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Quantifying uncertainty in pest risk maps and assessments: adopting a risk-averse decision maker's perspective

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Abstract

Pest risk maps are important decision support tools when devising strategies to minimize introductions of invasive organisms and mitigate their impacts. When possible management responses to an invader include costly or socially sensitive activities, decision-makers tend to follow a more certain (i.e., risk-averse) course of action. We presented a new mapping technique that assesses pest invasion risk from the perspective of a risk-averse decision maker.

We demonstrated the method by evaluating the likelihood that an invasive forest pest will be transported to one of the U.S. states or Canadian provinces in infested firewood by visitors to U.S. federal campgrounds. We tested the impact of the risk aversion assumption using distributions of plausible pest arrival scenarios generated with a geographically explicit model developed from data documenting camper travel across the study area. Next, we prioritized regions of high and low pest arrival risk via application of two stochastic ordering techniques that employed, respectively, first- and second-degree stochastic dominance rules, the latter of which incorporated the notion of risk aversion. We then identified regions in the study area where the pest risk value changed considerably after incorporating risk aversion.

While both methods identified similar areas of highest and lowest risk, they differed in how they demarcated moderate-risk areas. In general, the second-order stochastic dominance method assigned lower risk rankings to moderate-risk areas. Overall, this new method offers a better strategy to deal with the uncertainty typically associated with risk assessments and provides a tractable way to incorporate decision-making preferences into final risk estimates, and thus helps to better align these estimates with particular decision-making scenarios about a pest organism of concern. Incorporation of risk aversion also helps prioritize the set of locations to target for inspections and outreach activities, which can be costly. Our results are especially important and useful given the huge number of camping trips that occur each year in the United States and Canada.

Keywords
Risk aversion, stochastic dominance, decision-making under uncertainty, pest risk mapping, firewood movement, pathway invasion model

Introduction

Management of invasive species populations often requires making decisions about allocating scarce resources for surveillance or eradication of newly detected incursions. To aid in the decision-making process, agencies responsible for monitoring and controlling invasive species, such as the USDA Animal and Plant Health Inspection Service (APHIS) in the U.S. (APHIS 1999; Lance 2003) or the Canadian Food Inspection Agency (CFIA) in Canada (CFIA 2001), routinely assess the projected risk impacts of alien organisms on biological resources, trade and other economic activities (Simberloff 2005, Venette et al. 2010, Magarey et al. 2011). These risk assessments are usually based on the best available information about their target organisms. In general, knowledge about an organism's likely behaviour in its new environment is rarely complete, so any assessment of the potential risks and impacts includes a considerable amount of uncertainty. Consequently, a management decision based on such an assessment is dependent not only on the estimates of pest invasion risk and potential impacts but also on how the decision-makers perceive the uncertainty embedded in these estimates.

In cases where the need to manage invasive pest populations prompts calls for irreversible, costly or socially sensitive actions, decision-makers tend to follow a more certain course of action, thus exhibiting risk-averse behaviour (Gigerenzer 2002, Shefrin and Belotti 2007). Risk-averse behaviour may also be a response to a common situation when public appeals to eradicate or slow the spread of a recently detected invasive pest do not allow enough time to acquire the data necessary to adequately characterize the behaviour of the new invader. Often, the pressure to "do something" about expanding pest populations creates another incentive for decision-makers to follow a cautious, risk-averse strategy; basically, since resources for managing pest populations are limited, choices with a more certain chance of slowing the spread or eradicating new pest incursions are more likely to be adopted. Notably, government agencies tasked with monitoring and regulating the incursion and spread of unwanted invasive organisms are fundamentally risk-averse and have resources and legal power to minimize risks, even at the cost of regulating trade or other related economic activities.

When decision-makers follow a risk-averse strategy, the presence of uncertainty in pest risk assessments inevitably changes decision outcomes about managing the pests. However, uncertainty has rarely been represented in assessments of new pest incursions in a geographical domain. At best, pest risk maps presented uncertainty as separate maps or a combination of coarse risk-uncertainty classes (Koch et al. 2009, Yemshanov et al. 2009). This kind of risk mapping implicitly places the burden of addressing uncertainty on decision-makers which, in turn, may lead to risk-averse behaviour, biased assessments and sometimes ignorance (i.e., a wait-and-see strategy if the assessment of pest impact is highly uncertain). Ideally, the uncertainty associated with the estimated impact of an invasive organism should be directly incorporated into the species' risk map by the analyst, rather than interpreted by the decision-maker (Venette et al. 2010).

In this paper, we present a new risk mapping technique that helps quantify uncertainty in pest risk assessments from the perspective of a risk-averse decision maker. We consider a particular case of risk mapping when a decision-maker faces the problem of prioritizing a set of locations in a geographical domain based on imprecise estimates of the likelihood of pest arrival in a given area. Our goal with this paper is to present the method of prioritizing uncertain outcomes of ecological invasions that would agree with a risk-averse decision-making strategy, and also to explore how the notion of risk-aversion changes the delineation of pest risk in a geographical domain.

Methods

The risk aversion concept

In general, humans tend to place relatively low weights on uncertain outcomes and relatively high weights on certain outcomes (Kahneman and Tversky 1979, Kahneman et al. 1982). Prior studies have demonstrated risk aversion in decision-making attitudes over a range of anticipated economic losses (Markowitz 1952, Levy and Levy 2001, Levy 1998). Risk-averse decision-making is not limited to cases that involve economic losses (such as allocation of investment assets), but also applies to the general case of how humans perceive valuable outcomes under uncertain conditions. The expected utility hypothesis (Arrow 1971, Schoemaker 1982) considers preferences of individuals with regard to uncertain outcomes and represents these as a function of the payouts (whether in monetary or other valuable equivalents). The expected utility theory implies that rational individuals act to maximize their expected utility (i.e., a monetary or non-monetary value that the decision-making agent attributes to a specific asset, service or action). When the expected utility value is represented as a function of the payouts in a monetary or non-monetary equivalent, this condition implies that the function is increasing (i.e., the decision-maker always prefers more to less). Adding the risk aversion assumption (which implies that individuals prefer the more certain choice of two outcomes with the same expected value) adds the condition that the decision-maker's expected utility function (EUF) is concave (Fig.1; a more detailed discussion about risk-aversion and the concavity of the EUF can be found in Arrow 1971 and Levy 1998).

The notion of risk-averse decision preferences can be embedded into the process of mapping risks of pest invasions. In our case, the concept of payoff can be thought as analogous to estimating anticipated losses from an invasive organism (or the likelihood of an organism's arrival). Conceptually, the EUF value (Fig. 1) can be interpreted as analogous to a decision-making priority that indicates the degree of importance for the decision-maker of a particular geographical site that is under risk of infestation. Clearly, any rational decision-maker would assign a higher priority to geographical locations with a higher and more certain likelihood (or anticipated impact) of invasion. By adding the notion of risk-aversion we imply that the assessment of pest invasion risk should be done from the point of view of a decision-maker whose EUF is concave. In short, the notion of risk-aversion means that pest risk assessments (which, in our case as well as in general, translate to prioritization schemes) should include some sort of penalty for uncertain choices.

The use of the EUF's concavity assumption for representing risk-averse behaviour offers a formal treatment of risk aversion without the need to explicitly define the shape of the utility function. Essentially, the concavity condition is a very basic definition of general risk-averse preferences (i.e., by eliminating the cases when the decision-maker is risk-neutral or risk-seeking) and does not define a specific range of risk-averse preferences (such as moderate to extreme risk aversion). While it is possible to impose further restrictive assumptions on the type of risk-averse behaviour – for instance, by assuming a particular functional form of the EUF or limiting the degree of risk aversion to an upper and lower bounds (Meyer 1977, Meyer et al. 2009, Hardaker et al. 2004) – estimating the shape of the EUF in the invasive species management context could be problematic given the wide variety of pest invasion problems and the diverse spectrum of decision-making skills among pest management professionals.

Prioritizing pest invasion risk under the notion of risk-aversion

We consider a pest risk map that prioritizes geographical locations across a landscape based on the likelihood that the pest will arrive at a previously non-invaded locale. Ultimately, the assignment of decision-making priorities to a particular geographical location may depend on the decision-maker's perception of uncertainty in the assessment of the impact of the pest invasion. In this paper, we explore how the incorporation of risk-averse decision preferences changes the prioritization of areas of high and low pest invasion risk in a geographical setting. We use distributions of plausible invasion scenarios generated by a stochastic model to predict the movement of an invasive organism across a heterogeneous landscape. We then delineate regions of high and low risk of pest arrival across the landscape via the application of two simple stochas-

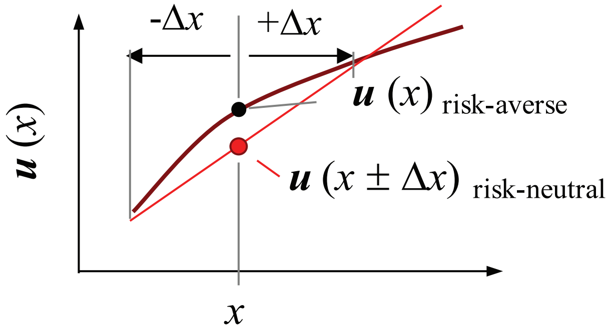

Figure 1. The expected utility function (EUF) concept. The EUF value can be interpreted as analogous to a decision-making priority that indicates the degree of importance for the decision-maker of a particular geographical site that is under risk of infestation. Bold line depicts an example of a concave EUF that denotes risk-averse decision-making preferences. The concavity condition means that a more certain amount of valuables (or degree of importance for the decision-maker) ($\boldsymbol{u}(x)$) would always be preferred over a less certain choice ($\boldsymbol{u}(x \pm \Delta x)$ with the same expected value, x. Dashed line shows an example EUF for a risk-neutral decision-maker (i.e., one who is indifferent between more certain and less certain choices with the same expected value).

tic ordering techniques, one of which incorporates the notion of risk aversion. For consistency, we use ordering techniques from the same family based on the stochastic dominance (SD) rule. Finally, we identify geographical regions in a landscape where adding the notion of risk aversion changes the location's pest risk value considerably.

Stochastic dominance (SD) rule

The stochastic dominance rule is a form of stochastic ordering that compares a pair of distributions. The concept was previously applied to compare distributions of investment portfolio returns in financial valuation studies (Hanoch and Levy 1969, Rothschild and Stiglitz 1970) and shares many technical aspects with the partial ordering of vectors and majorization theory in statistics (Whitemore and Findlay 1978, Levy 1992). The SD rule compares two distributions based on their cumulative distribution functions, or CDFs (Levy 1998). In our case, we compare two map locations, f and g, in a geographical setting. At each location, the multitude of plausible invasion outcomes is described by the distributions, $f(\varphi_{ij})$ or $g(\varphi_{ij})$, of the rates of invasive pest arrival, φ_{ij}, at locations f and g (Fig. 2) over an interval of possible arrival rate values, [a; b], where a = 0 (i.e., the likelihood of pest arrival is zero) and b = 1 (i.e., the arrival of the pest is certain,). The SD test compares the distributions at f and g as represented by their respective cumulative distribution functions, $F(\varphi_{ij}) = \int_a^{\varphi_{ij}} f(\varphi_{ij})d\varphi$ and $G(\varphi_{ij}) = \int_a^{\varphi_{ij}} g(\varphi_{ij})d\varphi$. Location f dominates g by the first-degree stochastic dominance rule (FSD) if

$G(\varphi_{ij}) - F(\varphi_{ij}) \geq 0$ for all φ_{ij}, and $G(\varphi_{ij}) - F(\varphi_{ij}) > 0$ for at least one φ_{ij} (1)

The FSD rule implies that the CDFs of *f* and *g* do not cross each other (Fig. 2A). The test for FSD also supposes that a decision-maker will always prefer the "higher-value" outcome (Levy 1998) at any realization of φ_{ij}, i.e., will place a greater management priority on a location with higher likelihood of pest arrival (depicted by estimates of φ_{ij}) than a location with lower likelihood.

The FSD conditions may fail when differences between $G(\varphi_{ij})$ and $F(\varphi_{ij})$ are small. Alternatively, second-degree stochastic dominance (SSD) provides weaker but more selective discrimination by comparing the integrals of the CDFs for $F(\varphi_{ij})$ and $G(\varphi_{ij})$: $\int_a^{\varphi_{ij}} F(\varphi_{ij})d\varphi$ and $\int_a^{\varphi_{ij}} G(\varphi_{ij})d\varphi$. Location *f* dominates the alternative *g* by SSD if

$$\int_a^{\varphi_{ij}} [G(\varphi_{ij}) - F(\varphi_{ij})]d\varphi \geq 0 \text{ for all } \varphi_{ij}\text{, and}$$

$$\int_a^{\varphi_{ij}} [G(\varphi_{ij}) - F(\varphi_{ij})]d\varphi > 0 \quad \text{for at least one } \varphi_{ij} \quad (2)$$

The SSD rule implies that the integrals of the CDFs for $F(\varphi_{ij})$ and $G(\varphi_{ij})$ do not cross (Fig. 2B). The SSD condition adds the assumption that the decision-maker is risk-averse, that is the dominance relationships based on the SSD rule (Eq. 2) satisfy the assumption that the decision-maker's EUF is concave (Levy 1992, Meyer et al. 2005, Gasbarro et al. 2009, see proofs and more details in Levy 1998 and Levy and Levy 2001).

The SSD and FSD tests are pairwise comparisons. However, our study required evaluating a set of *N* multiple geographical locations, or map elements, that constituted a landscape. For each rule, we applied multiple pairwise stochastic dominance tests of map elements to delineate a subset of elements, $\grave{A}_1$, from the total set *N* such that each element of $\grave{A}_1$ could not be dominated by any element in the rest of the set, *N* - $\grave{A}_1$. Formally, a non-dominant subset $\grave{A}_1$ is equivalent to an "efficient set" in financial investment valuation literature (Fishburn and Vickson 1978, Porter et al. 1973, Porter 1978, Post and Versijp 2007). While financial investment analyses often focus on evaluating a single non-dominant set and narrowing down the multitude of possible investment scenarios to the fewest possible choices, our study required evaluating each element (map location) in a set. Hence, we evaluated all nested non-dominated subsets (based on the FSD or SSD rules) in the total set *N* using the following algorithm (Goldberg 1989): After the first non-dominant subset $\grave{A}_1$ was found, it was assigned the highest invasion risk rank of 1 and removed from set *N* temporarily. Then, the next non-dominant subset was found from the rest of the set, *N* -$\grave{A}_1$, assigned a risk rank of 2, temporarily removed from set *N* -$\grave{A}_1$ and so on. The delineation of nested non-dominant sets continued until all elements in the set *N* were evaluated and assigned a corresponding decision-making priority rank. The final rank values based on the FSD and SSD rules were then plotted back to their geographical locations, resulting in a map for each SD rule.

The stochastic dominance rule assumes a very broad range of decision-making behaviours and has relatively low ability to discriminate small non-dominant sets. To improve the discriminative capacity, some alternative metrics have been proposed.

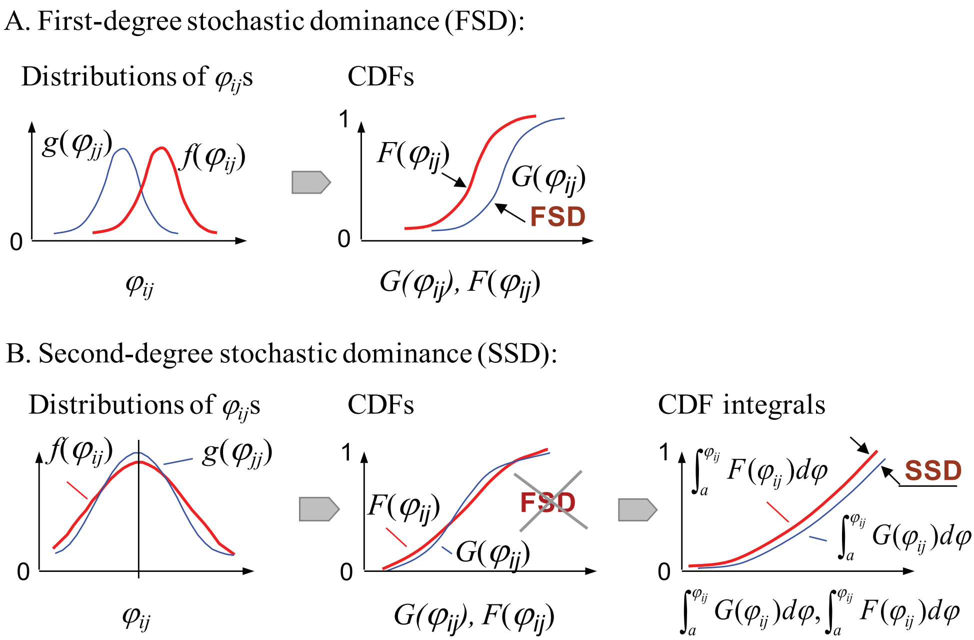

Figure 2. First-degree and second-degree stochastic dominance rules: **A** distributions, $f(\varphi_{ij})$ and $g(\varphi_{ij})$, of camper travel probabilities (φ_{ij}) at two corresponding map locations, *f* and *g* **B** the cumulative distribution functions (CDFs), $F(\varphi_{ij})$ and $G(\varphi_{ij})$, of $f(\varphi_{ij})$ and $g(\varphi_{ij})$ in Fig. 1(a). "FSD" indicates the first-degree stochastic dominance conditions are satisfied (i.e., $G(\varphi_{ij})$ and $F(\varphi_{ij})$ do not cross each other) **C** two additional example distributions of pest arrival rates at *f* and *g* **D** in this case, CDFs of $f(\varphi_{ij})$ and $g(\varphi_{ij})$ cross each other so that the first-degree stochastic dominance conditions fail **E** the integrals, $\int_a^{\varphi_{ij}} G(\varphi_{ij})d\varphi$, $\int_a^{\varphi_{ij}} F(\varphi_{ij})d\varphi$, of the CDFs. "SSD" indicates the second-degree stochastic dominance conditions are met (i.e., $\int_a^{\varphi_{ij}} F(\varphi_{ij})d\varphi$ and $\int_a^{\varphi_{ij}} G(\varphi_{ij})d\varphi$ do not cross each other).

The stochastic dominance with respect to a function, or SDRF (Meyer 1977), assumes that the absolute risk aversion measures of the decision-maker lie between arbitrarily defined lower and upper bounds. Another measure, the stochastic efficiency with respect to a function, or SERF (Hardaker et al. 2004; Hardaker and Lien 2010), ranks risky alternatives in terms of certainty equivalents (CE) while assuming that the degree of risk aversion varies within a defined range. The SERF method requires making additional assumptions about the functional form of a decision-maker's expected utility function and assumes that the decision-maker's risk aversion metric is of the same functional form as those lower and upper risk aversion bounds. Imposing these additional restrictions on risk-averse preferences enables the SERF metric to discriminate even smaller non-dominant sets than the stochastic dominance rule but requires eliciting the risk aversion bounds from decision-makers and identifying the functional form of the EUF. In our risk mapping case, these details about risk-averse preferences were unavailable, so we opted to use the more generalized but less discriminating SSD rule.

Case study

We explored the impact of decision-maker risk-aversion with a North American case study that estimates the likelihood of wood-boring forest pests arriving in firewood at campgrounds on U.S. federal lands in the 49 U.S. states by travellers from the continental U.S. and Canada. The potential for accidental, long-distance transport of alien species with recreational travel has become a topic of considerable concern in North America (Haack et al. 2010, Tobin et al. 2010, Jacobi et al. 2011, Koch et al. 2012). Visitors often bring untreated firewood to parks and campgrounds in the U.S. and Canada, and this material has been recognized as a significant vector of wood-boring forest pests (CFIA 2011, APHIS 2010, The Nature Conservancy 2011, Jacobi et al. 2011). For example, movement of firewood by campers has been deemed one of the major causes of the rapid expansion of populations of the emerald ash borer, an invasive pest of ash trees (*Fraxinus* spp.), throughout eastern Canada and the U.S. Midwest (Haack et al. 2002, 2010, Kovacs et al. 2010). Overall, recreational travel is considered a significant vector of firewood movement: campground surveys in various parts of the U.S. indicate that 8–57% of campers bring their own firewood from home, frequently travelling distances exceeding 160–320 km and crossing state and U.S.-Canada border lines (APHIS 2011). Moreover, staff at national, state and provincial campgrounds typically have scarce resources to check campers for firewood usage and lack the legal mandate to undertake random checks of firewood in visitors' vehicles. This makes it difficult to enforce preventive measures such as bans on the importation and use of outside firewood.

While the problem of moving forest pests with firewood is well recognized (APHIS 2010, The Nature Conservancy 2011), data on the movement of firewood across North America are generally lacking. Therefore, we undertake an alternative approach by exploring more general travel patterns of campers rather than their actual movement of firewood. For this study, we analyzed a 5-year (2004–2009) geographically referenced database of campground visits in the United States (including visits from Canada). Our primary data source for this study was the National Recreation Reservation Service (NRRS), which manages reservations for campgrounds at over 1700 locations that are operated by the U.S. Army Corps of Engineers, the USDA Forest Service, the National Park Service, and other federal agencies (see full description of the NRRS database in Koch et al. 2012). Each reservation record provided information including the name and state of the destination campground, reservation date, and the visitor's origin ZIP code (or postal code for Canadian visitors). The NRRS data set provided geographic coordinates for the campgrounds, and we assigned geographic coordinates for each visitor's home ZIP code (or postal code) in the data set (ESRI 2009, NRCan 2010). These records were then used to build a network of pathways that connected sets of origin and destination locations across North America (see further details in Koch et al. 2012).

Pathway model

We used the NRRS data set to undertake spatial stochastic pathway simulations of potential movements of invasive pests with firewood carried by campers. Spatial stochastic models have been increasingly used for assessing risks of ecological invasions (Rafoss 2003, Cook et al. 2007, Pitt et al. 2009, Muirhead et al. 2006, Yemshanov et al. 2009, 2010). We applied a pathway model that used vector-based information stored in the NRRS database to predict movements of recreational travellers to federal campgrounds in the U.S., including cross-border visits from Canada. Here, we assumed that there is a predictable relationship between camper travel and firewood usage (Jacobi et al. 2011), so the camper travel pattern is a proxy for the firewood transport pattern.

Our choice of a network-based model was aimed at emphasizing the importance of human-assisted movement of invasive organisms over long distances, a phenomenon that many classical dispersal models cannot predict well (see Andow et al. 1990, Buchan and Padilla 1999, Melbourne and Hastings 2009). The model is conceptually similar to that presented in Yemshanov et al. (2012a, b); here, we describe only the model updates required for this study.

We used the NRRS dataset to build a matrix of $n \times n$ origin–destination locations, where each matrix element defined the number of visits for a particular pair of origin–destination locations (i.e., the total number of reservations between a particular origin ZIP code and destination campground). Because the original NRRS records encompassed more than 500 000 unique spatial locations, we aggregated the data to a grid of 15 × 15 km cells. This aggregation decreased the size of the matrix and reduced the computational burden. The NRRS data were then parsed into a set of unique pathway segments, each connecting an origin map cell, i, and a destination map cell, j, in the network. Subsequently, the cumulative number of visits (based on the NRRS reservations) for each pathway segment ij were used to build an $n \times n$ pathway matrix where each element defined the rate, p_{ij}, of camper movement (and by extension, firewood-facilitated pest transport) from cell i to cell j. The pathway matrix stored the p_{ij} values for all possible pairs of (i, j) cells in the transportation network:

$$\mathbf{P}_t = \begin{bmatrix} 0 & p_{12} & \cdots & p_{1n} & 1-\sum_{j=1}^{n} p_{1j} \\ p_{21} & 0 & \cdots & p_{2n} & 1-\sum_{j=1}^{n} p_{2j} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{n1} & p_{n2} & \cdots & 0 & 1-\sum_{j=1}^{n} p_{nj} \end{bmatrix} \quad (3)$$

where the elements $1-\sum_{j=1}^{n} p_{ij}$ describe the probability that camper travel between i and j did not occur and

$$p_{ij} = m_{ij}\lambda \qquad (4)$$

where m_{ij} is the total number of reservations for the origin-destination vector ij and λ is a scaling parameter.

Ideally, the scaling parameter λ would define the likelihood that a pest is moved with firewood from any location i to j. In fact, knowing the precise value of λ would be critical in order to estimate p_{ij} exactly. However, our study did not require precise estimates of λ because we had the more basic aim of prioritizing the geographical locations (i.e., map cells) according to their level of risk. In short, our goal was to order the full set of map cells in the dimension of high–low relative infestation risk via multiple pairwise tests for first- and second-degree stochastic dominance (as described in Eqs. 1 and 2). In this case, the value of λ needed only to be sufficiently small to ensure that the sum of transmission rate values in the $\mathbf{P}_t$ matrix rows was below 1:

$$\sum_{j=1}^{n} p_{ij} \leq 1 \qquad (5).$$

We then used the $\mathbf{P}_t$ matrix to generate stochastic realizations of potential movements of campers (and by extension, pest-infested firewood) from a given cell i to other cells with recreational travel. With i set as the point of "origin", the model simulated subsequent camper movements from i to other destination cells j by extracting the transmission probabilities from $\mathbf{P}_t$ associated with i (Fig. 3). The process continued until a selected destination node had no outgoing paths or a terminal state was chosen based on the elements $1-\sum_{j=1}^{n} p_{ij}$ in $\mathbf{P}_t$. Finally, for each pair of origin–destination locations (i, j), a transmission probability, φ_{ij}, was estimated from the number of times the camper arrived at j from i over K multiple stochastic model realizations

$$\varphi_{ij} = J_{ij}/K \qquad (6)$$

where J_{ij} is the number of individual pathway simulations where a camper originated at i and ultimately arrived at j, and K is the total number of individual simulations of pathway spread from i (for this study, $K = 2\times10^6$ for each i). The values of φ_{ij} were estimated for each (i, j) pair of origin–destination cells, requiring a total of $K\times [n (n-1)]$ pathway simulations.

Prioritizing the geographical locations in the dimension of transmission risk

We used the transmission probabilities φ_{ij} (which, in relative terms, depict the potential of invasive pests to be moved by recreational travellers) to order the map cells across Canada and the U.S. in dimensions of high-low risk. We built separate maps for each of the continental 49 U.S. states and nine Canadian provinces (including the Yukon Territory). For each potential origin map cell, the model generated a list of other cells (with corresponding transmission probabilities φ_{ij}) to which the movement of campers (and, in turn, forest pests carried by firewood) was most likely. Since our primary

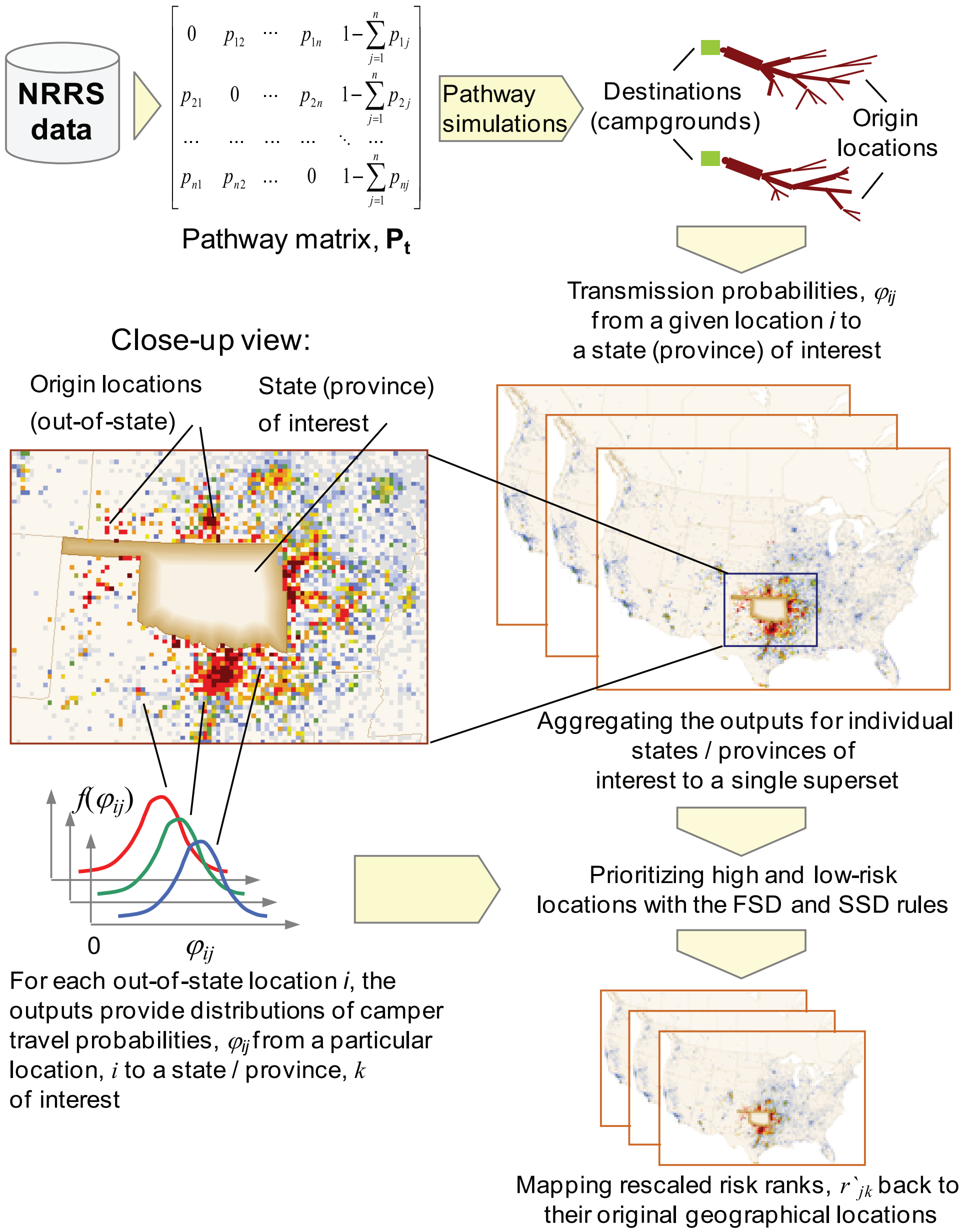

Figure 3. Mapping risks that invasive pests may be carried with infested firewood by campers (the analysis summary).

focus was to estimate the risk of pest movement to a particular state or province, we rearranged the results so each cell i outside of a state (province) of interest, k, had an associated distribution of the transmission probabilities φ_{ij} ($j \in k$), from that location to the state of interest (Fig. 3). In short, this distribution described the degree of the location's invasiveness in relation to the state (province) of interest.

Assuming that the map for each state (province) of interest k had n_k external locations that could potentially serve as sources of future pest arrivals with camper travel, the analysis produced a total (i.e., across all k)of $N = \sum_{k=1}^{k} n_k$ distributions of the j_{ij} transmission probability values. We then applied the FSD and SSD rules to this superset of distributions so that we could order them in the dimension of highest-to-lowest risk of transmission from i to k. Thus, each cell i was given two partial risk ranks, $r_{ik\,\mathrm{SSD}}$ and $r_{ik\,\mathrm{FSD}}$, of pest movement from i to k by campers. Importantly, since partial ordering of the distributions of transmission probabilities was done in a single superset (that included all sets of outputs representing risks of movement to all k states / provinces of interest), the final risk ranks for different states and provinces can be compared one with another.

Our next goal was to compare the ranks generated with the FSD and SSD techniques and to explore how much the risk aversion assumption in the delineations based on the SSD rule changed the geographical patterns of risk across the study area. Because the SSD rule is weaker than FSD and usually produces smaller-size non-dominant sets (Porter 1978, Post 2003), the total number of nested non-dominant sets (and subsequently the number of risk ranks) in the two classifications will be different. Therefore, we inverted and rescaled the risk ranks r_{ik} generated by the FSD and SSD techniques to a 0-1 range so the rescaled ranks, $r`_{ik\,\mathrm{FSD}}$ and $r`_{ik\,\mathrm{SSD}}$ denoting the highest risks were close to 1 and the lowest risks were close to 0. We then explored differences between the rescaled risk ranks generated with the FSD and SSD classifications and their variation across the study area. We also plotted the rescaled risk ranks $r`_{ik\,\mathrm{FSD}}$ and $r`_{ik\,\mathrm{SSD}}$ as maps, each depicting the risk of pest transport to a particular state (province) with recreational travel from elsewhere.

Results

Exploratory geospatial data analysis

Figure 4 depicts example maps of the rescaled risk ranks for Texas and California generated, using the second-degree stochastic dominance rule. (The maps of risk rankings based respectively, on the first- and second-degree stochastic dominance rules for the other U.S. states and the Canadian provinces are shown in online Appendices 1 and 2). The maps suggest some basic geographic trends in campers' travel behaviour. First, the highest-risk out-of-state locations (i.e., from where the movement of infested firewood is the most likely) are usually in close proximity to the state (provincial) border or, at longer travel distances, are associated with major urban centres. In addition, prominent recreational destinations such as Grand Canyon National Park (AZ) or Zion National Park (UT) are also high-risk locations. Notably, there are distinctive regional trends in camper behaviour. For instance, interior states in the mid-western and southeastern U.S. are characterized by predominantly local and medium-range travel from surrounding areas. While states in these regions have few high-profile recreational

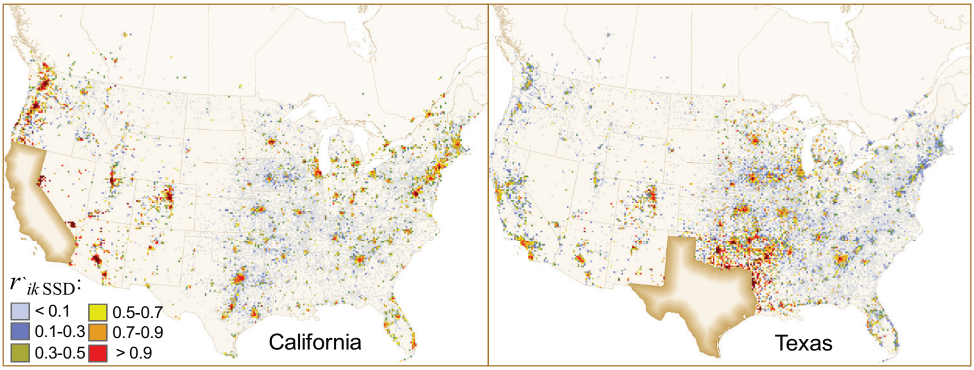

Figure 4. Examples of risk maps depicting the potential of invasive forest pests to be moved by recreational travelers to the states of Texas and California. The risk rank values are based on the second-degree stochastic dominance rule (SSD), which incorporates risk-averse decision preferences. The maps for the other U.S. states, Canadian provinces and the Yukon Territory can be found in online Appendix 2.

destinations such as national parks, they have a dense and fairly uniform network of campgrounds, situated near major water bodies or public forest lands, which are used more often by casual or short-term campers.

The western U.S. has vast areas of sparsely populated land, and so has a higher relative proportion of long-distance sources of campers (and thus potential firewood-associated pests) than the eastern U.S. The risk of pests being moved by campers returning to Canada is relatively low. However, the largest Canadian cities, such as Toronto (ON), Montreal (QC) and Vancouver (BC), have relatively high risks of being potential sources of infestations in neighbouring U.S. states.

Differences between risk ranks based on the FSD and SSD rules

We investigated the geographic differences between the risk rank maps based on the FSD and SSD criteria. Figure 5 and online Appendix 3 present maps of differences in rank values, $\Delta r`_{ik} = r`_{ik\ \mathrm{FSD}} - r`_{ij\ \mathrm{SSD},}$ composed for individual states and provinces. Overall, the FSD and SSD approaches provided similar delineations of the locations ranked with the most extreme risks, i.e., above 0.95 or below 0.05 (Table 1). The greatest differences between the ranks based on the FSD and SSD criteria were found in the areas in the peri-urban and rural zones (since information about camper travel to these locations is expected to be less certain because of a lack of well-documented links from the NRRS data).

For moderate risk ranks between 0.05 and 0.95, the methods appeared to place differing levels of emphasis on certainty in the φ_{ij} transmission probabilities. The SSD approach seemed to decrease the risk rank's value when the variation of the probability (i.e. uncertainty) was high and generally assigned lower rank values than the approach based on the FSD rule. This tendency is particularly evident in the range of moderate

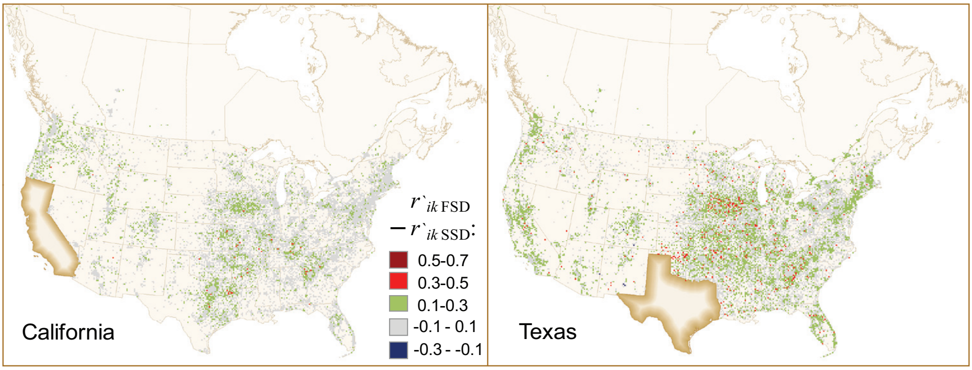

Figure 5. Maps of rank differences, $\Delta r`_{ik} = r`_{ik\,\mathrm{FSD}} - r`_{ik\,\mathrm{SSD}}$, between the delineations based on first- and second-degree stochastic dominance for Texas and California. Positive values indicate that the SSD-based risk rank is lower than the FSD-based rank (so adding the notion of risk aversion decreases the risk rank). The maps for the other U.S. states, Canadian provinces and the Yukon Territory can be found in online Appendix 3.

Table 1. Correspondence between the FSD and SSD rank classes as a percent of the map area. The numbers in the diagonal show the percentages of the map area where the rank class was the same in both FSD and SSD rankings. The largest percentage values in each row are marked on bold.

Risk rank based on the FSD rule	Risk rank based on the SSD rule					
	0–0.05 (lowest)	**0.05–0.25**	**0.25–0.5**	**0.5-.75**	**0.75–0.95**	**0.95–1 (highest)**
0–0.05 (lowest)	**100**					
0.05–0.25	**72.2**	27.7	0.1			
0.25–0.5	0.7	**89.8**	7.7	1.8		
0.5–0.75		30.5	**52.8**	15.0	1.7	
0.75–0.95		<0.01	3.5	24.6	**71.0**	0.9
0.95–1 (highest)					2.6	**97.4**

ranks 0.05–0.5 (Table 1). For example, almost 90% of ranks assigned to a 0.25–0.5 range in the FSD classification were classified into the 0.05–0.25 range in the SSD classification. Similarly, 72% of low-risk ranks classified within the range of 0.05–0.25 in the FSD classification had an SSD rank below 0.05, and roughly 83% of locations with FSD ranks in the 0.5–0.75 range were assigned lower risk ranking in the SSD delineations (Table 1).

Online Appendix 4 presents summaries of the differences, for individual states and provinces, between the FSD and SSD ranks allocated to broad rank classes: 0–0.05, 0.05–0.25, 0.5–0.75, 0.75–0.95 and 0.95–1. Most of the changes in rank values occurred in low–medium rank classes between 0.05 and 0.5, which is consistent with Table 1. For many states and provinces, the difference between the FSD and SSD-based ranks was at least one rank class (e.g., ranks in a 0.25–0.5 range under the FSD rule were assigned to a 0.05–0.25 range under the SSD rule).

Discussion

The maps in online Appendix 3 suggest that geographical patterns of changes between the FSD and SSD rank values, $\Delta r`_{ik}$, can be grouped into three general types. The first type represents states with very high volumes of out-of-state recreational visits (and thus higher risks of pest arrival with infested firewood from elsewhere), such as California and Texas (Table 2, Appendix 3). For these states, the high $\Delta r`_{ik}$ values are uniformly distributed in rural and suburban regions across much of the entire central and western U.S. However, the difference between the FSD and SSD ranks in large urban areas appeared to be small (Fig. 5).

The second type is represented by the mountain and desert states in the western U.S. (such as Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington and Wyoming), which show a less uniform pattern of $\Delta r`_{ik}$ values. Most of the highest changes in ranks were either associated with large urban areas in the central and eastern U.S. or were dispersed across rural and suburban areas in neighbouring states in the western U.S. (Appendix 3). This bifurcated distribution of changes in rank is likely caused by some campers travelling long distances from the central and eastern U.S. and Canada (i.e., for predominantly urban areas), as opposed to shorter-distance travels for campers from neighbouring states in the western U.S.

The third group is represented by states in the northeastern U.S. (Connecticut, Delaware, Maine, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, Vermont), more sparsely populated states in the north-central U.S. (North and South Dakota), and the most populous Canadian provinces (Alberta, British Columbia, Ontario and Quebec, Appendix 3). For this group, the highest changes in risk ranks were detected only in locations close to the state or provincial border, or in major urban areas in the western U.S., such as Denver (CO), Los Angeles (CA), Phoenix (AZ) and San Francisco (CA).

The rest of the Canadian provinces, the District of Columbia and Alaska showed extremely small changes in the rank values. Note that the risk rank values for these states and provinces were very low for both the FSD- and SSD-based delineations. The rest of the U.S. states can be characterized by a combination of the geographical patterns of high $\Delta r`_{ik}$ values noted above: relatively uniform allocations across rural and peri-urban areas in a sort of "fringe zone" adjacent to the state borders, as well as long-distance travel hotspots associated with densely populated urban areas or prominent recreational destinations (e.g., national parks) in the western U.S. (Appendix 3).

Impact of adding the notion of risk aversion

The general impact of adding risk-averse decision preferences can be illustrated (Fig. 6) using a simplified delineation of risk ranks in the dimensions of mean transmission probability, $\overline{\varphi}_{ij}$, and its degree of variation, represented by the standard deviation, $\sigma(\varphi_{ij})$. When uncertainty is ignored and the assignment of risk classes is based solely on

Table 2. State and provincial summaries based on the mean rank values, $r`_{ik\,\mathrm{FSD}}$ and $r`_{ik\,\mathrm{FSD}}$.

Country	State / Province	FSD-based risk rank		SSD-based risk rank	
		Mean $r`_{ik\,\mathrm{FSD}}$	Relative rank	Mean $r`_{ik\,\mathrm{SSD}}$	Relative rank
US	Texas	0.283	1	0.202	1
US	Arkansas	0.251	2	0.184	3
US	California	0.246	4	0.202	2
US	Missouri	0.246	3	0.167	4
US	Tennessee	0.226	5	0.157	5
US	Colorado	0.215	6	0.140	7
US	Georgia	0.201	8	0.143	6
US	Florida	0.205	7	0.128	8
US	Illinois	0.197	9	0.121	10
US	Iowa	0.185	10	0.123	9
US	Oklahoma	0.179	11	0.117	11
US	Washington	0.169	12	0.109	15
US	Oregon	0.168	13	0.110	14
US	Arizona	0.161	15	0.115	13
US	Utah	0.151	17	0.116	12
US	Kansas	0.166	14	0.100	17
US	North Carolina	0.150	18	0.101	16
US	Nevada	0.156	16	0.088	20
US	Kentucky	0.142	19	0.095	18
US	Alabama	0.137	21	0.093	19
US	Virginia	0.139	20	0.086	21
US	Pennsylvania	0.132	22	0.085	23
US	South Carolina	0.121	25	0.085	22
US	Idaho	0.127	23	0.081	24
US	Ohio	0.121	24	0.062	27
US	Mississippi	0.119	26	0.072	25
US	New York	0.116	27	0.063	26
US	Louisiana	0.113	29	0.062	28
US	Maryland	0.114	28	0.057	31
US	Indiana	0.111	30	0.058	30
US	West Virginia	0.092	32	0.059	29
US	Minnesota	0.106	31	0.053	33
US	Wisconsin	0.088	33	0.046	34
US	Montana	0.073	38	0.054	32
US	New Mexico	0.082	34	0.039	36
US	Michigan	0.080	35	0.037	38
US	Massachusetts	0.078	36	0.033	39
US	Nebraska	0.073	39	0.039	37
US	New Hampshire	0.067	41	0.044	35
US	New Jersey	0.075	37	0.028	41
Canada	British Columbia	0.068	40	0.024	43
US	Wyoming	0.053	44	0.031	40
Canada	Quebec	0.062	42	0.020	44
US	South Dakota	0.040	45	0.027	42

Country	State / Province	FSD-based risk rank		SSD-based risk rank	
		Mean $r`_{ik\,\mathrm{FSD}}$	Relative rank	Mean $r`_{ik\,\mathrm{SSD}}$	Relative rank
US	Connecticut	0.054	43	0.020	45
Canada	Alberta	0.028	47	0.012	46
US	Maine	0.027	48	0.012	47
Canada	Ontario	0.030	46	0.010	50
US	Vermont	0.024	49	0.010	49
US	North Dakota	0.017	51	0.010	48
US	Delaware	0.023	50	0.008	51
US	Rhode Island	0.016	52	0.006	52
US	Alaska	0.004	53	0.002	53
Canada	New Brunswick	0.001	54	0.002	54
Canada	Saskatchewan	0.001	55	0.001	55
Canada	Manitoba	0.001	56	0.001	56
Canada	Nova Scotia	<0.001	57	0.001	57
US	District of Columbia	<0.001	58	<0.001	58
Canada	Yukon Territory	<0.001	59	<0.001	59

the mean probability $\overline{\varphi}_{ij}$, broad risk ranks can be defined by parallel lines at certain constant probability thresholds (i.e., parallel dashed lines in Fig. 6). Adding the notion of risk aversion generally implies that between two geographic locations (represented by points in Fig. 6) with the same expected mean probability of the pest's arrival, the more certain choice (i.e., the location exhibiting lower variation) will be assigned a higher decision-making priority. In turn, the boundaries between risk classes under the risk-averse SSD rule (i.e., solid lines in Fig. 6) will always be tilted at an angle, *b*, below 90 degrees relative to their corresponding risk-neutral boundaries, since a location with the same mean transmission probability $\overline{\varphi}_{ij}$ as another location, but lower variability will receive a higher risk rank under SSD.

Notably, the SSD rule does not restrict the potential range of risk-averse preferences, i.e., it does not limit the degree of decision-makers' absolute risk-aversion. This suggests that the SSD rule allows for the possibility that the risk aversion of some decision-makers may be very large, such that small differences in the uncertainty of the risk estimates could receive unrealistically high importance. To address instances of extreme risk aversion, several alternative approaches that limit the potential range of risk aversion have been proposed. For example, stochastic dominance with respect to a function (SDRF) limits the range of the absolute risk aversion measure to arbitrary chosen limits (Meyer 1977; Meyer et al. 2009). Alternatively, stochastic efficiency with respect to a function (SERF) restricts the variation of the degree of risk aversion to an arbitrarily defined range but ranks risky alternatives in terms of their certainty equivalents (CE) (Hardaker et al. 2004; Hardaker and Lien 2010). The SERF method requires making additional inferences about the functional form of the expected utility function and adds the restrictive assumption that the measure of risk aversion used is held constant as the level of outcomes changes (Hardaker and Lien 2010). Overall, the SERF metric is capable of discriminat-

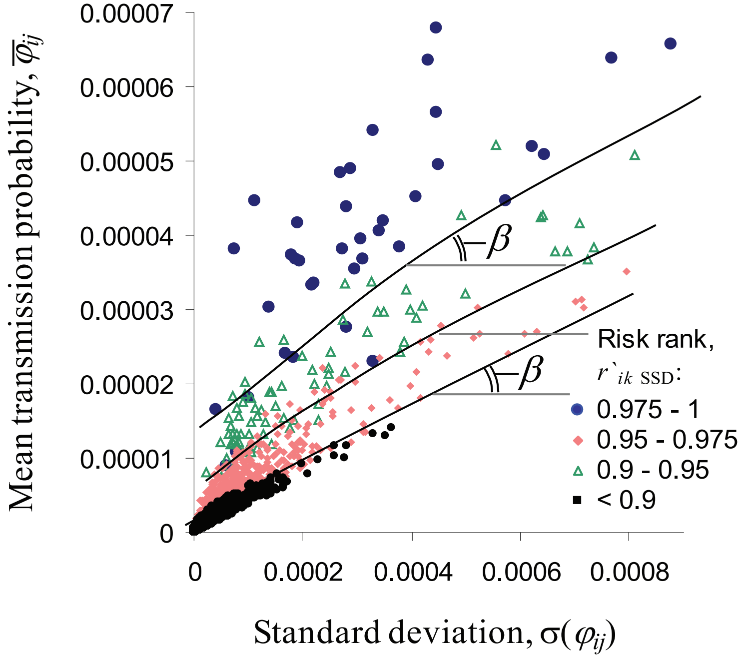

Figure 6. Schematic representation of broad risk classes delineated with the SSD rule, $r`_{ik}$, in dimensions of the mean camper travel probability, $\overline{\varphi}_{ij}$, and its standard deviation, $\sigma(\varphi_{ij})$. b denotes the tilt angle between the generalized boundaries of broad risk classes in the point cloud $\overline{\varphi}_{ij}$ - $\sigma(\varphi_{ij})$ and the horizontal line indicates a constant mean transmission rate (φ_{ij} = *const*). Dashed lines denote the boundaries between hypothetical risk classes in a risk-neutral classification (i.e., b = 0, when risk delineation is independent of the amount of uncertainty in the estimates). Points represent individual locations (15×15 km map cells, a 10% random subset of all locations).

ing smaller non-dominant sets than SSD (or SDRF), but this is achieved at the expense of imposing strong restrictive assumptions on decision-maker's risk-averse preferences.

In economic studies, the SSD rule has commonly been considered too coarse to be used effectively for practical purposes (Hardaker et al. 2004, Hardaker and Lien 2010). However, we found the discriminatory power of the SSD rule to be adequate for our geographical risk mapping case. Since our study required ranking of all spatial elements in the map (and the total number of map elements was very large), the performance of the SSD rule was sufficient to discriminate a large number of nested non-dominant sets and identify areas of high and low pest arrival risk with good spatial precision. Because the analysis delineated nested non-dominant sets (instead of finding a single non-dominant set of the smallest possible size), the impact of lower discriminatory capacity was less noticeable. Also, the magnitude of the variation in pest arrival rates in our study was considerably larger than the typical variability of net returns (or CE values) in economic studies, hence the differences between the CDFs were more discernible. Note that the discriminatory power of the SSD-based approach could be further improved by increasing the number of discrete percentile points in the calculations of the CDF integrals or by re-sampling the underlying geographical data to a higher spatial resolution and thereby increasing the total number of map elements in the study area (which would lead to a larger number of nested non-dominant sets).

Technical aspects of an application of the stochastic ordering techniques

In our study, we used the stochastic dominance concept to delineate nested non-dominant sets of map elements, based on a partial order of these elements, in a space defined by the distributions of pest transmission rates φ_{ij} to a state (province) of interest. The reliance on a partial order of elements makes this approach relatively stable to errors in data and underlying assumptions about the behaviour of the invader. Basically, it takes a higher degree of error to alter the partial ordering of elements in the set and change the dominance relations between the map elements.

The stochastic dominance concept (SD) provides an attractive framework for assessing risks of pest invasions under uncertainty. In our study, the theoretical attractiveness of the second-degree stochastic dominance (SSD) lies in its non-parametric nature (Fishburn and Vickson 1978). While the SSD rule operates from the general perspective of a risk-averse decision-maker (Porter et al. 1973, Meyer et al. 2005), it does not require an explicit specification of a decision-maker's expected utility function (i.e., defining a numerical "utility" value for every possible invasion outcome that a decision-maker may encounter). In fact, the precise determination of the degree of risk aversion (as well as the other behavioural aspects of managing invasive pests) is problematic as it would require tracking the history of decision-making actions within agencies responsible for managing pest incursions, as well as quantifying the associated risk preferences. Note that practical applications of the SSD rule still require careful consideration of the decision-making problem of interest.

The stochastic ordering techniques used in this study help resolve some troublesome issues in assessing invasion risks when knowledge about an invasive organism is insufficient for deriving precise estimates of risk. A lack of knowledge about the organism's behaviour in a new environment often causes experts to generate fairly coarse assessments (e.g., by assessing risk in vague "high-low" terms or deriving a broad distribution of plausible invasion outcomes instead of a single impact value). Although experts can discern the meaningful tendencies in the predicted outcome of an invasion (such as relatively high or low likelihood of invasion), they are rarely able to assign precise likelihood values. In techniques based on nested non-dominant sets like the FSD and SSD rules, every geographic location of interest is ordered along a risk gradient, which makes the issue of assigning precise pest arrival rate values less critical.

The estimation of non-dominant sets with the FSD or SSD rule requires undertaking multiple pairwise tests for stochastic dominance and has a computational complexity on the order of $N(N - 1)/2$. While calculation of non-dominant sets for large N can be computationally demanding, the basic algorithm that checks for non-dominance is relatively simple, and can be easily parallelized.

We must note that the use of nested non-dominant sets for ordering geographic locations provides only a partial ranking (so that ranks reflect relative "high-low" positions only within a given dataset). Since our intention was to develop comparable risk rankings derived for the U.S. states, eight Canadian provinces and the Yukon Territory, we undertook the extra step of aggregating all datasets into a single superset and ranking it with the FSD and SSD rules. Thus, the final ranks were mapped within a single frame of reference and the ranks for individual states and provinces were comparable one with another. While computationally demanding, we believe this method addresses a major criticism of risk mapping methods based on a partial ordering: an inability to generate a common ranking space. Table 2 shows a comparative level of risk that each state (or province) will receive infested firewood with recreational travelers as an average rank values, $r`_{ik}$ of firewood moved to a state (or province) of interest from all out-of-state locations as a risk metric. As Table 2 suggests, Texas, Arkansas, and California show the highest potential to receive forest pests in camper-transported firewood from elsewhere, whereas the District of Columbia, Yukon Territory, Nova Scotia, Manitoba and Saskatchewan have the lowest potential. These rankings assume a generalized risk of infestation. Knowledge of a specific potential source location for an infestation could, of course, change these rankings, but the approach used here to incorporate risk aversion in the mapping process would remain applicable.

Incorporation of risk-averse preferences into a delineation of high-risk locations has some important implications for the development of broad-scale pest surveys and public outreach campaigns. In regions where the areas with high-risk estimates based on the SSD rule are uniformly dispersed in relatively close proximity to a state or provincial border (such as for Alabama or Pennsylvania, Appendix 2), the development of large-scale public outreach programs could target nearby states because camper travel is mostly local and risk is distributed uniformly in close proximity to the state (or province) of interest. Alternatively, if the majority of high-ranked source locations indicate long-distance travel destinations (such as for the prominent national parks in Utah or Arizona), a statewide surveillance program may be inefficient and an alternative effort that targets specific high-risk recreation destinations would represent a more effective strategy.

Conclusions

This study demonstrated how the notion of a decision-maker's risk aversion can be incorporated into the process of mapping risks of ecological pest invasions. We believe that the approach based on the stochastic dominance rules represents a major step forward in model-based assessments of ecological risks because it provides a tractable way to incorporate decision-making preferences into the estimates of pest invasion risk and consecutively offers the appropriate treatment of uncertainty according to the anticipated preferences of decision-makers (the end users of risk assessments and maps). Overall, incorporation of risk-aversion adds credibility to the pest risk mapping process, helps narrow the set of geographical locations that would need to be targeted for costly inspection and public outreach activities, and could be easily applied to the threat of recreational firewood movement in North America.

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Appendix 1

Risk of out-of-state (out-of-province) locations to be the source of forest pests transported in firewood carried by campers. The risk rank values are based on the delineation of nested non-dominant sets via the first-degree stochastic dominance rule (FSD). The ranks close to 1.0 denote the highest risk of pest arrival and the ranks close to 0 denote the lowest risk. (doi: 10.3897/neobiota.18.4002.app1) File format: Adobe PDF File (pdf).

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Appendix 2

Risk of out-of-state (out-of-province) locations to be the source of forest pests transported in firewood carried by campers. The risk rank values are based on the delineation of nested non-dominant sets via the second-degree stochastic dominance rule (SSD), which embeds the notion of risk-averse decision choice. The ranks close to 1.0 denote the highest risk of pest arrival and the ranks close to 0 denote the lowest risk. (doi: 10.3897/neobiota.18.4002.app2) File format: Adobe PDF File (pdf).

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Appendix 3

Maps of differences in the risk ranks based on the first- and second-degree stochastic dominance rules, $\Delta r`_{ik} = r`_{ik\,\mathrm{FSD}} - r`_{ik\,\mathrm{SSD}}$. Positive values indicate that the FSD-based risk rank exceeds the SSD-based rank and vice versa. (doi: 10.3897/neobiota.18.4002.app3) File format: Adobe PDF File (pdf).

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Appendix 4

Summary of differences between risk rank classes, 0–0.05, 0.05–0.25, 0.25–0.5, 0.5–0.75, 0.75–0.95 and 0.95–1 in the delineations based on the FSD and SSD rules. (doi: 10.3897/neobiota.18.4002.app4) File format: Adobe PDF File (pdf).

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