Ecological Economics 247 (2026) 109053

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

ANALYSIS

Bioeconomic optimization of surveillance for detecting and eradicating quarantine forest pests and pathogens

Benno Andreas Augustinus [a,*], Rebecca Suzanne Epanchin-Niell [b], Valentin Queloz [a], Eckehard Gustav Brockerhoff [a]

[a] Swiss Federal Institute for Forest, Snow and Landscape Research WSL, Forest Health and Biotic Interactions, Zürcherstrasse 111, 8903 Birmensdorf, Switzerland
[b] University of Maryland, Department of Agricultural and Resource Economics, 2200 Symons Hall, College Park, MD 20742-5535, USA

ARTICLE INFO

Keywords:
Asian longhorn beetle
Bioeconomic model
Biological invasions
Emerald ash borer
Invasive pests
Risk-based surveillance

ABSTRACT

Early detection is critical for effective responses to incursions of invasive species, making surveillance programs for potential invaders essential. As resources are limited, surveillance activities must be as effective and efficient as possible. We used a bioeconomic model to develop an optimal surveillance programme for six priority quarantine and two quarantine forest pests in Switzerland. We aimed to minimize costs of management (i.e., surveillance and eradication) for species that are mandated for eradication based on collaborative biosecurity agreements with the European Union. The model determined optimal surveillance effort, accounting for differences in introduction likelihood, detectability, and spread rates, across pests and locales. The model suggested a likely underestimate of optimal investment of 1,187,000 CHF per year for surveillance using visual surveys and insect or spore traps, depending on the target species. Survey recommendations varied across locales and pest types with the greatest surveillance effort for *Agrilus planipennis*, *Bursaphelenchus xylophilus*, *Dendrolimus sibiricus*, *Fusarium circinatum*, and *Phytophthora ramorum*. Surveillance trapping would be economically irrational for two pests (*Anoplophora glabripennis*, *A. chinensis*), primarily because of high probability of background detection by the public, and low efficacy of formal surveys and low spread rates. The model indicates where in Switzerland surveillance yields the highest economic return, with greater survey effort in areas with highest introduction risk and for species with low likelihoods of public detection and fast spread rates. The model indicates that the use of more effective trapping methods and an increase in public awareness could reduce the needed investments in formal surveillance activities.

1. Introduction

Invasive forest pests can have devastating effects on forest health worldwide (Brockerhoff and Liebhold, 2017; Nahrung and Carnegie, 2020; Ramsfield et al., 2016), damaging or killing trees and reducing ecosystem services provided by forests (Freer-Smith and Webber, 2017; Raffa et al., 2023). These losses in ecosystem services, which come with high societal costs (Warziniack et al., 2021), are expected to increase as introductions of non-native species continue to increase with ongoing globalization (Seebens et al., 2021). Once an invasive forest pest arrives and establishes in a novel environment, eradication may be undertaken to reduce the detrimental effects of the pests early on in the invasion process (Liebhold and Kean, 2019). The methods and success of eradication efforts differ across target organisms and invasion conditions (Liebhold and Kean, 2019). Generally, smaller outbreaks have a higher probability of eradication success and are less costly than outbreaks that have spread across larger areas (Tobin et al., 2014). Therefore, detecting invasive species as early as possible in the invasion process is critical and serves as a primary motivation for phytosanitary agencies in many countries to invest in surveillance programs for the early detection of new pest introductions (Brockerhoff et al., 2010).

Surveillance for detecting new invasive species incursions is often carried out by national plant protection organizations (NPPOs) with limited resources, making cost-efficient design a key criterion (Epanchin-Niell, 2017). These programs are typically implemented at a national or regional level, across heterogeneous landscapes, and potentially for several target organisms. This involves trade-offs among species and locations, where the net benefits of different options depend

---

* Corresponding author.
E-mail addresses: Benno.augustinus@wsl.ch (B.A. Augustinus), Epanchin@umd.edu (R.S. Epanchin-Niell), Valentin.queloz@wsl.ch (V. Queloz), Eckehard.brockerhoff@wsl.ch (E.G. Brockerhoff).

https://doi.org/10.1016/j.ecolecon.2026.109053
Received 22 October 2025; Received in revised form 17 March 2026; Accepted 18 April 2026

on a range of species-specific and location-specific factors, such as introduction probabilities and spread rates, as well as survey and control costs (Epanchin-Niell et al., 2012; Welsh et al., 2021). Bioeconomic models can help explore trade-offs in resource allocation options for early detection of pests (Epanchin-Niell, 2020; Epanchin-Niell, 2017; Mastin et al., 2020; Nguyen et al., 2024; Welsh et al., 2021).

Here, we demonstrate a bioeconomic optimization of investment in a surveillance program aimed at the early detection of non-native invasive pests using the case of the Swiss territory surveillance for multiple quarantine pests affecting forests. To limit the spread and damage caused by particularly dangerous harmful organisms in the forest, Switzerland participates in international plant health measures. Within the framework of a bilateral agricultural agreement with the European Union (EU), Switzerland ensures the equivalence of phytosanitary regulations to enable the free movement of goods with the EU. The Swiss phytosanitary legislation therefore contains equivalent provisions to those of EU law. It is legally mandated that Switzerland conducts annual surveillance for six priority quarantine forest pests (Pflanzengesundheitsverordnung, PGesV, 2018; PGesV-WBF-UVEK, 2019). In addition, this survey program also includes two additional quarantine pests (Table 1, Table S1) (VpM-BAFU, 2017). The program specifies that upon detection of any quarantine pest, the initial response must be eradication. Only if eradication becomes infeasible shall the mandated course of action switch to containment (Pflanzengesundheitsverordnung, PGesV, 2018; PGesV-WBF-UVEK, 2019). To enable earlier detection of these species and hence lower costs and higher likelihood of success of attempted eradication if a population were to be detected, Switzerland's NPPO decided to implement a risk-based surveillance program. Risk-based surveillance in this context can be defined as surveillance that prioritizes monitoring efforts based on both the likelihood of a pest occurrence and its potential impact. The quarantine species can be surveyed using searches for visual symptoms, as well as spore and insect traps in selected plots. Some survey plots can target several organisms at once if the species share the same host tree species.

Because eradication is mandated for these quarantine pests, regardless of the specific damages they might cause within Switzerland, we here focus on designing a surveillance program in a way that minimizes anticipated survey and eradication costs across these species. Specifically, our approach accounts for the increasing expected costs of eradication with increasing pest incursion size, such that earlier detection can reduce the expected costs borne by authorities in the case of pest establishment. Our approach builds on past studies aimed at optimizing surveillance activities for the management of invasive pests. For example, prior work has focused on minimizing survey and eradication costs for a single species (Epanchin-Niell et al., 2012; Venette et al., 2010; Yemshanov et al., 2019) or optimizing surveys and control responses across generalized pest types (Epanchin-Niell et al., 2014). Spatial distribution of resource allocation for survey and control of invasive pests over low- and high-risk locations has been explored by Horie et al. (2013), Kompas et al. (2023), and Mastin et al. (2020). Nguyen et al. (2024) compared efficacy of surveillance with specific and generalist lures for traps for bark – and wood-boring beetles. We built on this prior literature to address a specific policy problem faced by Switzerland and other locales (i.e., mandated attempted eradication), with application to specific policy-relevant pests. The pests surveyed are diverse: five species of insects (wood-or bark-boring beetles and a lepidopteran defoliator), and three tree pathogens (a nematode, a fungus, and an oomycete) (Table 1, Table S1). We account for differences in introduction risk across species and the heterogeneity of the landscape (e.g., host species composition, human population density), as well as differences in detectability by formal surveys and by the public (i.e., passive surveillance). We leveraged diverse data sources to parameterise a bioeconomic model. The results of the model were used to design a species surveillance program on a national scale (Augustinus et al., 2022).

Table 1
Overview of forest pest species surveyed in the described program. 'prioQO' are priority quarantine organisms 'QO' are quarantine organisms (Pflanzengesundheitsverordnung, PGesV, 2018; PGesV-WBF-UVEK, 2019).

Species	Type
Agrilus anxius Gory, bronze birch borer (BBB)	Coleoptera, Buprestidae; phloem- and wood boring larvae (prioQO)
Agrilus planipennis Fairmaire, emerald ash borer (EAB)	Coleoptera, Buprestidae; phloem- and wood-boring larvae (prioQO)
Anoplophora glabripennis Motschulsky, Asian longhorn beetle (ALB)	Coleoptera, Cerambycidae, wood boring larvae (prioQO)
Anoplophora chinensis Forster, citrus longhorn beetle (CLB)	Coleoptera, Cerambycidae, wood boring larvae (prioQO)
Bursaphelenchus xylophilus Steiner&Buhrer, pine wood nematode (PWN)	Aphelenchida, Parasitaphelenchidae, plant parasitic nematode (prioQO)
Dendrolimus sibiricus Tschetverikov, Siberian silkmoth (SSM)	Lepidoptera, Lasiocampidae, needle-feeding larvae (prioQO)
Fusarium circinatum Nirenberg&O'Donnell, pine pitch canker (PPC)	Hypocreales, Nectriaceae, pathogenic fungus (QO)
Phytophthora ramorum Werres, De Cock & Man in't Veld, sudden oak death (SOD)	Pythiales, Pythiaceae, oomycete plant pathogen (QO)

The bioeconomic model was used to answer the following three questions:

- What is an optimal level of yearly survey investment overall?
- How should surveillance be partitioned across target organisms?
- Where (at which locations) should surveillance efforts be prioritised?

2. Material and methods

2.1. Target species

Switzerland shares a common phytosanitary area with the European Union and has mandated legal obligations to survey yearly for priority quarantine organisms ("prioQOs") (Pflanzengesundheitsverordnung, PGesV, 2018; PGesV-WBF-UVEK, 2019). Beyond the six species on the priority quarantine list, the Federal Office of the Environment includes two quarantine organisms ("QOs") (VpM-BAFU, 2017) for annual surveillance (see Table 1).

2.2. Model

2.2.1. Overview of the model

The model used in this work (Fig. 1) was adapted from the decision support tool CESAT ('Cost-Effective Surveillance Allocation Tool') which was developed under an agreement with the United States Department of Agriculture, Animal & Plant Health Inspection Service (Epanchin-Niell, 2020). The algorithm underlying CESAT identifies cost-effective resource allocation using information on pests' introduction and establishment probabilities, natural dispersal rates, eradication costs, and survey costs and sensitivity (Epanchin-Niell et al., 2014; Epanchin-Niell et al., 2012). The algorithm is based on a mechanistic model of pest population establishment, growth, detection, and control, and allocates resources across pests and sites to provide the greatest reduction in long term costs and damages by detecting invasions earlier when they are smaller and less costly to manage (Epanchin-Niell, 2020; Tobin et al., 2014). The original CESAT model assumed that once a pest was detected, decision-makers would optimally decide whether to eradicate the population, slow its spread, or forego control activities, with the value of surveys arising from how earlier detection of pests (through deployment of surveys) reduces long term invasion management costs (Epanchin-Niell, 2020).

In contrast to the original context for the CESAT model, management response for detected quarantine pests in Switzerland is determined by regulatory guidance, as opposed to cost-Optimization. Eradication effort is mandated. Thus, we adapted the model to evaluate the optimal

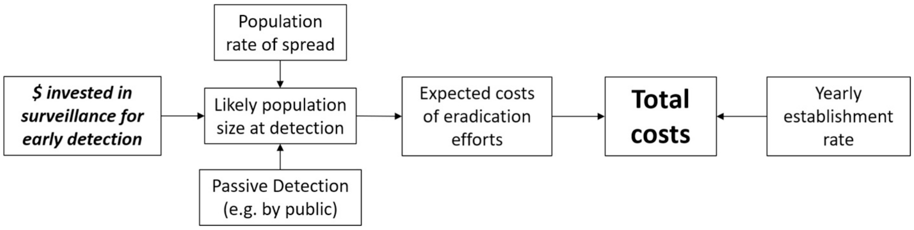

Fig. 1. Schematic overview of the model structure developed and employed in this study. Surveillance investment across sites and species is optimized to minimize total expected costs.

number of survey plots and locations for each target organism based on the goal of minimizing the expected costs of survey and eradication efforts for new incursions.

Importantly, for each organism, the benefits of surveys depend on the probability of establishment (Fig. 1) because this determines the likelihood that an incursion is present that demands detection. Following establishment, a pest spreads (e.g., through natural dispersal and human-assisted spread), occupying a greater area in each subsequent year, which we represent using an age class model, specifying the areal size of the invasion in each year following establishment (Fig. 1). The likelihood of detection in each year depends on the detection effort and efficacy, as well as the size of the infested area. We assume that a pest incursion can be detected by passive surveillance (e.g., detection by the public or citizen science) or through formal survey effort. The model, in turn, optimizes the level of formal survey effort for each species and across locales to minimize the combined costs of surveillance and eradication over time (Fig. 1).

2.3. *Model details*

We describe the mathematical details of the model next. We begin by describing the model for detecting a single species and a single site.

2.3.1. *Population establishment, growth and detection for a single species and site*

We assume an annual probability $e(t)$ of the pest arriving and establishing at the focal site in each time period t. Following establishment, the population grows and spreads according to a growth function, such that in the absence of any control measures the population occupies an area $A(a)$, dependent on its age a. In each time period, the population may be detected by deployed survey locations or non-survey methods (e.g. the public). Once detected, eradication efforts are applied, at a cost that increases with the population's size, $C_e(A(a))$.

Population dynamics are modelled using an age-class model, with population age classes $a \in \{1, 2, \ldots, a_{max}\}$. The expected probability of an undetected population of age a being present at the focal site at time t is represented as $x^a(t)$, which always equals the probability of establishment for age class $a = 1$. All populations of age class a then transition to age class $a + 1$ in the following time period if undetected, and new populations establish that are age 1. Thus, for each time period t, the age class model for undetected populations is specified as:

$$x^1(t+1) = e(t)\ x^a(t+1) = x^{a-1}(t)(1 - p_{detect}(a-1, I)) \text{ for } a = 2, \ldots, a_{max} \tag{1}$$

where $p_{detect}(a,I)$ is the probability of detecting a population of age a given an investment I in pest detection surveys.

The detection probability $p_{detect}(a,I)$ increases with survey investment I, the size of the population $A(a)$ (measured as areal extent), survey sensitivity y_{surv}, and the effectiveness of detection by the public y_{public}. Detection by a survey requires both that a survey location spatially intersects a population and that the population is successfully detected given such an intersection. We assume that, conditional on spatial overlap, a survey detects a population with probability y_{surv}, reflecting species- and survey-specific detectability. Analogous to Epanchin-Niell et al. (2012, 2014) survey placement within susceptible habitat is assumed to be random with respect to the location of each established population, through one or both being random in space. The probability that a given population is detected by a survey (i.e., at least one survey location successfully detects the population) can therefore be estimated as a binomial distribution, where the number of trials equals the number of deployed survey locations (investment level I divided by the cost per survey, c_s). The probability of success for each trial equals the probability of spatial intersection ($A(a)/M$, or 1 if the population exceeds the site area) multiplied by the conditional detection probability y_{surv}. We assume that detection by the public follows a similar probabilistic process as detection by a survey, where the probability of detection increases with the size of the population and the sensitivity of public detection, but public detection can occur across the site, as opposed to being limited to specific survey locations[1]. We define y_{public} as the probability that a population of a unit size will be detected by the public in a single time period, such that the probability $p_{detect}(a,I)$ that a population present at a site is detected by a survey or the public in a single time period equals $1 - (1 - y_{surv}A(a)/M)^{(I/Cs)}(1 - y_{public})^{A(a)}$ for populations whose area is less than or equal to the area M of the focal site, and equals $1 - (1 - y_{surv})^{(I/Cs)}(1 - y_{public})^{M}$ for populations larger than the focal, surveyed site. We assume that $p_{detect}(a_{max}, I) = 1$, such that any previously undetected populations are detected when they reach the maximum age.

2.3.2. *Calculating total invasion management costs*

Based on this model, the net present value of expected costs from invasion establishment, detection, and management can be determined dependent on the level of investment in pest detection surveys. We consider application of a constant surveillance strategy (i.e., a constant investment level) over a fixed time horizon (T) and evaluate the total net present value of costs from all populations that establish during the surveillance program and from populations that were present on the landscape (but not yet detected) at the start of the program.

We assume that, prior to the start of the surveillance program, populations had an annual probability of establishment $e(t)$ and probability of detection $p_{detect}(a,0)$. Thus, the expected number of undetected populations present on the landscape at the start of the program ($t = 1$) can be calculated by iteratively solving Eq. (1) beginning at $t = -T_{past}$ until $t = 1$, where T_{past} is the oldest population considered for detection at the start of the surveillance program.

Recognizing that $x^a(t)$ is a function of survey investment I, we can rewrite it as $x^a(t,I)$ and calculate the net present value of total expected eradication costs (with discount rate δ) for a survey program with annual investment I and lasting T years:

---

[1] In past work (e.g., Epanchin-Niell et al., 2012, 2014), we addressed the role of detection by the public by assuming that pest populations would be detected with certainty after a fixed number of years. However, there is large uncertainty and variability in the likelihood of detection by the public, which depends on the size of the population, the characteristics of the pest, and even the characteristics of the site and the people living and working in the area.

$$TC^{Erad}(I) = \sum\nolimits_{t=1}^{T}\sum\nolimits_{a=1}^{a_{max}} x^a(t,I)p_{detect}(a,I)C_e(A(a))(1+\delta)^{1-t} + \sum\nolimits_{t=T+1}^{T+a_{max}-1}\sum\nolimits_{a=t-T+1}^{a_{max}} x^a(t,0)p_{detect}(a,0)C_e(A(a))(1+\delta)^{1-t} \tag{2}$$

The first summations (over time and age class) capture the eradication costs of detected populations over the duration of the survey program, while the second summations account for the eradication costs from established populations that have not yet been detected at the end of the survey program.

The costs of surveys over the program time horizon T are calculated as:

$$TC^{Su}(I) = \sum\nolimits_{t=1}^{T} I(1+\delta)^{1-t} \tag{3}$$

And total invasion management costs are:

$$\mathrm{TC} = TC^{Su}(I) + TC^{Erad}(I) \tag{4}$$

2.3.3. *Consideration of multiple pests and sites*

To optimize surveillance for multiple pests and regions, we expand the model to sum expected costs (Eq. 4) across potential invaders $p \in P$ and sites $s \in S$. We also allow that multiple pests can be targeted by a single survey type tr, such that the benefits from that survey depend on the expected reduction in eradication costs across species detected by that survey type.

The overall objective of the resource allocation decision is to identify the optimal investment $I_{tr,s}$ in each survey type tr at site s to minimize costs across all pests and sites, including surveillance and eradication costs. All parameters and survey investments (I) can be indexed by species or trap type and site. $TC_{p,s}^{Erad}(I_{tr,s})$ is the present value of total

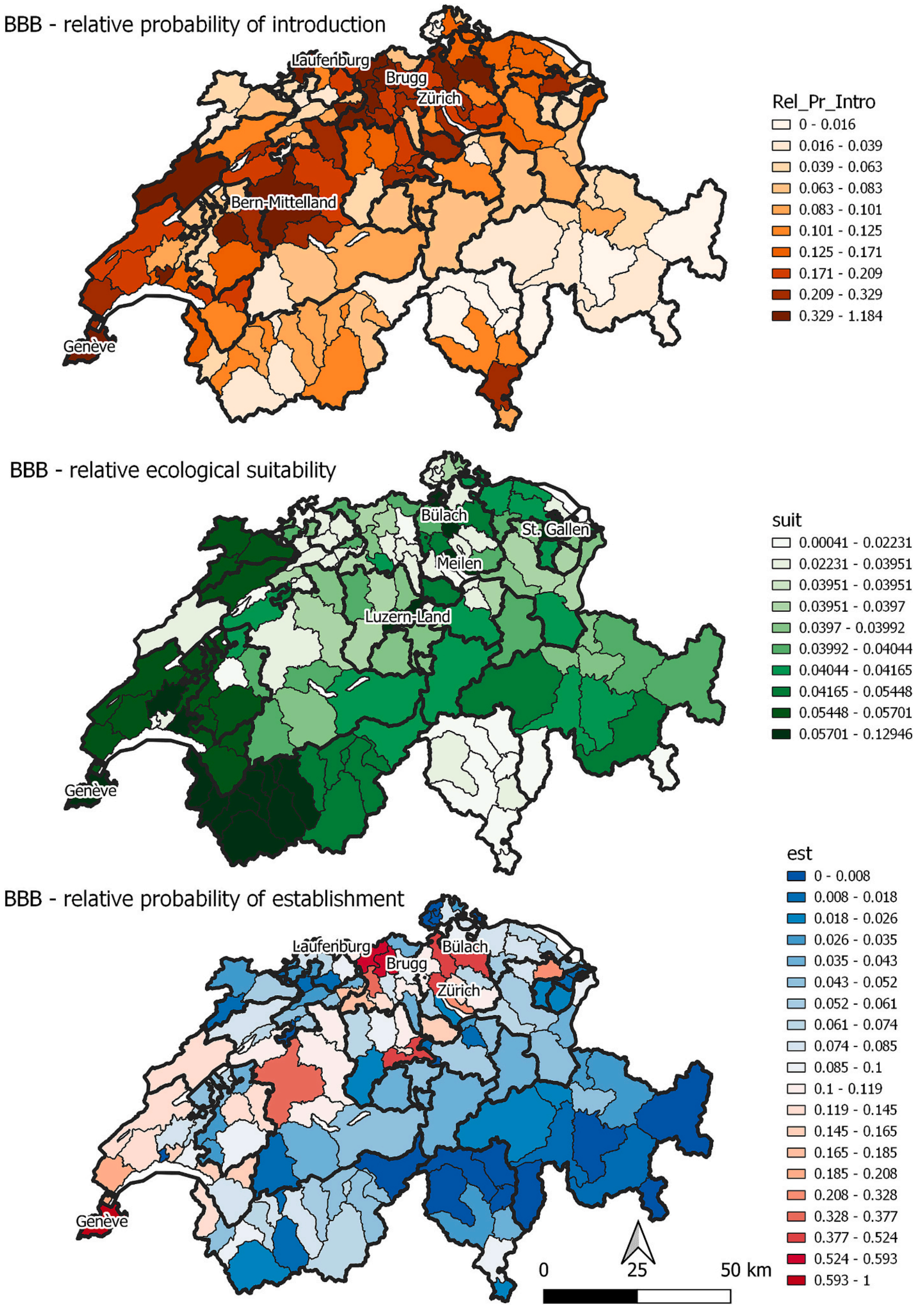

Fig. 2. Example of spatially distributed values for different parameters for BBB. The relative probability of introduction ('Rel_Pr_Intro)') and the relative ecological suitability ('suit') combined result in the relative probability of establishment ('est'). In the maps, the five districts with the highest values per parameter are named.

expected eradication costs for pest p and site s given investment $I_{tr,s}$, following eq. 2. Thus, across all sites, trap types, and species, the total costs is:

$$TC = \sum_{s\in S}\sum_{tr\in Tr}\left(TC^{Su}\left(I_{tr,s}\right) + \sum_{p\in P_{tr}} TC^{Erad}_{p,s}\left(I_{tr,s}\right)\right) \tag{5}$$

The surveillance optimization problem finds the level of investment in traps at each site for each pest type that minimizes the total expected costs from surveillance and eradication (Eq. 5).

The expected net present benefits of implementing the optimal surveillance program or any other potential surveillance program (defined by investment levels $I_{tr,s}$) relative to doing nothing, is calculated as the difference in total costs under the specified program and when all $I_{tr,s} = 0$.

To solve for the optimal survey investments in the absence of a budget constraint, one can simply identify the surveillance investment level that maximizes net benefits for each site and survey type individually, because the optimal survey investment for each survey type and site is independent of optimal levels at other sites or for other survey types, conditional on an objective function that accounts for expected invasion damages and eradication costs across all sites. However, when resources are constrained, the optimal survey investments are dependent across sites and trap types, with the optimal investment equalizing the marginal benefits of survey investments across sites and traps, such that reallocation of resources from one site or trap to another cannot improve outcomes.

To solve for optimal survey investments, we calculate the expected marginal benefits of investments for each site by survey type combination for a range of investment levels, and then we use a greedy algorithm to allocate investments to sites by trap combinations in order of decreasing marginal benefits of investment, until resources are fully allocated (Fig. 2). We calculate the marginal benefits as the reduction in expected eradication costs from an additional (marginal) investment i in survey type tr at site s, where expected costs reflect invasion outcomes throughout Switzerland rather than only within the focal site:

$$MB = TC^{Erad}{}_{tr,s}\left(I_{tr,s}\right) - TC^{Erad}{}_{tr,s}\left(I_{tr,s} + i\right) \tag{6}$$

In the absence of a budget constraint, a manager would invest in surveys at a site to the level where the marginal benefit of additional investment just equals the cost of the additional investment. This investment level maximizes the total net benefits (benefits of the investment minus the costs of investment).

2.4. Model parameterization

2.4.1. Geographical scope and context

Our analyses focus on nationwide surveys across Switzerland. Located in central Europe, Switzerland is landlocked with the Alps as natural internal barrier and the Jura mountains in the Northeast. Ranging in elevation from 193 to 4634 m AMSL it is divided into 26 cantons, subdivided into districts, constituencies, or regions, which again are subdivided into municipalities. We used the divisions of cantons (districts, constituencies, or regions; henceforth 'districts') as our regional unit of analysis (i.e., sites or districts) to capture spatial heterogeneity in arrival probabilities and habitat suitability. Our study covers $D = 143$ total districts.

Because most initial establishments of alien invasive forest insect pests are found in urban or peri-urban environments and not in forests or rural areas (Branco et al., 2019), we used data from the Swiss land use statistics (Bundesamt für Statistik, 2018) to estimate trappable areal extent within each district. These detailed land use data, provided by the Swiss Federal Office for Statistics, delineate the four land use/cover categories: developed (urban and traffic infrastructure), agricultural, forested, and unproductive (Bundesamt für Statistik, 2018). We used the amount of developed area (km^2) per district to represent the size of the potential survey area in each district, as surveys will be conducted in these areas.

2.4.2. Probability of introduction

Essential to determining the optimal allocation of survey effort is information about the probability of establishment at a site, which depends on the probability of introduction (i.e., arrival) and the suitability of sites for each organism. For our analysis we assume a constant establishment probability e over time but allow the probability to differ across species and sites. We estimate a metric of relative probability of introduction ('Rel_Pr_Intro') for district $d \in D$, using information on two primary introduction pathways, people and trade, using the following formula:

$$Rel\_Pr\_Intro_d = \left(\frac{Inhabitants_d}{max_D(\text{Inhabitats})} + \frac{Imports\ of\ relevant\ goods_d}{max_D(Imports\ of\ relevant\ goods)}\right) \tag{7}$$

Here, 'imports of relevant goods' refers to the quantity of vector materials (like wood-packaging, bark products, firewood, or live plants) originating from countries where the organism occurs and arriving in district d (as measured by subtracting the net from the gross weight of goods in kg). These data (from 2015 to 2021) were obtained from Swiss Customs and summarised per district. 'Inhabitants' refers to district population, according to the, 2019 census. Both component metrics (i.e., the number of inhabitants and imports of relevant goods for the respective organism) were scaled by dividing each by the district maximum, assigning the maximum value of that measure to be '1'. This ensured both variables were scaled to be equally important, capturing the roles of imports and the additional movement of organisms by people.

At the time of modelling, ALB and CLB had established populations near the Swiss border in France, Germany, and Italy (Branco et al., 2021), posing additional introduction risk. For these species we included an additional introduction risk measure based on road distance to nearby active outbreaks, accounting for hitchhiking pathways like firewood (Nardi et al., 2025). Distance from each outbreak to the capital (or, if not available, to the largest city) of the respective districts was measured using the ORS tools plugin in QGIS v3.16 (QGIS Development Team, 2020). Distances greater than 300 km were capped, corresponding to Eurostat's (the statistical office of the European Union) definition of the maximum daily short-distance mobility. Recognizing that introduction risk declines with distance from the source of an organism and that the vast majority of trips are within the maximum daily short-distance mobility, we assumed an inverse logarithmic relation between distance and likelihood of introduction:

$$Invlog\_dist = \frac{1}{log(Distance\ in\ km)} - \frac{1}{log(300)} \tag{8}$$

Afterwards, the Invlog_dist was scaled to a maximum value of 1. With this approach, established populations that are further than 300 km from a district are not given any introduction risk weight, while closer populations have higher introduction risk values. For ALB and CLB, the overall relative introduction probability ('Rel_Pr_Intro') was thus calculated as follows:

$$Rel\_Pr\_Intro_d = \left(\frac{Inhabitants_d}{\text{max}_D(\text{Inhabitats})} + \frac{Imports\ of\ relevant\ goods_d}{\text{max}_D(Imports\ of\ relevant\ goods)} + \frac{Invlog\_dist_d}{max_D(Invlog\_dist)}\right) \tag{9}$$

2.4.3. Ecological suitability

We calculated the ecological suitability for each organism and district based on host tree presence in urban and forest areas. Since about 90% of first invasive forest pest detections occur in urban areas (Branco et al., 2019), urban host trees were weighted heavier than forest host trees in the formula for ecological suitability:

$$suit = (0.9*Fraction\ of\ host\ trees\ in\ urban\ environments + 0.1*Fraction\ of\ host\ trees\ in\ forests) \tag{10}$$

To estimate the fraction of host trees in urban areas, we analysed tree inventories from 26 Swiss municipalities (Augustinus et al., 2024). All inventory included host species for all target organisms, but with different relative abundance. Since composition of urban tree genera in public and private urban environments in Switzerland is not significantly different (Christen et al., 2024), we considered the public tree composition in the inventories as representative for both. We found no spatial autocorrelation among urban tree compositions (Mantel statistic r: 0.0193, $p > 0.05$). However, Switzerland is geographically diverse, with four national languages, and we found that a location's linguistic region (bilingual French/German, French, German, or Italian) significantly explained the tree species composition (pairwise permutational analysis of variance, Table 2). For these analyses, we excluded trees of genera that occur less than ten times in total in all urban tree inventories combined to exclude the strong effect of these rare trees because permutational analyses of variance (PERMANOVA) is sensitive to differences in relative dispersion of points among groups (Staudhammer et al., 2018). We therefore assumed that municipalities lacking tree inventories have tree species compositions typical for each language region.

For forest trees, composition was aggregated per district based on plots in the Swiss national forest inventory (Brändli et al., 2020).

2.4.4. Relative probability of establishment

The relative probability of establishment ('est') in district d was calculated by multiplying the relative likelihood of introduction and the ecological suitability and then scaling the values by dividing by the maximum value for a given organism:

$$est_d = \frac{Rel\_Pr\_Intro_d * suit_d}{\max_D (Rel\_Pr\_Intro * suit)} \tag{11}$$

The district with the highest value for an organism takes a value of 1.

2.4.5. Establishment probabilities

For most of the organisms that we modelled here, no – or few – establishments have been recorded in Switzerland, so estimating annual probabilities of establishment is challenging. Border interception records are available for some of the species, but their value for making predictions has been debated (Caley et al., 2015). While modelling approaches for using absence data from interception records have been applied (Turner et al., 2020), the priority quarantine pests that we consider here are transported by different imported goods which are not surveyed in the same intensity. We therefore choose not to use border interception data for estimation. Instead, we rely on previously conducted expert assessments by EFSA (EFSA et al., 2020a; EFSA et al., 2020d; EFSA et al., 2020e; EFSA et al., 2020b; EFSA et al., 2020c; EFSA et al., 2019b; EFSA et al., 2019a), Möykkynen et al. (2015), and a risk assessment by the Conference of Cantonal Foresters and the federal office of the environment (BAFU and KoK, 2017).

Of the eight organisms considered in our analysis, ALB (Asian longhorn beetle) has the greatest number of prior establishments in Switzerland, with five establishments to date as of 2023 (Dubach et al., 2023). We set the theoretical maximum annual probability of establishment to 0.2, corresponding to about one establishment every five years, based on ALB establishment rates. We defined 'medium' establishment rates as once every 10 years (i.e., an annual establishment probability of 0.1), and low establishment rates as once every 25 years (0.04 establishment probability per year). When estimating each species establishment probability, we weighed the Swiss expert assessments (BAFU and KoK, 2017) higher than other expert assessments because they focus on Switzerland whereas the other assessments consider all of Europe. This resulted in the values shown in Table 3.

Table 2
P-values for outcomes of pairwise permutational analysis of variance of effect of the city being located in language region on tree species composition.

	German	German+French	French	Italian
German	x			
German+French	0.125	x		
French	**<0.001**	**0.037**	x	
Italian	**<0.001**	0.306	**<0.001**	x

2.4.6. Establishment probability per district

The annual probability of establishment in each district (i.e. site) ('e_d') was then calculated by allocating the country-level establishment probability across districts proportional to their relative establishment likelihood according to the following formula:

$$e_d = Establishment\ probability * \left(\frac{est_d}{\sum_D est}\right) \tag{12}$$

2.4.7. Natural spread

To calculate rates of spread following introduction of a new organism, we used data from pest survey documents called 'pest survey cards' prepared by EFSA (European Food Safety Authority) which predict natural spread per year for ALB, BBB, CLB, EAB, PPC, SOD and SSM (EFSA et al., 2020a, 2020e, 2020c, 2020b, 2020d, 2019a, 2019b). No pest survey card was available for PNW yet, so we used the values for potential spread by Möykkynen et al. (2015). We used the estimated mean maximal distribution per year from EFSA's pest survey cards. The values we used for potential yearly radial spread are shown in Table 4.

2.4.8. Background detection rate

To estimate the detection rate without surveillance, we used estimates of the time from introduction to detection provided in EFSA's pest surveys cards (EFSA et al., 2020a; EFSA et al., 2020d; EFSA et al., 2020e; EFSA et al., 2020b; EFSA et al., 2020c; EFSA et al., 2019b; EFSA et al., 2019a) and the values given in Möykkynen et al. (2015). We used the median estimated values from pest reports (i.e. estimated median age of detection). When these values were given for urban and for natural areas, we used the urban estimate, since we expect the pests to first establish in urban or peri-urban environments (Branco et al., 2019; Paap et al., 2017). Combined with the estimated spread rate for an organism (see above), we set the 'probability of public detection' parameter (y_{public}) to the value that resulted in a 50% likelihood of public detection by the organism's reported median detection age.

2.4.9. Organisms surveyed per trapping location

The Swiss national surveillance for priority quarantine pests

Table 3
Expected establishment probability (per year) per organism in Switzerland as used in the model, sources in the footnote below the table.

Organism	Assessment for Switzerland	Assessments for Europe	Annual Establishment Probability
BBB	low[1]	low-medium[2]	0.04
EAB	high[1]	medium[3]	0.2
CLB	high[1]	high[4]	0.2
ALB	high[1]	high[5]	0.2
PWN	medium[1]	high[6]	0.1
SSM	low[1]	high[7]	0.04
PPC	medium[1]	very high[8]	0.1
SOD	NA	high[9]	0.2

[1] (BAFU and KoK, 2017), [2](EFSA et al., 2020d), [3](EFSA et al., 2020b), [4](EFSA et al., 2019b), [5](EFSA et al., 2019a), [6](EFSA et al., 2020c; Möykkynen et al., 2015), [7](EFSA et al., 2020e), [8](EFSA et al., 2020a), [9](EFSA, 2011).

Table 4
Potential maximum spread per year per organism.

Organism	m/year
BBB	1300
EAB	1600
CLB	194
ALB	150
PWN	5000
SSM	9500
PPC	1300
SOD	1000

conducts annual surveillance based on inspections and trapping at specific location types (Augustinus et al., 2022). We identified five location types that cover our eight focal quarantine species. BBB is surveyed at locations with birch, EAB at locations with ash trees. ALB and CLB are surveyed together at locations with broadleaf trees, ideally maples. PWN and PPC are surveyed together at locations with pine trees, and SSS and SOD are surveyed together at locations with larch trees.

2.4.10. *Survey efficacy*

Each survey within a location type covers a 10,000 m^2 area and may include visual inspection and traps. These surveys are imperfect at detecting organisms even when overlapping with the organism's distribution because lures are imperfect and symptoms are not always clear enough for detection when an organism first attacks a host. We defined survey efficacy y_{surv} as the probability that an incursion would be detected by an overlapping survey. We estimated survey efficacy for each organism using species-specific information from multiple studies (Table 5).

Table 5
Probability of detection per year (as proportion) per organism, if the organism's population overlaps with the survey location of 10,000 m^2.

Organism	Probability of detection/year	Rationale
BBB	0.45	Limited efficiency of traps. If attacked, European birch trees tend to die off quickly (EFSA et al., 2020d; Miller et al., 1991)
EAB	0.4	Efficacy of traps is reported to be similarly low for EAB as for BBB, even with specific semiochemical lures (Silk and Ryall, 2015). However, ash trees in Switzerland are already suffering from ash dieback (Gross et al., 2014; Pautasso et al., 2013), which makes visual detection of affected trees less likely.
CLB	0.3	Traps are not very effective, because available lures are only moderately effective, and the beetle is not a very active flyer. CLB has long generational time (1–2 years) in Switzerland (Keena and Richards, 2022), so that substantial time must pass for the population to be big enough for symptoms to appear.
ALB	0.3	Like CLB (Keena and Moore, 2010)
PWN	0.5	Effective traps for the vector (*Monochamus* spp.) are available (Boone et al., 2019), but these only trap the vector from which nematodes can be extracted. Tree damage is easily observable (EFSA et al., 2020c).
SSS	0.7	Very effective pheromone traps are available; the moths are highly mobile (EFSA et al., 2020e). Caterpillars and eggs in low densities are inconspicuous.
PPC	0.4	Infected trees can be symptomless for long periods of time (Martín-García et al., 2019; Storer et al., 1998). The fungus is surveyed with spore traps, which are less directed than insect traps.
SOD	0.5	Longer lag time from infection to symptoms than PPC, and less distance is covered by the spores compared to PPC (Sansford et al., 2009). However, a larger number of spores can be expected compared to PPC if SOD sporulates, which is the case on larch, and the survey for SOD is conducted at locations with larch (Beenken et al., 2024; Sansford et al., 2009).

2.4.11. *Survey costs*

Costs per year for one survey location of 10,000 m^2 was calculated at 8000 CHF (Augustinus et al., 2022). When optimizing survey efforts, we considered allocations in steps of 1000 CHF. An allocation of 1000 CHF would represent a site (i.e., district) being surveyed once every 8 years.

2.4.12. *Eradication costs*

We calculated the eradication costs of an outbreak per square kilometer using a formula derived from a review of 672 arthropod eradication programmes in Tobin et al. (2014):

$$\log_{10}(costs, millions\ USD) = -0.254 + 0.416\left(\log_{10}\left(area, km^2\right)\right) \tag{13}$$

The values were transformed from USD to CHF.

2.5. *Model assumptions*

We consider optimal deployment of surveys, focusing on a 20-year surveillance program for early detection and eradication of populations that establish during the program or that established in the 10 years prior to the program start and were not detected by the public. When optimizing surveillance, we assume that all pest populations are found within 30 years of their establishment ($a_{max} = 30$). The priority quarantine and quarantine organisms in this study are unlikely to go undetected this long, even without formal surveys, because their damage to host trees is high and is likely to be detected by the public as the organisms spread. The maximum size of a hypothetical pest population is set to the area of Switzerland (41,285 km^2) since surveys and eradication efforts are focused in Switzerland, rather than encompassing neighbouring countries. When calculating costs over time we used a discount factor of 2% to adjust for inflation and time preference.

2.5.1. *Analysis of generalized pest types*

As an aid to interpret optimized results for Switzerland, we additionally ran the model for a single, theoretical representative district and examined survey allocations for a suite of generalized pest types that varied in their attributes. We assumed a district with the average size of the Swiss districts, and with the hypothetical species varying in their probability of public detection, survey efficacy, and establishment probability (each with their lowest, median and highest respective values of the real organisms modelled above), and eleven spread rates for every combination of the factors above. By examining these attribute combinations, we aimed to illuminate the roles of each attribute toward optimal survey investment.

2.5.2. *Software used*

Data manipulation and model runs were conducted in R version 4.3.2. (R Foundation for Statistical Computing, 2023). Data manipulation was done with readxl (Wickham, 2016), dplyr (Wickham et al., 2019), stringr (Wickham, 2022) and sf (Cook and Baston, 2023). The model code requires the packages sqldf (Grothendieck, 2022), data.table (Barrett et al., 2024) and knitr (Yihui, 2023) to run. For visualization, we used the r packages ggplot2 (Wickham and Chang, 2016) and ggpubr (Kassambara, 2016), as well as QGIS 3.16 (QGIS Development Team, 2020).

3. Results

3.1. Optimal investment

The model found that a survey investment of 1,187,000 CHF per year would minimize the combined expected costs of surveillance and eradication in Switzerland for the eight organisms shown in Table 1 (Fig. 3), with an overall net benefit of 48,180,500 CHF over the 20-year period of the surveillance program. No investment was allocated to surveys of ALB and CLB. For survey of BBB, 15,000 CHF per year was identified as the optimal investment. The model allocated 250,000 CHF yearly for the surveillance of EAB. For trapping of SSM and SOD on combined trapping locations, 437,000 CHF was calculated as optimal yearly investment for surveillance. Trapping locations that surveyed PWN and PPC got allocated the highest optimal investment of 485,000 CHF per year (Fig. 3).

3.2. Geographical distribution of investment

The optimal allocation of survey investment differed spatially across the organisms, with only four districts (Brugg AG, Geneva GE, Laufenburg AG and Zürich ZH) receiving survey investment for all organisms (Fig. 4).

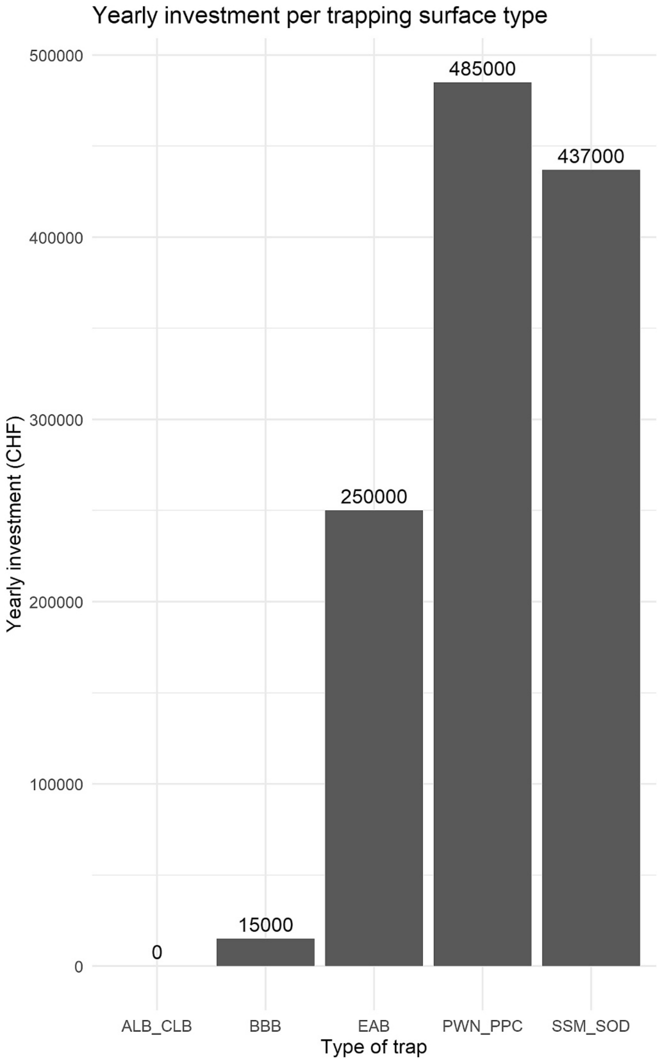

Fig. 3. Optimal investment in surveillance by target organism: ALB_CLB survey locations with broadleaved trees, BBB survey locations with birch trees, EAB survey locations with ash trees, PWN_PPC locations with pines, and SSM_SOD locations with larch trees.

3.3. Influence of pest attributes on model outcomes

We used sensitivity analysis to explore the role of annual establishment probability, public detection rate, survey efficacy, and spread rate on optimal survey investment. Specifically, comparing generalized pest types with differing attributes, we found that organisms with the highest public detection rate of the surveyed organisms did not receive any allocation of investment. The optimal survey investment generally increased with establishment probability and decreased with survey efficacy across the attribute combinations we examined (Fig. 5). In addition, optimal survey investment increased with spread rate.

4. Discussion

The model output calculated an optimal yearly investment of 1,187,000 CHF to survey the organisms listed in Table 1 and distributed the investments across Switzerland. This survey program is estimated to provide an expected annualized net benefit equivalent to approximately $2,946,521CHF per year relative to without a formal surveillance program. We discuss the distribution and magnitude of survey investments below, including some results that were initially surprising. For example, no investment was allocated to ALB and CLB, even though both are highly damaging and have been intercepted in Switzerland previously. Additionally, limited investment is directed toward Ticino, the region of Switzerland south of the Alps, even though the first detections of invasive species have often been made in this region.

4.1. Influence of pest attributes on model outcomes

Running the model on generalized pest types that have attribute values within the range (lowest to highest) of the priority quarantine pests in our study provided information about the relative influence of the various factors (i.e., annual establishment probability, public detection rate, spread rate, and survey efficacy). Organisms with low establishment rates received lower suggested survey investments than species with higher establishment probabilities. Similarly, species with lower spread rates tended to have lower optimal survey levels. In contrast, species with lower survey efficacy tended to have higher recommended survey investments. Public detection rate had a more pronounced effect than other factors we explored, as the model did not assign any investment to organisms with high public detection rates, regardless of other pest attributes (Fig. 5).

4.2. Optimal investment in total

The suggested optimum annual survey investment of 1,187,000 CHF may seem low when considering that an eradication program for a single ALB outbreak in the Swiss city of Winterthur in 2012 cost at least 3.3 million CHF (Oberpriller et al., 2017). Interpretation of the investment level depends on rarity of district-level establishments, likelihood of public detection, and modelling assumptions. For example, we assume that eradication costs depend on the incursion size when detected, but our analysis does not consider i) how likely eradication of each particular target organism is to be successful, ii) the magnitude of direct and indirect damage costs of an outbreak (e.g., loss of ecosystem services), or iii) trade effects (e.g., reduced internal trade or export of affected resources). The focus on eradication costs was based on the explicit guidance that attempted eradication is the legally mandated response for the organisms considered. Therefore, survey and eradication costs are key budgetary concerns. Accounting for eradication success of damages would likely raise optimal survey investments, especially as eradication becomes less likely with higher outbreak size (Tobin et al., 2014). This implies that earlier detection yields additional benefits beyond reduced control costs. Damages from the focal organisms could include market costs like yield loss (Petucco et al., 2020), property value loss in residential forests (Holmes et al., 2010), and reduction in market

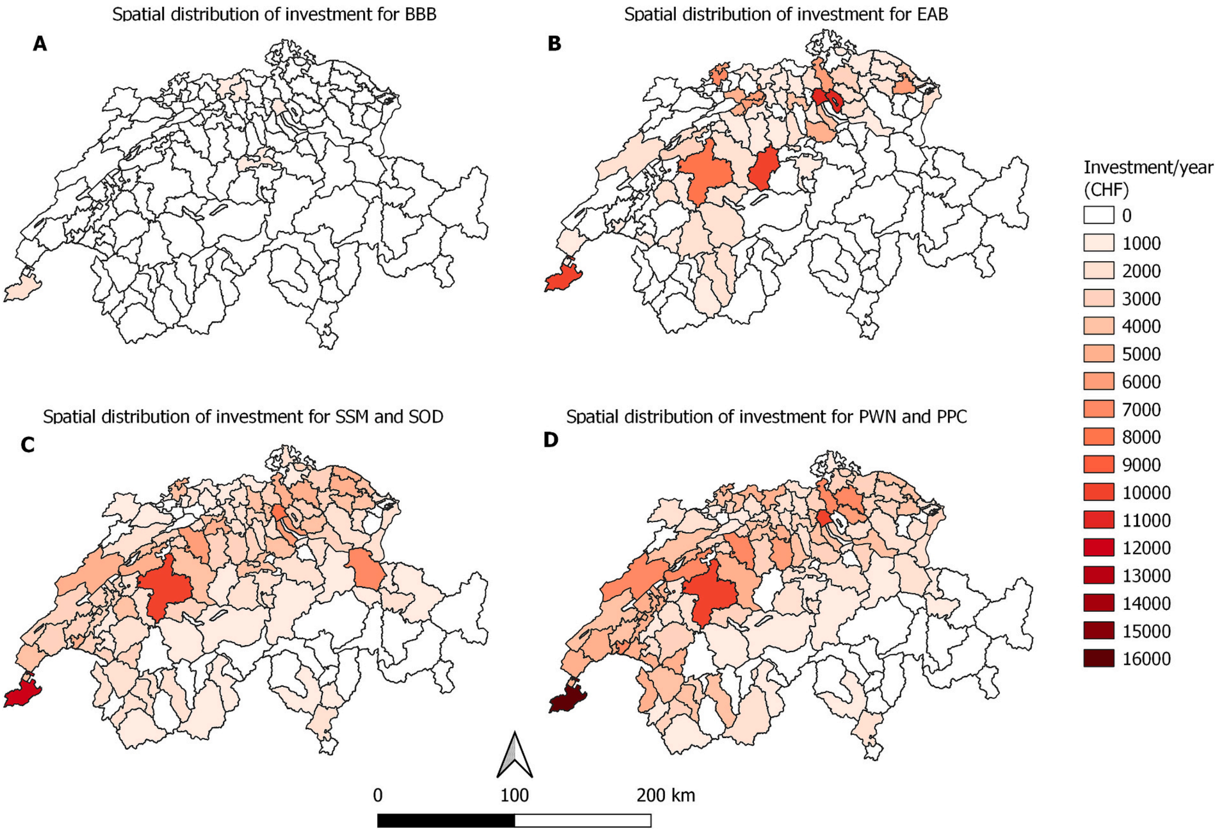

Fig. 4. Geographical distribution of yearly survey investments for the four survey location types that received allocations by the model. A. surveys for bronze birch borer on locations with birch, B. surveys for emerald ash borer on locations with ash, C. surveys for Siberian silk moth and sudden oak death on locations with larch, and D. surveys for Pine wood nematode and pine pitch canker on locations with pines. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

access for timber products (Prestemon et al., 2008). Non-market costs, like ecological, aesthetic, or spiritual or cultural costs of an outbreak could be high (Bradshaw et al., 2016), but reliable information for these costs is rarely available (Welsh et al., 2021). Hence, the identified optimal investment of >1 million CHF per year for surveillance is highly likely to be an underestimation. In 2025 and 2026, the Swiss surveillance program was conducted with 75 trapping locations, which would equate to a yearly investment of 600,000 CHF as calculated in this model. Including costs that would increase suggested optimal investment would be unlikely to raise the allocated investment in practice due to limited funds of the Federal Office for the Environment.

4.3. *Prioritization of organisms*

The model suggested investing more in location types used to survey two species at the same time, and for EAB (monitored alone). Comparably, little (~1.2%) was suggested to be allocated to locations used to survey for BBB, and no investment was suggested for ALB and CLB. The relatively low suggested survey investment for BBB can be explained by the low introduction probability, which reduces the benefits of the surveys. BBB and SSM are the only organisms to be surveyed that have not yet become established outside their native range (BAFU and KoK, 2017; EFSA et al., 2020d).

In contrast to BBB, several interceptions and establishments of ALB, along with at least one post-border interception of CLB, have been identified in Switzerland (Branco et al., 2021; Wermelinger, 2006). Still, the model did not allocate investment to survey these species. Two main factors can explain this counterintuitive finding: i) the public detection rate is high, and ii) the spread rates of ALB and CLB are low. The high public detection rate allows the pest to be detected even without any dedicated survey investment. The slow spread rate causes their population to remain small for a longer period after their establishment making them less costly to eradicate than faster spreading species. Our analysis of generalized pest types suggests these two factors have strong effects (Fig. 5): the model never allocated investments to organisms with the highest public detection rate (Fig. 5, C, F, I). However, it did allocate investments to organisms with lower public detection rates but low survey efficacy (Fig. 5 A, B). Indeed, many first detections of ALB and CLB have been facilitated by passive surveillance (Branco et al., 2021). Both insect species are charismatic organisms that are as large or larger than the biggest native longhorn beetles, and distinctive from them – and therefore very well suited for detection by passive surveillance or citizen scientists (Brown et al., 2020; Ciampitti and Cavagna, 2014; de Groot et al., 2023; Kompas et al., 2023). As an alternative to active trapping, public awareness campaigns might be a better investment in the early detection of these species than formal survey efforts.

Allocation of surveys across species may have been even further differentiated if eradication, market or non-market damage costs were considered. For example, SOD has a much wider host range than BBB (EFSA, 2011; EFSA et al., 2020d). Therefore, a SOD outbreak might be more costly than a BBB outbreak. However, these data were not part of the regulatory scope and are not available in a standardized way. This assumption could lead to less homogeneous costs of an outbreak for different organisms.

4.4. *Geographical distribution of suggested sampling*

The model allocated most investment for surveillance in the central plateau of Switzerland, which is the region with the highest economic activity and human population density. While this is in line with other

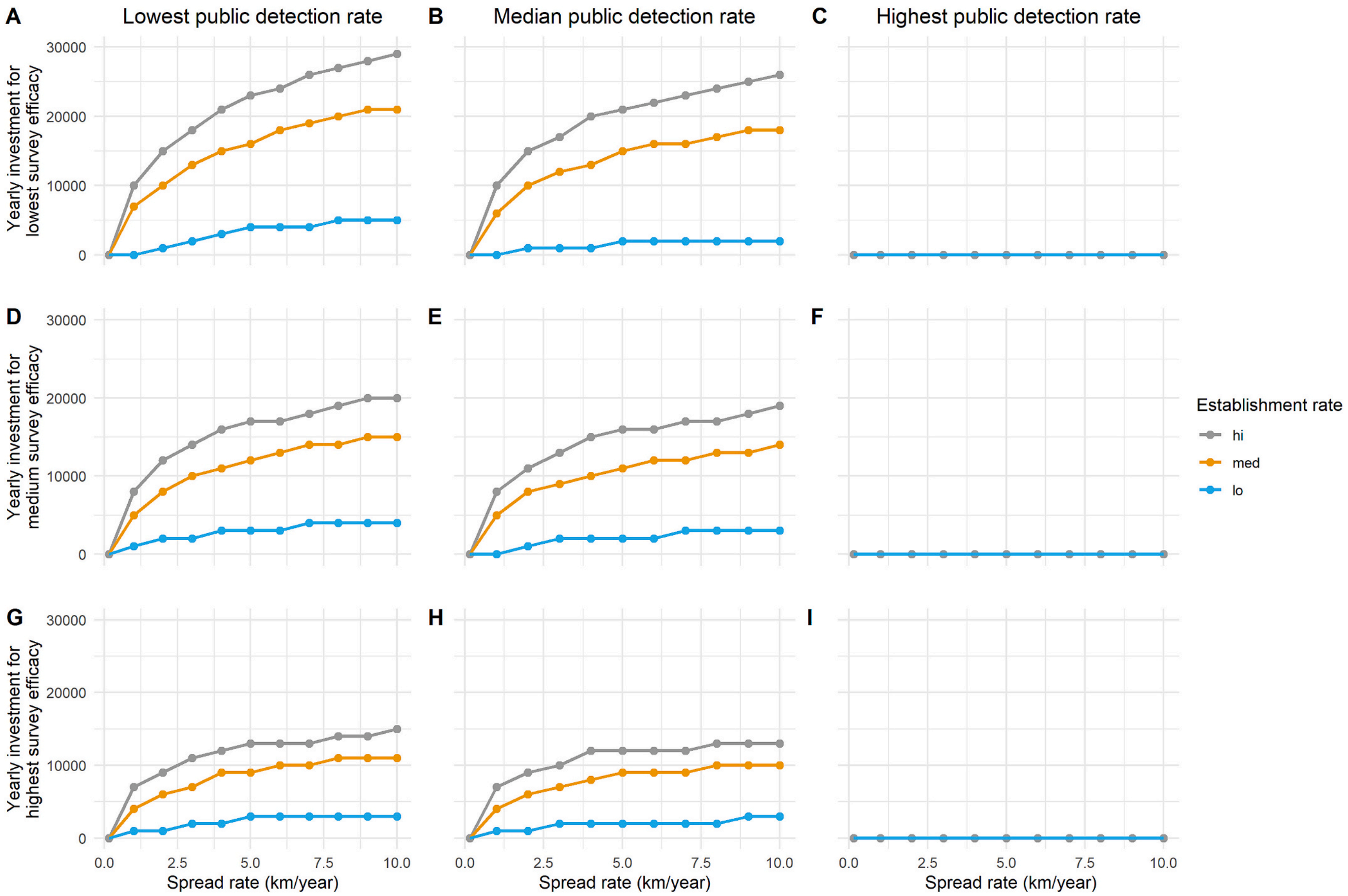

Fig. 5. Optimized yearly survey investment for simulated species in a single location, using parameter ranges from the organisms in Table 1. We used lowest, medium and highest survey efficacy (y_{surv}) of the organisms (from top to bottom plot), lowest, median and highest public detection rate (y_{public}; plots from left to right) and lowest, medium and highest establishment probabilities (e; different coloured lines) to show how the different parameters influence the model. Spread rate varies across the x-axis. Optimal survey investments minimize the total expected eradication and survey costs.

studies (Epanchin-Niell et al., 2014; Kompas et al., 2023; Nguyen et al., 2024), it is noteworthy that many invasive species in Switzerland are first found in its southernmost canton, Ticino. For example, the ambrosia beetle *Anisandrus maiche* was first detected in Ticino (Ribeiro-Correia et al., 2024), as well as the Japanese beetle *Popilia japonica* (Agroscope, 2017) and the powdery mildew *Erysiphe corylacearum* on hazelnut (Beenken et al., 2020). Therefore, it might be a surprise that only a small share of the suggested yearly investment was allocated to the districts in this canton, especially because there are active outbreaks of ALB and CLB in Northern Italy (Branco et al., 2021). However, there are active outbreaks of ALB close to the border of Switzerland in Germany and France (to the time of model running, S. Branco et al., 2021). The model does not allocate surveillance investment for ALB and CLB because of their high public detection rate, as discussed above. For the other organisms, no outbreaks close (i.e., $<$ 300 km driving distance) to the Swiss border are known, and, therefore, these organisms are more likely to be introduced by long-distance transport of goods. Economic activity and human population are higher in other parts of Switzerland than in Ticino, which are key factors driving surveillance investment.

Most forest pests that are new to Switzerland and first found in Ticino are likely to have spread after earlier introductions to bordering regions in northern Italy, an economically active and highly populated region. Northern Italy has been identified as a hotspot of first introductions of plant pests in Europe (Branco et al., 2019; Rosace et al., 2025). This highlights a general weakness of national surveillance programs: in principle, they treat countries like islands, even if potential short-distance transport or natural spread is considered, as we did in the model for ALB and CLB. While our approach only partially considered neighbouring countries, it did consider all districts of Switzerland, including those with low economic activity, low population density, or low ecological suitability, as suggested by previous work with bio-economic models to optimize surveillance (Epanchin-Niell et al., 2014; Mastin et al., 2020).

In the parameter ‘Ecological Suitability’ for the different organisms, we did not include climatic suitability, because no fine-scale data on Swiss microclimates are available and we expect first introductions of these organisms to occur in urban or peri-urban environments (Branco et al., 2019; Paap et al., 2017). The climate in these environments is subject to the urban heat island effect (Oke, 1982), with urban areas up to 10 °C warmer than surrounding environments. The intensity of this phenomenon can vary greatly among different cities due to spatial planning differences (Schwaab et al., 2021).

We used host availability as defining measure for environmental suitability. In Switzerland, urban and forest tree composition differ considerably (Augustinus et al., 2024). Therefore, we needed to consider urban tree inventory and forest inventory data separately. This approach resulted in the suggestion of trapping investment in locations that would not be considered if only forest trees were considered. For example, sampling on pine (*Pinus* sp.) trees was suggested for several locations in the central plateau of Switzerland (Fig. 4D). Since pines occur naturally mainly in mountainous areas (Brändli et al., 2020), this shows how including urban trees in surveys for forest pests changes optimal allocation for surveillance efforts. The finding that urban tree compositions differed in between language regions illustrates that it is important to consider cultural effects on planting preferences. In this case, planting preferences influenced which pests are most likely to have detrimental impacts on cities and surrounding forests.

5. Limitations

One key factor influencing the spread of an invasive organism is whether the organism has overcome the initial lag phase of the invasion process. EFSA's analyses assign potential yearly spread to hypothetical populations, that have established and reached high population densities. This means that these values do not consider the initial lag phase of the invasion of the organisms, in which spread can be dramatically slower. However, lag times can be influenced by many factors (Crooks, 2005), and the biology of the target organisms we dealt with is not well-known enough to make trustworthy predictions of lag times of their invasion processes. Therefore, we decided to exclude potential lag phases from the analyses. Historical local changes like land-use change and earlier survey efforts, as well as prior incursions could shift likelihood of introduction and detection (de Groot et al., 2023; O'Donnell et al., 2024). Including these factors could further refine the model outputs.Conclusions.

Here, we show how a bioeconomic model can be used to optimize national surveillance for invasive priority quarantine forest pests. This can be used to prioritize economically sensible choices for species and locations to survey. In general, we found that higher trapping efficacy, lower establishment probabilities, lower spread rates, and trapping locations surveying for fewer organisms simultaneously resulted in a lower amount of suggested survey investment. Most clearly, higher public detection rates resulted in lower recommended survey investment. Therefore, using more efficient traps (e.g., by using more specialized semiochemicals), increased phytosanitary measures, and increased public awareness could reduce the required surveillance investments for invasive forest pests and overall costs.

Future models could explore which parameters have the biggest effect on survey investment per organism, to inform optimization of surveillance, and could be used for a larger geographic area to inform international collaboration on quarantine pest surveillance. Furthermore, alternative objectives to the mandated eradication – like the choice to either contain or eradicate – could be included in models to make them more economically rational and applicable in national surveillance schemes.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT-5 to shorten parts of the manuscript in an early draft version. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Financial support

This work was supported by the Swiss Federal Office for the Environment (FOEN), in the grants of the Scientific and technical activities in the field of forest protection ‘Wissenschaftliche-technische Tätigkeiten im Bereich Waldschutz’ [Nr. 00.0482.PZ / S394-1025, Nr. 00.0482.PZ / 41AB248AE, Nr. 00.0482.PZ / B4387AFF4] and by core funding of the Swiss Federal Research Institute WSL.

CRediT authorship contribution statement

Benno Andreas Augustinus: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rebecca Suzanne Epanchin-Niell:** Writing – review & editing, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Valentin Queloz:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Eckehard Gustav Brockerhoff:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors have no conflict of interest to declare.

Data availability

The data used is in parts confidential. Data that's not confidential is available on request.

Acknowledgement

We thank Aline Knoblauch from the Swiss Federal Office for the Environment for commenting on an early draft.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2026.109053.

References

Agroscope, 2017. First report of *Popillia japonica* in Switzerland. EPPO Rep. Serv. 1, 1. https://gd.eppo.int/reporting/article-6128.

Augustinus, B.A., Epanchin-Niell, R.S., Queloz, V., Brockerhoff, E.G., 2022. Modellierungen für die gebietsüberwachung der schweiz. Birmensdorf, Switzerland. https://www.dora.lib4ri.ch/wsl/islandora/object/wsl%3A36737.

Augustinus, B.A., Abegg, M., Queloz, V., Brockerhoff, E.G., 2024. Higher tree species richness and diversity in urban areas than in forests: implications for host availability for invasive tree pests and pathogens. Landsc. Urban Plan. 250, 105144. https://doi.org/10.1016/j.landurbplan.2024.105144.

BAFU, KoK, 2017. Priorisierung von waldrelevanten Schadorganismen, Bericht der KOK und des BAFU. Bern.

Barrett, T., Dowle, M., Srinivasan, A., Gorecki, J., Chirico, M., Hocking, T., 2024. Package ‘data.table’ https://doi.org/10.32614/CRAN.package.data.table.

Beenken, L., Brodtbeck, T., De Marchi, R., 2020. First record of erysiphe corylacearum on corylus avellana in Switzerland and in central europe. New Dis. Rep. 41, 11. https://doi.org/10.5197/j.2044-0588.2020.041.011.

Beenken, L., Hölling, D., Brockerhoff, E.G., Queloz, V., 2024. Plötzlicher Eichentod. *Phytophthora ramorum* Werres, De Cock & Man., Factsheet Waldschutz Schweiz. Birmensdorf.

Boone, C.K., Sweeney, J., Silk, P., Hughes, C., Webster, R.P., Stephen, F., Maclauchlan, L., Bentz, B., Drumont, A., Zhao, B., Berkvens, N., Casteels, H., Grégoire, J.C., 2019. *Monochamus* species from different continents can be effectively detected with the same trapping protocol. J. Pest. Sci. 2004 (92), 3–11. https://doi.org/10.1007/s10340-018-0954-4.

Bradshaw, C.J.A., Leroy, B., Bellard, C., Roiz, D., Albert, C., Fournier, A., Barbet-Massin, M., Salles, J.M., Simard, F., Courchamp, F., 2016. Massive yet grossly underestimated global costs of invasive insects. Nat. Commun. 7. https://doi.org/10.1038/ncomms12986.

Branco, M., Nunes, P., Roques, A., Fernandes, M.R., Orazio, C., Jactel, H., 2019. Urban trees facilitate the establishment of non-native forest insects. NeoBiota 52, 25–46. https://doi.org/10.3897/neobiota.52.36358.

Branco, S., Faccoli, M., Brockerhoff, E.G., Roux, G., Jactel, H., Desneux, N., Gachet, E., Mouttet, R., Streito, J.C., Branco, M., 2021. Preventing invasions of Asian longhorn beetle and citrus longhorn beetle: Are we on the right track? J. Pest Sci. (2004). https://doi.org/10.1007/s10340-021-01431-x.

Brändli, U.-B., Abegg, M., Allgaier Leuch, B., 2020. Schweizerisches Landesforstinventar. Ergebnisse der vierten Erhebung 2009–2017. Eidgenössische Forschungsanstalt für Wald, Schnee und Landschaft WSL, Birmensdorf. Bern, Bundesamt für Umwelt.

Brockerhoff, E.G., Liebhold, A.M., 2017. Ecology of forest insect invasions. Biol. Invasions 19, 3141–3159. https://doi.org/10.1007/s10530-017-1514-1.

Brockerhoff, E.G., Liebhold, A.M., Richardson, B., Suckling, D.M., 2010. Eradication of invasive forest insects: concepts, methods, costs and benefits. N. Z. J. For. Sci. 40 (suppl), 117–135.

Brown, N., Pérez-Sierra, A., Crow, P., Parnell, S., 2020. The role of passive surveillance and citizen science in plant health. CABI Agric. Biosci. 1, 1–16. https://doi.org/10.1186/s43170-020-00016-5.

Bundesamt für Statistik, 2018. Arealstatistik der Schweiz [WWW Document]. https://www.bfs.admin.ch/bfs/de/home/dienstleistungen/geostat/geodaten-bundessta tistik/boden-nutzung-bedeckung-eignung/arealstatistik-schweiz.html (accessed 2.6.24).

Caley, P., Ingram, R., De Barro, P., 2015. Entry of exotic insects into Australia: does border interception count match incursion risk? Biol. Invasions 17, 1087–1094. https://doi.org/10.1007/s10530-014-0777-z.

Christen, S., Brockerhoff, E.G., Gossner, M.M., Augustinus, B.A., 2024. A biosecurity perspective on urban trees in public and private spaces and trees available from nurseries. Urban For. Urban Green. 101, 128529. https://doi.org/10.1016/j.ufug.2024.128529.

Ciampitti, M., Cavagna, B., 2014. Public awareness: a useful tool for the early detection and a successful eradication of the longhorned beetles anoplophora chinensis and a. glabripennis. EPPO Bullet. 44, 248–250. https://doi.org/10.1111/epp.12116.

Cook, I., Baston, D., 2023. Package "sf" https://doi.org/10.32614/CRAN.package.sf.

Crooks, J.A., 2005. Lag times and exotic species: the ecology and management of biological invasions in slow-motion. Ecoscience 12, 316–329. https://doi.org/10.2980/i1195-6860-12-3-316.1.

Dubach, V., Dennert, F., Blaser, S., Beenken, L., Hölling, D., Stroheker, S., Kupferschmid, A.D., Heinzelmann, R., Britt, E., Queloz, V., 2023. Waldschutzüberblick 2022. Birmensdorf.

EFSA, 2011. Scientific opinion on the pest risk analysis on *Phytophthora ramorum* prepared by the FP6 project RAPRA. EFSA J. 9, 1–108. https://doi.org/10.2903/j.efsa.2011.2186.

EFSA, Schrader, G., Hoppe, B., Kinkar, M., Vos, S., 2019a. Pest survey card on anoplophora glabripennis, 16(12). EFSA Supporting Publications, 1750E. https://doi.org/10.2903/sp.efsa.2019.EN-1750.

EFSA, Schrader, G., Kinkar, M., Vos, S., 2019b. Pest Survey Card on Anoplophora Chinensis, 16. EFSA Supporting Publications, 1749E. https://doi.org/10.2903/sp.efsa.2019.EN-1749.

EFSA, Kinkar, M., Vos, S., 2020a. Pest survey card on fusarium circinatum, 17. EFSA Supporting Publications. https://doi.org/10.2903/sp.efsa.2020.en-1842. EN-1842.

EFSA, Schans, J., Schrader, G., Delbianco, A., Graziosi, I., Vos, S., 2020b. Pest survey card on agrilus planipennis. EFSA Support. Publ. 17. https://doi.org/10.2903/sp.efsa.2020.en-1945.

EFSA, Schenk, M., Loomans, A., den Nijs, L., Hoppe, B., Kinkar, M., Vos, S., 2020c. Pest survey card on bursaphelenchus xylophilus. EFSA Support. Publ. 17. https://doi.org/10.2903/sp.efsa.2020.en-1782.

EFSA, Schrader, G., Kinkar, M., Vos, S., 2020d. Pest Survey card on Agrilus Anxius, 17. EFSA Supporting Publications. https://doi.org/10.2903/sp.efsa.2020.en-1777.

EFSA, Wilstermann, A., Schrader, G., Kinkar, M., Vos, S., 2020e. Pest Survey Card on Dendrolimus Sibiricus, 17. EFSA Supporting Publications. https://doi.org/10.2903/sp.efsa.2020.en-1779.

Epanchin-Niell, R.S., 2017. Economics of invasive species policy and management. Biol. Invasions 19, 3333–3354. https://doi.org/10.1007/s10530-017-1406-4.

Epanchin-Niell, R.S., 2020. Bioeconomic Modeling for Decision-Support: Optimizing Early Detection and Control of Invasive Pests. Washington DC. https://www.arec.umd.edu/sites/arec.umd.edu/files/files/documents/Seminars/2020/Bioeconomic%20modeling%20for%20decision%20support_Epanchin-Niell.pdf.

Epanchin-Niell, R.S., Haight, R.G., Berec, L., Kean, J.M., Liebhold, A.M., 2012. Optimal surveillance and eradication of invasive species in heterogeneous landscapes. Ecol. Lett. 15, 803–812. https://doi.org/10.1111/j.1461-0248.2012.01800.x.

Epanchin-Niell, R.S., Brockerhoff, E.G., Kean, J.M., Turner, J.A., 2014. Designing cost-efficient surveillance for early detection and control of multiple biological invaders. Ecol. Appl. 24, 1258–1274. https://doi.org/10.1890/13-1331.1.

Freer-Smith, P.H., Webber, J.F., 2017. Tree pests and diseases: the threat to biodiversity and the delivery of ecosystem services. Biodivers. Conserv. 26, 3167–3181. https://doi.org/10.1007/s10531-015-1019-0.

de Groot, M., Pocock, M.J.O., Bonte, J., Fernandez-Conradi, P., Valdés-Correcher, E., 2023. Citizen science and monitoring forest pests: a beneficial alliance? Curr. For. Rep. 9, 15–32. https://doi.org/10.1007/s40725-022-00176-9.

Gross, A., Holdenrieder, O., Pautasso, M., Queloz, V., Sieber, T.N., 2014. Hymenoscyphus pseudoalbidus, the causal agent of european ash dieback. Mol. Plant Pathol. 15, 5–21. https://doi.org/10.1111/mpp.12073.

Grothendieck, G., 2022. Package "Sqldf" Title Manipulate R Data Frames Using SQL.

Holmes, T.P., Murphy, E.A., Bell, K.P., Royle, D.D., 2010. Property value impacts of hemlock woolly adelgid in residential forests. For. Sci. 56, 529–540. https://doi.org/10.1016/j.ecolecon.2022.107354.

Horie, T., Haight, R.G., Homans, F.R., Venette, R.C., 2013. Optimal strategies for the surveillance and control of forest pathogens: a case study with oak wilt. Ecol. Econ. 86, 78–85. https://doi.org/10.1016/j.ecolecon.2012.09.017.

Kassambara, A., 2016. Package 'ggpubr'. http://www.sthda.com/english/rpkgs/ggpubr.

Keena, M.A., Moore, P.M., 2010. Effects of temperature on anoplophora glabripennis (coleoptera: Cerambycidae) larvae and pupae. Environ. Entomol. 39, 1323–1335. https://doi.org/10.1603/EN09369.

Keena, M.A., Richards, J.Y., 2022. Effects of temperature on anoplophora chinensis (coleoptera: Cerambycidae) larvae and pupae. Environ. Entomol. 51, 153–166. https://doi.org/10.1093/ee/nvab132.

Kompas, T., Chu, L., McKirdy, S., Thomas, M., Van Der Merwe, J., 2023. Optimal post-border surveillance against invasive pests to protect a valuable nature reserve and island asset. Ecol. Econ. 208, 107789. https://doi.org/10.1016/j.ecolecon.2023.107789.

Liebhold, A.M., Kean, J.M., 2019. Eradication and containment of non-native forest insects: successes and failures. J. Pest Sci. 92, 83–91. https://doi.org/10.1007/s10340-018-1056-z.

Martín-García, J., Zas, R., Solla, A., Woodward, S., Hantula, J., Vainio, E.J., Mullett, M., Morales-Rodríguez, C., Vannini, A., Martínez-Álvarez, P., Pinto, G., Alves, A., Amaral, J., Wingfield, M.J., Fourie, G., Steenkamp, E.T., Ahumada, R., Šerá, B., Sanz-Ros, A.V., Raposo, R., Elvira-Recuenco, M., Iturritxa, E., Gordon, T.R., Diez, J.J., 2019. Environmentally friendly methods for controlling pine pitch canker. Plant Pathol. 68, 843–860. https://doi.org/10.1111/ppa.13009.

Mastin, A.J., Gottwald, T.R., van den Bosch, F., Cunniffe, N.J., Parnell, S., 2020. Optimising risk-based surveillance for early detection of invasive plant pathogens. PLoS Biol. 18, 1–25. https://doi.org/10.1371/journal.pbio.3000863.

Miller, R.O., Bloese, P.D., Hanover, J.W., Haack, R.A., 1991. Paper birch and European white birch vary in growth and resistance to bronze birch borer. J. Am. Soc. Hortic. Sci. 116, 580–584. https://doi.org/10.21273/jashs.116.3.580.

Möykkynen, T., Capretti, P., Pukkala, T., 2015. Modelling the potential spread of fusarium circinatum, the causal agent of pitch canker in europe. Ann. For. Sci. 72, 169–181. https://doi.org/10.1007/s13595-014-0412-2.

Nahrung, H.F., Carnegie, A.J., 2020. Non-native forest insects and pathogens in Australia: establishment, spread, and impact. Front. Forests Global Change 3, 1–12. https://doi.org/10.3389/ffgc.2020.00037.

Nardi, D., Geppert, C., Thorn, M.J., Ward, S.F., Brown, R.L., Gordon, J.S., Riggins, J.J., 2025. Burning questions: how human behaviors and firewood characteristics influence the transport of wood-boring insects. Biol. Invasions 27, 1–13. https://doi.org/10.1007/s10530-024-03518-9.

Nguyen, H.T.M., Chu, L., Liebhold, A.M., Epanchin-Niell, R.S., Kean, J.M., Kompas, T., Robinson, A.P., Brockerhoff, E.G., Moore, J.L., 2024. Optimal allocation of resources among general and species-specific tools for plant pest biosecurity surveillance. Ecol. Appl. 34. https://doi.org/10.1002/eap.2955.

Oberpriller, Q., Vettori, A., Gelpke, G., 2017. Volkswirtschaftliche Beurteilung (VOBU): Gesetzesanpassung zur Strategie zu invasiven gebietsfremden Arten. Zürich.

O'Donnell, U., McGee, C.F., Bourke, A., Yearsley, J.M., 2024. Understanding observable historical pest dynamics through a data rescue approach. Biol. Invasions 27, 36. https://doi.org/10.1007/s10530-024-03485-1.

Oke, T.R., 1982. The energetic basis of the urban heat island. Q. J. Roy. Meteorol. Soc. 108, 1–24. https://doi.org/10.1002/qj.49710845502.

Paap, T., Burgess, T.I., Wingfield, M.J., 2017. Urban trees: bridge-heads for forest pest invasions and sentinels for early detection. Biol. Invasions 19, 3515–3526. https://doi.org/10.1007/s10530-017-1595-x.

Pautasso, M., Aas, G., Queloz, V., Holdenrieder, O., 2013. European ash (fraxinus excelsior) dieback - a conservation biology challenge. Biol. Conserv. 158, 37–49. https://doi.org/10.1016/j.biocon.2012.08.026.

Petucco, C., Lobianco, A., Caurla, S., 2020. Economic evaluation of an invasive forest pathogen at a large scale: the case of ash dieback in France. Environ. Model. Assess. 25, 1–21. https://doi.org/10.1007/s10666-019-09661-1.

Pflanzengesundheitsverordnung, 2018. PGesV. Schweizerische Bundesrat, Bern.

PGesV-WBF-UVEK, 2019. Das Eidgenössische Departement für Wirtschaft, Bildung und Forschung (WBF) und das Eidgenössische Departement für Umwelt. Energie und Kommunikation (UVEK), Verkehr.

Prestemon, J.P., Turner, J.A., Buongiorno, J., Zhu, S., Li, R., 2008. Some timber product market and trade implications of an invasive defoliator: the case of asian lymantria in the United States. J. For. 106, 409–415.

QGIS Development team, 2020. QGIS.Org [WWW document]. http://qgis.org.

Raffa, K.F., Brockerhoff, E.G., Grégoire, J.-C., Hamelin, R.C., Liebhold, A.M., Santini, A., Venette, R.C., Wingfield, M.J., 2023. Approaches to forecasting damage by invasive forest insects and pathogens: a cross-assessment. Bioscience 73, 85–111. https://doi.org/10.1093/biosci/biac108.

Ramsfield, T.D., Bentz, B.J., Faccoli, M., Jactel, H., Brockerhoff, E.G., 2016. Forest health in a changing world: effects of globalization and climate change on forest insect and pathogen impacts. Forestry 89, 245–252. https://doi.org/10.1093/forestry/cpw018.

Ribeiro-Correia, J.P., Prospero, S., Beenken, L., Biedermann, P.H.W., Blaser, S., Branco, M., Chittaro, Y., Frey, D., Hölling, D., Kaya, S.O., Knížek, M., Mittelstrass, J., Ruffner, B., Sanchez, A., Brockerhoff, E.G., 2024. Distribution of the invasive ambrosia beetle anisandrus maiche (coleoptera, scolytinae) in Switzerland and first record in europe of its ambrosia fungus ambrosiella cleistominuta. Alpine Entomol. 8, 35–49. https://doi.org/10.3897/alpento.8.117537.

Rosace, M.C., López-quílez, A., Rossi, V., 2025. Hotspot mapping of pest introductions in the EU : a regional analysis of environmental, anthropogenic and spatial effects. Biol. Invasions 1–28. https://doi.org/10.1007/s10530-024-03461-9.

Sansford, C., Inman, A.J., Baker, R., Brasier, C., Frankel, S., De Gruyter, J., Husson, C., Kehlenbeck, H., Kessel, G., Moralejo, E., Steeghs, M., Webber, J., Werres, S., 2009. Risk analysis of phytophthora ramorum, a newly recognised pathogen threat to Europe and the cause of sudden oak death in the USA (Acronym – RAPRA) (Doctoral Dissertation).

Schwaab, J., Meier, R., Mussetti, G., Seneviratne, S., Bürgi, C., Davin, E.L., 2021. The role of urban trees in reducing land surface temperatures in European cities. Nat. Commun. 12, 1–11. https://doi.org/10.1038/s41467-021-26768-w.

Seebens, H., Bacher, S., Blackburn, T.M., Capinha, C., Dawson, W., Dullinger, S., Genovesi, P., Hulme, P.E., van Kleunen, M., Kühn, I., Jeschke, J.M., Lenzner, B., Liebhold, A.M., Pattison, Z., Pergl, J., Pyšek, P., Winter, M., Essl, F., 2021. Projecting the continental accumulation of alien species through to 2050. Glob. Chang. Biol. 27, 970–982. https://doi.org/10.1111/gcb.15333.

Silk, P., Ryall, K., 2015. Semiochemistry and chemical ecology of the emerald ash borer agrilus planipennis (coleoptera: Buprestidae). Can. Entomol. 147, 277–289. https://doi.org/10.4039/tce.2014.58.

Staudhammer, C.L., Escobedo, F.J., Blood, A., 2018. Assessing methods for comparing species diversity from disparate data sources: the case of urban and peri-urban forests. Ecosphere 9. https://doi.org/10.1002/ecs2.2450.

Storer, A.J., Gordon, T.R., Clark, S.L., 1998. Association of the pitch canker fungus, fusarium subglutinans f.sp. pini, with Monterey pine seeds and seedlings in California. Plant Pathol. 47, 649–656. https://doi.org/10.1046/j.1365-3059.1998.00288.x.

Tobin, P.C., Kean, J.M., Suckling, D.M., McCullough, D.G., Herms, D.A., Stringer, L.D., 2014. Determinants of successful arthropod eradication programs. Biol. Invasions 16, 401–414. https://doi.org/10.1007/s10530-013-0529-5.

Turner, R.M., Plank, M.J., Brockerhoff, E.G., Pawson, S., Liebhold, A., James, A., 2020. Considering unseen arrivals in predictions of establishment risk based on border biosecurity interceptions. Ecol. Appl. 30. https://doi.org/10.1002/eap.2194.

Venette, R.C., Kriticos, D.J., Magarey, R.D., Koch, F.H., Baker, R.H.A., Worner, S.P., Raboteaux, N.N.G., McKenney, D.W., Dobesberger, E.J., Yemshanov, D., Barro, P.J. D., Hutchison, W.D., Fowler, G., Kalaris, T.M., Pedlar, J., 2010. Pest risk maps for invasive alien species: a roadmap for improvement. Bioscience 60, 349–362. https://doi.org/10.1525/bio.2010.60.5.5.

VpM-BAFU, 2017. Das Bundesamt für Umwelt (BAFU), Bern.

Warziniack, T., Haight, R.G., Yemshanov, D., Apriesnig, J.L., Holmes, T.P., Countryman, A.M., Rothlisberger, J.D., Haberland, C., 2021. Economics of invasive species. In: Poland, T.M., Patel-Weynand, T., Finch, D.M., Ford Miniat, C., Hayes, D. C., Lopez, V.M. (Eds.), Invasive Species in Forests and Rangelands of the United States. Cham, Switzerland, pp. 305–317. https://doi.org/10.1007/978-3-030-45367-1.

Welsh, M.J., Turner, J.A., Epanchin-Niell, R.S., Monge, J.J., Soliman, T., Robinson, A.P., Kean, J.M., Phillips, C., Stringer, L.D., Vereijssen, J., Liebhold, A.M., Kompas, T., Ormsby, M., Brockerhoff, E.G., 2021. Approaches for estimating benefits and costs of interventions in plant biosecurity across invasion phases. Ecol. Appl. 31, e02319. https://doi.org/10.1002/eap.2319.

Wermelinger, B., 2006. Augen auf für einen bislang unbekannten schädling. Gartenbau 46 (2), 4.

Wickham, H., 2016. Readxl: Read excel files.

Wickham, H., 2022. Package “stringr.”.

Wickham, H., Chang, W., 2016. Package ggplot2: an Implementation of the Grammar of Graphics, 2. Create Elegant Data Visualisations using the Grammar of Graphics, pp. 1–189.

Wickham, H., François, R., Henry, L., Müller, K., 2019. Dplyr: A Grammar of Data Manipulation. R package, Media.

Yemshanov, D., Haight, R.G., Koch, F.H., Venette, R.C., Swystun, T., Fournier, R.E., Marcotte, M., Chen, Y., Turgeon, J.J., 2019. Optimizing surveillance strategies for early detection of invasive alien species. Ecol. Econ. 162, 87–99. https://doi.org/10.1016/j.ecolecon.2019.04.030.

Yihui, X., 2023. Package ‘knitr.’.