive species on an ecosystem service. *Ecological Applications*, **17**, 1832–1840.

Demeritt, D., Cloke, H., Pappenberger, F., Theilen, J., Bartholmes, J. & Ramos, M.-H. (2007) Ensemble predictions and perceptions of risks, uncertainty, and error in flood forecasting. *Environmental Hazards*, **7**, 115–127.

Elith, J., Burgman, M.A. & Regan, H.M. (2002) Mapping epistemic uncertainties and vague concepts in predictions of species distribution. *Ecological Modelling*, **157**, 313–329.

Elton, E.J. & Gruber, M.J. (1995) *Modern portfolio theory and investment analysis*, 5th edn. Wiley, New York.

Fishburn, P.C. & Vickson, R.C. (1978) Theoretical foundations of stochastic dominance. *Stochastic dominance. An approach to decision-making under risk* (ed. by G.A. Whitemore and M.C. Findlay), pp. 39–144, Lexington Books, D.C. Heath and Co., Lexington, MA.

Foxcroft, L.C., Rouget, M. & Richardson, D.M. (2007) Risk assessment of riparian plant invasions into protected areas. *Conservation Biology*, **21**, 412–421.

Gandhi, D.K. & Saunders, A. (1981) The superiority of stochastic dominance over mean variance efficiency criteria: some clarifications. *Journal of Business Finance and Accounting*, **8**, 51–59.

Gigerenzer, G. (2002) *Calculated risks: how to know when numbers deceive you*. Simon & Schuster, New York.

Goldberg, D.E. (1989) *Genetic algorithms in search, optimization, and machine learning*, Addison-Wesley Publ. Co., Reading, MA.

Götze, U., Northcott, D. & Schuster, P. (2008) *Investment appraisal – methods and models*, Springer, Berlin.

de Groot, P., Grant, G.G., Poland, T.M., Scharbach, R., Buchan, L., Nott, R.W., MacDonald, L. & Pitt, D. (2008) Electrophysiological response and attraction of emerald ash borer to green leaf volatiles (GLVs) emitted by host foliage. *Journal of Chemical Ecology*, **34**, 1170–1179.

Haack, R.A., Jendek, E., Liu, H., Marchant, K.R., Petrice, T.R., Poland, T.M. & Ye, H. (2002) The emerald ash borer: a new exotic pest in North America. *Newsletter of the Michigan Entomological Society*, **47**, 1–5.

Hadar, J. & Russel, W.R. (1969) Rules for ordering uncertain prospects. *American Economic Review*, **59**, 25–34.

Hanoch, G. & Levy, H. (1969) The efficiency analysis of choices involving risk. *Review of Economic Studies*, **36**, 335–346.

Harris, T.R. & Mapp, H.P. (1986) A stochastic dominance comparison of water-conserving irrigation strategies. *American Journal of Agricultural Economics*, **68**, 298–305.

Hartley, S., Harris, R. & Lester, P.J. (2006) Quantifying uncertainty in the potential distribution of an invasive species: climate and the Argentine ant. *Ecology Letters*, **9**, 1068–1079.

Henderson-Sellers, B. & Henderson-Sellers, A. (1996) Sensitivity evaluation of environmental models using fractional factorial experimentation. *Ecological Modelling*, **86**, 291–295.

Hildebrandt, P. & Knoke, T. (2011) Investment decisions under uncertainty – a methodological review on forest science studies. *Forest Policy and Economics*, **13**, 1–15.

Kahneman, D., Kahneman, P. and Tversky, A. (eds) (1982) *Judgment under uncertainty: heuristics and biases*. Cambridge University Press, New York.

Knight, K.S., Herms, D.A., Cardina, J., Long, R., Rebbeck, J., Gandi, K.J.K., Smith, A., Klooster, W.S., Herms, C.P. & Royo, A.A. (2010) Emerald ash borer aftermath forests: the dynamics of ash mortality and the responses of other plant species (abstract). *Proceedings of symposium on ash in North America*; 2010 March 9-11; West Lafayette, IN (ed. by C.H. Michler and M.D. Ginzel), pp. 11, Gen. Tech. Rep. NRS-P-72. U.S. Department of Agriculture, Forest Service, Northern Research Station, St. Paul, MN.

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 Analysis*, **29**, 1227–1241.

Koch, F.H., Yemshanov, D., Colunga-Garcia, M., Magarey, R.D. & Smith, W.D. (2011) Establishment of alien-invasive forest insect species in the United States: where and how many? *Biological Invasions*, **13**, 969–985.

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. *Ecological Economics*, **69**, 569–578.

Kramer, R.A. & Pope, R.D. (1981) Participation in farm commodity programs: a stochastic dominance analysis. *American Journal of Agricultural Economics*, **63**, 119–128.

Kuosmanen, T. (2001) *Stochastic dominance efficiency tests under diversification*. Helsinki School of Economics Working Paper W-283. Helsinki School of Economics, Helsinki.

Lee, J.G., Ellis, J.R. & Lacewell, R.D. (1987) Evaluation of production and financial risk: a stochastic dominance approach. *Canadian Journal of Agricultural Economics*, **35**, 109–126.

Leshno, M. & Levy, H. (2002) Preferred by ''all'' and preferred by ''most'' decision makers: almost stochastic dominance. *Management Science*, **48**, 1074–1085.

Levy, H. (1992) Stochastic dominance and expected utility: survey and analysis. *Management Science*, **38**, 555–593.

Levy, H. (1998) *Stochastic dominance: investment decision making under uncertainty*. Kluwer Academic Publishers, Dordrect.

Levy, M. & Levy, H. (2001) Testing for risk aversion: a stochastic dominance approach. *Economics Letters*, **71**, 233–240.

Levy, H. & Markowitz, H. (1979) Approximating expected utility by a function of mean and variance. *The American Economic Review*, **69**, 308–317.

Little, E.L. Jr (1971) *Atlas of United states trees. Volume 1. Conifers and important hardwoods*. USDA Forest Service, Timber Management Research Division Miscellaneous Publication No.1146. USDA Forest Service, Washington, DC.

Magarey, R.D., Borchert, D.M., Engle, J.S., Colunga-Garcia, M., Koch, F.H. & Yemshanov, D. (2011) Risk maps for targeting exotic plant pest detection programs in the United States. *OEPP/EPPO Bulletin*, **41**, 1–11.

Markowitz, H. (1952) Portfolio selection. *The Journal of Finance*, **7**, 77–91.

Melbourne, B.A. & Hastings, A. (2009) Highly variable spread rates in replicated biological invasions: fundamental limits to predictability. *Science*, **325**, 1536–1539.

Meyer, T., Xiao-Ming, L. & Rose, L.C. (2005) Comparing mean variance tests with stochastic dominance tests when assessing international portfolio diversification benefits. *Financial Services Review*, **14**, 149–168.

Morgan, M.G. & Henrion, M. (1990) *Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis*. Cambridge University Press, New York.

Muirhead, J.R., Leung, B., van Overdijk, C., Kelly, D.W., Nandakumar, K., Marchant, K.R. & MacIsaac, H.J. (2006) Modelling local and long-distance dispersal of invasive emerald ash borer *Agrilus planipennis* (Coleoptera) in North America. *Diversity and Distributions*, **12**, 71–79.

Nathan, R., Perry, G., Cronin, J.T., Strand, A.E. & Cain, M.L. (2003) Methods for estimating long-distance dispersal. *Oikos*, **103**, 261–273.

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

Ng, M.-C. (2000) A remark on third degree stochastic dominance. *Management Science*, **46**, 870–873.

Perrings, C., Dehnen-Schmutz, K., Touza, J. & Williamson, M. (2005) How to manage biological invasions under globalization. *Trends in Ecology and Evolution*, **20**, 212–215.

Pimentel, D., McNair, S., Janecka, J., Wightman, J., Simmonds, C., O'Connell, C., Wong, E., Russel, L., Zern, J., Aquino, T. & Tsomondo, T. (2001) Economic and environmental threats of alien plant, animal, and microbe invasions. *Agriculture, Ecosystems and Environment*, **84**, 1–20.

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. *Ecological Applications*, **19**, 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. *Journal of Forestry*, **104**, 118–124.

Porter, R.B. (1978) Portfolio applications: empirical studies. *Stochastic dominance. An approach to decision-making under risk* (ed. by G.A. Whitemore and M.C. Findlay), pp. 117–162, Lexington Books, D.C. Heath and Co., Lexington, MA.

Porter, R.B., Wart, J.R. & Ferguson, D.L. (1973) Efficient algorithms for conducting stochastic dominance tests on large numbers of portfolios. *Journal of Financial and Quantitative Analysis*, **8**, 71–81.

Post, T. (2003) Empirical tests for stochastic dominance efficiency. *Journal of Finance*, **58**, 1905–1931.

Post, T. & Versijp, P. (2007) Multivariate tests for stochastic dominance efficiency of a given portfolio. *Journal of Financial and Quantitative Analysis*, **42**, 489–515.

Prasad, A.M., Iverson, L.R., Peters, M.P., Bossenbroek, J.M., Matthews, S.N., Syndor, T.D. & Schwartz, M.W. (2010) Modeling the invasive emerald ash borer risk of spread using a spatially explicit cellular model. *Landscape Ecology*, **25**, 353–369.

Rafoss, T. (2003) Spatial stochastic simulation offers potential as a quantitative method for pest risk analysis. *Risk Analysis*, **23**, 651–661.

Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L. & Vanrolleghem, P.A. (2007) Uncertainty in the environmental modelling process – a framework and guidance. *Environmental Modelling & Software*, **22**, 1543–1556.

Regan, H.M., Colyvan, M. & Burgman, M.A. (2002) A taxonomy and treatment of uncertainty for ecology and conservation biology. *Ecological Applications*, **12**, 618–628.

Rothschild, M. & Stiglitz, J.E. (1970) Increasing risk. I. A definition. *Journal of Economic Theory*, **2**, 225–243.

Sharpe, W.F. (1964) Capital asset prices: a theory of market equilibrium under conditions of risk. *Journal of Finance*, **14**, 425–442.

Simberloff, D. (2005) The politics of assessing risk for biological invasions: the USA as a case study. *Trends in Ecology & Evolution*, **20**, 216–222.

Swartzman, G.L. & Kaluzny, S.P. (1987) *Ecological simulation primer*. MacMillan Publ. Co., New York.

Taylor, R.A.J., Bauer, L.S., Poland, T.M. & Windell, K.N. (2010) Flight performance of *Agrilus planipennis* (Coleoptera: Buprestidae) on a flight mill and in free flight. *Journal of Insect Behavior*, **23**, 128–148.

US Department of Agriculture, Animal and Plant Health Inspection Service (APHIS). (2011a) Cooperative emerald ash borer project EAB locations in Illinois, Indiana, Iowa, Kentucky, Maryland, Michigan, Minnesota, Missouri, New York, Ohio, Pennsylvania, Virginia, Wisconsin, West Virginia and Canada. Available at: http://www.aphis.usda.gov/plant_health/plant_pest_info/emerald_ash_b/downloads/multistateeab.pdf (accessed 30 March 2011).

US Department of Agriculture, Animal and Plant Health Inspection Service (APHIS). (2011b) 2011 Emerald Ash Borer survey guidelines. Available at: http://www.aphis.usda.gov/plant_health/plant_pest_info/emerald_ash_b/downloads/survey_guidelines_2011.pdf (accessed 30 March 2011).

US Department of Agriculture, Forest Health Technology Enterprise Team (FHTET). (2007a). Sirex woodwasp risk maps. Available at: http://www.fs.fed.us/foresthealth/technology/invasives_sirexnoctilio_riskmaps.shtml (accessed 10 June 2010).

US Department of Agriculture, Forest Health Technology Enterprise Team (FHTET). (2007b). Sirex woodwasp – *Sirex noctilio*. Methods. Available at: http://www.fs.fed.us/foresthealth/technology/pdfs/SirexIntroductionSummary.pdf; http://www.fs.fed.us/foresthealth/technology/pdfs/SirexEstablishmentSummary.pdf; http://www.fs.fed.us/foresthealth/technology/pdfs/SirexSusceptibilitySummary.pdf (accessed 12 July 2010).

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

Walker, W.E., Harramoës, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B.A., Janssen, P. & Krayer von Krauss, M.P. (2003) Defining uncertainty – a conceptual basis for uncertainty management in model-based decision support. *Integrated Assessment*, **4**, 5–17.

Westphal, M.I., Browne, M., MacKinnon, K. & Noble, I. (2008) The link between international trade and the global distribution of invasive alien species. *Biological Invasions*, **10**, 391–398.

Whitemore, G.A. (1970) Third degree stochastic dominance. *American Economic Review*, **60**, 457–459.

Worner, S.P. & Gevrey, M. (2006) Modelling global insect pest species assemblages to determine risk of invasion. *Journal of Applied Ecology*, **43**, 858–867.

Yemshanov, D., Koch, F.H., McKenney, D.W., Downing, M.C. & Sapio, F. (2009) Mapping invasive species risks with stochastic models: a cross-border United States-Canada application for *Sirex noctilio* Fabricius. *Risk Analysis*, **29**, 868–884.

Yemshanov, D., Koch, F.H., Ben-Haim, Y. & Smith, W.D. (2010) Detection capacity, information gaps and the design of surveillance programs for invasive forest pests. *Journal of Environmental Management*, **91**, 2535–2546.

SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

Appendix S1 Probabilistic pathway model of human-assisted emerald ash borer spread via freight transport.

As a service to our authors and readers, this journal provides supporting information supplied by the authors. Such materials are peer-reviewed and may be re-organized for online delivery, but are not copy-edited or typeset. Technical support issues arising from supporting information (other than missing files) should be addressed to the authors.

BIOSKETCH

Denys Yemshanov is a research scientist in the Canadian Forest Service at Natural Resources Canada. His research specialization can be described as development of spatial models focused on various ecological and bioeconomic aspects of forest resources. Areas of his special interest include the development of risk modelling and mapping techniques and bioeconomic impact models for invasive alien species. His recent work is focused on modelling pathways of human-assisted spread of invasive alien species with international trade and commercial transportation in North America.

Author contributions: D.Y. led the concept of the study; developed and programmed the SSD ranking algorithm and the probabilistic pathway model; undertook numeric simulations; developed the first draft; F.K. and D.Y. linked the problem with the pest risk mapping context and the pathway model with the EAB case study; B.L. helped in the discussion of main results, provided EAB expertise and data on EAB observations/evidence of the pest's human-assisted spread; M.D. was involved in the discussion on the theoretical foundations and performance of the SSD algorithm; K.K. was an expert in the Canadian roadside survey database and identified EAB-specific commodities in the dataset; All authors contributed to the writing and editing of the manuscript.

Editor: Reuben Keller