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ORIGINAL ARTICLE

Cost-Plus-Loss Evaluation of Double Sampling Strategies for Insect Defoliator Mitigation Decisions

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Abstract
Forest damage may increase in frequency, extent and severity as a consequence of climate change and global trade. To mitigate the negative consequences of forest damage caused by insects and fungi, pest management strategies need to be established. An important component of such strategies is the assessment of pest population densities to predict subsequent potential damage during outbreaks. In this study we evaluated different inventory strategies for assessing the population density of Scots pine (*Pinus sylvestris*) insect defoliators through cost-plus-loss analysis where the cost of the inventory is added to the expected losses, mainly from incorrect decisions due to inaccurate information. We assessed what inventory strategy minimized the expected cost-plus-loss for differentspatial distribution of pupae populations, forest stand ages and forest areas affected. The results showed that double sampling was a more efficient sampling strategy than a single-phase survey. With the double sampling strategy, a second phase sample was selected if the first phase results were inconclusive regarding whether pest mitigation efforts should be implemented. The average cost-plus-loss varied widely over all simulated defoliator pupae populations and stand ages. For the double sampling strategy, the average cost-plus-loss was between ~ 18.7 thousand SEK and 5.6 million SEK, while the alternative cost-plus-loss ranged between ~ 18.7 thousand SEK and 9.7 million SEK. The results underscored the importance of accurate information for decision-making in defoliator control, and that a double sampling strategy is better than a single sampling scheme for most scenarios evaluated. We found that the least inventory efforts should be used to evaluate defoliator populations in stands close to a scheduled harvest, and more efforts should be allocated to younger standsdue to the higher expected loss from incorrect decisions. In younger stands, salvage logging due to defoliation induced mortality resulted in higher costs.

Keywords Cost-plus-loss · Inventory · Forest damage · Pest mitigation · Double sampling

Extended author information available on the last page of the article

Background

Because of climate change and global trade, forest damage may increase in intensity, severity and frequency (Mery et al. 2005; Allen et al. 2010). Defoliating insects may influence larger areas and cause increasing damage regarding tree mortality and growth loss (Schelhaas et al. 2003; Seidl et al. 2011a, 2011b). Forest damage has considerable consequences; Dale et al. (2001) estimated the annual costs of forest pathogens and insects in the United States to about 1.5 million USD year^{-1}.

If initial signs of large-scale damage can be observed, pest management measures may limit the negative consequences (Nyrop et al 2000). Since forest damage may be more frequent in the future, society needs to set up comprehensive pest mitigation strategies (Wulff 2011). This includes a need for monitoring population levels of pest species known to have a potential to cause forest damage and establishing systems to handle sudden outbreaks and detect increased outbreak risks. An important component of such systems is inventories which are adapted to provide the specific information needed for mitigation decisions and to develop mitigation schemes (hereafter denoted target tailored forest damage inventories (ibid.)).

Target tailored forest damage inventories may be of different kinds, ranging from aerial detection surveys from helicopters (e.g. Kärvemo, et al. 2014), through assessments using various types of imagery from remote sensing (e.g. Ciesla 2000; Hall et al. 2016), to field surveys based on either purposive or random selection of the sampling locations (e.g. Knight 1958; Connola et al. 1959; Stehman and Davis 1997; Samalens et al. 2007), and systems of traps to monitor pest population levels (e.g. Lindelöw & Schroeder 2001). The different methods have different advantages and disadvantages, related to simplicity of implementation, the type of information that can be acquired, cost, and accuracy of the information.

In planning inventories, cost-plus-loss analysis has been suggested as an analytical tool for evaluating the suitability of different inventory strategies (Cochran 1977; Hamilton 1979). This framework allows for finding an optimal inventory strategy, given knowledge of how information will be used for decisions and what losses would follow from incorrect decisions due to inaccurate information. The approach is to minimize a cost-plus-loss function where the cost of inventory is added to the expected losses, mainly due to incorrect decisions (e.g. Ståhl et al 1994). In the context of pest management, this means finding inventory strategies that provide the information needed to implement appropriate mitigation measures, including doing nothing in cases where the risk of damage is low (e.g. Waters & Stark 1980). The cost-plus-loss framework has been applied in many different contexts, especially for finding inventory strategies for deciding upon forest management activities such as thinning and clearcutting (Ståhl et al. 1994; Eid 2000; Mäkinen et al. 2012). While it is often straightforward to estimate the cost component of cost-plus-loss analysis, the expected loss is usually more difficult to assess. To do this, knowledge is required about how the information will be used in the decision making, and what the economic consequences of incorrect decisions are (e.g. Barth et al. 2006; Kangas 2010). This requires detailed knowledge of the processes involved. In the case of pest management, this involves knowledge of the pest's biology and likely forest damage at different population levels, the cost and likely success of a pest mitigation measures, and the cost of forest damage after an uncontrolled pest outbreak (Waters & Stark 1980).

Herrick (1981) used cost-plus-loss theory in evaluating effective investment in forest pest management from the viewpoint of a large public forest and the decreased provision of forest goods from areas with forest damage. Through pest management, the negative impacts of damage could be reduced, and the optimal level of pest management could be identified as the one with the lowest cost-plus-loss (Herrick 1981). However, that study did not consider the accuracy of the information or the decision about whether or not to control the outbreak; rather, it focused on selecting the right intensity of mitigation efforts (ibid.). Several authors have called for making increased use of economic theory in analyzing forest pest management strategies (e.g. Bicknell 1993; Fox et al. 1997; Corbett et al. 2015; Niquidet et al. 2015). One popular framework is called economic threshold analysis (Fox, et al 1997). This framework for finding the appropriate integrated pest management system has been intensively studied (e.g. Fettig et al. 2005) and has many similarities with cost-plus-loss analysis. However, most studies on economic threshold analysis neither consider the cost or the uncertainty of information, nor the loss due to incorrect decision. Another popular framework is cost–benefit-analysis, which typically takes a broader view on the values protected by pest control, but in essence also evaluates the costs and benefits in monetary terms. It has been applied in Europe in evaluating the management of the pine processionary moth (*Thaumetopoea pityocampa;* e.g. Gatto et al. 2009, Cayuela et al. 2011).

Economic threshold analysis has revealed that the costs of assessing pest populations are often substantial and need to be considered in keeping the total costs as small as possible (Binns and Nyrop 1992). Thus, several research studies have addressed the development of sequential sampling plans to assess pest populations with regards to economic thresholds for deciding upon pest management (ibid., Fettig et al. 2005). These plans have typically used either a model of the mean-to-variance of pest abundance or Taylor's power law to infer stop lines according to economic thresholds, which allow the sampling to continue until it reaches a conclusion by deviating from a specified "window" (Binns and Nyrop 1992). Binns and Nyrop (1992) also refer to a strategy called double sampling, which is related to sequential sampling, but where only one or two samples are selected; the size of the second phase sample (which may be zero) depends on the estimates obtained from the first phase sample. This sampling strategy was first described by Cox (1952), and it has been less widely implemented compared to sequential sampling in the context of pest mitigation (Binns & Nyrop 1992). The method is useful in cases where the analysis of the sample requires substantial time and cost (ibid.). If the estimate from the first sample is far from the threshold for mitigation, the second sample size is set to zero and additional costs are avoided.

Different outbreaks may call for different tools in their evaluation, for example, a defoliation event in Sweden that has necessitated pest control was caused by the pine looper (*Bupalus pinaria* L.) which affected 7 000 ha in 1996 (Långström, et al. 1999; Långström et al. 2004). The pine looper is a geometrid moth which is a defoliator of pine trees (Barbour 1988). After hibernation in the pupal stage, the adults emerge and fly in June, laying eggs on the needles (Schwenke 1978). Larvae hatch in end of June and have slow larval growth during summer which then rapidly increases in the fall, along with a high consumption of needles (ibid.). Before winter, the larvae descend to the ground and pupate in the litter. Defoliation events can run 2–5 consecutive years, and are sometimes not observed the first year, as densities of larvae are low and therefore often overlooked at that stage. However, early detection is important for successful mitigation. Estimation of pupal density for population estimates can be used for evaluating mitigation needs (Långström et al. 1999). Typically the inventory of pupae in the litter is time-consuming and expensive, and in addition the pupae need to be evaluated for their vitality which requires additional laboratory work to avoid erroneous results. Thus, in this situation a double sampling scheme may be preferred to a single-phase or a sequential sampling strategy.

Although there are many IPM strategies developed in an international context (e.g. Fettig et al., 2001 and 2005), there are very few examples in a Nordic Forest context. Two years of defoliation by the pine looper may result in extensive tree mortality (Bevan 1974; Långström et al. 1999). In Sweden there have been repeated defoliation events in Hökensås in Västergötland, most recently in 1996–1997 and before that in 1944–1945 (Butovitsch 1946; Långström et al. 1999, 2004). Other defoliating insects causing extensive damages in Nordic conditions are the pine sawflies *Diprion pini* and *Neodiprion sertifer* (Hanski 1987). Infestations by the pine sawflies are often limited to certain stand and site conditions (McMillin et al. 1996). From 1997 to 2001 a *Diprion pini* outbreak of 500,000 ha occurred in Finland (De Somviele et al. 2004). During this outbreak, young trees were most severely affected (ibid.). A previous outbreak of the same species in Finland is described by Långström et al. (2001) where, in non-treated areas, the defoliation continued and led to 50–75% tree mortality and reduced growth of surviving trees (ibid.). In France, defoliations by the pine sawflies led to substantial growth reductions over many years, in addition to considerable tree mortality and salvage loggings (Laurent-Hervouet 1986). For each of these three defoliating insects the inventory of pupae (at different time-points) may provide a good means of assessing the population and thus the likely continuation of an outbreak for IPM decision.

The objective of this study was to compare simple random sampling with double-sampling inventory strategies, using fixed-area plots, to assess the population density of a defoliator insect, once initial signs of damage have been observed in an area. The inventory is performed to evaluate the need for pest mitigation, and the pupae are analysed in a lab to determine their viability to avoid unnecessary pest mitigation. To make the comparison, cost-plus-loss analysis was applied, considering the cost of the inventory, the cost of the mitigation measure, as well as the expected losses due to mortality in the event of a continued pest outbreak. We evaluated the use of different numbers of sample plotsfor different pupae densities, spatial patterns, stand types, and areas affected by the potential pest outbreak.

Methods

Our assessment focuses on what efforts should be allocated to field inventories to assess the population density of a defoliator insect – such as the pine looper or the pine sawflies *Diprion pini* or *Neodiprion sertifer* – once initial signs of damage have been detected. This initial detection can come from local knowledge or change detection in satellite imagery for instance. This cost is not included in the cost-plus-loss analysis in the present study. The target parameter in the inventories is the population density of insect pupae in the ground, which is used for deciding whether mitigation measures should be implemented (Fig. 1).

Field inventories and subsequent vitality verification for determining the density of pupae in a forest area are costly. Thus, we evaluate what inventory effort is adequate through cost-plus-loss analysis. On the cost side, we have the inventory cost and the cost of implementing the mitigation program if the estimated density of pupae exceeds the threshold for mitigation. On the loss side, we have the decreased

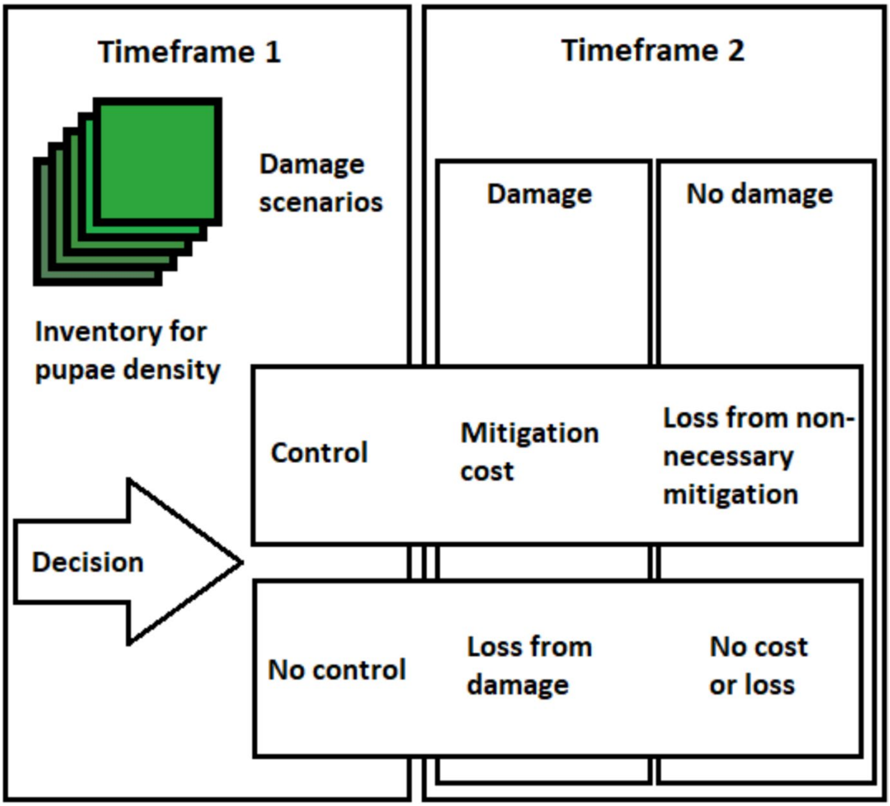

Fig. 1 Schematic illustration of the study – An inventory of the number of pupae m^{-2}, a decision, and the possible consequences. Each damage scenario has different initial and outcome states, but in each the decision is based on the inventory results

net present values (NPV) from additional forest management costs following severe defoliation mortality and subsequent salvage logging, and the loss due to potentially erroneous implementation of mitigation measures when the pupae density is low.

Inventory Strategies

We evaluated two different inventory strategies: simple random sampling (SI) and double sampling (DS). We used fixed-area plots (squares of 0.25×0.25 m) for both. In the case of DS, sampling is performed in one or two phases using simple random sampling. Whether or not a second phase sample is selected depends on the outcome of the first phase sample of n_1 plots.

For the SI inventory strategy the following estimator of the pupae density was used

$$\hat{\lambda} = \frac{1}{an} \sum_{i=1}^{n} u_i \tag{1}$$

where n is the number of sample plots, a is the area of the sample plot, and u_i is the number of pupae found in the i:th sample plot *(c.f.* Gregoire & Valentine 2008). The following variance estimator was applied:

$$\hat{V}\left(\hat{\lambda}\right) = \frac{1}{n(n-1)} \sum_{i=1}^{n} \left(\frac{u_i}{a} - \hat{\lambda}\right)^2 \tag{2}$$

The area of interest for the survey was treated as a torus (a doughnut-shaped surface) to avoid edge-effects (e.g. Gregoire & Valentine 2008*)* in the simulations.

Different decision rules about whether to implement pest mitigation measures were used for the two different sampling strategies:

- For SI, Eq. 1 was used to estimate the pupae density. If the density estimate exceeded the threshold value (λ_T; described in more detail below) mitigation measures were implemented.
- For DS, Eq. 1 and 2 were applied using data from the first phase sample to compute and evaluate the test statistic $\left|\frac{\hat{\lambda}-\lambda_T}{\sqrt{\hat{V}\left(\hat{\lambda}\right)}}\right|$. We rejected the null hypothesis $\lambda = \lambda_T$ if the test statistic exceeded $t_{0.025}(n_1 - 1)$, i.e. we used a 5% error level for the test. Following rejection, a decision to either implement mitigation measures or not was made based on data from the first phase sample. If the null hypothesis could not be rejected, a second phase sample was selected according to principles described below to better evaluate the need for treatment.

The second phase sample was *also* selected with simple random sampling; it utilized the estimated variance and mean from the first phase sample to determine the second phase sample size, n_2. Utilizing the information from the first phase sample, repeated conditioning, and the fact that the second sample is independent of the first (for all things but sample size), with an assumption that the distribution of the estimator of Q and $\hat{\lambda}$ is normal as well as the underlying population, the sample size of the second phase sample is calculated as:

$$n_2 = round\left(\frac{n_1\hat{V}\left(\hat{\lambda}\right)}{CQ^2}\left(1 + 8C + \frac{\hat{V}\left(\hat{\lambda}\right)}{Q^2} + \frac{2}{n_1}\right) - n_1\right) \tag{3}$$

where $= \hat{\lambda} - \lambda_T$, aiming for a desired coefficient of variation of $cv = \sigma/\theta = 0.05$ where σ is the true population standard deviation and θ is the true difference$Q$. Thus $C = (cv)^2 = 0.0025$ (c.f. Cochran 1977, p. 79; Cox 1952). In order to avoid extreme values for n_2 we added some constraints: 1.) For $n_2 > 20A^{1/3}$ the second phase sample size was set as $n_2 = 20A^{1/3}$ plots, where A is the area of interest; 2.) If Q = 0 (i.e. $\hat{\lambda} = \lambda_T$) Q was set to 0.0001 and 3.) if n_2 was rounded to zero, we set it to 1 for the second phase.

The estimates from the two inventory phases were then used to form a weighted estimate of the pupae density from both inventories:

$$\hat{\lambda}_{DS} = \frac{\left(n_1\hat{\lambda}_1 + n_2\hat{\lambda}_2\right)}{\left(n_1 + n_2\right)} \tag{4}$$

Here, $\hat{\lambda}_1$ is the estimator from the first phase sample and $\hat{\lambda}_2$ the estimator from the second phase sample. Following a second phase sample, the decision about implementing a mitigation measure was based on whether or not $\hat{\lambda}_{DS}$ was smaller or larger than the threshold pupae density.

Forest Stands

We simulated five forest stand types dominated by Scots pine (Pinus sylvestris) with the Heureka system (e.g.Lämås et al. 2023; Wikström et al. 2011). The Heureka system is a decision support system for the analysis and planning of forest landscape management developed and maintained at the Swedish University of Agricultural Sciences (SLU). The foundation of Heureka is projections of the development of single trees, based on which the outcome of several forest ecosystem services can be evaluated (ibid.). Data on current forest condition, the applied forest management activities, and known ecosystem processes are used to predict the future states of the forest. The projections include predictions of several core variables, such as timber volume, forest age, and tree species distribution. In our study, each stand represents forests of different age but with the same site index, defined as the dominant height at 100-year average stand age (H100 for Pine), and geographic area (Table 1).

To estimate the loss if the forest is damaged, the NPV from future forest management was calculated. The NPV in Heureka is defined as the income from future activities (such as thinning and clear-cutting) for an approximately infinite time horizon, minus the cost for harvests and silviculture (i.e. regeneration, fellings and cleaning) from the start of the simulations to final felling, discounted to current time

Table 1 The five stand types for which defoliation damage was evaluated, with Heureka results in terms of NPV (SEK ha^{-1}) for healthy stands and the loss (in terms of NPV) for damaged stands

Age	DG	H	N	G	V	Prop Pine	Prop Spruce	Prop Birch	NPV Healthy	Loss
23	7.5	5.4	2073	6.6	21.8	0.90	0.05	0.04	13643	7253
33	11.8	8.5	1955	17.1	77.6	0.93	0.03	0.03	18147	5201
43	15.5	11.8	1098	17.6	102.1	0.93	0.03	0.03	22619	2285
53	18.6	14.4	1057	24.8	169.4	0.92	0.04	0.04	31570	315
97	31.2	21.8	536	26.3	249	0.87	0.07	0.04	52009	889

[#]DG is the quadratic mean diameter (cm), H is the basal area weighted mean height (m), G is the basal area (m^2 ha^{-1}), and V is the volume (m^3sk ha^{-1}), Prop Pine/Spruce/Birch is the proportion of stems of each tree species for the youngest stand, and the proportion of the basal area per species for stands with H > 7 m. NPV Healthy is the discounted net present value of the undamaged stand (SEK ha^{-1}), Loss is NPV Damaged subtracted from NPV Healthy (SEK ha^{-1})

with a user selected fixed interest rate. In this study we used a 3% interest rate without accounting for inflation (as did Straw et al. 2002, and Cedervind 2003). This is consistent with the expected value for an investment of moderate risk (Ibbotson and Sinquefield 1976). First, we calculated the NPV for healthy development of all stands. Here, management was based on standard silvicultural procedures for southern Sweden, with normal thinning intensity and rotation periods which maximize the NPV. The cost and income associated with each action was based on the default Heureka timber price list for southern Sweden. Next, the NPV for the stands where damage is incurred was calculated. It was assumed that the damaged stemmed from the loss from a second year of defoliation (which is typically more severe than that of the first year) and that it caused a 60% mortality in trees. Here, a 60% thinning was forced in each stand. For calculating the loss, the ordinary price list was used for the harvested damaged wood, i.e. no loss of timber value was considered nor were growth loss in surviving trees included *or assumed*. The loss in NPV ha^{-1}, L, was then calculated as the difference between NPV for the healthy undamaged forest and the damaged forest (Table 1).

The Insect Pupae Populations

Six different populations of pine looper pupae were simulated with two different spatial patterns and three densities (Small, Medium, Large). Three of the populations were simulated with complete spatial randomness (CSR) from a Poisson process, and three were simulated as clustered populations (CLU) from a Thomas process (Thomas 1949) with 150 cluster centres, 0.01 standard deviation of the "children points", and with an average density of 66, 266 and 466 per cluster. The parameters were used to simulate the different point patterns in a 1 ha square using the package Spatstat in R (Baddeley & Turner 2005, R Core Team 2021). The populations were denoted CSRS and CLUS for small densities of ~ 1 pupae m^{-2}, CSRM and CLUM for medium intensities of ~ 4 pupae m^{-2} and finally CSRL and CLUL with large intensities of ~ 7 pupae m^{-2} (Fig. 2, Table 2).

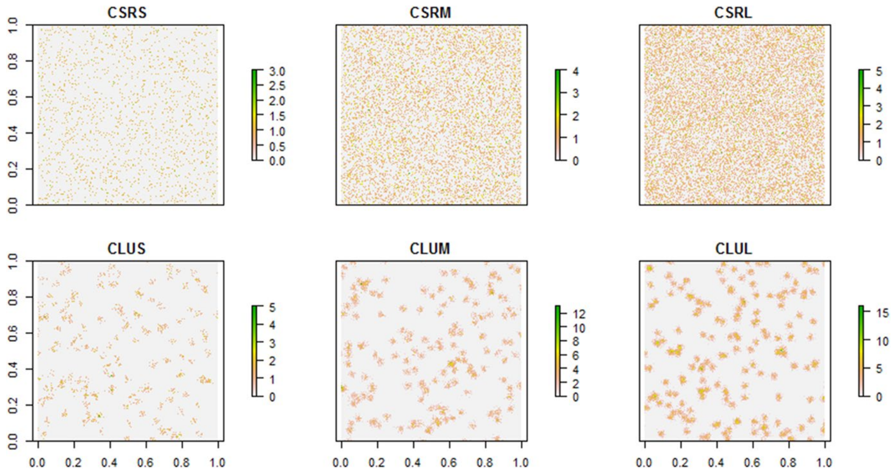

Fig. 2 The six simulated populations (CSR = complete spatial randomness, CLU = Clustered combined with S for small, M for medium and L for large population densities). The three above follow a stationary Poisson process and the three below follow a Thomas process of approximately the same density of pupae

Table 2 Numbers of pupae m^{-2} in the simulated populations (CSR = complete spatial randomness, CLU = clustered population combined with S for small, M for medium and L for large population densities) of healthy pupae

Population	# of pupae m^{-2}	Min # pupae grid-cell^{-1}	Max # pupae grid-cell^{-1}	True population variance
CSRS	0.9943	0	3	0.062
CSRM	4.0327	0	4	0.252
CSRL	6.9666	0	6	0.436
CLUS	0.9597	0	5	0.080
CLUM	4.104	0	13	0.596
CLUL	7.4859	0	16	1.564

Min, max and variance of grid-cell values representing 25 × 25 cm fixed-area-plots for inventory

The populations were modelled to resemble the cases presented in Långström et al. (1999) for the pine looper. The stands were assumed to be of damage class 3 at the first time point when damage outbreak was observed, and continued defoliation was assumed to happen when healthy pupae ranged between 2 and 5 pupae m^{-2}. A risk function based on *a* logistic model was used to set the probability of an outbreak the subsequent year to fit this information (presented in the next section).

Modeling the Probability of Severe Damage

In the present study, the stands are assumed to show minor initial signs of defoliation, which have triggered the inventory. The risk of severe defoliation in the following year was modelled using the density of healthy pupae as a predictor variable (Långström et al. 1999). The risk of complete defoliation of 60% of the trees was modelled using the numbers of vital pupae in the humus of the infested area as an independent variable. $f(\lambda) = P(severedamage|numberofpupae = \lambda)$ is the probability of severe damage, i.e. complete defoliation and mortality of 60% of the trees in the stand:

$$f(\lambda) = \frac{e^{(\alpha+\beta\lambda)}}{1 + e^{(\alpha+\beta\lambda)}} \tag{4}$$

with parameters $\alpha = -5.38$ and $\beta = 1.49$ (Fig. 3).

Calculating the Threshold Pupae Density for Mitigation

The threshold pupae population density above which the expected loss exceeds the cost of spraying with *Bacillus thuringiensis* (Bt) was calculated using the results from the Heureka calculations (assuming 60% mortality and salvage logging of dead trees):

$$L \times A \times F(\lambda) \geq C_{Bt} \tag{5}$$

Here, L is the expected loss due to defoliation, A is the evaluated area, $C_{Bt} = C_{HF} + C_{HV} \times A$ where C_{HV} is the cost per area unit for the mitigation, and C_{HF} is the corresponding fixed cost. This equation was solved for each scenario yielding a threshold pupae density λ_T above which mitigation through spraying with Bt was implemented. We assumed that Bt spraying was always successful in preventing

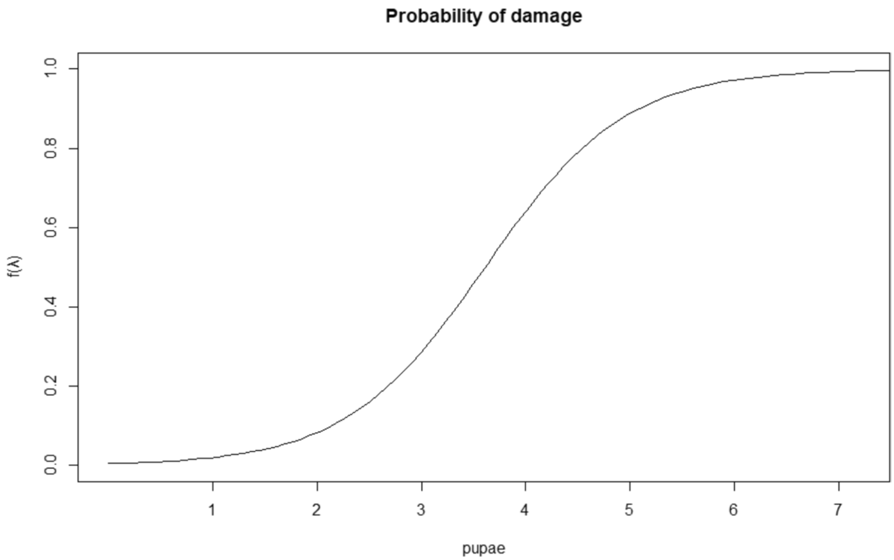

Fig. 3 Probability of severe damage *during a second year,* depending on the density of pupae (number m^{-2}) in the forest stand

additional defoliation. The following cost parameters were utilized: $C_{HF} = 28000$ SEK for almost two weeks of planning, applying for permits, communication with spraying contractor, etc. and $C_{HV} = 600$ SEK ha^{-1} for Bt and aircraft time. The areas investigated in our study were 50, 200, 1 000, 5 000 and 10 000 ha in size.

Cost-Plus-Loss Analysis

We wish to minimize the cost-plus-loss of the two different inventory strategies (SI and DS). This was achieved by minimizing the function:

$$E(C+L) = \hat{p}_{Bt} \times C_{Bt} + \hat{p}_{noBt}(E(L) \times A) + C_{inv} \tag{6}$$

Utilizing Monte Carlo (MC) simulations, we estimated the cost-plus-loss outcome of each iteration's costs and losses. $\hat{p}_{Bt}$ is the proportion of MC-repetitions where Bt was applied and $\hat{p}_{noBt}$ the proportion of occasions where it was not. $E(L)$ is the expected loss based on the true number of pupae in the pupae population. The cost of inventory is modelled as:

$$C_{inv} = C_F + n_1\left(c_h t_p + \frac{c_h E(d)}{v}\right) + I_{ds}\left(C_{Fds} + n_2\left(c_h t_p + \frac{c_h E(d)}{v}\right)\right) \tag{7}$$

where C_F is the fixed inventory cost (planning, tools, laboratory, etc.) and n_1 and n_2 are the numbers of inventoried plots if a second phase sample is selected, as indicated by the binary variable I_{ds}. t_p is the time spent on a plot, c_h ist the cost of inventory staff h^{-1}, v is the speed of walking between plots (m h^{-1}) and $E(d)$ is the expected average between-plot distance (m). These costs were set to be C_F=6 000 SEK for the fixed costs of personnel, laboratory for the verification of pupae vitality, maps and tools, $c_h = 350$ SEK h^{-1}, t_p=0.5 h for each plot. The average walking-speed was set to v=3 000 m h^{-1} and the average between-plot distance $E(d) = \sqrt{A/n}$, which is an approximation. In case a second phase sample was selected, a lower fixed cost C_{Fseq}=3 000 SEK was used, as tools and maps are already in place.

Results

Results from 1 000 MC-repetitions for each scenario suggest that for stands and pupae populations leading to larger losses ha^{-1} from no control, there is great advantage in performing an inventory (Fig. 4). The inventory costs over all evaluated sample sizes for the SI inventory strategy ranged from ~ 9 900 SEK to ~ 89 thousand SEK for all evaluated populations and area sizes, with an average of ~ 39 thousand SEK. For the DS strategy the inventory costs ranged from ~ 9.9 thousand SEK to ~ 181 thousand SEK, with an average of ~ 52 thousand SEK, over all initial sample sizes evaluated. The inventory costs reflect the size of the area

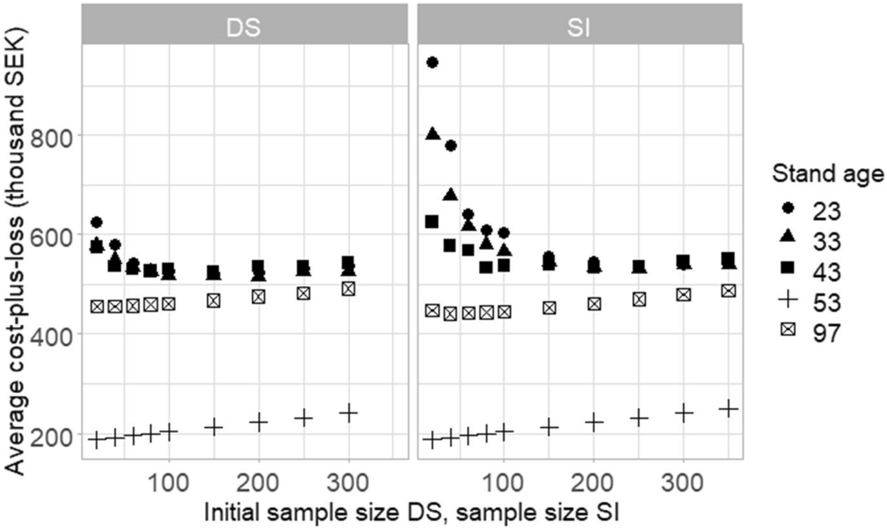

Fig. 4 Average cost-plus-loss over all pupae populations (Area = 1000 ha) with initial sample size (DS) and total sample size (SI) on the x-axis, average expected cost-plus-loss on the y-axis from the simulations and the different stand age categories (legend) shows that the highest stand ages had non-relevant losses and almost never merited inventory or mitigation costs

and the evaluated sample sizes for the SI, but also varies with the damage populations, mostly so for the DS strategy.

The cost-plus-loss across all stands and pupae populations ranged from 10 thousand SEK to ~ 72.3 million SEK, for both the DS and the SI strategy depending on the area of the outbreak. The median cost-plus-loss over all stand ages and pupae scenarios was 217 thousand SEK for the DS strategy, and the mean 1.3 million SEK for the DS strategy, while the median was 218 thousand SEK, and the mean 1.5 million SEK for the SI strategy, indicating high extreme values for both strategies but more so for the SI strategy despite the lower inventory costs. The average cost-plus-loss over all pupae populations (i.e. assuming that they are all equally likely) was between ~ 18.7 thousand SEK and 5.6 million SEK for the DS strategy, while for the SI strategy it was between 18. 7 thousand SEK and 9.7 million SEK. The average cost-plus-loss for most stand ages decrease with higher sample sizes, but not for the 53-year-old stand which had the lowest expected loss from additional defoliation (Fig. 4, Table 1). For a direct comparison between the two sampling strategies, the average over all pupae populations and stand ages was calculated. In this case the best inventory strategy is a DS strategy with a first phase sample size of 100 plots (Fig. 5) and for the SI strategy a sample size of 200.

When pupae populations are clustered the variance of the estimators increase and thus the cost-plus-loss (Fig. 6). Generally, the larger the affected area, the higher benefit from utilizing DS sampling strategy, especially for clustered populations.

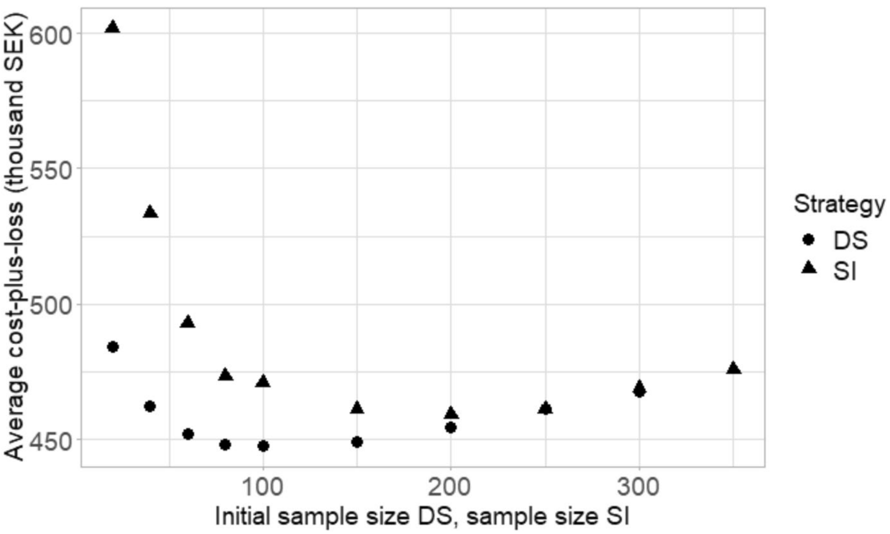

Fig. 5 The average cost-plus-loss for a 1000 ha outbreak, for the two inventory strategies over all true populations of pupae and stand ages (i.e. assuming that all pupae populations and stand ages are equally likely within the area). DS consistently implies lower cost-plus-loss up to an initial sample size of 200; the lowest cost-plus-loss was obtained for an initial sample size of 100 plots

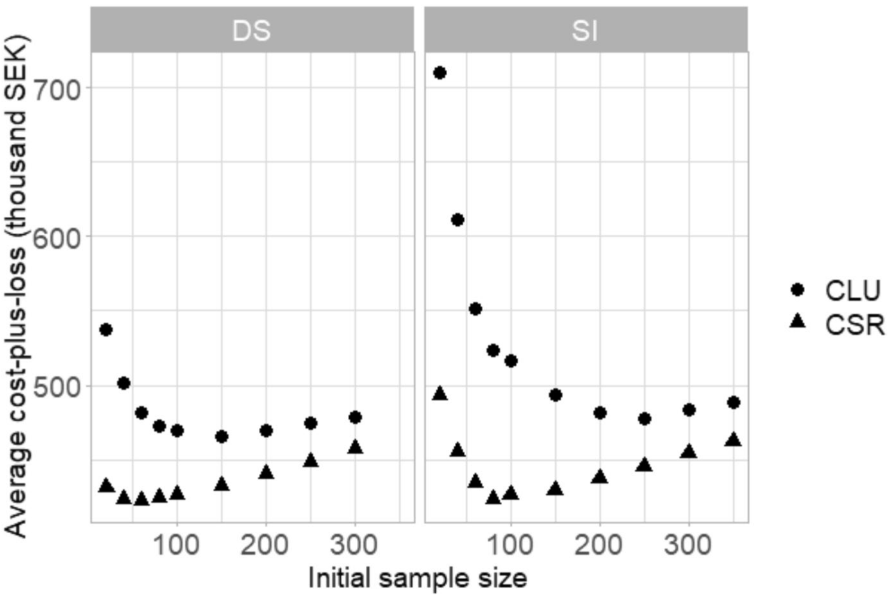

Fig. 6 The average cost-plus-loss from the two inventory strategies over all evaluated sample sizes, pupae populations and stand agesfor a 1000 ha outbreak, illustrating the effects of increased variance of the estimators when pupae populations are clustered, shifting the minimum cost-plus-loss toward higher sample sizes and increasing differences between the strategies

Discussion

This study investigated what inventory strategy should be applied in the acquisition of data for deciding upon the use of pest control measures. The inventory is performed to evaluate the population density of a defoliator insect to assess the risk of additional, severe, defoliation. Since the inventory of pupae in the humus is expensive and requires the pupae vitality to be assessed in a lab, proper evaluation of the potential benefits in terms of reduced losses following a correct decision is an important step. Thus, cost-plus-loss analysis (Cochran 1977; Hamilton 1979) was applied and the inventory strategy minimizing the expected cost-plus-loss searched for. It was found that a double sampling strategy was more efficient than a single-phase survey. These results were expected from previous studies with regards to sequential sampling plans for forest defoliator population estimation (e.g. Nyrop et al. 2000; Fettig et al. 2005). Averaging the results over all pupae populations, i.e. mimicking a real-world situation where the true density and spatial distribution of pupae is unknown, the double sampling strategy clearly outperformed the simple random sampling strategy in terms of cost-plus-loss. However, the gain of using the double sampling strategy depended on what stand type was defoliated: in some cases the mitigation measures were not profitable due to the low losses incurred by defoliation and subsequent salvage logging. For double sampling the optimal initial sampling effort was 100 plots. If, for some reason, only one phase of inventory can be used then an inventory of 200 fixed-area plots is recommended. In the older stands there may be reason to abstain from inventory completely.

The study shows the benefit of having accurate data for the decision making in cases where substantial losses can be avoided, i.e. when losses following incorrect decisions are large. Our case builds on a landscape dominated by younger forests (young forests under 60 years of age constitute 83% of the area) and hence is most relevant to estates or areas where the average stand age is relatively low. In the southern parts of Sweden the average area of forests younger than 60 years is approximately 67% of the productive forest land area (Anon. 2016). For one of the stand ages we were unable to locate the optimum sampling intensity since we did not evaluate small enough sample sizes (Fig. 4). This was the case for the 53 year-old forest where the NPV losses from defoliation were very small. This, however, could be a consequence of the assumptions of losses merely as mortality and salvage logging costs since at this age a thinning activity is quite normal management practice. The study results might be different if growth losses from the defoliation had also been included (e.g. Laurent-Hervouet 1986). The timing of the defoliation and the thinning is in line with the normal thinning age and as such the costs are somewhat within the normal costs of an ordinary thinning activity thus minimizing the damage losses.

In related sequential sampling plans, the inventory proceeds with additional sample plots until an estimate is reached which has a relative error of a certain level (i.e. Kolodny-Hirsch 1986). In our sampling strategy this was not a possibility, as there is a need for vitality checking of the pupae in a laboratory before deciding on a second phase of the inventory. Checking the vitality of the pupae is a precautionary step, as it allows for better estimation of the coming population of defoliating insect compared to a simple gross pupae count. Pupae vitality can be affected by viruses and weather conditions may also impact the need for treatment (Speight and Wainhouse 1989).

Traditional sequential sampling designs have been shown to overestimate accuracy (i.e. to stop the inventory too soon) when the underlying population's distribution is unknown, particularly in the presence of spatial auto-correlation (Robinson & Burk 1998; Robinson & Hamann 2008). In the present study, the assumption of normality (based on the central limit theorem) when the initial sample size is as low as 20 units may be problematic; this was probably one of the contributing factors to the higher cost-plus-loss for this initial sample size. However, contrary to some sequential sampling plans, we did not add additional samples close to the first sample, which could have introduced auto-correlation issues as described in Robinson & Hamann (2008).

The evaluated cost-plus-loss from the decision on pest control was made under the assumption of a forest manager who is risk-neutral. A more risk-averse manager would perhaps choose a lower threshold for Bt-application than the threshold used in this study, while the opposite would be the case for a manager who is more inclined to take risks (i.e. would not be willing to pay for Bt-application, but rather hope that an outbreak will not occur). The strategy used in this study was to search for a threshold value set to be the break-even point where mitigation costs equals the expected avoided losses. In Sweden, systems of this kind have not been used yet, as over the last 20 years there have been few outbreaks where damage pest control have been considered necessary (Eastern Skåne 1997 (*Lymantria monacha*); Hökensås 1997 (*Bupalus pinaria*); Långström et al 1999; Anon. 2012). However, potential increases in the severity and frequency of outbreaks in the future could result in increased interest for such systems.

The simulated damage in our scenarios resembles the tree mortality in Långström et al. (2001). However, we did not consider the potential reduction in growth from defoliation on the trees that were not killed by the event. Cedervind (2003) looked at losses in NPV from incurred growth loss ignoring mortality, whereas we included the loss from mortality but disregarded losses from reduced growth. In Cedervind (2003) growth loss in trees with 90–100% one-year defoliation is estimated to approximately 730 SEK ha^{-1}, for trees with an average of 70% defoliation to 580 SEK ha^{-1} and for trees with 50% defoliation on average the estimated cost was 370 SEK ha^{-1}. In our study the mortality losses ranged between 315 and 7300 SEK ha^{-1}. Lyytikäinen-Saarenma and Tomppo (2002) estimated losses from one year of defoliation, including both mortality and growth loss, to 40 USD ha^{-1} for *N. sertifer* and 310 USD ha^{-1} for *D. pini*. Thus, the losses in our simulated damage scenarios appear to be within the range of other studies of similar kind.

If there is damage over a larger area comprising many different stand ages and damage intensities, a stratified sampling scheme or local pivotal method (LPM, Grafström et al. 2012) should be advised with more sampling in stands where larger losses are at stake. In the present example, these would be the younger forest stands, whereas for damage which jeopardize wood quality (e.g. wood borers, fire or rot making the wood unsuitable as saw timber) larger losses would occur from damage to mature stands.

Our approach assumes that information about the location and extent of the area affected by the defoliator is readily available at no additional costs. In many cases, this is an increasingly plausible assumption considering advances in remote sensing for damage detection and mapping (e.g. Solberg et al., 2006, Gilichinsky et al. 2012, Mozgeris and Augustaitis 2013, Morresi et al. 2024).

Another assumption that may have influenced the results of the present study is the model linking the fixed level of mortality to numbers of healthy pupae. This model would require verification if the results of this study are to be applied to actual outbreak situations. The present study also assumes that the defoliation is affecting the same area at both points in time, i.e. no expansion or change in defoliated area is considered. Hence, the losses assumed in our models should be considered conservative. The two sets of pupae distributions that we used may also have limitations. Some studies suggest that pupae may be more abundant under the crown of previously defoliated trees (Pine looper: in Butovitsch 1946; Diprionidae: Simandl 1992) and Simandl (1992) also found that there were more pupae closer to stand edges. Under these conditions, the inventory would benefit from spatially spreading the plots (i.e. by systematic sampling or LPM) or an increased sampling effort to higher probability areas if such auxiliary information is available.

The present study shows that evaluation through cost-plus-loss analysis is a promising tool for evaluating inventory strategies in forest pest management and that for the inventory of pupae with vitality verification double sampling was more effective than a simple random sampling strategy.

Abbreviations *Bt*: *Bacillus thuringiensis*; *CLU (-S, -M and -L)*: Clustered population of pupae (small, medium and large); *CSR (-S, -M and –L)*: Completely spatially random population of pupae (small, medium and large); *DS*: Double sampling strategy; *MC*: Monte-Carlo; *NPV*: Net Present Value; *SEK*: Swedish krona; *SI*: Simple random sampling strategy; *USD*: US dollar

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Declarations

Ethics Approval and Consent to Participate Not applicable.

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