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Research Article

Application of a theoretical simulator to the optimisation of risk-based invasive species surveillance

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Abstract

Early detection and rapid response are critical to the successful management of non-indigenous species (NIS) and rely on effective surveillance programmes. Risk-based surveillance, where surveillance targets high risk locations, is the most efficient form of NIS surveillance. However, further research is required on the impact of different levels of emphasis on risk, in sampling designs and on surveillance efficacy. This study implements a theoretical surveillance simulator to model the relative merit of different surveillance strategies with different levels of focus on NIS risk for NIS detection at one or more sites. Three potential surveillance scenarios were modelled: random, risk-based and heavy risk-based surveillance, each with three distributions of combined NIS risks of introduction and establishment: exponential, random and uniform. An example analysis using model derived NIS risk data is also provided. Sensitivity and elasticity analyses were conducted to identify variables which influence model outputs. The interaction between sampling method detection probability and changes in NIS abundance was modelled. It was found that NIS risk distribution influences the relative performance of different surveillance strategies and that risk- and heavy risk-based surveillance have lower times to detections and, generally, higher surveillance probabilities of detection compared to random surveillance at more skewed NIS risk distributions. However, there was a trade-off between short detection time and detection failure in risk-based and particularly heavy risk-based surveillance. Therefore, an over-emphasis on risk-based surveillance could provide suboptimal NIS detection. Sensitivity and elasticity analysis showed that the number of NIS seed sites, mean site visit rate and method detection probability had the largest effects on detection time, highlighting the complexity of designing surveillance programmes. In conclusion, the optimal surveillance strategy is conditional on the risk distribution and this study highlights the value of model-based simulators to guide decision-making in the design of NIS surveillance programmes.

Key words: Establishment risk, introduction risk, non-indigenous species, risk-based surveillance, surveillance design, theoretical model

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Introduction

Non-indigenous species (**NIS**) are species which have spread to new regions outside their natural biogeographical range with the aid of human actions (Essl et al. 2018). Some NIS can have substantial environmental impacts and are referred to as invasive NIS: they are the second largest driver of species extinction (Bellard et al. 2016), can reduce species genetic diversity (Vera-Escalona et al. 2019) and may have substantial ecological impacts (Gallardo et al. 2016; Guy-Haim et al. 2018), resulting in negative effects on ecosystem services (Vilà et al. 2010; Castro-Díez et al. 2019). They may also pose a direct threat to human health (Mazza et al. 2014) and have cost the global economy a minimum of 1.288 trillion US dollars from 1970 to 2017. This cost is rising every year (Diagne et al. 2021).

NIS introductions occur via various pathways. Five key pathways in the marine environment are commercial shipping, recreational boating, movement of aquaculture stock, the aquarium trade and natural dispersal (Ricciardi and Rasmussen 1998; Molnar et al. 2008; Acosta and Forrest 2009; Katsanevakis et al. 2013). Given multiple introduction pathways, the interception of all potentially invasive NIS is unrealistic. Prevention, early detection and rapid response are therefore critical to the successful management of NIS (Pyšek and Richardson 2010; Koch et al. 2020). This is particularly the case in the marine environment, where high environmental connectivity, via the water column, makes containment and eradication very challenging (Giakoumi et al. 2019). However, early detection can be difficult given that, when NIS arrive and become established, they are often initially rare (Hulme 2006; Koch et al. 2020). Early detection and rapid response rely on effective surveillance programmes. However, despite multiple legislative drivers (Wood et al. 2024), most European countries lack dedicated marine NIS surveillance programmes and NIS often receive limited attention in existing biological monitoring initiatives (Wood et al. 2021; Stæhr et al. 2022; Katsanevakis et al. 2023). Within the UK, the limited dedicated monitoring which does occurs at marinas, remains spatially, temporally and taxonomically patchy (Bishop et al. 2015; Wood et al. 2017). In fact, the detection of NIS often occurs incidentally in more general environmental monitoring surveys (e.g. the detection of Pink Salmon, *Oncorhynchus gorbuscha*, in the Tees Estuary in northern England, UK, Gibson et al. (2024)).

Early detection and rapid response rely on effective surveillance programmes which must be in place prior to NIS arrival to allow early detection (Mastin et al. 2020). Risk-based surveillance, where surveillance targets high risk locations (e.g. where introduction pathway activity is high, Stärk et al. (2006); Tidbury et al. (2016)), is the most cost-effective form of hazard surveillance (Mastin et al. 2020; Stæhr et al. 2022). Risk-based surveillance may incorporate variation in establishment risk as well as introduction risk, given that the establishment risk of NIS varies spatially, based on parameters such as habitat suitability (Leidenberger et al. 2015; Richgels et al. 2016; Zhang et al. 2019). Risk-based surveillance confers efficiency by narrowing the survey sampling frame (Koch et al. 2020) and its use has been recommended for the early detection of colonising aquatic NIS based on empirical data (Harvey et al. 2009). However, risk-based surveillance is not always applied in practice. For example, in Europe and the UK, there is currently limited sampling at high-risk locations, for example, ports, marinas and aquaculture sites for marine NIS (Stæhr et al. 2022; Wood et al. 2024). Therefore, further work is required to develop and apply risk-based surveillance methods. Risk-based surveillance is, however, a broad term, with surveillance strategies taking many forms with respect to the sampling effort used to monitor high-risk sites, relative to low-risk sites (i.e. the level of risk focus). Therefore, studying the effect of different levels of risk focus during sampling on NIS detection is a useful exercise when designing surveillance programmes.

Computer simulations which compare the effect of using simulated risk-based surveillance designs to random and other surveillance designs, on parameters which are of importance to NIS surveillance, such as time to detection or detection probability, provide a useful method to address this knowledge gap. These models vary in their sophistication and have been used in research into invasive plant pathogens (Parnell et al. 2014; Martinetti and Soubeyrand 2019; Mastin et al. 2020). While more general network models can evaluate the likely level of success of regional NIS management using multilayer network analysis (Garrett 2021), these models may have substantial species-specific data requirements (Martinetti and Soubeyrand 2019; Mastin et al. 2020). There is, thus, a requirement for the continued development of simple models which can be used to provide information for early warning surveillance of unanticipated new arrivals, where detailed information, underpinning prediction of their likelihood of spreading, is lacking (Parnell et al. 2014). This situation may apply to newly-introduced marine species. In fact, a lack of data on occurrence and distribution is a limiting factor in the response to marine NIS in the UK (Wood et al. 2024).

This study develops and implements a theoretical model, referred to as a surveillance simulator, to assess the relative merit of different surveillance strategies, which differ in their level of risk focus, for NIS detection. Although developed for early warning monitoring of marine NIS, where the species is established at a relatively small number of sites, the simulator is generic and can be applied to any terrestrial or aquatic organisms while requiring a minimal amount of species-specific data. The simulator calculates the time to NIS detection across multiple simulations, following the introduction and establishment of a NIS at one or more sites. The survey probability of detection, over time, is also calculated across simulations. Differential risk of introduction and establishment between sites is incorporated. Surveillance is simulated under three potential scenarios: random surveillance, risk-based surveillance and heavy risk-based surveillance. For risk-based surveillance, the visit rate is increased by the relative risk of NIS introduction and establishment. For heavy risk-based surveillance, this relative increase is enhanced for the highest risk sites. The simulator also incorporates the interaction between the detection probability of a method and changes in the abundance of NIS. Sensitivity and elasticity analyses are performed to determine the effect of changes in selected parameters on time to NIS detection and the failure to detect NIS. Findings are discussed in the context of optimisation of surveillance for NIS and the operation of the model rather than providing detailed differences between theoretical scenarios. Application of the model is further illustrated using NIS risk scores for 10,249 sites, derived from model predictions based on empirical data, for three scenarios focused on: risk of introduction, risk of spread and risk of impact and representing three different risk distributions.

Methods

Simulator structure

The simulator was developed in the statistical software R v.4.1.2 (R Core Team 2021). The simulator has several core components: functions which establish the NIS risk at each site (from the introduction and establishment probability) and which calculate the site visit rate based on surveillance strategy, the surveillance simulator function (run separately for each strategy) and functions which implement optional sensitivity and elasticity analyses (Fig. 1). Additional supporting functions process outputs and create graphs. The user inputs the following parameters: introduction and establishment probability distribution, mean annual visit rate, number of survey sites, the method detection probability, a minimum and maximum detection probability for the method and the detection dynamic. The detection dynamic indicates if the method detection probability remains constant or changes with NIS abundance at a site. The user specifies starting abundance changes according to a growth model with user-controlled parameters. The user may also specify the number of seed sites (sites at which NIS are introduced and become established) and the way in which detection outputs from multiple sites are summarised. The surveillance time period (in years) and number of simulations to run are also set. Definitions for parameters and other terms are in Table 1.

User-specified parameters

The input parameters are controlled via the config_sim.yaml file. The user specifies the number of sites and a probability of introduction (getIntroProbability) and establishment per site (getEstablishProbability). The distributions from which to randomly draw probabilities of introduction and establishment are either: an equal uniform distribution which requires a user specified probability value, random uniform distribution, truncated normal distribution (bounded by 0 and 1), truncated exponential (bounded by 0 and 1) or lognormal distribution (bounded by 0 and 1). Example distributions, used in the later simulator application example, are shown in Fig. 2. An overall NIS risk probability per site (Nr_s) is calculated: $Nr_s = Pi_s$, where Pi_s is the probability of introduction per site and Pe_s is the probability of establishment per site.

A mean site visit rate is defined by the user and used to calculate the visit rate for each individual site. Under random surveillance, the visit rate for each individual site is identical. Under risk-based surveillance, the risk-based visit rate for each site (Vr_s) is calculated as: $Vr_s = V_s \cdot (Nr_s / Nr_{\bar{x}})$, where V_s is the visit rate per site and $Nr_{\bar{x}}$ is the overall mean NIS risk probability across sites. Under heavy risk-based surveillance, the visit rate for each site (Vhr_s) is calculated in the same manner, but the site NIS risk and mean NIS risk across all sites are raised to the power of three: $Vhr_s = V_s \cdot (Nr_s^3 / Nr_{\bar{x}}^3)$. Therefore, under the risk-based surveillance scenarios, the simulator assigns a relatively higher visit rate to those sites with greater NIS risk. Higher visit rates at high-risk sites are further enhanced under heavy risk-based surveillance. See Fig. 3 for a conceptual example of the relationship between NIS risk and site visits under different surveillance scenarios. If NIS abundance is included in the simulation, for a single site, a user-defined starting abundance value is set. For multiple

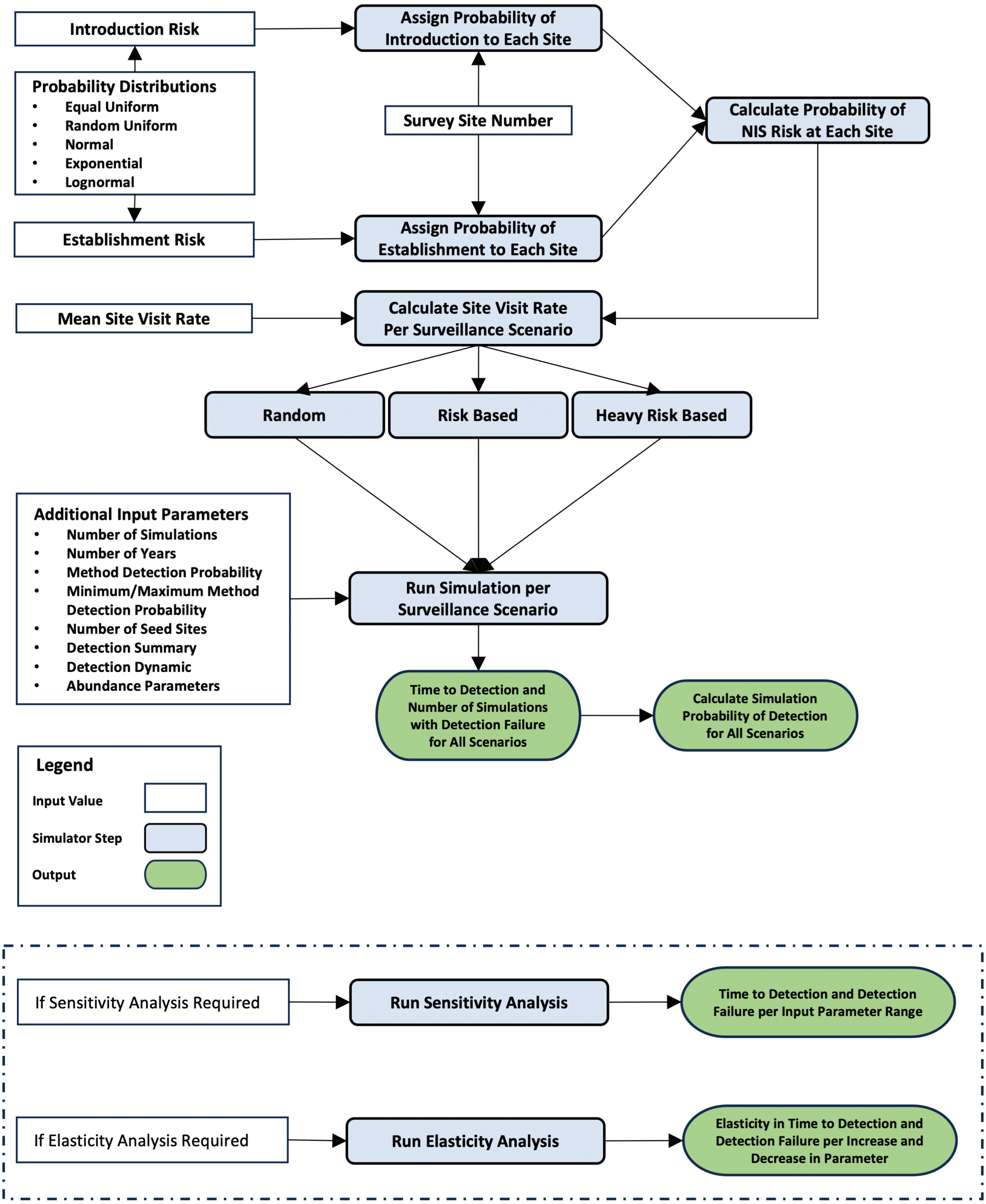

Figure 1. Schematic of the overall simulator structure showing key inputs and outputs and the role of the elasticity and sensitivity analysis, around the core surveillance simulation. The detailed structure of the surveillance simulations is given in Fig. 4.

sites, abundance starting values are set by the user or randomly drawn from a Poisson distribution with a user-specified mean. Abundance at each time step is determined by an exponential (Suppl. material 1: eqn. 1) or logistic growth model (Suppl. material 1: eqn. 2; Rockwood and Witt (2015)) with user-defined parameters (GetAbundance). This allows populations at site(s) to grow, decline or maintain at carrying capacity throughout the simulation.

Table 1. Glossary of key terms.

Parameter/ Term	Description*
Risk-Based Surveillance	Surveillance strategy where the site visit rate is biased towards higher risk sites.
Heavy Risk-Based Surveillance	Surveillance strategy where the site visit rate is heavily biased towards higher risk sites.
Introduction risk probability distribution	The statistical distribution which determines the probability of NIS introduction at a site.
Establishment risk probability distribution	The statistical distribution which determines the probability of NIS establishment at a site.
NIS risk	The probability of NIS introduction and establishment at a site, calculated by multiplying the introduction and establishment probability together.
Surveillance time period	The maximum time period (in years) over which a simulation may run.
Seed site(s)	A site(s) into which a NIS becomes introduced and established based on its relative NIS risk during a simulation.
Mean site visit rate	The mean number of times which a site is visited in a year.
Method detection probability	The probability of detecting a NIS at a site when it is searched during a simulation.
Survey probability of detection	The probability of detecting NIS at a site(s), at a given time point by a simulation, as calculated using all simulations in a simulator run.
Detection dynamic	The relationship between method detection probability and the abundance of a NIS. Either fixed, threshold or linear.
Detection summary	Method used to summarise the time to detection if multiple seed sites are used in a simulation.

*For further details, refer to text.

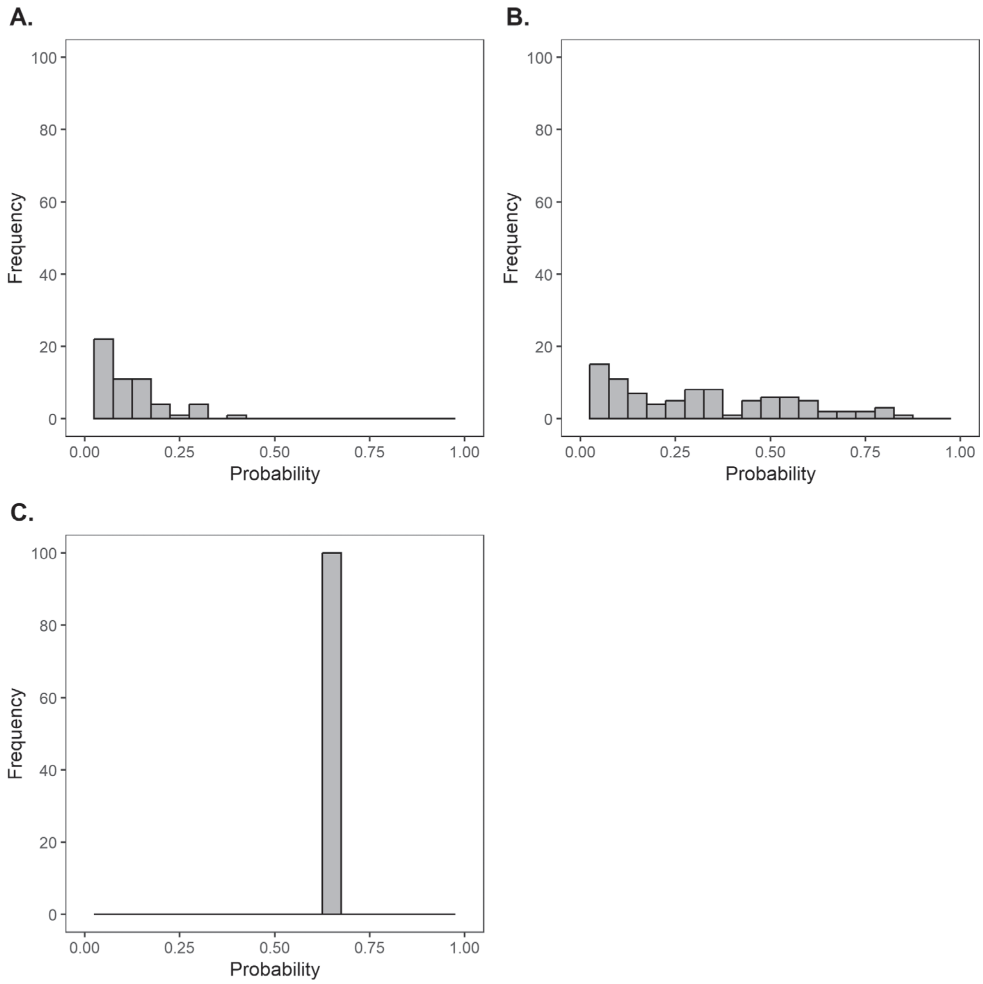

Figure 2. NIS risk distributions of the probability of NIS becoming introduced and established at a site, showing exponential (**A**), random uniform (**B**) and equal uniform (**C**) risk distributions used in the simulator application example.

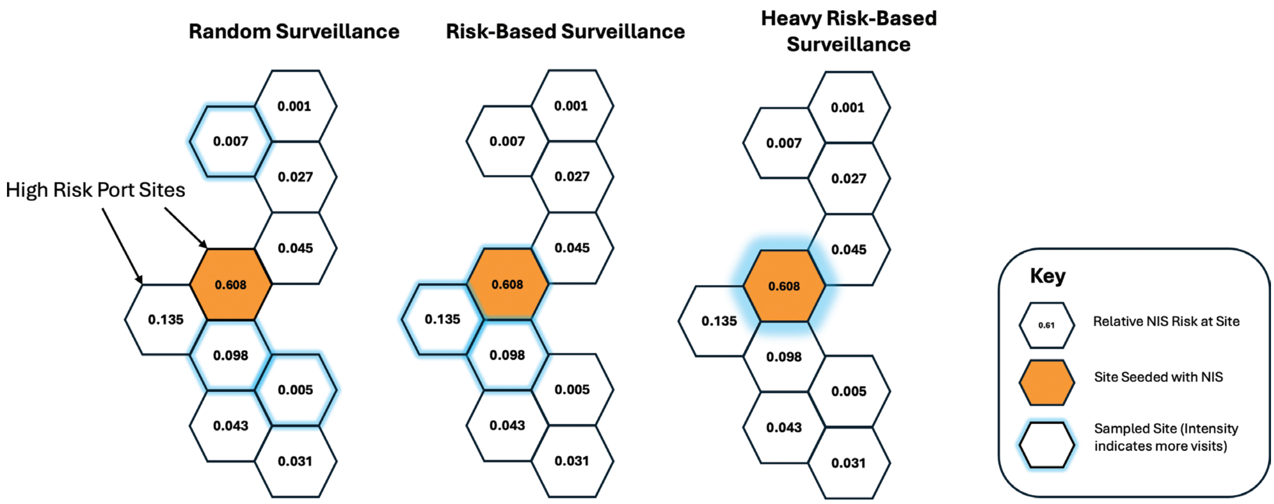

Figure 3. A conceptual example of the relationship between the relative NIS risk at each site (numbers within hexagons, assuming an exponential distribution) and the site visit rate assuming random, risk-based and heavy risk-based surveillance, over three site visits (blue outline) during a model run. The highest risk hexagons in this example represent two port sites, one seeded with a NIS at the beginning of the simulation (orange fill). Under random surveillance three sites are visited with no relationship to risk, under risk-based, three high risk sites are visited and under heavy risk-based surveillance, the highest risk site, only, is visited three times.

The method detection probability defines the probability of the sampling method detecting the NIS during a site visit. The method detection probability may be fixed or vary with NIS abundance linearly or in a threshold manner. Under a linear relationship, the user defines the abundance required to change the detection probability by 0.01. Under a threshold relationship, the user defines a threshold abundance value and two detection probabilities to use when abundance is below, above or equal to the threshold value.

Introductions at multiple seed sites, up to the number of sites in the simulation, may also be selected by the user. If abundance is required, values for multiple sites are either set by the user or randomly drawn from a Poisson distribution with a user specified mean. For multiple sites, the user must select the detection summary method, i.e. how the time to detection is summarised over multiple seed sites in that simulation (ProcessMultipleResults). Time to detection may be taken from the first seed site to be detected or the last seed site.

Simulation process

The simulation is run by the function runSurveillanceSimulation (Fig. 4). At the starting time point, a site is selected with its relative NIS risk used as a probability weighting to bias random selection to higher NIS risk sites (base R function: sample) and seeded with a NIS (Fig. 3). For simulations which include multiple (n) seed sites, this process is repeated n times (once for each seed site). The simulator time step (in days) is calculated by dividing the user-defined number of visits per year by 365, assuming that the total visits each year is equal to the sum of visit rates across all sites. The time counter is increased, based on the average time taken to visit one site assuming that the total visits each year is equal to the sum of visit rates across all sites.

At each time step, a single site is selected to be visited dependent on the mean visit rate (Fig. 3). At each site visit, detection of the NIS is determined by drawing a value from a random binomial distribution with a success rate

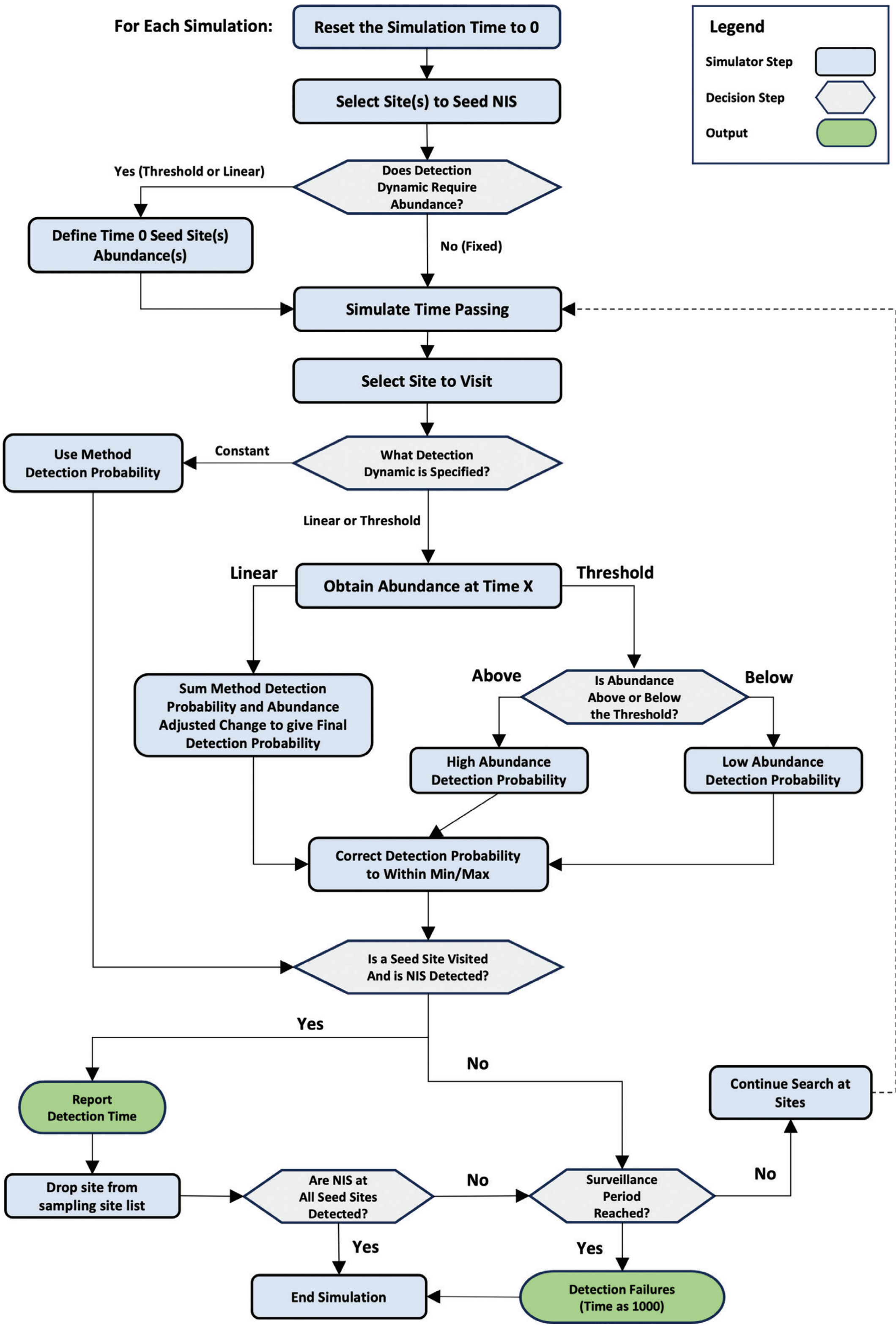

Figure 4. Schematic of the surveillance simulation showing key steps and outputs, as defined by the *runSurveillanceSimulation* function.

defined by the method detection probability. If the seed site is visited and the NIS is successfully detected, the simulation stops and the time to detection is recorded. When NIS are seeded at multiple sites and when NIS is detected at a seeded site, the time is stored and the simulation continues until NIS is found at all sites. The multi-site simulation will run until NIS are detected at all seeded sites or the surveillance period elapses. If the simulation period elapses prior to the NIS being detected, the run is stored as a 'detection failure' (and internally stored as time to detection = 1000). The results for multiple seed sites are then summarised by the function ProcessMultipleResults, for each simulation. The default detection summary method, used in this study, is used to output the time at which the last seed site was detected. This means that the results of multiple seed sites are counted as a detection failure when NIS remain undetected at even just one of the seeded sites within the timeframe. Other detection summary options can output the mean, median or first time to detection across seed sites or the time taken to detect a user-specified number of sites. The simulator repeats according to the number of simulations set. The outputs are time to detection and proportion of total simulations which are classed as 'detection failures' (across all simulations). This second output is also used to calculate the survey probability of detection over all sites across time. Outputs across all surveillance simulations are generated by the report-NIS-intro-detect-sim.Rmd markdown file.

Sensitivity and elasticity analysis

Sensitivity analysis determines the impact that absolute changes in each model parameter have on the output, i.e. time taken to detect NIS and forms a component of the surveillance simulator. Sensitivity analysis can be implemented for the number of sites, number of years, mean visit rate, method detection probability and number of seed sites (makeSensitivityParamsTable). The simulator runs iteratively (runSurveillanceSensitivity; results formatted by formatSensitivityResults), incrementally altering input parameters, one at a time, by a user-defined interval within a specified range and plotting the results. Summary statistics such as number of times a NIS was detected/not detected and the mean, maximum and minimum time to detection are output for each parameter. Outputs are generated by the report-NIS-intro-detect-sensitivity.Rmd R Markdown file and other helper functions.

Elasticity analysis is also included in the simulator. Elasticity (ξ) is proportional sensitivity, it estimates the effect of a proportional change in a parameter on the proportional change in the output, i.e. time taken to detect NIS (Benton and Grant 1999; Teixeira Alves et al. 2021). Elasticity is dimensionless and independent of the parameter scale, allowing comparison between parameters. Elasticity analysis can be implemented and compared with sensitivity analysis to better understand the impact of changes in model parameters on outputs. Users define the default parameter values and the proportion (between 0 to 1) by which to change each parameter (defined in the config_sim.yaml file; makeElasticityParamsTable). The simulator is run iteratively, with one parameter varied at a time (using runSurveillanceSensitivity; results formatted by summariseElasticityResults). Elasticity is calculated (Suppl. material 1: eqn. 3; Teixeira Alves et al. (2021)) and plotted for each parameter (by report-NIS-intro-detect-elasticity.Rmd and other helper functions). Elasticity values below 1 indicate a parameter is inelastic. Elasticity values above 1 indicate the parameter is elastic, i.e. changes in elastic parameters have the greatest impact on outputs (Teixeira Alves et al. 2021).

Simulator application

Theoretical risk distributions

Three different NIS introduction and establishment risk distributions were implemented for each surveillance strategy (random, risk-based and heavy risk-based). These risk distributions were equal uniform (probability: 0.8), random uniform and exponential. The equal uniform distribution was selected to provide a default example with no variation in risk. The random uniform distribution provided a scenario where risk varied between sites, whereas the exponential distribution was used to represent a situation where most sites are of no or low risk and a small number of sites are of high risk (Wood et al. 2021). All other parameters were kept constant between runs. The number of seed sites was 1. This was used for baseline comparisons because the aim of the simulator is to optimise detection of NIS early after arrival. The number of years was set to 30, to allow the majority of simulations to detect the NIS and, therefore, provide valid comparisons between detection times. All other parameters were selected according to the authors' knowledge of sampling programmes. Specifically, the number of survey sites was 100, mean visit rate was 1 and method detection probability was 0.8. The number of simulations in each run was set to 10,000 as experimentation showed that simulator outputs were consistent between identical runs at this number of simulations.

Sensitivity and elasticity analysis

For sensitivity and elasticity analysis, the exponential risk distribution was used as, under this risk distribution, the largest differences between sampling programmes were seen. For the sensitivity analysis, the number of seed sites, survey sites, years, mean visit rate and detection probability were run with selected parameters defined, based on the authors' knowledge of sampling programmes (Table 2). For the elasticity analysis, the default parameters ± 25% for the number of sites, number of years, mean visit rate and method detection probability from the sensitivity analysis were used (Table 2), as they were considered practically sensible and allowed clear comparison between parameters. The number of seed sites was not included in the elasticity analysis as it was difficult to generate proportional increases in the default number of seed sites (i.e. 1 seed site), which would have an impact on the simulations.

Detection dynamic

The effect of dynamic detection (where the method detection probability is linked to NIS abundance) was explored using an exponential risk distribution and with seed site set to 1 and 10. The abundance model parameters assumed a starting population of 1, intrinsic growth rate of 1.5 with logistic growth and a population carrying capacity at each site of 100,000 individuals. For a linear relationship between abundance and detection method sensitivity, the starting detection method sensitivity was set to 0.1 with an increase of 0.01 per abundance increase of 500, up to 0.8. For a threshold relationship between abundance and detection method sensitivity, an abundance threshold of 10,000 was set such that method detection sensitivity below and above this threshold was 0.1 and 0.8, respectively. Parameter values were arbitrarily selected to demonstrate the functionality of the simulator.

Table 2. Sensitivity and elasticity parameters.

Parameters	Sensitivity Values			Elasticity Values		
	Minimum	Maximum	Interval	Default	25% Decrease	25% Increase
Number of Seed Sites	1	100	10			
Number of Survey Sites	50	200	25	100	75	125
Number of Years	10	50	5	30	22.5	37.5
Mean Visit Rate	0.25	4	0.25	1	0.75	1.25
Method Detection Probability	0.1	1	0.1	0.8	0.6	1.0

'Site Prioritisation Tool' derived marine NIS risk distributions

As a practical example, the surveillance simulator was used to assess the relative performance of random, risk-based and heavy risk-based surveillance for three marine NIS introduction and spread scenarios created by a model to prioritise surveillance activities for NIS species for the UK coastline (the 'Site Prioritisation Tool' or SPT model, Cefas, in prep.). This hierarchical model was developed to provide information for surveillance programmes by scoring and ranking 10,249/5 km × 5 km grid squares representing the UK coastline. Empirical data for a range of risk parameters was grouped into pathways, distributed amongst four risk categories: Introduction risk (pathways: intentional introduction, shipping, recreational boating, fishery and aquaculture release), Establishment risk (temperature, salinity and substrate), Impact risk (environment and industry) and Spread risk (recreational boating, fishery and aquaculture release; Suppl. material 1: table S1). Separate weighting factors were assigned to each parameter, theme and category to reflect their relative importance and determine their contribution to risk scores. Resulting risk scores are standardised (between 0 and 1) at each level of the SPT model (parameter, pathway, category) to provide comparable relative values between pathways and categories. Risk scores were output for three scenarios: Scenario A, monitoring weighted towards sites at greatest risk of introduction through the shipping pathway (e.g. species introduction via ballast water and hull fouling); Scenario B, monitoring weighted towards sites where spread risk is greatest; and Scenario C, monitoring weighted towards sites where the impact of NIS is likely to be greatest (Suppl. material 1: fig. S1). The simulator was run with NIS risk scores from each scenario (Fig. 5), with the per cell risk data from the SPT model used to provide the overall NIS risk probability per site (*Nrs*). The simulator was run for 1000 simulations, at 10,249 sites (grid cells), to determine time to detection assuming a constant detection dynamic with all other parameters as default (as in section Theoretical risk distributions).

Results

The risk distribution

Comparison of the time to detection between different risk distributions showed that results varied with surveillance strategy (Table 3; Fig. 6). For an equal-uniform distribution, there was almost no variation in time to detection or survey probability of detection between surveillance strategies. In addition, all NIS were detected regardless of surveillance strategy (Table 3; Fig. 6C). With a random uniform risk distribution, the median time to detection was 0.89 years for random surveillance

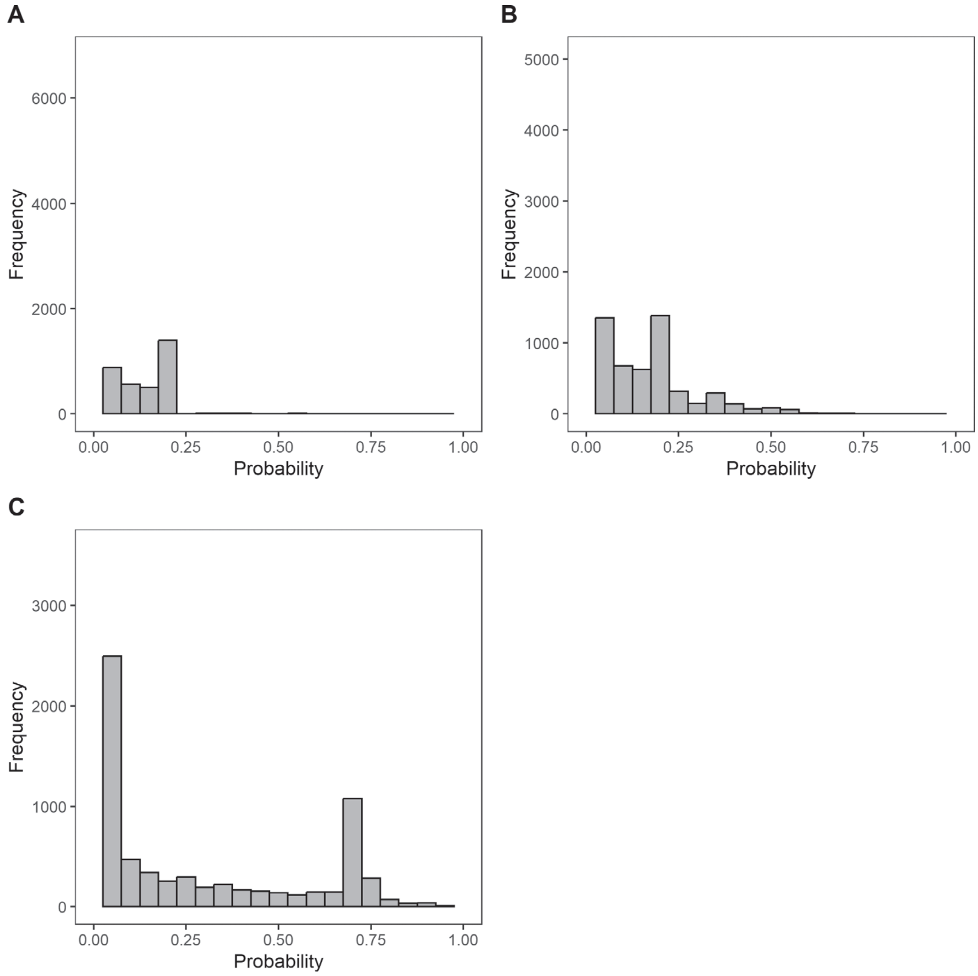

Figure 5. Risk distributions of the combined probability of marine NIS becoming introduced and established at a site, spread from that site and the site being negatively impacted. Scores generated using the SPT model (Cefas, in prep.) for Scenario **A** shipping risk weighted, Scenario **B** spread risk weighted and Scenario **C** impact risk weighted.

and decreased to 0.56 years for risk-based surveillance and 0.52 years for heavy risk-based surveillance. Probability of detection at 1 year was highest for risk-based surveillance (0.68) and was progressively lower for heavy risk-based (0.61) and random surveillance (0.54). However, heavy risk-based surveillance had the lowest detection probability after 5 years (Table 3; Fig. 6B). Under an exponential risk distribution, median time to detection was longest under random surveillance (0.85 years) and was shortest under risk-based surveillance (0.41 years), but the time to detection under heavy risk-based surveillance was marginally longer than risk-based surveillance (0.47 years). Probability of detection at 1 year showed risk-based surveillance to have the highest survey probabilities of detection (0.75) and random and heavy risk-based surveillance to have similar lower scores (0.56 and 0.57). However, heavy risk-based surveillance had the lowest detection probability after 5 years (Table 3; Fig. 6A). For risk-based and heavy risk-based surveillance, time to detection progressively fell from an equal uniform, random uniform to an exponential risk distribution (Table 3). Risk-based surveillance showed a progressive increase in probability of detection, but heavy risk-based surveillance showed a limited change across distributions. For random surveillance, the time to detection and probability of detection remained the same across risk distributions and NIS were always detected (Fig. 6; Table 3). Under exponential and random uniform

Table 3. Model outputs for variable risk distributions.

Model Run	Distribution	Detection Dynamic	Number of Seed Sites	Scenario	Detection Time (Years)		Detection Failure (%)	Survey Probability of Detection at Time (Years)			
					Median Detection Time	Interquartile Range		1	5	10	30
Run 1	**Exponential**	**Constant**	**1**	**Random**	0.85	1.34	0.00	0.56	0.98	1.00	1.00
				Risk-Based	0.41	0.85	0.28	0.75	0.96	0.99	1.00
				Heavy Risk-Based	0.47	1.86	10.68	0.57	0.78	0.83	0.89
Run 2	**Random Uniform**		**1**	**Random**	0.89	1.39	0.00	0.54	0.98	1.00	1.00
				Risk-Based	0.56	1.01	0.15	0.68	0.97	0.99	1.00
				Heavy Risk-Based	0.52	1.45	7.49	0.61	0.84	0.88	0.93
Run 3	**Equal Uniform**		**1**	**Random**	0.87	1.39	0.00	0.54	0.98	1.00	1.00
				Risk-Based	0.86	1.36	0.00	0.56	0.98	1.00	1.00
				Heavy Risk-Based	0.88	1.35	0.00	0.55	0.98	1.00	1.00
Run 4	**Exponential**	**Linear**	**1**	**Random**	6.03	4.39	0.00	0.09	0.40	0.97	1.00
				Risk-Based	3.34	5.03	0.50	0.20	0.63	0.95	0.99
				Heavy Risk-Based	3.55	6.70	12.48	0.24	0.49	0.76	0.88
Run 5			**10**	**Random**	8.79	1.78	0.00	0.00	0.00	0.78	1.00
				Risk-Based	8.31	3.51	3.02	0.00	0.02	0.68	0.97
				Heavy Risk-Based	14.52	11.25	68.87	0.00	0.00	0.08	0.31
Run 6	**Exponential**	**Threshold**	**1**	**Random**	6.29	4.23	0.00	0.09	0.39	0.97	1.00
				Risk-Based	3.20	5.20	0.29	0.21	0.63	0.96	1.00
				Heavy Risk-Based	3.63	6.54	12.39	0.24	0.49	0.76	0.88
Run 7			**10**	**Random**	8.61	1.79	0.00	0.00	0.00	0.81	1.00
				Risk-Based	8.14	3.54	3.16	0.00	0.01	0.69	0.97
				Heavy Risk-Based	14.71	11.45	67.67	0.00	0.00	0.09	0.32

risk distributions, NIS are not always detected within 30 years using risk-based and heavy risk-based surveillance. Under a random uniform risk distribution, 0.15% of simulations ended with no NIS detected with risk-based surveillance and this increased to 7.5% under heavy risk-based surveillance (Table 3). For an exponential risk distribution, 0.28% of simulations ended with detection failure for risk-based surveillance and this increased to 10.68% of simulations for heavy risk-based surveillance (Table 3).

Sensitivity analysis

Assuming an exponential risk distribution, an increase in the number of seed sites from 1 to 20 led to an increase in median time to detection across surveillance scenarios: from 0.87 to 3.6 years for random surveillance, 0.35 to 4.11 years for risk-based surveillance and 0.43 to 17.61 years for heavy risk-based surveillance (Fig. 7A), although there was substantial variability in the results. At 30 seed sites or greater, time to detection decreased across surveillance scenarios from 3.69 years for random surveillance, 3.82 years for risk-based surveillance and 17.02 years for random surveillance to 1.25 years at 100 seed sites across all scenarios (Fig. 7A). This decrease was the consequence of the adaptive sampling design where sites were not revisited after NIS detection, thereby creating a smaller pool of sites from which to sample at each step, therefore reducing the time to detect all sites with a

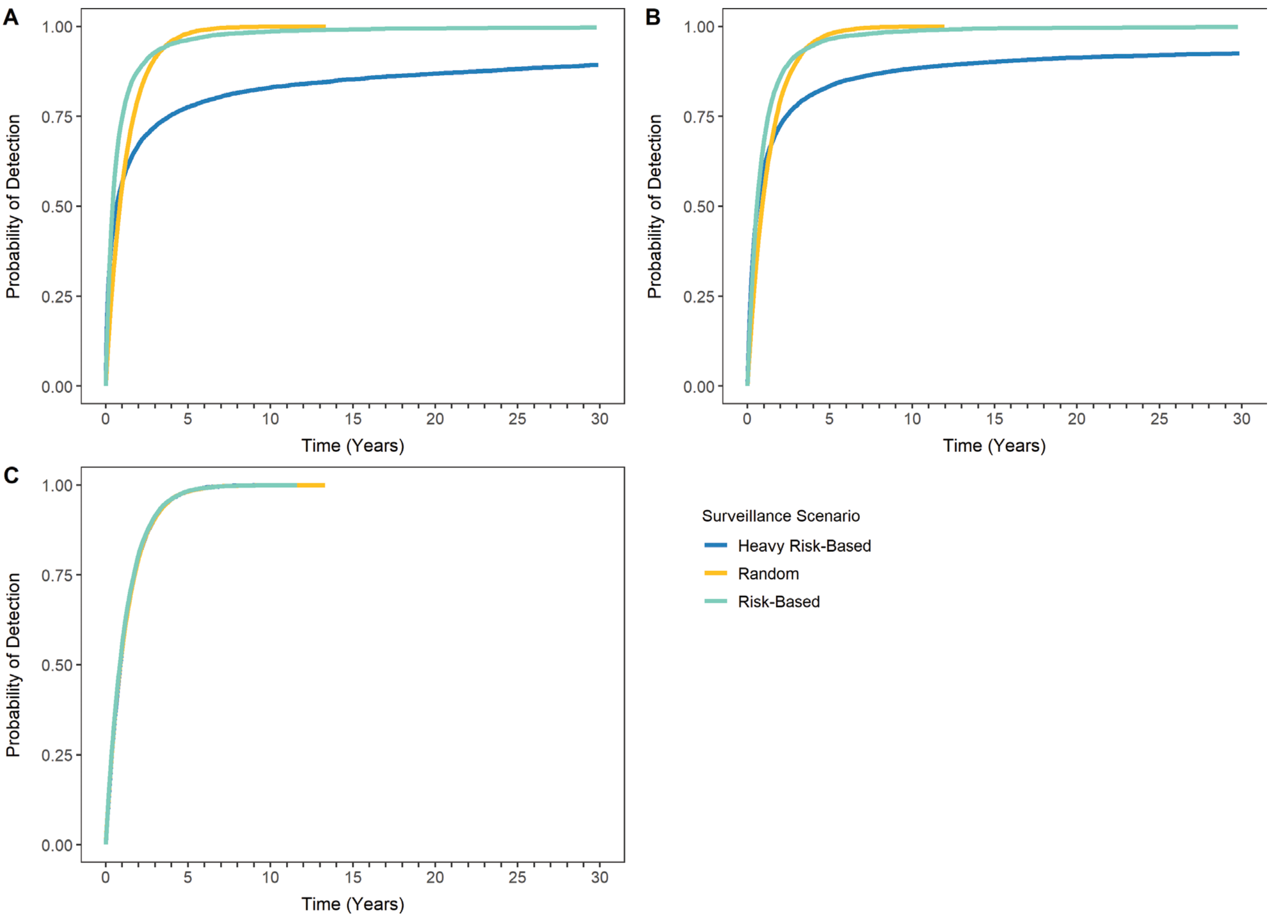

Figure 6. The overall survey detection probability of NIS over time, calculated across 10,000 simulations, assuming an exponential (**A**), random uniform (**B**) and equal uniform (**C**) risk distribution.

NIS. This effect was most pronounced where all 100 sites used in the simulation were seeded with NIS. Relative differences in median detection time showed heavy risk-based surveillance performed extremely poorly with more than one seed site, whereas random and risk-based scenarios both showed much lower and comparable median times to detection (Fig. 7A). The percentage of simulations from which the NIS was not detected was much higher for heavy risk-based surveillance compared to risk-based surveillance, but risk-based surveillance showed a similar relative trend to heavy risk-based surveillance in changes to detection failures with the number of seed sites (Fig. 7A). For example, with 20 seed sites, heavy risk-based surveillance failed to detect NIS in 89.2% of simulations, whereas this number was only 2.2% for risk-based surveillance.

The number of sampling sites had little impact on the median time to detection or the detection failure of random or risk-based surveillance (Fig. 7B). Heavy risk-based surveillance showed some small effect of number of sampling sites on median time to detection and detection failure (Fig. 7B). The number of sampling years had no influence on the median time to detection or detection failure of random surveillance (Fig. 7C). However, there was an increase in the number of simulations which were long time to detection outliers in both risk and heavy risk-based surveillance as the number of sampling years increased (Fig. 7C). Comparably, detection failure fell slightly across risk and heavy risk-based surveillance as the number of sampling years increased (Fig. 7C). Increases in mean visit rate, from

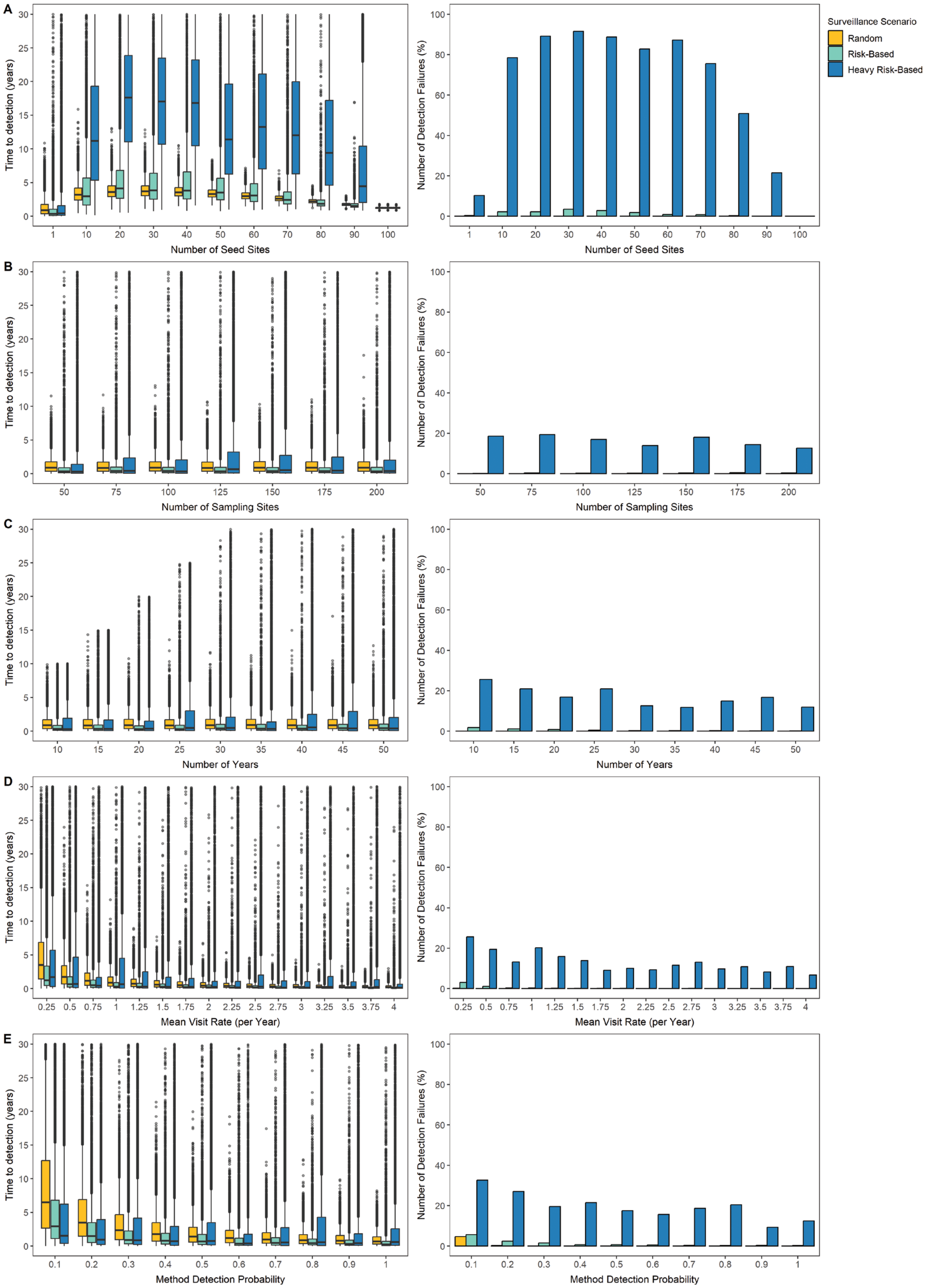

Figure 7. The results of the sensitivity analysis, assuming an exponential risk distribution, for the parameters: number of seed sites (**A**), number of sampling sites (**B**), number of sampling years (**C**), mean visit rate (**D**) and method detection probability (**E**), showing their effect on median time to detection (left hand column) and the percentage of simulations in each model run where no NIS was detected (right hand column).

0.25 to 1 visits per year, caused a decline in median time to detection across scenarios, for risk-based (from 1.25 to 0.30 years), heavy risk-based (1.68 to 0.64 years) and random surveillance (3.49 to 0.88 years, Fig. 7D). Time to detection continued to decline with increasing visit rates above one per year, though this was less pronounced for risk-based surveillance (Fig. 7D). There were overall declines in detection failure across surveillance scenarios as mean visit rate increased, although this relationship was non-linear (Fig. 7D). This was particularly evident for heavy risk-based surveillance (Fig. 7D). For random surveillance, an increase in method detection probability from 0.1 to 0.5 caused the median time to detection to fall from 6.49 to 1.40 years (Fig. 7E). Detection failure under random surveillance also fell from 4.7% at detection probability 0.1, to 0.0% at detection probability 0.3 (Fig. 7E). Under risk-based surveillance a similar, but more subtle, decline for median time to detection occurred over the same range (2.93 to 0.67 years, Fig. 7E). Detection failure also decreased, but never reached zero. Median time to detection under heavy risk-based surveillance showed little response to method detection probability between 0.1 to 0.5 (1.51 to 0.75 years, Fig. 7E). However, detection failure decreased overall as method detection probability increased (Fig. 7E).

Elasticity analysis

Assuming an exponential distribution, the elasticity of median time to detection and detection failure varied between surveillance scenarios, parameters and the direction of change in parameter values (Fig. 8). Under random surveillance, no change in detection failure was seen over the parameter ranges; therefore, elasticity was not calculated (Fig. 8B). Median time to detection was generally inelastic and only elastic to increases in the number of sites sampled under risk-based surveillance ($\xi = 1.07$, Fig. 8A). Under heavy risk-based surveillance, the detection failure was elastic to a decrease ($\xi = 2.32$) and increase ($\xi = 1.15$) in the number of sites sampled (Fig. 8B). Median time to detection was generally inelastic to changes in the number of years, but was elastic to an increase ($\xi = 1.05$) and decrease ($\xi = 1.20$) in the number of simulation years under risk-based and heavy risk-based surveillance, respectively (Fig. 8A). Detection failure generally showed an elastic response to the number of simulation years, though an increase in the number of years was inelastic under risk-based surveillance (Fig. 8B). Median time to detection generally showed an elastic response to mean visit rate, in particular under heavy risk-based surveillance, where time to detection showed strong elasticity to reductions in mean visit rate ($\xi = 2.21$, Fig. 8A). However, time to detection was inelastic to an increase in mean visit rate under random surveillance (Fig. 8A). Detection failure was elastic to increases in mean visit rate under risk-based surveillance ($\xi = 1.70$, Fig. 8B). Median time to detection was generally inelastic to changes in the method detection probability, except under risk-based surveillance where it was elastic to increases in the method detection probability ($\xi = 1.55$) and under random surveillance where it was elastic to decreases in the method detection probability ($\xi = 1.33$, Fig. 8A). Detection failure was generally elastic to changes in the method detection probability, particularly to a reduction in detection probability under risk-based surveillance ($\xi = 2.55$, Fig. 8B). Under heavy risk-based surveillance, detection failure was inelastic to an increase in method detection probability (Fig. 8B).

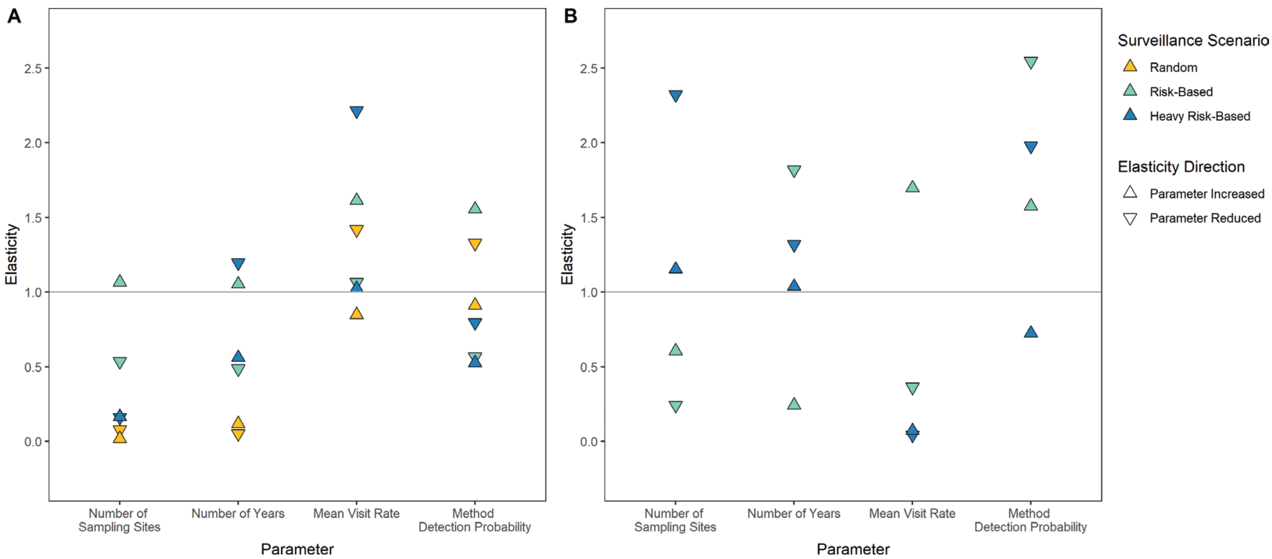

Figure 8. The elasticity of the median time to detection (years; **A**) and the detection failure (%; **B**) to a 25% increase and decrease in the default values of mean visit rate, number of sampling sites, number of years and method detection probability in each model run, assuming an exponential risk distribution.

Detection dynamic

Assuming an exponential risk distribution, inclusion of a linear relationship between method detection probability and NIS abundance (i.e. a linear detection dynamic), which grew logistically, resulted in a similar pattern of median time to detection and detection failure, between surveillance scenarios, for one seed site (model run 4; Table 3) compared to when the relationship with NIS abundance was excluded (model run 1; Table 3). However, median times to detection were much longer for all scenarios (random: 6.03 vs. 0.85 years, risk-based: 3.34 vs. 0.41 years and heavy risk-based surveillance: 3.55 vs. 0.47 years) when a linear relationship was included vs. excluded (Table 3). In addition, detection failure was marginally higher for risk-based (0.50 vs. 0.28%) and heavy risk-based surveillance (12.48 vs. 10.68%). Survey probability of detection had a different relationship when a linear detection dynamic was included: at 1 and 5 years, random surveillance had the lowest value, with detection probability being higher in risk- and heavy risk-based surveillance (Table 3, Fig. 9A). However, this changed over time, when, at 10 years, heavy risk-based surveillance had the lowest probability of detection (Table 3, Fig. 9A). When 10 seed sites were included with a linear detection dynamic, median time to detection lengthened for all surveillance scenarios (model run 5; Table 3). Risk-based surveillance had the shortest time to detection as before (8.31 years), but heavy risk-based surveillance had a much longer median time to detection (14.52 years) compared to random surveillance (8.79 years), in contrast to model runs 4 and 1 (Table 3). Heavy risk-based surveillance had a higher detection failure (68.87%) compared to risk-based surveillance (3.02%, Table 3). Survey probability of detection was at or near zero for all scenarios at 1 and 5 years. It remained low for heavy risk-based surveillance at 10 and 30 years, but increased for random and risk-based surveillance, with random surveillance having the highest value from 10 years (Table 3, Fig. 10B).

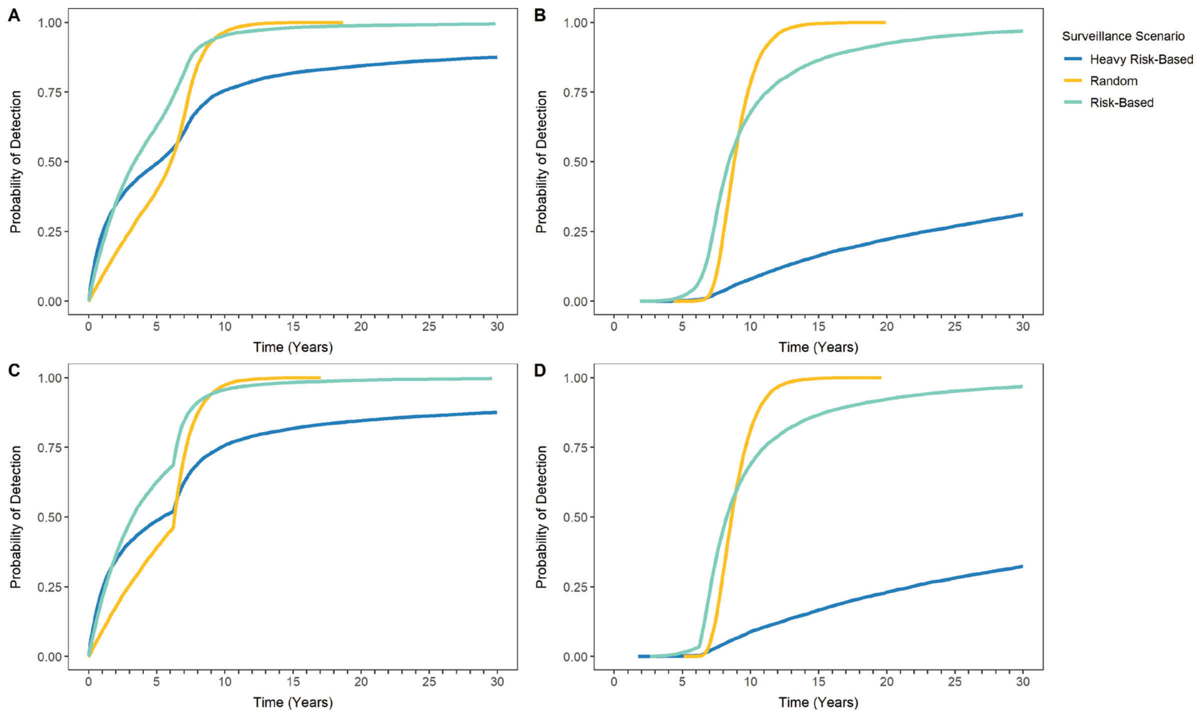

Figure 9. The survey probability of detection of NIS at a site, or all sites, over time, assuming an exponential NIS risk distribution, calculated across 10,000 simulations, for a linear (panels **A** and **B**) and threshold detection dynamic (panels **C** and **D**) between NIS abundance and method detection probability for one (left hand panels) and ten seed sites (right hand panels).

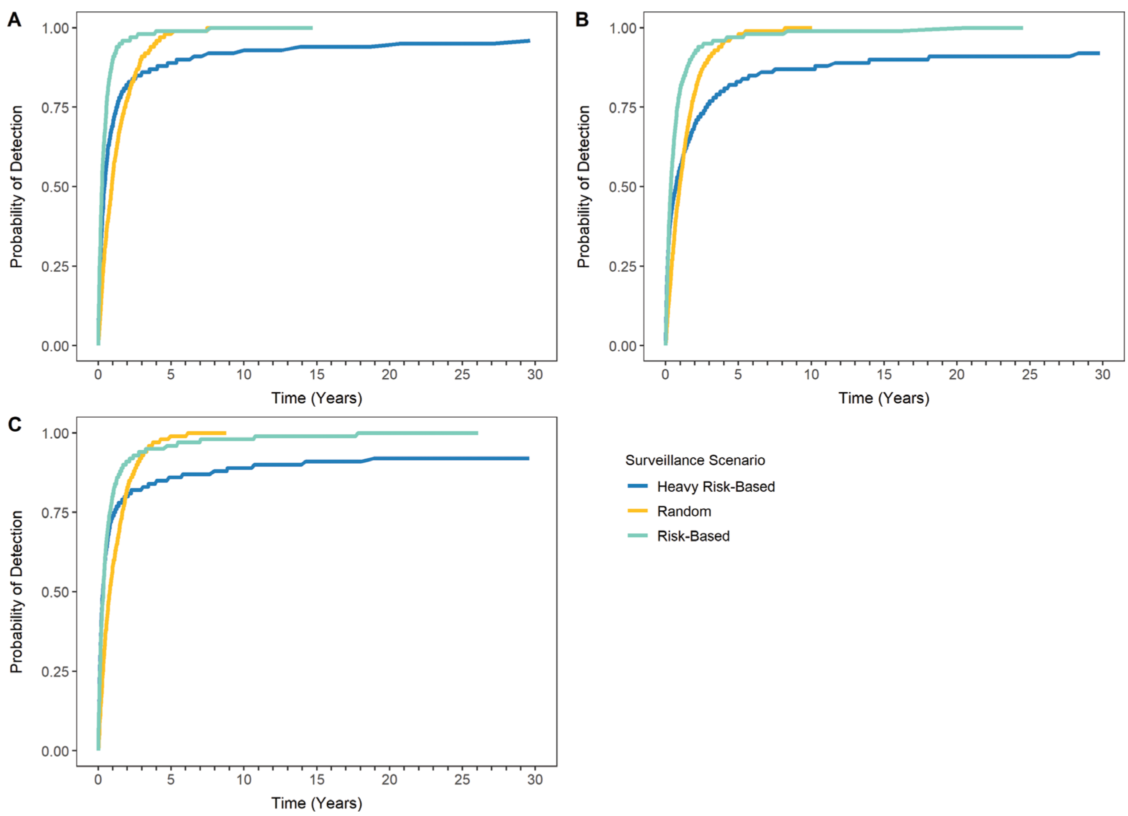

Figure 10. The overall survey detection probability of NIS over time, calculated across 1000 simulations, assuming the risk distribution in the combined probability of NIS becoming introduced and established at a site, spread from that site and the site being negatively impacted. Scores generated using the 'Site Prioritisation Tool' (Cefas, in prep.) for Scenario **A** shipping risk weighted, Scenario **B** spread risk weighted and Scenario **C** impact risk weighted.

Assuming a threshold detection dynamic between method detection probability and NIS abundance, simulations with one seed site (model run 6) produced similar median times to detection and detection failure to a linear detection dynamic with one site (model run 4), across surveillance scenarios (Table 3). Similarly, when 10 seed sites (model run 7) were included using a threshold detection dynamic, the results were similar to those with a linear detection dynamic with 10 seed sites (model run 5), in that heavy risk-based surveillance had the longest time to detection (14.71 years) and highest detection failure (67.67%, Fig. 9; Table 3). Detection probabilities showed a similar pattern across scenarios and simulations to those for a linear detection dynamic (Fig. 9C, D).

'Site Prioritisation Tool' derived marine NIS risk distributions

The time to detection and other outputs varied between surveillance strategies for each SPT modelled site risk distribution (Table 4; Fig. 10). For Scenario A (shipping risk weighted), the median time to detection was shortest for risk-based surveillance (0.25 years) and progressively longer for heavy risk-based (0.37 years) and random surveillance (0.93 years, Table 4). The survey probability of detection at Year 1 was also highest for risk-based surveillance (0.90) compared to heavy risk-based (0.70) and random (0.53) surveillance (Table 4, Fig. 10A). Heavy risk-based surveillance, however, had the highest detection failure (4.40%) compared to risk-based and random surveillance (both 0.00%, Table 4). Scenario B (spread risk weighted) had overall similar relative results to Scenario A: risk-based surveillance had the shortest detection time (0.34 years) and highest survey probability of detection at Year 1 (0.81, Table 4, Fig. 10B). However, risk-based surveillance also showed detection failure (0.30%), whereas random surveillance did not (0.0%, Table 4). For Scenario C (impact risk weighted), median time to detection was shortest for heavy risk-based surveillance (0.27 years), compared to risk-based (0.34 years) and random surveillance (0.78 years, Table 4). Similar to the other scenarios, detection failure was highest for heavy risk-based surveillance (7.70%) compared to risk-based (0.10%) and random surveillance (0.00%, Table 4). Similarly, the survey probability of detection at Year 1 was also highest for risk-based surveillance (0.80) followed by heavy risk-based (0.74) and random surveillance (0.58, Table 4, Fig. 10C).

Table 4. Model outputs from empirically derived risk distributions.

Model Run	Surveillance Scenario	Detection Time (Years)		Detection Failure (%)	Survey Probability of Detection at Time (Years)			
		Median Detection Time	Interquartile Range		1	5	10	30
Scenario A	**Random**	0.93	1.47	0.00	0.53	0.98	1.00	1.00
Shipping Risk Weighted	**Risk-Based**	0.25	0.47	0.00	0.90	0.99	1.00	1.00
	Heavy Risk-Based	0.37	0.94	4.40	0.70	0.89	0.93	0.96
Scenario B	**Random**	0.95	1.36	0.00	0.52	0.98	1.00	1.00
Spread Risk Weighted	**Risk-Based**	0.34	0.66	0.30	0.81	0.97	0.99	1.00
	Heavy Risk-Based	0.52	1.85	8.10	0.56	0.83	0.87	0.92
Scenario C	**Random**	0.78	1.33	0.00	0.58	0.99	1.00	1.00
Impact Risk Weighted	**Risk-Based**	0.34	0.68	0.10	0.80	0.96	0.98	1.00
	Heavy Risk-Based	0.27	0.63	7.70	0.74	0.86	0.89	

Discussion

Variation in the risk of NIS introduction and establishment between survey sites (NIS risk distribution) and the level of risk focus which the surveillance strategy adopts have important implications for optimising NIS detection. This study shows that the relative performance of surveillance strategies changes with NIS risk distributions derived both theoretically and with model estimates from the SPT model. Generally, under risk- and heavy risk-based surveillance, time to detection was shorter and survey probability of detection was greater than random surveillance for sites with random or exponential NIS risk distributions. For example, assuming an exponential risk distribution, risk-based surveillance detected NIS twice as fast as random surveillance. Risk-based surveillance also had a substantially higher survey probability of detection after 1 year compared to random and heavy risk-based surveillance. This observation generally held for risk and heavy risk-based surveillance for the marine NIS risk distributions derived from the SPT model, with risk-based and heavy risk-based surveillance having the shortest detection times and highest detection probabilities after 1 year across all three scenarios. This is comparable to the performance between risk-based and random surveillance in other studies (Parnell et al. 2014; Martinetti and Soubeyrand 2019; Mastin et al. 2020). There was, however, a trade-off between short detection time and detection failure in some risk-based simulations, particularly for heavy risk-based surveillance for both theoretical and SPT model-derived risk distributions. Heavy risk-based surveillance over-samples the highest risk sites, rapidly detecting NIS at high-risk sites, but failing to detect NIS at lower risk sites, which, while less likely, can occur. This surveillance method could, therefore, allow NIS to spread undetected at lower risk sites. Heavy risk-based surveillance also had a poor survey probability of detection compared to risk-based surveillance at 1 year and had smaller increases over the long term for both theoretical and SPT model-derived risk distributions. However, trade-offs depend on the risk distribution so that it is conceivable that heavy risk-based surveillance may be advantageous at certain risk distributions. For example, heavy risk-based surveillance performed relatively well for the bimodal risk distribution from the SPT model associated with Scenario C (Impact Risk Weighted). One advantage of the simulator is that the effect of any risk distribution can be tested, which was showcased by the SPT model-derived distributions used here.

An over-emphasis on the highest risk sites can, in some instances, lead to a failure to detect NIS with little benefit in terms of reduced detection time. Concentrating on a small number of sites has also been shown to be detrimental by a spatially-explicit plant pathogen model (Mastin et al. 2020). Inclusion of detection dynamics which varied with NIS abundance had little effect on overall detection time for an exponential risk distribution, suggesting conclusions around the optimum risk focus to reduce the detection time were robust to changes in method detection probability over time. Comparably, probability of detection for heavy risk-based surveillance was similar to risk-based surveillance at year 1, but performed relatively poorly to risk-based and then random surveillance at longer time periods, with the exact relationship changing with the detection dynamic. This suggests the relative performance of different surveillance strategies can vary over time. Overall, for the most likely risk distributions, risk-based surveillance provides the best balance between short detection rates, success in detecting NIS and high probability of detection over the short term.

The model assumes that the risk distribution of sites can be effectively quantified to guide surveillance. Typically, this information is uncertain, particularly for newly-recorded and poorly-understood NIS. However, there is often enough data for effective survey design (Koch et al. 2020). Site introduction risk is often driven by assessment of introduction pathway activity level (e.g. Tidbury et al. 2016, 2021). However, for many NIS, attribution of introduction to a particular pathway with certainty is not possible; rather the link between a species and introduction pathway is based on species biological traits, historical introduction events or introduction events in very different locations, as well as expert opinion. Site establishment risk assessment involves consideration of many factors including environmental suitability (Copp et al. 2016 Davidson et al. 2017). In addition, if 'risk' is based on impact on native species, spread between sites or a combination of factors (e.g. in the SPT model-derived risk distributions used here), then there is a requirement to consider other factors. Impact risk factors may include NIS life history traits and potential NIS impacts on native species via predation, competition, transmission of disease, as well as site-specific factors, such as the presence of vulnerable or protected species (Blackburn et al. 2014). However, translating NIS occurrence into impact is challenging and understanding of NIS impact is a significant evidence gap (Crystal-Ornelas and Lockwood 2020). It should be noted that further work is required to fully integrate this broader concept of risk into the surveillance simulator. When applying the simulator to SPT model-derived site risk distributions, we assumed that the combined risk of introduction, establishment, spread and impact would influence the occurrence of NIS. However, factors driving NIS risk of impact are likely to differ from, or lack spatial correlation with, those affecting introduction and establishment. To better implement this in the model, the option to define different distributions for the risk of introduction and establishment and the combined risk of other factors, on which basis sites are sampled, is required. More generally, the fact that the optimal NIS surveillance strategy varied with risk distribution highlights the importance of improving our understanding of NIS risk and the factors which influence it, whether these be introduction, establishment, impact or potential for spread, at different sites.

Sensitivity and elasticity analyses were performed in parallel to allow both the absolute effect of parameter changes on outputs to be examined and the impact of parameter changes to be compared across parameters. These analyses highlighted the key factors which should be considered when designing a surveillance strategy and the utility of the simulator to explore different approaches. For an exponential risk distribution, the number of seed sites, mean visit rate and method detection probability had the strongest effect on detection time, whereas the effects of all parameters on detection failure were more variable. Differential responses of surveillance strategies occurred between risk distributions. When seed site numbers were greater than one, heavy risk-based surveillance performed poorly for time to detection and detection failure, relative to risk-based and random surveillance. It is possible for NIS to establish at multiple sites early in an invasion (Herborg et al. 2003), such that risk-based surveillance would be effective at ensuring NIS detection over multiple sites. The analyses indicated the minimum desirable visit rate was once per year because time to detection and detection failure increased substantially at lower visit rates. At one or more visits per year, heavy risk-based surveillance generally had the most variable detection times and highest levels of detection failure, suggesting that risk-based surveillance would be more efficient at visit rates greater than one. The sensitivity and elasticity analyses also allow the impact of changes in sampling effort, potentially linked to funding/resource changes, to be determined. For example, a fall in visit rate from once per year to once every two years, would increase the median detection time from 0.3 to 0.7 years and increase detection failure from 0.3% to 1.1%. Method detection probabilities below 0.5 were associated with long times to detection and high detection failures for random and risk-based surveillance, suggesting that this was the minimum desirable method detection probability. However, at or below a method detection probability of 0.3, heavy risk-based surveillance had the shortest detection times, suggesting heavy risk-based surveillance may be advantageous with low detection probability methods. The need for greater focus on a small number of high-risk sites when using low detection probability methods has been shown in spatially-explicit models (Mastin et al. 2020). The details of sampling methods at individual sites, for example, number of sampling replicates, were not modelled in detail here, but variations in protocols and the method used are likely to change the probability of detection. Detection probability can be calculated statistically (MacKenzie et al. 2002) and high detection probability for marine NIS is achievable using eDNA methods (Fonseca et al. 2023). Overall, these results support the assertion that risk-based surveillance would outperform heavy risk-based surveillance. However, this is conditional on the risk distribution, the default parameters and the outcomes which are most important to the survey objectives. These can be varied to be most suitable to the purpose of the surveillance programme using the simulator.

The simulator is an efficient and valuable tool for planning surveillance programmes. While outside the scope of the current study, several opportunities exist for further development into the future. For example, a spatially-explicit model, incorporating NIS distribution and spread of NIS over time, would allow study of how the spatial distribution of sampled sites influences the utility of risk-based surveillance. Spatially-explicit models of pathogen entry and spread have shown that spatial correlations in risk can make it suboptimal to focus on the highest risk sites and a geographic spread of resources to cover all areas of risk is desirable (Mastin et al. 2020). The rationale for not including a spatially-explicit model of NIS spread was that this model is focused on supporting early warning monitoring, when a NIS is likely only present at a small number of sites (but see Herborg et al. (2003)). This is valid given the likelihood of NIS eradication or successful local management is increased when a NIS is detected quickly after introduction, when the population is localised within a small area (Simberloff 2001; Anderson 2005; Olenin et al. 2011). The risk of spread may differ to the risk of introduction, with potentially different risk factors and should be calculated independently (Oidtmann et al. 2011; Thrush et al. 2017). This study focuses on exploration of the impact of overall risk distribution on efficacy of surveillance under different risk-based sampling designs. The simulator allows both the introduction and establishment risk to be defined (and can be extended to include other risk components such as impact and spread). In our illustrative application, we assume that sites have the same risk in terms of introduction and establishment. However, differences may be expected which, depending on the specific scenario, could impact the conclusion as to which sampling strategy would be optimal. Extending functionality of the temporal component to include different months or seasons would allow incorporation of temporal variation in NIS risk and detection probability. NIS risk may change temporally with seasons (Faulkner et al. 2016) or socio-economic changes impacting risk pathways, for example, changes in shipping activity (Ojaveer et al. 2017). Detection probability may vary over time with a species life cycle and sampling should be targeted to periods where detection is most likely (Harvey et al. 2009), although this is challenging when designing a multi-species detection programme if species differ in their life-history and are associated with different pathways. In this study, it was assumed that only a single species was being sampled. Although this is not unrealistic for a targeted species-specific surveillance programme (Gust and Inglis 2006), NIS surveillance campaigns may also be multi-species, particularly as eDNA methods allow the targeting of multiple species of interest from the same sample via metabarcoding using generic primers or multiplex PCR (Fonseca et al. 2023). Incorporation of multiple introduction and establishment of risk distributions into the simulator will allow output for multiple species to be created, enabling exploration as to whether risk-based approaches, based on average multi-species NIS risks, are appropriate for sampling all species. Finally, the current study is only a theoretical framework and would benefit from further validation. Although we have provided a first step in this direction by parameterising the model with model-derived risk distributions for marine NIS around the UK coastline, further work is required using species occurrence data to determine empirical risk distributions and detailed statistical analysis of model outputs would allow full testing of the robustness of this model.

Conclusion

In conclusion, variation in the risk of NIS introduction and establishment and the level of risk focus of surveillance programmes interact to influence the efficacy of surveillance regimes. Assuming a skewed risk distribution, an over-emphasis on sampling high risk sites will be outperformed by a more balanced focus on high as well as lower risk sites. However, the optimum approach is dependent on the NIS risk distribution. The relative risk of sites and other survey parameters, has to be quantified for the optimal surveillance design to be selected. Overall, this study highlights the utility of model-based simulators to guide decision-making in the design of the surveillance of NIS and other hazards.

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Additional information

Conflict of interest

The authors have declared that no competing interests exist.

Ethical statement

The authors see no ethical implications of this research. All data created by the simulator was synthetic. For the data used by the SPT model, open source data or data available on request was used. No personal data was used in this study.

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Author contributions

Conceptualisation: HT. Methodology: HT, NT, TG, RM, MT, IM. Software: RM, TG, NT. Investigation: TG, RM, MT, IM. Writing - Original draft: TG. Writing - Review and Editing: TG, HT, RM, MT, IM. Visualisation: TG, RM, IM. Supervision: HT. Funding Acquisition: HT.

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Data availability

The simulator code is located in Cefas' reproducible research account on GitHub in the "C8389-NIS-surveillance-simulator" repository (https://github.com/CefasRepRes/C8389-NIS-surveillance-simulator). The data and outputs, including example mark-down files from theoretical and SPT model runs used in this publication, are available via Zenodo (https://zenodo.org/doi/10.5281/zenodo.10355963). For the SPT model runs, the adjusted code is included along with the data.

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Supplementary material 1

Abundance models, exponential growth model, logistic growth model, elasticity analysis, table and figure

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Data type: docx

Explanation note: Abundance Models; Exponential Growth Model; Logistic Growth Model; Elasticity Analysis; **fig. S1.** Spatial representation of the site risk scores output from the Site Prioritisation Tool; **table S1.** Data sources for each parameter used in the Site Prioritisation Tool.

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