Inventory Strategies for Monitoring and Evaluation of Forest Damage

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Abstract

Under global change, increasing stresses on forests require strategies for monitoring and mitigation of damages caused by pests and diseases. While the threats to forests increase, so do the possibilities to set up efficient monitoring programmes and detect forest damage by utilising new technologies. This thesis focuses on strategies for forest damage inventories where different auxiliary data are combined to improve information for pest mitigation programmes. First, the efficiency of National Forest Inventories (NFIs; or similar inventories) for detecting and estimating state and change of forest damage across large regions was evaluated. NFIs were found efficient for assessing widely distributed damage, but unable to detect clustered and local outbreaks with adequate precision. Second, targeted forest damage inventories directed to areas with potential or suspected damage were investigated. It was found that two-phase sampling for stratification taking the first phase information from existing NFIs was an efficient strategy. Remotely-sensed auxiliary information and post-stratification was shown to further improve the precision. Third, the use of a new sampling design was evaluated: the local pivotal method (LPM), which spreads the sample in the multi-dimensional space of available auxiliary data. The LPM was found to be more efficient than simple random sampling in all scenarios and, depending on the allocation of the sample and the properties of the auxiliary data, it sometimes outperformed two-phase sampling for stratification. Thus, the LPM may be a valuable tool for practical forest damage inventories. Fourth, the cost-plus-loss method was applied to evaluate inventory strategies in a pest mitigation context. If inventory costs are large, it is especially important to quantify the inventory efforts necessary to evaluate the need for mitigation. The optimal sampling effort necessary for deciding whether or not a defoliator outbreak should be treated was quantified. Double sampling was found to be a cost-effective sampling strategy, i.e. the size of the second phase sample was determined based on the estimates from a small first phase sample. As an overall conclusion, the thesis points out the importance of making use of existing information in setting up effective inventories of forest damage and of using appropriate sampling strategies for making use of the information in the best possible way.

Keywords: cost-plus-loss, forest damage, forest inventory, forest pests, Monte-Carlo simulation, survey sampling, target tailored inventories

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Contents

List of Publications

This thesis is based on the work contained in the following papers, referred to by Roman numerals in the text:

I Wulff, S., Roberge, C., Hedström Ringvall, A., Holm, S. & Ståhl, G. (2013). On the possibility to assess and monitor forest damage within large-scale monitoring programmes – a simulation study. *Silva Fennica*, 47(3), 1000. Doi: 10.14214/sf.1000

II Roberge, C., Wulff, S., Reese, H. & Ståhl, G. (2016). Improving the precision of sample-based forest damage inventories through two-phase sampling and post-stratification using remotely sensed auxiliary information. *Environmental Monitoring and Assessment*, 188(4), 1-21. Doi:10.1007/s10661-016-5208-4

III Roberge, C., Grafström, A. & Ståhl, G. Sample based forest damage inventory using the local pivotal method for sample selection. *Canadian Journal of Forest Research*. In press. Doi: 10.1139/cjfr-2016-0411

IV Roberge, C., Öhman, K., Lindelöw, Å., Schroeder, M., Grafström, A. & Ståhl, G. Cost-plus-loss evaluation of sample-based forest damage inventories: assessing the population density of a defoliator insect. (*manuscript*)

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The contribution of Cornelia Roberge to the papers included in this thesis was as follows:

I Planned the study in collaboration with co-authors. Ran simulations and contributed to the analysis and presentation of results. Contributed to writing the manuscript.

II Planned the study with co-authors. Programmed simulator, analysed and presented results. Wrote most of the manuscript. Corresponding author, responsible for response to reviewers.

III Planned the study with co-authors. Programmed simulator, analysed and presented results. Wrote most of the manuscript. Corresponding author, responsible for response to reviewers.

IV Planned the study with co-authors. Programmed simulator, analysed and presented results. Wrote most of the manuscript.

Abbreviations

2PS	Two-Phase Sampling for stratification design
ADS	Aerial Detection Survey
DEM	Digital Elevation Model
DTC	Damage Tree Count
ECR	Empirical Coverage Rate
ERSD	Empirical Relative Standard Deviation
EU	European Union
FAO	Food and Agriculture Organization of the United Nations
FIA	Forest Inventory and Analysis
FRA	Forest Resources Assessment
GIS	Geographical Information System
GPS	Geographical Positioning System
GRE*	Simulated damage populations for *Gremmeniella abietina*
HT	Horvitz-Thompson estimator
IPCC	Intergovernmental Panel on Climate Change
IPS*	Simulated damage populations for *Ips typographus*
LAI	Leaf Area Index
LiDAR	Light Detection And Ranging
LPM	Local Pivotal Method
MSE	Mean Square Error
NFI	National Forest Inventory
NPV	Net Present Value
PPS	Probability Proportional to Size
PS2PS	Post-Stratified Two-Phase Sampling for stratification design
RE	Relative Efficiency of the estimator
REDD+	Reducing Emissions from Deforestation and forest Degradation
RRMSE	Relative Root Mean Square Error
RS	Remotely Sensed
SI	SImple random sampling design
SPR	Sampling with Partial Replacement
STSI	STratified SImple random sampling design
TFDI	Targeted Forest Damage Inventory
TP1, TP2	Time Point 1 and Time Point 2

1 Introduction

1.1 Forest health and forest damage

There is a need for effective environmental monitoring programs to enable detection and mitigation of large-scale environmental problems (Stevens 1994). This spans all ecosystem types and natural resources, including forests. The world's forests are a valuable resource providing a range of ecosystem services on which society relies (e.g. Mery et al. 2005). This thesis concerns the development of efficient inventory strategies for monitoring and evaluation of forest damage. Due to global change, the importance of strategies of this kind is likely to increase in the future.

1.1.1 Climate change

Climate change may impact the sustainable use of the world's forests and their resilience to disturbance (Schelhaas, Naaburs & Schuck 2003; Seidl et al. 2011, Trumbore et al. 2015). Particularly, conifers are predicted to be sensitive to climate change and may be under threat (McDowell et al 2015a). Hence, forest management will face increasing challenges to preserve valuable ecosystems (Dale et al. 2001). Here, it is crucial to efficiently identify the threats in order to mitigate negative effects (Carnegie 2008). The dependence on ecosystem services from forests is predicted to increase, as global change will likely result in increasing demands for forest products (e.g. Mery et al. 2005) and stresses to forest trees (Allen et al. 2010). Hence, risks and impacts of forest damage may become more severe (Dale et al. 2001). As a consequence of climate change the distribution ranges of forest pest species (i.e. organisms that compete with humans for forest resources such as fibre; Berryman 1986) may shift towards the higher latitudes (Bale and Hayward 2010, Ammunét et al. 2012). In the Nordic countries it may result in extended areas of vulnerability to outbreaks of existing damaging agents (Vanhanen et al. 2007) and increased outbreak frequencies (Virtanen et al. 1996). For example, there is an augmented risk of higher numbers of broods of bark beetles (Coleoptera: Curculionidae) per season, due to increasing temperatures (Jönsson at al. 2007; Jönsson et al. 2009; Jönsson et al. 2011). This could result in larger bark beetle populations and hence increased risk of damage (ibid). Climate change and pests may also interact in such a way that the outbreaks may themselves influence future climate change. For example, in addition to climate change influencing the extent and severity of the recent mountain pine beetle (*Dendroctonus ponderosae*) outbreak in North America, the outbreak itself may affect the carbon uptake and storage capacity of these northern forests, which in turn may contribute to climate change (e.g. Kurtz et al. 2008).

1.1.2 Invasive species

Another threat to forest health is increasing biological invasions, i.e. the introduction and spread of species outside their indigenous range (e.g. Holmes et al. 2009). This anthropogenic problem stems largely from the growing global world trade and other activities such as tourism (Margolis et al. 2005). Invasive species are a threat to biodiversity (e.g. Kenis et al. 2009; Clavero & Garcia-Berthou 2005; Liebhold 2003) and to economic values of natural resources (e.g. Holmes et al. 2009). Climate change may exacerbate the negative impacts of species invasions, as it may increase the probability of establishment and spread of new invasive species, i.e. increase the risk that introduced species act as forest pests (Vanhanen, Veteli & Niemelä 2008; Ammunét et al. 2012).

There are many examples of large-scale outbreaks of invasive species with widespread consequences around the world, such as the Dutch elm disease affecting *Ulmus* spp., caused by different fungal pathogens (*Ophiostoma ulmi*, *O. novo-ulmi* and *O. himal-ulmi*) and facilitated by different insect vectors (Brasier, 2000). Another example is the fungal pathogen *Phytophthora ramorum* which has caused extensive ecosystem impacts in the United States (e.g. sudden oak death) due to its widespread damage and wide range of hosts (Rizzo et al. 2005). *P. ramorum* has also caused problems in Great Britain and Ireland, where it also affects the dwarf-shrub *Vaccinium myrtillus*. This may imply risks for Fennoscandia, where *Vaccinium* is typically a major component of the forest field layer (Samuelsson et al. 2012). Yet another example is posed by the pine wood nematode (*Bursaphelenchus xylophilus*) causing pine wilt disease, risking to affect pine forests across the globe (Mota and Vieira 2008). This species is high on the agenda from a European and Scandinavian perspective (Ökland et al. 2010, Eriksson et al. 2008). Among insects, the emerald ash-borer (*Agrilus planipennis*) is a serious damaging agent to *Fraxinus* spp. and another example of an eastern species threatening to be introduced in Sweden as it has made its way to western Russia (Villari et al. 2015; Orlova-Bienkowskaja & Bienkowski 2015). Two Asian long-horned beetles, *Anoplophora chinensis* and *A. glabripennis*, which have caused extensive damages to broadleaved species in North America (Dodds & Orwigg 2011) have been found in different parts of Europe (Haack et al. 2010). Another example is the European gypsy moth (*Lymantria dispar*), which has had widespread consequences since its introduction into the northeastern United States (Davidson et al. 1999).

Currently in Sweden, important diseases which are caused by non-native pests and pathogens include the Dutch elm disease (see above) and the ash dieback (caused by the fungus *Hymenoscyphus fraxineus*). This has even led to the red-listing of elms and European ash (*Fraxinus excelsior*) at the national level (Ahrné et al. 2015). In addition, non-native species that have potential to become new forest pests have established in Sweden over the last decades, for example the two larch-feeding beetles *Tetropium gabrieli* and *Ips cembrae*, and the bark beetle *Ips amitinus* which is able to reproduce in all available conifer substrates in Sweden (Samuelsson et al. 2012). Another recent development is that the sap feeding scale *Physokermes inopinatus*, coupled with a black sooty mould encrustation forming on the needles, has caused premature felling of 400 ha of spruce forest in southern Sweden in the summer of 2010 (Samuelsson et al. 2012). This is the first known outbreak of its kind; however, it is unknown if the species is a new introduction (Lindelöw, pers com).

1.1.3 Forest damage

Forest health can be approached from many different perspectives, from the broad sense of a healthy ecosystem to the protection of the forest commodities. Hence, there is ample potential for misunderstandings (Kolb et al. 1994). Tree senescence and mortality are natural phenomena in forest ecosystems. Therefore, some damage to individual trees is vital to the health of the forest ecosystem as a whole (e.g. Franklin, Shugart & Harmon 1987).

While forest health is a wide concept which is mainly applicable at the level of the ecosystem, forest damage can be defined at the scale of individual trees. Forest damage can be defined as “any factor that negatively affects the vitality of trees or their economic value” (Wulff 2011). This is an admittedly subjective definition, based on societal understanding of what will constitute an economic loss (Reimoser, Armstrong & Suchant 1999). Forest damage can be due to an injury or a disease that has biotic or abiotic causes. Forest damage can be classified into three categories (e.g. Manion 1991):

- biotic (insects, fungi, nematodes, etc.)
- abiotic (drought, wind, pollution, etc.)
- decline where different factors interact (i.e. drought and insect)

This thesis evaluates inventory strategies directed towards biotic forest damaging agents, although Paper I also has relevance to abiotic agents. However, the results and methods presented could potentially be applied to a broader range of damaging agents. The thesis focuses on damage or population inventories for the following biotic damaging agents:

Cronartium flaccidum

Resin top disease (or Scots pine blister rust) can be caused by two basidiomycete rust fungi (Pucciniales: Cronartiaceae), the host-alternating *Cronartium flaccidum* and the non-alternating form *Peridermium pini* (Eidmann & Klingström 1990). The fungus enters the host pine through the stomata of the needles and proceeds to infect the branch. The usually slow process of infection is visible first as dead twigs and later as necrosis on the stem (Eidmann & Klingström 1990). In 2007 and 2008 a targeted forest damage inventory (TFDI) was performed to provide additional information with regards to the host-alternating *Cronartium flaccidum* in the counties of Västerbotten and Norrbotten where infections appeared to have increased (Wulff & Hansson 2009, SLU, 2016).

Gremmeniella abietina

The ascomycete fungus *Gremmeniella abietina* (Lagerb.) Morelet (Helotiales: Helotiaceae) is the pathogen causing scleroderris cancer on conifers in Asia, Europe and North America (Roll-Hansen 1964; Skilling 1972; Yokota, Uozumi, & Matsuzaki 1974; Laflamme, Hopkin & Harrison 1998). In Sweden, *G. abietina* is the severest shoot pathogen on Scots pine *Pinus sylvestris* L. (Lagerberg 1912; Wulff et al., 2006). Its presence has been noted on several conifer species in the northern hemisphere, such as spruces, firs (*Abies* spp.), pines, larches (*Larix* spp.) and junipers (*Juniperus* spp.), but the largest economical damage has been on pines in Europe and North America (Donaubauer 1972; Roll-Hansen 1972; Skilling, Schneider & Fasking 1986). In Sweden, *G. abietina* also causes damage to the introduced lodgepole pine *Pinus contorta* var. *latifolia* Engelm. (Karlman et al. 1994; Karlman 2001) and infects and damages native Norway spruce (Hansson 1998). In southern Sweden, German provenances of Scots pine were attacked at the age of 30-50 years (Kohh 1964). In northern Sweden in the same period, *G. abietina* damage was mainly found on naturally regenerated young forest of Scots pine on poor heath land (Kohh 1964). During the late 1970s, *G. abietina* caused shoot dieback in Norway spruce in southern and southwestern Sweden (Barklund & Rowe 1981). In the late 1980s, a severe outbreak by *G. abietina* was observed in young lodgepole pine plantations in Northern Sweden (Karlman et al. 1994). In 2001-2003 there was an outbreak of *G. abietina* in Sweden unusually seeming to attack the whole crown at an initial stage of infection, causing rapid tree mortality and resulting in extensive sanitary fellings and thinnings (Wulff et al. 2006).

Ips typographus

The spruce bark beetle (*Ips typographus* (L.); Coleoptera: Curculionidae) is one of the most important forest pests in Europe (Schelhaas, Naaburs & Schuck 2003), and the most damaging insect on Norway spruce in northern Europe (Weslien 1992). It has also been identified as an important keystone species for forest biodiversity, creating habitat for many other species (Müller et al. 2008). After windthrow, spruce bark beetles often quickly colonize the recently fallen trees, leading to rapid population buildup. At large population densities, they are able to kill healthy spruces (Raffa & Berryman 1983). In southern and central Europe, they commonly have two generations each year (Wermelinger & Seifert 1999). In southern Sweden and Denmark they can occasionally have up to two generations per year, whereas further north and in Norway only one generation is usually possible (Bakke 1983, Harding & Ravn 1985, Jönsson et al. 2007). Since the number of generations is dependent on temperature, the numbers of generations may change in the future as a consequence of climate change (Jönsson at al. 2007; Jönsson et al. 2009; Jönsson et al. 2011). In Sweden, populations are annually monitored using pheromone traps (Marini et al. 2013; Lindelöw & Schroeder 2001). After storms, additional traps may be set out for improved monitoring accuracy in the affected area (Swedish Forest Agency 2012). Available mitigation activities against spruce bark beetle damage include: early harvesting of wind-felled spruces, search and removal of colonized trees before the next generation of beetles has emerged from the breeding material, and an array of different traps or "trap trees" set to lower bark beetle abundance (e.g. Faccoli & Stergulc 2008). Rules and policies surrounding bark beetle management are outlined in Keskitalo et al. (2016), where comparisons are made between Sweden and Canada in terms of bark beetle management policies.

Bupalus piniaria

The pine looper (*Bupalus piniaria* L.; Lepidoptera: Geometridae) is a moth which is a defoliator of pine trees. It has had some considerable outbreaks in Fennoscandian Scots pine forests (Butovitsch 1946, Långström, Hellqvist & Cedervind 2004). It also affects forests in Central Europe. Typically, the trees survive single-year defoliation events (e.g. Straw 1996). However, if the trees are severely defoliated a second year there is a high risk of mortality (Långström et al. 2001). One of the few defoliation events in Sweden that has necessitated pest control was caused by the pine looper in 1996 (Långström, Hellqvist & Cedervind 2004). The total extent of this outbreak was estimated to 7,000 ha of Scots pine dominated forest in Västergötland, in southern Sweden. After intense defoliation, over 4,000 ha were sprayed with Bt (*Bacillus thuringensis*) in 1997.

Diprion pini and Neodiprion sertifer

Two other important defoliators on scots pine are the pine sawflies (*Diprion pini* and *Neodiprion sertifer*; Hymenoptera: Diprionidae) (Hanski, 1987). Outbreaks of pine sawflies occasionally affect thousands to tens of thousands of hectares, but in an outbreak of *D. pini* in Finland in 1998-2000 an exceptional 500,000 ha were defoliated (De Somviele, Lyytikäinen-Saarenmaa & Niemelä 2004). *N. sertifer* also has a history of outbreaks: 1937-38, 1942-43, and in the 1960s and then again in 1977-78 in Sweden (Larsson & Tenow 1984 and references therein). *D. pini* has an univoltine life-cycle and feeds on all needle age classes of the host trees late in the summer and in the beginning of the autumn and spends the winter in cocoons (Schwenke 1978). *N. sertifer* feeds on pine needles from previous growing seasons, pupates on the ground during the summer, swarms in the autumn and places its eggs on the current-year needles (Larsson & Tenow 1984). Defoliation outbreaks may involve two or more sawfly species (Schwenke 1982).

1.2 Costs of forest damage

This thesis focuses on the forest's value as an economic resource in the context of sustainable forest management. Forest damage can imply substantial costs for society in terms of economic losses. For example, Dale et al. (2001) estimated that the annual cost of damage incurred by forest pathogens and insects in the United States amounted to approximately 1500 million USD year^{-1}. In an assessment of economic impacts of spruce budworm (*Choristoneura fumiferana*) outbreaks and control in New Brunswick (Canada), Chang et al. (2012) estimated the economic impacts from one outbreak to 3.3-4.7 billion CAD in terms of net present value (NPV) over a 30 year-period. Similar studies have been made in the western parts of Canada with regards to the recent large outbreak of mountain pine beetle, where losses up to 53 billion CAD were estimated for the province of British Columbia (Corbett et al. 2015).

In 2005, a large winter storm felled 75 million m^3 of timber in the southern parts of Sweden, and two years later additional storms felled another 12 million m^3 (Jonsson 2008). Before these storm events, populations of spruce bark beetle were relatively low, but they increased rapidly after (Lindelöw & Schroeder 2008). During the years 2006-2010, it is estimated that the spruce bark beetle killed approximately 3 million m^3 of spruce in that area (Långström et al. 2010), causing large economic losses. As mentioned above, one of the few defoliation events in Sweden that has necessitated active mitigation was that caused by the pine looper in 1996. For that outbreak, Cedervind (2003) estimated the economic loss to 730 SEK ha^{-1} for 90-100% defoliation and 580 SEK ha^{-1} for 50-70%

defoliation, without including tree mortality from the defoliation, i.e. only considering growth loss in defoliated trees (Cedervind 2003). Another important defoliator on Scots pine is the pine sawfly (*Diprion pini*). A preliminary study on economic losses from the 1998-2000 Finnish outbreak which affected 500,000 ha (see above) estimated the losses from the pine sawfly to be 310 USD ha^{-1}, an estimate which is relatively high compared to other European studies (Lyytikäinen-Saarenmaa & Tomppo 2002).

The largest regular economic losses from forest damage in Sweden stem from root rot, mostly caused by the basidiomycete fungus *Heterobasidion annosum*. This pathogen alone is estimated to cost the Swedish forest industry up to ~1 billion SEK $year^{-1}$ (Oliva et al. 2010). Another forest pest of considerable magnitude is the large pine weevil *Hylobius abietis*, which feeds on and kills planted seedlings in regenerations, primarily in the southern parts of Sweden, but increasingly also towards the north (Nordlander et al., 2009; Nordlander & Hellqvist, 2011). The costs have been estimated to approximately 0.5-1 billion SEK $year^{-1}$ (Samuelsson & Örlander 2001). The 2001-2003 outbreak of *Gremmeniella abietina* in Sweden affected approx. 484 000 ha (Wulff, et al. 2006) and caused losses exceeding 1.2 billion SEK, without considering subsequent growth reductions (Hansson et al. 2005). Another cause of damage is browsing by large ungulates (Reimoser & Putman 2011, Wallgren et al. 2013). In Sweden, the economic impact of moose (*Alces alces*) on pine wood quality has been estimated to exceed 50 million EUR $year^{-1}$ (Liberg et al. 2010).

The economic aspects of integrated forest pest management and control have been reviewed for pest insects such as the processionary moth (*Thaumetopoea pityocampa*) in south European pine forests (Gatto et al. 2009; Cayuela et al. 2011). Herrick (1981) examined an incremental evaluation of least-cost-plus-loss economic theory applied to gypsy moth management in Pennsylvania (United States), considering a reduction in the flow of forest goods over larger areas. In another study, searching for the optimal level of expenditure to control the southern pine beetle (*Dendroctonus frontalis*) in the United States, it was found that most money would need to be spent on detection surveys (sketch mapping) and evaluation surveys in the field (De Steiguer et al. 1987).

1.3 Information needs

Because of increasing demands on the forest in terms of different ecosystem services and products (Mery et al. 2005) and increasing threats, some of which are outlined in previous sections, there are increasing needs for information on forests and forest damage (Wulff et al. 2011, Kovac, Bauer & Ståhl 2014). Sweden has signed treaties and conventions promising to report statistics to the international community, some with relevance to forest health. Some of these are: the International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests (ICP Forests; operating under the UNECE Convention on Long-range Transboundary Air Pollution), the International Plant Protection Convention (IPPC) which provides an international framework for phytosanitary measures and control, the Convention on Biological Diversity, and REDD+ (Reducing Emissions from Deforestation and forest Degradation) under the Convention on Climate Change. For each treaty or convention, there is a request for national reports in which forest damage are included when these have impacts on the issue at hand. An example of a reported variable from Sweden as part of ICP Forests is crown condition, described by defoliation and damage to conifers (Michel & Seidling 2016). Crown condition refers to the vitality of a tree as expressed by its outer appearance, for which defoliation is a major indicator (Lorenz 1995). Defoliation is foliage loss compared to a reference tree (e.g. Wulff 2002). The Forest Resources Assessment (FRA) by FAO has presented information on the world's forests since 1947. In the Temperate-Boreal FRA-2000, information on forest condition (defined as the vitality of the trees) was presented for the first time (UN-ECE/FAO FRA 2000, Chapter V). In the FRA 2015 reporting specifications, the following types of damage are listed: numbers of fires, total area affected by fires, outbreaks of insects and diseases (bacteria, fungi, phytoplasma or viruses) that cause detectable reduction in forest health, and damage caused by severe weather events (FAO 2015). It is likely that the FAO will continue to refine its reporting requirements as the knowledge about causes and consequences of forest damage continues to develop.

For the evaluation of forest damage from outbreaks, Knight (1967) concluded that in addition to the many different methods available to evaluate insect population trends, still other methods and definitions are needed to include an evaluation of the damage. Important factors for the evaluation of the insect populations are that they must be based on a thorough understanding of the population dynamics and biology of the insect at hand, that they must be practical and economically feasible, and that there is a need for interpretation and presentation of data in ways that can be used in practice. Factors to consider in the evaluation of forest damage included tree mortality, growth loss or other effects on timber quality (ibid.). When performing forest damage surveys, the need for information must balance with potential costs of poor decisions due to inaccurate information (e.g. Barth et al. 2006; Barth & Ståhl 2012). To avoid unnecessary inventory costs, or damage mitigation costs stemming from poor information, forest damage and forest pest inventories should be kept to an appropriate level of effort for the decision at hand (Herrick 1981, Binns & Nyrop 1992, Fox et al. 1997).

The need for information and the relevant scales and levels of information will vary according to the stakeholders and damaging agents (e.g. Wulff et al. 2011, Bennett & Tkacz 2008). A key concept which is widely used in the context of forest damage is captured by the term 'integrated pest management' or 'integrated pest control', which has been discussed widely over the years (e.g. Kogan 1998). Integrated pest management or control can be defined as by the FAO Panel of Experts: "Integrated Pest Control is a pest management system that, in the context of the associated environment and the population dynamics of the pest species, utilizes all suitable techniques and methods in as compatible a manner as possible and maintains the pest population at levels below those causing economic injury" (in Kogan 1998). Upon this definition it is clear that this work has several scales, from policy development and the decision makers, ranging from governmental organizations responsible for mitigation strategies, information, and law enforcement, to landowners who try to avoid damage on their property (e.g., Keskitalo et al. 2016). At the strategic level (*cf.* Barth & Ståhl 2012), information supporting assessments of general risks for pest and disease outbreaks are needed, but also statistical estimates of actual damage due to both biotic and abiotic causes. Statistical estimates allow for the evaluation of trends and change detection in the measured variables (Scott 1998). From a national forest management perspective it is important to predict and control that sustainable harvesting levels are upheld, but also in order to evaluate changes in forest management practices as a consequence of new information (e.g. Wulff et al. 2011). In order to make inference as to the cause of the observed damage or the estimated change, experiments may need to be performed, which is problematic in large-scale monitoring programs (Schreuder & Czaplewski 1993; Olsen & Schreuder 1997; Aamlid et al. 2000).

Based on information on changes in forest damage, forest agencies may recommend new silvicultural policies, law enforcement, and additional tailored monitoring schemes or experiments to ascertain cause-effect inference (e.g. Olsen & Schreuder 1997, Wulff et al. 2011). On a different scale, forest owners may adapt management plans and practises to decrease the risk of large losses (Seely et al. 2004, Roberge et al. 2016). There are different time-frames: one is about planning the forest management for sustainable yield according to known damage risks, whereas another is about reacting when an unforeseen damage situation occurs. The latter situation may require mitigation schemes, or the collection of additional information to advise future forest management choices (Wulff et al. 2011). Forest agencies may be in charge of implementing coordinated mitigation activities or schemes and the landowners may need to implement changes to their regular management (Lindelöw & Schroeder 2008).

1.4 Forest damage monitoring and inventory

Different types of inventories of forest damage, forest health assessments, as well as forest and tree condition assessments have been performed for nearly a century (e.g., Thorell and Ostlin 1931; Innes et al. 1993, Ciesla and Donaubauer 1994). Long-term monitoring of forest damage is currently being performed in several countries (FAO 2015). As an example of this, the Swedish National Forest Inventory (NFI) collects data on a range of forest damage symptoms (from various biotic and abiotic agents) as part of the long-term monitoring of forest damage at a national scale (Table 1).

Table 1. *Damage symptoms and damaging agents recorded in the Swedish NFI. Adapted from Wulff et al. (2011).*

Tree damage symptoms		**Cause of damage**	
Affected parts	**Symptom**	**Agent group**	**Agent/factor**
Stem/collar	Fallen	Abiotic/climate	Wind/snow; frost; other
	Tilted	Anthropogenic	Forestry; other
	Broken	Mammals	Moose; reindeer; roe deer; wild boar;
	Wounds (debarking,		other large mammals; beaver;
	cracks, etc)		rodents; other mammals.
	Necrotic part	Insects	*Tomicus* sp.; *Ips typographus*
	Resin flow		other bark beetles; Pityogenes;
	Signs of fungi		other insects
	Signs of insects	Fungi	Resin top disease; rot or cancer;
	Decay/rot		*Gremmeniella abietina*; needle cast;
	Planting damage		*Melampsora pinitorqua*; unspecified
	Spike knot		rust fungi; other fungi
	Multiple stems		
Tree crown	Dry top	Competition	Physical interactions
	Defoliation	Fire	
	Discoloration	Other	

1.4.1 Monitoring

Forest health monitoring had an upswing in the early 1980s due to fears of extensive tree death and decline thought to be caused by air pollution and acid rain (e.g. Nihlgård 1985; Hinrichsen, 1987). However, this work has not been without discussion as tree vitality, damage and health are not straightforward to assess, and links between damage and health are often unclear (Innes 1988, Ferretti, 1997, Moffat 2002, Percy & Ferretti, 2004). Accurate field identification and quantification of damage can also be problematic due to subjective classifications and indicators, and imperfect detection (e.g. Wulff 2002; Ringvall et al. 2005; Smith et al. 2005; Wulff 2011). Work within different processes and projects such as CLRTAP, FUTMON and COST actions has aimed to improve and harmonize the indicators and evaluations used (Köhl, Traub & Päivinen 2000).

In many countries, forest damage is being monitored as part of NFIs and similar regular inventory programs. These are generally quite sensitive to systematic errors, whereas randomly occurring errors contribute to increased variance, but do not generally bias the estimates (Gertner & Köhl 1992). Another challenge to the monitoring of forest damage in regular inventory programs is the sparse inventory design with temporal gaps between revisits on permanent plots (typically several years to decades). This is a problem because forest damage may sometimes be a sparse object – due to limited spatial extent and rapid temporal dynamics (e.g. Masek et al. 2013) − which is difficult to accurately assess in such surveys (Schreuder, Gregoire & Wood 1993).

In a review of environmental monitoring programs by Lindenmayer & Likens (2010), monitoring was defined as "repeated field-based empirical measurements [that] are collected continuously and then analyzed for at least 10 years." They concluded that "while mandated monitoring can be useful for producing coarse level summaries of temporal changes in a target population or resource condition they may not identify the mechanism influencing a change in an ecosystem or an entity", and emphasize the need for adapted finer-scaled question-driven monitoring (ibid.). In a review on quality assurance in forest monitoring programs in Europe and East Asia, Ferretti et al. (2009) found that much efforts were dedicated to promoting comparable measurements among countries, especially with regards to analytical chemistry, but that less attention had been placed on the field sampling and monitoring designs. Olsen et al. (1999) emphasize that "a statistical assessment of the certainty of the estimates from the monitoring programs is an essential element in determining whether their information will contribute to policy".

From a Swedish perspective, Wulff et al. (2011) presented a long-term forest health assessment system, based on statistical monitoring of indicators and field measurements of forest damage performed as a part of the Swedish NFI, with calibration and control inventory routines. In addition, directed inventories for monitoring of forest damage are performed when outbreaks are suspected or identified, which is in line with many of the recommendations mentioned above (e.g. Wulff 2011).

1.4.2 Targeted forest damage inventories

Directed forest damage inventories for specific forest health concerns are called ‘evaluation monitoring’ in North America (Bechtold et al. 2012) and ‘targeted forest damage inventories’ (TFDI) in Sweden (Wulff et al. 2011). There are however different forms of directed inventories with regards to forest damage and health in many parts of the world, and they are extremely diverse in terms of the information acquired, inventory strategies and measurements or assessments made, which is illustrated by the following examples.

Inventories for monitoring of new potential invasive pests are difficult, as each introduction starts out small, and the invasion needs to be detected and halted before it has spread to a larger area (e.g. Tobin et al. 2013, Ökland et al. 2010, Eriksson et al. 2008, Coulston et al. 2008). In New Zealand, a risk assessment has been conducted and a field inventory has been designed to inventory the 7500 transitional facilities (e.g. harbours and airports, including their surroundings) that had been identified as having a high risk of invasion (Bulman 2008). An inventory has been dimensioned and implemented using the volume of imported goods received, the proximity and volume of vegetation, and the vegetation diversity in the sample selection of transect plots for the detection of forest damage symptoms. The inventory has been designed to achieve a specified detection probability (ibid.). Coulston et al. (2008) used a risk model for a fictive introduced pest to the United States for planning the placement of pheromone traps using a two-phase sampling strategy and a cost function to evaluate the cost of different sample sizes. The traps were placed within the traditional Forest Inventory and Analysis (FIA) tessellated hexagonal grid (ibid.). In Sweden, an inventory based on risk assessments has been implemented on approximately 800 recently harvested areas where vector beetles are captured and analyzed for the presence of the pine wood nematode. This inventory is mandated by the European Union (EU) decision 2012/535/EU, at a cost of approximately 1.9 milllion SEK year^{-1} (Swedish Forest Agency 2012).

Knight (1958) evaluated different inventory designs for estimating the numbers of ponderosa pines (*Pinus ponderosa*), and the area infested by the mountain pine beetle and found that the sample size, the percent coverage of the sampled area relative to the total area of interest (AOI), and the intensity of the infestation were the factors that significantly affected the error of the estimates from the surveys. Stehman and Davis (1997) investigated a sampling strategy for estimating residual stand damage from harvesting operations using two strata, one for the trail system within the stand, and one for off-trail parts of the stand. These were then inventoried for residual stand damage for objective design-based estimates. Ducey and O'Brien (2010) applied randomised graph sampling to road networks for invasive species monitoring. Samalens et al. (2007) also utilized road networks in a sampling strategy, evaluating an adaptive roadside sampling strategy for the evaluation of forest damage from bark beetles to pine plantations in France.

Still in France, Lucas (2009) evaluated damage from the storm Klaus using a two-phase sampling for stratification (2PS) design, revisiting inventoried NFI plots through examination of aerial photographs. In Belgium, directed regional inventories are performed to assess bark peeling damage by roe deer (*Capreolus capreolus)* on Norway spruce plantations (Gheysen et al. 2011). In western Canada, Coggins et al. (2010) used adaptive cluster sampling applied to fine-scale digital aerial imagery to improve estimates of mountain pine beetle damage and outbreak expansion rates. Safranyik and Linton (2002) investigated the use of line transect sampling for the inventory of mountain pine beetle damaged trees. Their recommendation was that each surveyor should estimate her/his own detection curve for estimation. Systematic parallel line transects were also used in the United States by Baker et al. (2012) for estimating the incidence of dwarf mistletoe (*Arceuthobium pucillum*) in black spruce (*Picea mariana*) stands. The results were compared to the incidence estimated from FIA plots in the same area. The authors concluded that mistletoe damages were probably underestimated by the large scale systematic sample. In New Zealand, brushtail possum (*Trichosurus vulpecula*) damage and abundance were estimated in Monterey pine (*Pinus radiata*) plantations using transects in forest blocks sampled through stratified simple random sampling (STSI) (Jacometti et al. 1997). Each block was surveyed with transects running in random directions.

In agricultural pest management and in forest pest management there has been great developments of sequential sampling inventories of insect populations of different life stages (Kuno, 1991). For forestry these have mainly been developed regarding insect defoliators (Ravlin 1991; Fettig et al. 2005, Kolodny-Hirsch 1986, McKnight et al. 1970). In these cases sampling continues until an action is decided, most plans involve a predefined interval for continued sampling, usually involving for instance counts of egg masses or larvae on tree branches and that new branches are added until the tree or the sample plot has been classified (e.g. McKnight et al. 1970, Sheperd et al. 1984). Other inventory strategies for insect population evaluation have been timed walks and “fixed-number of trees per plot” sampling plans (e.g. Buss, McCullough & Ramm 1999).

All these examples of different inventories and methods are a reflection of the multifaceted difficulties that arise when the objective is the quantification of forest damage associated with a specific causal agent, severity and scale. Further, there is not always a clear distinction between the two concepts “monitoring” and “inventory”.

1.4.3 Auxiliary data for forest damage monitoring and inventory

There are a multitude of different techniques and designs for sampling of forest damage and forest pests. Some are based on subjective classifications and subjective searching or mapping, from which statistical inference may be limited, but costs are kept at a low level (e.g. Ståhl 1992). Other inventories are objective, based on statistical probability sampling designs, for which inference is design-based. Auxiliary data can be explained as: “data that may explain some of the variation in the targeted inventory data, but which is not part of it”, e.g. an old stand register, measurements from remote sensing (RS), or data from other sources. When auxiliary data are available for the entire study population, a model may be developed for the relationship between the target variable and the auxiliary variables and then inference may be model-based (e.g. Gregoire 1998).

NFIs and most other monitoring programs are founded on design-based inference which means that the population of interest, e.g. the trees, are considered fixed, i.e. there is a true value, a true number linked to each population element at any given time. Within this framework the estimates of population parameters, such as totals, means and population variance, are random variables because only parts of the population are included in any given sample (e.g. Gregoire & Valentine 2008, Särndal, Swensson & Wretman 1992). Inference is then based on the known sampling design without any assumptions about the underlying population (ibid.). In model-based inference (e.g. Gregoire 1998, Ståhl et al. 2016), there is an assumption of an underlying model which generates random values of population elements. In this framework, samples need not be selected randomly as in the case of design-based inference. Target quantities such as the population total and mean are also random variables under the assumption of the so-called super-population-model. This is an important and popular mode of inference, e.g. in landscape ecology, where models of forest pest and forest disturbance regimes are being developed (e.g. Liebhold 1994, Peltonen et al. 2002, Wulder & Franklin 2007, Lierop et al. 2015). Another advantage of model-based inference is that so-called synthetic estimators can be applied for prediction within small areas where no or only few samples have been recorded (e.g. Rao 2003, Breidenbach & Astrup 2012). Similarly, model-based inference may be suitable for application in remote areas where selection of field samples is very expensive (e.g. McRoberts & Tomppo 2007, Ståhl et al. 2011). However, a drawback of model-based inference is the non-avoidable reliance on the validity of the model assumed.

Within the framework of design-based inference there are several ways of utilizing auxiliary information for improving the results. The two main approaches are (1) to use the auxiliary information for improving the sample selection and (2) to use the auxiliary information for improving the estimators once sample data have been collected (e.g. Särndal, Swensson & Wretman 1992).

In the sample selection it is possible to direct the sample through techniques such as stratification, which is the division of the population into separate parts. In each stratum, separate samples are selected. If the strata are fairly homogenous (i.e. with low variance within strata), one can reduce the variance of the estimator of the target population parameter considerably (Cochran 1977). If no information for stratification exists, two-phase sampling for stratification (2PS) can be an efficient strategy (Gregoire & Valentine 2008), in which case a sample of auxiliary information is acquired in a first phase and used for stratification. Other ways to use auxiliary information for the sample selection is by sampling with unequal probabilities determined by the auxiliary variable(s), e.g. Poisson sampling and probability-proportional-to-size (PPS) sampling (Gregoire & Valentine 2008). The better the auxiliary variable explains the variation in the target variable, the lower the variance of the estimator (ibid.). In the field of probability sampling, recent developments allow the selection of samples using many auxiliary variates. One such method is the local pivotal method (LPM) developed by Grafström, Lundström & Schelin (2012).

Several techniques are available also for improving estimators once sample data have been acquired. One such technique is post-stratification (e.g. Nilsson et al. 2005) where auxiliary information for the stratification is used after the sample has been selected. Other techniques to improve estimators are ratio and regression estimators (Särndal, Swensson & Wretman 1992, Thompson 2002). A more general category of similar estimators is called model-assisted estimators (Särndal, Swensson & Wretman 1992). A model-assisted estimator first computes a crude estimate of the population parameter based on the auxiliary data and a model. Secondly it removes any bias of this crude estimate through calculating a correction term using the deviations between observed values and the model predictions from the probability sample (ibid.).

Since forest pest outbreaks and forest damage often are relatively sparse events, inventory methods and strategies typically need to be specially designed for particular events, as exemplified in Section 1.4 above. Different types of damage require the use of different auxiliary data to efficiently direct the sampling. Sources of auxiliary data can be, for example, existing NFI plots which can be used as a first phase sample (e.g. Lucas 2009) or forest stand registers (e.g. Vuletic et al. 2014). Other types of auxiliary data are expert knowledge on species biology and available geographical information system (GIS) data (such as used in the Swedish pine wood nematode surveillance program) or models of risk and spread of invasive species (e.g. Coulston et al. 2008). Information from RS technologies offer increasing possibilities to inform the sample selection (e.g. Coggins et al. 2013) or to improve the estimation (e.g. Schroeder et al. 2014). If there is a strong link between the auxiliary information and the variable of interest, the use of auxiliary information to direct the sample can result in a considerable improvement of the precision of the estimates from the inventory (e.g. Gregoire & Valentine 2008, p. 63). However, for multi-purpose inventory designs like large monitoring schemes and NFIs, multiple parameters are of interest and the optimization of the sample for one variable of interest may decrease the precision for another variable. In such cases, utilizing auxiliary information in the estimation stage is often preferred (Tomppo et al. 2008, Schroeder et al. 2014).

In detection of forest damage that affect the canopy, RS techniques have been utilized for many years (e.g. Ciesla 2000). Common techniques have been aerial detection surveys (ADS), photo interpretation surveys (PIS) (e.g. Backsen & Howell 2013) and more recent heli-GPS surveys (Wulder et al. 2006). ADS has the advantage of providing a quick overview of forest condition. It is generally faster and cheaper than PIS, but the latter may give more accurate and quantifiable information from a sample of the area which can then be used in the estimation stage (Backsen & Howell 2013) or to direct sampling for further field inventories. In Sweden, the Swedish Forest Agency, forest owners associations, and forestry companies have utilized heli-GPS inventories to map and assess the damage to forest trees after storm events and for spruce bark beetle mitigation (e.g. Swedish Forest Agency 2012, Kärvemo et al. 2014).

Over the last decades, large developments with regards to GIS, geographical positioning systems (GPS), and other advances in the field of computer science, technology and mathematical statistics have allowed for new models of risk and susceptibility of forest to pests, but also of pest distributions, synchrony and spread (e.g. Haines-Young, Green & Cousins 1993; Liebhold, Rossi & Kemp 1993, Köhl & Gertner 1997). These have resulted in the emergence of new fields of research at the intersection of forest pest management, forest pest biology, landscape ecology and landscape pathology (e.g. Turner & Gardner 1991, Williams et al. 2000, Wichmann & Ravn 2001, Holdenrieder et al. 2004, Aukema et al. 2006, Kärvemo et al. 2014). This information can in turn feed-back to facilitate improved sampling of the populations using risk predictions as auxiliary information in directing the sample or in estimation (e.g. Olofsson & Blennow 2005, Coggins et al 2008, Coops et al. 2012, Coggins et al. 2013) or as decision support. Thanks to advances in remote sensing (e.g. Wulder & Franklin 2007), the world's forests are now being monitored as a whole (e.g. Hansen et al. 2013) for certain aspects of forest degradation and damage. Satellite imagery based change detection has been suggested as a means of constructing a global forest health monitoring system (Hansen et al. 2013, McDowell et al. 2015b).

One example of the potential of RS data in this area is provided by the outbreak of the invasive species *Physokermes inopinatus* in south Sweden during the summer of 2010 (see above), which was later shown to have been visible on SPOT and MODIS satellite imagery in 2009, before it had been detected in the field (Olsson et al. 2012). Satellite imagery in time-series evaluation may provide objective and consistent assessment of gradual ecosystem change (Vogelmann et al. 2009 and Vogelmann et al. 2012), a component of which is the detection and mapping of forest pest damage. In the EU there are ongoing plans and a research program for the development of such a forest damage monitoring system. A satellite based detection and early-warning-system for forest pests is being developed within the DIABOLO research program (DIABOLO, 2016). Similar monitoring systems are being evaluated in Canada (Hall et al. 2016) and the United States (Hargrove et al. 2009). Such technological advances may have implications for the future use of traditionally assessed indicators of forest health and condition, such as defoliation and crown condition assessed by eye in many countries (Michel & Seidling 2016). For measurements of leaf area index (LAI), for example, methods using hemispherical photographs from the ground may be a step toward objective monitoring of the tree crown status. In addition, there are ongoing developments for objective measurements of crown condition (e.g. Dobbertin et al. 2005, Nakajima et al. 2011) and defoliation assessments using LAI by remote sensing techniques (e.g. Bréda 2003, Hall et al. 2007, Zheng and Moskal 2009, Solberg 2010).

Although there is great promise in RS and other new technology all things will not be measurable remotely. It may be possible to find likely changes in forest condition in an area, but it may not be possible to detect damage, ascertain reliably the damaging agent, pest abundance or other interesting explanatory variables from these technologies (e.g. Hall et al. 2016). Thus, combinations of GIS, RS and field inventory measurements will continue to be important.

2 Objectives

The main objective of the thesis was to evaluate the usefulness of different sampling strategies for acquiring data about forest damage, considering specific information demands and population properties. Special attention was paid to how auxiliary information of different kinds can be utilised, either for improving the designs or the estimators. In most of the studies (Papers I-III), the different sampling strategies were compared with regards to the precision they yielded for core forest damage parameters, whereas one of the studies (Paper IV) was based on cost-plus-loss analysis, where the inventory strategy which minimises the sum of the inventory cost and the expected losses, mainly from inappropriate decisions due to non-correct information, is selected.

The specific objectives of the different papers were to:

Paper I: Evaluate how well damage of different kinds can be detected and assessed with a traditional NFI-type inventory (i.e. a sparse inventory of clusters with fixed area plots laid out systematically across large regions.).

Paper II: Evaluate how existing information from NFIs and from remote sensing can be utilised for improving the precision of sample-based forest damage inventories within regions with known pest outbreaks.

Paper III: Evaluate the use of the LPM in sample selection under an ongoing forest pest outbreak at the municipality scale.

Paper IV: Evaluate what sampling strategy minimises the cost-plus-loss in a case where an inventory is performed to decide whether or not a mitigation scheme should be implemented to halt a potential outbreak of a defoliator insect.

3 Material and methods

3.1 Methodological approach

In this thesis I take a pragmatic stance by defining forest damage as damage to a forest tree that reduces its economic value. Information on damage to forest trees is an essential first step in the process of monitoring forest health, integrated pest management, and ultimately sustainable forest management. The populations and scenarios utilized in this thesis all pertain to different regions and areas in Sweden (Figure 1).

Figure 1. Sweden with Götaland (G) in the south, Västernorrland (V) in the centre, and a black square representing the fictitious municipality used in Paper III.

Paper I uses the region of Götaland (approx. 100,000 km^2 with approximately 50% productive forest land) as a study area. Paper II investigated TFDI in the county of Västernorrland (18,198 km^2 with approx. 80% productive forest land), and Paper III utilized a 900 km^2 square (i.e. the size of a typical Swedish municipality) located in the same area. Paper IV was conducted at the scale of an outbreak affecting an individual private forest owner in the south-central parts of the country.

3.1.1 Inventory designs

To evaluate parts of a forest health monitoring system, Paper I investigated the use of systematic inventory of clusters of fixed-area plots (Ranneby et al. 1987, Axelsson et al. 2010, Fridman et al. 2014), mimicking the permanent NFI plots across Götaland (Figure 1) to evaluate estimators of state and change in forest damage for different forest damage scenarios. In Paper II a current method of TFDI was evaluated, and a possible improvement utilizing auxiliary information in the estimation stage by post-stratification was evaluated. In Paper III another possible design for a TFDI was introduced, utilizing auxiliary data in the sample selection. In Paper IV two different inventory strategies were evaluated with regards to the decision on pest mitigation during a forest pest outbreak. The sampling strategies evaluated in this thesis are:

- Random sampling with replacement (SI)
- Stratified random sampling (STSI)
- Systematic inventory (SYS)
- Double sampling (DS)
- Two-phase sampling for stratification design (2PS)
- Post-stratified two-phase sampling for stratification (PS2PS)
- Local pivotal method (LPM)

Each of these strategies is described in detail below.

Paper I

State and change in numbers of damaged trees ha^{-1} were estimated using the current Swedish NFI inventory design for a region for which precise estimates are commonly required (Ranneby et al. 1987, Axelsson et al. 2010, Fridman et al. 2014). Each cluster of sample plots had eight plots in a square, with adjacent plots separated by 250 m. The radius of each plot was 10 m. As the AOI was large, we utilized a simulated set of squares representing a large landscape covering 50,000 km^2 of forestland, i.e. approximately the area of productive forestland in Götaland (Fig. 1). For areas of this size there are many land cover types, but only forest land is of interest when estimating numbers of forest trees with certain types of damage. This difference is usually handled by using ratio estimation (e.g. Zarnoch and Bechtold, 2000). With this approach, the number of plots falling on forest land is utilized, as well as estimators of variance based on the variation in numbers of damaged trees on plots falling on forest land. Because of the large size of the area, it was divided into 500 equally sized non-overlapping squares. The side of each square had the length of the distance between NFI tracts in Götaland (10×10 km^2). Simulated sampling of one tract cluster of eight fixed-area plots was performed in each of the 500 simulated squares. Monte Carlo simulations involving 10,000 repetitions were used to estimate the within square sample variance $\hat{V}(\hat{y}_i) = \frac{1}{r-1}\sum_{r=1}^{r}\left(\hat{y}_{ij} - \bar{\hat{y}}_i\right)^2$. The estimator for the mean number of damage trees ha^{-1} in the whole region is $\hat{\bar{Y}} = \frac{1}{n}\sum_{i=1}^{n}\hat{y}_i$ where n is the number of sampled squares and $\hat{y}_i$ the estimator of number of trees ha^{-1} in square i. All simulated plot clusters were permanent plots, i.e. revisited and measured at certain time intervals. Inventory edge effects were avoided by wrapping each square and inventorying it as a torus. Estimators for the whole region were based on a two-stage sampling design with the assumption of simple random sampling (SI) of squares in the first stage and plot clusters in the second. For the full inventory, where one cluster is inventoried in each square, the design is unaligned systematic sampling (Quenouille 1943; Cochran 1977, p 228). More recently, a similar design in a continuous framework has been called Tessellation Stratified Sampling (Stevens 1997; Barabesi & Franceschi 2010). The variance was calculated for each scenario population by varying the proportion of damage squares ($P = \frac{N_d}{N}$) in the following expression:

$$V\left(\hat{\hat{Y}}\right) = \frac{P}{n}\left((1-f)(\sigma_d^2 + (1-P)\bar{Y}_d^2) + \frac{\sum_{i=1}^{N_d} \hat{V}(\hat{y}_i)}{N_d}\right)$$

where N_d is the total number of squares containing damaged trees and $\overline{Y}_d$ is the mean number of trees ha^{-1} in the subpopulation of squares containing damaged trees. The between-square variance in the subpopulation is σ_d^2 and the last expression is the mean within-square variance in the subpopulation containing damage trees. This allowed comparing the variance of the estimator of mean numbers of damage trees ha^{-1} for varying damage extents in the landscape.

Paper II

NFI tract clusters of plots were used as the first phase in a 2PS design. In this way information was straightforwardly acquired with regard to whether or not a plot was prone to damage. Only the first-phase plots at risk of infection/attack by the damaging agent of interest were selected in the second phase. The second-phase sample was selected using SI and the following estimator was applied:

$$\hat{Y} = \frac{n}{N}\frac{n_d}{m}\sum_{i=1}^{m} y_i = Nw_d\bar{y}_d = N\hat{\bar{y}}_U$$

where n is the number of plots in the first-phase NFI sample, N is the total number of grid cells in the AOI, n_d is the number of NFI plots falling within the domain at risk (e.g. spruce forest for *Ips typographus* inventory) and m is the second-phase sample size. As a means of improving the estimates using remotely sensed auxiliary information I applied post-stratification in the estimation stage, i.e. a PS2PS design. For this design the following estimator was developed and applied:

$$\hat{Y} = \sum_{h=1}^{H}\left[\sum_{q=1}^{Q_h} N_h \frac{n_{hq}}{m_{hq}n_h}\left(\sum_{i=1}^{m_{hq}} y_i\right)\right]$$

where H is the number of strata from RS auxiliary data, N_h is the number of grid cells within post-stratum h, Q_h is the number of strata in post-stratum h, n_h is the total number of NFI plots within post-stratum h, $m_{hq} = m_h$ is the number of NFI plots sub-sampled within stratum q, domain D, and post-stratum h, and

y_i is the number of damaged trees. A core assumption is that there can be no damage outside stratum D, and thus there is only one stratum in which sampling is required (the observations in the other stratum are known to be zero). Hence the above estimator simplifies to

$$\hat{Y} = \sum_{h=1}^{H} \frac{N_h}{n_h} \frac{n_{hd}}{m_h} \left(\sum_{i=1}^{m_h} y_i \right) = \sum_{h=1}^{H} N_h w_{hd} \hat{\bar{y}}_{hd} = \sum_{h=1}^{H} N_h \hat{\bar{y}}_h$$

where n_{hd} is the number of NFI plots in stratum D within post-stratum h. Similarly w_{hd} is the share of $s1$ in post-stratum h that fell within stratum D, and $\hat{\bar{y}}_{hd}$ is the mean for the entire post-stratum h. Note that in case the NFI plots do not have the same size as a grid cell, the values of y_i must be rescaled to correspond to the grid cell area.

A variance estimator adapted from Särndal, Swenson &Wretman (1992; p. 353, eq. 5) was applied. Conditioning on the realized sample and an assumption of SI in the first phase, the following variance estimator was used:

$$\hat{V}(\hat{Y}) = \sum_{h=1}^{H} \left[\frac{N_h^2 \hat{\bar{y}}_{hd}^{\ 2}}{n_h^2} s_{yhd}^2 + \frac{N_h^2}{n_h} \left(w_{hd} (\hat{\bar{y}}_{hd} - \hat{\bar{y}}_h)^2 + (1 - w_{hd})(0 - \hat{\bar{y}}_h)^2 \right) \right]$$

where $s_{yhd}{}^2$ is the sample variance of y in stratum D and post-stratum h.

Paper III

A TFDI was simulated at a municipality level to investigate the use of auxiliary information in the selection of the sample. Utilizing available information in sample selection ensures that the sample will be representative, in the sense that it contains observations from all parts of the population. One common way of achieving this is by utilizing stratification (e.g. Lohr 2010). A sample that is well spread in the auxiliary variables provides a good representation of the sampled population (Grafström & Schelin 2013; Grafström & Lundström 2013). If there is a strong relationship between the auxiliary variable and the target variable this results in a precise estimate. The local pivotal method (LPM) was introduced by Grafström et al. (2012) and has shown promising results for forestry applications in estimates of basal area, standing volume and mean height (Grafström & Ringvall 2013; Grafström et al. 2014). We applied SI and 2PS sampling as baseline strategies and compared their performance to that of the LPM design where the sample is spread in auxiliary space.

One small drawback of many designs that spread the sample in geographic space (e.g. systematic sampling, GRTS) is that unbiased estimators of the variance cannot be developed, because of zero second-order inclusion probabilities (e.g. Madow and Madow 1944; Cochran 1946; Wolter 1984; Stevens and Olsen 2003). Thus we investigated two different variance estimators following LPM sample selection. The Grafström-Schelin variance estimator proposed by Grafström and Schelin (2013)

$$\hat{V}_{GS}(\hat{Y}_{LPM}) = \frac{1}{2}\sum_{i\in s}\left(\frac{y_i}{\pi_i} - \frac{y_{j_i}}{\pi_{j_i}}\right)^2$$

where π_i is the inclusion probability of the i^{th} grid cell with value y_i and j_i is the nearest neighbour to *i* in the realized sample, i.e. the nearest neighbour in terms of the auxiliary space in which the sample is balanced (see Grafström and Schelin 2013). The second was the Deville variance estimator

$$\hat{V}_D(\hat{Y}_{LPM}) = \frac{1}{1 - \sum_{i\in s} a_i^2}\sum_{i\in s}(1-\pi_i)\left(\frac{y_i}{\pi_i} - \sum_{j\in s} a_j \frac{y_j}{\pi_j}\right)^2$$

proposed by Deville (1993). Where $a_i = (1-\pi_i)/\sum_{j\in s}(1-\pi_j)$ and *s* refers to the selected sample.

Paper IV

In this study SI sampling with fixed area sample plots were used, as a basis for deciding on active pest-control to mitigate a defoliation outbreak on pine. In addition to SI, a double sampling strategy (DS) was evaluated. An initial sample was selected and, if the confidence interval constructed from this sample included the threshold value for pest control, an additional sample was selected to improve the precision of the estimate upon which the mitigation decision was based. This sampling strategy was first described by Cox (1952), but it has found rather limited application in practice compared to sequential sampling (Binns & Nyrop 1992). The method is useful in situations where the analysis of the sample requires more time and cost (ibid.). If the estimate from the first sample is far from the threshold, the second sample size is set to zero and additional inventory cost is avoided. The target variable in the study was the average number of pupae of a defoliator insect m^{-2}, estimated through inventory of fixed area plots of size 0.25×0.25 m. This inventory is expensive as the search for pupae in the humus is time consuming and the pupae then need to be verified for vitality in a lab. For the SI inventory strategy the following estimator of the pupae density was used:

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

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. This is a well-known estimator, known as the replicated sampling estimator (e.g. Barabesi & Fattorini 1998, Gregoire & Valentine 2008 p. 220). The following variance estimator was applied:

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

The AOI for the survey was treated as a torus to avoid edge-effects (e.g. Gregoire & Valentine 2008, p.223-224). Two inventory strategies were investigated, these were:

(SI) A single-stage inventory with SI to estimate the pupae density. If the density estimate exceeded the threshold value (λ_T) mitigation measures were implemented.

(DS) A double sampling strategy, where the estimators above were used based on the first phase sample to compute the test statistic $\left|\frac{\hat{\lambda}-\lambda_T}{\sqrt{\hat{V}(\hat{\lambda})}}\right|$.

We rejected the null hypothesis $\lambda = \lambda_T$ if the test statistic exceeded $t_{0.025}(n_1 - 1)$, i.e. we used an approximate 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. The size of the second phase sample is estimated as:

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

where $Q = \hat{\lambda} - \lambda_T$, 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 $C = (cv)^2 = 0.0025$ (Cochran 1977, p. 79; Cox 1952). For $n_2 > 20A^{1/3}$ the second phase sample size was set as $n_2 = 20A^{1/3}$ plots to avoid overly expensive inventories. In addition, if Q=0 (i.e. $\hat{\lambda} = \lambda_T$) Q was set to 0.0001 in the calculation of the second phase sample size, also, if n_2 is rounded to zero, we set it to 1.

The estimates from the two inventory phases were then used to form a weighted estimate of the mean number of pupae m^{-2}:

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

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

3.1.2 Monte Carlo simulation

Theoretical comparisons of the properties of different inventory strategies in some cases can be conducted if complete knowledge about the study population is available. Since such knowledge is uncommon, and since theoretical comparisons are often complicated or impossible, it is common to use simulated populations that resemble the real-world conditions, and to apply repeated sampling in order to evaluate the inventory strategies based on the empirical distributions from repeated sampling (e.g. Gregoire & Valentine, 2008). Monte-Carlo simulations allow straightforward assessment of the bias and variance of the estimators applied, given a certain strategy (e.g. Cochran, 1977, Särndal, Swensson & Wretman 1992). Such simulations have proven useful in several contexts (e.g. Cochran, 1977, Kalos & Whitlock 2008). For example, Monte-Carlo simulations have been widely used in the evaluation of sampling strategies for biological populations (Stevens & Olsen 2003, Legendre et al. 2002, Gregoire & Schabenberger 1999) and in the field of forest inventory (e.g. O'Regan & Palley 1965, Ene et al. 2012). For forest damage inventory, Edgar & Burk (2006) utilized Monte-Carlo simulation to assess the sensitivity of a sparse sample of clustered plots in detecting defoliation outbreaks.

The bias and variance of an estimator

The different populations used to evaluate the different inventory strategies are described briefly in section 3.2.1 (*cf.* the respective papers for more detailed descriptions). For each population, sample size and auxiliary dataset, Monte Carlo sampling was applied to estimate the same statistic many times. This was done to ascertain empirical knowledge of the distribution of the estimator under conditions likely to be observed from actual (unknown) populations of forest damage. Different measures of the performance of the evaluated sampling design for the estimator $\hat{Y}$ were calculated. First we calculated the mean of the estimated values over the R MC-repetitions as

$$\bar{\hat{Y}} = \left(\frac{1}{R}\sum_{r=1}^{R}\hat{Y}_r\right)$$

where $\hat{Y}_r$ is the estimated value from the rth Monte Carlo repetition. Then the relative bias (%) of the estimator was calculated as

$$\widehat{RBIAS}(\hat{Y}) = \frac{\bar{\hat{Y}} - Y}{Y} * 100$$

where Y is the true population parameter.

The relative standard errors of the estimators are an important performance measure. In Paper I it was estimated as the square root of the estimated variance of the mean value estimator divided by the true population mean and multiplied by 100. Similarly, in Paper II we estimated the empirical variance of all estimators for population totals (area and numbers of damage trees) over all R MC-repetitions as

$$\hat{V}(\hat{\mathrm{Y}})_{MC} = \frac{1}{R-1}\sum_{r=1}^{R}\left(\hat{Y}_r - \bar{\hat{Y}}\right)^2$$

where $\bar{\hat{Y}}$ is the mean of the estimator from the repetitions . The precision was expressed as the coefficient of variation (%), i.e., as

$$\widehat{CV} = \left(\sqrt{\hat{V}(\hat{\mathrm{Y}})_{MC}}/Y\right) \times 100.$$

The mean square error was computed as

$$\widehat{MSE} = \hat{V}(\hat{\mathrm{Y}})_{MC} + \widehat{Bias}^2$$

where $\widehat{Bias} = \bar{\hat{Y}} - Y$

In Paper III, knowing that the estimator is unbiased, I evaluated the empirical relative standard deviation as the squared deviation between the estimated value in each repetition and the true population total:

$$\widehat{ERSD}(\hat{Y}) = \frac{\sqrt{\frac{1}{R}\sum_{r=1}^{R}\left(\hat{Y}_r - Y\right)^2}}{Y} * 100$$

Hence, in Paper II and Paper III I used different names (coefficient of variation and relative standard deviation) for the same thing. In order to compare inventory designs, the ratio of the mean square error of the evaluated design to the mean square error of the SI design with equal sample size was used.

The distribution of variance estimators

For evaluation of variance estimators, the empirical variance was compared to the mean of the estimated variances. It was then reported in terms of the relative bias of the variance estimator (Paper II), or as the ratio of the empirical mean of each variance estimator to the empirical variance of the estimator (Paper III).

In Paper II, the Monte Carlo confidence level for the confidence interval estimated at each Monte-Carlo repetition (e.g. Särndal et al. 1992) was evaluated by calculating the empirical coverage rate (ECR) and the from-above and from-below failure rates, as described by Gregoire and Schabenberger (1999).

Power calculations

In Paper I, the power of the sampling strategy, was estimated to determine the potential for using the inventory strategy to detect an increase of 1 damaged tree ha^{-1}. The power is the probability of rejecting the null-hypothesis given that it is false (Zar 1999). Power analysis and the comparison of power among sampling strategies is a useful tool when designing monitoring programs (Green 1989, Christiansen & Ringvall 2013). In Paper I, the test was whether or not the increase for the whole study area was greater than 1 damaged tree ha^{-1}, i.e. H_0:$Y \leq 1$ against H_1:$Y > 1$. Numbers of damaged trees is a count variable, and the estimator of the mean number of damage trees ha^{-1} within an area is not necessarily normally distributed, especially if the density is low. However, this study dealt with a large-scale survey, which implies the use of large sample sizes (at least 100 clusters, with eight plots within each). Given these large sample sizes, it was assumed based on the central limit theorem (e.g. Särndal et al 1992, Hogg & Tanis 2010) that the estimates would be normally distributed, i.e. $\hat{\bar{Y}} \sim N(\bar{Y}, \sigma)$, where $\sigma = \sqrt{V(\hat{\bar{Y}})}$.

H_0 would then be rejected at the 0.05 significance level if the estimated value $\hat{\bar{Y}} \geq 1 + 1.645 \times \sigma$, where 1.645 is the critical value of the normal distribution at the 0.05 significance level. The statistical power of this test, when the true increase is $\bar{Y}$, is then $1 - \theta((1 - \bar{Y})/\sigma \times 1.645\bar{)}$ where θ is the cumulative distribution function of the standard normal distribution.

3.1.3 Cost-plus-loss analysis

In Paper IV we perform a cost-plus-loss analysis for the inventory of pupae in the humus for evaluation of a defoliator population to decide whether or not to control the outbreak by Bt-application. 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 1978). This framework allows for finding an optimal inventory strategy, given knowledge of how information will be used for decisions and what losses follow from incorrect decisions due to inaccurate information. The approach is to minimize a cost-plus-loss function, i.e. 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 to find inventory strategies that provide the information needed to implement appropriate mitigation measures, including no mitigation, in case it is assessed that the risk of damage is small (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 final-felling (Ståhl et al. 1994; Holmström et al. 2003; Eid 2000). 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, it must be known 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). In assessing this, detailed knowledge of the processes involved is needed. In the case of pest management, this involves knowledge of the likely forest damage at different pest population levels, the cost and likely success of a pest mitigation measure, and the cost of forest damage after an uncontrolled pest outbreak (Waters & Stark 1980). One of the earliest evaluations of this kind in forest pest management was introduced by Herrick (1981). Through pest management the negative impacts of damage from the gypsy moth could be reduced, and the optimal level of pest management could be found as the one with the lowest cost-plus-loss (ibid.). In this study, however, there were no links to the accuracy of the information or the decision whether or not to control the outbreak, but only to the question how intensive the mitigation effort should be (ibid.). Increased use of economic theories and frameworks in analyzing forest pest management strategies has been advocated by several authors (e.g. Bicknell 1993; Fox et al. 1997; Corbett et al. 2015; Niquidet et al. 2015). One popular framework is called economic threshold analysis, in which decisions about pest control activities are considered (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, described above; however most studies on economic threshold analysis neither consider the cost and 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 it also evaluates the costs and benefits in monetary terms. It has been applied in Europe in evaluating the management of the processionary moth (*Thaumetopoea piyyocampa;* e.g Gatto et al. 2009, Cayuela et al. 2011).

A cost-plus-loss framework was applied in Paper IV for the analysis of inventory strategies for defoliator outbreaks on pine (Figure 2).

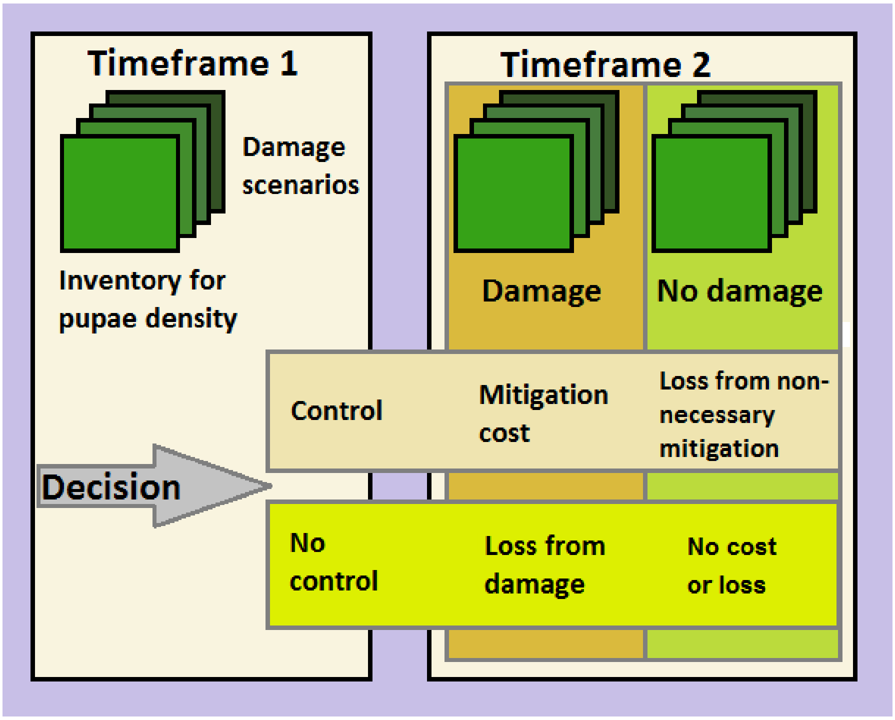

Figure 2. Framework of cost-plus-loss analysis in an area with initial signs of damage which is evaluated through an inventory of pupae, upon which a decision to control or not to control the pest insect is made. In all evaluated outcomes an inventory cost is included.

Taking control action expenses unnecessarily, or to suffer the losses incurred due to the full blow of the uncontrolled damage outbreak (that could have been avoided) are crucial parts of a cost-plus-loss evaluation of forest pest mitigation.

To analyse expected costs and losses, Monte Carlo simulation was applied, i.e. the same decision making problem was revisited 1000 times for each scenario, inventory strategy and sample size.

The expected cost-plus-loss was then calculated as:

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

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 from the true number of pupae in the pupae population. The cost of inventory is modelled as:

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

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=6000 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=3000 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}=3000 SEK was used, as tools and maps are already in place.

3.2 Material

All studies involved simulated populations which were constructed with the help of actual forest damage inventory data from the Swedish NFI, the Swedish TFDI and data from a defoliation outbreak (pine looper) in the late 1990s. The damage scenarios and auxiliary information used in Papers I-IV are presented in the following sections.

3.2.1 Damage scenarios

Paper I:

Simulations of tree damage were made in a continuous square plane (10×10 km^2) with damaged trees represented as points as in a Poisson point process (e.g. Stoyan & Penttinen, 2000). Between the two time points (TP1 and TP2) trees did not recover, so there was monotonic increase in damaged trees. Two main damage scenarios were simulated (*cf.* Figure 3 for an example):

1. Sparsely and uniformly distributed damage. The damage covers the entire area and is dispersed slowly with low aggregation. Scenario 1 was based on the outbreak of resin top disease, which was estimated to affect 3.6 trees ha^{-1} in middle aged and older pine forests in Götaland (estimate from Swedish NFI).

2. Local or regional outbreaks with aggregated centres. In this scenario, the damage is typically present at a low level, but can rapidly increase under favourable conditions. The dispersion of damage is typically rapid and aggregated. Scenario 2 was based on the *Gremmeniella* outbreak of 2001-

2003, which is estimated to have affected 61 trees ha^{-1} in middle aged and older pine forests in Götaland (estimate from Swedish NFI).

For each of the two event scenarios, varying proportions (*P*) of squares with damaged trees were studied to account for the fact that damage rarely occurs uniformly in the whole AOI. For both scenarios, two different levels of intensity with regards to the density of trees, i.e. the number of damaged trees ha^{-1}, were simulated. In the case of TP1, the two levels were referred to as the 'sparse intensity' and 'medium intensity' of each scenario. Two levels were simulated for the increase between TP1 and TP2 ('small increase' and 'large increase'; *cf.* Paper I). Hence, a total of four sub-scenarios were constructed for each of the two main damage scenarios.

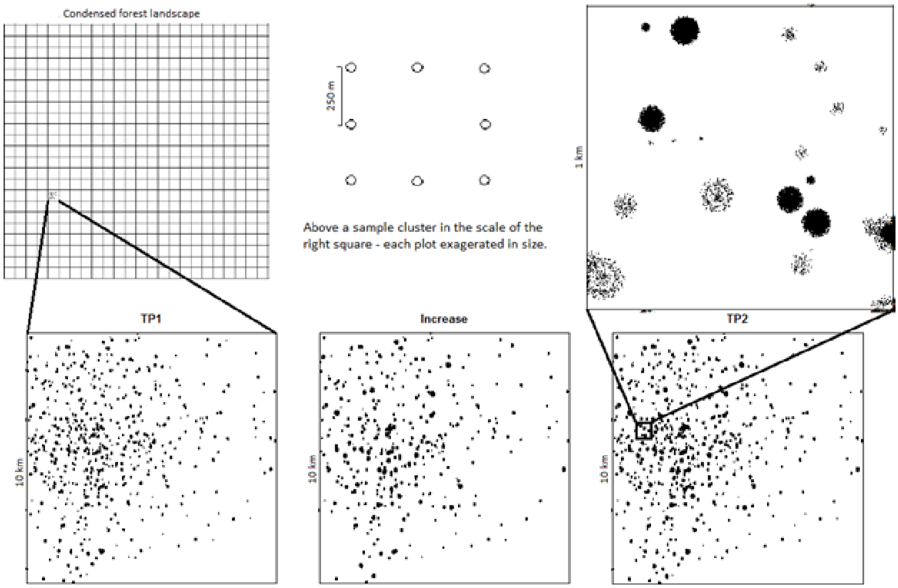

Figure 3. Example of a simulated population in Scenario 2 for Paper I. *Top-left figure*: The study area, containing a total of 500 squares of 10×10 km each. *TP1*: Square containing 238 tree damage aggregation centres at the initial time point. *Increase*: The intensity of all of the aggregation centres has been increased, and 38 of them have increased in radius. *TP2*: Resulting populations at time point 2. *Top-right figure*: Zoom into part of TP2.

Paper II:

The AOI was located in the county of Västernorrland in northern Sweden (Fig. 1). Forest stands were simulated in grid cells of 25×25 m using a GIS. Each grid cell received the mean values of the forest parameters from the polygon in which its center point was located, based on a spatial database of 366,810 forest stands obtained from the segmented kNN-Sweden data (a satellite-based product describing the country's forest (Reese et al. 2003, Reese et al. 2005). The following forest parameter raster layers were produced (all snapped to the same grid and resolution): Norway spruce volume, Scots pine volume, mean age, mean height, total volume, volume percentage of deciduous trees, and volume percentage of pine. These layers represented the vegetation's true state, used as measured inventory data from the first-phase NFI-plots.

Two different forest damage agents, with different host trees, spatial patterns and damage intensities were simulated using combinations of these layers. The first simulated damage agent was the spruce bark beetle (*Ips typographus*). Damage was simulated based on Schroeder and Lindelöw (2002), Kärvemo et al. (2014), Kautz et al. (2013), and from TFDI data from the study area (S. Wulff, pers. comm. 2012). Damage in each grid cell was simulated with probability proportional to spruce volume using a logistic function to calculate the damage probability. For each grid cell, a uniform random number between 0 and 1 was drawn and subtracted from the probability of damage calculated with the logistic function. If the resulting number exceeded 0 the grid cell was affected by damage. For each affected grid cell, the number of damaged trees was simulated independently as $y_i \in (1 + Po(2))$. Three different scenarios were simulated, hereafter referred to as IPS, IPSALT and IPSLOC (Figure 4):

- IPS: Intense damage highly dependent on spruce volume.
- IPSALT: More sporadic occurrences, less dependent on spruce volume. Reduced numbers of damage grid cells by dividing the probability of damage by 3.
- IPSLOC: Damage localized along forest edges. The variance of [spruce volume + age + height] within a moving window of 3×3 grid cells was calculated. Each grid cell's variance was added to the spruce volume and this layer was used in the logistic function with adapted parameters.

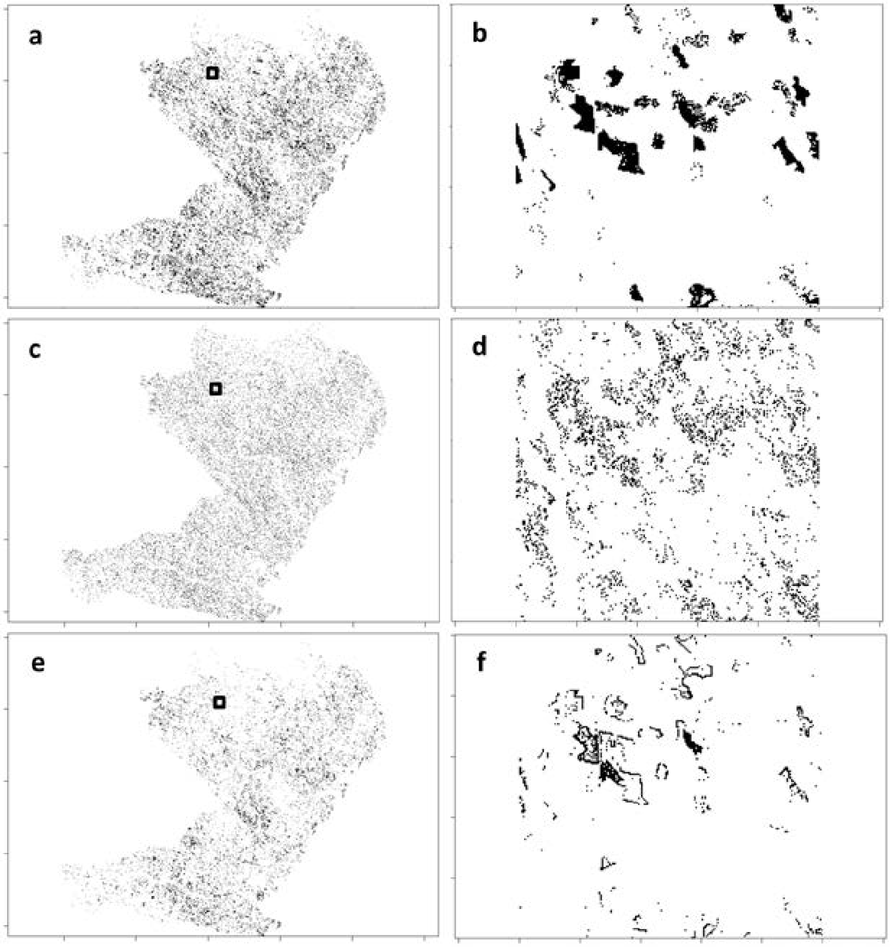

Figure 4. Visualization of simulated *Ips typographus* damage populations under the IPS (a-b), IPSALT (c-d) and IPSLOC (e-f) damage scenarios of Paper II. Black areas indicate grid cells with damage. Left panes (a,c,e) depict the whole county of Västernorrland and right panes (b,d,f) zoom into an example square (shown in the northwest of the study area in the left panes) used to visually illustrate the spatial characteristics of the damage on a smaller scale. (Note that this example square is different from that in Fig. 1, which depicts the larger square study area for Paper III, also located in Västernorrland.)

The second simulated damage agent was the fungal pathogen *Gremmeniella abietina*, affecting Scots pine. It was simulated with damage probability as a function of pine proportion. The same logistic function as for *Ips typographus* scenarios was used, but with the proportion of pine in each grid cell (instead of spruce volume) as an explanatory variable, and different parameter values. For affected grid cells, we simulated damaged trees as $y_i = 1 + ||\lfloor N(55{,}65\rfloor||$.

Gremmeniella abietina damage was simulated in three scenarios: GRE, GREALT, and GRELOC (Figure 5):

- GRE: Whole-stand and large-scale forest damage with stationary damage intensity for the entire county.
- GREALT: Less frequent than GRE.
- GRELOC: Whole-stand and large-scale forest damage with stationary damage intensity, but increasing risk of damage close to an epicenter in the north.

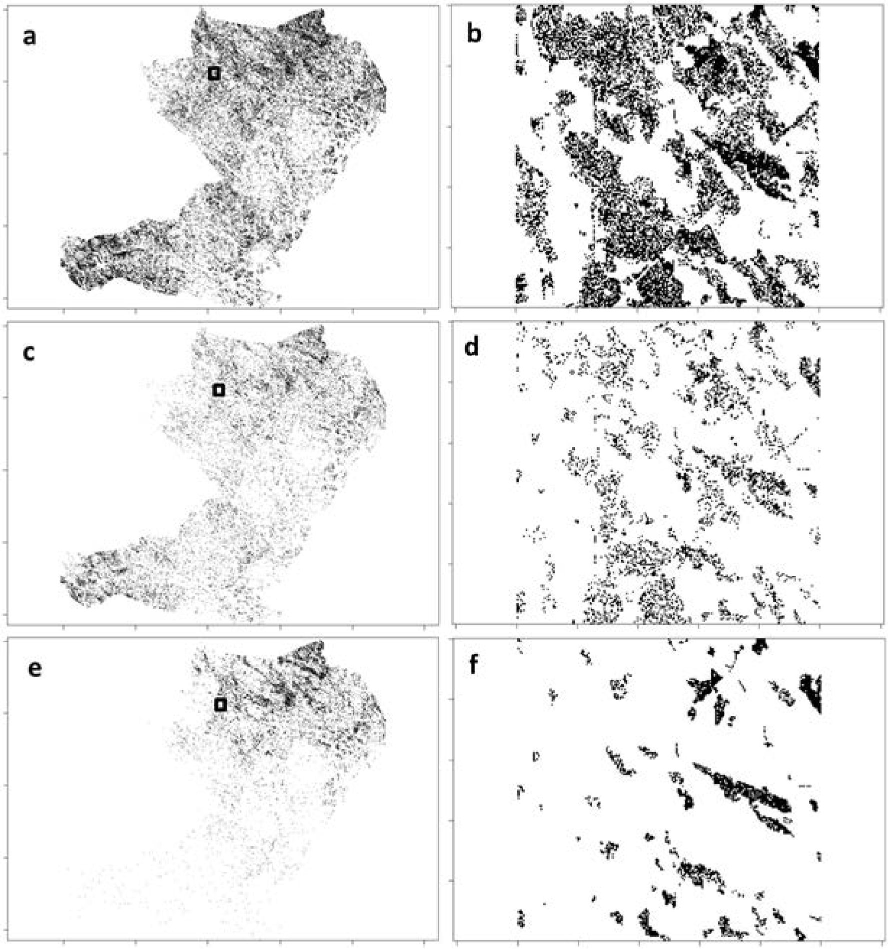

Figure 5. Visualization of simulated *Gremmeniella abietina* damage populations under the GRE (a-b), GREALT (c-d) and GRELOC (e-f) damage scenarios. Black areas indicates grid cells with damage. Left panes (a,c,e) depict the whole county of Västernorrland and right panes (b,d,f) zoom into an example square in the northwest of the study area. See caption of Fig. 4 for details.

Paper III:

The AOI for Paper III was a square subset (totalling 900 km^2) of the study area used in Paper II. The scenarios for *Ips typographus* damage from Paper II (IPS and IPSALT) were utilized with two additional populations (IPSS and IPSALTS) that were based on new realizations of IPS and IPSALT. In these two additional populations, the damage intensity, in terms of numbers of damaged trees per grid cell, was dependent on where the damaged grid cell occurred in the municipality. Both additional populations had more damage trees towards an epicentre in the north central part of the municipality and then the damage was reduced toward the municipality's edges. Key simulated population figures are presented in Table 2; a graphical visualization would resemble panes *b* and *d* in Figure 4.

Table 2. *True populations of Paper III, numbers of damaged trees (y) and affected grid cells (1/0) in the simulated populations.*

	IPS		**IPSS**		**IPSALT**		**IPSALTS**	
	1/0	***Y***	**1/0**	***Y***	**1/0**	***y***	**1/0**	***Y***
True total	282×10^3	846×10^3	282×10^3	662×10^3	167×10^3	502×10^3	171×10^3	396×10^3
Mean	0.20	0.59	0.20	0.46	0.12	0.35	0.12	0.27
Σ	0.40	1.34	0.40	1.05	0.32	1.07	0.32	0.83
Maximum	1	12	1	10	1	12	1	10
Minimum	0	0	0	0	0	0	0	0

Another noteworthy aspect of these new populations is that they had equal damage area, but smaller population variance in terms of numbers of damage trees (Table 2).

Paper IV

For a simulation based cost-plus-loss evaluation, different populations and assumptions were needed. First the forest stands with damage scenarios and associated losses were simulated, then the quantities and spatial configuration of the damaging agent was simulated. This information was used to evaluate the risk of additional defoliation and damage to the stand and the decision on mitigation activities. Damage scenarios were based on previous outbreaks of defoliator insects (Långström et al. 1999, Butovitsch 1946) and consequences in terms of forest damage Långström et al. (2001 and 2004).

We simulated four pine dominated forest stands with the Heureka system (e.g. Wikström et al. 2011). The projections include predictions of several core variables, such as timber volume, forest age, and tree species distribution. In our study, each stand represents forest of different age but with the same site quality

(Table 3). The net present value (NPV) for the undamaged forest was estimated for all stands, based on standard management procedures for southern Sweden. The cost and income associated with each action was based on the default Heureka timber price list for southern Sweden and NPV for the damaged stands were calculated by a forced 60% thinning in each stand. No loss of timber value was considered. The losses in NPV ha^{-1}, *L*, were then calculated as the difference between NPV for the healthy undamaged forest and the damaged forest (Table 3).

Table 3. *Each stand for which defoliation damage was evaluated with results in terms of NPV (SEK ha^{-1})*

Age	DG	H	N	G	V	Prop Pine	NPV Healthy	Loss
23	7.5	5.4	2073	6.6	21.8	0.9	13643	7253
33	11.8	8.5	1955	17.1	77.6	0.93	18147	5201
43	15.5	11.8	1098	17.6	102.1	0.93	22619	2285
53	18.6	14.4	1057	24.8	169.4	0.92	31570	315
97	31.2	21.8	536	26.3	249	0.87	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}), 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}).

The area with initial signs of damage, the AOI, was assumed delineated (e.g. by RS data, CIR-photo interpretation). An inventory of pupae in the humus was performed for evaluation of the mean intensity of healthy pupae m^{-2}. The estimated mean intensity of pupae m^{-2} was used to evaluate the risk of additional severe defoliation (Långström et al. 1999). The defoliation extent and numbers of pupae m^{-2} were varied between scenarios. Area extents varied from 50 to 10000 ha and the six different pupae populations were simulated. Three with complete spatial randomness (CSR) from a Poisson process, and three clustered populations (CLU) from a Thomas process (Thomas 1949) with approximately equal overall intensities (Figure 6, Table 4).

It was assumed that additional defoliation and damage can be avoided perfectly by applying *Bt*-control spraying. In addition it was assumed that there is a known relationship between numbers of pupae m^{-2} and defoliation risk during the coming growth season.

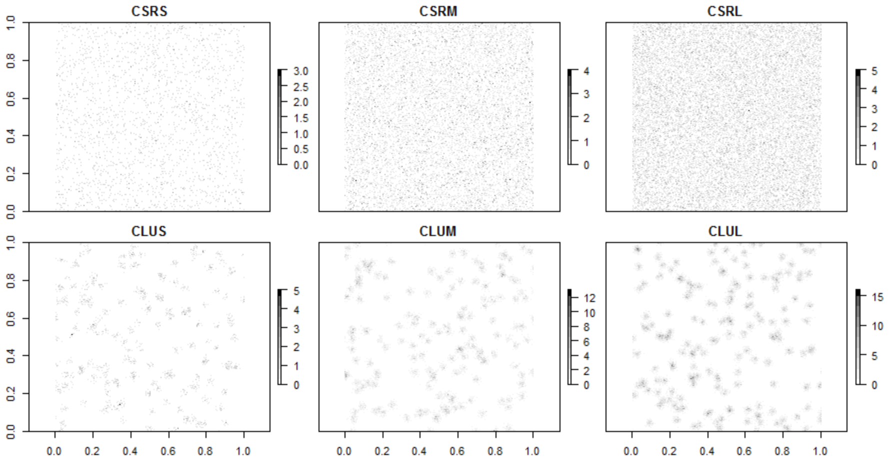

Figure 6. The six simulated populations of healthy pupae of 1 ha each (i.e. each side represents 100 m). The three above follow a stationary Poisson process and the three below follow different Thomas processes with approximately the same density of pupae.

Table 4. *Numbers of pupae m^{-2} in simulated populations. Min, max and variance of grid cell values.*

Population	**True # of pupae m^{-2}**	**Min # pupae grid cell^{-1}**	**Max # pupae grid cell^{-1}**	**True population variance of y_j**
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

3.2.2 Auxiliary data

Different types of (artificial) auxiliary data were used in the different papers: NFI data as well as data mimicking what would be obtained from RS data. Errors in the auxiliary data (e.g. Congalton and Green 2009) were also simulated in order to be controlled in the studies. Auxiliary data were simulated in a similar manner for Papers II and III: fine resolution grid cell based detections of damage (1/0) called RS in Paper II and D in Paper III. In Paper III, damage tree counts (DTC) from PIS by skilled professionals were utilized, either as D for stratification in a 2PS design or as DTC for the LPM sample selection. In the DTC layers, each grid cell contained a value (0-12) based on the number of detected damaged trees. In Paper II the auxiliary data were available for the whole AOI, whereas for Paper III auxiliary data were only available for first phase sample grid cells.

In Paper II, auxiliary data were simulated for each of the different damage scenarios in the form of classified remote sensing (RS) data, with the same extent and final resolution as the raster layers of true population values. For the *Gremmeniella* scenarios (GRE, GREALT and GRELOC), detection of damage with probabilities equal to 90% and 60% were simulated if there were > 4 damaged trees in the grid cell. Grid cells with less damage went undetected. Commission errors were simulated by assigning each undamaged grid cell a probability of 0.0001 or 0.01, respectively, of being falsely classified as damaged.

For the *Ips typographus* scenarios used in Papers II and III (IPS, IPSS, IPSALT, IPSALTS and IPSLOC), we envisaged detection of damaged trees from very high resolution imagery (i.e., aerial photos) within all 25×25 m grid cells. The number of damaged trees per grid cell was simulated with detection probabilities equal to 90%, 80%, 70% and 60% for each damaged tree in a cell. Commission errors were also assigned with 0.0001 and 0.01 risk, respectively, in order to simulate the risk of q 'false-damage-trees' (q $\in 1 + Po(2)$) for each grid cell without damage. From this DTC layer, a RS layer (Paper II) or D layer (Paper III) was created. If ≥ 1 damaged trees were detected in a grid cell, it was assigned the value of 1 and if no damaged tree was detected it was assigned the value of 0. For Paper II, the different combinations of detection probabilities and commission errors were named as follows: RS ("remote sensing"), then a number corresponding to the detection probability (90% etc.), and finally a suffix providing the level of commission error (L for 0.0001 and H for 0.01). For example, RS90_L and RS90_H refer to 90 % detection and the lowest and highest probabilities of commission error, respectively. For Paper III, these were named similarly as in Paper II, except that the prefix DTC was used.

4 Results

First, we evaluated the possibility to detect an increase in forest damage from a sparse monitoring program of systematically placed inventory plot clusters, e.g. an NFI. With this design for scenario 1 it was found that the power to detect an increase above 1 damaged trees ha^{-1} was above 80% already at true increments in mean numbers of 1.5 damaged trees ha^{-1} for the full panel of 500 tracts. For 100 tracts the true change needed to be above 2.5 or 3.6 depending on the initial state (Figure 7). Results indicate that clustered outbreaks over a shorter time-frame (100 tracts) would very likely go undetected.

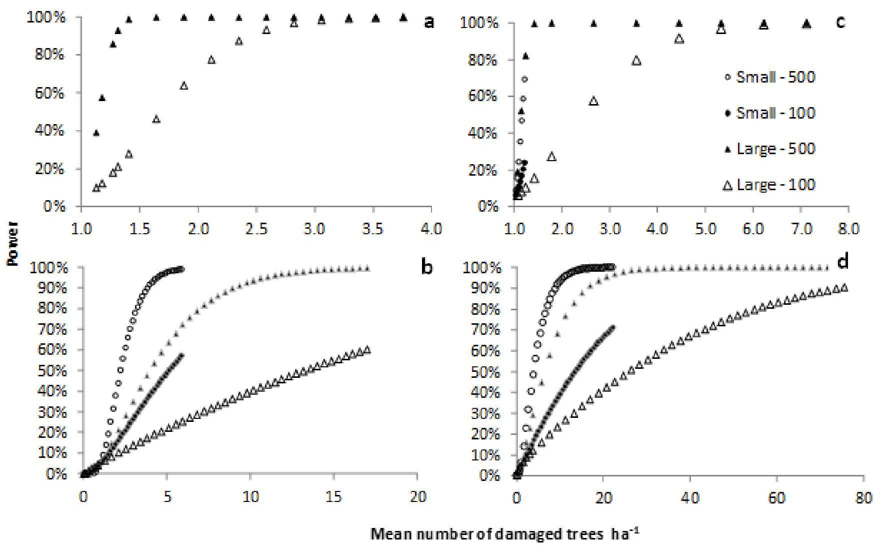

Figure 7. The power to detect an increase > 1 damage trees ha^{-1} in Scenario 1 (A and C) and Scenario 2 (B and D). Panes A and B show the results for the sub-scenario with a sparse initial damage level while C and D show the results for the sub-scenario with an intermediate initial damage level. Data for the small sub-scenario are omitted in A since the increase never exceeded 1 damaged tree ha^{-1} in this case.

In Paper II we evaluated a TFDI utilizing NFI plots in the first phase in a 2PS design, directing the inventory toward plots with host tree species. The relative efficiency of this strategy was evaluated with six different damage populations in two main sets of scenarios: one involving *Ips typographus* and another involving *Gremmeniella abietina* damage. Additional auxiliary data were used for estimation purposes in a PS2PS design. This strategy was evaluated for the same populations utilizing auxiliary data with different known errors. For both sets of damage scenarios, the damage area estimators had a lower estimated CV than for estimates of the numbers of damage trees (Figure 8). For the PS2PS estimator applied to the *Ips typographus* scenarios, even with the least accurate auxiliary data, the CV was reduced by almost one-half for area estimates and by a third for estimates of numbers of damaged trees. For the *Gremmeniella* scenarios, the effects of PS2PS estimators were less pronounced. The GRE population still had a decrease in CV of almost one-fourth even with the least accurate auxiliary data and for estimates of damage area. For the numbers of damage trees the estimated CV was reduced by almost one-tenth.

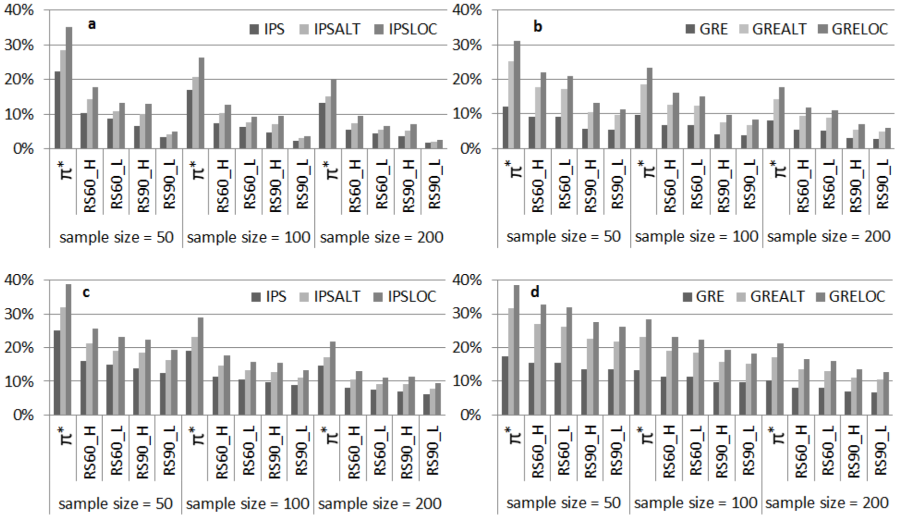

Figure 8. Coefficient of variation (CV, in %) for the estimates of total affected area for *Ips typographus* scenarios (**a**) and *Gremmeniella abietina* scenarios (**b**)**,** and of total number of damaged trees for *Ips typographus* scenarios (**c**) and *Gremmeniella abietina* scenarios (**d**).

ECRs of 95% confidence intervals from evaluated variance estimators were close to the nominal coverage percentage (Table 5). However, at higher sample sizes there was increasing bias.

Table 5. *Empirical confidence rates (ECR) of 95% confidence intervals for estimators of numbers of damaged trees in Paper II.*

	sample size = 50					sample size = 200				
	π*	RS60H	RS60L	RS90H	RS90L	π*	RS60H	RS60L	RS90H	RS90L
IPS	92	92	92	93	93	90	93	94	94	94
IPSALT	92	91	90	92	91	93	94	94	94	94
IPSLOC	90	89	87	90	88	91	92	93	93	93
GRE	93	94	93	94	94	91	93	93	94	94
GRELOC	90	88	88	89	89	91	92	92	93	93
GREALT	91	91	90	91	91	92	93	93	94	94

In Paper III, the 2PS was once again found to be highly efficient, especially with good auxiliary information and favourable allocation of the sample. The LPM was also efficient and had consistently lower ERSD compared to the SI design (Figure 9). The populations with a spatial trend had less variation in terms of numbers of damaged trees than the original populations. The larger twin populations IPS and IPSS could also be compared to the twin population IPSALT and IPSALTS, which were more scattered but with less damaged trees. For the LPM estimator, ERSD was lower for accurate auxiliary data and for the population with spatial trend, and for the population with lower population variance comparing all populations. For the 2PS design there was a large difference in ERSD between different auxiliary data, where the best auxiliary data gave large improvements in the ERSD relative to the worst auxiliary data. With poor auxiliary data and high proportion of the sample allocated to the damage strata, the ERSD of 2PS sampling was higher than the ERSD of LPM with the same auxiliary data. The improvement in ERSD following 2PS with better auxiliary data was more pronounced in the scenarios with spatial trend.

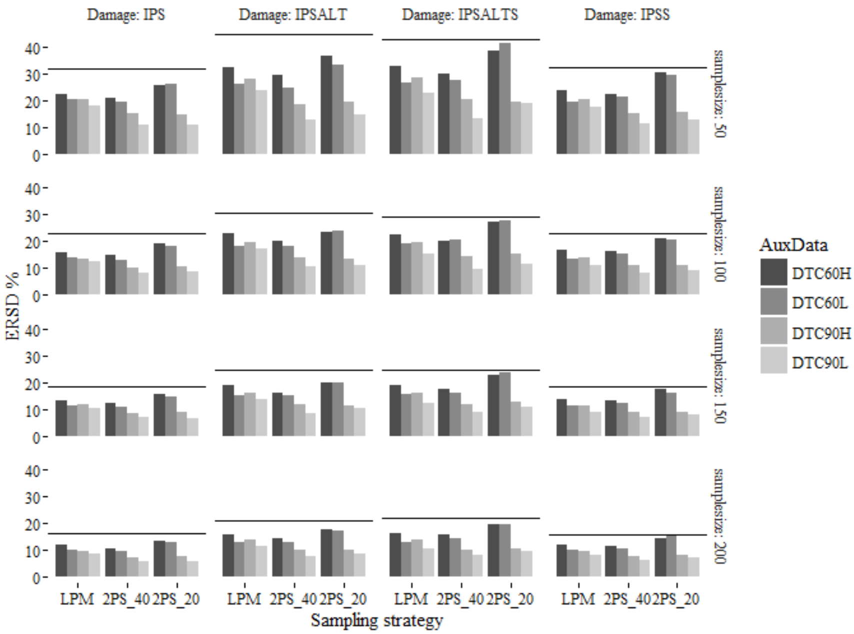

Figure 9. Empirical relative standard deviation (ERSD, in %) for first-phase sample size n1 = 3600, for all combinations of damage, sample size, sampling strategy and auxiliary data. The ERSD from the SI design is depicted as a horizontal line.

In addition to the evaluation of the LPM we also tested two variance estimators, with clear advantages found for the Grafström-Schelin variance estimator following a LPM sample. This estimator had a mean estimated variance to empirical variance ratio of approximately 1, whereas the alternative variance estimator overestimated the variance for all evaluated combinations with a mean estimated variance to empirical variance ratio of 1.7-4.7.

In Paper IV results from 1000 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 (Figure 10). The inventory costs over all evaluated sample sizes for the SI inventory strategy ranged from ~9900 SEK to ~89000 SEK, with an average of ~39000 SEK. For the DS strategy the inventory costs ranged from ~9900 SEK to ~181000 SEK, with an average of ~52000 SEK, over all initial sample sizes evaluated.

The cost-plus-loss across all stands and pupae populations ranged from 10000 SEK to ~72.3 million SEK, for both the DS and the SI strategy. The median cost-plus-loss over all stand ages and pupae scenarios was 217000 SEK for the DS strategy, and the mean 1.3 million SEK for the DS strategy, while the median was 218000 SEK, and the mean 1.5 million SEK for the SI strategy, indicating very high extreme values for both strategies but more so for the SI strategy. 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 (Figure 10). Generally, the larger the area, the higher benefit from utilizing DS sampling strategy (Figure 11).

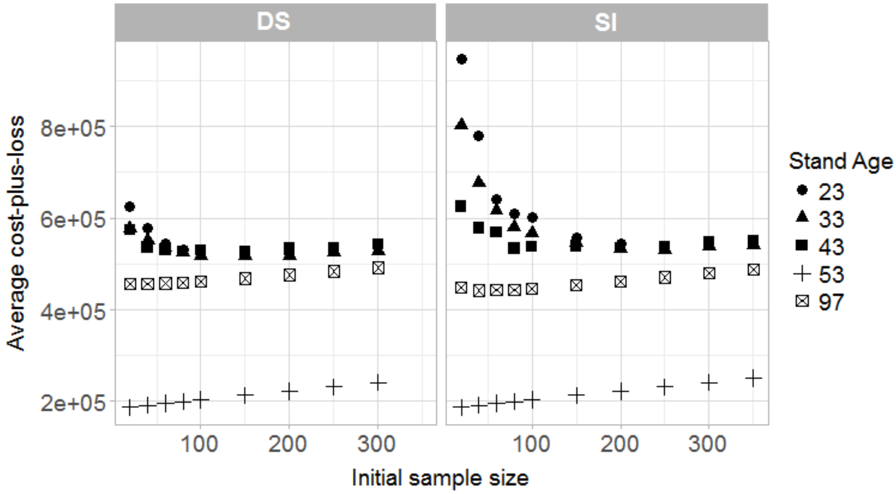

Figure 10. The average cost-plus-loss for a 1000 ha outbreak, for the two inventory strategies over all true populations of pupae and stand ages (i.e. assuming that all pupae populations and stand ages are equally likely within the area).

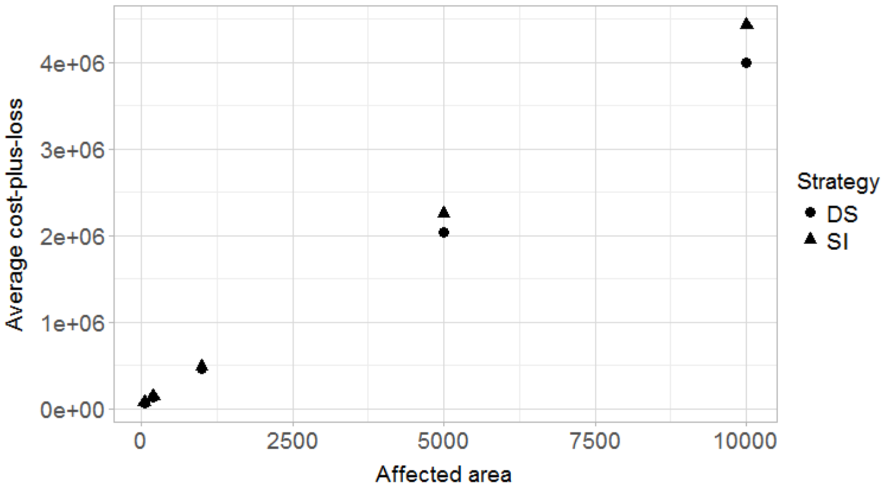

Figure 11. The average cost-plus-loss from the two inventory strategies over all evaluated sample sizes, pupae populations and stand ages.

5 Discussion

This thesis illustrates some limitations of traditional NFIs for detecting and precisely estimating some forms of forest damage, and it shows how directed damage inventories can be improved by the use of auxiliary data and cost-plus-loss analysis. Paper I concluded that NFI-type inventories perform well when estimating the damage increase (or state) for damage which is well spread over a large area with moderate to large intensity. It should also be noted that they may perform better for trends over longer time-frames because then more panels of inventory data can be included in the sample, i.e. it allows a larger sample size for the estimate. NFI inventories can be useful for detecting large-scale damage in the landscape, like diffuse increase in drought damage, rot damage or ungulate browsing (Paper I; Nevalainen et al. 2016). These results fit well with other, empirical studies where large scale *Gremmeniella abietina* damage (Nevalainen, 1999; Wulff, Hansson & Witzell 2006), extensive drought related damage on pinyon-juniper woodlands (Shaw et al. 2005) and moose browsing damage (Nevalainen et al. 2016) were estimated from NFI inventories. These are strong cases for the usefulness of systematic large-scale inventories and the inclusion of damage assessments in NFIs, especially for damage that may have relatively slow progress over a large area. However, as shown in Paper I, there is also a need for alternative inventory methods in the evaluation of forest damage, as NFI-type inventories are unable to ascertain adequate information on clustered or localized outbreaks or for damage that develops over short time-periods. Edgar and Burk (2006) also concluded that a large scale inventory of sparse systematic clusters of plots was inadequate to detect clustered damage of more localized extents.

An important contribution to forest damage monitoring from NFIs is the fact that their plots can be used as a first-phase ground sample which can be stratified for revisits of the kind used in Paper II. This design was highly efficient and has found practical application both in Sweden (Wulff, 2011) and France (Lucas, 2009). Paper II also showed that post-stratification using auxiliary data was a feasible way to improve the estimate even after the first phase auxiliary data had been utilized. Post-stratification using NFI data and RS auxiliary data has been evaluated previously, with empirical data, with good results (e.g. Nilsson et al. 2005, Tipton et al. 2013, Schroeder et al. 2014). In Paper II it was shown that 2PS using NFI data in the first phase worked very well as compared to SI of the same size: the relative efficiency was below 50% in all scenarios, meaning that the variance of the estimator from 2PS sampling was less than half of that of the SI sampling estimator. In the 2PS design, it was also feasible to utilize additional auxiliary data through post-stratification, in addition to the auxiliary NFI data in the first phase. The proposed PS2PS design and estimators can be used in case RS data are not available when the sample is selected and the inventory is planned. In other words, the planning of the inventory can be made irrespective of the availability of RS data. Thus, 2PS using NFI plots in the first phase is a very flexible inventory strategy, especially since it is possible to further improve the precision of the estimate using PS2PS (*cf.* Paper II) if additional data becomes available for the whole AOI. Indeed, PS2PS sampling utilizing classified RS data improved the estimates further and provided an efficient way of utilizing additional auxiliary information that was perhaps unavailable in planning the inventory. Such data will likely become increasingly available in the future thanks to development in RS technologies (e.g. Hargrove et al. 2009). The estimators and variance estimators studied in Paper II were found to perform well, in most cases, as ECRs were close to the nominal coverage rate. However, for large second-phase sample sizes the relative bias of the variance estimator increased, probably as a result of the assumption of SI sampling in the first phase, where plots from NFI clusters (i.e. 'tracts') were used.

In Paper III, a new design for use in forest damage inventory was evaluated: the local pivotal method (LPM). The design showed great promise in the field of forest damage inventory since it is possible to utilize many different auxiliary spaces (e.g. classified data, unclassified data, DEM and other GIS data) without much processing and modelling to precede the selection of the sample. This is especially valuable in urgent situations where an inventory must be performed rapidly (e.g. while characteristic symptoms are visible) to allow quick action and avoid further spread of the damage. Systematic sampling and the benefits of spreading the sample in geographical space has been known and utilized for many years to avoid spatial autocorrelation and hence obtain more representative samples. Most NFIs utilize probability sampling (design-based inference) with a systematic sample based on two-dimensional grids with randomly selected starting points (e.g. the Swedish NFI). Other NFIs utilize a tessellated sampling design where plot locations are randomly selected within tessellated polygons. This second type of design resembles the one we applied in Paper I, although the tessellation can differ between countries (Tomppo et al. 2010). Other designs have also been suggested for spreading the sample in geographic space: systematic sampling, stratification and Generalized Random Tessellation Stratified design are examples (e.g. Madow and Madow 1944; Cochran 1946; Wolter 1984; Stevens and Olsen 2003). A benefit of the LPM sampling strategy is that it allows taking advantage of the increased availability of additional auxiliary data (in addition to those related to the geographical space) that may be pertinent to the variable of interest.

A drawback with systematic sampling and LPM sampling is that traditional variance estimators based on second order inclusion probabilities cannot be applied. In papers I and II approximate estimators were applied and shown to perform well, using SI sampling assumptions. In paper III, two different variance estimators were evaluated for the LPM design. The Deville estimator assumes a high level of randomness in the sample selection and works well for SI samples whereas for LPM sampling it overestimated the variance consistently over the different sample sizes and populations evaluated. As it does not exploit the induced stratification effect by the LPM, the Deville estimator results in conservative variance estimation for such designs. The Grafström-Schelin variance estimator performed better, with a mean estimated variance to empirical variance ratio of approximately 1 for all evaluated scenarios and sample sizes. As the Grafström-Schelin variance estimator is tailored for well-spread samples and has previously been shown to sometimes slightly overestimate the variance for large samples for volume estimates (Grafström and Ringvall, 2013) our results contribute to showing its robustness.

Change detection in Paper I was based on panels of permanent plots. Such designs are ideal for change detection (e.g. Gregoire et al 2008), but may be less efficient for estimation of state, and may also be sensitive to problems concerning site representativity over time (Scott and Köhl 1994). In Papers II and III the focus was on estimates of state rather than estimates of change. To allow change detection, the designs assessed in Papers II and III could be complemented by revisiting all the second-phase plots again, or applying some form of sampling with partial replacement of plots (SPR; Ware and Cunia, 1962). SPR offers a compromise allowing a relatively efficient estimation of both state and change from combined inventories in time. Hence, it is often used because inventories and monitoring schemes are generally not conducted exclusively for change detection. Revisiting the second phase sample in 2PS sampling was suggested by Bickford, Mayer & Ware (1963) and Scott and Köhl (1994), and SPR from 2PS designs is explored in Scott (1998). This may be a natural evolution for the designs tested in this thesis, as damage outbreaks may affect the forest for longer time periods.

As illustrated in this thesis there is a lot of possible information relevant to forest health monitoring and integrated pest management. However, this also means that there are increasing numbers of different models and other information to consider for each decision. With increasing possibilities in information sources and alternatives in management, it may be difficult to predict the consequences or the results of different choices. In Canada, there is a decision support system for forest managers to help spatial decision making in the management of spruce budworm (MacLean et al. 2002; MacLean et al. 2001;

MacLean et al. 2000) weighting the cost of pest control and the loss caused by the defoliation. The results from paper IV could potentially be used as a small contribution toward such a system for the pine looper. The results of Paper IV also clearly suggests that in case inventory costs are high there is great potential in applying a sequential sampling scheme, such as the double sampling design applied in the study. It was also found that the inventory cost was a substantial part of the total cost-plus-loss and thus it is important to consider inventory strategies in this type of decision making. Moreover, the losses following decisions based on inaccurate information were sometime extremely large. This highlights the importance of an appropriate inventory strategy as part of pest mitigation schemes. However, Paper IV was based on several assumptions regarding the link between pupae density and the risk of defoliation as well as the losses in NPV due to defoliation. Thus, it is suggested that the main merit of this study is the theoretical approach rather than the numerical results.

Considerable effort and funds are dedicated to monitoring forest damage and forest health. The results from this thesis contributes to improving forest damage inventory strategies for making efficient use of these resources. Paper I showed that intermediate and large damage outbreaks of random occurrence are likely to be captured by NFI-type inventories, but that scattered, clustered or more localized damage outbreaks are likely to go undetected. Paper II showed that an inventory strategy building on two-phase sampling for stratification based on existing field plots from a NFI is highly efficient for estimating forest damage specialized on specific host trees, and that the use of high quality remotely sensed auxiliary data and post-stratification can further improve precision. Another promising design for inventory of forest damage outbreaks was the LPM sampling method, especially in the light of new emerging RS data sources: Paper III showed that it was a better choice than SI in all tested scenarios and populations. Forest damage inventories are made to ascertain valuable information, either for managerial decisions – or for improving knowledge to adapt forest management with regards to the new knowledge. So, in essence the right amount of information is needed – just enough, otherwise it is too costly. The future of our forest resources depend on our ability to make good decisions based on adequate information. To achieve that, forest policy and forest managers will need information on forest damage and forest pests. Hence, forest damage inventories will need to make clever use of all available data, and collect new information in an efficient way. Some such inventories are investigated and evaluated in this thesis.

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