12 Towards Reliable Mapping of Biosecurity Risk: Incorporating Uncertainty and Decision Makers' Risk Aversion

Denys Yemshanov,[1]* Frank H. Koch,[2] Mark Ducey[3] and Robert A. Haack[4]

[1]*Natural Resources Canada, Canadian Forest Service, Sault Ste Marie, Canada;* [2]*USDA Forest Service, Southern Research Station, North Carolina, USA;* [3]*University of New Hampshire, Durham, USA;* [4]*USDA Forest Service, Northern Research Station, Michigan, USA*

Abstract

Pest risk maps are an important source of decision support 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 present a new mapping technique that assesses pest invasion risk from the perspective of a risk-averse decision maker. We demonstrate the approach by evaluating the likelihood that an invasive forest pest will be transported to one of the continental US states or Canadian provinces in infested firewood that may be carried by visitors to US federal campgrounds. We test 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 prioritize regions of high and low pest arrival risk via application of two stochastic ordering techniques that employ, respectively, first- and second-degree stochastic dominance rules, the latter of which incorporates the notion of risk aversion. We then identify regions in the study area where incorporating risk aversion changes a region's pest risk value considerably.

While both methods identified similar areas of highest and lowest risk, they differed in how they demarcated moderate-risk areas. Each method 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 an organism of concern. Overall, incorporation of risk aversion helps to refine the set of locations that could be confidently targeted for costly inspections and outreach activities.

12.1 Introduction

Management of alien or non-native invasive species populations often requires making decisions on allocating resources. These

*Denys.Yemshanov@NRCan-RNCan.gc.ca

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include resources for management or eradication of recently detected or anticipated incursions of new pests. To aid in the decision-making process, agencies responsible for monitoring and controlling invasive species, such as the United States Department of Agriculture (USDA) Animal and Plant Health Inspection Service (APHIS) in the USA (USDA/APHIS, 1999; Lance, 2003) or the Canadian Food Inspection Agency (CFIA) in Canada (CFIA, 2001), routinely assess the risk and projected impacts of alien organisms on biological resources, trade and other economic activities (Simberloff, 2005; Venette *et al.*, 2010; Magarey *et al.*, 2011; Chapters 2, 5 and 13, this volume). Geographic mapping of risks associated with invasive organisms is becoming common in these assessments (Boender *et al.*, 2007; Magarey *et al.*, 2009; Venette *et al.*, 2010; Chapter 14, this volume). In general terms, 'pest risk mapping' can be described as the prioritization of geographic domains facing the threat of establishment of a non-native insect or disease (Koch *et al.*, 2009; Yemshanov *et al.*, 2009a; Magarey *et al.*, 2011). The geographic area of concern is divided into a set of small spatial units (such as a grid of map cells) so each element can be prioritized by the potential for the organism of concern to become established and cause damage to a host resource. Formally, the prioritization provides ranking of all spatial locations (map elements), which makes this task different from other risk assessment tasks that just generally distinguish the most (or least) risky domains.

Risk maps can use a variety of metrics, such as the probability of the pest's arrival (Koch *et al.*, 2009; Yemshanov *et al.*, 2012a) or projected resource losses (Borchert *et al.*, 2007; Yemshanov *et al.*, 2009b), to describe the estimated (or perceived) risk of pest incursions. Often, the choice of risk metric is driven by a manager's decision objectives. For example, if a pest risk map is aimed at guiding surveillance and early detection then a metric related to the probability of an organism's arrival may be more relevant than one that measures the potential impact of established populations (Magarey *et al.*, 2009; Venette *et al.*, 2010). Frequently, the measure of risk is translated into an ordinal-scale variable (a risk rank) which, in turn, is applied to all locations in the geographic area of interest (Venette *et al.*, 2010; Magarey *et al.*, 2011).

Risk assessments are commonly undertaken in anticipation that an organism will soon arrive in the area of interest, or instead, immediately following the first detection of a new invader. In either situation, knowledge about the likely behaviour of the organism in a new environment may not be precise and thus could lead to ambiguous estimates of the pest invasion risk. Consequently, analysts tend to depict the risk of invasion in coarse, 'high–low' terms and often cannot assign precise meaning to these coarse ranks (Andersen *et al.*, 2004; Baker *et al.*, 2005; Simberloff, 2005). Thus, the use of imprecise data and assumptions leads to considerable uncertainty in estimated risk values (Andrews *et al.*, 2004; Koch *et al.*, 2009). Unfortunately, these uncertainties are not always conveyed to the decision makers, who rely on the risk estimates as guidance for management choices (Koch *et al.*, 2009).

When risk assessments and maps do not incorporate or communicate uncertainty, this places an extra burden on decision makers to address the uncertainty implicitly. Subsequently, the decision makers' perceptions and beliefs may influence their treatment of the uncertainty without requiring them to feed this information back to the analysts who created the assessments and maps (Morgan and Henrion, 1990; Gigerenzer, 2002). Moreover, since experts (including pest management professionals and regulators) tend to misjudge uncertainty by a considerable margin (Kahneman *et al.*, 1982) this may lead decision makers to be overconfident in their own interpretations of the risk or, alternatively, cause them to be unduly sceptical if knowledge about the organism seems to be poor. Therefore, the uncertainty associated with the level of estimated risk from an invasive organism stands as an important decision criterion that should be incorporated by the analyst, rather than the decision maker, into the species' risk map (Venette *et al.*, 2010). In practice, the uncertainty of risk values, if addressed at all, is rarely integrated, and instead is usually presented as a separate map (Koch *et al.*, 2009; Yemshanov *et al.*, 2009a), which may further confuse the decision makers.

Typically, decision makers and pest management professionals responsible for managing incursions of unwanted organisms are risk averse: they tend to follow a more certain course of action when the need to manage invasive pest populations prompts calls for irreversible or socially sensitive actions (Gigerenzer, 2002; Shefrin and Belotti, 2007). Risk-averse behaviour also occurs as a common response to the situation when public calls to eradicate or slow the spread of a recently detected invader do not allow enough time to collect sufficient data about the new organism. In short, the political pressure to 'do something' about recently detected pest populations creates another incentive to follow a cautious strategy. When 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 regulating the incursion and spread of invasive organisms (such as APHIS in the USA or CFIA in Canada), are fundamentally risk averse and have resources and legal power to minimize risks, even at the cost of regulating trade or restricting other related economic activities.

In this chapter, we describe a pest-risk-mapping methodology that helps to combine estimates of pest invasion risk and their uncertainty in a single metric such that the final risk allocation satisfies a specific preference of a decision maker tasked with the management of an invasive species. In particular, we focus on how the technique may be used to allocate risk priorities in agreement with risk-averse decision-making behaviour. The approach is illustrated with a case study that prioritizes geographical locations using imprecise estimates of pest arrival rates to a given area generated with a stochastic invasion model.

12.2 Methodological Overview

12.2.1 The risk aversion concept

In general, humans tend to place relatively low weights on uncertain outcomes and relatively high weights on certain outcomes when they are making decisions (Kahneman and Tversky, 1979; Kahneman *et al.*, 1982). Prior economic studies have demonstrated risk- and uncertainty-averse decision-making attitudes in a wide variety of investment scenarios (Markowitz, 1952; Levy, 1998; Levy and Levy, 2001). Risk aversion is not limited to cases that involve allocation of investment assets, but also applies to the broader case of how humans perceive valuable outcomes under uncertain conditions. In economic studies, the expected utility hypothesis (Arrow, 1971; Schoemaker, 1982) has been used to depict preferences of individuals with regard to uncertain outcomes. The expected utility hypothesis asserts that rational individuals act to maximize their expected utility (i.e. a monetary or non-monetary 'utility' value that the individual attributes to a specific asset, service, action or an outcome of his or her actions). In short, individuals extract utility from consuming goods or services that can be purchased with their wealth. The utility value describes the preferences of individuals and their expectations with regard to uncertain outcomes and is often represented as a function of the payoffs (in monetary or non-monetary form). For example, consider a decision maker who faces the choice between two scenarios, one with a guaranteed payoff and one without (i.e. an uncertain gamble with the same expected payoff value). In the guaranteed scenario, the person receives x units of payoff. In the uncertain scenario, there is an equal chance of receiving an $x + \Delta x$ payoff or $x - \Delta x$. The expected payoff value for both scenarios is equal to x. If a decision maker is indifferent to uncertainty around the payoff value (so he or she does not make a distinction between the guaranteed payoff and a gamble with the same expected value), his or her preferences are called 'risk neutral' and the shape of the expected utility function, or EUF (which depicts the utility the decision maker expects to receive versus the payoff value) is linear (Fig. 12.1). Alternatively, a decision maker may prefer a guaranteed payoff to an uncertain gamble with the same expected value, or instead, would accept a guaranteed payoff of less than x, rather than accepting the scenario with the uncertain payoff value x. In this case his or her preferences are called risk averse and the point demarcating the decision maker's perception of the utility of a guaranteed payoff is positioned above the utility value of an uncertain scenario (Fig. 12.1). This also implies that the EUF of a risk-averse decision maker is generally concave in shape. In general, concavity of the EUF is one of the most basic definitions of risk-averse preferences; further discussion about risk aversion and concavity of the EUF can be found in Arrow (1971) and Levy (1998).

The notion of risk aversion can be embedded in the process of geographical mapping of the risk of pest invasion. In our case, the concept of payoff can be thought of as analogous to estimating the anticipated likelihood of an organism's arrival (or the potential losses if an invasive organism were to establish a viable population in a given area). Conceptually, the EUF utility value ($u(x)$, Fig. 12.1) can be interpreted as analogous to a decision-making priority for a given payoff value x (i.e. the likelihood of pest arrival or other metric that indicates the degree of importance of a particular geographical location for the decision maker). Clearly, any rational decision maker would assign a higher priority to geographical locations that have both a higher and a more certain likelihood (or anticipated impact) of invasion. By adding the notion of risk aversion we suggest that pest risk assessments should include some sort of penalty for uncertain estimates of risk. Formally, these assessments (and geographical mapping procedures) should be done from the point of view of a decision maker whose EUF is concave (as it follows from a general definition of risk-averse preferences; Arrow, 1971). Ideally, one would be able to explicitly define the shape of a decision maker's EUF. However, estimating the shape of the EUF in practical terms can be problematic given the diverse spectrum of decision-making skills and perceptions among pest management professionals, and the range of goods and values at stake in pest management and surveillance decisions. Hence, we limit our discussions to a generalized case where the EUF of a risk-averse decision maker is assumed to be increasing and concave, but the exact shape of the function is unknown.

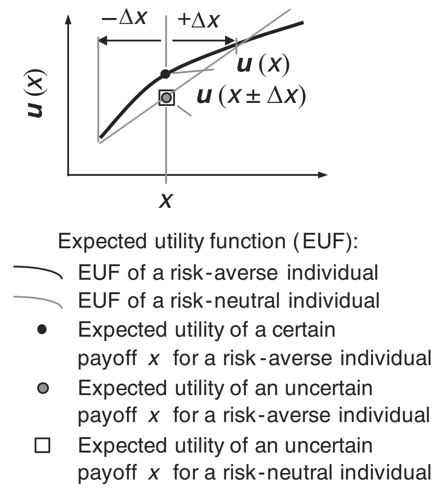

Fig.12.1. The expected utility function (EUF) concept. The EUF value can be interpreted as analogous to a decision-making priority that indicates the degree of importance for the decision maker of a particular geographical site that is under risk of infestation. Bold line depicts an example of a concave 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) ($u(x)$) would always be preferred over a less certain choice ($u(x \pm \Delta x)$ 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).

12.2.2 Assessing risk of pest arrival under the notion of risk aversion

Consider the task of prioritizing geographical locations in a landscape based on imprecise estimates that a pest may arrive at a previously non-invaded locale. When a decision maker is risk averse (i.e. his or her expected utility function is concave), accounting for this preference inevitably changes the allocation of high and low priority domains in the landscape. Furthermore, when there is a range of plausible invasion scenarios (such as multiple realizations from a stochastic simulation model of invasion), one would need to prioritize the high (and low) risk domains within a set *N*, each element of which represents a distribution of plausible invasion outcomes for a location of interest (i.e. estimates of pest arrival risk in our case).

The aforementioned problem of mapping risks under uncertainty is conceptually close to the problem of identifying 'efficient' portfolio sets in the economic literature (Levy, 1998). Originally developed to help with cost-effective allocations of financial assets in volatile markets (Levy, 1998; Götze *et al*., 2008), portfolio allocation techniques have proliferated in other disciplines facing a similar problem of addressing uncertainty in decision making, such as assessing the feasibility of farm community programmes (Kramer and Pope, 1981), irrigation practices (Harris and Mapp, 1986), crop selection (Lee *et al*., 1987), resource allocation for efficient environmental management (McCarthy *et al*., 2010) and surveillance planning to control multiple diseases in animal health (Prattley *et al*., 2007). In our case, the estimated arrival probability of an invasive pest can be seen as analogous to the concept of 'net return' in financial literature, while the uncertainty of that probability estimate is, in turn, analogous to the concept of 'volatility' (cf. Arrow, 1971; Elton and Gruber, 1995). In our pest-risk-mapping case, each location in a landscape can be considered as an individual 'portfolio' with an associated distribution of plausible (i.e. estimated or expected) pest arrival estimates. Note that in portfolio allocation, the usual objective is to narrow down a theoretically infinite set of portfolio combinations to the fewest possible choices ('efficient sets') that have the best combinations of expected net returns and their volatilities (Elton and Gruber, 1995). In our pest-risk-mapping scenario, the 'efficient' set represents the combination of the highest estimated pest arrival likelihood and the uncertainty of those estimates. Since each map element is treated as an individual portfolio the total number of portfolios is equal to the number of elements in the map (so it can be very large for high-resolution maps, but still finite). The risk mapping problem can then be formulated as a portfolio selection strategy: The highest-risk locations in the map can be delineated by finding an 'efficient set' of 'portfolios' (individual map elements). Importantly, the process of finding an efficient set can be undertaken while accounting for risk aversion (Levy, 1992).

12.2.3 Finding efficient sets with the stochastic ordering techniques

Classical portfolio theory offers several basic techniques to allocate efficient sets, such as methods employing the concepts of mean-variance frontier (Markowitz, 1952; Arrow, 1971), certainty equivalent (Gerber and Pafumi, 1998) and stochastic dominance (Levy, 1998, Porter, 1978). In this chapter, we focus on the non-parametric stochastic dominance technique, which does not require specification of the shape of the EUF or testing the underlying data distributions for normality (Fishburn and Vickson, 1978).

Stochastic dominance 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 stochastic dominance 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 distribution, $f(\varphi)$ or $g(\varphi)$, of the rates of invasive pest arrival, φ, at location f or g over an interval of possible pest arrival probabilities, $[a; b]$, where $a = 0$ (i.e. the probability of pest arrival is zero) and $b = 1$ (the arrival of the pest is certain, Fig. 12.2). The stochastic dominance test compares the distributions at f and g as represented by their respective cumulative distribution functions: $F(\varphi)=\int_a^{\phi} f(\varphi)d\varphi$ and $G(\varphi)=\int_a^{\phi} g(\varphi)d\varphi$. Location f dominates g by the first-degree stochastic dominance (FSD) rule if:

$$G(\varphi) - F(\varphi) \geq 0 \text{ for all } \varphi \text{, and}$$
$$G(\varphi) - F(\varphi) > 0 \text{ for at least one } \varphi \qquad \textbf{(12.1)}$$

The FSD rule implies that the CDFs of f and g do not cross each other (Fig. 12.2b). The test for FSD also supposes that a decision maker will always prefer the 'higher value' outcome (Levy, 1998) at any realization of φ, that is, a greater management priority is placed on a location with higher likelihood of pest arrival (depicted by estimates of φ) than a location with lower likelihood.

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

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

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

(12.2)

The SSD rule implies that the integrals of the CDFs for $F(\varphi)$ and $G(\varphi)$ do not cross (Fig. 12.2b). Importantly, the SSD condition adds the explicit assumption that the decision maker is risk averse, that is, the dominance relationships based on the SSD

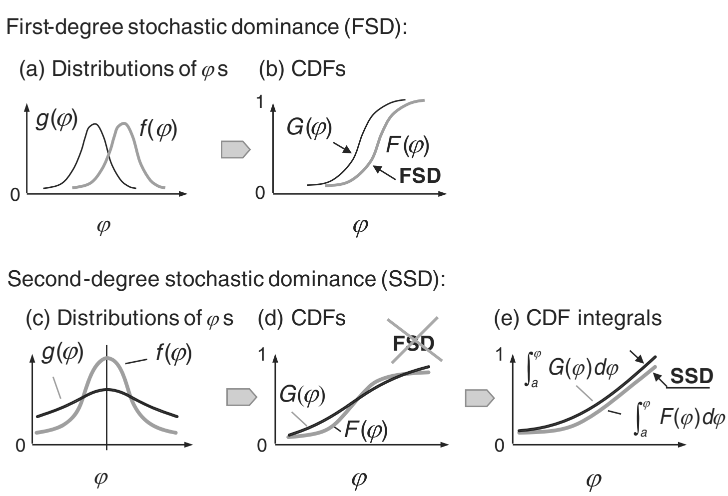

Fig. 12.2. First-degree and second-degree stochastic dominance rules. (a) Distributions, $f(\varphi)$ and $g(\varphi)$, of camper travel probabilities (φ) at two corresponding map locations, f and g. (b) The cumulative distribution functions (CDFs), $F(\varphi)$ and $G(\varphi)$, of $f(\varphi)$ and $g(\varphi)$ in (a). 'FSD' indicates the first-degree stochastic dominance conditions are satisfied (i.e. $G(\varphi)$ and $F(\varphi)$ do not cross each other). (c) Two additional example distributions of pest arrival rates at f and g. (d) In this case, CDFs of $f(\varphi)$ and $g(\varphi)$ cross each other so that the first-degree stochastic dominance conditions fail. (e) The integrals of the CDFs. 'SSD' indicates the second-degree stochastic dominance conditions are met (i.e. the integrals of the CDFs do not cross each other).

rule (Equation 12.2) satisfy the assumption that the decision maker's EUF is increasing and concave (Levy, 1992; Meyer *et al*., 2005, Gasbarro *et al*., 2009; see more details in Levy, 1998 and Levy and Levy, 2001).

The SSD and FSD tests are pairwise comparisons. However, our pest-risk-mapping example required that we evaluate risk for all map elements constituting a set of N multiple geographical locations. In such a case, multiple pairwise stochastic dominance tests of map elements can be used to delineate a subset of elements, $\aleph_1$, from the total set N such that each element of $\aleph_1$ could not be dominated by any element in the rest of the set, N - $\aleph_1$ and the dominance conditions fail between the elements within the subset $\aleph_1$. Formally, a non-dominant subset $\aleph_1$ is equivalent to an 'efficient set' in economic literature (Porter *et al*., 1973; Fishburn and Vickson, 1978; Porter, 1978; Post and Versijp, 2007).

Finding nested efficient sets

Under classical portfolio theory, allocation usually aims to define a single most efficient set of portfolios (Ingersoll, 1987; Elton and Gruber, 1995). A single set is sufficient because it is assumed that any investment amount can be allocated simply in specified proportions to the set of portfolios. However, allocation of resources according to a pest risk map is a more complex exercise, and as outlined above, typically requires the assessment of every map element. This can be accomplished by extending the traditional methods of finding an efficient set to a nested scenario which undertakes subsequent delineations of nested efficient sets that identify successively lower risks. After the first efficient subset $\aleph_1$ is found, it is assigned the highest invasion risk rank of 1 and removed from set N temporarily. Then, the next non-dominant subset is found from the rest of the set, $N - \aleph_1$, assigned a risk rank of 2, temporarily removed from set N - $\aleph_1$ and so on. The delineation of nested non-dominant sets continues until all elements in the set N are evaluated and assigned a corresponding decision-making priority rank. Given that the geographical location of each map element belonging to any of the nested efficient sets is known, the corresponding priority ranks can be assigned to each element, resulting in a map of risk ranks. Furthermore, the FSD and SSD techniques offer an opportunity to explore the impact of the notion of risk aversion on final risk delineations via a comparison of risk ranks based on the SSD technique (which incorporates the notion of risk aversion) with the ranks based on the FSD rule (which does not specify risk-averse preferences explicitly).

12.3 Case Study Example: Assessing Risk of Human-mediated Movement of Wood-boring Insects in Firewood with Recreational Travel in the USA and Canada

The presented risk allocation technique requires that we estimate distributions of plausible pest arrival rates for each map element. These measures can be generated with stochastic invasion models. Stochastic models have been widely used for assessing risks of ecological invasions (Rafoss, 2003; Muirhead *et al*., 2006; Cook *et al*., 2007; Pitt *et al*., 2009; Yemshanov *et al*., 2009a; Prasad *et al*., 2010) and the human-mediated movements of invasive organisms (Robinet *et al*., 2009; Carrasco *et al*., 2010). Here, we illustrate our methodology with a case study that estimates the probability of wood-boring forest pests arriving in firewood at campgrounds on federal lands in the 48 continental US states (and Washington, DC) by travellers from continental USA 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 USA and Canada, and this material has been recognized as a significant vector of wood-boring forest pests (USDA/APHIS, 2010; The Nature Conservancy, 2011; Jacobi *et al*., 2011; CFIA, 2012). 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 US 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 USA indicate that 8–57% of campers bring their own firewood from home, frequently travelling distances exceeding 320 km and crossing state and US–Canada border lines (USDA/APHIS, 2011).

While the problem of moving forest pests with firewood is well recognized (USDA/APHIS, 2010; The Nature Conservancy, 2011), data on the movement of firewood across North America are generally lacking. Therefore, we modelled more general travel patterns of campers rather than their actual movement of firewood and analysed a geographically referenced database of campground visits in the USA between 2004 and 2009 (including cross-border visits from Canada). Our primary data source was the US National Recreation Reservation Service (NRRS), which manages reservations for campgrounds at over 2500 locations that are operated by the US Army Corps of Engineers, USDA Forest Service, 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 dataset provided geographic coordinates for the campgrounds, and we assigned geographic coordinates for each visitor's home ZIP code (or postal code for Canadian locations) in the dataset (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).

12.3.1 Stochastic invasion model

The information stored in the NRRS database was used to undertake stochastic pathway simulations of potential movements of recreational travellers to and from campgrounds in the USA, including visits from Canada. 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.

The pathway model is conceptually similar to that presented in Yemshanov *et al.* (2012a, b). Using the NRRS data, we composed 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/postal 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 approximately 15,000 of 15 × 15 km cells (so the locations within a single 15 km^2 cell were merged and treated as a single node). This aggregation decreased the size of the matrix and reduced the simulation time. Individual NRRS records were aggregated into a set of unique pathway segments, each connecting an origin map cell, i, and a destination map cell, j, in the network. The total number of travels through each pathway segment ij (based on the NRRS reservations) was used to build a 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 in n rows and (n + 1) columns:

$$\mathbf{P}_t = \begin{bmatrix} 0 & p_{12} & \cdots & p_{1n} & 1-\sum_{j=1}^{n} p_{1j} \\ p_{21} & 0 & \cdots & p_{2n} & 1-\sum_{j=1}^{n} p_{2j} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{n1} & p_{n2} & \cdots & 0 & 1-\sum_{j=1}^{n} p_{nj} \end{bmatrix} \qquad \textbf{(12.3)}$$

where the elements $1-\sum_{j=1}^{n} p_{ij}$ in the far right column describe the probability that no camper travel from i to any j occurs. If the value of this column is equal to 1 for any matrix row (a relatively rare occurrence), then the location i associated with that row does not function as a point of origin in the model. However, the location may still serve as a potential destination j.

The p_{ij} values were estimated as:

$$p_{ij} = m_{ij}\lambda \quad \textbf{(12.4)}$$

where m_{ij} is the total number of reservations for the origin–destination vector ij and λ is a scaling parameter. Ideally, knowing the precise value of λ would be critical for an exact estimate of the p_{ij} values. However, our study did not require precise estimates of λ because we had the simpler objective of ordering all map cells in the dimension of high–low relative infestation risk via multiple pairwise tests for FSD and SSD (as described in Equations 12.1 and 12.2). In that sense, our approach is able to generate relative risk rankings even in the absence of an exact model of the temporal rates of transmission. In this case, the value of λ needed only to be sufficiently small to keep the sums of transmission rate values in the $\mathbf{P}_t$ matrix rows below 1:

$$\sum_{j=1}^{n} p_{ij} \leq 1 \quad \textbf{(12.5)}$$

The $\mathbf{P}_t$ matrix was then used 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 by extracting the transmission probabilities from $\mathbf{P}_t$ associated with i (Fig. 12.3). 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 geographic location i, a summary transmission probability, φ_{ij}, was estimated from the number of times travel from i to another cell j occurred over K multiple stochastic model realizations:

$$\varphi_{ij} = J_{ij}/K \quad \textbf{(12.6)}$$

where J_{ij} is the number of individual pathway simulations where travel from i to j was simulated to occur, and K is the total number of individual pathway simulations (for this study, $K = 2 \times 10^6$ for each origin location). The values of φ_{ij} were estimated for each pair of origin–destination cells, requiring a total of $K\,[n\,(n-1)]$ pathway simulations.

We should clarify that, while the p_{ij} values in the $\mathbf{P}_t$ matrix and the φ_{ij} summary probabilities both refer to pairs of origin–destination cells, they represent quite different things. Briefly, each p_{ij} value represents only the probability of travel along a particular pathway segment ij, as fundamentally derived from the camper reservations data. Note that p_{ij} is often zero because not all (i, j) pairs were connected in the underlying data (i.e. many pairs did not have any associated reservation records). In contrast, the φ_{ij} values represent the total probability of travel from a given location i to another location j via any feasible pathway (i.e. a combination of one or more pathway segments). Importantly, this total probability includes cases where j was only an intermediate destination along a pathway. Thus, the φ_{ij} values also incorporate possible multi-stop travel as simulated by the model.

12.3.2 Ordering the geographical locations in the dimension of pest arrival risk

We used the transmission probabilities φ_{ij} (which, in relative terms, depict the location-specific potential of invasive pests to be moved by recreational travellers) to order the map cells across Canada and the USA in the dimension of high-to-low risk. We built separate maps for each of the 48 continental US states (and Washington, DC) and nine Canadian provinces (including the Yukon Territory). For each potential origin map cell i outside a target state or province, k, the model generated a list of all destination cells within the state (province) of interest to which the movement of campers (and, in turn, forest pests carried by firewood) was predicted from i (i.e. where the associated φ_{ij} values were positive). We then rearranged the list so that each origin cell i was

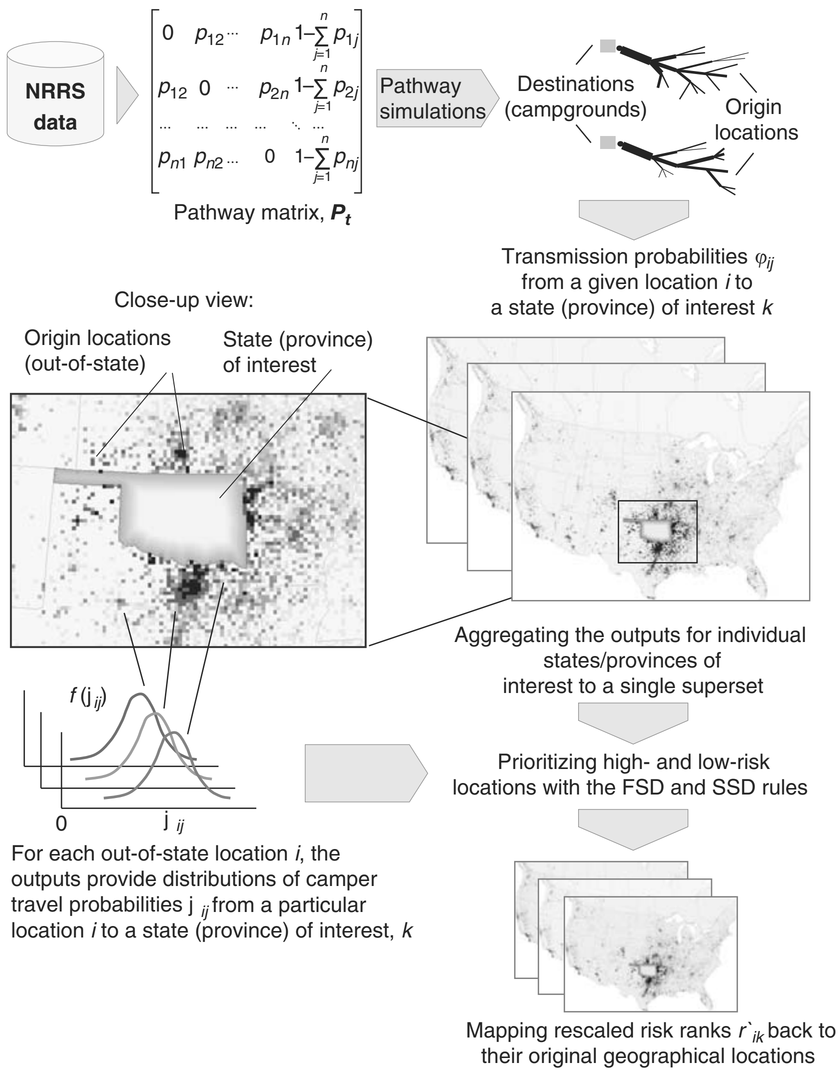

Fig. 12.3. Mapping risks that invasive pests may be carried with infested firewood by campers (the analysis summary).

characterized by a distribution of the transmission probability values φ_{ij} from that location to some destination (i.e. any cell) within state (province) k (Fig. 12.3). In short, this distribution described the origin location's potential to be the source of firewood-transported forest pests for the state (or 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 states/provinces) of $M = \sum_{k=1}^{k} n_k$ distributions of the φ_{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 based on the first- and second-degree stochastic dominance rule, $r_{ik\ \mathrm{FSD}}$ and $r_{ik\ \mathrm{SSD}}$, 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 M 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 rules and to explore how much the risk aversion assumption changed the geographical patterns of risk across the study area. Because the SSD rule is weaker than FSD and usually produces smaller-size efficient sets (Porter, 1978; Post, 2003), the number of nested efficient sets in the FSD and SSD classifications can 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 as well as their variation across the study area.

12.4 Summary of Results: State- and Province-wide Risks of Likely Pest Transmissions With Recreational Travel

12.4.1 Broad geographical patterns or pest transmission risk

The methodology described above yielded distinct maps for every US state and Canadian province. Here, we illustrate our results using the four representative examples of Arkansas, California, Colorado and Quebec (Canada) (Fig. 12.4). The risk maps generated with the SSD rule suggest some basic geographic trends in camper travel behaviour. First, the highest-risk out-of-state origin locations (i.e. from where the movement of infested firewood is the most likely) are usually in close proximity to the state (or provincial) border or, at longer travel distances, are associated with major urban centres. In addition, most prominent recreational destinations (such as Grand Canyon National Park in Arizona) are also high-risk locations. Notably, there are distinctive regional trends in camper behaviour. For instance, interior states in the mid-western and south-eastern USA are characterized by predominantly local- and medium-range travel from surrounding areas. While states in these regions have few high-profile recreational 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 USA 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 USA. The risk of pests being moved by campers returning to Canada is relatively low. However, the largest Canadian cities, such as Toronto (Ontario), Montreal (Quebec) and Vancouver (British Columbia), have relatively high risks of being potential sources of infestations in neighbouring US states.

12.4.2 Impact of adding the notion of risk aversion

The general impact of adding risk-averse decision preferences can be illustrated using a simplified delineation of risk ranks in the dimensions of mean transmission probability, $\bar{\varphi}$, and its degree of variation, represented by $\sigma(\varphi_{ij})$, the standard deviation of φ_{ij} (Fig. 12.5). When uncertainty is ignored and the assignment of risk classes is based solely on the mean probability $\bar{\varphi}_{ij}$, broad risk ranks can be defined by parallel lines at certain constant probability thresholds (i.e. the parallel dashed lines in Fig. 12.5). Adding the notion of risk aversion generally implies that between two geographic locations (represented by points in Fig. 12.5) with the same expected mean probability of the pest's arrival, the more certain choice (i.e. the location with lower

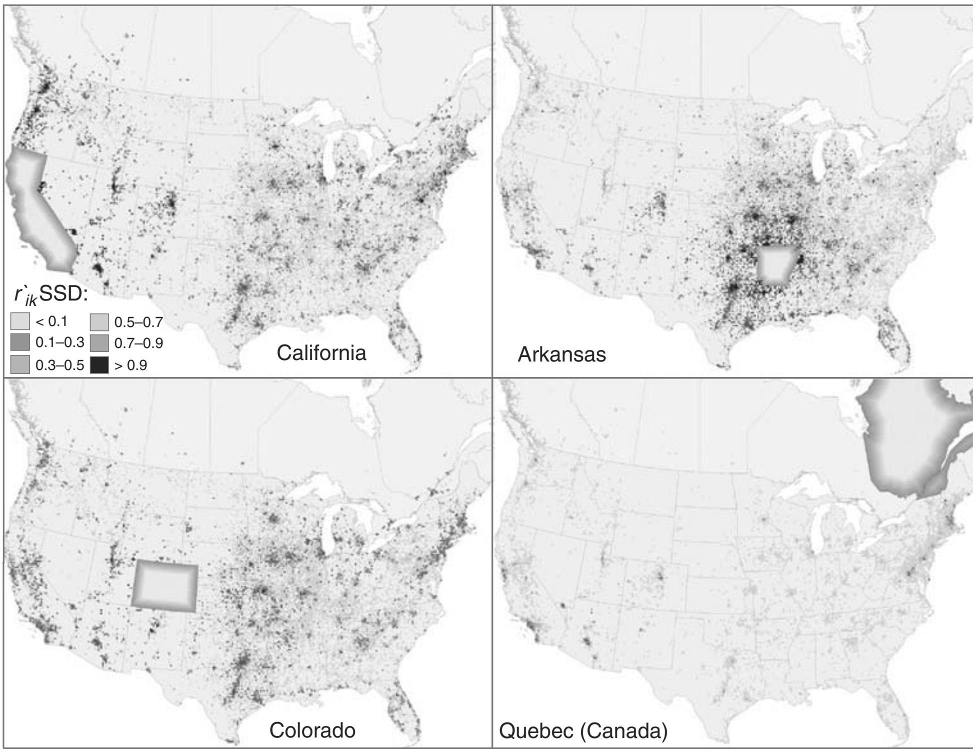

Fig. 12.4. Examples of risk maps depicting the potential of invasive forest pests to be moved by recreational travellers to the states of Arkansas, California and Colorado and the province of Quebec. The risk rank values are based on the second-degree stochastic dominance rule (SSD), which incorporates risk-averse decision preferences.

variation of φ_{ij}) will be assigned a higher decision-making priority (in relative terms). In turn, the boundaries between risk classes under the risk-averse SSD rule (i.e. solid lines in Fig. 12.5) will always be tilted at an angle, β, below 90° relative to their corresponding risk-neutral boundaries, since a location with the same mean transmission probability $\bar{\varphi}_{ij}$ as another location, but lower variability, will receive a higher risk rank under SSD.

The impact of adding the risk aversion assumption also shows discernable geographical patterns. Figure 12.6 presents example maps of differences in risk values delineated with the FSD and SSD rules, $\Delta r`_{ik} = r`_{ik\ \mathrm{FSD}} - r`_{ik\ \mathrm{SSD}}$, for Arkansas, California, Colorado and Quebec (Canada). Overall, the greatest differences between the risk ranks based on the FSD and SSD rules were found in suburban and rural areas. While both FSD- and SSD-based rankings were similar for the extreme risk ranks (i.e. above 0.95 or below 0.05), for moderate risk ranks between 0.05 and 0.95, the two methods appeared to place differing levels of emphasis on certainty in the φ_{ij} values. The ranks derived with the SSD rule appeared to be lower than the FSD ranks when the variation of the pest arrival rates was high. This tendency was particularly evident in the range of moderate and low risk ranks between 0.05 and 0.50 (Table 12.1).

In general, the geographical patterns of changes between the FSD and SSD rank values, $\Delta r`_{ik}$, can be grouped into three broad types. The first type represents states, such as Arkansas, California and Texas, with

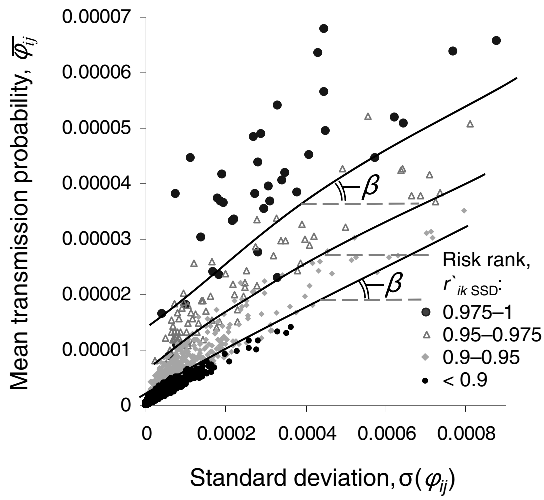

Fig. 12.5. Schematic representation of broad risk classes (i.e. classes of the rescaled risk values, $r`_{ik}$) delineated with the SSD rule in dimensions of the mean camper travel probability, $\bar{\varphi}$, and its standard deviation, $\sigma(\varphi_{ij})$. β denotes the tilt angle between the generalized boundaries of the risk classes in the point cloud $\bar{\varphi}_{ij} - \sigma(\varphi_{ij})$ 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. $\beta = 0$, 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).

very high volumes of out-of-state recreational visits and subsequently higher risks of pest arrival with camper travellers from elsewhere. 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 USA. However, the differences between the FSD and SSD ranks in large urban areas appear to be small (Fig. 12.6).

The second type of geographical pattern is represented by the mountain and desert states in the western USA (such as Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington and Wyoming), which show irregular uniform patterns of $\Delta r`_{ik}$ values. As exemplified by Colorado (Fig. 12.6), most of the greatest changes in ranks are either associated with large urban areas in the central and eastern USA or are dispersed across rural and suburban areas in neighbouring states in the western USA. This duality in the geographical distribution of changes in rank is probably caused by some campers travelling long distances from the central and eastern USA and Canada to prominent national parks in the western USA, as opposed to shorter-distance travel for campers from neighbouring states.

The third group is represented by states in the north-eastern USA (Connecticut, Delaware, Maine, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, Vermont), more sparsely populated states in the north-central USA (North and South Dakota), and the most populous Canadian provinces (Alberta, British Columbia, Ontario and Quebec). As illustrated by the map for Quebec (Fig. 12.6), the highest changes in risk ranks were detected only in locations close to the state or provincial border, or in most prominent urban centres in the western USA, such as Denver (Colorado), Los Angeles (California), Phoenix (Arizona) and San Francisco (California).

The other Canadian provinces, the District of Columbia and Alaska showed extremely small changes in the rank values. The rest of the US states can be characterized

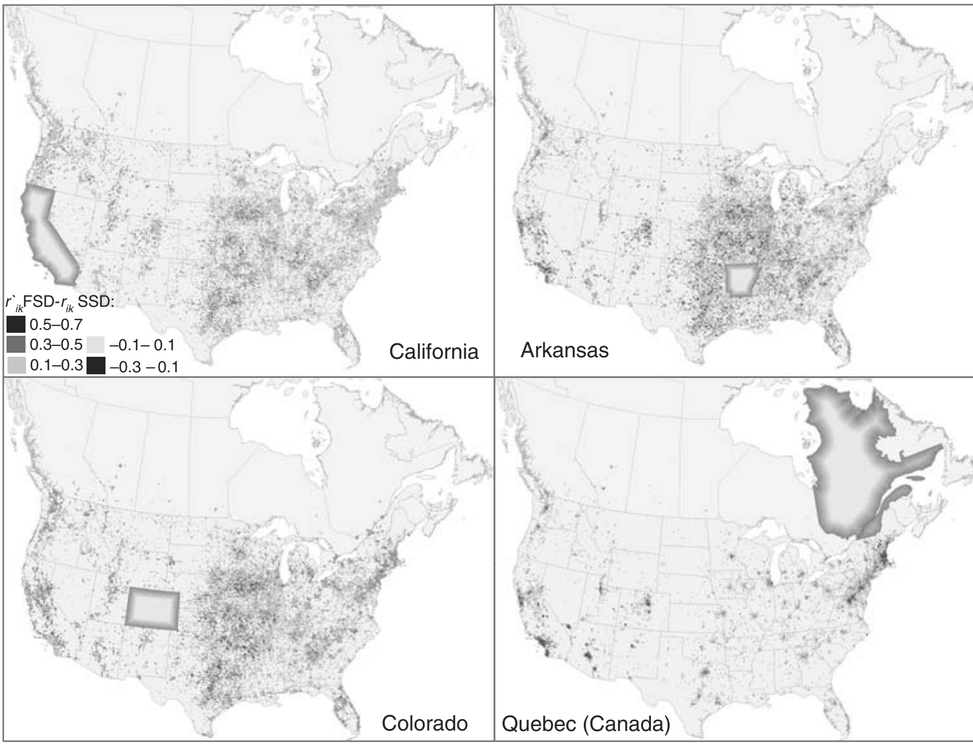

Fig. 12.6. Maps of rank differences, $\Delta r`_{ik} = r`_{ik\,\mathrm{FSD}} - r`_{ik\,\mathrm{SSD}}$, between the delineations based on first- and second-degree stochastic dominance for Arkansas, California, Colorado and Quebec (Canada). Positive values indicate that the SSD-based risk rank is lower than the FSD-based rank (so adding the notion of risk aversion decreases the risk rank).

Table 12.1. Correspondence between the FSD and SSD rank classes as a percentage of the map area. The numbers in the highlighted 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 in bold.

	Risk rank based on the SSD rule					
Risk rank based on the FSD rule	0–0.05 (lowest)	0.05–0.25	0.25–0.50	0.50–0.75	0.75–0.95	0.95–1 (highest)
0–0.05 (lowest)	**100**					
0.05–0.25	**72.2**	27.7	0.1			
0.25–0.50	0.7	**89.8**	7.7	1.8		
0.50–0.75		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**

by some combination of the geographical patterns of high $\Delta r`_{ik}$ values described above: a relatively uniform distribution across rural and suburban areas adjacent to the state borders, as well as long-distance travel hotspots associated with the largest urban centres and most prominent recreational destinations (e.g. national parks and national monuments) in the western USA.

12.4.3 Insights for pest management and surveillance

Despite their technical complexity, the application of stochastic ordering techniques represents a step forward in model-based assessments of pest invasion risk because it offers the appropriate treatment of uncertainty according to the specific preferences of decision makers, the end users of risk assessments and maps. Overall, incorporation of risk aversion helps narrow the set of geographical locations that would need to be targeted for costly or socially sensitive biosecurity surveillance and inspection activities. The methodology offers a strategy for dealing with the typical problem of combining a multitude of uncertain assessments of pest invasion risk into a one-dimensional risk estimate and generating consistent rankings based on imprecise data. In general, coarse risk assessments are the result of a lack of knowledge about the invasive organism of interest, such that the potential outcomes of invasions are assessed in vague 'high–low' terms, or are represented by distributions of plausible invasion outcomes. Although experts and pest management professionals can identify the meaningful trends in the predicted outcomes of an invasion, they are rarely able to assign precise probabilities of the organism's arrival risk or the level of damage it is likely to cause. In the stochastic ordering technique, each geographic location is ordered along a 'high–low' risk gradient by finding nested 'efficient' sets, which makes the issue of assigning precise values less critical.

It should be noted that the technique based on nested non-dominant sets provides only a partial ranking (so that ranks reflect relative 'high–low' positions only within a given dataset). When comparable risk rankings need to be developed for multiple datasets (as was required in our case for each individual US state and Canadian province), an extra step is required of aggregating all datasets into a single superset which can be ranked with the stochastic dominance rule. The final ranks are then mapped to the individual spatial location and their values appear within a single frame of reference, so the ranks for different states and provinces are comparable, one with another. Despite its serious computational burden, this technique addresses a major criticism of risk assessments based on partial ordering: an inability to generate a common ranking space for multiple datasets.

Furthermore, the ability to generate comparable rankings helps provide further insights for decision makers tasked with the development of nationwide pest regulation and surveillance programmes. For example, a simple summary comparison of the risk that each US state (or Canadian province) will receive infested firewood with recreational travellers can be used for better coordination of surveillance and biosecurity screening programmes among states and provinces. Table 12.2 shows comparative risk levels for all US states and Canadian provinces, represented in this case by their mean rescaled risk estimates, $r`_{ik\,\mathrm{FSD}}$ and $r`_{ik\,\mathrm{SSD}}$. As Table 12.2 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.

Incorporation of risk-averse preferences into the pest risk assessment and mapping process has some important implications for the development of broad-scale pest surveillance programmes, or alternatively, for public outreach campaigns. In regions where the locations (i.e. map cells) with high risk ranks based on the SSD rule are uniformly dispersed in relatively close proximity to a state or provincial border, the development of large-scale biosurveillance programmes 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. Instead, if the majority of high-ranked source locations are associated with long-distance travel destinations (such as heavily visited national parks in western USA), a broad regional surveillance programme may be inefficient and a substitute strategy targeting these prominent high-risk locations would be more effective.

Table 12.2. State and provincial summaries based on the mean rank values, $r`_{ik\,FSD}$ and $r`_{ik\,SSD}$.

		FSD-based risk rank		SSD-based risk rank	
Country	State/province	Mean $r`_{ik\,FSD}$	Relative rank	Mean $r`_{ik\,SSD}$	Relative rank
USA	Texas	0.283	1	0.202	1
USA	Arkansas	0.251	2	0.184	3
USA	California	0.246	4	0.202	2
USA	Missouri	0.246	3	0.167	4
USA	Tennessee	0.226	5	0.157	5
USA	Colorado	0.215	6	0.140	7
USA	Georgia	0.201	8	0.143	6
USA	Florida	0.205	7	0.128	8
USA	Illinois	0.197	9	0.121	10
USA	Iowa	0.185	10	0.123	9
USA	Oklahoma	0.179	11	0.117	11
USA	Washington	0.169	12	0.109	15
USA	Oregon	0.168	13	0.110	14
USA	Arizona	0.161	15	0.115	13
USA	Utah	0.151	17	0.116	12
USA	Kansas	0.166	14	0.100	17
USA	North Carolina	0.150	18	0.101	16
USA	Nevada	0.156	16	0.088	20
USA	Kentucky	0.142	19	0.095	18
USA	Alabama	0.137	21	0.093	19
USA	Virginia	0.139	20	0.086	21
USA	Pennsylvania	0.132	22	0.085	23
USA	South Carolina	0.121	25	0.085	22
USA	Idaho	0.127	23	0.081	24
USA	Ohio	0.121	24	0.062	27
USA	Mississippi	0.119	26	0.072	25
USA	New York	0.116	27	0.063	26
USA	Louisiana	0.113	29	0.062	28
USA	Maryland	0.114	28	0.057	31
USA	Indiana	0.111	30	0.058	30
USA	West Virginia	0.092	32	0.059	29
USA	Minnesota	0.106	31	0.053	33
USA	Wisconsin	0.088	33	0.046	34
USA	Montana	0.073	38	0.054	32
USA	New Mexico	0.082	34	0.039	36
USA	Michigan	0.080	35	0.037	38
USA	Massachusetts	0.078	36	0.033	39
USA	Nebraska	0.073	39	0.039	37
USA	New Hampshire	0.067	41	0.044	35
USA	New Jersey	0.075	37	0.028	41
Canada	British Columbia	0.068	40	0.024	43
USA	Wyoming	0.053	44	0.031	40
Canada	Quebec	0.062	42	0.020	44
USA	South Dakota	0.040	45	0.027	42
USA	Connecticut	0.054	43	0.020	45
Canada	Alberta	0.028	47	0.012	46
USA	Maine	0.027	48	0.012	47
Canada	Ontario	0.030	46	0.010	50
USA	Vermont	0.024	49	0.010	49
USA	North Dakota	0.017	51	0.010	48
USA	Delaware	0.023	50	0.008	51
USA	Rhode Island	0.016	52	0.006	52
USA	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
USA	District of Columbia	<0.001	58	<0.001	58
Canada	Yukon Territory	<0.001	59	<0.001	59

In general, risk maps based on SSD-based ranks can be interpreted in the same way as the other pest risk maps that are based on direct invasion model outputs (such as probabilities of pest arrival, see also Venette *et al.* (2010) and Chapters 3 and 4, this volume). Since the SSD-based ranks align better with known risk-averse preferences among decision makers they provide more conservative rankings and further improve the utility of pest invasion models for decision making. Because the SSD-based ranks do account for uncertainty (via explicit consideration of CDFs in the stochastic dominance tests) they emphasize more certainly estimated risk values and thus provide a better indication of priorities for decision makers. As the ranks based on a partial order of elements (i.e. nested efficient frontiers), the SSD ranks can be used directly for prioritization in geographical domain (so the locations identified with the highest ranks could be visited first, the second highest ranks visited second, and so on).

12.4.4 Computational remarks

On a formal basis, the second-degree stochastic dominance rule used in this case study provides an attractive framework for assessing pest invasion risks under uncertainty. The attractiveness of the SSD rule lies in its non-parametric nature (Fishburn and Vickson, 1978). The SSD rule provides a risk-averse delineation (Porter *et al*., 1973; Meyer *et al*., 2005) without an explicit specification of a decision maker's expected utility function (i.e. defining a numerical 'utility', or decision priority, value for every possible invasion outcome that a decision maker may encounter). In fact, the precise determination of the degree of risk aversion and other related behavioural aspects of decision makers' preferences is problematic as it would require tracking the history of decision-making actions within the agency responsible for managing pest incursions, as well as quantifying the associated risk preferences among the groups of experts involved in analysing and generating major regulatory policies and decisions in response to recent pest incursions in North America. Note that practical applications of the SSD rule still require careful consideration of the decision-making problem of interest.

The presented methodology also places high importance on the choice of the risk metric. In short, the choice of metric may change the interpretation of the uncertainty associated with the metric's variation and subsequently the nature of risk-averse delineations made with the SSD rule. In our case study, the probability of pest arrival with camper travel was employed as a risk metric. The use of this sort of metric seems well justified if the associated risk map is intended to support costly decisions (such as setting up inspections and public outreach campaigns or imposing a regulation on certain areas). Furthermore, if the risk metric (or the 'utility' value) takes into account costs or is represented in a monetary equivalent (cf. Hauser and McCarthy, 2009), then the SSD rule could be used effectively to prioritize cost-effective management actions in spatially heterogeneous environments.

Alternatively, when a risk map is intended to assist with early pest surveillance (i.e. gathering new information about the distribution of a pest), the arrival probability value is not sufficient to characterize the potential information gain from, for example, an unexpected detection of the pest in a low-probability location. In such a case, an alternative metric is required that would depict an anticipated increase of knowledge about the invasive pest per se as a result of planned survey. Possible candidates for information gain metrics include the utility of a survey effort (Yemshanov *et al*., 2010) and the probability of pest detection (Cacho and Hester, 2011). Furthermore, the information gain can be considered as a trade-off between the estimated rate of pest arrival and the uncertainty of that estimate, and so the prioritization could be done in the two dimensions of the arrival rate and its variance. These two dimensions could be further aggregated into a single-dimensional information gain metric using various multi-criteria aggregation methods (Roy and Bouyssou, 1986) or a multi-attribute frontier aggregation technique (see details in Yemshanov *et al.*, 2013). Testing the alternative information gain risk metrics and adapting the stochastic dominance approach for practical bio-surveillance scenarios will be the focus of our future work.[1]

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Note

[1] Readers who are interested in evaluating the approach can find a copy of the stochastic dominance ranking utility (the software archive ssd_utility.zip) and the documentation (SD_rank_readme.pdf) in the open resources for this book, available at http://www.cabi.org/openresources/43595.

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