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Mapping Invasive Species Risks with Stochastic Models: A Cross-Border United States-Canada Application for *Sirex noctilio* Fabricius

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Nonindigenous species have caused significant impacts to North American forests despite past and present international phytosanitary efforts. Though broadly acknowledged, the risks of pest invasions are difficult to quantify as they involve interactions between many factors that operate across a range of spatial and temporal scales: the transmission of invading organisms via various pathways, their spread and establishment in new environments. Our study presents a stochastic simulation approach to quantify these risks and associated uncertainties through time in a unified fashion. We outline this approach with an example of a forest pest recently detected in North America, *Sirex noctilio* Fabricius. We simulate new potential entries of *S. noctilio* as a stochastic process, based on recent volumes of marine shipments of commodities from countries where *S. noctilio* is established, as well as the broad dynamics of foreign marine imports. The results are then linked with a spatial model that simulates the spread of *S. noctilio* within the geographical distribution of its hosts (pines) while incorporating existing knowledge about its behavior in North American landscapes. Through replications, this approach yields a spatial representation of *S. noctilio* risks and uncertainties in a single integrated product. The approach should also be appealing to decisionmakers, since it accounts for projected flows of commodities that may serve as conduits for pest entry. Our 30-year forecasts indicate high establishment probability in Ontario, Quebec, and the northeastern United States, but further southward expansion of *S. noctilio* is uncertain, ultimately depending on the impact of recent international treatment standards for wood packing materials.

KEY WORDS: Binary entropy; global entry potential; host resource; marine imports; ports of entry; risk mapping; *Sirex noctilio*; stochastic model

1. INTRODUCTION

Invasive species are widely acknowledged as a serious economic concern in North America and worldwide. Recent estimates of economic impacts on U.S. agricultural, forestry, and public health sectors due to nonindigenous species exceed

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US$120 billion annually;[1,2] similarly, costs to agricultural and forestry sectors in Canada have been estimated at CDN$7.5 billion per year.[3] Both of these estimates may be low since they do not account for the full spectrum of indirect and nonmarket costs.[4] Risk assessments for nonindigenous species are now a standard procedure prescribed by the World Trade Organization Agreement on Sanitary and Phytosanitary Procedures.[5] In the United States, the National Invasive Species Council (NISC) was established by Executive Order 13112[6] to coordinate the efforts of federal agencies to manage invasive species. The USDA Forest Service and the USDA Animal and Plant Health Inspection Service (APHIS), in particular, perform research, management, and regulatory activities under the mandate of EO 13112. Notably, the 2001 NISC National Management Plan identifies the development of a risk analysis system for nonindigenous species as a major policy priority.[7] In Canada, the Canadian Food Inspection Agency (CFIA) is responsible for assessing the risks and regulating activities related to the transport and movement of invasive organisms[8] with support from science-based organizations such as Natural Resources Canada.

Traditional approaches for quantifying risks associated with nonindigenous species typically involve independent assessments of factors such as pathways and processes of introduction and movement, susceptible hosts, and the potential biophysical or economic consequences of spread in previously uninvaded areas.[9] Unfortunately, data on the biology and life history of these species, even in their native environments, are often sparse, leading to a fair number of conceptual risk models that rely heavily on expert judgment or simple analytical approaches.[9–12] Although conceptual models may be sufficient in explaining general causes and consequences of an invasion, more formalized and quantitative estimates of risk are often perceived as better support for policy discussions.[12] These increasingly rely on the use of more spatially explicit multi-scale decision support systems capable of handling significant amounts of geographical information.[13] Risk assessments become even more useful for decision support when accompanied by uncertainty estimates.[14–16] Many approaches available to quantify uncertainty use Monte Carlo simulation techniques.[17,18] Consideration of uncertainties usually changes the degree of confidence in the prediction scenarios, their meaning, and interpretation (see, e.g., recent climate change forecasts).[15,18]

Formally, risk can be defined as the probability of an undesired event along with some evaluation of the consequences of the event.[19] This definition differs from a common perception of risk as a probabilistically quantifiable degree of randomness.[20] In the case of nonindigenous species, risk can be seen as the probability that an invader will become established in a specific area (or domain with a certain population size) and would potentially cause damage to a host resource at this area. The fact that an invasion establishes at a minimum area or population size means that there must be a certain minimum level of impact on a host resource. Risk estimates are also dependent on the area being infested, the amount and susceptibility of local host resource, and the time the invading population occupied a given area. Importantly, an invasion should be viewed as a dynamic process and the risks (and their mapped representations) change during the time span of the forecast.

In this article, we depart somewhat from more traditional compartmentalized approaches to risk assessment[21] and instead describe a stochastic integrated modeling approach that evaluates risks of nonindigenous species on a subcontinental scale. We integrate the three major phases of an invasion—entry, establishment, and spread—in a single spatial model. Through multiple randomized model simulations, we generate a probabilistic risk map based on potential entry locations, existing detections of the invading organism, and a representation of the distribution of host resources across the eastern United States and Canada. We also simulate these invasion components as a chain of spatially interdependent events, hence addressing the issue of their potential interactions over time. To create a more comprehensive and robust product, we also map the corresponding uncertainty estimates.

1.1. Species of Concern

We demonstrate this approach with an invasive woodwasp species, *Sirex noctilio* Fabricius, that has been recently detected in southeastern Ontario[22] and upstate New York, USA.[23] *S. noctilio* is native to Europe, western Asia, and northern Africa. Through accidental introductions it has become an important pest of pine plantations in the Southern Hemisphere.[24–26] It is now considered a serious threat to pines in the United States and Canada, with the total projected losses above US$0.76 billion over 30 years in the United States[27] and CDN$0.7 billion in Canada.[28] Introduced pine species appear to be the prime target, but native pines, especially those endemic to the southeastern United States, are also considered to be highly susceptible.[29] *S. noctilio* has a broad bioclimatic tolerance[30] and is expected to survive across the entire range of temperate forests in eastern North America. Although relatively little is known about the population ecology of *S. noctilio* in North America, some knowledge about its behavior can be gathered from studies in Australia[25] and Argentina.[24]

2. MODEL AND DATA

We used a modified version of the Canadian Forest Service Forest Bioeconomic Model (CFS-FBM) to map the risks associated with *S. noctilio* infestation in eastern North American landscapes. Briefly, the model combines biophysical and economic analyses in one spatially explicit framework.[28,31] We simulate entry, establishment, and spread of an invading organism in discrete time steps.[32,33] Our choice of model structure was guided by the limited amount of available knowledge about *S. noctilio* in North America. Severe knowledge gaps about *S. noctilio* in North American conditions restricted our choice to a relatively simple model with minimum data requirements. Essentially, the model fits the progress of invasion to experts' beliefs regarding the pest's behavior in a new environment. We believe that such an approach would likely be necessary for many newly discovered pests with little or no history of prior observations in new environments.

2.1. Entry

Many risk assessments link the introduction potential of an invading organism with imports of commodities and tradable goods.[34–37] For *S. noctilio*, we associate entries with certain categories of maritime imports (based on historical inspection data) and relate them to the geographic locations of marine ports that receive foreign cargo shipments in those categories. Notably, the first detection of *S. noctilio* in the United States was near such a port (Oswego, NY).

The APHIS Port Information Network (PIN) database suggests that marine cargo is the only significant possible delivery pathway for *S. noctilio*. Given the broad geographic distribution of *S. noctilio*, we assumed that the probability of the pest entering North America could be represented as a function of import cargo arriving at marine ports of entry. We define a function, $F(t)$, that describes the flow of marine imports through time. Based on historical import values,[38] the shape of $F(t)$ can be described as close to exponential (Fig. 1). When the date of the species' first successful introduction, T_{entry}, is known, $F(t)$ can be rescaled to a probability density function, $P(t)$, so:

$$\int_{t_0}^{T_{\mathrm{entry}}} P(t)\,dt = 1. \tag{1}$$

When t is represented as a discrete time step, the value of $P(t)$ can be found numerically. To define the shape of $F(t)$, we combined 1960–2006 U.S. value of imports[38,39] with similar 1971–2006 Canadian data from Statistics Canada.[40] Here, we have made a simplifying assumption that the historical volumes of cargo shipments from the countries with *S. noctilio* would correlate with the historical trends of all marine imports to the United States and Canada. We used 1971 as t_0 and 1999 as T_{entry}, thus assuming a five-year lag between the entry of *S. noctilio* in North America and its first detection in 2004; this lag is conjectural since the exact date of entry is unknown, but a time lag of several years is common before an invader is first noticed.[41,42] This gave an estimate of entry potential for 2006, $P(2006) = 0.172$ (Fig. 1).

In 2002, the International Plant Protection Convention adopted phytosanitary standards for all wood packaging and raw material to minimize the chances of survival for invasive organisms in imported cargoes.[43] Both the United States and Canada fully implemented the new standards in 2006. The adoption, enforcement, and outcome of

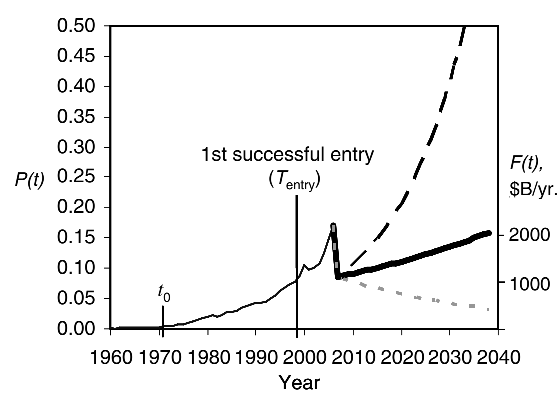

Fig. 1. $P(t)$ based on the historic trade data and three future scenario projections. Dashed line: high-risk scenario; bold line: medium-risk scenario; dotted line: low-risk scenario. $F(t)$-values are shown for historic data period 1960–2006. See text for descriptions of terms.

these standards are complex processes with many unknowns, such as the efficacy of trade control and port inspections and real-life compliance of foreign cargo shipments. Quantitative knowledge of how the new standards might change a pest's entry potential is currently nonexistent, given the short timeframe since implementation. Furthermore, control and enforcement actions are often undertaken at the level of individual port authorities and are thus difficult to track due to confidentiality issues. Therefore, we assumed a 50% immediate impact of the new standards on the probability of entry in 2007, supposing that port authorities would boost their inspection efforts in order to enforce the new phytosanitary standards. These additional inspections would likely increase the probability of early detection and containment of infested cargoes and hence reduce the probability of new *S. noctilio* establishments. We subsequently represented three possible scenarios in the years following 2007. The "high risk" scenario assumes relatively little impact of the new standards through time, such that entry potential, $P(t)$, will follow the ports' growing capacities and increase at 7% per year. The "medium risk" scenario assumes that $P(t)$ will grow at 2% per year, and the "low risk" scenario assumes $P(t)$ will decline at 3% per year (Fig. 1). Although somewhat conjectural these scenarios provide benchmarks for decisionmakers to judge relative outcomes.

After entry potential $P(t)$ was defined, the next stage of the analysis was to apportion the value of $P(t)$ among major marine ports in the United States and Canada. We characterize each port of entry, x, by a unique probability function, $W_{x(t)}$ that depends on how much of the cargo a port has historically received. For each time step t we assume that the sum of $W_{x(t)}$ is equal to $P(t)$. To find values of $W_{x(t)}$ in the United States, we used the U.S. Army Corps of Engineers database of foreign cargo shipments to U.S. marine ports.[44] The database reports tonnages of imports received between 1997 and 2005, by commodity category. For Canadian ports, we used Statistics Canada "Shipping in Canada" 2000–2004 reports for major marine ports.[45–49] The latter, however, provided coarser estimates for major ports only, and over a shorter time period (five instead of eight years in USACE database). Given the available data, we limited our assumptions about the dynamics of $W_{x(t)}$ to a linear trend. For each port, we determined total annual volumes of commodities that could potentially harbor *S. noctilio* (based on Forest Health Technology Enterprise Team (FHTET)[50] list) coming from countries where *S. noctilio* is known to exist (see FHTET[51] list). The FHTET list[50] includes two big groups, raw wood commodities and goods shipped with wood packing materials. Table I lists the 19 marine ports in eastern North America with the largest flows of imports associated with *S. noctilio*. Compared to U.S. ports, eastern Canadian ports receive much lower quantities of imports.

A preliminary examination of the U.S. and Canadian marine cargo import data revealed port-to-port variations of seven orders of magnitude in received volumes of *S. noctilio*-associated commodities (based on the FHTET[51] list of relevant commodities). The existing range of interceptions recorded in the APHIS PIN database for taxa pertinent to forest invasions (e.g., Curculionidae, Scolytidae, and Siricidae), however, suggested the range of the probabilities of entry would likely be within three orders of magnitude, with minimum values starting at 0.0008–0.005 per year depending on the value of $P(t)$. Hence, we used the following transformation to convert the original cargo volumes, $v_{x(t)}$, into $W_x(t)$:

$$W_{x(t)} = 10^{-[3/(1+12\cdot\exp[-1.72\cdot\lg(V_{x(t)})])]} \quad \text{where}$$

$$V_{x(t)} = v_{x(t)} \Big/ \sum_{x=1}^{N} v_{x(t)} \tag{2}$$

and then rescaling $W_{x(t)}$ to fit $P(t)$, so:

$$\sum_{x=1}^{N} W_{x(t)} = P(t), \tag{3}$$

where $v_{x(t)}$ is the tonnage of the marine cargo shipments for port x at the year t. Fig. 2 illustrates the dependence between $v_{x(t)}$ and $W_{x(t)}$ for the $P(t)$ values equal to 0.1, 0.2, and 0.3. The transformation was aimed to fit probabilities of entry to a general trend observed in the APHIS PIN interceptions. Basically, the calculation represents entry potential at the minimum value for ports with cargo imports below $\sim 2 \times 10^5$ t per year and then applies the log transform for ports with capacities above $\sim 2 \times 10^5$ t per year (Fig. 2). The coefficients were fitted to ensure the same shape of the transformation curve for a wide range in the overall global entry probability, $P(t)$ (Fig. 2). Note that ports in close proximity (20 km or less) have been aggregated to simplify and speed up the model calculations. Preliminary model runs suggested that the aggregation does not jeopardize the continental projections of spread and impact.

The probability values were then used to simulate entries of *S. noctilio* into eastern North America.

Table I. Entry Potential for 19 Largest-Capacity Marine Ports in Eastern North America

Port of Entry	Average Value of Imports—Potential Carriers of *S. noctilio** (1997–2005), $\times 10^6$ *t*	Linear Trend, % Per Year	Probability of Entry, $W_{x(2006)}$
Houston, TX	5.75	+4.3	0.0094
New York, NY & NJ	5.57	+4.1	0.0089
New Orleans, LA	4.26	−4.9	0.0081
Charleston, SC	4.11	+10.4	0.0077
Baltimore, MD	3.11	+8.3	0.0051
South Louisiana, LA	2.78	+5.1	0.0040
Norfolk Harbor, VA	2.30	−0.4	0.0028
Philadelphia, PA	2.10	+0.4	0.0026
Port Everglades, FL	2.00	+6.9	0.0022
Baton Rouge, LA	1.76	−7.5	0.0020
Penn Manor, PA	1.28	+1.1	0.0019
Savannah, GA	1.26	−0.5	0.0018
Miami, FL	0.98	+6.3	0.0018
Mobile, AL	0.93	+0.3	0.0015
Detroit, MI	0.64	−10**	0.0014
Jacksonville, FL	0.61	+9.5	0.0014
Camden-Gloucester, NJ	0.59	+2.9	0.0013
Chicago, IL	0.58	−10**	0.0011
Cleveland, OH	0.57	−10**	0.0011

*The value of imports represents the average annual tonnage of incoming shipments in commodity categories with the potential to harbor *S. noctilio* either directly (e.g., forest products) or in packing materials (e.g., crates, pallets): "All Manufactured Equipment, Machinery and Products," "Building Cement & Concrete; Lime; Glass," "Forest Products, Lumber, Logs, Woodchips," "Primary Iron and Steel Products (Ingots, Bars, Rods, etc.)," "Primary Nonferrous Metal Products; Fabricated Metal Products," "Sand, Gravel, Stone, Rock, Limestone, Soil, Dredged Material," "Paper and Allied Products," and "Primary Wood Products; Veneer; Plywood" (USACE 2006).
**Negative trend above 10%, insufficient data.

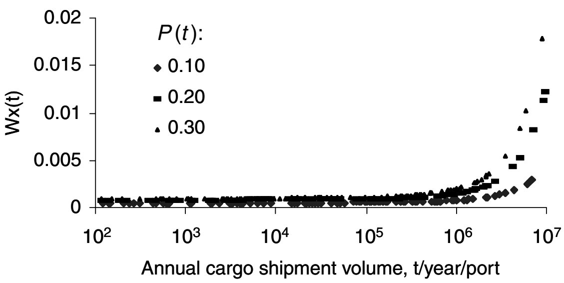

Fig. 2. Rescaling the cargo shipment volumes, $v_{x(t)}$, to the weighting coefficients, $W_{x(t)}$.

We follow the concept, outlined by Rafoss,[52] of using discrete stochastic simulation of entry locations to predict the establishment potential of an invading organism. Before the simulations, the model generates $W_{x(t)}$ for each port of entry for the entire simulation horizon, and then recreates the stochastic realization of the entry process for each year. The successful entries are added to a temporary map of known *S. noctilio* locations and the model then proceeds with the simulation of spread and establishment.

Note that our model only depicts possible *S. noctilio* entries at the marine ports. Depending on values of $W_{x(t)}$ the spatial configuration of entry points may have a substantial effect on the patterns of *S. noctilio* spread and establishment. For example, entries at inland locations would generate additional infestation nuclei and alter the overall rate of *S. noctilio* expansion. However, representing this process in our model would require a better portrayal of the movement of commodities—potential carriers of *S. noctilio*—via a transportation network including directional flows of commodities from the marine ports of entry. This aspect was beyond the scope of the current study.

2.2. Spread and Establishment

Our generalized assumptions about *S. noctilio* behavior were based on past observations in

Australia,[25,53] Argentina,[24] and recent detections in North America.[22] The timeframe and detection accuracy of existing field observations in North America were insufficient to validate the rate of *S. noctilio* spread. Hence, we chose a relatively simple spread model over more complex reaction-diffusion or dispersal kernel models. Our spread model used a traveling wave approach adapted from Sharov and Liebhold[54] and simulated spread in a two-dimensional landscape constrained by a maximum annual colonization rate. Here, we provide only a brief summary (a more details can be found in Reference 28). For any location, the model calculates the colonization rate as a function of the distance from the nearest location with an established *S. noctilio* population, $b(d)$. The values of $b(d)$ for *S. noctilio* were based on expert estimates (P. de Groot and D. Haugen, pers. comm.) and fitted to a decay shape:

$$b(d) = p_0/(1.13 + 0.096d^{1.492}), \quad \text{for } d < d_{\max} \quad \text{and}$$
$$b(d) = 0 \quad \text{for } d \geq d_{\max}, \tag{4}$$

where p_0 is the probability of dispersal to the nearest spatial location (a 1 × 1 km grid cell in the current study), d is the distance from the nearest infested area in km, and $d_{\max}$ is the maximum distance at which *S. noctilio* meta-populations become established.[28] $d_{\max}$ was set to 50 km per year and p_0 to 0.2 based primarily on recent *S. noctilio* detections in Ontario and New York as well as experience with the pest in the Southern Hemisphere.[30] The $d_{\max}$ value also describes the flight potential for *S. noctilio*. There was not enough existing information about *S. noctilio* behavior in Canada and the United States to adequately estimate the population pressure that would be necessary to change $d_{\max}$, the local infestation potential, p_0, and the shape of the $b(d)$ kernel (P. de Groot, D. Haugen, pers. comm.). For this reason, we did not include any direct feedback of the *S. noctilio* population density on the maximum rate of spread or the colonization probability, $b(d)$. For each year, the model tracks locations with established populations and uses the spread model to propagate *S. noctilio* through the landscape.

Pine stands have different susceptibility to *S. noctilio* attacks that depend on stand conditions, stem size composition, age, and other factors.[55] In the model, species susceptibility is portrayed as a species- and age-dependent probability, s_v:

$$s_v = 0 \quad \text{for } a < a_0;$$
$$s_v = s_{\max} \times a/(a_{\max} - a_0) \quad \text{for } a_0 < a < a_{\max} \quad \text{and}$$
$$s_v = s_{\max} \quad \text{for } a > a_{\max}, \tag{5}$$

where a is age in years, a_0 is the age of stand closure (20 years), $a_{\max}$ is the age when susceptibility reaches its maximum (65 years), and $s_{\max}$ is the maximum susceptibility value for aging stands. Pine species susceptibility ratings were obtained from the FHTET[29] to define the $s_{\max}$ values.

We generated models of pine forests to estimate the availability of host resources for *S. noctilio* establishment. These models provide average age and volume of pine stands, in cubic meters per hectare, for each map cell. We used Canada's National Forest Inventory (CanFI) database[56] to build the Canadian portion and the USDA Forest Service Forest Inventory and Analysis (FIA) database[57,58] to generate the U.S. portion of the pine map. The U.S. and Canadian databases had different structures (i.e., sample plot observations in the U.S. FIA and area records in the CanFI) and required different spatial interpolation techniques to map pine volumes and stand age. For the U.S. portion, we performed ordinary kriging of the FIA plots with a spherical semivariogram. The Canadian portion of the map was generated by integrating CanFI data with a satellite-based land cover classification[59] using spatial randomization techniques.

When combining the U.S. and Canadian portions, maps for individual pine species were aggregated into two large species groups based on their susceptibility to *S. noctilio*. We assumed $s_{\max} = 0.95$ for the "very high" and "high" susceptibility groups in the FHTET list[29] and $s_{\max} = 0.5$ for the "low" and "medium" groups.[29]

The model also required the representation of pine growth over time. For the Canadian portion of the study, we used the normal yield equations from Ung *et al.*[60] These models provide generalized yield curves as a function of two basic climate variables, degree-days and annual precipitation. We used the USDA Forest Service Forest Vegetation Simulator (FVS)[61] to build the yield curves for the U.S. portion of the study area. By integrating growth equations for most common tree species with other environmental parameters, FVS predicts stand species composition and associated volumes at user-specified time steps. The FVS has several regional variants that employ distinct, region-specific tree species growth equations.[61] During the modeling process, we applied four regional variants: the Southern, Northeast, Lake States, and Central States variants. The final yield curves were aggregated at the level of ecoregion provinces.[62]

2.3. Mapping Risks and Uncertainties

We interpret risk as the probability of *S. noctilio* invasion, $p_{i,T}$, for a given area i over a forecast horizon T. These are not the probabilities of *S. noctilio* detection *per se*, since they only describe the risk of established populations occupying a minimum area domain, i. We believe that the risk of invasion should reference a minimum area infested, which in our case is one map cell (1 km^2). This minimum area notion also provides a context for assessing the potential impact on the host resource. Such populations are likely to develop in regions with fairly abundant pines and thus have a high potential to damage the host resource.

Our simulation model calculates the probability of *S. noctilio* spread as a function of the distance to the nearest infested nuclei, d (Equation (4)). For each spatial location, i, at time step t the model evaluates d and then generates *S. noctilio* spread and establishment events, $\tau_{i,n,,T}$ (Equation (6)) via two uniform random draws: first using the value of $b(d)$ from (Equation (4)) and then generating the establishment based on the host susceptibility value, s_v, and the availability of the host resource (Equation (5)). As a result, a single model simulation generates a randomized map of binary presences and absences of invasion, $\tau_{i,n,T}$, across the study area at the end of the forecast horizon. Multiple model replications are then used to generate a binary distribution of $\tau_{i,n,T}$ values and calculate the risk of infestation, $p_{i,T}$ (p hereafter):

$$p_{i,T} = \frac{\sum_{n=1}^{N_{\mathrm{obs}}} \tau_{i,n,T}}{N_{\mathrm{obs}}} \forall\, \tau_{i,n,T} = [0 \,|\, 1], \tag{6}$$

where $\tau_{i,n,T}$ denotes the presence or absence of invasion in map cell i at the end of the forecast horizon T for a single model replication n, and N_{obs} is the total number of model replications. Note that p can only be identified for map cells with at least one successful introduction over N_{obs}.[63] The estimate of risk, $p_{i,T}$, is based on the model simulations that integrate entry, spread, and establishment in a dynamic fashion, and thus it is an aggregation of the potential risks associated with every stage of invasion. Because the entry, spread, and establishment events are spatially interdependent, we also believe that the risk estimates account for the potential dependencies between these components. For instance, an introduction of a new pest to a given area may lead to higher survival rates, more frequent establishment, further spread to other locations, and higher damage to the host resource.

To characterize the uncertainty in the risk estimates, we calculate the standard deviation of the probability of invasion at a location over the forecast horizon, $\sigma(p_{i,T})$, and the binary entropy value, $H(p_{i,T})$[64]:

$$H(p_i, T) = -\,p_{i,T}\log_2 - (1 - p_{i,T})\log_2(1 - p_{i,T}). \tag{7}$$

The value of $H(p_{i,T})$ reaches a maximum of 1 at $p_{i,T} = 0.5$ and a minimum of 0 when $p_{i,T} = 0$ or 1 (when knowledge about the presence or absence of the invasion is certain). Although both $\sigma(p_{i,T})$ and $H(p_{i,T})$ show a similar response, a symmetric shape and fixed range makes binary entropy a more consistent and interpretable metric.

Our results show six possible invasion scenarios divided into two groups. The first group (scenarios 1–3; Table II) assesses the risk of invasion from North American ports of entry only. Although these scenarios may be perceived as primarily theoretical, they depict the geographical distribution of risks associated with the foreign marine cargo pathways of introduction, and may help to prioritize monitoring and regulatory policies. The second group of scenarios (scenarios 4–6; Table II) adds the existing *S. noctilio* locations in North America to the simulation of new entries at marine ports. We initialized scenarios 4–6

Table II. Simulation Scenarios

Scenario Group	Growth Rate for the Probability of Entry, $\Delta P(t)$ (% per Year from 2007)		
	+7 (High Risk)	+2 (Medium Risk)	–3 (Low Risk)
Entries from the ports only	Scenario 1	Scenario 2	Scenario 3
Entries from the ports plus existing infestations	Scenario 4	Scenario 5	Scenario 6

with the 2006 *S. noctilio* surveys in Canada and the United States.[22,23]

The scenarios in each group examine three possible effects of the new international wood treatment standards on the entry potential of *S. noctilio*, $P(t)$: "high risk" scenarios 1 and 4 with $\Delta P(t) = +7\%$ per year, "medium risk" scenarios 2 and 5 with $\Delta P(t) = +2\%$, and "low risk" scenarios 3 and 6 with $\Delta P(t) = -3\%$ per year (Table II).

The stochastic simulations usually require a sufficient number of replications to stabilize the moments of the distributions.[52] We tested the summary statistics versus the number of replications and the distribution of areas with particular ranges of p and $\sigma(p)$ values. The most informative indicators were the total areas with $\sigma(p) < 0.2$ and $p < 0.1$, and also the sum of squared differences in p-values between the trials using different numbers of replications:

$$S_{XY} = \sqrt{\sum_{i=1}^{M} [(p_{i_X} - p_{i_Y})^2]}, \tag{8}$$

where S_{XY} sums the differences in p between consecutive trials based on X and Y replications; M is the total number of spatial elements in the map (~4 million); p_{iX} and p_{iY} are the infestation probabilities for a map cell i in the trials X and Y.

3. RESULTS

3.1. The Number of Replications

Fig. 3 shows the minimum number of replications required to stabilize the values of p and $H(p)$ in the final risk maps. Low-, medium-, and high-risk scenarios required at least 960, 500, and 360 replications, respectively (Fig. 3). Medium- and low-risk scenarios show the S_{XY} values never reaching zero but instead leveling off at a certain positive value. This value indicates the reliability of the local estimates of p, that is, approximately $\sim 2 \times 10^{-5}$ per year for the high-risk scenarios, $\sim 1 \times 10^{-4}$ for the medium-risk, and $\sim 5 \times 10^{-4}$ for the low-risk scenarios. Depending on the abundance of the host resource, the model suggests a maximum rate of expansion from established populations between ~41 and ~50 km per year. The predicted rates of *S. noctilio* expansion were thus slightly lower than a 50-km expected maximum spread limit due to high host heterogeneity and overall lower susceptibility of native pine species in the northern United States and Canada.

3.2. Risk Maps

For *S. noctilio*, we show maps of p and $H(p)$ for a 30-year time horizon. Fig. 4 shows risk and uncertainty maps for the "ports-only" scenarios 1–3. The maps show the highest p- and $H(p)$-values near the southern and eastern U.S. coasts and then declining toward inland locations. The high-risk scenario (scenario 1) shows two major regions of concern: (1) the southeastern U.S. coast, particularly along the Gulf of Mexico, with its abundant pine forests and a number of high-volume ports; and (2) the area of the eastern U.S. coast around Baltimore, Maryland, with a concentration of high-volume ports and local pine resources available in close proximity (Fig. 4A). The northeastern and midwestern United States, the Great Lakes region, and eastern Canada have relatively low risks mostly due to low volume of *S. noctilio*-associated commodities at the regions' ports and overall lower susceptibility of northern pines.[29] Inland areas usually exhibit the lowest risks. This is a result of the limitations imposed by the maximum rate of spread assumption (50 km in this study) and the geographical distribution of pine resources. Notably, the entire Great Lakes region shows a low but consistent risk of infestation; in fact, *S. noctilio* has successfully established near low-capacity ports in this region (e.g., Oswego, NY). As with the high-risk scenario, the medium- and low-risk scenarios (Figs. 4C and 4E) show the southeastern U.S. coast as a major area of concern. The risks of infestation in the northeastern United States and the Great Lakes regions are also similar to those in the high-risk scenario and do not appear to correlate with entry potential, $P(t)$.

The maps of the uncertainties exhibit somewhat similar geographical patterns. Inland low-risk areas have low uncertainties (Figs. 4B, 4D, and 4F). Coastal areas in the southern United States have medium uncertainty that correlates with the distribution and abundance of pine forests.

Fig. 5 shows the risk and uncertainty maps for scenarios 4–6, which include the existing area of *S. noctilio* infestation. As expected, the projected path of the current *S. noctilio* infestation is characterized by very high p-values close to 1. For example, our 30-year forecast shows high risks of infestation and high uncertainties in the entire northeastern United States, Ontario, and Quebec, with the invasion extending into southern U.S. pine forests (Figs. 5A, 5C, and 5E). The uncertainty values range from low to average in the projected path but become

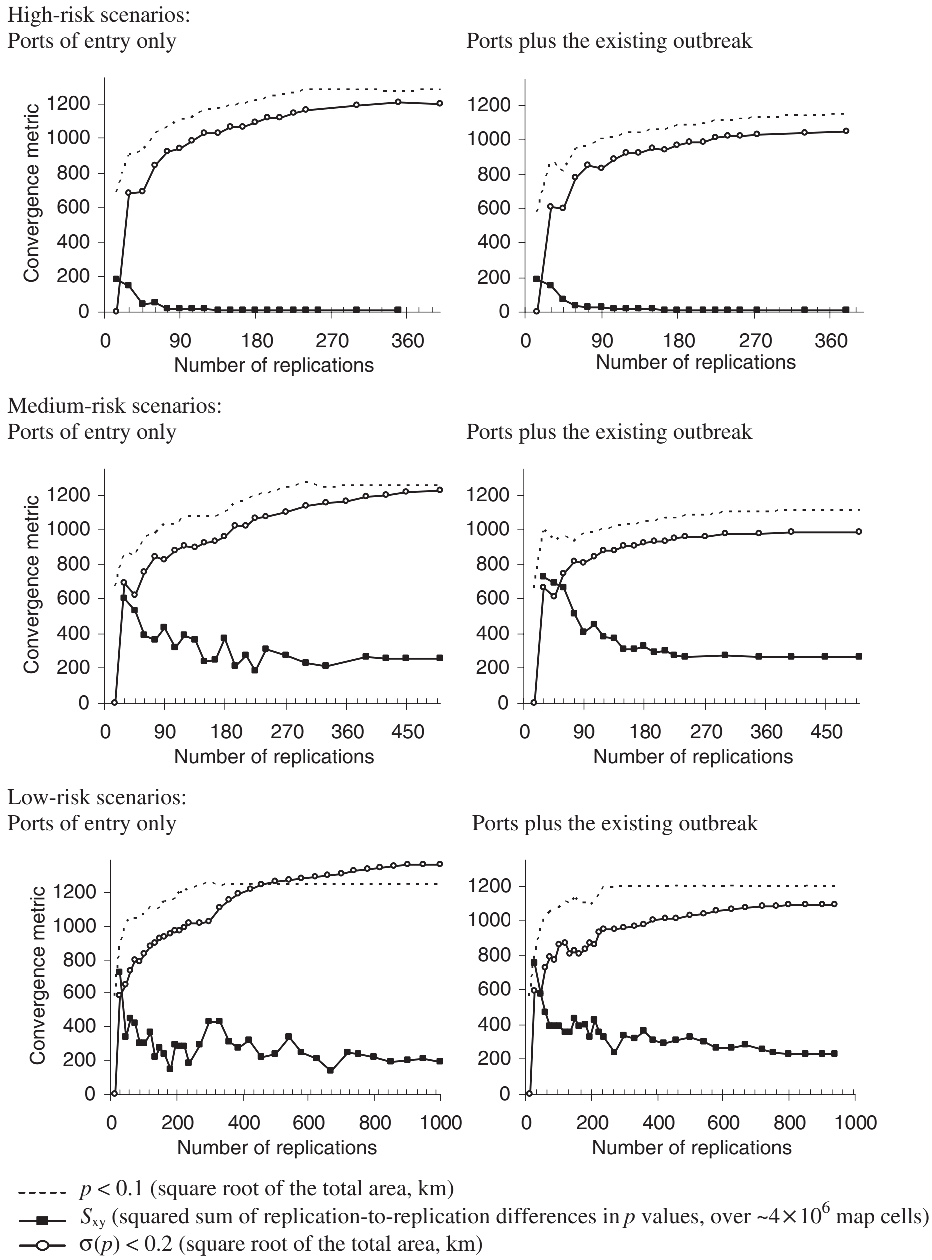

Fig. 3. Area distribution of p- and $\sigma(p)$-values versus the number of replications.

high in the peripheral zones of invasion. Overall, the $H(p)$-values are sensitive to the spatial distribution of pine resources and show higher values in the areas where the host resource is less abundant (Figs. 5B, 5D, and 5F). Outside the projected extent of the *S. noctilio* invasion, p-values are lower and show values similar to the "ports-only" scenarios 1–3. The infestation risks near major ports of entry outside the projected invasion extent are usually 2–4 times lower than those associated with the invasion but have higher uncertainty.

3.3. "Risk-Uncertainty" Classification Maps

Maps of risks and uncertainties can be combined in a single classification. Fig. 6 shows the areas with $\sigma(p)$ less than 0.2 as "low uncertainty," with $\sigma(p)$ between 0.2 and 0.4 as "medium uncertainty," and

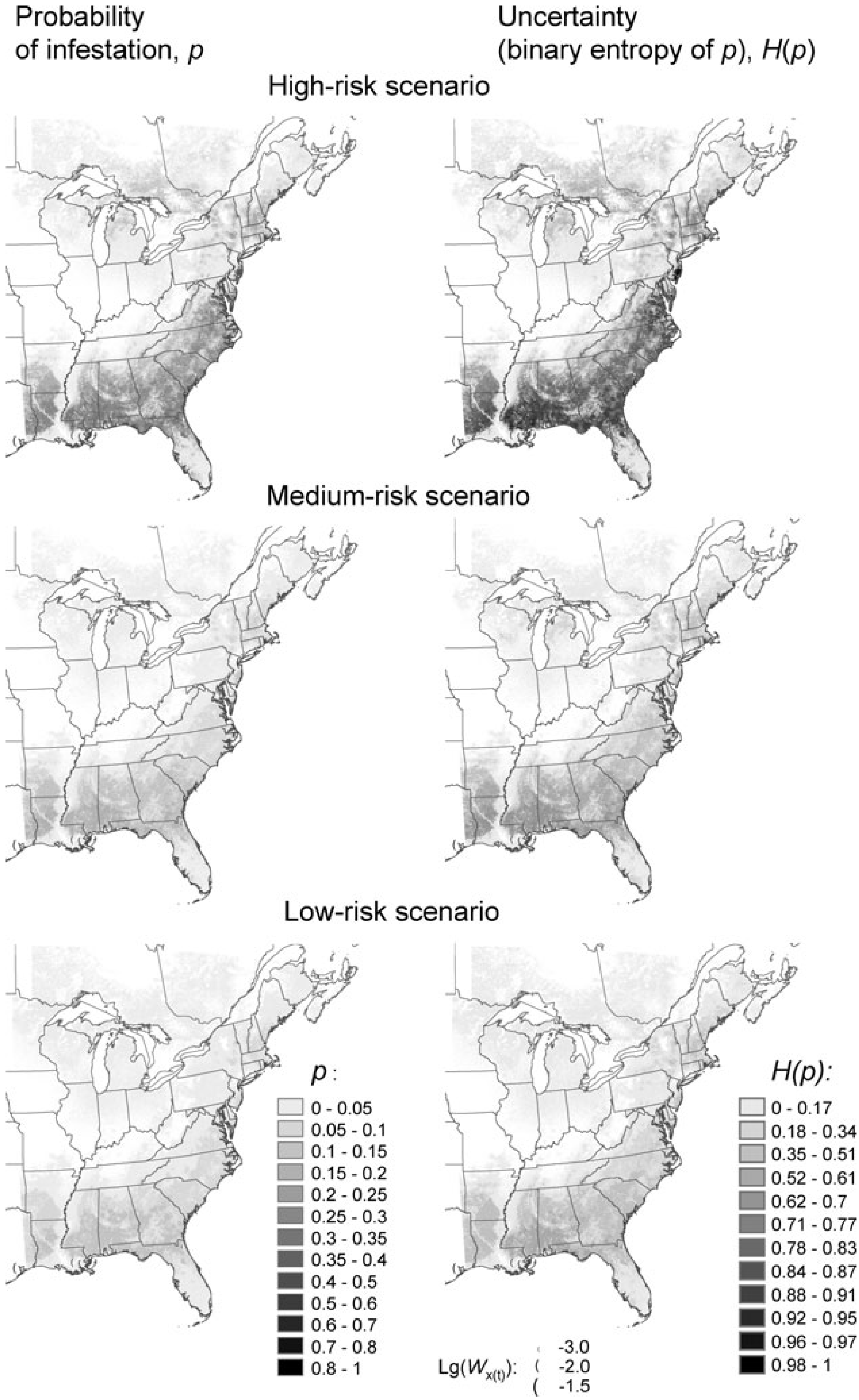

Fig. 4. Risk and uncertainty maps, invasion potential from the ports of entry only (not including the existing *S. noctilio* outbreak).

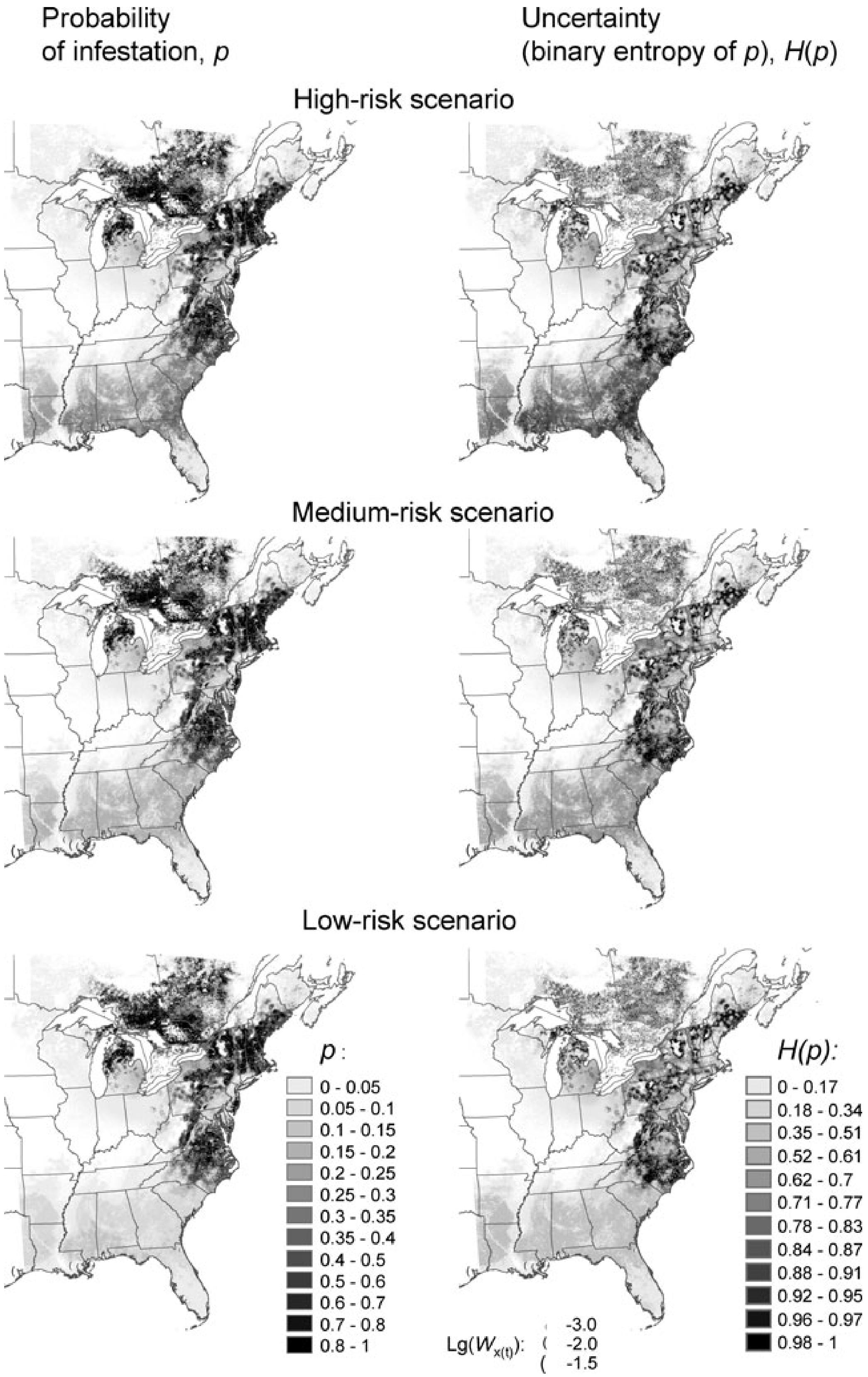

Fig. 5. Risk and uncertainty maps, invasion potential from the ports of entry and the existing *S. noctilio* outbreak.

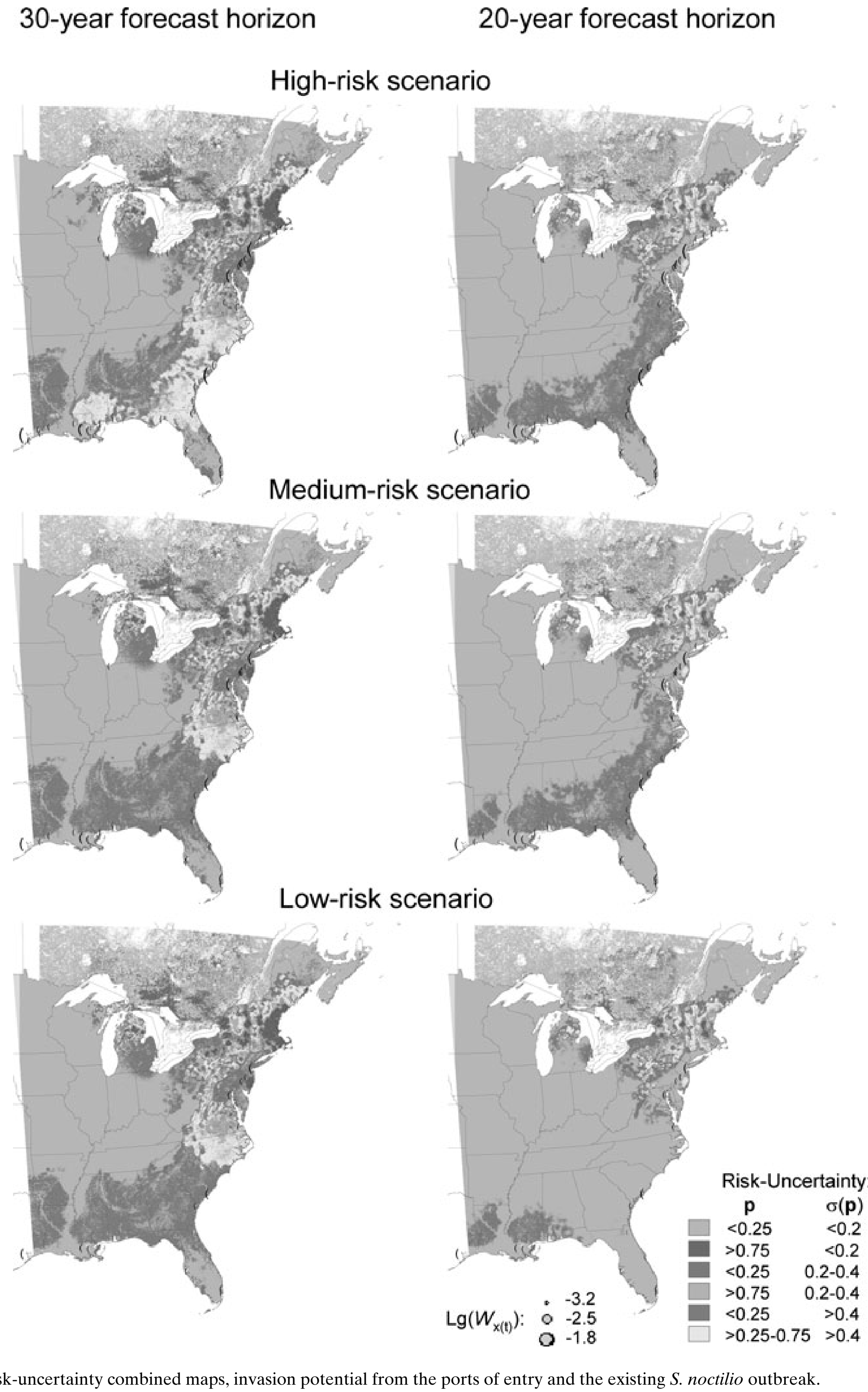

Fig. 6. Risk-uncertainty combined maps, invasion potential from the ports of entry and the existing *S. noctilio* outbreak.

Table III. Areas of Different Risks and Uncertainties of *S. Noctilio* Infestation, $\times\ 10^3\ km^2$

Region	Forecast, Years	Low p-Low $\sigma(p)$*	High p-Low $\sigma(p)$	Low p-Med. $\sigma(p)$	High p-Med. $\sigma(p)$	Low p-High $\sigma(p)$.	Med.p-High $\sigma(p)$	High p-High $\sigma(p)$
Ports + Existing Infestation, $\Delta P(t) = 7\%$								
Eastern Canada	10	810.3	0.4	31.8	1.9	5.5	22.6	0.9
	20	622.7	23.1	92.7	28.0	15.9	83.3	7.7
	30	472.0	83.1	98.1	57.6	17.9	131.2	13.1
Northeastern United States	10	1561.1	0.06	60.2	0.04	6.8	18.2	0.2
	20	1317	6.9	175.6	29.2	16.6	91.7	9.7
	30	1063	51.2	302.9	59.0	32.7	123.2	14.0
Southeastern United States	10	1380.1						
	20	915.5		**463.9**		**0.7**	**0.09**	
	30	625.9	**1.9****	**271.3**	26.7	**155.0**	**290.5**	8.5
Ports + Existing Infestation, $\Delta P(t) = 2\%$								
Eastern Canada	10	810.1	0.4	32.0	2.0	5.2	22.9	0.9
	20	623.2	22.8	92.7	28.0	15.2	84.2	7.4
	30	476.6	83.2	94.4	58.0	17.5	131.0	12.8
Northeastern United States	10	1561.2	0.06	60.2	0.05	6.6	18.3	0.1
	20	1318.9	6.6	175.6	29.0	15.9	91.2	9.5
	30	1076.2	50.9	291.5	59.3	31.8	123.7	13.3
Southeastern United States	10	1380.1						
	20	956.3		**423.4**		**0.4**	**0.04**	
	30	642.2	**0.8**	**596.7**	22.4	**13.9**	**96.8**	7.4
Ports + Existing infestation, $\Delta P(t) = -3\%$								
Eastern Canada	10	810.5	0.4	31.8	2.0	5.4	22.6	0.9
	20	623.8	22.8	92.2	28.1	15.4	83.9	7.4
	30	480.3	83.6	91.5	57.8	17.1	130.3	12.8
Northeastern United States	10	1564.2	0.1	57.5	0.0	6.5	18.2	0.2
	20	1324.9	6.5	170.2	28.9	15.9	90.9	9.4
	30	1078.8	51.2	292.2	59.0	29.7	122.4	13.3
Southeastern United States	10	1380.1						
	20	1254.0		**125.7**		**0.4**	**0.0**	
	30	671.3	**0.8**	**580.8**	21.8	**9.8**	**88.7**	6.9

*Infestation risk and uncertainty classes:
Low p-low $\sigma(p)$: low risk, low uncertainty: $p \in [0; 0.25[$; $\sigma(p) \in [0; 0.2[$;
High p-low $\sigma(p)$: high risk, low uncertainty: $p \in [0.75; 1]$; $\sigma(p) \in [0; 0.2[$;
Low p-med $\sigma(p)$: low risk, medium uncertainty: $p \in [0; 0.25[$; $\sigma(p) \in [0.2; 0.4[$;
High p-med.$\sigma(p)$: high risk, medium uncertainty: $p \in [0.75; 1]$; $\sigma(p) \in [0.2; 0.4[$;
Low p-high $\sigma(p)$: low risk, high uncertainty: $p \in [0; 0.25[$; $\sigma(p) \in [0.4; 0.6]$;
Med.p-high $\sigma(p)$: medium risk, high uncertainty: $p \in [0.25; 0.75[$; $\sigma(p) \in [0.4; 0.6]$;
High p-high $\sigma(p)$: high risk, high uncertainty: $p \in [0.75; 1]$; $\sigma(p) \in [0.4; 0.6]$;
Area estimates changing more the 50% between the scenarios are marked in **bold.

with $\sigma(p)$ above 0.4 as "high uncertainty." Values of p above 0.75 are classified as "high risk," between 0.25 and 0.75 as "medium risk," and less than 0.25 as "low risk" areas. The area to which the existing *S. noctilio* infestation is projected to expand generally appears as "high-medium risk" and "low-medium uncertainty." However, areas within the projected invasion extent with heterogeneous host resources are classified as "high uncertainty."

Table III summarizes the areas of the risk-uncertainty classes for three broad regions—eastern Canada, the southeastern United States, and the northeastern United States—for scenarios 4–6. Most of the study areas are classified as "low risk" and "low uncertainty," meaning one can be reasonably confident in the predicted outcome. This includes most of the U.S. Midwest and also the northern parts of Canada. "High risk" areas are usually associated with the projected extent of the *S. noctilio* invasion (Figs. 5A, 5C, and 5E) and do not change much among the scenarios. "Low risk" and "medium risk" areas with high uncertainties in the southeastern United States reveal greater influence of the global *S. noctilio* entry potential, $P(t)$ (Table III). The global entry potential, however, does not affect the areas of "low risk" and "high uncertainty" in Canada and the northeastern United States because the host distribution is sparse and heterogeneous in these areas and thus provides limited potential for large-scale outbreaks.

4. DISCUSSION

The ability to map the potential risks is one of the key attributes of effective response and management of nonindigenous species.(65) Although the problem sounds simple, no common standards exist for quantifying risks spatially.(66) Furthermore, many pest risk assessments analyze major components of invasion separately and the resulting maps are often presented as stand-alone products.(67–69) Combining these products *a posteriori* requires the subjective use of assorted aggregation methods.(50,70,71) The integrated simulation approach presented here addresses these issues and potentially provides a better decision support tool in a number of ways. First, risk estimates can be undertaken at large spatial scales, but with spatial accuracy sufficient to outline particular geographic hotspots, providing useful management information in a broad cross-border context. Second, the model is driven by existing knowledge about the invading organism and hence can be used to test the implications of particular ecological assumptions and identify knowledge gaps. This is an important consideration as many recently detected nonnative species had no prior observations in North America. Finally, the outputs provide the means of estimating the long-term cumulative risks of several introductions. Because the entry process is fully integrated with the spread and establishment components of the model, spatial dependencies that might occur as a result of multiple introductions are taken into account.(52) Overall, this provides a more comprehensive portrayal of risk of introduction than "once-off" static estimates(50) or point-based analytic approaches.(70)

4.1. Effect of New Wood Treatment Standards

Our three hypothesized scenarios regarding the impact of new international wood treatment standards on the global entry potential had markedly different effects on the geographical distribution of the risks of *S. noctilio* invasion. The potential effect of the new standards is more visible on the "ports-only" risk maps (scenarios 1–3; Fig. 4). The scenario assuming a 7% annual growth of the global *S. noctilio* entry potential, $P(t)$, shows medium-level risks of infestation with medium-to-high uncertainties (Figs. 4A and 4B). The scenario with a 2% annual growth rate of $P(t)$ shows relatively low risks and medium uncertainties (Figs. 4C and 4D). The scenario with a 3% annual decline in $P(t)$ shows very low risk and uncertainty values (Figs. 4E and 4F). For all three scenarios, the areas of medium and high risk varied between the three scenarios, whereas the low-risk areas did not change much. This suggests that, if our portrayal of the outcome of new treatment standards is at all reasonable, *S. noctilio* entry potential at medium- and high-volume ports will be affected first.

However, the impact of phytosanitary rules presented here does not include feedback from particular management options such as quarantine or inspection efforts. Although consideration of this issue would greatly improve the utility of risk maps, it would require a clear understanding of the impacts of management and control options on *S. noctilio* establishment potential in the North America. This task would also require the formulation and validation of a dynamic model that depicts management actions and their influence on characteristics of *S. noctilio* invasion (e.g., the susceptibility of host, the maximum rate of spread, or the population carrying capacity). Current knowledge about potential management and control options for *S. noctilio* in North America appears to be insufficient to validate such a model and will require further research efforts.

4.2. Representation of Entry Potential

A formulation of entry potential as a global probability, $P(t)$, apportioned across a spatially explicit set of potential entry points with individual weights, $W_{x(t)}$, makes it possible to test a variety of other entry hypotheses (e.g., pathway models(72)). The values of $W_{x(t)}$ and their spatial distribution appear to be an important factor defining the geographical patterns of high- and low-risk areas. Thus, adding potential entry points from inland locations could help to better define the invasion risks in continental regions of the North America. This, however, would require additional work linking entry potential with a commodity transportation network and further search for other data that could be used to depict inland entry potential.

The scenarios also illustrate the capability of generating risk assessments for species other than *S. noctilio* with high potential to be introduced in North America; for example, the Asian gypsy moth (*Lymantria dispar* L., Asian biotype), a strong disperser with a broad host range, has been intercepted in North America on several occasions since 1991.[(73)]

4.3. Data Integration

Differences between U.S. and Canadian data and historical risk modeling approaches represent another source of spatial inconsistencies. Figs. 4 and 5 reveal differences in fine-scale spatial features between Canada and the United States. This is the result of the different modeling techniques used to create the pine distribution maps (stochastic randomization for the Canadian portion and geostatistical interpolation for the U.S. portion) as well as differences in the sampling design and spatial resolution of the primary data sources (i.e., the CanFI and U.S. FIA forest inventory databases). Nevertheless, our effort represents an important first step in developing more integrated continent-wide risk assessments. We are currently exploring a more consistent data development approach for future cross-border analyses.

5. CONCLUSIONS

Management decisions about invasive species often have to be made quickly, with insufficient knowledge of their ecology. When little is known about how species might behave in a new environment, obtaining quantitative risk estimates for these invaders becomes a daunting task. Even if the risks of a species invasion cannot be computed exactly, it can be useful to think about the invasion in terms of frequent or rare outcomes. The stochastic risk assessment approach presented here formalizes certain basic assumptions about an invading organism in an integrated simulation model, which is then used to map the risk of invasion. Our method uses multiple stochastic simulations that help quantify and map the output uncertainties propagated from parameters and inputs, especially their spatial components. The risk mapping framework is generic and can be adapted to perform risk assessments of other species. Of course, fitting the parameter values and defining the appropriate functional forms of spread parameters, host species maps, and growth models will remain case specific.

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