Optimization of Harvest Planning of Forest Stands Infested by Spruce Budworm Using Stochastic Programming Approach

by

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OPTIMISATION DE LA PLANIFICATION DE LA RÉCOLTE DE BOIS INFESTÉ PAR LA TBE EN UTILISANT LA PROGRAMMATION STOCHASTIQUE

Iris ZHU CHEN

RÉSUMÉ

La planification de la récolte du bois est considérée comme le processus le plus important dans la chaîne d'approvisionnement de l'industrie forestière car elle assure l'apport du matériel brut dans les scieries. Toutefois, en raison des évènements d'incertitude stochastiques comme l'infestation des insectes, en l'occurrence, l'épidémie de la Tordeuse des Bourgeons de L´Épinette (TBE), la planification tactique de l'approvisionnement peut être affectée de façon irréversible. Avec le temps, cette infestation cause la vulnérabilité des arbres, en augmentant le taux de mortalité par défoliation. L´objectif de ce projet de recherche est utiliser des méthodes avancées comme la Programmation Stochastique, à maximiser la valeur marchande du bois récolté en considérant la récurrence de l'infestation dans tous les cas possibles. De ce fait, un modèle déterministe de Programmation Linéaire Entier Mixte, auquel est ajouté un module d'optimisation stochastique à deux étapes, est proposé pour traiter l´incertitude quant à la sévérité et la propagation de l'infestation. Ces modèles nous aiderons à suivre le niveau du stock des blocs de coupe de bois, pour chaque phase d´infestation de l'épidémie de la TBE selon son cycle de vie. Les modèles d´optimisation sont programmés en langage AMPL et ils sont résolus avec le solveur CPLEX. Premièrement, on a testé les modèles pour évaluer et analyser les résultats préliminaires qui démontrent l'avantage d'utiliser la Programmation Stochastique pour la planification avec incertitudes et le coût d´obtenir l'information précise sur l´incertitude due à l'infestation. Afin de valider que le modèle est véridique et adéquat pour ce projet de recherche, un cas réel est étudié, sur la Côte-Nord au Québec. Les résultats et la qualité de l´information des paramètres des modèles déterministe et stochastique sont analysés et comparés aux EVPI (Valeur Attendue avec Information Parfaite) et VSS (Valeur de la Solution Stochastique) lorsque les gestionnaires forestiers ne considèrent pas l´incertitude. Ces modèles fournissent une meilleure planification en milieu forestier en réduisant les coûts d'exploitation, en augmentant la valeur de toute la chaîne d'approvisionnement et en réduisant

les pertes reliées à l'infestation. Finalement, nous proposons quelques aperçues sur les paramètres d´incertitude qui peuvent affecter les résultats des modèles d´optimisation et expliquer certaines suggestions qui pourraient améliorer le modèle si d´autres attributs sont inclus dans la planification de la récolte du bois et la pertinence d´inclure d´autres paramètres d´incertitude dans la planification forestière.

Mots-clés: Programmation Stochastique à deux étapes, Programmation Linéaire Entier Mixte, Chaînes des approvisionnements forestières, Infestation dans la forêt, Tordeuse des Bourgeons de L´Épinette, Planification de la récolte de bois.

OPTIMIZATION OF HARVEST PLANNING OF FOREST STANDS INFESTED BY SPRUCE BUDWORM USING STOCHASTIC PROGRAMMING APPROACH

Iris ZHU CHEN

ABSTRACT

In the forest industry, harvesting process is one of the key critical processes as it supplies the primary raw material for different mills. However, due to several natural disturbances such as insect outbreaks, the impact and the effects on the tactical planning of forest supply chain can be irreversible. We consider the susceptibility, vulnerability, and increasing mortality by defoliation in trees over time caused by Spruce Budworm (SBW) infestation. The aim of this project is to use advanced optimization methods, in our case Stochastic Programming (SP), to maximize the market value of the harvested logs considering the occurrence of infestation over all the possible infestation scenarios. In our research method, we formulate a deterministic Mixed Integer Linear Programming (MIP) model which has then been extended into a Two-Stage SP model to deal with uncertainty related to the severity and propagation of the infestation; we also, as well, track the levels of infested volume inventory of the forest stands under the phases of SBW infestation according to their life cycle. The models are implemented in the modelling language of AMPL and solved using the commercial CPLEX solver. We tested the model for analyzing preliminary results to show the value of using SP in planning under uncertainty and the cost of the information. Then, we applied the model to a real case study in the North Shore region of the province of Québec (Côte-Nord) and compared deterministic and Stochastic Optimization (SO) methods with standard metrics for their evaluation. More precisely, we compute the Expected Value with Perfect Information (EVPI) and Value of Stochastic Solution (VSS) parameters, to analyze whether the method of Stochastic Programming is adequate for the project and the cost of the quality of the information and when we do not consider uncertainty. The optimization models offer better decision-making in forest management, reduce costs, increase the value in the entire chain and loss of trees as Spruce Budworm can lead to future outbreaks. Finally, we suggest some insights of the uncertain parameter that can affect the results of the optimization models and explain some suggestions that could improve the model if other attributes are included in the harvesting planning and the relevance of including other uncertainty parameters in forest planning.

Keywords: Forest Supply Chain, Mixed Integer Linear Programming, Spruce Budworm Infestation, Two-Stage Stochastic Programming, Harvest Planning.

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LIST OF ABREVIATIONS

AAC	Allowable Annual Cut
AMPL	A Mathematical Programming Language (modelling language)
DEM	Deterministic Equivalent Model
DSS	Decision Support System
EEV	Expected of Expected Value
EPB	*Épinette Blanche* or White Spruce
EPN	*Épinette Noire* or Black Spruce
EV	Expected Value
EVPI	Expected Value with Perfect Information
FMU	Forest Management Unit
LP	Linear Programming
MFFP	*Ministère des Forêts, de la Faune et des Parcs*
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Programming
NPV	Net Present Value
OR	Operations Research
PROPS	Protection Planning System
RP	Recourse Problem
SAA	Sample Average Approximation
SAB	*Sapin Baumier* or Balsam Fir
SBW	Spruce Budworm

SBW-DSS	Spruce Budworm Decision Support System
SLP	Stochastic Linear Programming
SO	Stochastic Optimization
SP	Stochastic Programming
TBE	*Tordeuse des Bourgeons de L´Épinette*
VSS	Value of Stochastic Solution
WS	Wait-and-See Solution

LIST OF SYMBOLS

$\$/m^3$	dollar per cubic meter
$M	Currency in Millions
ha(s)	hectare(s)
km^2	square kilometers
m^3	cubic meter
m^3/ha	cubic meter per hectare
±	more or less
CAD	currency in Canadian dollars

INTRODUCTION

In the forestry industry, supply chain planning has played a significant role in decision-making over a planning horizon that can start from the following hierarchical levels: strategic, tactical, and operational. In tactical planning, it is mostly associated with making decisions on how to manage the operations of forest stands ranging over several periods, specifically annual harvest planning in different supply chains of the forest industry as Carlsson et al. (2006) explains in their overview paper. The use of Operations Research (OR) is necessary for forest managers to support the aims of maximizing total profit or of minimizing total cost when making these types of decisions related to harvesting processes. These many important decisions can often be the place and time to harvest several forest stands that will have an affect on a strategic level and the forest supply chain performance as harvesting is and has been one of the first processes for obtaining the raw material and essential primary processes in the wood supply chain (D'Amours, Rönnqvist et Weintraub, 2008) (see Figure 0.1).

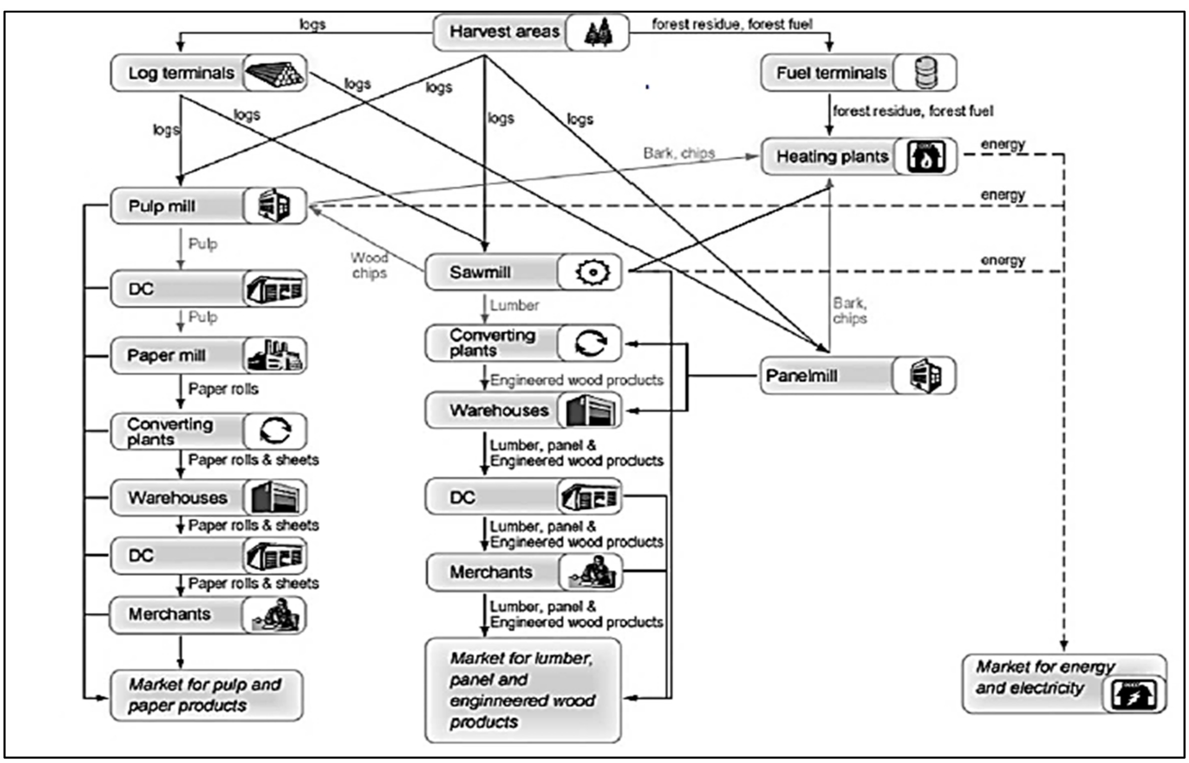

Figure 0. 1 Different supply chains in the forest products industry taken from D'Amours, Rönnqvist et Weintraub (2008).

As described in Troncoso et al. (2015), logs are the raw material for the primary transformation mills. They produce final or intermediate products for customers and second transformation mills. Therefore, it is essential to focus more on the harvesting process. However, this process faces uncertainty in forest management as it is not completely understandable and it is uncertain. It affects the future growth of trees or their yield by events such as windthrows, insect damage, fungi damage, other animals, climate change, air pollution, forest fires, and many others which are regarded as stochastic disturbances (Lohmander, 2007). Also, these stochastic parameters, as Church (2007) explains in his approach, are generally ignored when developing tactical models as the uncertainty can add a significant degree of complexity to modelling forest systems.

We propose to include, at the tactical planning level, the uncertainty caused by forest insect infestation by Spruce Budworm (SBW) *(Choristoneura fumiferana*) in the province of Québec, Canada. This living organism is a native North American defoliator and is considered as one of the most harmful forest insects. It causes defoliation and increases tree mortality of specific species. The ability to predict the occurrence period and understand the severity of SBW outbreaks would significantly enhance the capacity of the forest industry to manage forest resources and to mitigate and to minimize the impact of SBW (Gray, Régnière et Boulet, 2000). Tree species such as White Spruce (*Picea glauca*), Red Spruce (*Picea rubens*), and Black Spruce (*Picea mariana*) and Balsam Fir *(Abies balsamea)* host this type of living organism, particularly SBW. These tree species are important in the forest supply chain due to their high value on the market. Their many and extensive applications are diverse, supplying all kinds of products (e.g. paper, fuel, tools, construction, building materials, furniture making, musical instruments, flooring, and other wood-made tools) as described in Ouhimmou et al. (2008).

There have been several attempts, or methods to increase the harvest planning of the hosting tree species as they are essential in the forest value chain. Some efforts like commercial thinning are common and recognized as preventing timber losses. This method changes the composition of the trees increasing the defences against diseases and insects by promoting more abundant foliage, but this may affect the quality of the product. Other methods like salvage cutting or salvage harvesting; for instance, forest managers first harvest the most vulnerable stands before outbreaks occur or harvest the trees that have been dead for a brief period of time. However, there will be a significant loss of healthy trees. Despite the fact that massive outbreaks of SBW take several years to happen, some of the measures that forest management has taken to face this problem before it occurs are planning like scheduling of the harvesting process.

The aim of this project is to use an advanced optimization technique due to the uncertainty found when discussing the problem of the tactical planning of harvesting forest stands attacked by SBW. The contributions will be the integration of uncertainty at the tactical planning level of harvesting, using Two-Stage Stochastic Programming (SP) to maximize the value of the forest stands and comparing it to current practices that ignore such uncertainty.

We apply the proposed research method to a case study after being preliminarily validated to evaluate its impact on harvesting planning and therefore, on the entire value chain. The wood value chain in the forest industry starts with harvesting operations where it produces different log types (e.g. saw logs, pulp logs, and fuel logs) during the bucking process.

The main contribution of this research is the application of advanced OR tools in the forest sector in harvest planning due to one of the many uncertainties, specifically nature disturbances, by modelling using Stochastic Programming (SP) and maximizing the value or profit of forest stands. Also, the ability to plan while the occurrence, the extent, and the severity of SBW outbreaks can manage forest resources to minimize the impact of outbreaks on forest-level productivity.

The outline of the thesis is as follows: we start with the description of the problem of forest harvest planning under uncertainty in Chapter 1 followed by a Literature Review of several existing approaches of OR and SP for harvest planning in the forestry under uncertainty as well as existing approaches for dealing with SBW infestation in Chapter 2. Then, we describe the research method in Chapter 3, with the use of OR, for the identified components and parameters of the problem to formulate the mathematical optimization model. Next, the Linear Programming (LP) model is preliminarily validated in Chapter 4 based on MOSIM CONFERENCE PAPER 2016 (Zhu Chen, Ouhimmou et Rönnqvist, 2016) (see APPENDIX I, p.117-128). and applied for a study case (Côte Nord du Québec) in Chapter 5. We show the results with the proposed method for several generated scenarios in Chapter 6 and, we analyze these results in Chapter 7 as we compare and evaluate whether the proposed models are adequate and/or useful. Finally, we describe some further research opportunities in Chapter 7, followed by the conclusions and recommendations for improving the research problem.

CHAPTER 1

FOREST HARVEST PLANNING UNDER UNCERTAINTY

In this Chapter, we will introduce the research problem consistent with the requirements of a forest harvest planning and explain in general context how the Spruce Budworm (SBW) infestation behaves and the relation between its life cycle and the harvest planning. In the first section, we will describe the importance and issues of harvesting process under uncertainty in the forest supply chain. Finally, in the second section we will describe the SBW lifecycle in more detail.

1.1 Problem Description: Harvesting Planning under Uncertainty

The focus of this research consists in the following: harvest schedule planning considering forest insect infestation. This natural disturbance is one of the significant issues that forest managers must deal with, as it causes a great amount of damage to the raw material of the wood supply chain, leading to a significant loss to the forest industry and increased tree mortality that affects the harvesting process (see Figure 1.1). The figure illustrates the defoliation of an individual tree that could host the SBW (synchronized with the SBW life cycle explained later in Section 1.2). The line between three and four shows that it would be highly recommended to harvest during these phases, as the forest stands will still have higher commercial value on the market. Forest managers suggest that we can harvest the forest stands once for at least one period (year) as it is necessary to let them grow in a natural way or need the application of silviculture, to avoid excessive deforestation.

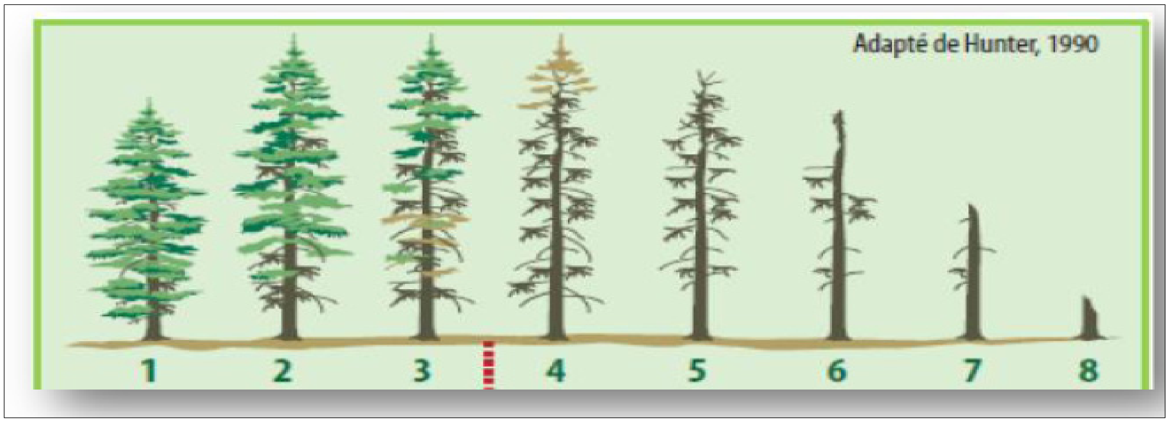

Figure 1.1 Instar or phases of infestation of Spruce Budworm in Balsam Fir taken from Lepage (2014).

The research problem has the following characteristics according to Figure 1.2. Starting from the raw material which is obtained in the forest stands (initial inventory or volume per cubic meter: m^3), the harvest areas will supply one or many mills with trees to satisfy their demand for different logs and species. Once we know the amount of forest stands to harvest or cut, trees will be processed by removing the leaves and branches. Then we transport these trees (transformed into logs) to terminals. The demand is fulfilled to the final customers and/or stored (e.g. heating plants, sawmills, pulp mills, and panel mills). This allocation, now logs, will be possible with transportation from the terminals.

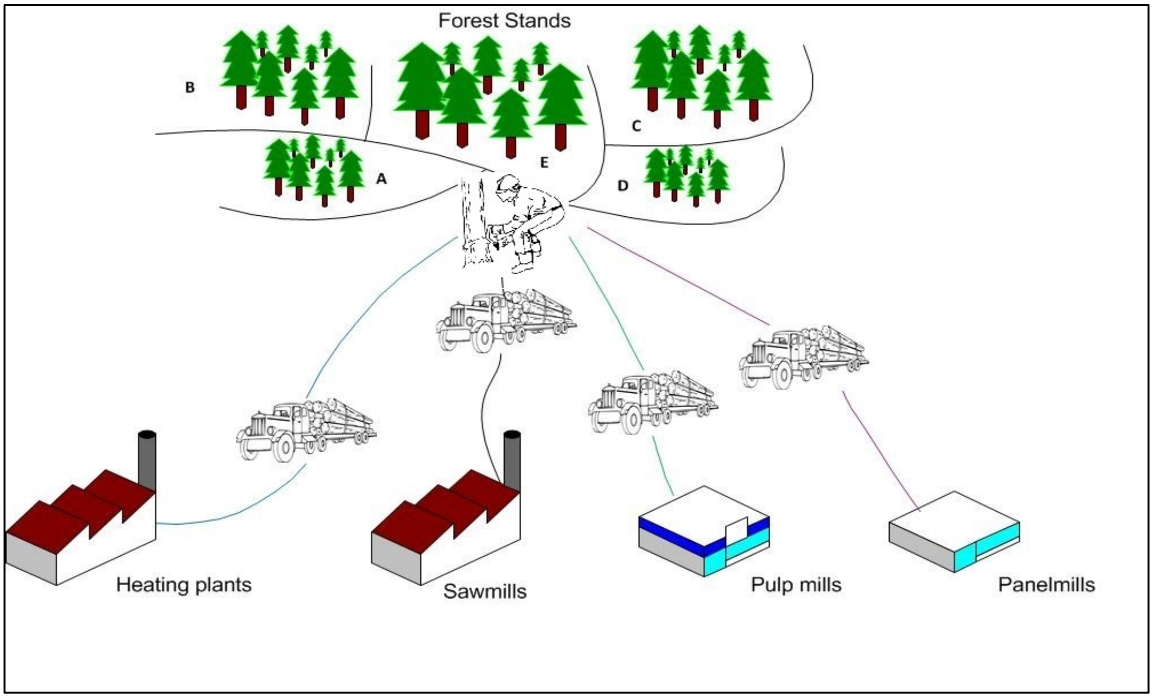

Figure 1.2 Basic harvesting process in the different forest supply chain industries.

Also, each volume percentage of trees in the harvest area is in a specific phase of infestation, also called instar of the SBW life cycle (see Table 1.1). These trees can be salvaged, and they have a ranked quality corresponding to a price on the market or for sale according to their attributes. The better the quality of the trees, the higher the sale price on the market will be. For example, in the forest stand "i", some volume percentage "A" is in phase two of the SBW cycle while other volume percentage "B" is in phase five. A decision should be taken by harvesting both amounts "A" and "B", either one of them or none, as "A" takes several periods for SBW to evolve into the next instars. In contrast, the percentage of volume "B" will progressively continue to grow into another random phase or still be in the current phase with lower value; or it will be better to harvest both amounts. However, it is necessary to have the best quality log as possible, based on the market value (see APPENDIX II, p.129-130), to reduce the harvesting and processing cost of trees that are severely infested, across the forest supply chain.

Table 1.1 Transition matrix of the Spruce Budworm infestation phases reproduced and adapted from Lepage (2014).

From \ To	FIRST	SECOND	THIRD	FOURTH	FIFTH	SIXTH	SEVEN	Total area
FIRST	**0.58**	0	0.42	0	0	0	0	**1**
SECOND	0.11	**0.61**	0.21	0.07	0	0	0	**1**
THIRD	0	0.11	**0.34**	0.41	0.14	0	0	**1**
FOURTH	0	0.05	0.25	**0.06**	0.54	0.1	0	**1**
FIFTH	0	0.01	0.05	0.17	**0.05**	0.72	0	**1**
SIXTH	0	0	0	0.08	0.13	**0.16**	0.63	**1**
SEVEN	0	0	0	0	0	0	**1**	**1**

Nevertheless, there is an initial inventory, but it is necessary to supply sawmills as the growth and yield of harvest areas depend on time. Once we cut a certain volume of trees and we transport it to terminals, we make another set of decisions: allocation of volumes to the final customer in proportion to the forest supply-chain diagram of Figure 1.2. This operation refers to the distribution and delivery of the volume harvested per their characteristics and their suitability for manufacture at the proper mills.

As mentioned above, the present state of damage that can affect forest stands can start from the lowest, moderate, or high defoliation evolving into an outbreak time. We consider these states as one of the many scenarios of defoliation seen in Table 1.1. Many types of events that can reduce or increase the dynamic population of SBW can affect these scenarios and thus make it difficult to make decisions compared to a mathematical deterministic Linear Programming (LP) model, as it is uncertain what the outcome of scenarios will be. They can still be in the same phase, or evolve into greater or lesser quality, randomly affecting the quality of yield.

It will be necessary to model the problem considering uncertainty and add a shortfall or penalty. There are several uncertainty parameters that forest managers regard as stochastic such as demand and price, planning costs, crop and yield, but in this case, the only stochastic parameter will be the number of total trees that will jump from one phase to another. We also consider the planning horizon of the forest stand (tactical planning) and the SBW life cycle. So, it is necessary to know the location and the time to cut or to harvest the forest stands before the SBW outbreak arrives. Moreover, expect the following or further cuts for the next period over the planning horizon; but also, keeping in mind that it is necessary to minimize the loss to have the highest quality of the logs as possible for the sawmills.

It is possible to apply the clear-cut method or other ways of cut treatment. However, most of the harvest optimization models assume that all trees have the same quality (which is generally not the case), and they are not necessarily healthy. Besides, these methods will affect the forest ecosystem. Also, harvest stands do not have similar attributes such as size, shape, and age. These natural events cause changes that cannot be controlled as trees are different. The planning production will be affected in the industry positively by knowing which harvest areas should be cut, and it will help reduce the time and cost of separating the quality of the logs during transportation to the terminals.

The objective is to minimize the costs of damaged harvest areas and the impact of SBW on the entire forest value chain by deciding which harvest area will be better to cut and maximize the value of the product. The decisions should be taken before the SBW outbreak appears, becomes wide-spread, defoliates and kills, as time passes during the planning horizon in most of the forest stands and so salvaging cannot take place. Also, the aim of this research is to minimize the loss of harvested area once there is infestation and keep (as high as possible) the best quality of wood for the entire supply chain with the aid of advanced OR tools.

1.2 Spruce Budworm Life Cycle

Since this research deals with uncertainty focused on natural disturbances, specifically Spruce Budworm (SBW), it is necessary to understand how this event behaves to understand how SBW transition matrix goes from one phase to another. The SBW, *Choristoneura funiferana* (Clemens), is the most widely destructive forest defoliator in North America. Their massive outbreaks destroy hundreds of thousands of hectares (ha) of valuable forest stands (e.g. Balsam Fir, White Spruce, and Black Spruce) and other softwood species (SOPFIM) (2011).

The SBW life cycle spans a single year, one generation per year (see Figure1.3). Normally there are six instars, sometimes even seven or more and it starts with an egg stage during the larval development (moth) consisting of ten days to hatch them. For the **first-stage or instar**, the female moth lays its eggs in early July on the underside of needles. Then, the larvae molts to the second-stage (overwintering stage); here, the tiny larvae spin silken covers under buds called “hibernacula” and in bark crevices and they stay in the shelter until the following spring. They come out of hibernation and young caterpillars emerge. Moreover, instead of feeding, they quickly weave a silk cocoon, spending time in it for the next winter months after the first instar (Ministère des Forêts, 2015).

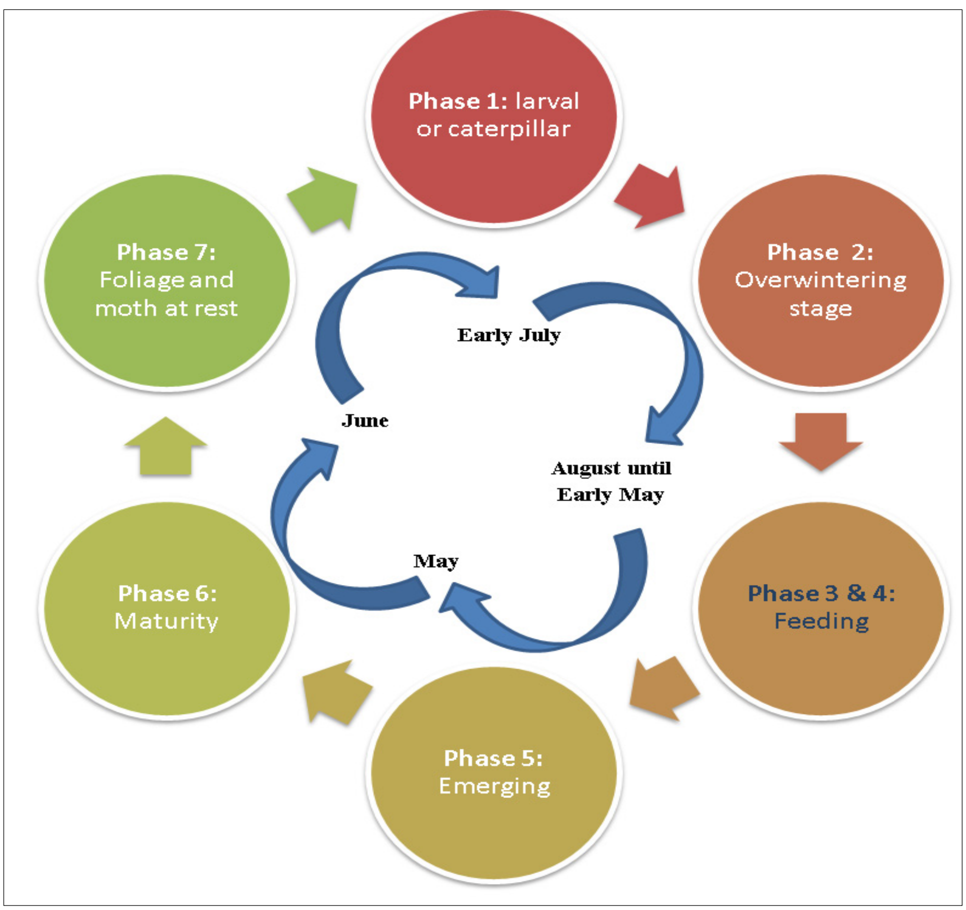

Figure 1.3 Spruce Budworm Life Cycle reproduced and adapted with the permission of the Ministère des Forêts (2015).

During the **second-stage**, they emerge in early May, just prior to bud expansion. Larvae mine old needles, unopened buds or, when available, staminate flowers. It is suggested that harvesting process is appropriate during this instar as lethal phases are found in first, second and last instar or phase known as the larval or caterpillar phase (Ministère des Forêts, 2015). Later, **third and fourth stage,** SBW feed on the expanding buds and as the new shoots grow, spin fine silk threads among the needles and between shoots. In epidemic populations, the SBW has consumed the old foliage. Feeding is completed in about five weeks depending on weather conditions.

After that, in **fifth instar**, adults emerge in early July, mate, and lay their eggs. Finally, for the **last instar**, in July and August, the female lays up to 200 eggs which it leaves in clusters of ten to fifty on the lower side of host tree´s needles, in the upper part of the canopy. The eggs are imbricated forming masses or clusters in the host´s inner surface needle and another SBW life cycle starts again.

The SBW life cycle spans over a single year´s defoliation that has minor impact on the tree. So that over a period equal to one, the harvesting process occurs over the same time. This is the reason why these decisions are considered as tactical planning due to the planning horizon. Also, because the uncertain parameter must be synchronized with the period for a better approach to reality. However, with each year of defoliation, it causes weakening of the tree making it more susceptible to other pests. Defoliation over a few consecutive years causes tree growth loss. However, if defoliation of current-and-previous-year shoots continues uninterrupted over several years, some trees will die, while others will continue to gradually decline for several years, even after the end of the infestation (e.g. Balsam Fir) (NRCAN, 2015).

In this first Chapter, we have introduced and described the research problem. The next Chapter will present current studies or/and existing approaches of research methods that have dealt with forest harvest planning with and without uncertainty to compare the existent practices.

CHAPTER 2

LITERATURE REVIEW

In this section, we will offer an extensive review of different existing approaches to forest harvest planning (see Figure 2.1) as well as some case studies for forest management planning under uncertainty. Moreover, we present a review of some optimization models that include uncertain parameters. Finally, we present a review of existing methods that have dealt with Spruce Budworm (SBW) in forest management. We will focus on the aspect of application of Operation Research (OR) on these issues of forest planning and SBW in forest management.

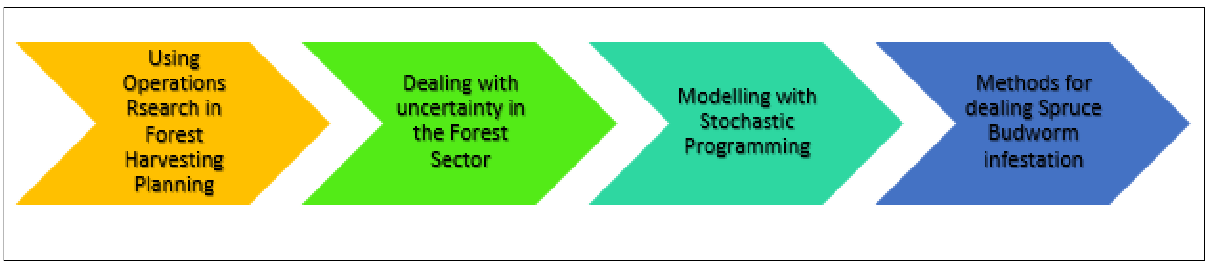

Figure 2.1 Scope of Literature Review on Forest Harvesting Planning.

2.1 Literature Review on Forest Harvest Planning

D'Amours, Rönnqvist et Weintraub (2008) explain that the harvest process starts when trees are cut and branches are removed; then the tree is bucked (or cross-out) into logs of specific dimensions and quality. Trees and logs are transported directly to mills or terminals for intermediate storage. This harvesting operation is part of the procurement process of the wood supply chain at the tactical level, according to the matrix for different hierarchical levels in the pulp and paper industry of Carlsson et al. (2006). Also, Figure 2.2 of Troncoso et al. (2015) shows a structure of a simple forest value chain. Here, we will focus only from Part One to Part Two where the area has several forest stands and this is the part where the harvesting process will occur. Once the forest managers treat them, these logs are shipped to different mills. Therefore, harvest planning is considered as the tactical level due to the number of periods over the planning horizon and the type of decisions needed to be taken for forest management.

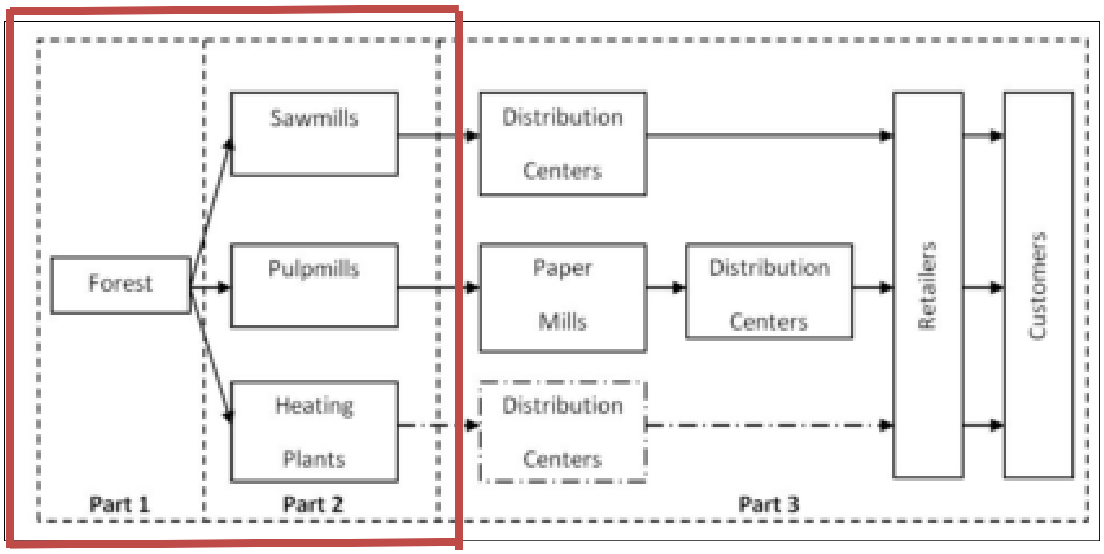

Figure 2.2 Structure of the forest value chain taken from Troncoso et al. (2015).

There are several existing approaches that have dealt with forest management and harvest scheduling in a deterministic context, and only a few have dealt with uncertainties like infestation. D'Amours, Rönnqvist et Weintraub (2008) suggested that for harvesting in tactical planning, Mixed Integer Linear Programming (MIP or MILP) and Stochastic Programming (SP) methods are better to model in the matter of decision-making about at which location and time we should harvest the timber. In general, Rönnqvist (2003) describes that for harvesting, a base model can easily be expanded or changed to include several log-types, storage between periods, crew capacity, road decisions, time constraints and priorities to direct harvesting of areas to specific periods. Rönnqvist (2003) suggests that there should be robust decision support tools based on optimization models and methods to support the forest planning systems.

Basic optimization models for forest harvesting considers decisions about which areas to cut, which forest stands, in which per period, what flows to mills, which equipment or crews to use and assign or any attributes that can be added or applied to different models according to each specific context. Other models consider the bucking process as decision variables like

Troncoso et al. (2015) who proposes an integrated planning strategy and a generic MIP model to evaluate integrated strategies in the forest value chain by maximizing the Net Value of the forest including decisions of bucking pattern. The MIP model is implemented in the modelling language AMPL (2003), and CPLEX 11 is used to solve the model and has been applied in different scenarios in a Chilean case. Another approach as in Epstein et al. (2007) includes the basic operational activities related to harvesting, taking into account several characteristics such as quality, length, diameter and delivery. The bucking process tries to obtain as many high-value logs as possible in descending order. The market value will be higher if diameter logs are significantly higher. This approach discusses the total cutting units that we should harvest in each period, technologies, and transportation. In the case of SBW it is similar; if the infestation is higher, the market value of the product is lower, due to the low quality of logs. Therefore, these types of problems should be formulated as Mixed Integer Programming (MIP) models as Rönnqvist (2003) suggests, and when obtained in deterministic context, the results of deterministic models will likely be suboptimal or even infeasible if applied in real life because they do not consider uncertainty.

Studies and contributions like Beaudoin, LeBel et Frayret (2007) for detailed tactical model planning, integrate harvesting decisions with a given log distribution, and mills aggregate production planning by allowing wood exchanges between companies with a proposed MIP for a five-year horizon planning. It manages the wood flow to extract higher value from the logs processed in the mills, through Monte Carlo sampling and probability distribution function for generating scenarios. Also, a sensitivity analysis was applied to find the stochastic parameters. Another example of using MIP for harvesting plan is presented in Karlsson, Rönnqvist et Bergström (2004), who propose a model for an annual harvesting problem compared to the other levels of harvesting planning (see Figure 2.3), including decisions about harvest areas, allocation of crews and transportation. The model is implemented in AMPL language solved with the CPLEX solver by testing the usefulness and comparing the performance of the heuristic procedure.

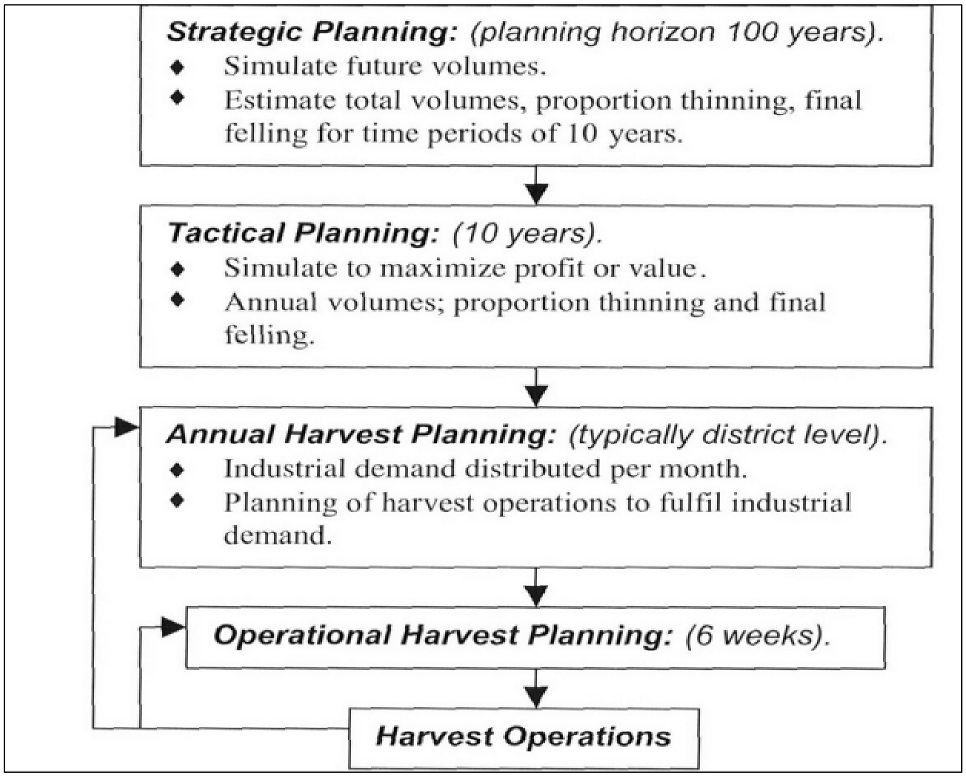

Figure 2.3 Different levels of harvest planning taken from Karlsson, Rönnqvist et Bergström (2004).

However, when it comes to solving the harvesting models, sometimes it can be complex depending on the model. For example, Vera et al. (2003) uses a Lagrangian relaxation approach for improving the solution process for machinery location problem between towers and skidders in forest harvesting in an MILP model by determining the total amount of timber volume, timber flow, the roads that are going to be built and the location of machinery. Andalaft et al. (2003) introduce a solution approach based on Lagrangian relaxation and a strengthening of the LP formulation of seventeen forests related by demand constraints at the firm level. Andalaft et al. (2003) solved the problem considering deterministic demand and price conditions for each period for log exports, sawmills and pulp plants, and the roads to build for access and storage of timber. The proposed model integrated planning aims to decrease the total cost of different steps of harvesting in the forest to the delivery of logs at the mills. They describe some uncertainties involved in the model.

Moreover, there are several approaches considering area restrictions and analyzing the state of spatial forest management adding cutting blocks such as Murray (2007) that develops a harvest-scheduling optimization model considering the adjacency between areas. On the other hand, Weintraub et Murray (2006) proposes an MIP for spatial restrictions in forest planning, modelled as combinatorial problems. Weintraub et Murray (2006) considered earlier models and compared for several cases, depending on the blocks or clusters that can be harvested according to the spatial requirements. Their aim is to analyze the state of spatial forest management models as well as highlight research challenges such as adding cutting blocks or other characteristics in the harvesting process. In contrast, Dems, Rousseau et Frayret (2015) tries to find the nearest best wood procurement plan for a planning horizon of one year as well as compare different scenarios by applying an MIP model, discussing the integration of a wood-procurement plan that respects the harvesting practices used in Eastern Canada. This is done by minimizing the nonlinear costs and maximizing the product value. Epstein et al. (1999) uses an LP model to address the problem of short term harvesting involving decisions about which stands to harvest, type of machinery, volume to cut, bucking patterns and delivery of products to destinations to satisfy demand in order to match supply of standing timber with demand, so as to minimize degradation and maximize the quality. The model solves the problem by using a branch and bound method in CPLEX.

In the case for long-term harvesting planning like Gunn et Rai (1987) studies a systematic dynamic model for determining optimal policies considering previous models with growth and regeneration of harvest units. Gunn et Rai (1987) adds more complexity and more characteristics will allow forest managers to obtain better results. The work proposed consists of a model framework that calculates the regeneration harvest policies by using an augmented decomposition Lagrangian approach in a strategic context of wood supply to an integrated industry.

There are many recent researches that illustrate how to model and solve the forest harvesting planning problem (e.g. Goycoolea et al. (2005), Caro et al. (2003), Kong, Rönnqvist et Frisk (2015), Kong et Rönnqvist (2014), Constantino, Martins et Borges (2008), Marques (2012), and Murray, Goycoolea et Weintraub (2004)). All of them consider distinctive characteristics that forest stands could have or other existing approaches with assumptions about the state of the forest stands for harvesting planning problems. All these models will vary depending on the requirements of forest managers that are based on to discuss the problem.

2.2 Literature Review on Forest Planning under Uncertainty

One of many uncertainties in the forest industry is natural disasters. Even though several approaches address harvesting planning, few of them have applied Stochastic Optimization (SO) to deal such uncertainty. Martell, Gunn et Weintraub (1998) explain that typical uncertainties occur in forestry planning like market uncertainties, natural variations in future growth yields, the effect of fires or pests, floods, earthquakes, hurricanes, storms and windthrows. Martell (2007) suggests that stochastic modelling and optimization will be adequate to manage the forest in the case of any occurrence of fire events. For forest management, insect infestation, like fire (e.g. Cohan et al. (1984), Broido, McConnen et O'Regan (1965), and Kuhlmann et al. (2015)) is but one of many factors that forest land managers must consider. Therefore, it will be necessary to develop integrated insect/forest management. It is important to highlight that in Stochastic Programming (SP) randomness is crucial. For our approach, randomness is the transition phase of SBW.

SP solves multiple scenarios at the same time instead of solving each scenario independently. Moreover, Savage, Martell et Wotton (2011) suggest that for reducing uncertainty and risk through forest management planning, some factors should be considered as a test for robustness in harvest scheduling models. Most of the disturbance events that approaches had been dealing with are uncertainty in characteristics of yield and windthrow, but other events such as fire and pests are more complex to model, therefore few have dealt with this issue. As has been seen, for forest harvesting problems, MIP is adequate as Veliz et al. (2015) suggest that harvesting decisions are naturally modelled with binary variables. In this existing approach, it describes the uncertainties involved in their SO model considering a tactical planning model developed for a Chilean forest firm. Lohmander (2007) suggests that for addressing economic forest management problems, we should consider uncertainty and use less deterministic assumptions for mathematical optimization. Rönnqvist et al. (2015) explains that normally in tactical planning there is integration between harvesting and transportation processes. One of the methodological challenges is to deal with uncertainty planning with catastrophic events such as climate, fire, storm, and pests. Although there is some literature that shows how to handle uncertainty like scenario planning, where many scenarios are generated and analyzed independently, not many use advanced optimization methods like SP to analyze scenarios together.

Most of the previous studies focused on planning to create new policies for harvesting and implementing actions before these uncertainties occur, but not for some. An example of this is demonstrated in the approach of Broman, Frisk et Rönnqvist (2006). They developed and designed a new supply chain operations and transportation system with a Decision Support System (DSS), StormOpt, after the storm Gudrun had already affected forests in the southern part of Sweden, with close to 70 million m^3 wind felled. It is formulated as a deterministic MIP; the difficulty of this approach is the planning after the uncertainty had already occurred. These actions aimed to harvest most of the damaged forest in a planning horizon. Compared to an infested forest, it is similar. MIP will be adequately useful for modelling and solving in the case of SBW outbreaks when it tends to consider that not all harvest areas are healthy for cutting process in each period and these events cannot be controlled (Broman, Frisk et Rönnqvist, 2006). Another type of disturbance such as fire is illustrated by Martell (2007), which is a natural component of many forest ecosystems, but forest fires can and often do expose significant threats to public safety, and overall forest resources. Martell (2007) suggests that OR has been important due to the impact that it has had on forest fire management. The definition of forest fire management is getting the right amount of fire to the right place at the right time at the right cost. One of the challenges of forest fire management is predicting fire occurrence, therefore, modelling these types of events is difficult as there is uncertainty.

Mosquera, Henig et Weintraub (2011) explains that previous studies have used deterministic models in forestry planning to address the major sources of uncertainty that exist in relevant factors such as prices, timber sales, the real productivity of harvest units, future plagues and fires and real extraction costs. However, this is difficult to implement in the forest industry due to the lack of reliable data. Therefore, in forest management, we see it as a controlled Markov process in which method and growth vary as discrete events due to economies of scale. We seek for solutions that maximize the expected value of the net revenues subject to satisfying constraints under all scenarios. Likewise, Fox, Ades et Bi (2001) describes several individual-tree models where stochastic components should be integrated with these so that there is more chance of being accurate in predictions incorporating random variables such as matrix formulations, transition probabilities in stochastic, stand-level growth models. They emphasized the importance of integrating stochasticity or random components for better benefits and improvements to the model. Other stochastic approaches like Zhou et Buongiorno (2011) consist in analyzing the effects of stochastic interest rates in forest management using Markov Decision Process, comparing the fixed and stochastic interest rate for many several system states. Their aim is to maximize the expected Net Present Value (NPV) over an infinite horizon with a fixed interest rate and a stochastic rate.

Most existing approaches dealing with forest planning under uncertainty are found in Acuna et al. (2010) for dealing with forest fire or applying methods for forest growth for harvesting and thinning discussed in Helmes et Stockbridge (2011). In addition, Eriksson (2006) describes how LP models are used in forest management under uncertainty. Likewise Alonso-Ayuso et al. (2011), Piazza et Pagnoncelli (2014), Norstrøm (1975), Bormann et Kiester (2004), and Kurokawa (2006) explain OR methodologies to address the forest planning under uncertainty.

2.3 Literature Review on Optimization Models including random parameters

Dupačová (2002) explains that when solving a decision problem under uncertainty, it is essential to take into account the nature of the real-life problem. Dupačová (2002) discusses different applications used in SP like financial portfolio analysis, planning and allocation of resources (including water), energy production and transmission, production planning and optimization of technological processes, logistic problems (including aircraft allocation and yield management), and telecommunications.

Several approaches have been applied to many cases using SP for planning problems with uncertainty, such as the production planning that refers to the quality of raw material and cutting patterns of the logs, considering random natural processes in yields in sawmill production planning (Kazemi Zanjani, Ait-Kadi et Nourelfath, 2013). This approach considers the sawing yield as the uncertain parameter with recourse action as inventory backorder. The first-stage decisions consist of production decisions and second-stage decisions are backorder when the demand is not fulfilled. Another example of modelling with SP in forestry can be seen in Shabani et al. (2014), which incorporates uncertainty in a model of forest biomass supply chain into a reformulated LP model with a one-year planning horizon. The uncertainty is the availability of biomass into monthly planning. After the reformulation, a Two-Stage SP model is formulated in which generated scenarios vary between ±20%.

There are many examples of modelling harvesting problems with SP such as Rinaldi et Jonsson (2013) that proposes a model of harvesting decisions of private forest owners. They considered timber price uncertainty under risk-aversion. The SP model analyzes the effect of the information on harvesting decisions. Another example can be seen in Meilby, Strange et Thorsen (2001) that proposed a maximization model of optimal spatial harvesting when forest stands are faced with the risk of windthrows, estimating the expected value of many stands under certain probability of future states. Another approach to the harvesting process is discussed in Lohmander (2007), who suggests several SP formulations for harvesting problems using a multi-period Stochastic Dynamic Programming in discrete time with continuous probability density functions of stochastic prices for optimizing the stand level in forest management.

In addition, Veliz et al. (2015) planned an integrated approach considering both harvesting and road construction decisions in the presence of uncertainty modelled as a multi-stage problem. The scenarios for testing their modelling include uncertainty in timber growth and yield. Also, Mosquera, Henig et Weintraub (2011) find the best plan for harvesting and road construction, given the timber availability and harvest cost, by designing insurance contracts using SP in forestry planning. Some harvest problems consider road building but in this research, it will be assumed that it does not suffer from changes and will still be constant during the planning horizon. Another example of the application of SP is illustrated in Yeh et al. (2015) who proposes an approach to a supply-allocation problem in a timberland system: harvester and manufacturer decision makers who have their own separate objectives to maximize their own profits. Yeh et al. (2015) use Two-Stage Stochastic Integer Programming considering the penalties, the shortfall, and the excess. The first-stage decisions involve strategic decisions around biorefinery investments, such as location and capacity and second-stage decisions involve bi-level timberlands.

Other overview approaches like Kazemi Zanjani, Aït-Kadi et Nourelfath (2009) and Kazemi Zanjani, Aït-Kadi et Nourelfath (2013) include uncertain parameters for production planning in sawmills. Ntaimo et al. (2013) use Two-Stage SP to aid fire planning, and Teeter, Somers et Sullivan (1993) proposes a stochastic dynamic programming to support economic analyses of harvesting planning. All these proposed methods integrate uncertain parameters in the forestry.

2.3.1 Theoretical framework of Two-Stage Stochastic Programming Formulation

When there is not full information or available data of some parameters in the model, these are considered as uncertain. Birge et Louveaux (2011) explain that Stochastic Linear Programs are linear programs in which some problem data may be regarded as uncertain, and these are random variables. Others, such as Dupačová (2002) explains that for modelling Two-Stage SP, the first-stage decisions consist of all decisions that have to be selected before further information is revealed, whereas second-stage decisions are allowed to adapt to this information. The stages do not necessarily refer to time periods; they correspond to steps in the decision process. It is important to highlight that for Stochastic Programming (SP) the randomness is very important. In this research project, the randomness is the transition phases as well as the initial inventory for the forest stands. When talking about SP it is necessary to consider that instead of solving for every scenario, this OR technique allows solving multiple scenarios that can likely happen in the future.

More theoretical formulations and applications of how to model SP are found in Ziemba et Gassmann (2013), Schultz (2003), and Kall et Mayer (2005).

2.3.1.1 General Formulation of Two-Stage Stochastic Program with Recourse

Normally, modelling in SP consists in choosing some initial decision that minimizes current costs plus the expected value of future recourse actions. The representation of Full Deterministic Equivalent Model (DEM) or the extensive form is the most common formulation. This form is used only for finite number of second-stage realizations and all linear functions (Birge et Louveaux, 2011).

When we need to make decisions without full information on some random events, they are identified as first-stage decisions. These decisions are usually represented by a vector x: $Z(x) = E_{\xi} Q\ (x, \xi)$. Then, we make second-stage or corrective decisions “y”: $Q\ (x, \xi) = \min\ \{\ q^T y |\ Wy = h - Tx, y \geq 0\}\ (W\ is\ fixed\ recourse)$. For more details about the formulation, see the approach of Birge et Louveaux (2011).The general formulation of Two-Stage is illustrated as follows:

$$\min c^T x + E_{\xi} Q\ (x, \xi) \quad \text{or} \quad \min c^T x + \mathrm{Z}(x) \tag{2.1}$$

$$\text{s.t.}\ \ Ax = b\ , \tag{2.2}$$

$$x \geq 0 \tag{2.3}$$

Where $\xi\ is\ the\ vector\ formed\ by\ the\ components\ q^T, h^T, and\ T, and\ E_{\xi}.$

In our project, the first-stage decision is the opening of the forest stand and once we know this information, the second-stage decisions are the volume of forest stands to be cut, the inventory level for the period and the allocation of the logs to the sawmills. The second-stage decisions are the corrective actions or the recourse, in this case, especially; the quantity of volume harvested as we are talking about salvaging trees from the SBW infestation. We can observe an example of the Stochastic Programing formulation in the “farmer problem”, in Birge et Louveaux (2011) that illustrates that such a model of stochastic decision program is known as the extensive form of the stochastic program. It explicitly describes the second-stage decision variables for all scenarios. This example stands for a finite number of realizations, but also, any problem can represent multiple stages of decisions and it provides a foundation for multistage methods (Birge et Louveaux, 2011).

Sometimes when we do not have reliable data, or when we do not have full information on the events, we consider them as uncertain parameters. Birge et Louveaux (2011) explains that Stochastic Linear Programs are linear programs in which some problem data may be considered uncertain and these are random variables. Therefore, an accurate probabilistic description of these variables is assumed to be available under the form of probability measures or even in this research the probability is also stochastic. Recourse programs are those in which some decisions or recourse actions can be taken after the uncertainty is disclosed. To be more precise, data uncertainty means that some of the problem data can be represented as random variables.

A Two-Stage Stochastic Programming is considered in the set of decisions is the divided into two groups:

- First-stage decisions: Several decisions should be taken before the experiment. The period when these decisions are taken is called the first-stage. This means that the information is unknown or uncertain.
- Second-stage decisions: Several decisions should be taken after the experiment. The corresponding period is called the second-stage. This means that once the information is known, the second-stage decisions are taken based on the information on the previous stage.

King et Wallace (2012) defines many recourse models which can minimize the impact of bad events using multiple resources that are available to the decision maker but that may not be available to investors. The importance of Stochastic Programming (SP) compared to deterministic models, is that, SP gives us better solution quality rather than others as we consider uncertainty theoretically, is because we are considering several scenarios that could possibly apply Linear Programming (LP) and therefore, there would be a value. As we are dealing with randomness for certain parameters we could have on the right-hand side or in the objective function.

2.3.2 Methods for solving Two-Stage Stochastic Programming

There are some existing methods for solving SP models, most of them are heuristic methods. The most common ones are SAA (Sample Approximation Average) for Mixed Integer Linear Programming Models with continuous probability distributions, Scenario-Based analysis, Progressive Hedging Algorithm (PHA) for multi-stage SP, and L-Shaped Method or Benders Decomposition approach. The L-Shaped method consists of building an outer linearization of the recourse cost function and a solution of the first-stage problem plus this linearization. This cutting plane technique is called the L-shaped method in Stochastic Programming (Birge et Louveaux, 2011).

An example of solving SP using these methods applied on supply chains is included in Santoso et al. (2005) that proposes a Two-Stage SP model and solution algorithm for solving supply chain network design problem. The overall goal is to minimize the cost of the first-stage strategic decisions, the expected production and distribution costs over the uncertain demand scenarios and second-stage decisions consists of processing and transporting products. For a small number of scenarios, it suits the existing SP approaches for supply chain design under uncertainty. This approach integrates and solves it with the Sample Average Approximation (SAA) scheme, with an accelerated Benders decomposition algorithm to solve supply chain design problems with continuous distributions for the uncertain parameters. The approach compares these methods regarding performance and acceleration of the solution. Another example of applying SAA, is described in Chouinard, D’Amours et Aït-Kadi (2008) that designed a network with reverse logistics for a wheelchairs allocation in Québec, as this wheelchairs allocation is facing high uncertainty levels for quality and quantity of the product recovery, redistribution and location. These networks (open and closed supply loop) are modelled as a Two-Stage SP model and solved using SAA method based on Monte-Carlo sampling with a finite but large number of scenarios. The first-stage decisions are the location of service and processing centres, warehouses to service centres for the collection and for second-stage decisions are the sites and the strategic proportions of product flows to direct toward processing alternatives.

Marufuzzaman, Eksioglu et Huang (2014) developed an L-shaped based algorithm to solve a model proposed for the design and management of biodiesel supply chains into Two-Stage location-transportation SP model to capture the trade-offs that exist between location and emission in this supply chain and the uncertain nature of sludge supply and technology development. Within the L-shaped algorithm, they incorporated a Lagrangian relaxation model to solve the master problem. And last but not least, scenario-based analysis is useful like Azadeh, Vafa Arani et Dashti (2014) that proposes a stochastic model for optimizing a biofuel supply chain network considering the uncertainty in demand and price by defining some probabilistic scenarios and including several capacitated biomass resources, bio refineries and demand points. Azadeh, Vafa Arani et Dashti (2014) suggests that including a robust programming approach in the work integrating a model solution, scenario solution and scenario analysis into one step, reduces the amount of the bias in the values of the objective function.

2.4 Literature Review on dealing with Spruce Budworm in Forest Management

The SBW is one of the most destructive insect defoliators in North America with outbreaks recurring every 30-35 years, resulting in tree mortality after 5-6 years of severe defoliation. The *Ministère des Forêts, de la Faune et des Parcs* (MFFP) (2014) suggests that two main factors can help to determine if the forest presents a case of SBW infestation due to the susceptibility of trees and its vulnerability depending on the characteristics of the tree (e.g. shape, size, colour, species, and age) as this living organism is a great threat to the forest due to the severity of damage caused by these elements and more importantly, a great quantity of trees can die causing loss of revenues (Ministère des Forêts, 2015). The more susceptible trees affected by SBW are (in descending order): White Spruce, Balsam Fir, and Black Spruce. On the other hand, the most vulnerable ones are Balsam Fir, then White Spruce and then Black

Spruce. We focus more on the vulnerability of the trees as this characteristic defines the probability that trees will die after several years of severe defoliation. Even though SBW affects these trees, they continue to degrade and die, but not progressively. For example, fire can destroy all trees, however insect infestation like SBW can only affect certain species like Balsam Fir, White Spruce, Red Spruce, Black Spruce, and Norwegian Spruce.

Focusing particularly on dealing with Spruce Budworm Infestation (SBW), research methods like Chinneck et Moll (1995) propose a Linear Programming (LP) model for addressing a processing network formulation of the forest management problems, precisely regarding decisions of location and time to harvest using graphical tools for formulating forest management linear programs using what-if scenarios. Chinneck et Moll (1995) modelled a process flow model on a timber supply area to see the susceptibility of trees, without controlling the infestation. Chinneck et Moll (1995) states that pest infestation models are like fire models where a processing node is used to be a fixed fraction of the area in each classification which becomes infested. These fractions can vary depending the species and age class. The model keeps track of the infested and non-infested hectares separately. Other existing approaches like Levy, Hipel et Kilgour (2000) propose a multicriteria methodology integrating uncertainty by identifying different alternatives that are robust to environmental uncertainty using sustainable development indicators such as forest volume, spray area, and harvest area to take complex decisions using forest management decision policies on SBW populations in New Brunswick.

For instance, Shoemaker (1981) discusses the methods for addressing the pest management models suggesting that Stochastic Optimization (SO) is a good approach for dealing with pest problems as well as dynamic programming. However, several other optimization methods have also proven useful for random environments as they provide previous information also. The most exhaustive systems analysis of forest pest management has focused on the SBW, a pest which in recent years has killed hundreds of thousands of hectares of coniferous trees in eastern Canada and United States. Shoemaker (1981) does not consider the age for the planning horizon of the model (over a hundred years) analyzing their economic value when harvested because of SBW damage.

Other researches like Hennigar et al. (2007), optimize the harvest planning under alternative foliage-protection scenarios to reduce volume losses to SBW by understanding relationships between SBW outbreaks, management scenarios, and timber supply to predict future forest dynamics in eastern Canada. Hennigar et al. (2007) use a DSS, which applies growth loss and mortality versus defoliation relationships to host species. Their aims were to use re-optimized harvest scheduling, salvage, and spatially optimized insecticide applications to minimize effects of SBW on projected timber supply and to project effects of 195 scenarios of SBW outbreak severity and insecticide application strategies on softwood harvest levels. Last but not least, Benjamin et al. (2013) addresses the problem of non-existent consensus among foresters and the logging industry about the thinning of stands. Benjamin et al. (2013) proposes two different systems: two whole tree (WT) and two cut-to length (CTL). Both methods are compared in terms of residual stand damage, product use, and unit cost of production for early commercial thinning treatments in Maine. For our research problem, commercial thinning will play an influential role as it affects the transition matrix of to what degree many stands can recover from infestation, hence this characteristic might be included as part of the harvesting costs.

In contrast, some existing approaches modelled and studied the behaviour of the dynamic population of SBW to include as a parameter in the optimization models which is essential for discussing this type of problem. For example, Gray, Régnière et Boulet (2000) defines defoliation as taking the leaves or branches off a tree or bush. A tree can be defoliated naturally due to certain external factors. The less resistant species like Balsam Fir dies first (this one is more vulnerable than spruce, as its foliage is less abundant and because the insect development better synchronizes with the growth of new shoots). If defoliation does not occur, the thinning process takes place, but over a much longer period compared to an insect plague. During an outbreak, the weaker trees usually die after three or four years of heavy defoliation (see Figure 2.4). The damaged trees continue to die even when SBW population returns to its endemic level. The approach of Gray, Régnière et Boulet (2000) consisted in studying previous patterns based on population dynamics of the SBW to forecast the course of the next SBW outbreak, making several assumptions that it will be repeated for each period. Moreover, Gray, Régnière et Boulet (2000) analyzes other conditions that have affected the SBW historical data of their population, such as geographical location using regression methods for predicting the next SBW outbreak, which is helpful for harvest-scheduling problems, in this case to obtain the probabilities of transition.

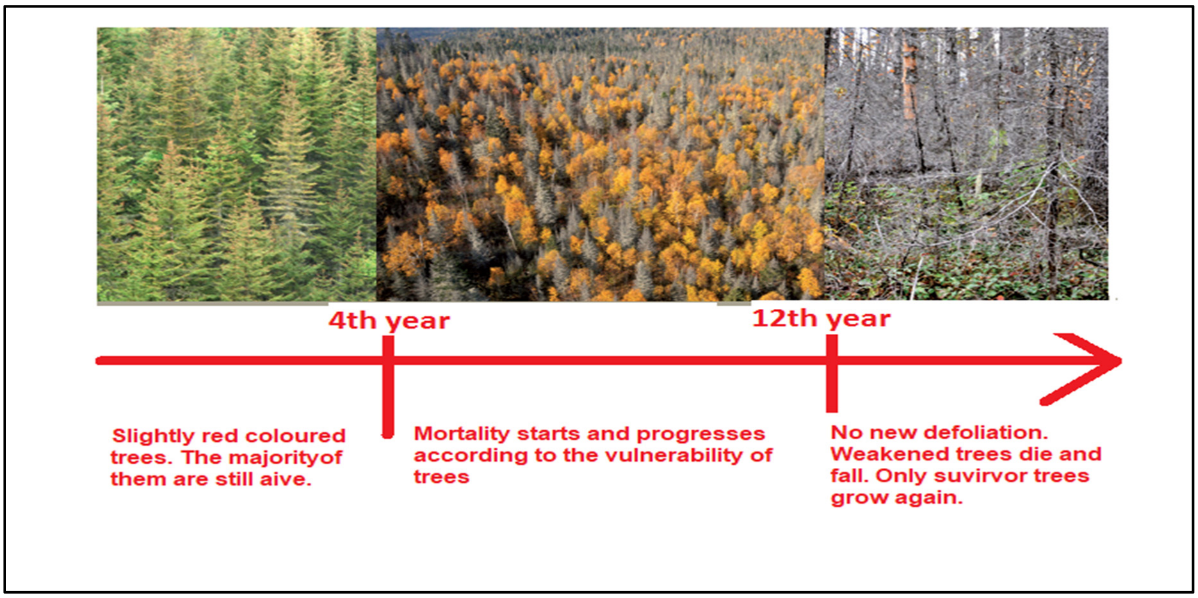

Figure 2.4 Progressive defoliation of forest stands reproduced and adapted with the permission of Ministère des Forêts (2014).

Other current approaches design and develop Spruce Budworm Decision Support Systems (SBW-DSS) like MacLean et al. (2000b). This approach assists in forest resource management and defoliation when outbreaks of SBW results in large uncertainty in the future forest structure and productivity. The SBW-DSS of MacLean et al. (2000b) models a marginal timber supply benefit (m^3/ha), and the forest structure consequences of alternative management actions by facilitating the incorporation of effects of insect damage into forest management planning. It allows evaluation of costs, benefits, and consequences of management, optimizes pesticide use, and improves visualization of the consequences of pest outbreaks and management strategies on forest performance indicators. When developing the tool, the vision of MacLean et al. (2000b) was to incorporate the impact of the insect into growth and yield forecasting, timber supply analysis, sustainable harvest calculation, and harvest scheduling.

Another approach for predicting and modelling SBW population is explained in Bergeron et al. (1995). This approach is related to predicting the SBW outbreak based on earlier historical data using experimental design. This approach studies the sites belonging to a complex natural forest mosaic originally from different fires in northwestern Québec where multiple regression analysis assesses the respective effects of stand structure, species composition, site characteristics, and the forest composition surrounding the stand on observed stand mortality with a suite of DSS tools, such as the Protection Planning System (PROPS). The tool has been adopted because the uncertainty associated with predicting the timing in real time, the real value and severity of SBW outbreaks can only be predicted by simulating probable scenarios (e.g. alternative disturbance, management regimes, future forest growing stock, sustainable harvest levels, and wildlife habitat) into the best and worst and their effects. Compared to MacLean et al. (2000a), Bergeron et al. (1995) applies the same DSS for inventory and monitoring data to predict SBW outbreak effects on forest structure and productivity, forecast forest growing stock and sustainable harvest levels, optimize protection programs, and use silviculture and harvest scheduling to restructure forests to reduce future damage. SBW outbreaks stand for the most important natural disturbance in the boreal Balsam Fir forest of Canada, killing trees over wide areas and thus generating enormous amounts of dead wood.

A common response to natural disturbances is salvage logging, which is now widely used throughout the world to recover some of the economic value that would otherwise be lost. Equivalent to Norvez, Hébert et Bélanger (2013) describes stand structure and used beetles as biodiversity indicators to compare the ecological value of salvaged stands, managed afterwards with three different silvicultural treatments, twenty years after the last SBW outbreak. The approach focuses on the boreal Balsam Fir forest of Québec, Canada. Balsam Fir, is the dominant tree species of this ecosystem, along with, White Spruce, Black Spruce, and White Birch. The methodology used in this approach by Norvez, Hébert et Bélanger (2013) uses experimental design for the approach by statistical analysis of ANOVA. Here, it compares the effects of salvage logging and silvicultural treatments on forest structure, on beetle communities, and the increasing number of human interventions in silvicultural treatments and beetle communities.

More approaches or detailed information about SBW, whether they apply Operations Research or not to understand this insect, are mentioned in Payette et al. (1998), Robert, Kneeshaw et Sturtevant (2012), Bouchard et Auger (2014), Chang et al. (2012), Williams et Liebhold (2000), or combining two natural disturbances that affect the forest structures like Kneeshaw et al. (2011), James et al. (2011), and Gray (2013).

In this Chapter, we have discussed some of existing approaches, illustrated and exemplified earlier methods that we can apply to solve similar problems for harvesting planning with and without uncertainty. In the next Chapter, we will describe the method to deal with the research problem and propose a new mathematical formulation to deal with uncertainty due to the SBW outbreak.

CHAPTER 3

RESEARCH METHOD

There are several methods for modelling and solving problems dealing with uncertainty in some parameters (e.g. Scenario-based analysis, Sensitivity analysis, Markov Chains, Stochastic Optimization and Robust optimization). However, for this research methodology approach, with previous literature review, Two-Stage Stochastic Programming will be the most suitable to address the problem of forest harvesting process due to the uncertainty of forest infestation and the unavailable information for the decision-making process, as few forest managers have applied Stochastic Optimization (SO) in forestry.

The methodology to address this project specifically, will be the following process (see Figure 3.1). First, the harvest planning problem is described, and any necessary assumptions or simplifications will be made within the definition of the decision variables, the objective function, and constraints. Then, when all the necessary characteristics of the problem are gathered together, the description of the problem will be proposed as a mathematical deterministic LP model. Once we have the deterministic version, considering the uncertainty in the harvesting process of forest stands, a Two-Stage SP with recourse will be used to formulate for the same problem under different scenarios. Later, solvers such as CPLEX compiled in AMPL language will be used to solve the problem for the deterministic LP model. Moreover, a set of independent scenarios are created around the random parameter to compare the results; the Two-Stage SP can also be solved as a Deterministic Equivalent Model (DEM) mode or extensive form. Thus, these scenarios will be run according to the desired planning horizon. Eventually, input data will be collected to solve the problem (i.e. information about forest stands, infestation severity, costs, area database and spatial maps). The data will be collected in collaboration with our two partners: FPInnovations and *Ministère des Forêts, Faune et Parcs du Québec*. When input data is implemented and processed through the optimization model, solution and evaluation will be shown as an output of the system. The different models will be analyzed, compared and discussed regarding their solution quality.

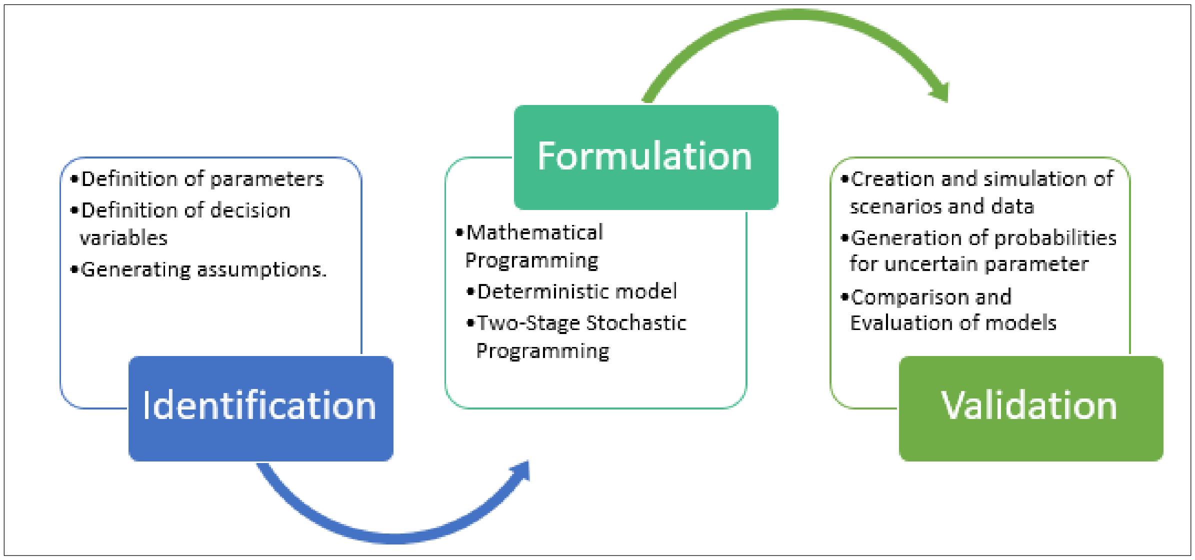

Figure 3.1 Methodology for addressing the process of harvesting of the forest stands.

In SP, the uncertainty can be found on the right-hand side of the constraints or in the objective function. It is well known that some parameters such as market value price, feedstock yield, logistics costs, crop, yield, and demand are considered as stochastic; however, for this research problem, these are consdered to be known; meaning that the process is considered as pull strategy (the harvesting process is driven by the demand of different mills).

3.1 Mathematical Formulation: General Assumptions

As mentioned before, all parameters are known, as well as the market value based on the classification of the quality of the trees according to the infestation phase. The propagation of SBW seems like the fire disturbance in which it slowly starts destroying the forest, and if nothing can be recovered from one phase to the other, SBW will continuously evolve until nothing remains. This means that once the tree is dead, the raw material cannot be recovered. However, if these trees are cut before the event occurs, then the infestation will not spread, avoiding outbreaks. Also, it is assumed for this research that the characteristics of the forest stand will not affect the transition phases of the SBW since the age, colour, diameter, and size is assumed to be same during the planning horizon. The same applies to road building for transportation, it will remain constant and it will not suffer changes over the same planning horizon. We assume to know the demand as well as the forest supply with certainty: Annual Allowable Cut (AAC). The AAC represents the total volume per m^3 that forest managers can cut per year; therefore, this parameter is not considered random for this research project. Moreover, this amount of AAC is proposed as a Forest Management Planning by Ministère des Forêts (2012).

3.2 Deterministic Mathematical Linear Programming Model for Forest Harvest Planning

According to the characteristics of the problem, here, we consider a set of harvest areas as forest stands I, a set of industries J (i.e. sawmills, panelmills, heating plants and papermills), a set of species tree per forest stand N which hosts the SBW (i.e. Black Spruce, White Spruce, Red Spruce, and Balsam Fir), a set of infestation phases of the SBW: Q, and the planning horizon of T periods. First, a deterministic model must be formulated before the Two-Stage stochastic model.

Therefore, the deterministic Linear Programming proposed model for formulating the problem has the following notations:

3.2.1 Sets and Indexes

$\boldsymbol{i} \in \boldsymbol{I}$: forest stands

$\boldsymbol{j} \in \boldsymbol{J}$: industry

$\boldsymbol{n} \in \boldsymbol{N}$: type species tree by forest stands

$\boldsymbol{q} \in \boldsymbol{Q}$: infestation phase of SBW life cycle

$\boldsymbol{q'} \in \boldsymbol{Q}$: infestation phase of SBW life cycle

$\boldsymbol{t} \in \boldsymbol{T}$: period

3.2.2 Parameters of the Mathematical Model

$\boldsymbol{f_{it}}$: cost if forest stand i in period t is open to harvest in CAD

$\boldsymbol{e_{int}}$: cost of forest stand i, species tree n, in period t is harvested in $\$/\mathrm{m}^3$

$\boldsymbol{a_{ijnt}}$: wood allocation cost of forest stand i to industry j, species tree n in period t in $\frac{\$}{\mathrm{m}^3}$

$\boldsymbol{d_{jnt}}$: demand of industry j, species tree n in period t in m^3

$\boldsymbol{m_{nqt}}$: market price value of species n, phase q in period t in $\$/\mathrm{m}^3$

$\boldsymbol{l_{inqt-1}}$: initial inventory of forest stand i, species tree n, phase q in period $t = 0$

$\boldsymbol{k_{nqq'}}$: percentage of forest stand volume per species n initial and final phase from q to q'

3.2.3 Decision variables of the Mathematical Model

$\boldsymbol{x_{inqt}}$: volume harvested in forest stand i, phase q species n in period t in m^3

$\boldsymbol{z_{int}}$: volume harvested in forest stand i, species n in period t in m^3

$\boldsymbol{y_{it}}: \begin{cases} 1, & \text{if forest stand } i \text{ is open in period } t \\ 0, & \text{otherwise} \end{cases}$

$\boldsymbol{l_{inqt}}$: inventory level of forest stand i, species n and SBW phase q in period t in m^3

$\boldsymbol{w_{ijnt}}$: quantity of logs allocated from forest stand i to industry j, species n in period t in m^3

3.2.4 Objective Function of the MILP

We want to maximize the total profit or value obtained from the harvesting process. The total profit is denominated by the difference between the Net Value or market value less the total costs implicated for the harvesting processes.

$$Maximize\, Z = \sum_{i}^{I}\sum_{j}^{J}\sum_{t=1}^{T}\sum_{q}^{Q}\sum_{n}^{N}(m_{inqt}x_{inqt} - a_{ijnt}w_{ijnt} - f_{it}y_{it} - e_{it}z_{int}) \tag{3.1}$$

3.2.5 Constraints

- Balance Flow Inventory level

$$l_{inq'1} = l_{inq'0} - x_{inq'1} - \sum_{\substack{q \\ q \neq q'}}^{Q} (l_{inq'0} - x_{inq'1})\left(k_{nq'q}\right) + \sum_{\substack{q \\ q \neq q'}}^{Q} (l_{inq0} - x_{inq1})\left(k_{nqq'}\right) \forall i \in I, \forall n \in N, \forall q' \in Q \quad (3.2)$$

$$l_{inq't} = l_{inq't-1} - x_{inq't} - \sum_{\substack{q \\ q \neq q'}}^{Q} (l_{inq't-1} - x_{inq't})\left(k_{nqq'q}\right) + \sum_{\substack{q \\ q \neq q'}}^{Q} (l_{inqt-1} - x_{inqt})\left(k_{nqq'}\right) \forall i \in I, \forall t \in T, \forall n \in N, \quad (3.3)$$

$\forall q' \in Q$

- Capacity of forest stands harvested

$$\sum_{t}^{T} y_{it} \leq 1 \quad \forall i \in I \quad (3.4)$$

$$\sum_{q}^{Q} \sum_{n}^{N} x_{inqt} \leq M y_{it} \quad \forall i \in I, \forall t \in T \quad (3.5)$$

Where M is the value of the total volume available in each area of the forest.

$$\sum_{n}^{N} z_{int} \leq M y_{it} \quad \forall i \in I, \forall t \in T \quad (3.6)$$

Where M is the value of the total volume available in each area of the forest.

- Volume of forest stands harvested

$$\sum_{q}^{Q} x_{inqt} = z_{int} \quad \forall i \in I, \forall n \in N, \forall t \in T \quad (3.7)$$

- Wood allocation constraints

$$\sum_{\boldsymbol{i}}^{\boldsymbol{I}} \boldsymbol{w_{ijnt}} = \boldsymbol{d_{jnt}} \quad \forall \boldsymbol{n} \in \boldsymbol{N}, \ \forall \boldsymbol{j} \in \boldsymbol{J}, \ \forall \boldsymbol{t} \in \boldsymbol{T} \quad (3.8)$$

$$\sum_{\boldsymbol{j}}^{\boldsymbol{J}} \boldsymbol{w_{ijnt}} = \sum_{\mathbf{q}}^{\mathbf{Q}} \boldsymbol{x_{inqt}} \quad \forall \boldsymbol{t} \in \boldsymbol{T}, \forall \boldsymbol{n} \in \boldsymbol{N}, \ \forall \boldsymbol{i} \in \boldsymbol{I} \quad (3.9)$$

- Non-negativity constraints

$$y_{it} \in \{0,1\}, x_{inqt} \geq 0, l_{inqt} \geq 0, w_{ijt} \geq 0 \quad \forall t \in T, \forall i \in I, \forall n \in N, \forall q \in \mathrm{Q}, \forall j \in J \quad (3.10)$$

3.3 Description of the Deterministic Optimization Model

It is important to mention that when formulating the deterministic model, all the parameters are known, and for Two-Stage stochastic, one or more parameters are uncertain. The decision variables that are considered for the problem: the volume harvested in m^3 (as it is required to know exactly the quantity of forest stands harvested), the inventory level and volume of logs allocated to the industry according to the demand. Also, another important decision to make is where or which harvest area should be available for harvesting (consider this one as a binary decision as there are only two possibilities).

The main objective function (3.1) is to maximize the Net Value obtained from the sale of logs which have a market price according to quality (this quality will be referred to as the phase or instar in which each tree has a defoliation degree) less the costs of opening the area and harvesting or transformation as well as transportation to the terminal and wood allocation, considered as transportation costs.

The constraints (3.2) and (3.3), referred to as the inventory constraint or balance-flow constraint (forest stands available to harvest) consist of tracking the transition of the SBW evolution. Both consider that the final inventory with the final infestation phase will be equal to the sum of the initial inventory (with the previous final phase of infestation) less what is cut or harvested (with its current final phase). It is important to state the fact that the parameter of transition is a probability that consists in the chances that a certain amount of forest stands of species *n* will jump to another possible phase or remain in the same state. As this is a balance-flow inventory constraint, not only the final inventory level considers the initial inventory less the volume harvested in their last phase of infestation, but also the initial phase infestation for both the original inventory less the volume harvested. This is due to the fact that what it is trying to accomplish is the tracing of the infestation phase.
Constraint (3.4) refers to a total number of harvest areas, which should be a minimum of at least one area collected from each period. The number of harvest areas is also related to the capacity of volume harvested (3.5) and (3.6), which should not exceed the availability of the

area harvested. Because the industries (e.g. sawmills, panelmills, and heating plants) do not consider which state of infestation phase of the SBW the product (log) presents, the decision variable x_{inqt} will act as an intermediate variable, another decision variable z_{int} is defined equally to the harvested area (3.7), but without considering the infestation phase of the SBW, which is why it strictly equals these two variables. For constraint (3.8), it consists of supplying or allocating the logs (once the trees are transformed) in proportion to the demand (mills). Also, the volume harvested (3.9) should be cut only according to what is desired to allocate. Finally, constraint (3.10) states that all decisions variables should be non-negative.

3.4 Two-Stage Stochastic Linear Programming for Forest Harvest Planning

As explained before in the literature review of the theoretical framework for modelling SP models in Chapter 2, we define the first-stage decisions and second-stage decisions. For this problem, the first-stage decisions will be the opening of the harvest area or forest stands before realizing which trees should be harvested. The second-stage decisions describe the quantity or volume that should be cut as well as the inventory level of the logs and the allocation to each mill. As before, distributing them through the supply chain, it is necessary to know the information about which areas or forest stands should be opened and then the harvest operations or activities will be done once this information is known.

We consider the previous notation of the deterministic MILP model, but for the formulation of the Two-Stage Stochastic Linear Program with recourse we add new sets of scenarios S for each possible realization of scenarios or probability of occurrence for those scenarios.

3.4.1 Sets and Indexes

$\boldsymbol{i} \in \boldsymbol{I}$: forest stands

$\boldsymbol{j} \in \boldsymbol{J}$: industry

$\boldsymbol{n} \in \boldsymbol{N}$: type species tree by forest stands

$\boldsymbol{q} \in \boldsymbol{Q}$: infestation phase of SBW life cycle

$\boldsymbol{q'} \in \boldsymbol{Q}$: infestation phase of SBW life cycle

$\boldsymbol{t} \in \boldsymbol{T}$: period

$\boldsymbol{s} \in \boldsymbol{S}$: scenario

$\boldsymbol{\xi} \epsilon \boldsymbol{S}$: realization of random transition phase

3.4.2 Parameters of the Mathematical Model

$\boldsymbol{f_{it}}$: cost if forest stand i if in period t is open in CAD

$\boldsymbol{p^s}$: probability of occurrence for scenario s

$\boldsymbol{e_{int}}$: cost of forest stand i, species tree n, in period t is harvested in $\$/\mathrm{m}^3$

$\boldsymbol{a_{ijnt}}$: wood allocation cost of forest stand i to industry j, species tree n in period t in $\$/\mathrm{m}^3$

$\boldsymbol{d_{jnt}}$: demand of industry j, species tree n in period t in m^3

$\boldsymbol{m_{nqt}}$: market price value of species n, phase q in period t in $\frac{\$}{\mathrm{m}^3}$

$\boldsymbol{l_{inqt-1}}$: initial inventory of forest stand i, species tree n, phase q in period $t = 0$

$\boldsymbol{k^s_{nqq'}}$: percentage of forest stand volume per species n initial and final phase from q to q' under scenario s

3.4.3 Decision variables of the Mathematical Model

$\boldsymbol{x^s_{inqt}}$: volume harvested in forest stand i, phase q species n in period t in scenario s in m^3

$\boldsymbol{z^s_{int}}$: volume harvested in forest stand i, species n in period t in scenario s in m^3

$\boldsymbol{y_{it}}$: $\begin{cases} 1, & \text{if forest stand } i \text{ is open in period } t \\ 0, & \text{otherwise} \end{cases}$

$\boldsymbol{l^s_{inqt}}$: inventory level of forest stand i, species n and SBW phase q in period t in scenario s in m^3

$\boldsymbol{w^s_{ijnt}}$: quantity of logs allocated from forest stand i to industry j, species n in period t in scenario s in m^3

MIXED INTEGER LINEAR PROGRAMMING FORMULATION

3.4.4 First-Stage model

- Objective function

$$Maximize\, Z = -\sum_{i}^{I}\sum_{t=1}^{J} f_{it} y_{it} + E_{\xi}\left[Q\left(y_{it},\xi\right)\right] \tag{3.11}$$

- Number of forest stands harvested constraints

$$\sum_{t}^{T} y_{it} \leq 1 \quad \forall i \in I \tag{3.12}$$

- Non-negativity constraints

$$y_{it} \in \{0,1\} \quad \forall t \in T, \forall i \in I \tag{3.13}$$

- Where $Q(y_{it},\xi)$ is the optimal value equivalent to:

$$Q\left(y_{it},\xi\right) = \sum_{i}^{I}\sum_{j}^{J}\sum_{t=1}^{T}\sum_{q}^{Q}\sum_{n}^{N}(m_{inqt}x_{inqt} - a_{ijnt}w_{ijnt} - e_{it}z_{int}) \tag{3.14}$$

- Inventory level constraints

$$l_{inq'1} = l_{inq'0} - x_{inq'1} - \sum_{\substack{q \\ q \neq q'}}^{Q}(l_{inq'0} - x_{inq'1})\left(k_{nq'q}\left(\xi\right)\right) + \sum_{\substack{q \\ q \neq q'}}^{Q}(l_{inq0} - x_{inq1})\left(k_{nqq'}\left(\xi\right)\right) \tag{3.15}$$

$$\forall i \in I, \forall n \in N, \forall t \in T\ , \forall \xi \in S, \forall q' \in Q$$

$$l_{inq't} = l_{inq't-1} - x_{inq't} - \sum_{\substack{q \\ q \neq q'}}^{Q}(l_{inq't-1} - x_{inq't})\left(k_{nq'q}\left(\xi\right)\right) + \sum_{\substack{q \\ q \neq q'}}^{Q}(l_{inqt-1} - x_{inqt})\left(k_{nqq'}\left(\xi\right)\right) \tag{3.16}$$

$$\forall i \in I, \forall t \in T, \forall n \in N\ , \forall \xi \in S, \forall q' \in Q$$

- Number of forest stands harvested constraints

$$\sum_{q}^{Q}\sum_{n}^{N}x_{inqt} \le My_{it} \quad \forall i \in I, \forall t \in T \tag{3.17}$$

Where M is the value of the total volume available in each area of the forest.

$$\sum_{n}^{N}z_{int} \le My_{it} \quad \forall i \in I, \forall t \in T \tag{3.18}$$

Where M is the value of the total volume available in each area of the forest.

- Volume of forest stands harvested constraints

$$\sum_{q}^{Q}x_{inqt} = z_{int} \quad \forall i \in I, \forall n \in N, \forall t \in T \tag{3.19}$$

- Wood allocation constraints

$$\sum_{i}^{I}w_{ijnt} = d_{jnt} \quad \forall n \in N, \forall j \in J, \forall t \in T \tag{3.20}$$

$$\sum_{j}^{J}w_{ijnt} = \sum_{q}^{Q}x_{inqt} \quad \forall t \in T, \forall n \in N, \forall i \in I \tag{3.21}$$

- Non-negativity constraints

$$y_{it} \in \{0,1\}, x_{inqt} \ge 0, l_{inqt} \ge 0, w_{ijt} \ge 0, z_{int} \ge 0 \quad \forall t \in T, \forall i \in I, \forall n \in N, \forall q \in Q, \forall j \in J \tag{3.22}$$

Notice that ξ is a random vector corresponding to different scenarios for the uncertain transition phases, and the optimal value $Q(y_{it}, \xi)$ of the second-stage problem, from equations (3.14) to (3.22) is the function of the first-stage decision variable y_{it} and a realization of the uncertain parameter $k_{nqq'}(\xi)$.

3.4.5 Two-Stage model (DEM: Deterministic Equivalent Model)

From the previous Section of this Chapter, we reformulate the deterministic model into DEM form of the Stochastic Model as the following:

- Objective function

$$Maximize\, Z = \sum_{i}^{I}\sum_{j}^{J}\sum_{t=1}^{T}\sum_{q}^{Q}\sum_{n}^{N}\sum_{s}^{S} p^{s}\,(m_{inqt}x_{inqt}^{s} - a_{ijnt}w_{ijnt}^{s} - e_{it}z_{int}^{s}) - \sum_{i}^{I}\sum_{t=1}^{J} f_{it}y_{it} \tag{3.23}$$

- Inventory level constraints

$$l_{inq'1}^{s} = l_{inq'0}^{s} - x_{inq'1}^{s} - \sum_{\substack{q \\ q\neq q'}}^{Q}(l_{inq'0}^{s} - x_{inq'1}^{s})\left(k_{nq'q}\left(\xi\right)\right) + \sum_{\substack{q \\ q\neq q'}}^{Q}(l_{inq0}^{s} - x_{inq1}^{s})\left(k_{nqq'}\left(\xi\right)\right) \tag{3.24}$$

$\forall i \in I, \forall n \in N, \forall q' \in Q, \forall s \in S, \forall \xi \in S$

$$l_{inq't}^{s} = l_{inq't-1}^{s} - x_{inq't}^{s} - \sum_{\substack{q \\ q\neq q'}}^{Q}(l_{inq't-1}^{s} - x_{inq't}^{s})\left(k_{nq'q}\left(\xi\right)\right) + \sum_{\substack{q \\ q\neq q'}}^{Q}(l_{inqt-1}^{s} - x_{inqt}^{s})\left(k_{nqq'}\left(\xi\right)\right) \tag{3.25}$$

$\forall i \in I, \forall t \in T, \forall n \in N, \forall q' \in Q, \forall s \in S, \forall \xi \in S$

- Number of forest stands harvested constraints

$$\sum_{q}^{Q}\sum_{n}^{N} x_{inqt}^{s} \leq My_{it} \quad \forall i \in I, \forall t \in T, \forall s \in S \tag{3.26}$$

Where M is the value of the total volume available in each area of the forest.

$$\sum_{n}^{N} z_{int}^{s} \leq My_{it} \quad \forall i \in I, \forall t \in T, \forall s \in S \tag{3.27}$$

Where M is the value of the total volume available in each area of the forest.

- Volume of forest stands harvested constraints

$$\sum_{q}^{Q} x_{inqt}^{s} = z_{int}^{s} \qquad \forall i \in I, \forall n \in N, \forall t \in T, \forall s \in S \tag{3.28}$$

- Wood allocation constraints

$$\sum_{i}^{I} w_{ijnt}^{s} = d_{jnt} \quad \forall n \in N, \forall j \in J\,, \forall t \in T, \forall s \in S \tag{3.29}$$

$$\sum_{j}^{J} w_{ijnt}^{s} = \sum_{q}^{Q} x_{inqt}^{s} \quad \forall t \in T, \forall n \in N, \forall i \in I, \forall s \in S \tag{3.30}$$

- Non-negativity constraints

$$y_{it} \in \{0,1\}, x^{s}_{inqt} \geq 0, l^{s}_{inqt} \geq 0, w^{s}_{ijt} \geq 0, z^{s}_{int} \geq 0 \quad (3.31)$$
$$\forall t \in T, \forall i \in I, \forall n \in N, \forall q \in \mathrm{Q}, \forall j \in J, \forall s \in S$$

3.5 Description of the Two-Stage Stochastic Model

The description of the model is the same as this Chapter, Section 3.3, for deterministic model with the exception of the second-stage decision variables that are under the scenarios. The main objective function (3.23) is to maximize the Net Value obtained from the sale of logs which have a market price according to quality (this quality will be referred to as the phase or instar in which each tree has a defoliation degree) less the costs of opening the area and harvesting or transformation as well as transportation to the terminal and wood allocation, considered as transportation costs. This objective function is the equal to the probabilities of realization of the scenarios times the profit obtained for every scenario. We assume equal probabilities of realization of scenarios in order to be neutral about the risk of occurrence of the possible infestation.

The constraints (3.24) and (3.25), referred to as the inventory constraint or balance-flow constraint (forest stands available to harvest) consist of tracking the transition of the SBW evolution. Both consider that the final inventory with the final infestation phase will be equal to the sum of the initial inventory (with the previous final phase of infestation) less what is cut or harvested (with its current final phase) under the different scenarios. It is important to state the fact that the parameter of transition is a probability that consists in the chances that a certain amount of forest stands of species *n* will jump to another possible phase or remain in the same state. As this is a balance-flow inventory constraint, not only the final inventory level considers the initial inventory less the volume harvested in their last phase of infestation, but also the initial phase infestation for both the original inventory less the volume harvested. This is due to the fact that what it is trying to accomplish is the tracing of the infestation phase.

Constraint (3.26) refers to a total number of harvest areas, which should be a minimum of at least one area collected from each period in each scenario. The number of harvest areas is also related to the capacity of volume harvested (3.27), which should not exceed the availability of the area harvested for each scenario. Because the industries (e.g. sawmills, panelmills, and heating plants) do not consider which state of infestation phase of the SBW the product (log) presents, the decision variable x_{inqt}^{s} will act as an intermediate variable, another decision variable z_{int}^{s} is defined equally to the harvested area (3.28), but without considering the infestation phase of the SBW, which is why it strictly equals these two variables. For constraint (3.29), it consists of supplying or allocating the logs (once the trees are transformed) according to the demand (mills). Also, the volume harvested (3.30) should be cut only according to what is required by the mills. Finally, constraint (3.31) states that all decisions variables should be non-negative.

3.6 Transition Matrix: Generating Scenarios

To solve the Stochastic Programming, it is necessary to create independent scenarios over the planning scenarios and solve these in Deterministic scenario by scenario and SP form. To generate these scenarios, as we mentioned, we take the transition matrix or the uncertain parameter. We will categorize the transition matrix and denominate as the best and worst scenario depending on the probability of the transition matrix from one phase of infestation to another phase.

Kall et Mayer (2005) describes that in SP, scenario generation means generating a discrete approximation to the probability distribution of ξ, in the form of a scenario tree (see Figure 3.2). This means that scenarios are developed as independent sub-problems, they are considered as part of a heuristic procedure of the main problem. These scenarios are the chances of the possible states of the transition matrix categorized (below and above the average of the transition matrix) depending on the mortality the forest stands will have as: no infestation, low infestation, medium infestation, high infestation, and severe infestation depending on the probability the volume of the forest stands should change from one phase to another.

According to the Ministère des Forêts (2015), they classify the mortality by percentage of mortality evaluated 1% to 10% low, 11% to 50% moderate and 90% to 99% high infestation which the last one means less volume for harvesting per unit surface in presence of SBW and no matter what percentage of mortality the forest stands present a high impact over the harvest productivity and the costs.

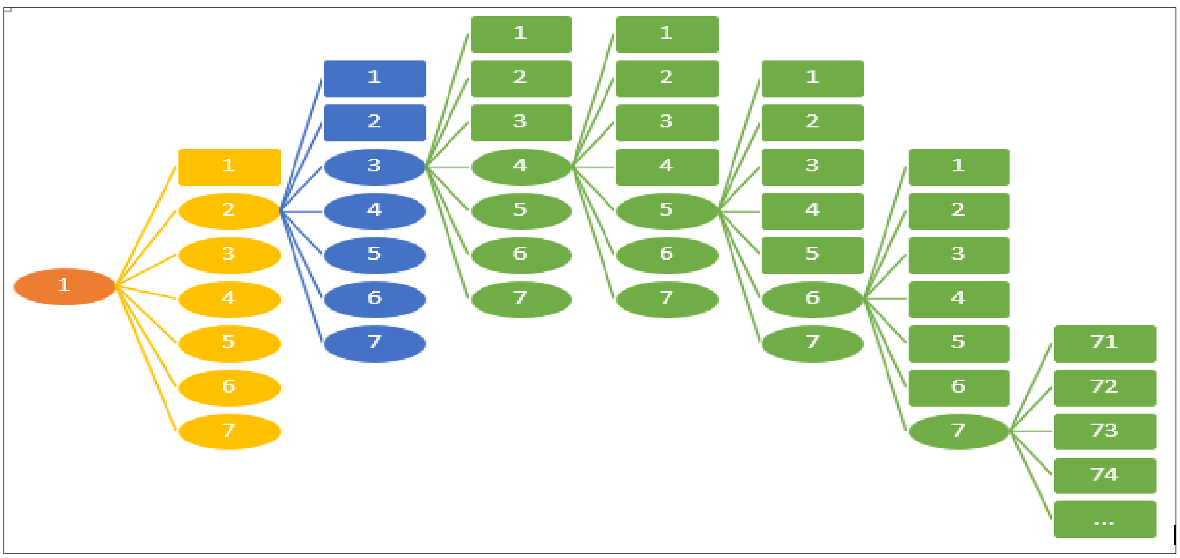

Figure 3.2 Possible future states of transition phases of Spruce Budworm.

To be clear about how the transition matrix works, there are several transition phases of the scenarios that one infested area or forest stand can evolve to another stage or could still be in the same state (see Table 3.1). For example, we harvest several trees in area A but the ones that are not harvested will continue to evolve into another stage of the SBW´s life cycle (up to seven instars), depending on the external factors that will help accelerate the growth of these insects or whether it would help control the population. The parameter to measure the risk class consists of 0 to 74, and 75 where 0-7 is increasing risk, 71-74 increasing wood deterioration. 74 stands for 4 years after the deterioration has significantly started as well as 75 where it is 5 years after the continuing deterioration of 74, and so on. The chances of evolving into another of the probable states are different, despite the growth process. The other not harvested forest stands will continue to change too and evolve to another instar or remain as the previous one with certain probabilities. This is the reason harvest planning should be done at a tactical level as the life cycle of this living organism spans over a year. The sub-scenarios or states 71, 72, 73, 74, and 75 mean the periods or years of continuous infestation after reaching the mortality of phase 75, where the forest stand is completely dead or can never be recovered.

Table 3.1 Matrix of the SBW transition from initial to final infestation phase.

Initial phase infestation \ Final phase infestation	1	2	3	4	5	6	7	71	72
1	**58%**		42%						
2	45%	**25%**	20%	10%					
3			**1**						
4				**1**					
5					**1**				
6						**1**			
7							**1**		
71								**1**	
72									**1**

The matrix defines the transition probability for risk classes between two consecutive years, and it is valid for all years. This transition matrix shows the distribution of volume over Hunter Classes for each Risk class. The Hunter class is a metric to evaluate the degradation level of individual trees that are classified as Hunter 4 and Hunter 4+ and defines the proportion of trees in each Hunter class in a stand based on its Risk Class. The last class of defoliation means that stands will no longer have value for the industry. The remaining volume at year "i" equals the initial volume less the volume in Hunter classes 4 and 4+ at year "i". As the risk class varies over years for the same area, the % of trees in Hunter classes 4 and 4+ varies also (e.g. if a stand has a risk class of 6 at year i, 14% of *Sapin Baumier* or Balsam Fir (SAB) is Hunter 4 and 12% is Hunter 4+, meaning 26% of the total volume of the SAB volume of the stand has no more value for the industry).

In this third Chapter, we described the research method for solving the problem. In the next Chapter, we will validate the proposed model with generated database to test, demonstrate and analyze the theoretical model, to assure that the method functions correctly before applying it to a real case study.

CHAPTER 4

VALIDATING THE OPTIMIZATION MODEL

This Chapter is based on the MOSIM CONFERENCE PAPER 2016 (Zhu Chen, Ouhimmou et Rönnqvist, 2016) (see APPENDIX I, p.117-128).

The objective of testing the model is to compare the results and the functionality of the proposed model. In Table 4.1, the following SBW scenarios are introduced consistent with the different probabilities of the transition matrix (see APPENDIX III, p.131-138). The values for the parameters are tested in the model. Then, it is programmed in AMPL language and solved in CPLEX solver for different infestation scenarios with certain different initial inventory level cases of seventy-five forest stands, five industries to supply, four types of tree species, and seven infestation phases over five periods.

As for the parameters, the data is proposed for validating the model in a congruent way. For example, the market value depends on the transition phase of the SBW (see APPENDIX II, p.129-130). This means the price value will decrease whenever the forest stand goes to the last phase of infestation and increases if there is no probability of infestation. Table 4.1 shows the expected profit value where the deterministic model is solved scenario by scenario and the average of them is calculated. Then, the Two-Stage SP is solved considering the overall of scenarios. The third column is the average of the scenarios when implementing first-stage solution (when perfect information is available) for one period. The reason why it is one period is to allow more flexibility on decision-making in forest management.

Table 4.1 Expected profit of deterministic, stochastic and average scenario in $M.

Expected value of profit for case	Deterministic model (Scenario by Scenario analysis)	Stochastic Model	Deterministic model-first-stage decisions with average scenario
Case 1	44.66	43.67	44.23
Case 2	48.38	47.49	48.27
Case 3	50.39	49.73	50.39

4.1 Preliminary Optimization Results: Implementing solutions

Nevertheless, Table 4.2 describes the profit of each scenario of the stochastic and deterministic model (using the average scenario) as well as for the optimal solution. The profit for each scenario is different. The comparison of the profits between using the stochastic model and the deterministic model shows that the solution of the deterministic model is higher than a stochastic solution as the last one considers all the scenarios rather than per each scenario. If we compare between the "Deterministic Model-Average scenario", we can observe that the stochastic solution is better. Moreover, it can be observed that if the scenario of infestation gets worse, the profit decreases too and vice-versa due to the great loss that forest management could face. This demonstrates that developing and implementing stochastic model reduces the loss and maximizes more the value of the forest taking into account that it also considers all the scenarios.

Table 4.2 Comparison of the different scenarios when implementing stochastic solution in ($M).

Case	Scenario	Optimal Solution	Stochastic Model	Deterministic Model-Average scenario	Difference
1	S1	52.29	52.09	51.88	0.21
	S2	51	50.92	50.6	0.32
	S3	48.02	47.99	47.59	0.4
	S4	45.91	45.86	45.48	0.38
	S5	26.07	25.96	25.58	0.38
Average case 1		**44.66**	**44.56**	**44.23**	**0.34**
2	S1	55.46	55.46	55.41	0.05
	S2	54.55	54.5	54.45	0.05
	S3	52.23	52.21	52.23	-0.02
	S4	50.2	50.17	50.17	0
	S5	29.44	29.09	29.11	-0.02
Average case 2		**48.376**	**48.286**	**48.274**	**0.012**
3	S1	56.8	56.8	56.8	0
	S2	56.4	56.4	56.4	0
	S3	54.25	54.25	54.25	0
	S4	52.85	52.83	52.83	0
	S5	31.65	31.65	31.65	0
Average case 3		**50.39**	**50.386**	**50.386**	**0**

Furthermore, the solutions of the first-stage are different for Two-Stage SP and deterministic solution. As for the total quantity of forest stands harvested per period, they are shown in Table 4.3 and an example of taking into account when to harvest for only one forest stand is observed in Table 4.4. These tables show how the decisions are different in each period for each of the scenarios

Table 4.3 Total number of forest stands harvested for each period.

Period	1	2	3	4	5	Total
1 datacase	9	5	6	5	6	**31**
2 no infestation	7	5	7	9	11	**39**
3 low infestation	5	7	10	16	25	**63**
4 medium infestation	4	6	11	16	30	**67**
5 high infestation	4	22	42	4	3	**75**
Average Deterministic Model	6	7	9	14	23	**59**
Stochastic Model	4	15	23	15	18	**75**

Table 4.4 Example results of first-stage solution of one forest stand where 1 means the area is opened and 0 otherwise.

Scenario	Period				
	1	2	3	4	5
S1	**1**	0	0	0	0
S2	0	0	**1**	0	0
S3	0	**1**	0	0	0
S4	0	0	**1**	0	0
S5	0	0	0	**1**	0
Average Deterministic Model	0	**1**	0	0	0
Stochastic Model	0	0	**1**	0	0

Finally, Table 4.5 shows the profit of each scenario when implementing or fixing the solution of each scenario for one period. This shows that sometimes it can improve the value of the objective function or it can reduce it and/or make it infeasible.

Table 4.5 Profit in ($M) of each scenario when implementing each first-stage per scenario solution.

		Solution of scenario				
		S1	**S2**	**S3**	**S4**	**S5**
Case 1	**S1**	**52.29**	52.24	52.14	51.95	51.85
	S2	50.9	**51.02**	50.97	50.82	50.82
	S3	47.37	47.83	**48.05**	47.95	47.95
	S4	44.97	45.56	45.87	**45.87**	45.88
	S5	24.49	25.23	25.75	26.07	**26.07**
Case 2	**S1**	**55.47**	55.39	54.45	55.2	55.03
	S2	54.43	**54.55**	53.94	54.32	54.18
	S3	51.8	52.14	**52.05**	52.06	52.05
	S4	49.71	52.17	50.18	**50.2**	50.19
	S5	28.35	29.09	29.11	29.29	**29.44**
Case 3	**S1**	**56.8**	56.8	56.8	56.77	56.8
	S2	56.24	**56.4**	56.4	56.35	56.4
	S3	53.66	54.18	**54.25**	54.25	54.25
	S4	52.12	52.78	52.83	**52.85**	52.83
	S5	30.81	31.52	31.65	31.57	**31.65**

There are many situations where one is faced with problems where decisions should be made sequentially at certain periods of time based on information available at each period. That means that if the first-stage decision for the first period is fixed, then this will become the available information for solving the actual period, which will be helpful as it will improve the value of the objective function. This will be an extension of the Two-Stage SP into a multi-stage SP (Shapiro et Philpott, 2007).

4.2 Metrics for evaluating the quality of solution: EVPI and VSS

The quality of solution of the deterministic and stochastic solution is evaluated through the following metrics: Expected Value with the Perfect Information (EVPI) and Value of

Stochastic Solution (VSS). If we know the values of EVPI and the VSS, these allow the decision maker to analyze how much the forest manager should spend to gain more information on the future for the EVPI and how well the deterministic model solutions perform compared to the solution of an SP for the VSS.

4.2.1 Expected Value with Perfect Information: EVPI

The EVPI is the cost that the decision maker is willing to pay for a study of the uncertainty or the maximum amount that the decision maker would be ready to pay in return for complete and accurate information about the future. Kall et Mayer (2005) mentions that this metric consists of solving scenario by scenario the models less the recourse problem solution (RP). The EVPI compares the expected value when solving with perfect information, known as Wait-and-See solutions (WS), and the value that the forest manager will be willing to pay for that information (see equations 4.1-4.3). If we know the bounds of EVPI values, they will be useful to identify whether the decision maker should invest more or not in forecasting models (see equation 4.4). The bounds of these metrics are explained in Escudero et al. (2007) and Maggioni et Wallace (2012).

$$EVPI = RP - WS \tag{4.1}$$

$$WS = E_{\xi}\left[\min_{x} z(x,\xi)\right] = E_{\xi}\big(z(\bar{x}(\xi),\xi)\big) \tag{4.2}$$

$$RP = \left[\min_{x} E_{\xi}\, z(x,\xi)\right] \tag{4.3}$$

$$0 \leq EVPI \tag{4.4}$$

Continuing with Table 4.2, the difference between solving scenario by scenario analysis and solving the model with the Two-Stage stochastic model is the EVPI, in which is \$0.99M, \$0.89M, and \$0.66M (see Table 4.6). This value is the cost that the decision maker will pay more for perfect information where applying with deterministic is much higher than when solving with a stochastic model as the last one considers all the scenarios.

Table 4.6 Expected profit of deterministic, stochastic, average scenario, and VSS in $M.

Expected value of profit for case	Deterministic model (Scenario by Scenario analysis)	Stochastic Model	Deterministic model-first-stage decisions with average scenario	EVPI
Case 1	44.66	43.67	44.23	0.99
Case 2	48.38	47.49	48.27	0.89
Case 3	50.39	49.73	50.39	0.66

4.2.2 Value of Stochastic Solution: VSS

On the other hand, the Value of Stochastic Solution (VSS) is the price or cost that the decision maker pays when uncertainty is not considered. The VSS measures how good, or more often, how bad a solution of the expected value (EV) or mean value problem is. The VSS bounds show an interval of expected loss of neglecting stochasticity when finding the first-stage decision. The bounds of these metrics are explained in Escudero et al. (2007) and Maggioni et Wallace (2012) (see equation 4.7). Compared to Wait-and-See approach, the VSS delivers a set of solutions instead of one solution that would be implementable. For obtaining the VSS value, we consider the difference between the expected value of implementable solutions (EEV), and the Two-Stage SP solution or RP solution (see equations 4.5 and 4.6). The EEV replaces random variables by their expected values.

$$VSS = EEV - RP \tag{4.5}$$

Where

$$EEV = E_{\xi}\left(z\left(\bar{x}\left(\bar{\xi}\right), \xi\right)\right) \tag{4.6}$$

$$WS \leq RP \leq EEV \tag{4.7}$$

For the preliminary results of the proposed model, the value of $0.56M, $0.78M, and $0.66M explained in the last column of Table 4.7 is the VSS which indicates that if the uncertainty is not considered, that will be the cost that decision maker should pay for the stochastic solution rather than the mean value solution. This is the difference between the solution of the stochastic model and the expected value of the scenarios when implementing the first-stage solution of the average scenario. However, as it is a maximization problem, the VSS should be negative as there is no value to consider uncertainty and arrive at a worse solution. If it was a minimization problem the value should be positive.

Table 4.7 Expected profit of deterministic, stochastic, average scenario, EVPI and VSS in $M.

Expected value of profit for case	**Deterministic model (Scenario by Scenario analysis)**	**Stochastic Model**	**Deterministic model first-stage decisions with average scenario**	**EVPI**	**VSS**
Case 1	44.66	43.67	44.23	0.99	0.56
Case 2	48.38	47.49	48.27	0.89	0.78
Case 3	50.39	49.73	50.39	0.66	0.66

In this fourth Chapter, we have generated data and solved the proposed model for a small-scale size problem to validate the model and prove that is feasible and realizable. Now, for the next Chapter we will apply the same proposed model to real case study in the North Shore region of the province of Québec (*Côte-Nord du Québec*).

CHAPTER 5

APPLICATION TO REAL CASE STUDY

After obtaining previous preliminary results and explanation in Chapter 4, the model will be applied on the North Shore region in the province of Québec, well-known as "*Côte-Nord du Québec.*"

5.1 Case Study: Côte-Nord du Québec (North Shore region in the province of Québec)

In this research, the problem of harvesting planning at the tactical level will be applied in the case of Côte-Nord du Québec or North Shore region in the province of Québec, the second largest forest area of the province in terms of scope, where 98% of forest land is publicly owned, extending over 103,146 km^2. Dotted with countless lakes and rivers, the northeast coastal forest is one of the key drivers in economic development of the region. The northeastern coastal forest also provides a coveted place for the development of forest knowledge and for practicing numerous recreational activities (Ministère des Forêts, 2015).

According to the National Forestry Database (NFD) (2015), the province of Québec had the major forest insect damage in Canada in 2015 (see Figure 5.1). Around 6,315,100 of ha were considered as suffering moderate to severe defoliation by Spruce Budworm (SBW) compared to other provinces in Canada. The Côte-Nord area is around 351,523 km^2 (35,152,300 ha), which corresponds to 21% of the total area of the province of Québec. The forest region covers around 198,936 km^2 (19,893,600 ha), meaning 73% of the region is forest cover, constituting the most vast wood surface of Québec and nearly 12% of potential Québec public forest (MERN, 2007).

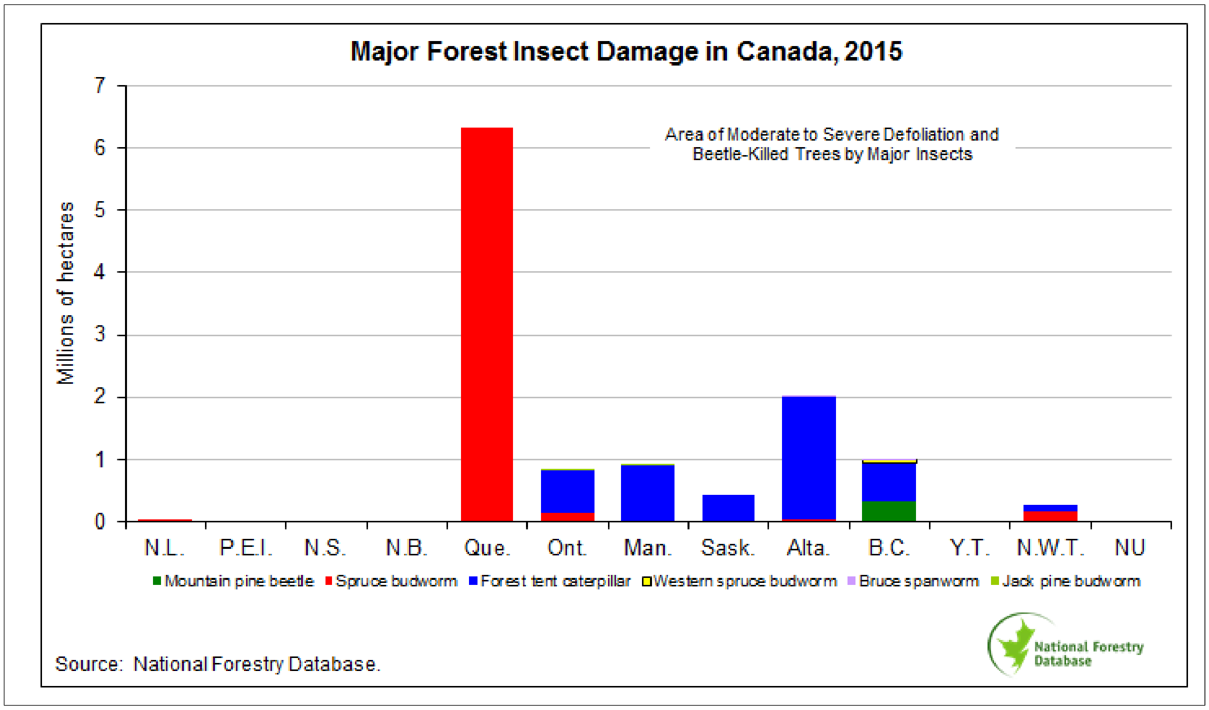

Figure 5.1 Major Forest Insect Damage in Canada, 2015 taken from The National Forestry Database (NFD) (2015).

5.1.1 Outbreak History of Spruce Budworm

The SBW is a native insect whose presence is normal inside the Québec forest and whose populations evolve in cyclical ways over an interval of thirty years. The common species that the SBW hosts are the Balsam Fir and White spruce in this area, but also Black Spruce. In Figure 5.2, we can see the increasing severe annual defoliation of the area over the years since 1995 in all the province of Québec.

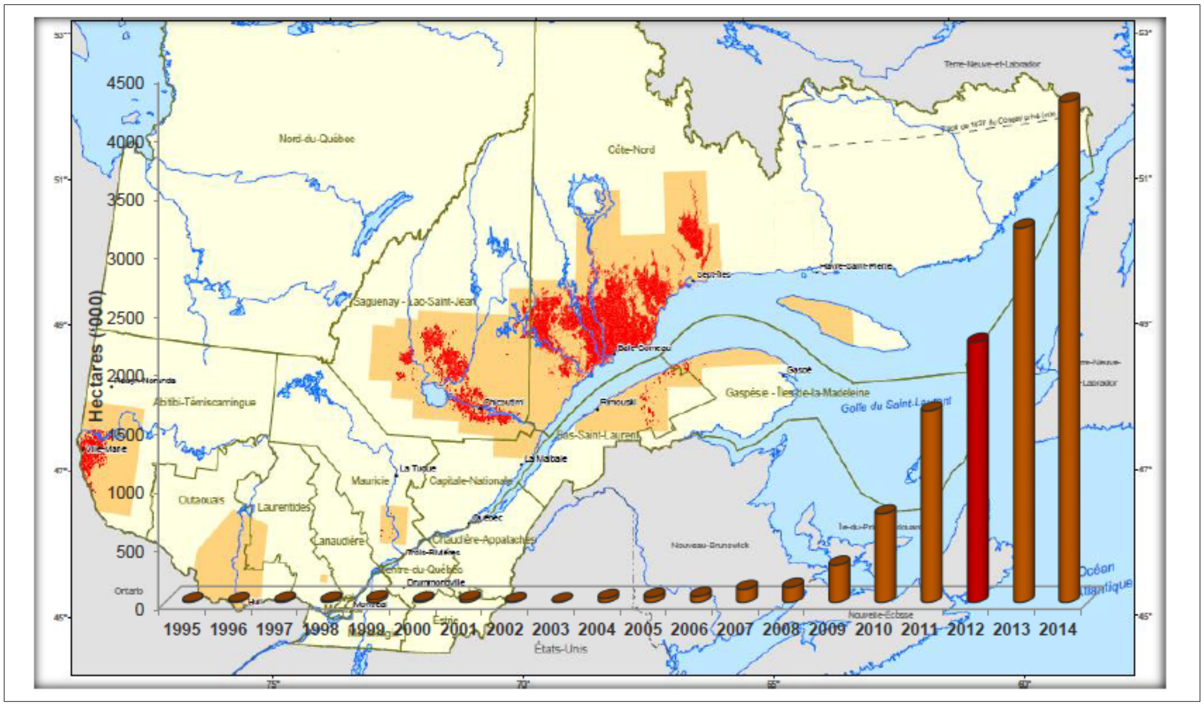

Figure 5.2 Annual defoliation of Spruce Budworm over time in the province of Québec taken from Charette et al. (2015).

The actual epidemic has been raging over most regions of Québec since 2007. In 2013, the defoliated areas were over 3,206,019 ha as shown in Table 5.1 compared to 2,225,054 ha in 2012 and a total amount of 1,642,187 ha in 2011. It has been increasing since then. The most affected regions are located in *Côte-Nord, Saguenay-Lac, Saint-Jean* and *Abitibi-Témiscamingue* with distribution damage of 77%, 15% and 5% of the total province, respectively (Ministère des Forêts, 2015). However, the administrative region of *Côte-Nord* is the most affected region by SBW and has the highest levels of defoliation at the three levels compared to the other regions.

Table 5.1 Defoliated areas by the Spruce Budworm from 2007-2015 of the affected administrative regions in ha in Québec taken from Salmon (2016).

	2007	2008	2009	2010	2011	2012	2013	2014	2015
01 Bas-Saint-Laurent	-	-	-	-	-	9 413	60 812	316 102	894 562
02 Saguenay–Lac-Saint-Jean	6 910	17 817	73 908	156 289	244 669	370 937	470 217	643 103	1 055 931
03 Capitale-Nationale	-	-	-	-	-	-	-	-	101
04 Mauricie	594	723	798	2 761	2 261	105	26	42	77
05 Estrie	-	-	-	-	-	-	-	-	-
07 Outaouais	43 271	16 579	30 231	16 214	2 578	-	-	-	-
08 Abitibi-Témiscamingue	5 948	6 805	26 696	57 274	67 166	96 503	152 483	190 820	330 507
09 Côte-Nord	53 990	91 590	189 280	532 463	1 325 427	1 745 040	2 465 714	2 946 357	3 754 605
11 Gaspésie–Îles-de-la-Madeleine	-	-	-	-	-	3 056	56 769	178 588	279 430
15 Laurentides	26	86	233	147	85	-	-	52	50
17 Centre-du-Québec	4	3	-	-	-	-	-	-	-
Total	**110 743**	**133 603**	**321 146**	**765 148**	**1 642 187**	**2 225 054**	**3 206 019**	**4 275 065**	**6 315 262**

Focusing on the major problem of forest insect damage by SBW, the *Côte-Nord* has increasingly been affected over the years. This area has been the most affected compared to other forest lands of Québec. We have noticed that the Spruce Budworm population started increasing again in 2015 since the last outbreak in Québec in 1975 (see Figure 5.3).

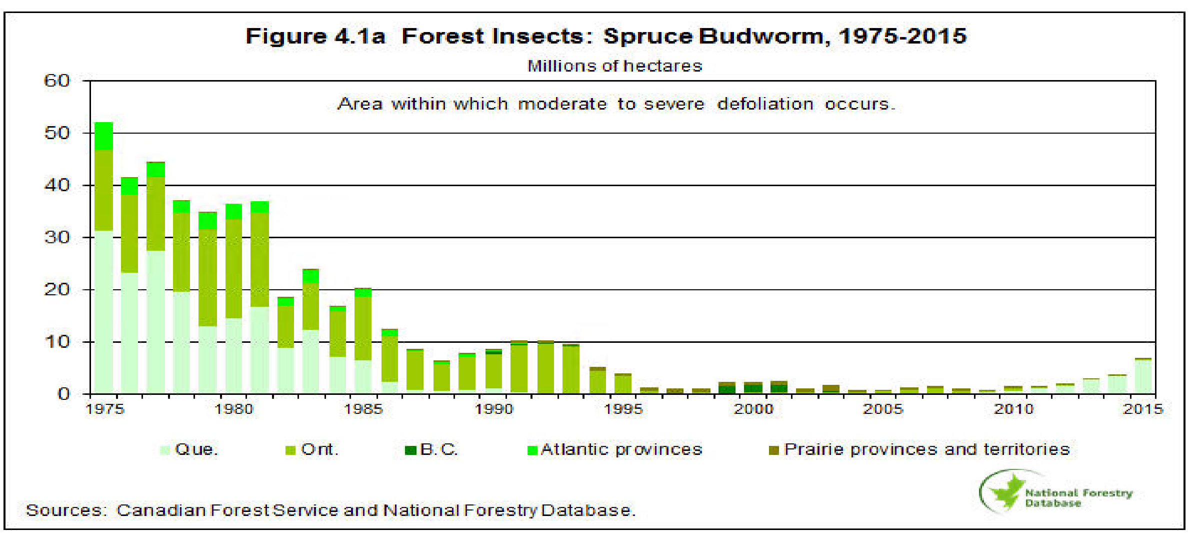

Figure 5.3 Spruce Budworm defoliation in Canada from 1975-2015 taken from (NFD) (2015).

According to the Ministère des Forêts (2015), there is an outbreak of the SBW underway in some regions of Québec. The *Ministère des Forêts, de la Faune et des Parcs* (MFFP) follows the evolution of poulations of this insect closely, both in private and public forest. Since 1992, the outbreaks have affected many parts that are part of the North Shore region of the province of Québec. Since 2012, the epidemic has also affected regions such as *Bas-St-Laurent* and *Gaspésie-Îles-de-la-Madeleine*, which are considered the least affected or infested areas by SBW (see Figure 5.4).

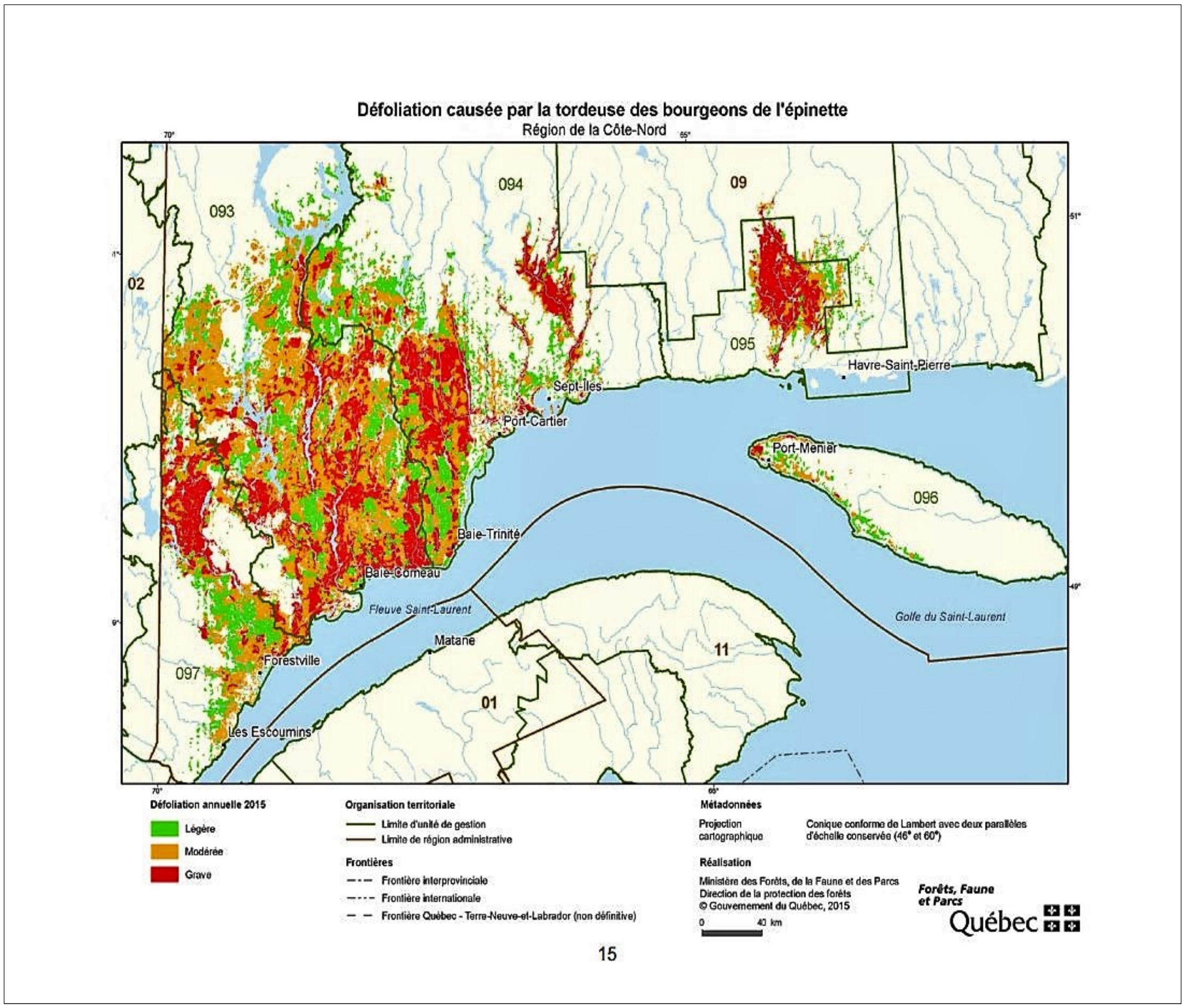

Figure 5.4 Annual Defoliation in the North-Shore region of Québec for 2015 caused by Spruce Budworm taken from Ministère des Forêts (2015).

5.2 Description of Real Database for Solving the Optimization Model

Since 2013, the North Shore (Côte-Nord du Québec) area has been distributed in six forest management units (FMU). These units have their own classification of forest stands with common characteristics and species. The distribution of the North Shore is essential because these units of forest stands are important for harvesting planning aggregation which allows us to reduce the size of the model by clustering between the same units of the FMU. These FMUs are 093-51, 094-51, 094-52, and 097-51 (see Figure 5.2). The database given by FPInnovations, shows the evolution of the SBW over time in the North Shore region (Côte-Nord du Québec) is susceptible to SBW infestation for main species of Balsam Fir and White Spruce. However, certain species such as Black Spruce are also considered as non-affected for a better real approach to the results when applying the proposed model with the real data, as Black Spruce is integrated with the other species of the forest stands.

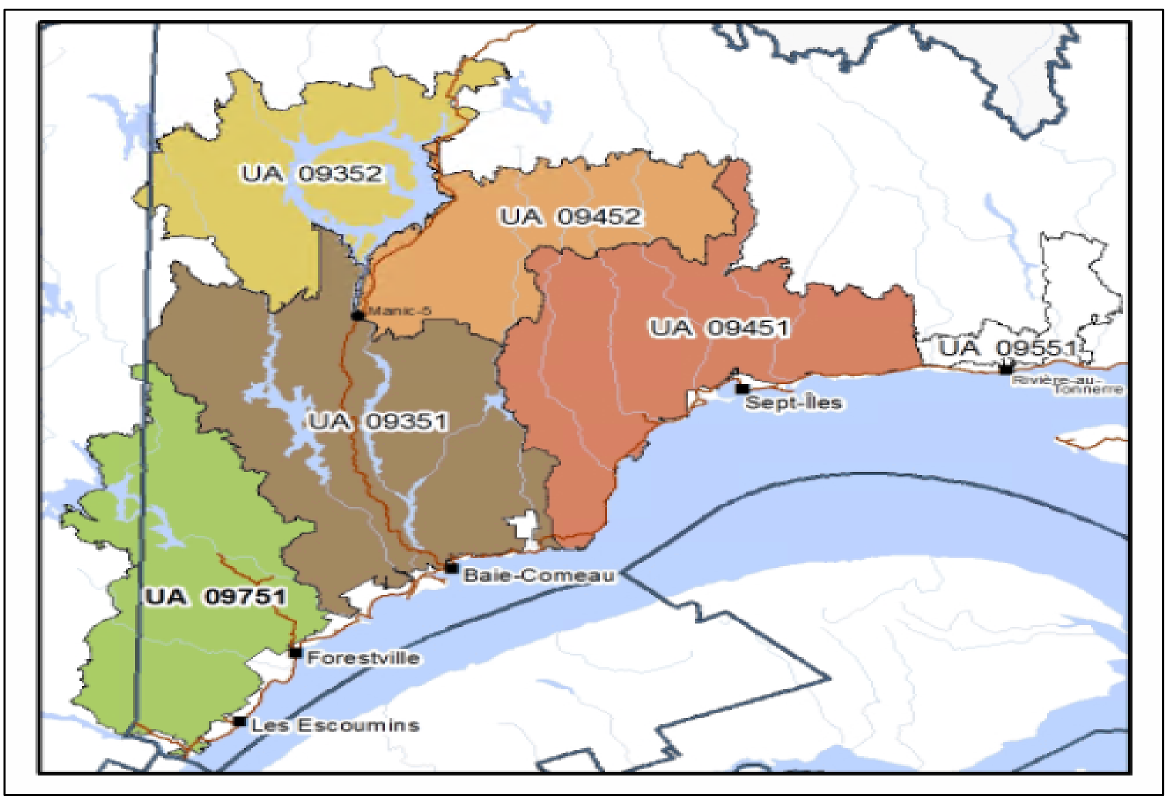

Figure 5.5 Integrated Forest Management Plan of the North Shore region of Québec (Côte-Nord) taken from Ministère des Forêts (2016).

In this case study, we considered six cases of initial volume inventory of forest stands or known as "stat", six different types of infestation scenarios and five different amounts of demand according to each AAC. The six cases of initial inventory correspond to the amount of volume that the region has over the years from stat14, stat15, stat16, stat17, stat18, and until stat19 (see APPENDIX V, p.141-148). The amount of volume of forest stands has previously been described and modelled by FPInnovations in which the distribution of volume varies over the planning horizon (see APPENDIX IV, p.139-140). The amount of volume inventory is obtained with the transition matrix and the development of the SBW over time is considered (values obtained previously by modelling the SBW dynamic population).

We define six different scenarios for the uncertain parameter as the following: "1 datacase", "2 no infestation", "3 low infestation", "4 medium infestation", "5 high infestation", and "6 severe infestation". The uncertain parameter is defined according to the probability of the amount of volume inventory of phase of infestation that will change to another phase. These scenarios are defined by the transition matrix which depends on the type of tree species and the degree of mortality of the trees. The first scenario of datacase is considered as the real probability of transition matrix provided by FPInnovations which does not fit in any of the other categories considered as perfect scenario (without infestation) or worst scenario (severe infestation). The rest of the scenarios ("2 no infestation", "3 low infestation", "4 medium infestation", "5 high infestation", and "6 severe infestation") are considered in ascendant order from the best to the worst possibilities of SBW infestation.

As for the demand, it refers to the total amount of logs in m^3 that will be harvested and shipped to the sawmills over the different regions once the forest stands are aggregated by common characteristics (see Figure 5.6). The sawmills need the equivalent of AAC (Allowable Annual Cut) which is around 2.7 million m^3 (equivalent to 0.50% of the forest inventory on average). This demand will start from 0.10%, 0.25%, 0.50%, 1%, and 2% of the total volume (forest inventory) of the region (see APPENDIX VI, p.149-150) of each initial stat. This is the purpose behind solving the model for less and more volume around the AAC. The different stats and the different percentages of AAC are independent cases. We will compare the differences between the deterministic model and the Two-Stage stochastic model with the given results along with implementing the first-stage solution. Finally, the Net Value or revenue obtained from the land consists of the difference between the market value the forest manager can obtain from the area less the costs (e.g. harvesting costs, opening costs, transformation costs, supply costs, infrastructure costs, road transportation and transportation costs). We ran different simulations of the model combining the cases and the scenarios as well as demand to compare how the transition and initial volume inventory will affect the results.

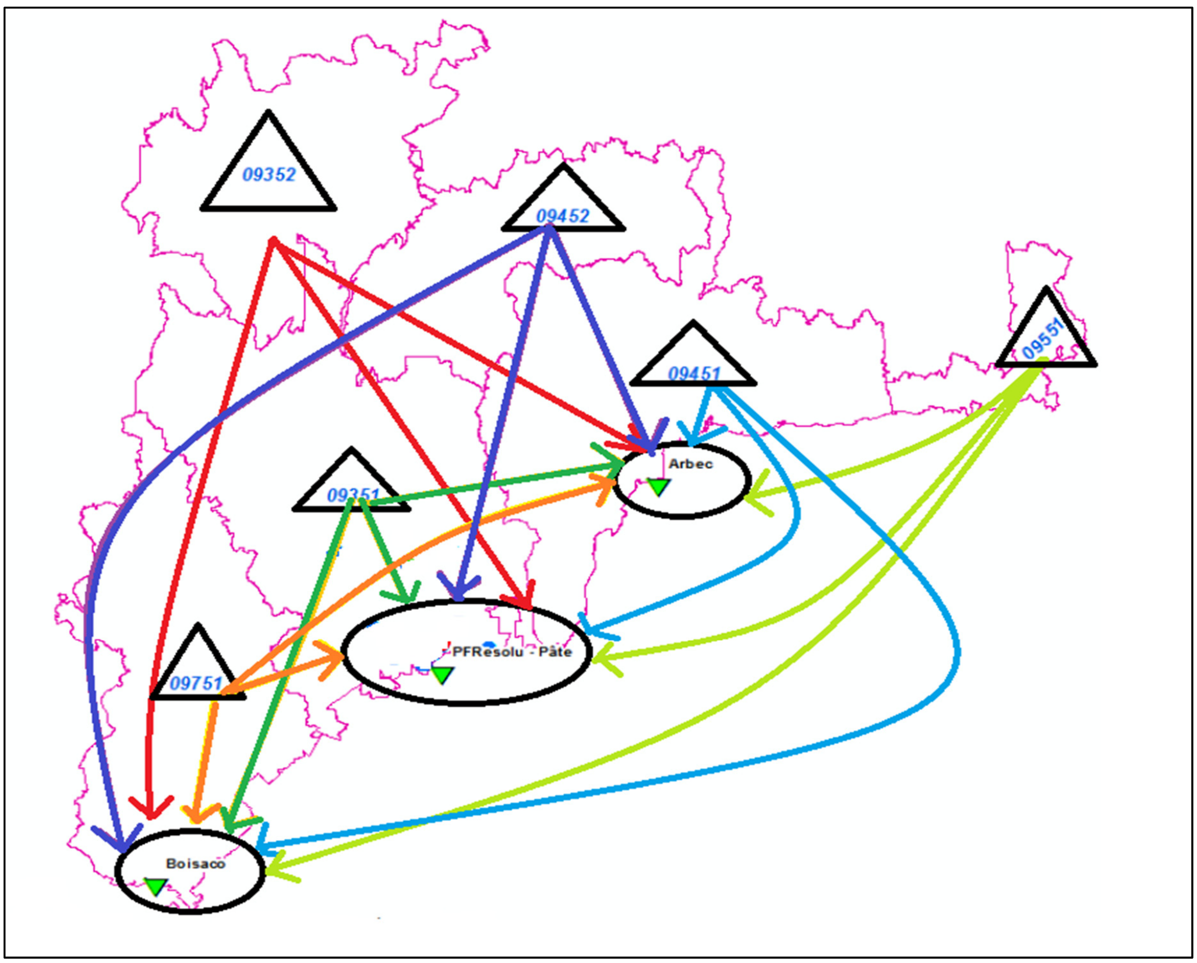

Figure 5.6 Supply to sawmills from Integrated Forest Management Plan of the North Shore region of the province of Québec (Côte-Nord) reproduced and adapted with the permission of Charette et al. (2015).

In this fifth Chapter, we have illustrated the current context of the case study and highlighted the importance of applying our research method for this problem. For the following Chapter, we will present the results of implementing the described data from this Chapter, which were provided by FPInnovations for each and one of the independent cases with their respective Annual Allowable Cut (AAC).

CHAPTER 6

RESULTS OF THE OPTIMIZATION MODELS

6.1 Results of the Deterministic and Stochastic Optimization Model for case study.

In this Chapter, we will present the results after running the optimization models, in AMPL with CPLEX solver, applied for the case study. These tables and figures are classified per each AAC (e.g. 0.10%, 0.25%, 0.50%, 1%, and 2%) with their respective initial volume "stat" (see APPENDIX VI, p.149-150). It is important to highlight that the initial volume "stat" is independent from the others, as our aim is to compare what would happen if we consider different proportions of initial inventory of infested areas. The total profit presented on the tables are for three industries (i.e. sawmills) over the planning horizon of three years.

For solving the deterministic models in AMPL, the size of the problem consists on a total of 64,230 binary variables, more than 5 million linear variables subject to more than 2 million constraints. However, for solving stochastic models in AMPL, we solved for a problem size of same number of binary variables (first-stage decision) but because of the number of scenarios we have, we solved for more than 34 million linear variables (second-stage decisions) subject to more than 16 million constraints.

6.1.1 Case of AAC equivalent to 0.10% of forest inventory

In this section, we present the results of each scenario per initial stat case of AAC equivalent to 0.10% of initial forest inventory. We solved for all the possible realizations of scenarios (see Table 6.1). The row "AVERAGE" means the expected value of the six scenarios considered as Wait-and-See solutions (WS) of deterministic models. The row "AVERAGE TRANSITION" consists of using as data, the average of the uncertain parameter (average of all transition matrices) and solving it deterministically. Finally, the row "STOCHASTIC" means applying and integrating all the possible scenarios into one DEM formulation for solving Two-Stage SP model.

Table 6.1 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP per stat for AAC equivalent to 0.10% in CAD.

AAC equivalent to 0.10% of initial forest inventory						
	stat14	**stat15**	**stat16**	**stat17**	**stat18**	**stat19**
1 datacase	32,775,508	36,856,548	32,138,209	32,645,124	31,934,088	36,194,672
2 no infestation	32,807,612	36,910,414	32,191,289	32,712,436	32,002,122	36,284,031
3 low infestation	32,788,541	36,877,766	32,164,790	32,677,603	31,959,442	36,213,723
4 medium infestation	32,779,453	36,865,056	32,144,858	32,649,697	31,938,943	36,196,274
5 high infestation	32,773,465	36,858,627	32,144,408	32,647,068	31,934,448	36,194,982
6 severe infestation	32,761,114	36,851,765	32,131,041	32,634,913	31,927,966	36,187,583
AVERAGE	**32,780,949**	**36,870,029**	**32,152,432**	**32,661,140**	**31,949,502**	**36,211,877**
AVERAGE TRANSITION	**32,786,198**	**36,882,755**	**32,164,105**	**32,680,434**	**31,970,473**	**36,240,212**
STOCHASTIC	**32,776,455**	**36,868,632**	**32,144,363**	**32,647,892**	**NO RESULT**	**36,210,757**

We can observe the results for case of AAC equivalent to 0.10% of initial forest inventory with their respective initial “stat” in Table 6.1 that the profit of the scenarios decreases starting from “2 no infestation”, “3 low infestation”, “4 medium infestation”, “5 high infestation”, and “6 severe infestation”; however, scenario “2 no infestation” has the highest profit compared to the other scenarios. For scenario “1 datacase”, this scenario is positioned between scenarios “4 medium infestation” to “6 severe infestation” depending on their independent initial inventory case. The results of the profit depend on the probability of the sensibility of the transition matrix for these scenarios (see APPENDIX III, p.131-138). Moreover, when solving for Two-Stage SP for stat18, none of the solvers (e.g. CPLEX or Gurobi) in AMPL could find a feasible solution in a reasonable time of one or two days. However, if we let the AMPL solve for more time for this specific case, it is possible we can find a feasible solution. For better visualization of the results of Table 6.1, we present the graphs of the profit obtained for each stat of the AAC (see Figures 6.1-6.6).

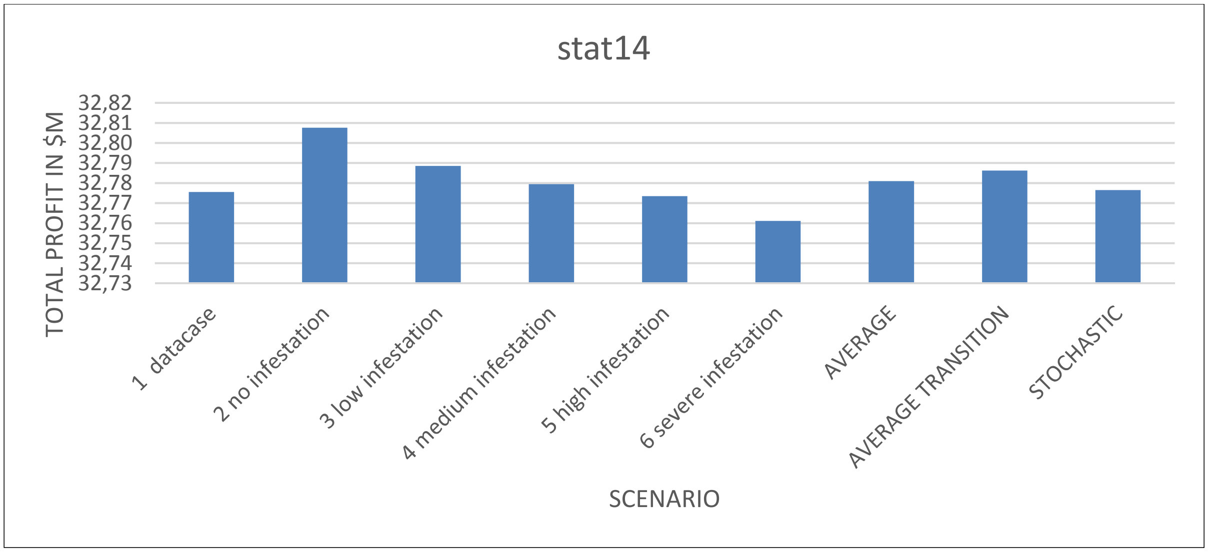

Figure 6.1 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 14 for Allowable Annual Cut (AAC) equivalent to 0.10% in $M.

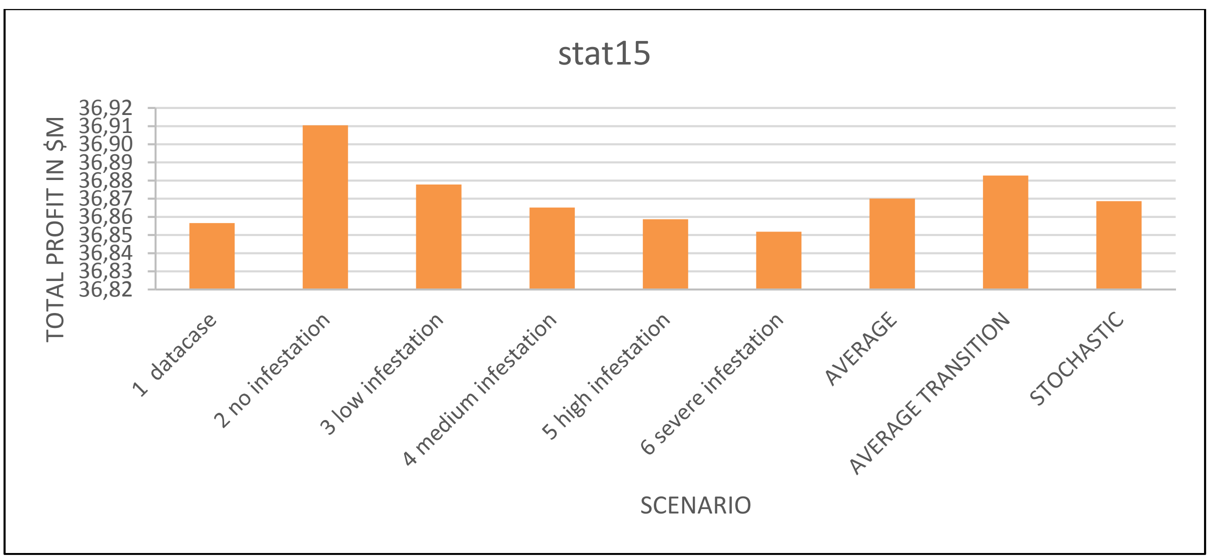

Figure 6.2 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 15 for Allowable Annual Cut (AAC) equivalent to 0.10% in $M.

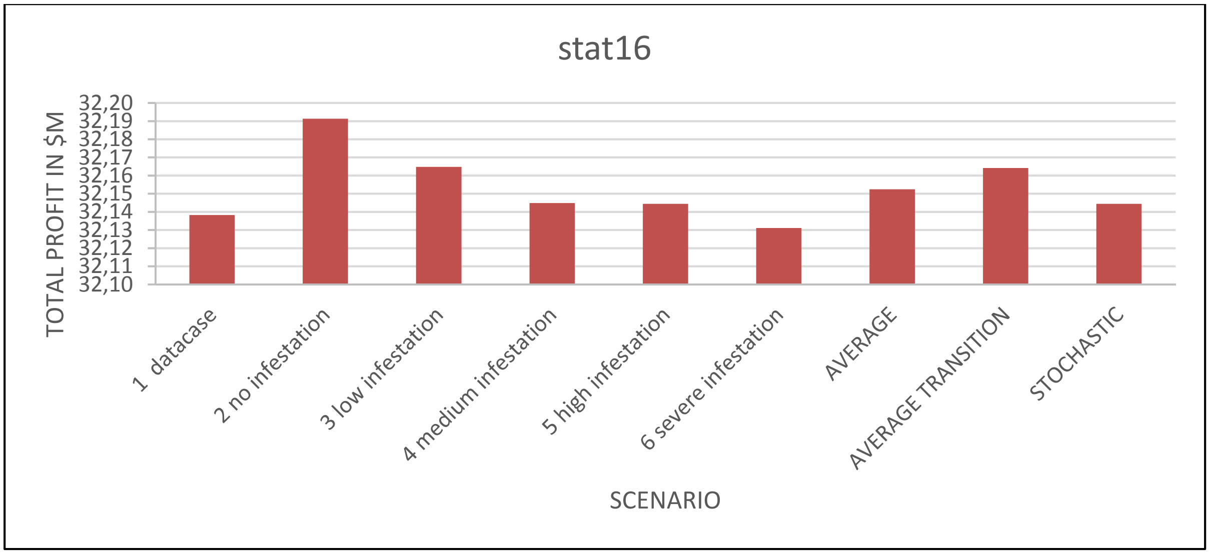

Figure 6.3 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 16 for Allowable Annual Cut (AAC) equivalent to 0.10% in $M.

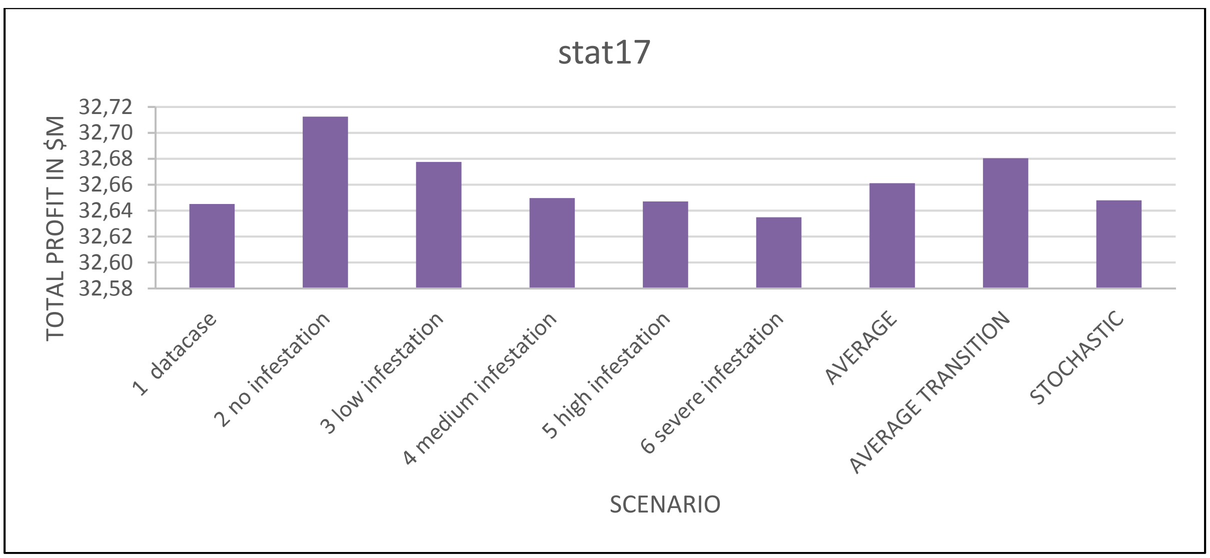

Figure 6.4 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 17 for Allowable Annual Cut (AAC) equivalent to 0.10% in $M.

As there is no result found for solving the Two-Stage SP model for stat18, the profit for Figure 6.5 for all scenarios and the average transition matrix are very close and the values are not easy to compare.

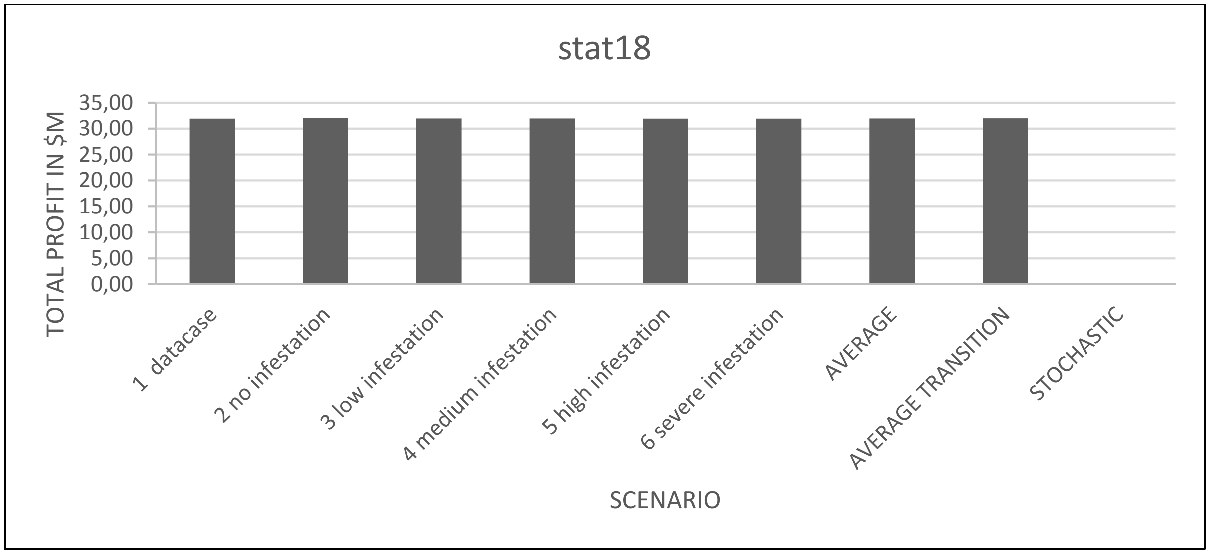

Figure 6.5 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 18 for Allowable Annual Cut (AAC) equivalent to 0.10% in $M.

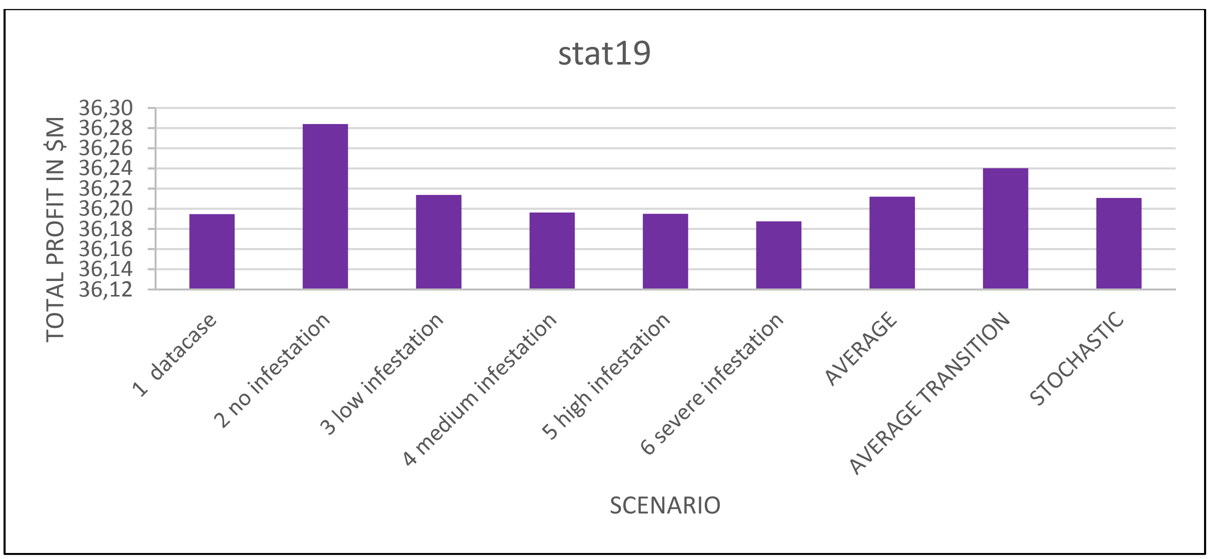

Figure 6.6 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 19 for Allowable Annual Cut (AAC) equivalent to 0.10% in $M.

6.1.2 Case of AAC equivalent to 0.25% of forest inventory

In this section, we present the results of each scenario per initial stat case of AAC equivalent to 0.25% of initial forest inventory. We solved for all the possible realizations of scenarios (see Table 6.2). The row "AVERAGE" means the expected value of the six scenarios considered as Wait-and-See solutions (WS) of deterministic models. The row "AVERAGE TRANSITION" consists of using as data, the average of the uncertain parameter (average of all transition matrices) and solving it deterministically. Finally, the row "STOCHASTIC" means applying and integrating all the possible scenarios into one DEM formulation for solving Two-Stage SP model.

Table 6.2 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP per stat for AAC equivalent to 0.25% in CAD.

AAC equivalent to 0.25% of initial forest inventory						
	stat14	**stat15**	**stat16**	**stat17**	**stat18**	**stat19**
1 datacase	81,288,596	91,293,272	79,714,497	80,978,830	79,217,475	89,611,259
2 no infestation	81,357,768	91,443,624	79,834,660	81,123,134	79,359,108	89,900,784
3 low infestation	81,309,184	91,347,236	79,767,148	81,045,280	79,267,710	89,693,896
4 medium infestation	81,295,934	91,312,516	79,727,882	80,987,360	79,224,254	89,644,455
5 high infestation	81,286,817	91,298,687	79,727,080	80,978,975	79,221,364	89,610,741
6 severe infestation	81,260,832	91,275,039	79,701,318	80,963,219	79,201,564	89,597,130
AVERAGE	**81,299,855**	**91,328,396**	**79,745,431**	**81,012,800**	**79,248,579**	**89,676,377**
AVERAGE TRANSITION	**81,313,734**	**91,357,284**	**79,768,085**	**81,050,069**	**79,285,241**	**89,763,355**
STOCHASTIC	**81,285,845**	**91,291,402**	**79,714,493**	**80,993,102**	**79,241,005**	**89,517,756**

As seen in Section 6.1.1, we can observe in the results for case of AAC equivalent to 0.25% of initial forest inventory with their respective initial "stat" in Table 6.2 that the profit of the scenarios is decreasing starting from "2 no infestation", "3 low infestation", "4 medium infestation", "5 high infestation", and "6 severe infestation". However, scenario "2 no infestation" has the highest profit compared to the other scenarios. For scenario "1 datacase", this scenario is positioned between scenarios "4 medium infestation" to "6 severe infestation" depending on their independent initial inventory case. The results of the profit depend on the probability of the sensibility of the transition matrix for these scenarios (see APPENDIX III, p.131-138). For better visualization of the results of Table 6.2, we present the graphs of the profit obtained for each stat of the AAC (see Figures 6.7-6.12).

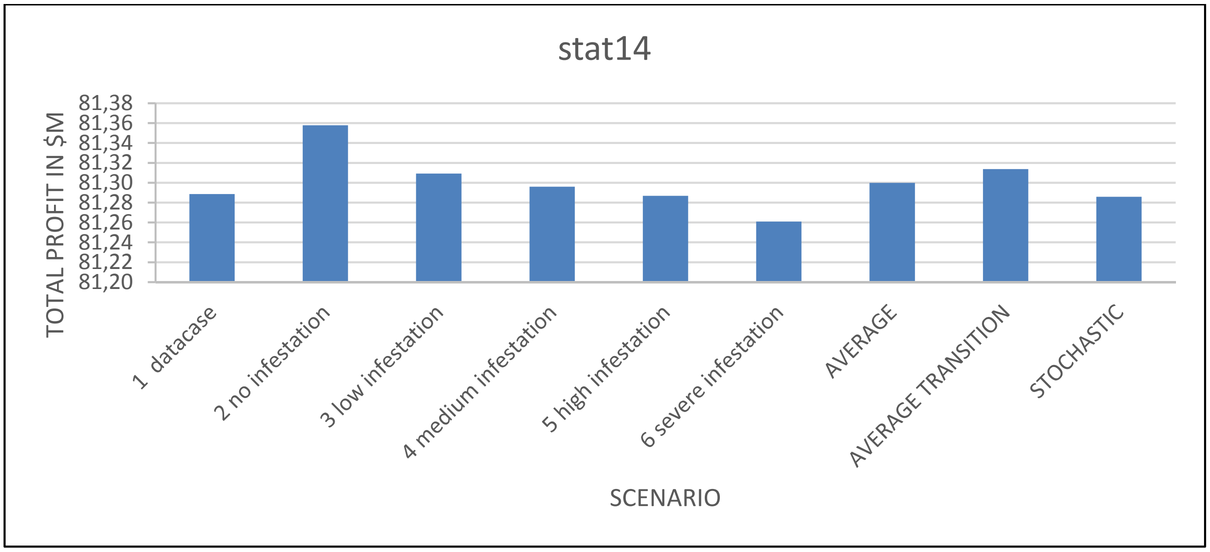

Figure 6.7 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 14 for Allowable Annual Cut (AAC) equivalent to 0.25% in $M.

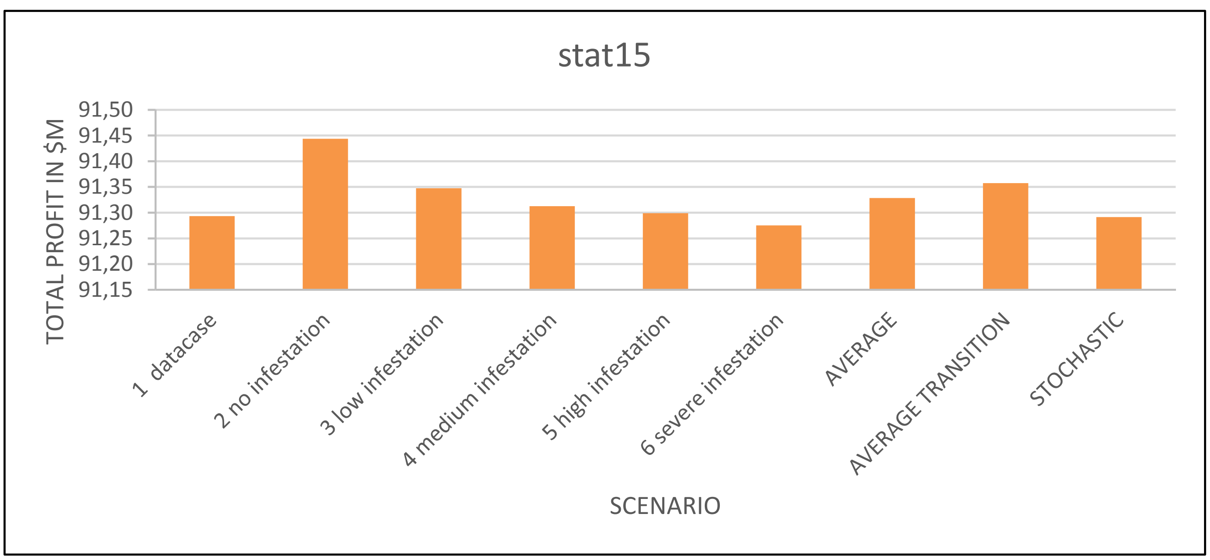

Figure 6.8 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 15 for Allowable Annual Cut (AAC) equivalent to 0.25% in $M.

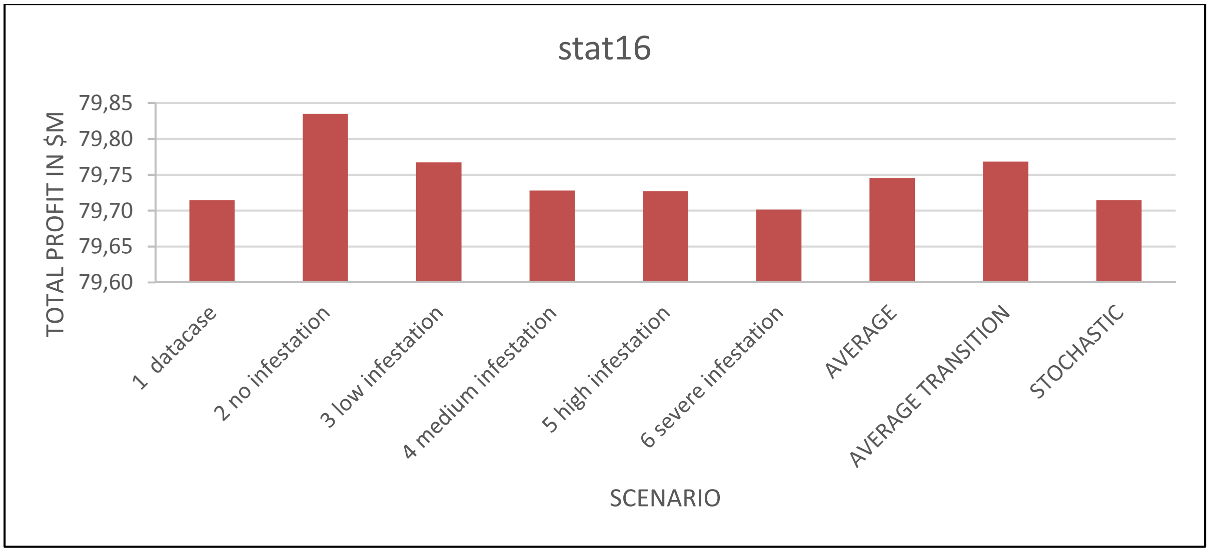

Figure 6.9 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat16 for Allowable Annual Cut (AAC) equivalent to 0.25%. in $M

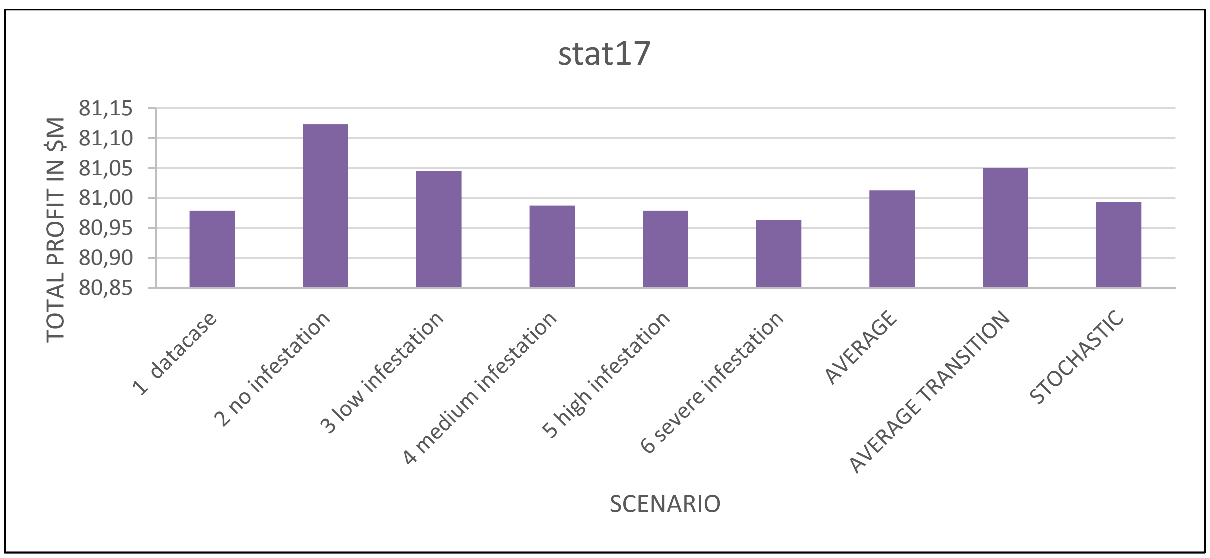

Figure 6.10 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 17 for Allowable Annual Cut (AAC) equivalent to 0.25% in $M.

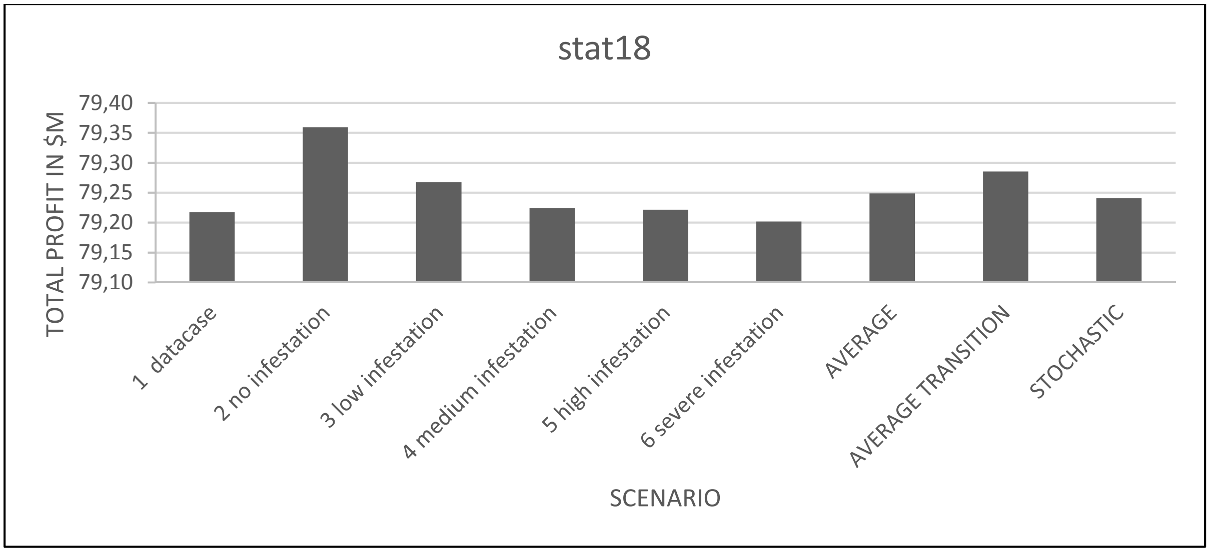

Figure 6.11 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 18 for Allowable Annual Cut (AAC) equivalent to 0.25% in $M.

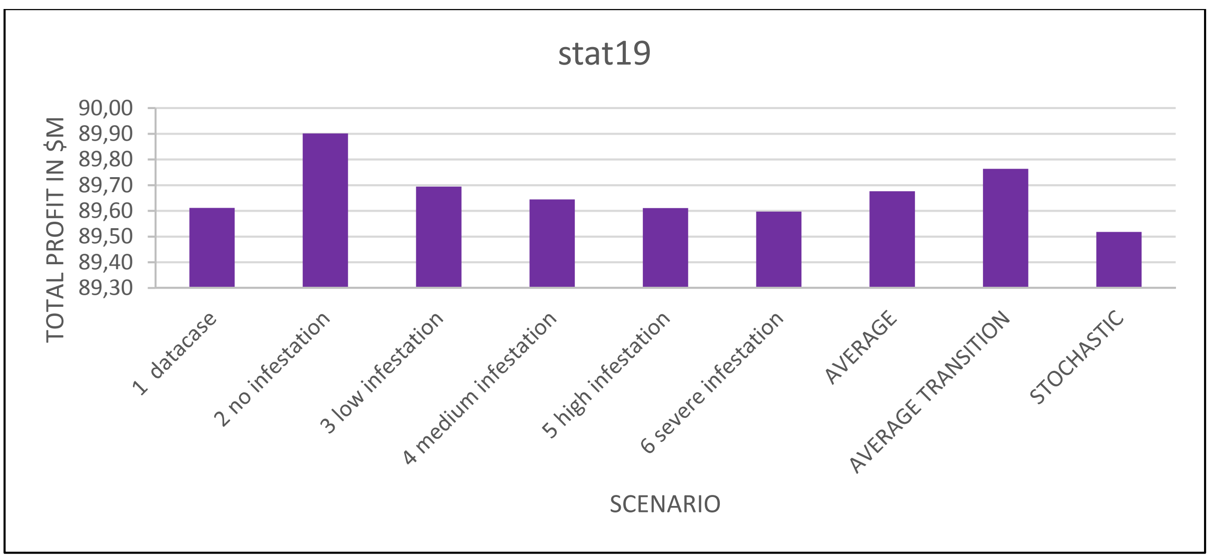

Figure 6.12 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 19 for Allowable Annual Cut (AAC) equivalent to 0.25% in $M.

6.1.3 Case of AAC equivalent to 0.50% of forest inventory

In this section, we present the results of each scenario per initial stat case of AAC equivalent to 0.50% of initial forest inventory. We solved for all the possible realizations of scenarios (see Table 6.3). The row “AVERAGE” means the expected value of the six scenarios considered as Wait-and-See solutions (WS) of deterministic models. The row “AVERAGE TRANSITION” consists of using as data, the average of the uncertain parameter (average of all transition matrices) and solving it deterministically. Finally, the row “STOCHASTIC” means applying and integrating all the possible scenarios into one DEM formulation for solving Two-Stage SP model.

Table 6.3 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP per stat for AAC equivalent to 0.50% in CAD.

AAC equivalent to 0.50% of initial forest inventory						
	stat14	**stat15**	**stat16**	**stat17**	**stat18**	**stat19**
1 datacase	161,594,831	181,046,009	158,477,303	160,967,614	157,470,965	177,654,911
2 no infestation	161,753,738	181,434,045	158,716,261	161,283,928	157,778,139	178,368,779
3 low infestation	161,659,439	181,196,536	158,581,277	161,113,016	157,592,300	177,699,203
4 medium infestation	161,613,589	181,103,735	158,503,600	160,993,308	157,487,654	177,664,741
5 high infestation	161,594,576	181,053,477	158,503,137	160,990,873	157,483,418	177,647,670
6 severe infestation	161,549,210	181,001,230	158,430,517	160,925,227	157,432,897	177,612,674
AVERAGE	**161,627,564**	**181,139,172**	**158,535,349**	**161,045,661**	**157,540,895**	**177,774,663**
AVERAGE TRANSITION	**161,659,997**	**181,162,481**	**158,601,752**	**161,141,147**	**157,629,745**	**178,011,082**
STOCHASTIC	**161,561,824**	**181,021,929**	**158,487,989**	**161,004,914**	**157,475,619**	**177,321,104**

As seen in Section 6.1.2, we can observe in the results for case of AAC equivalent to 0.50% of initial forest inventory with their respective initial “stat” in Table 6.3 that the profit of the scenarios decreases starting from “2 no infestation”, “3 low infestation”, “4 medium infestation”, “5 high infestation”, and “6 severe infestation.” However, scenario “2 no infestation” has the highest profit compared to the other scenarios. For the scenario “1 datacase”, this scenario is positioned between scenarios “4 medium infestation” to “6 severe infestation” depending on their independent initial inventory case. The results of the profit depend on the probability of the sensibility of the transition matrix for these scenarios (see APPENDIX III, p.131-138). For better visualization of the results of Table 6.3, we present the graphs of the profit obtained for each stat of the AAC (see Figures 6.13-6.18).

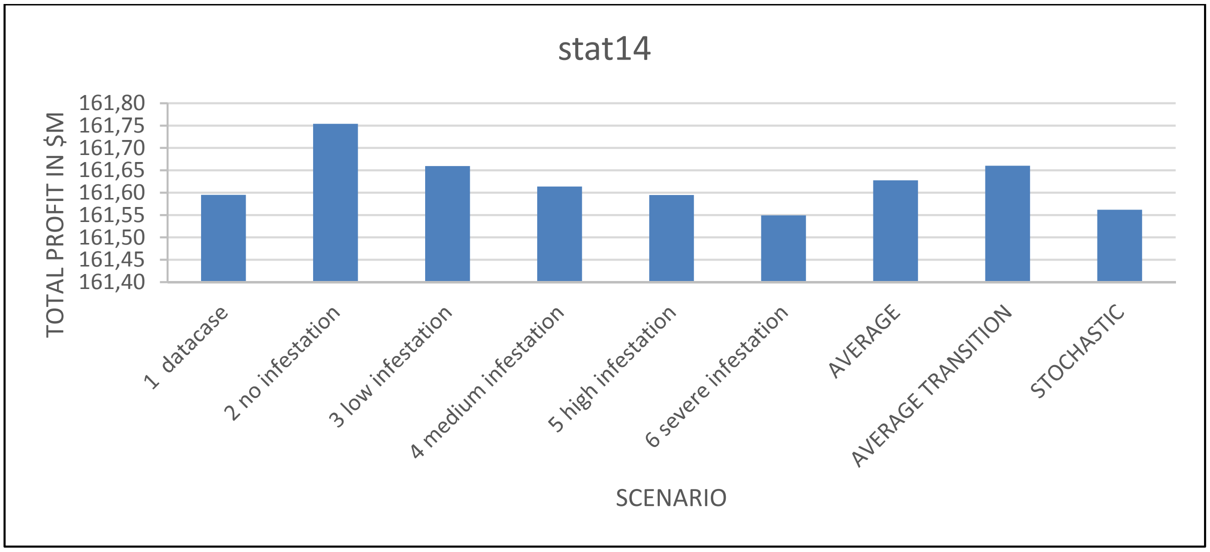

Figure 6.13 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 14 for Allowable Annual Cut (AAC) equivalent to 0.50% in $M.

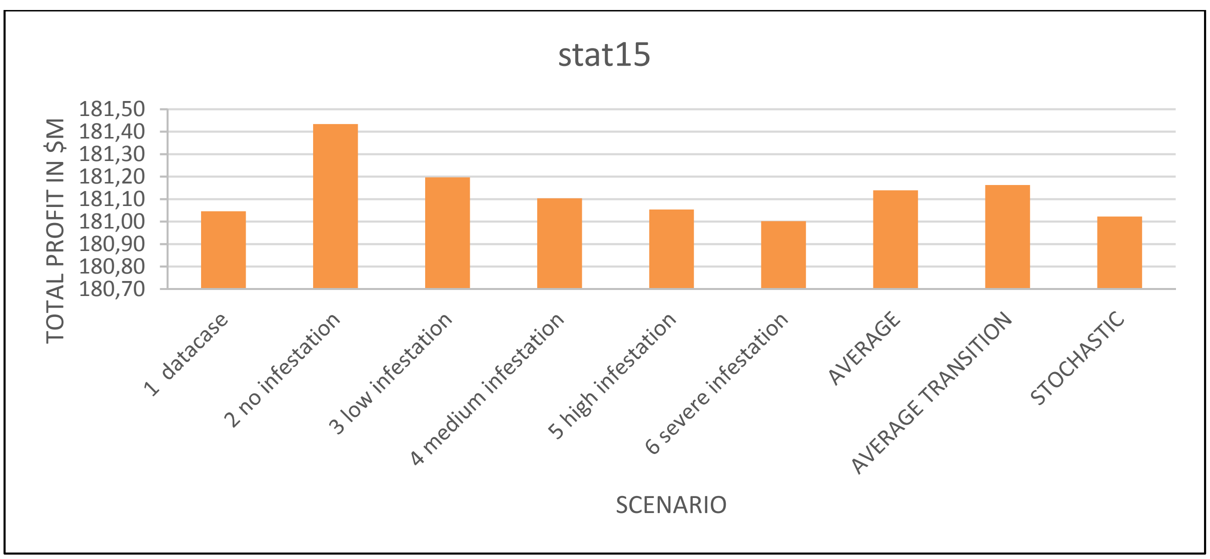

Figure 6.14 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 15 for Allowable Annual Cut (AAC) equivalent to 0.50% in $M.

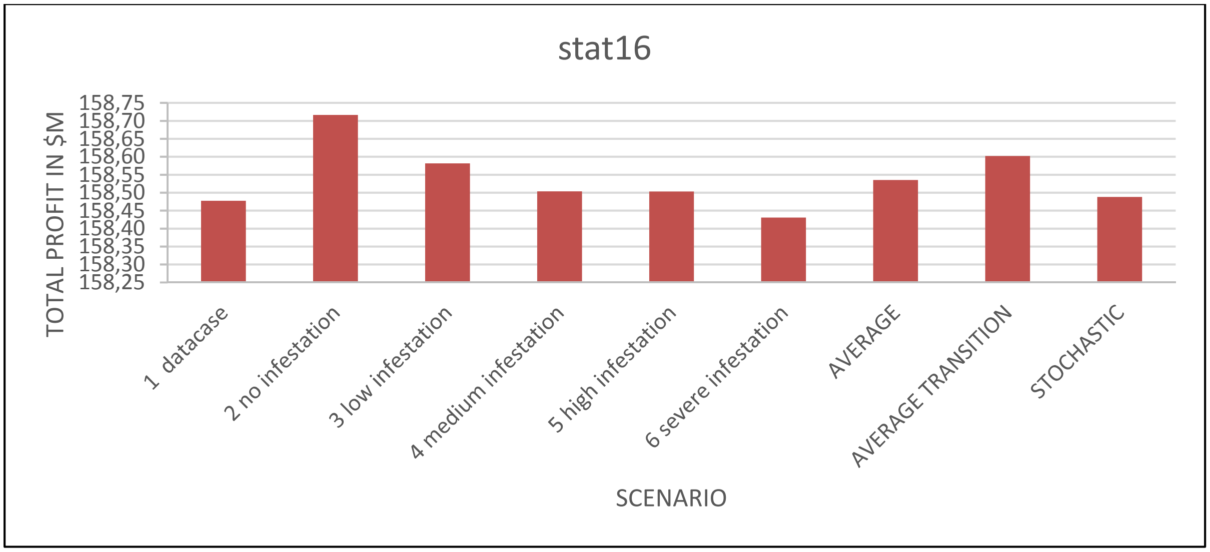

Figure 6.15 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 16 for Allowable Annual Cut (AAC) equivalent to 0.50% in $M.

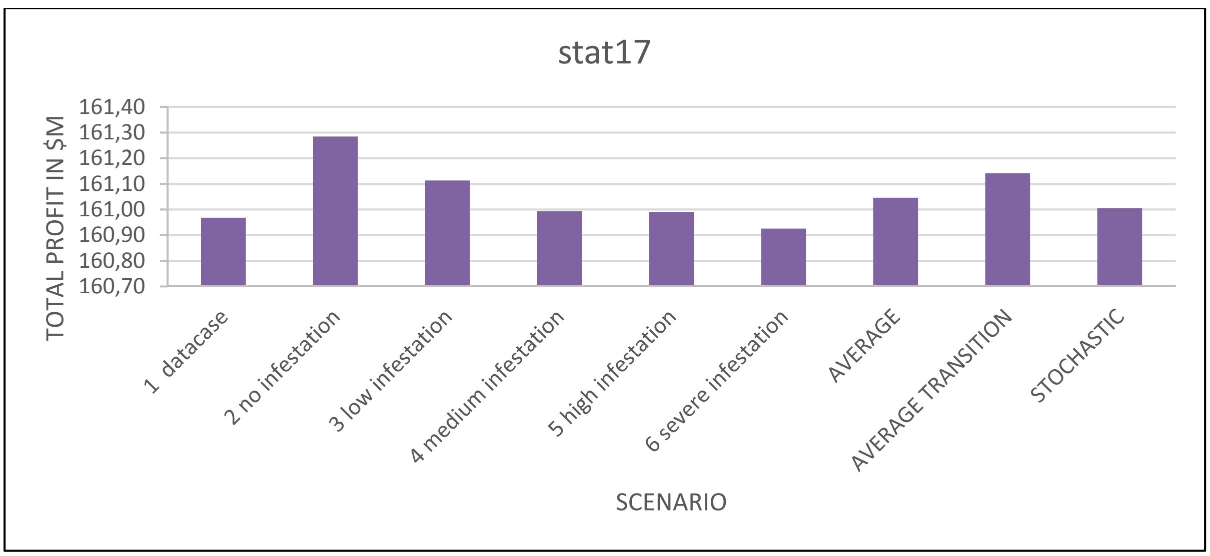

Figure 6.16 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 17 for Allowable Annual Cut (AAC) equivalent to 0.50% in $M.

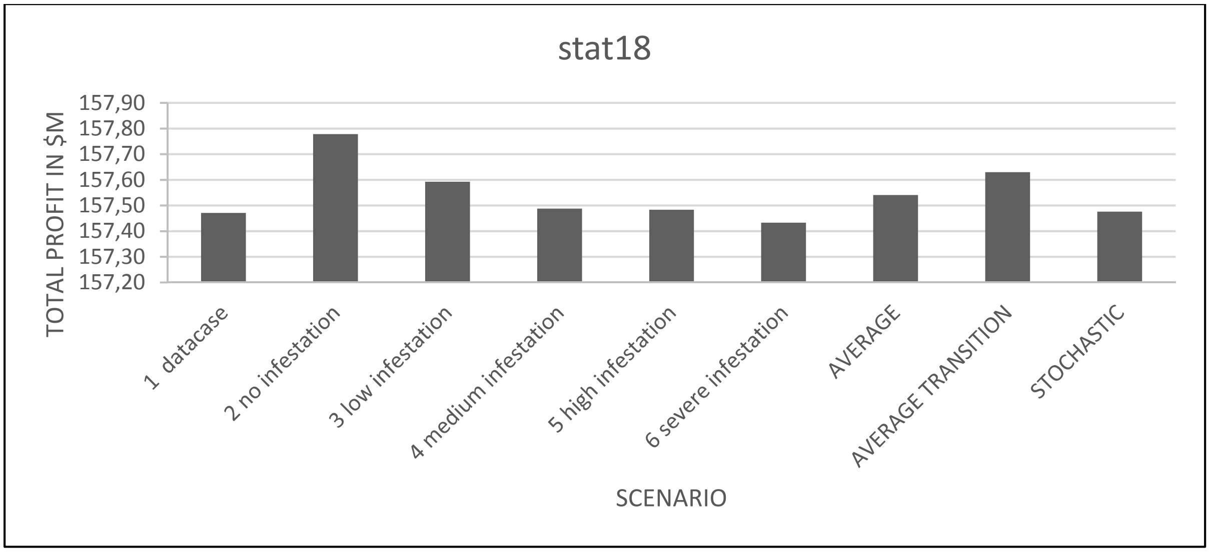

Figure 6.17 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 18 for Allowable Annual Cut (AAC) equivalent to 0.50% in $M.

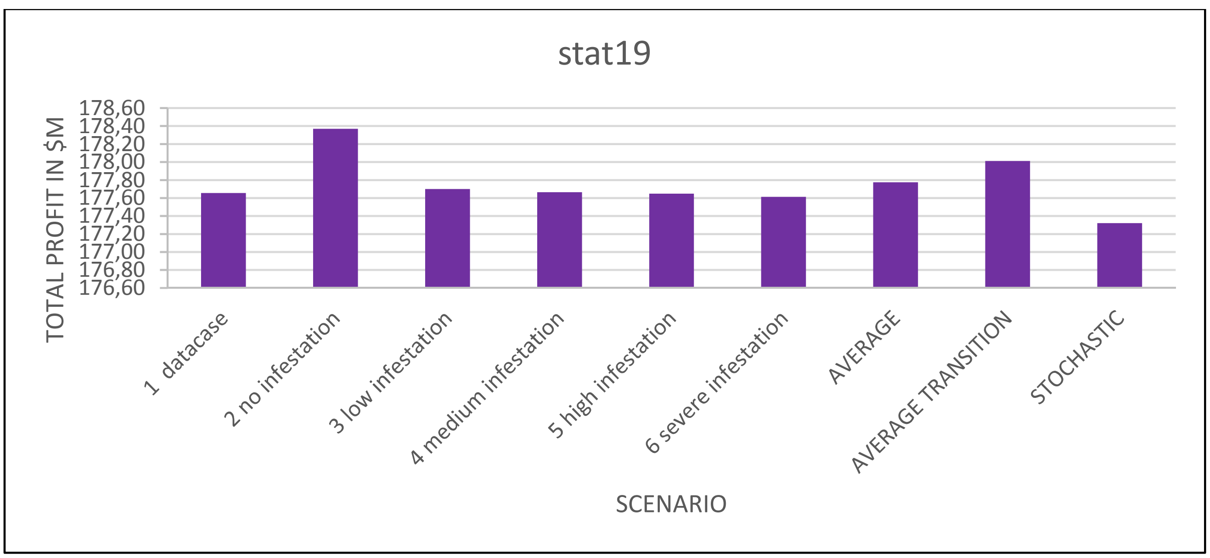

Figure 6.18 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 19 for Allowable Annual Cut (AAC) equivalent to 0.50% in $M.

6.1.4 Case of AAC equivalent to 1% of forest inventory

In this section, we present the results of each scenario per initial stat case of AAC equivalent to 1% of initial forest inventory. We solved for all the possible realizations of scenarios (see Table 6.4). The row "AVERAGE" means the expected value of the six scenarios considered as Wait-and-See solutions (WS) of deterministic models. The row "AVERAGE TRANSITION" consists of using as data, the average of the uncertain parameter (average of all transition matrices) and solve it deterministically. Finally, the row "STOCHASTIC" means applying and integrating all the possible scenarios into one DEM formulation for solving Two-Stage SP model.

Table 6.4 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP per stat for AAC equivalent to 1% in CAD.

AAC equivalent to 1% of initial forest inventory						
	stat14	**stat15**	**stat16**	**stat17**	**stat18**	**stat19**
1 datacase	321,151,214	358,794,230	314,947,270	319,929,356	312,960,170	351,915,321
2 no infestation	321,563,868	359,771,559	315,545,194	320,635,721	313,691,756	353,734,160
3 low infestation	321,306,932	359,168,383	315,161,850	320,163,844	313,188,389	352,217,462
4 medium infestation	321,196,860	358,844,440	315,012,365	319,978,327	313,010,503	352,020,687
5 high infestation	321,167,442	358,758,850	314,967,561	319,959,922	312,963,412	351,735,156
6 severe infestation	321,048,328	358,648,219	314,910,787	319,854,818	312,906,556	351,474,512
AVERAGE	**321,239,107**	**358,997,613**	**315,090,838**	**320,086,998**	**313,120,131**	**352,182,883**
AVERAGE TRANSITION	**321,323,699**	**359,221,648**	**315,217,986**	**320,263,679**	**313,312,753**	**352,824,770**
STOCHASTIC	**321,173,662**	**358,811,433**	**315,044,550**	**319,980,752**	**312,978,723**	**352,150,579**

As seen in Section 6.1.3, we can observe the results for case of AAC equivalent to 1% of initial forest inventory with their respective initial "stat" in Table 6.4 that the profit of the scenarios decreases starting from "2 no infestation", "3 low infestation", "4 medium infestation", "5 high infestation", and "6 severe infestation." However, scenario "2 no infestation" has the highest profit compared to the other scenarios. For scenario "1 datacase", this scenario is positioned between scenarios "4 medium infestation" to "6 severe infestation" depending on their independent initial inventory case. The results of the profit depend on the probability of the sensibility of the transition matrix for these scenarios (see APPENDIX III, p.131-138). For better visualization of the results of Table 6.4, we present the graphs of the profit obtained for each stat of the AAC (see Figures 6.19-6.24).

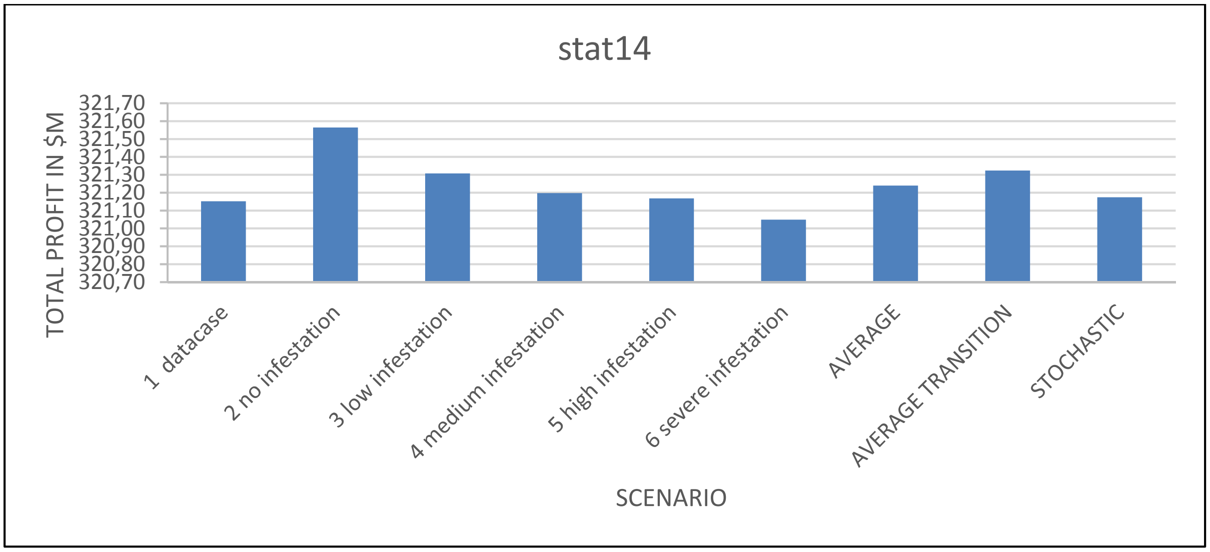

Figure 6.19 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 14 for Allowable Annual Cut (AAC) equivalent to 1% in $M.

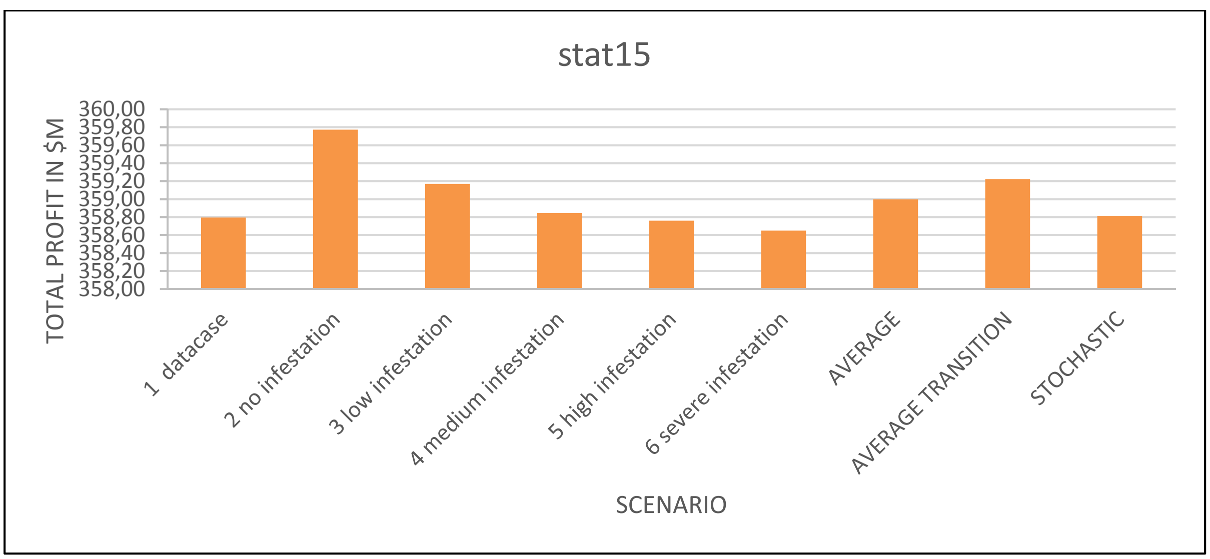

Figure 6.20 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 15 for Allowable Annual Cut (AAC) equivalent to 1% in $M.

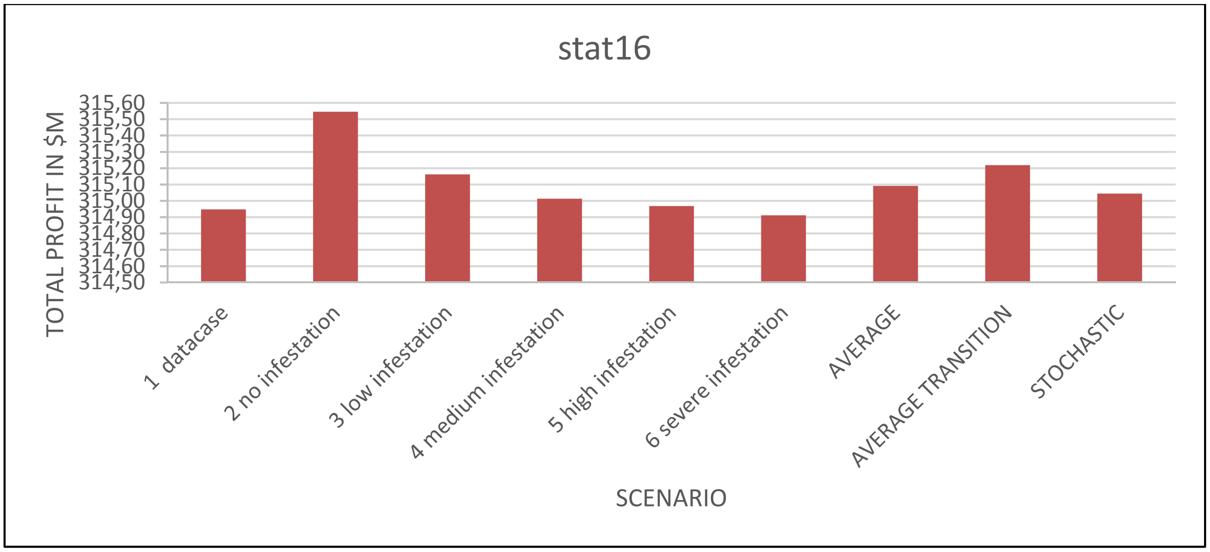

Figure 6.21 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 16 for Allowable Annual Cut (AAC) equivalent to 1% in $M.

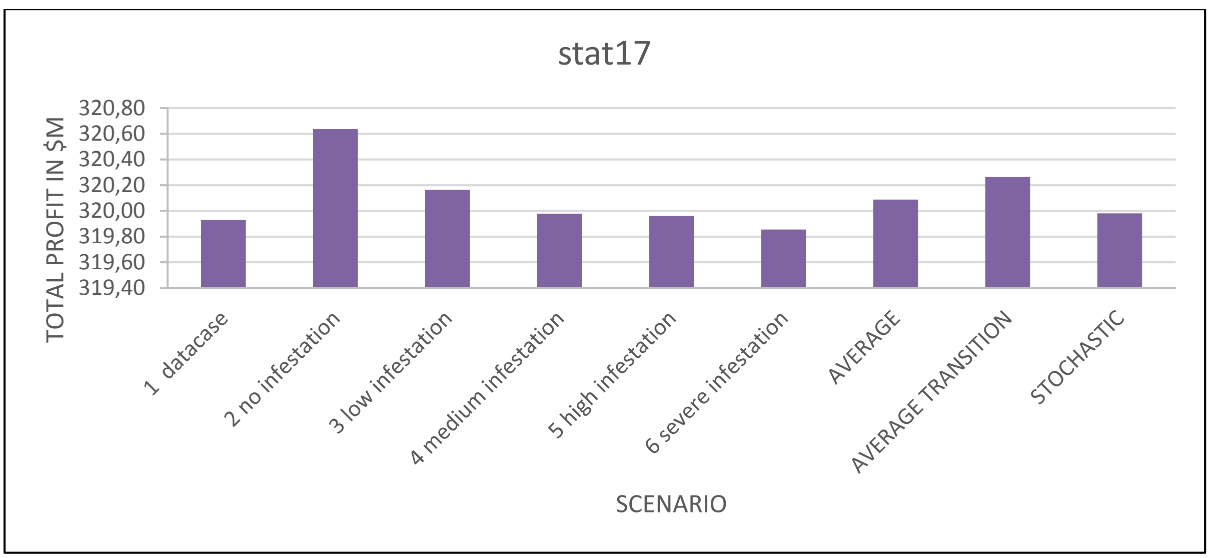

Figure 6.22 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 17 for Allowable Annual Cut (AAC) equivalent to 1% in $M.

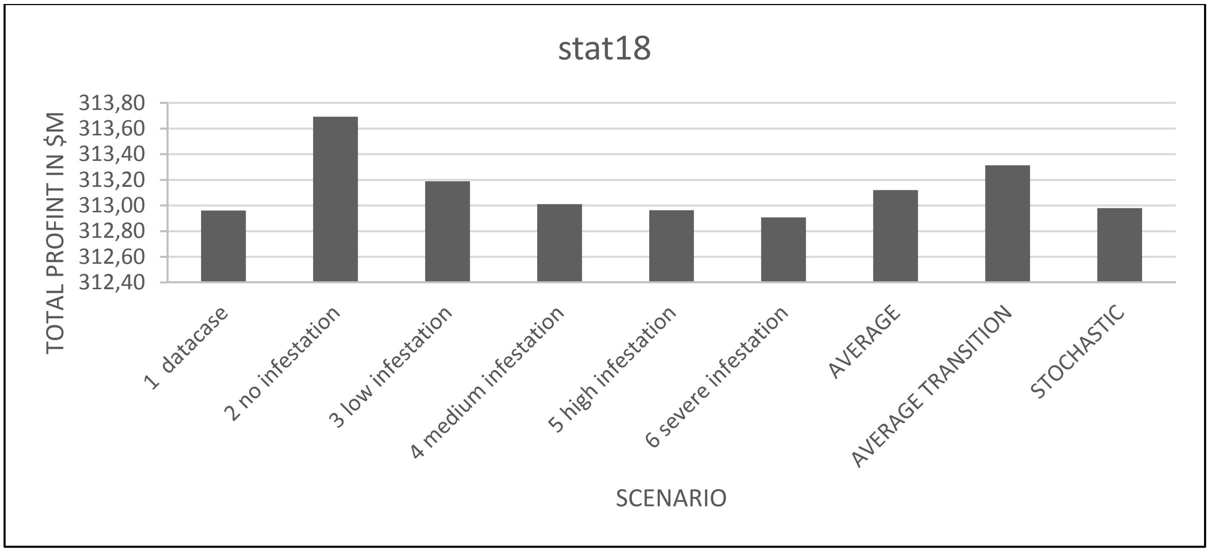

Figure 6.23 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 18 for Allowable Annual Cut (AAC) equivalent to 1% in $M.

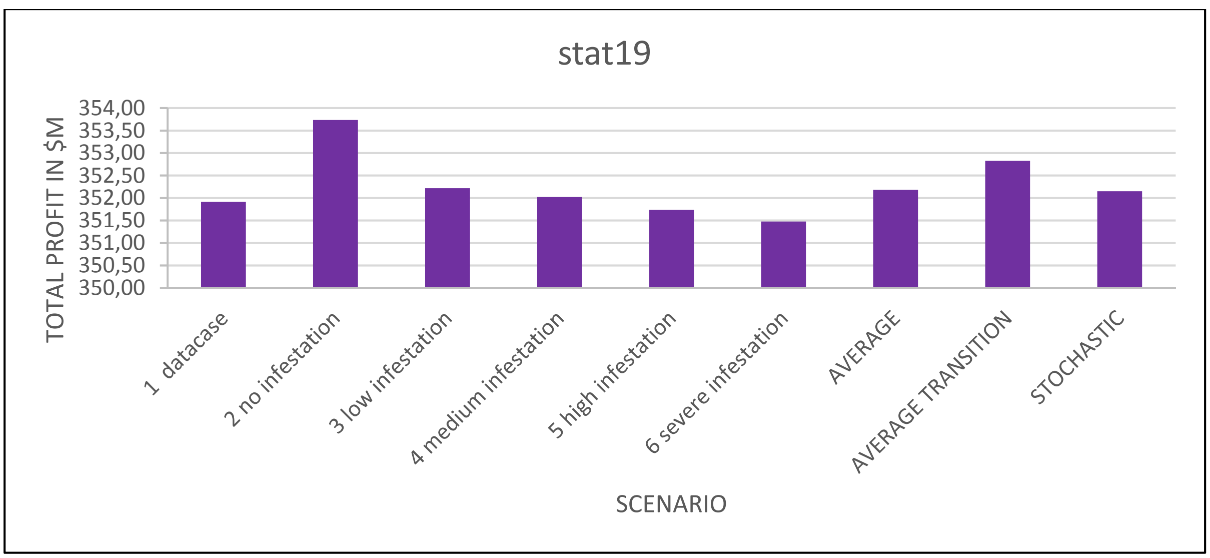

Figure 6.24 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 19 for Allowable Annual Cut (AAC) equivalent to 1% in $M.

6.1.5 Case of AAC equivalent to 2% of forest inventory

In this section, we present the results of each scenario per initial stat case of AAC equivalent to 2% of initial forest inventory. We solved for all the possible realizations of scenarios (see Table 6.5). The row “AVERAGE” means the expected value of the six scenarios considered as Wait-and-See solutions (WS) of deterministic models. The row “AVERAGE TRANSITION” consists of using as data, the average of the uncertain parameter (average of all transition matrices) and solve it deterministically. Finally, the row “STOCHASTIC” means applying and integrating all the possible scenarios into one DEM formulation for solving Two-Stage SP model.

Table 6.5 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP per stat for AAC equivalent to 2% in CAD.

AAC equivalent to 2% of initial forest inventory						
	stat14	**stat15**	**stat16**	**stat17**	**stat18**	**stat19**
1 datacase	638,144,680	709,932,847	625,795,015	635,603,802	621,694,119	695,832,278
2 no infestation	638,967,175	712,528,233	627,006,952	637,107,152	623,324,933	700,557,253
3 low infestation	638,437,420	710,974,064	626,000,680	636,105,281	622,121,127	697,564,706
4 medium infestation	638,210,677	710,281,164	625,899,840	635,720,376	621,779,328	696,558,171
5 high infestation	638,137,709	709,913,179	625,855,647	635,548,659	621,676,670	695,857,382
6 severe infestation	637,908,017	709,649,078	625,663,662	635,410,438	621,605,685	694,714,619
AVERAGE	**638,300,946**	**710,546,427**	**626,036,966**	**635,915,951**	**622,033,644**	**696,847,401**
AVERAGE TRANSITION	**638,456,909**	**711,128,935**	**626,326,712**	**636,311,042**	**622,499,476**	**698,268,245**
STOCHASTIC	**638,182,972**	**710,138,965**	**625,932,153**	**635,788,794**	**621,984,293**	**696,566,567**

As seen in Section 6.1.4, we can observe in the results for case of AAC equivalent to 2% of initial forest inventory with their respective initial “stat” in Table 6.5 that the profit of the scenarios decreases starting from “2 no infestation”, “3 low infestation”, “4 medium infestation”, “5 high infestation”, and “6 severe infestation.” However, scenario “2 no infestation” has the highest profit compared to the other scenarios. For the scenario “1 datacase”, this scenario is positioned between scenarios “4 medium infestation” to “6 severe infestation” depending on their independent initial inventory case. The results of the profit depend on the probability of the sensibility of the transition matrix for these scenarios (see APPENDIX III, p.131-138). For better visualization of the results of Table 6.5, we present the graphs of the profit obtained for each stat of the AAC (see Figures 6.25-6.30).

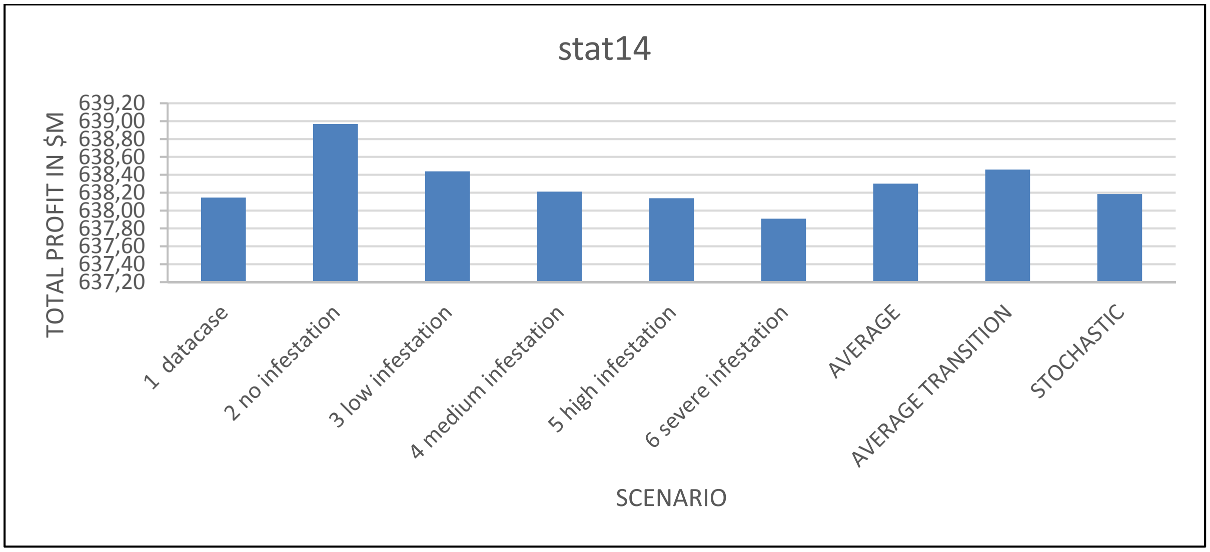

Figure 6.25 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 14 for Allowable Annual Cut (AAC) equivalent to 2% in $M.

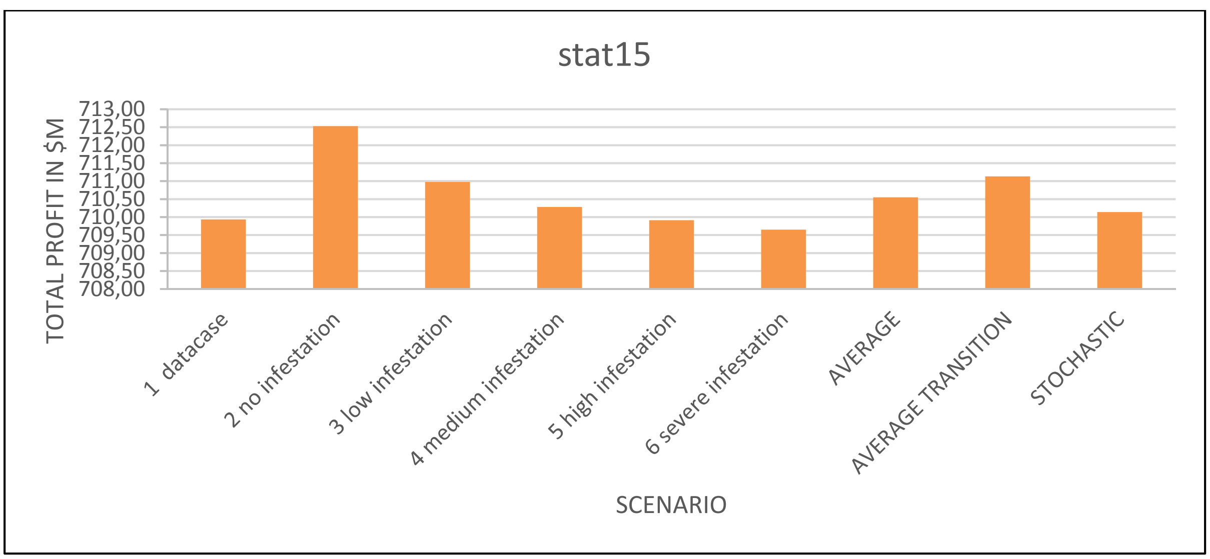

Figure 6.26 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 15 for Allowable Annual Cut (AAC) equivalent to 2% in $M.

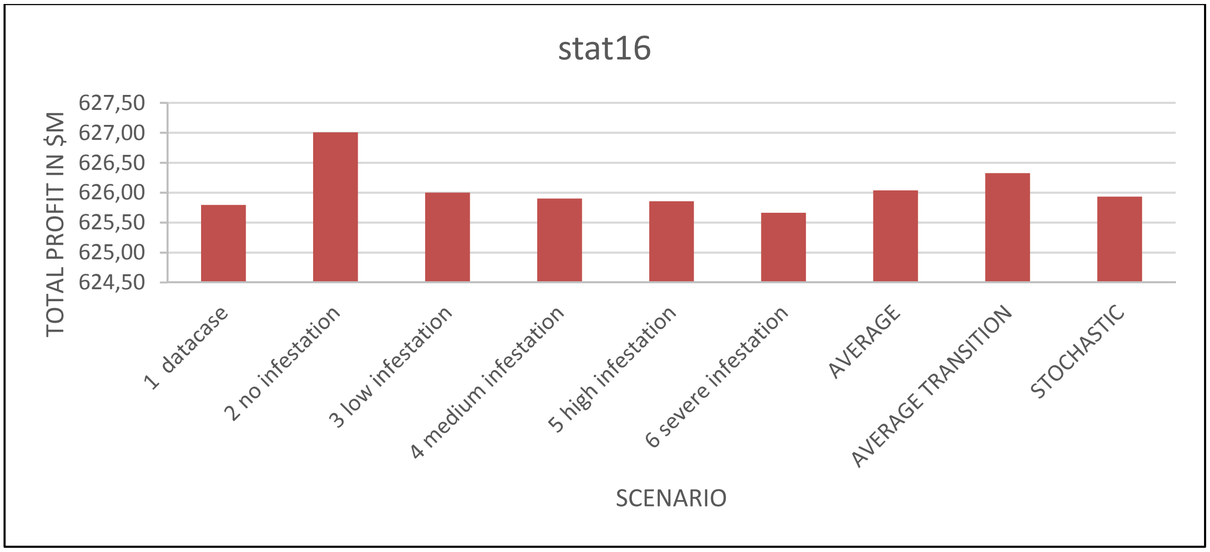

Figure 6.27 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 16 for Allowable Annual Cut (AAC) equivalent to 2% in $M.

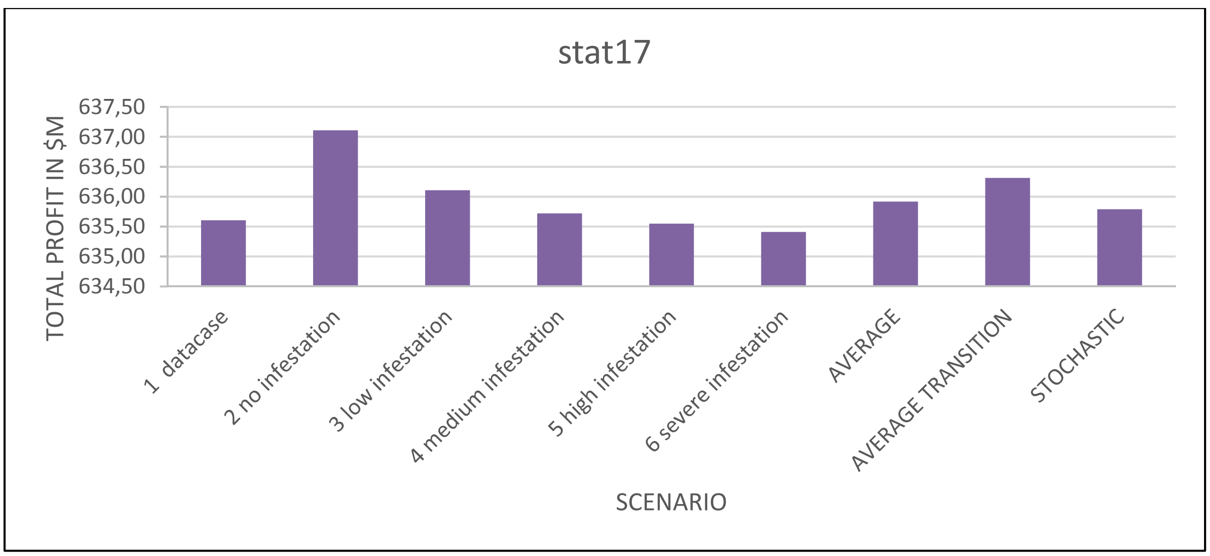

Figure 6.28 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 17 for Allowable Annual Cut (AAC) equivalent to 2% in $M.

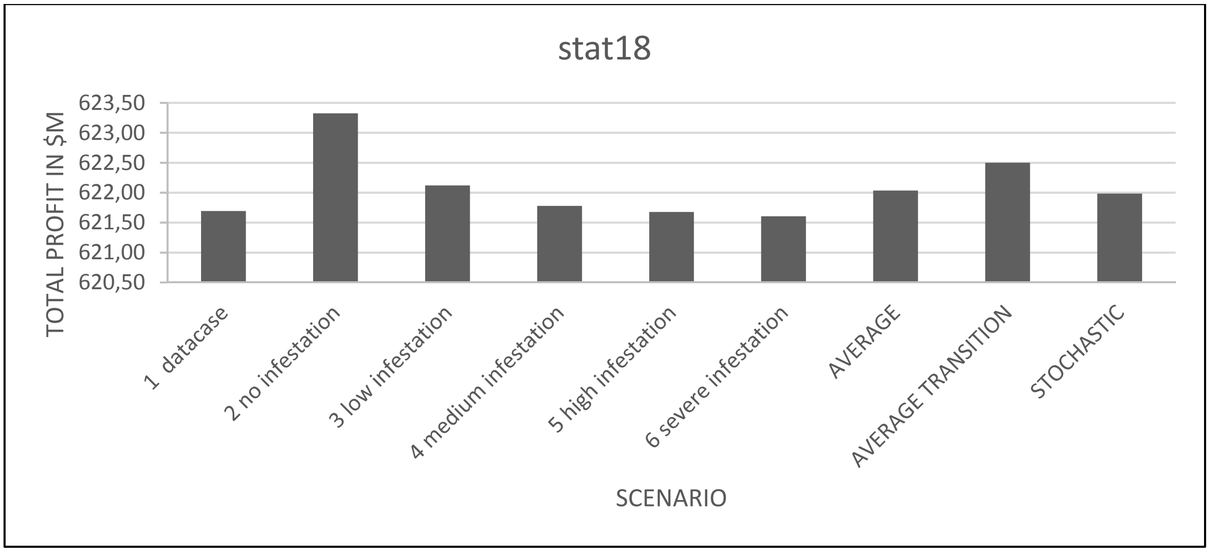

Figure 6.29 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 18 for Allowable Annual Cut (AAC) equivalent to 2% in $M.

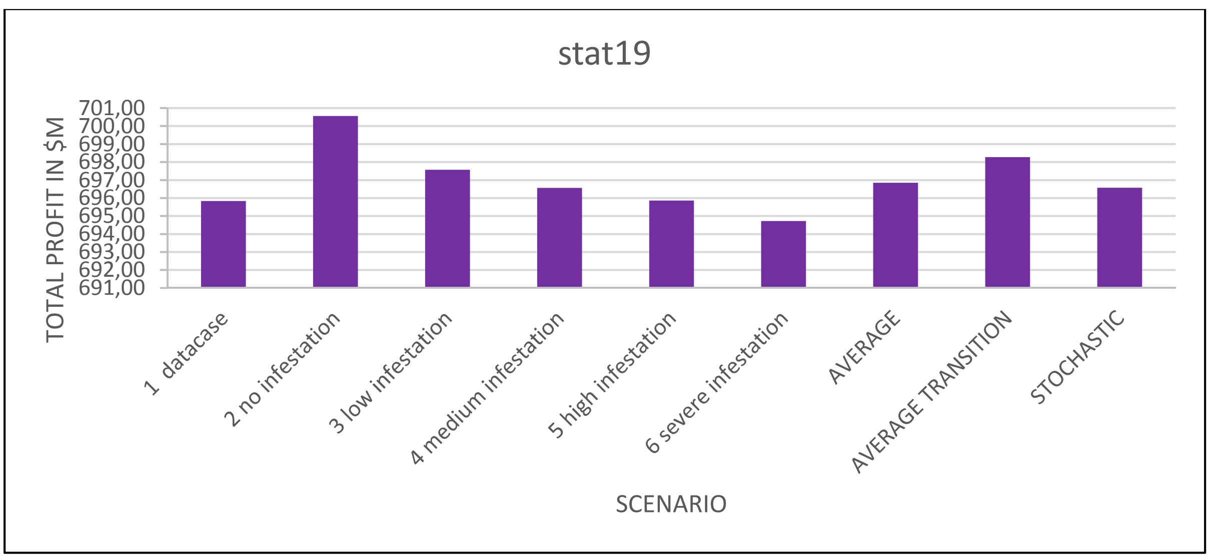

Figure 6.30 Total profit of deterministic per scenario, average of transition matrix and Two-Stage SP for stat 19 for Allowable Annual Cut (AAC) equivalent to 2% in $M.

6.2 First-Stage decision variable: Opening Harvesting Areas

The following tables present the number of harvest areas that are cut per period when solving for each scenario (this is considered as first-stage solution), deterministic average of transition matrix and when solving for Stochastic Programming. Each table is solved for different cases or stat and even if we consider initially 21,410 aggregated forest stands, most of them are considered as zero m^3 as there are other types of species that are not White Spruce, Balsam Fir, and Black Spruce. The more detailed number of the results of this first-stage decision variable of knowing the quantity of forest stands opened are observed in APPENDIX VII, p.151-158.

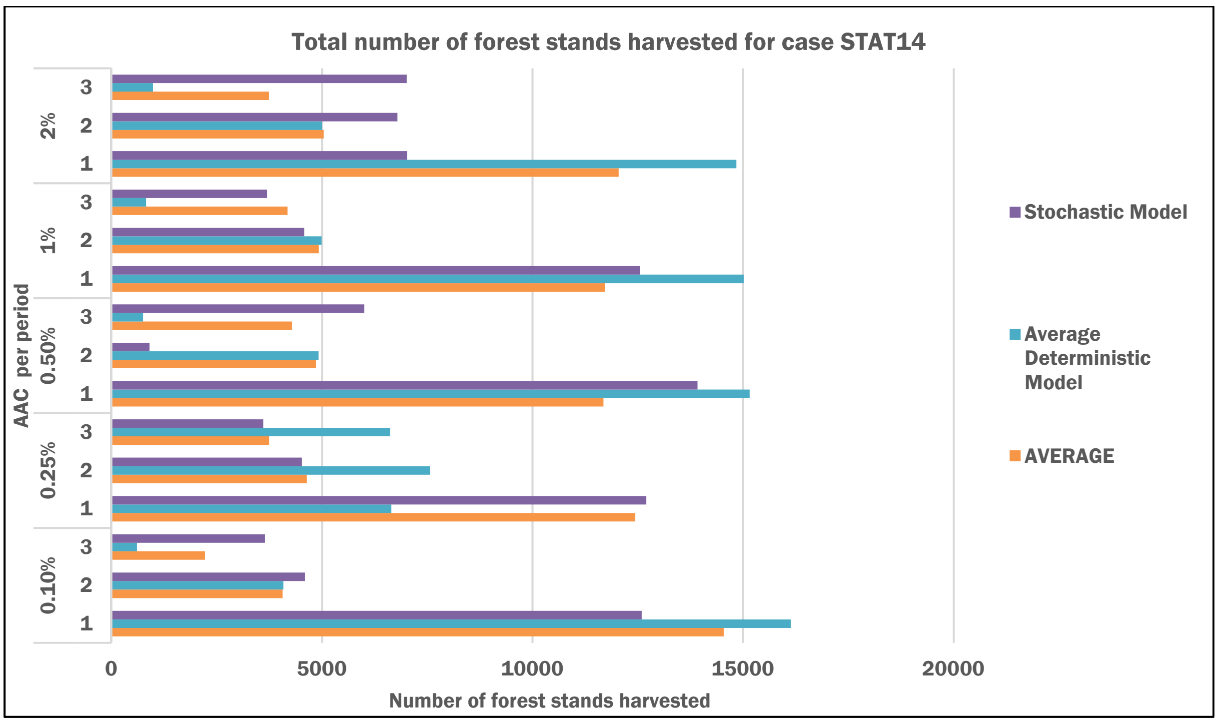

Figure 6.31 Total number of forest stands harvested for stat14 for all percentages of AAC for each period for deterministic, average transition matrix and Stochastic Programming.

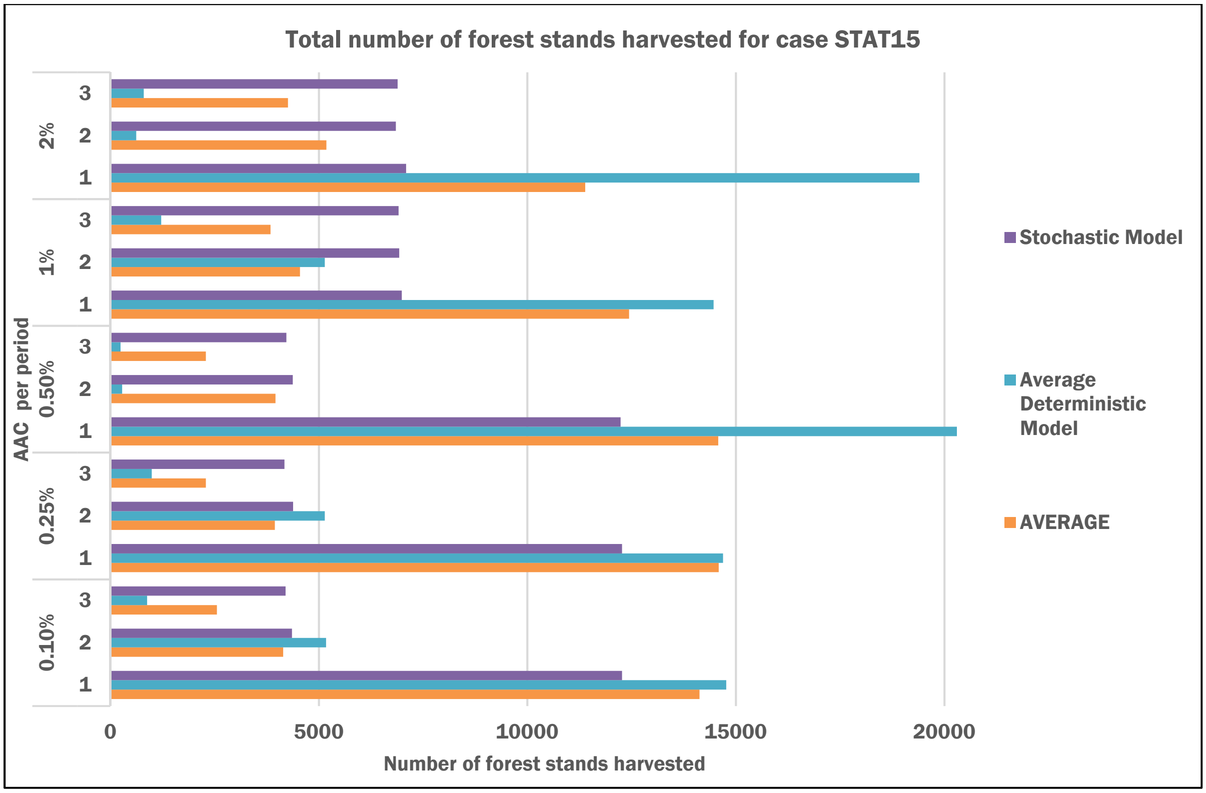

Figure 6.32 Total number of forest stands harvested for stat15 for all percentages of AAC for each period for deterministic, average transition matrix and Stochastic Programming.

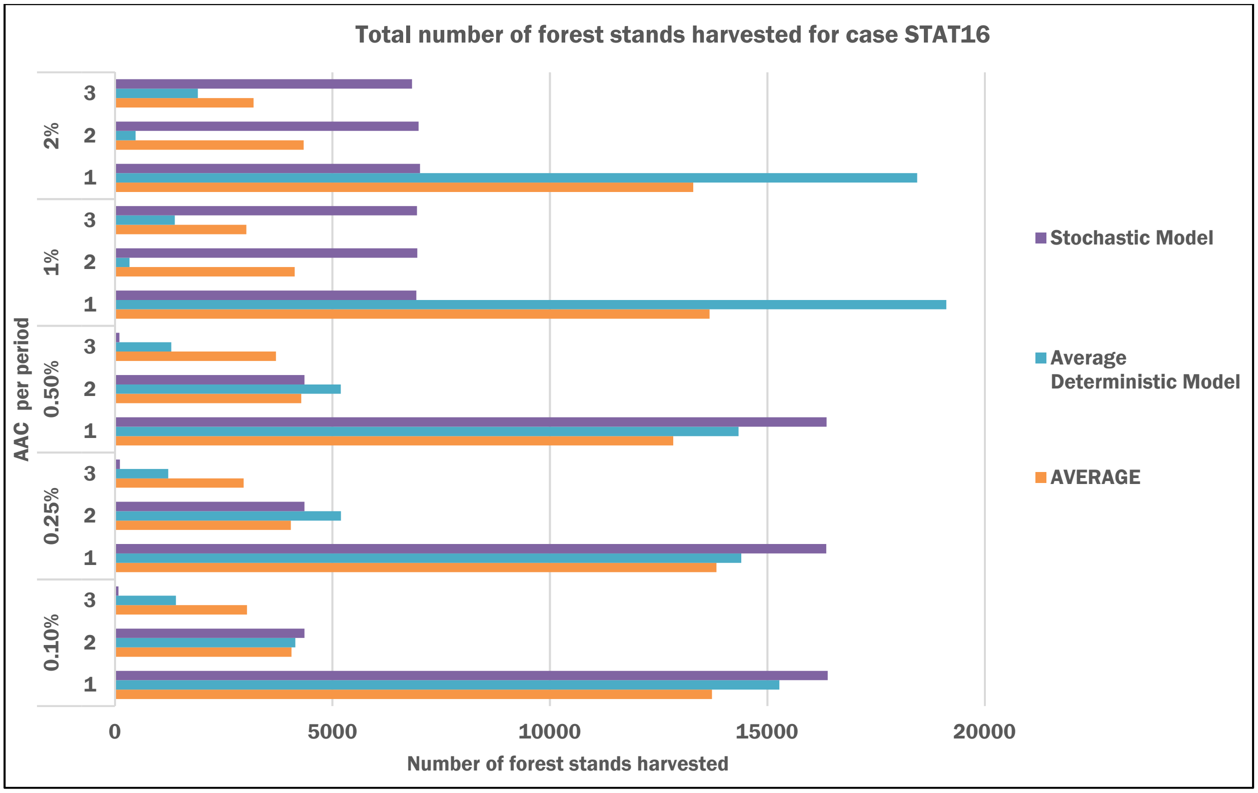

Figure 6.33 Total number of forest stands harvested for stat16 for all percentages of AAC for each period for deterministic, average transition matrix and Stochastic Programming.

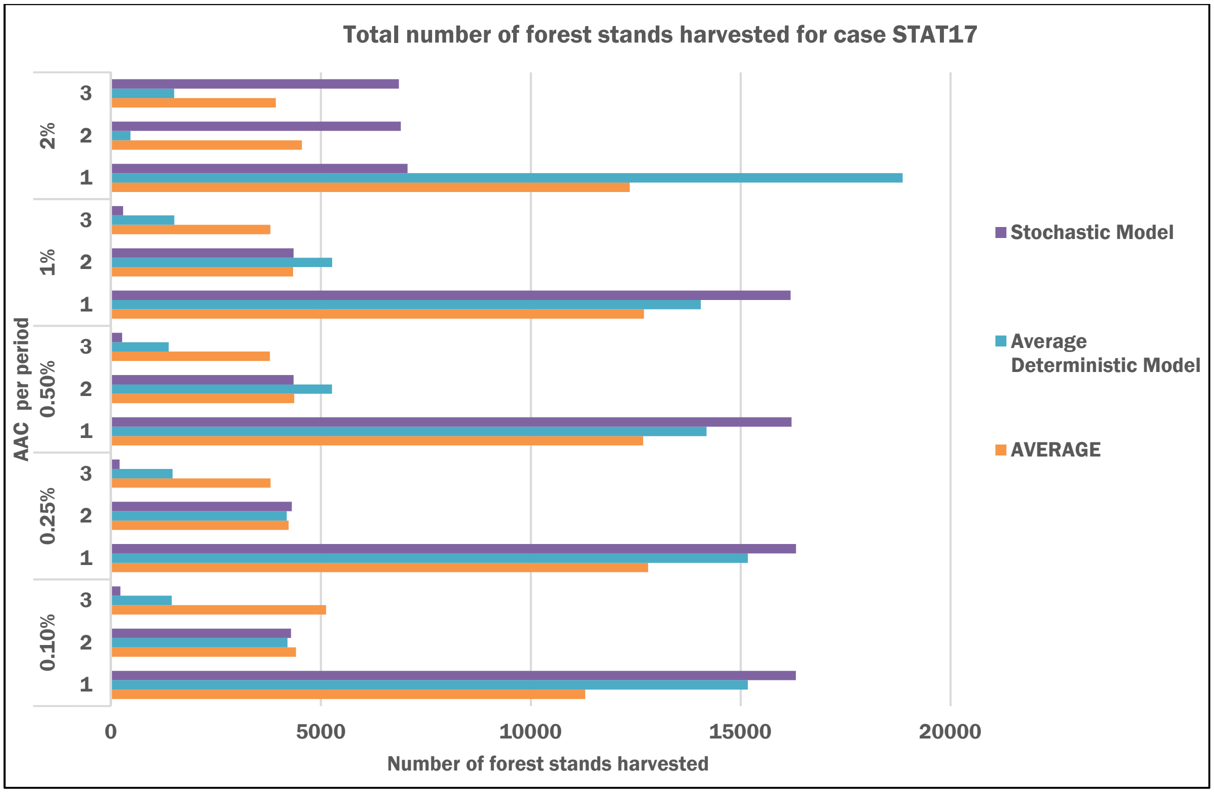

Figure 6.34 Total number of forest stands harvested for stat17 for all percentages of AAC for each period for deterministic, average transition matrix and Stochastic Programming.

As there is no result found for solving the Two-Stage SP model for stat18, the quantity for forest stands opened for Figure 6.35, for the case of AAC equivalent to 0.10% of initial forest inventory, is unknown.

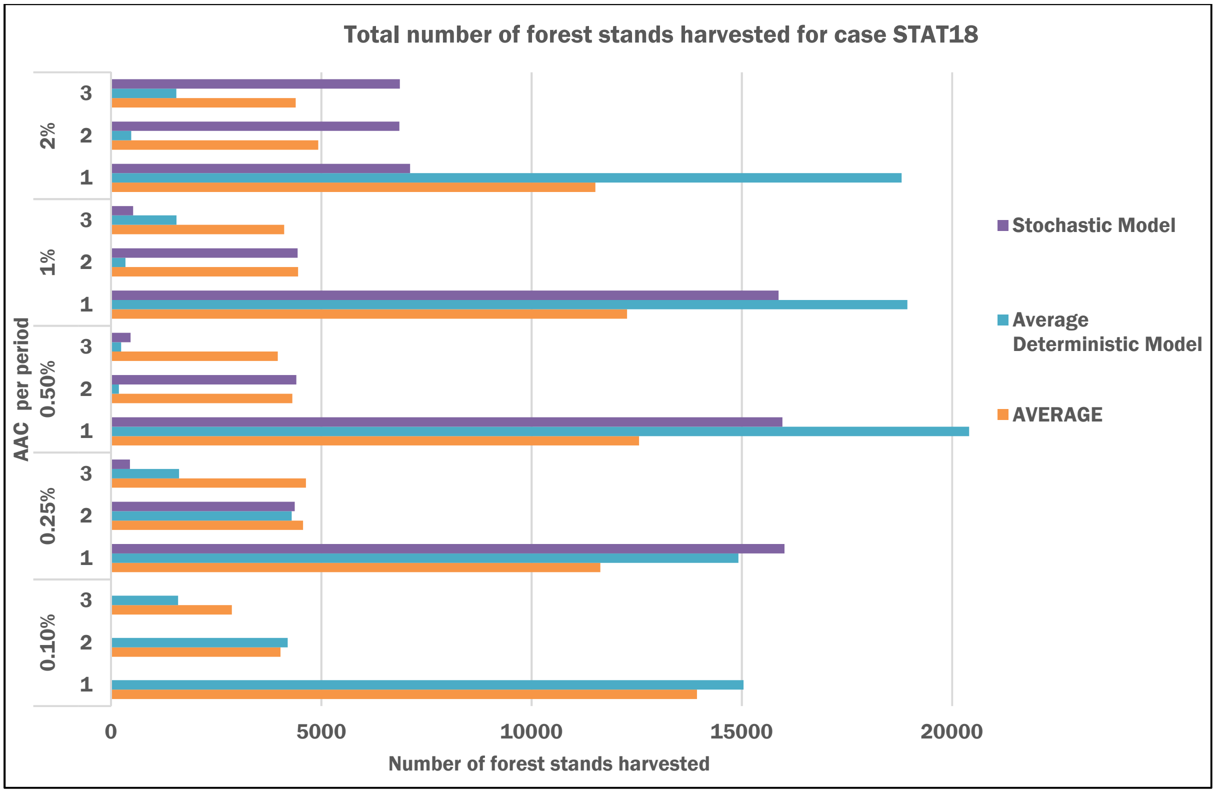

Figure 6.35 Total number of forest stands harvested for stat18 for all percentages of AAC for each period for deterministic, average transition matrix and Stochastic Programming.

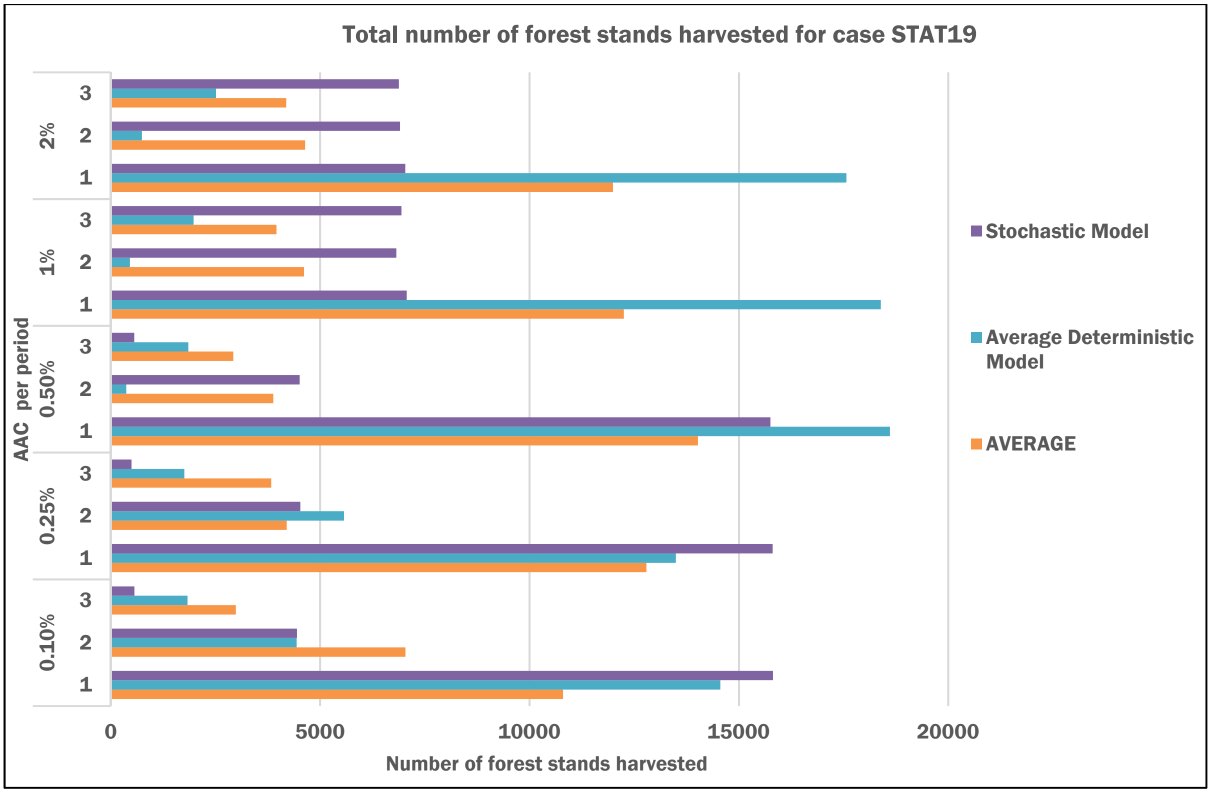

Figure 6.36 Total number of forest stands harvested for stat19 for all percentages of AAC for each period for deterministic, average transition matrix and Stochastic Programming.

6.3 Second-Stage decision variable: Volume of Forest Stands

In this section, we will show the results of the amount of volume of forest stands per cubic meter (m^3) times the value of the bloc or the forest stand according to their final transition phase at the end of the third period for the deterministic models (see APPENDIX VIII, p.159-188). We will show these results to verify that the proposed model works for the applied case study, considering the tracing of the inventory information. The total value of the inventory at the end of the planning horizon explains how much value is left for each infestation phase. This amount will be shown according to the percentage of AAC, per their initial "stat" and per tree species.

In this Chapter, we have shown the results of the profit for all the cases with their respective AAC for the deterministic and Two-Stage SP as well as the values obtained for the first-stage and second-stage decision variables for the deterministic optimization models. In the next Chapter, we will discuss the results obtained and the insights of these (objective value and the decision variables) corresponding to the applied case study.

CHAPTER 7

ANALYSIS OF THE OPTIMIZATION MODELS

7.1 Insights of the Harvesting Planning Models

As we can see from Tables 6.1-6.5 and Figures 6.1-6.30 of Chapter 6, for the profits between the scenarios for each stat with their respective AAC, the values are very close and they do not show how much value or change the transition matrix can have over the results. Therefore, we analyze the value of the inventory levels at the end of the planning horizon (see APPENDIX VIII, p.159-188) to see how much Net Value of the forest inventory remains for the different scenarios even if the forest managers satisfy the demand. The difference between the scenarios for the independent cases of the demand and the initial inventory, are large as the value starts decreasing from “2 no infestation” to “6 severe infestation”, for all tree species “SAB” and “EPB.” For scenario “1 datacase” in most of the cases, the value of the inventory is positioned between scenario “3 low infestation” to “4 medium infestation”. The value for tree species “EPN” does not have a higher impact as the SBW does not have a negative impact on this specie.

Another aspect that we can see when solving for the deterministic models is that if we consider different values of the transition matrix even for one phase of infestation, the value of the profit is very sensitive as well as the values obtained for the decision variables (see Figure 6.31-6.35). For instance, the first-stage decision related to which forest stands we should harvest varies for each scenario, average and stochastic models. This is due to the susceptibility the trees have over the region to become infested by SBW.

As we discussed before and highlighted in the literature review, Chapter 2, the importance of using SP compared deterministic models, is that it will take more time to solve with what-if analysis method (deterministic models). However, we can solve all the possible scenarios in one model with SO. We also can have the best result of the decision variables as we are facing uncertainty. Compared to deterministic models, we wait until the information arrives and we make a lot of assumptions in the parameters and all solutions are different from each model. Even if we find an optimal scenario that finds the best optimal solution, it cannot satisfy or be the best scenario to choose as it is necessary to balance or hedge against the various scenarios under uncertainty. If we get the information of the probability of the transition matrix, then we will choose over scenario per scenario depending on the information received. This is the situation under perfect information.

7.2 Implementing Deterministic and Stochastic Solutions

The following tables show the results of the deterministic optimization model when we implement the first-stage solution or fix the first solution after solving the models obtained from the average transition matrix and the Two-Stage stochastic solution for obtaining better quality as we know the information. Also, if we implement or fix the first-stage solution of other scenarios and solve for the scenarios. We consider fixing the first-stage solution only for the first period out of three years, so that this will enable more flexibility for the forest manager for decision-making and thus the uncertainty they will deal with in the following years. We implement the results of the average of transition matrix and stochastic in the scenarios to calculate the EVPI and VSS mentioned in Chapter 4 and evaluate the quality of the information. We read these following tables from row to column, meaning we implement the solution of 1 datacase or stochastic or average if the uncertain parameter or transition matrix is in scenario *s*.

Table 7.1 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat14 in CAD.

stat14						
AAC equivalent to 0.10% of initial forest inventory						
For / Solution	1 datacase	2 no infestation	3 low infestation	4 medium infestation	5 high infestation	6 severe infestation
1 datacase	**32,775,508**	32,802,461	32,785,921	32,775,699	32,766,731	32,731,563
2 no infestation	32,765,374	**32,807,612**	32,776,091	32,768,791	32,760,679	32,743,690

Table 7.1 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat14 in CAD (Continued).

3 low infestation	**32,775,533**	**32,808,801**	32,788,541	**32,777,646**	**32,765,742**	**32,719,505**
4 medium infestation	32,775,686	32,808,694	32,788,096	**32,779,453**	32,769,445	32,733,022
5 high infestation	32,772,002	32,805,084	32,784,515	32,777,985	**32,773,465**	32,738,312
6 severe infestation	32,765,631	32,798,835	32,773,234	32,768,795	32,762,546	**32,761,114**
Average	**32,762,936**	**32,805,324**	**32,783,661**	**32,762,679**	**32,763,446**	**32,730,954**
Stochastic	**32,772,302**	**32,808,168**	**32,783,482**	**32,776,838**	**32,767,789**	**32,752,913**
AAC equivalent to 0.25% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**81,288,596**	81,357,965	81,313,109	81,292,299	81,265,626	81,171,033
2 no infestation	81,275,718	**81,357,768**	81,296,226	81,284,843	81,259,333	81,196,272
3 low infestation	81,288,736	81,356,498	**81,309,184**	81,295,285	81,267,529	81,185,782
4 medium infestation	81,287,355	81,360,932	81,311,726	**81,295,934**	81,275,749	81,222,377
5 high infestation	81,286,252	81,360,676	81,307,197	81,290,378	**81,286,817**	81,232,268
6 severe infestation	81,264,700	81,341,833	81,283,370	81,275,153	81,260,625	**81,260,832**
Average	**81,286,343**	**81,357,410**	**81,310,178**	**81,294,564**	**81,279,357**	**81,231,069**
Stochastic	**81,274,678**	**81,361,068**	**81,293,873**	**81,276,232**	**81,270,042**	**81,245,391**
AAC equivalent to 0.50% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**161,594,831**	161,745,827	161,652,003	161,610,704	161,545,904	161,420,365
2 no infestation	161,581,898	**161,753,738**	161,641,708	161,600,510	161,555,917	161,434,713
3 low infestation	161,603,099	161,740,332	**161,659,439**	161,617,748	161,557,184	161,410,323
4 medium infestation	161,592,357	161,741,585	161,656,967	**161,613,589**	161,570,424	161,419,109
5 high infestation	161,599,390	161,746,616	161,650,870	161,614,385	**161,594,576**	161,500,674
6 severe infestation	161,560,685	161,711,393	161,597,162	161,569,622	161,549,795	**161,549,210**
Average	**161,555,596**	**161,744,989**	**161,649,477**	**161,588,759**	**161,560,887**	**161,429,986**
Stochastic	**161,537,332**	**161,711,431**	**161,579,245**	**161,547,250**	**161,525,766**	**161,502,006**
AAC equivalent to 1% of initial forest inventory						

Table 7.1 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat14 in CAD (Continued).

For / Solution	1 datacase	2 no infestation	3 low infestation	4 medium infestation	5 high infestation	6 severe infestation
1 datacase	**321,151,214**	321,524,607	321,271,573	321,180,348	321,054,478	320,833,918
2 no infestation	321,111,011	**321,563,868**	321,223,801	321,166,552	321,016,973	320,745,423
3 low infestation	321,164,365	321,535,324	**321,306,932**	321,195,178	321,051,396	320,663,704
4 medium infestation	321,141,159	321,520,479	321,302,879	**321,196,860**	321,135,037	320,895,197
5 high infestation	321,146,171	321,544,156	321,257,299	321,189,337	**321,167,442**	320,963,413
6 severe infestation	321,075,875	321,434,001	321,161,880	321,120,792	321,066,727	**321,048,328**
Average	**321,159,252**	**321,532,910**	**321,297,725**	**321,189,015**	**321,124,048**	**320,901,796**
Stochastic	**321,133,695**	**321,545,428**	**321,240,525**	**321,163,503**	**321,102,713**	**320,953,782**
AAC equivalent to 2% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**638,144,680**	638,904,082	638,377,387	638,166,516	638,013,593	637,510,346
2 no infestation	638,022,498	**638,967,175**	638,298,265	638,113,572	637,851,282	637,195,574
3 low infestation	638,099,243	638,954,189	**638,437,420**	638,178,607	637,840,532	636,889,562
4 medium infestation	638,144,366	638,965,287	638,364,652	**638,210,677**	638,005,931	637,401,141
5 high infestation	638,093,676	638,946,492	638,322,453	638,180,639	**638,137,709**	637,739,196
6 severe infestation	638,083,321	638,980,542	638,321,065	638,084,234	637,871,366	**637,908,017**
Average	**638,112,013**	**638,913,016**	**638,356,194**	**638,194,575**	**638,074,952**	**637,533,671**
Stochastic	**638,042,822**	**638,919,171**	**638,264,888**	**638,117,116**	**637,952,522**	**637,694,605**

Table 7.2 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat15 in CAD.

stat15						
AAC equivalent to 0.10% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**36,856,548**	36,907,716	36,875,463	36,862,292	36,852,302	36,835,647
2 no infestation	36,851,547	**36,910,414**	36,871,208	36,857,035	36,835,707	36,816,953
3 low infestation	36,853,208	36,910,339	**36,877,766**	36,860,050	36,848,620	36,836,806
4 medium infestation	36,853,926	36,903,401	36,876,209	**36,865,056**	36,852,140	36,841,023
5 high infestation	36,852,365	36,904,526	36,874,326	36,858,907	**36,858,627**	36,847,865
6 severe infestation	36,853,170	36,892,285	36,868,744	36,858,223	36,858,280	**36,851,765**
Average	**36,850,161**	**36,908,810**	**36,876,717**	**36,859,054**	**36,841,654**	**36,823,286**
Stochastic	**36,842,638**	**36,902,278**	**36,863,788**	**36,849,772**	**36,841,761**	**36,825,870**
AAC equivalent to 0.25% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**91,293,272**	91,446,826	91,344,730	91,311,487	91,271,992	91,227,406
2 no infestation	91,271,512	**91,443,624**	91,325,493	91,303,299	91,228,663	91,145,967
3 low infestation	91,282,764	91,445,056	**91,347,236**	91,311,082	91,257,994	91,210,018
4 medium infestation	91,284,623	91,445,208	91,342,507	**91,312,516**	91,252,868	91,196,655
5 high infestation	91,281,314	91,436,065	91,329,338	91,302,175	**91,298,687**	91,276,812
6 severe infestation	91,277,272	91,429,360	91,322,195	91,303,103	91,289,055	**91,275,039**
Average	**91,268,399**	**91,445,353**	**91,346,625**	**91,299,055**	**91,242,847**	**91,196,815**
Stochastic	**91,279,266**	**91,438,194**	**91,328,423**	**91,300,124**	**91,272,063**	**91,232,024**
AAC equivalent to 0.50% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**181,046,009**	181,431,902	181,183,293	181,093,695	180,991,544	180,877,239
2 no infestation	180,991,877	**181,434,045**	181,141,239	181,052,886	180,822,321	180,536,870
3 low infestation	181,025,373	181,419,850	**181,196,536**	181,093,004	180,957,364	180,823,842

Table 7.2 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat15 in CAD (Continued).

4 medium infestation	**181,033,880**	**181,430,661**	**181,186,007**	181,103,735	**180,986,877**	**180,860,495**
5 high infestation	181,022,681	181,374,512	181,129,358	181,061,730	**181,053,477**	180,998,635
6 severe infestation	181,012,012	181,365,994	181,115,720	181,045,899	181,048,902	**181,001,230**
Average	**180,923,822**	**181,416,112**	**181,128,127**	**181,007,249**	**180,877,790**	**180,724,313**
Stochastic	**180,991,087**	**181,399,156**	**181,124,581**	**181,051,157**	**180,928,014**	**180,792,157**
AAC equivalent to 1% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**358,794,230**	359,768,359	359,136,647	358,910,306	358,663,729	358,460,077
2 no infestation	358,638,963	**359,771,559**	359,042,814	358,820,577	358,229,950	357,593,686
3 low infestation	358,724,466	359,749,029	**359,168,383**	358,923,972	358,455,230	358,121,895
4 medium infestation	358,721,327	359,784,789	359,058,758	**358,844,440**	358,388,250	357,896,519
5 high infestation	358,736,090	359,670,343	358,970,305	358,825,554	**358,758,850**	358,624,886
6 severe infestation	358,730,475	359,541,375	358,944,562	358,805,089	358,747,147	**358,648,219**
Average	**358,755,893**	**359,765,704**	**359,153,265**	**358,912,246**	**358,567,560**	**358,314,121**
Stochastic	**358,736,977**	**359,794,610**	**359,074,623**	**358,875,242**	**358,521,468**	**358,161,510**
AAC equivalent to 2% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**709,932,847**	712,563,231	710,866,820	710,328,363	709,263,814	708,231,162
2 no infestation	709,755,897	**712,528,233**	710,826,535	710,227,056	708,713,609	707,116,347
3 low infestation	709,995,430	712,568,695	**710,974,064**	710,426,746	709,329,130	708,468,597
4 medium infestation	709,948,127	712,579,901	710,868,780	**710,281,164**	709,126,008	708,015,410
5 high infestation	709,937,197	712,153,092	710,622,989	710,181,672	**709,913,179**	709,595,549
6 severe infestation	709,930,917	711,883,161	710,461,210	710,107,924	709,890,245	**709,649,078**
Average	**709,657,651**	**712,537,122**	**711,065,116**	**710,305,684**	**708,474,213**	**701,398,146**
Stochastic	**709,945,694**	**712,579,163**	**710,851,783**	**710,312,015**	**709,403,171**	**708,523,590**

Table 7.3 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat16 CAD.

stat16						
AAC equivalent to 0.10% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**32,138,209**	32,184,232	32,162,261	32,143,653	32,136,463	32,113,920
2 no infestation	32,108,481	**32,191,289**	32,151,066	32,116,417	32,108,956	32,072,825
3 low infestation	32,132,684	32,192,400	**32,164,790**	32,135,389	32,134,220	32,106,296
4 medium infestation	32,137,254	32,185,472	32,158,801	**32,144,858**	32,140,122	32,123,228
5 high infestation	32,137,444	32,190,132	32,160,004	32,141,152	**32,144,408**	32,123,924
6 severe infestation	32,132,546	32,170,726	32,142,103	32,137,159	32,138,736	**32,131,041**
Average	**32,124,196**	**32,185,797**	**32,163,690**	**32,132,943**	**32,131,392**	**32,102,096**
Stochastic	**32,135,578**	**32,192,072**	**32,159,451**	**32,139,212**	**32,136,830**	**32,117,362**
AAC equivalent to 0.25% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**79,714,497**	79,821,691	79,759,725	79,723,272	79,716,792	79,667,528
2 no infestation	79,701,742	**79,834,660**	79,750,602	79,713,371	79,705,362	79,654,888
3 low infestation	79,710,938	79,830,143	**79,767,148**	79,716,759	79,717,864	79,674,979
4 medium infestation	79,712,432	79,831,903	79,764,514	**79,727,882**	79,722,661	79,685,918
5 high infestation	79,704,595	79,833,526	79,749,698	79,723,805	**79,727,080**	79,701,044
6 severe infestation	79,697,751	79,798,753	79,726,870	79,709,203	79,710,143	**79,701,318**
Average	**79,707,370**	**79,834,585**	**79,766,049**	**79,716,953**	**79,713,098**	**79,665,796**
Stochastic	**79,707,384**	**79,831,348**	**79,741,908**	**79,717,373**	**79,718,782**	**79,688,468**
AAC equivalent to 0.50% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**158,477,303**	158,672,213	158,571,396	158,498,460	158,482,879	158,382,466
2 no infestation	158,457,007	**158,716,261**	158,540,315	158,479,735	158,464,454	158,377,028
3 low infestation	158,460,559	158,715,766	**158,581,277**	158,484,448	158,472,011	158,360,858
4 medium infestation	158,462,965	158,687,754	158,571,030	**158,503,600**	158,489,201	158,395,124
5 high infestation	158,463,192	158,705,921	158,553,828	158,495,746	**158,503,137**	158,427,739

Table 7.3 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat16 in CAD (Continued).

6 severe infestation	**158,441,126**	**158,676,295**	**158,516,366**	**158,469,034**	**158,481,539**	158,430,517
Average	**158,425,117**	**158,714,617**	**158,570,356**	**158,454,912**	**158,443,022**	**158,341,666**
Stochastic	**158,447,447**	**158,712,143**	**158,532,288**	**158,479,610**	**158,477,657**	**158,396,943**
AAC equivalent to 1% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**314,947,270**	315,492,014	315,145,061	314,979,079	314,962,242	314,803,253
2 no infestation	314,906,068	**315,545,194**	315,086,518	314,956,561	314,887,582	314,704,573
3 low infestation	314,938,361	315,516,223	**315,161,850**	314,990,654	314,949,995	314,744,855
4 medium infestation	314,940,876	315,493,481	315,127,799	**315,012,365**	314,971,941	314,805,734
5 high infestation	314,923,377	315,478,061	315,091,407	314,979,518	**314,967,561**	314,870,606
6 severe infestation	314,916,443	315,376,149	315,043,562	314,966,378	314,979,667	**314,910,787**
Average	**314,924,863**	**315,537,927**	**315,145,129**	**314,960,747**	**314,934,242**	**314,693,882**
Stochastic	**314,944,725**	**315,544,724**	**315,118,492**	**314,991,404**	**314,935,274**	**314,835,006**
AAC equivalent to 2% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**625,795,015**	626,868,733	626,177,045	625,890,145	625,801,473	625,510,184
2 no infestation	625,659,092	**627,006,952**	626,003,035	625,778,463	625,641,790	625,192,310
3 low infestation	625,669,087	626,962,135	**626,000,680**	625,816,351	625,685,550	625,351,713
4 medium infestation	625,785,516	626,910,885	626,153,989	**625,899,840**	625,777,133	625,462,216
5 high infestation	625,728,643	626,983,528	626,050,782	625,842,830	**625,855,647**	625,615,893
6 severe infestation	625,678,375	626,733,469	625,930,196	625,792,653	625,804,231	**625,663,662**
Average	**625,652,132**	**626,987,918**	**626,111,760**	**625,789,111**	**625,693,180**	**625,073,653**
Stochastic	**625,682,770**	**627,024,191**	**626,035,748**	**625,810,349**	**625,707,170**	**625,473,032**

Table 7.4 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat17 CAD.

stat17						
AAC equivalent to 0.10% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**32,645,124**	32,713,492	32,674,297	32,649,384	32,641,849	32,629,571
2 no infestation	32,632,877	**32,712,436**	32,651,354	32,637,295	32,634,416	32,626,101
3 low infestation	32,642,915	32,707,697	**32,677,603**	32,646,480	32,644,500	32,629,859
4 medium infestation	32,644,404	32,706,259	32,673,343	**32,649,697**	32,642,478	32,628,933
5 high infestation	32,643,877	32,711,006	32,669,358	32,647,752	**32,647,068**	32,635,294
6 severe infestation	32,639,445	32,703,711	32,657,965	32,642,735	32,643,188	**32,634,913**
Average	**32,625,721**	**32,712,511**	**32,677,411**	**32,634,077**	**32,631,402**	**32,608,623**
Stochastic	**32,632,958**	**32,709,226**	**32,666,036**	**32,639,216**	**32,632,791**	**32,618,946**
AAC equivalent to 0.25% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**80,978,830**	81,104,326	81,028,576	80,985,160	80,979,026	80,936,283
2 no infestation	80,962,972	**81,123,134**	81,004,082	80,975,468	80,971,890	80,942,421
3 low infestation	80,965,168	81,122,953	**81,045,280**	80,983,155	80,972,493	80,936,196
4 medium infestation	80,977,627	81,111,446	81,030,175	**80,987,360**	80,978,550	80,951,841
5 high infestation	80,966,002	81,098,739	80,994,101	80,978,537	**80,978,975**	80,959,949
6 severe infestation	80,961,999	81,095,182	80,995,508	80,971,793	80,976,130	**80,963,219**
Average	**80,949,970**	**81,124,010**	**81,042,289**	**80,966,890**	**80,964,206**	**80,913,490**
Stochastic	**80,963,345**	**81,125,504**	**81,016,578**	**80,980,217**	**80,972,739**	**80,941,642**
AAC equivalent to 0.50% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**160,967,614**	161,271,747	161,116,417	160,991,284	160,978,350	160,892,832
2 no infestation	160,918,618	**161,283,928**	161,037,289	160,940,927	160,933,637	160,863,896
3 low infestation	160,963,769	161,263,611	**161,113,016**	160,980,737	160,973,427	160,871,377

Table 7.4 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat17 in CAD (Continued).

4 medium infestation	**160,963,930**	**161,244,924**	**161,102,485**	160,993,308	**160,977,482**	**160,884,660**
5 high infestation	160,954,117	161,276,767	161,087,444	160,986,317	**160,990,873**	160,913,324
6 severe infestation	160,928,374	161,212,126	161,002,633	160,967,123	160,973,601	**160,925,227**
Average	**160,924,984**	**161,272,620**	**161,112,034**	**160,957,669**	**160,949,987**	**160,855,155**
Stochastic	**160,925,649**	**161,261,373**	**161,043,223**	**160,966,214**	**160,950,122**	**160,883,707**
AAC equivalent to 1% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**319,929,356**	320,604,636	320,172,214	319,948,979	319,926,161	319,760,522
2 no infestation	319,797,061	**320,635,721**	320,092,730	319,864,459	319,784,051	319,645,214
3 low infestation	319,872,777	320,623,817	**320,163,844**	319,908,526	319,879,973	319,679,086
4 medium infestation	319,919,920	320,584,725	320,171,899	**319,978,327**	319,911,235	319,751,673
5 high infestation	319,887,828	320,592,441	320,125,024	319,940,986	**319,959,922**	319,833,463
6 severe infestation	319,860,533	320,522,566	320,014,618	319,932,060	319,935,942	**319,854,818**
Average	**319,844,269**	**320,617,289**	**320,171,537**	**319,930,315**	**319,871,194**	**319,667,670**
Stochastic	**319,855,417**	**320,611,100**	**320,070,580**	**319,916,993**	**319,871,564**	**319,692,563**
AAC equivalent to 2% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**635,603,802**	637,018,246	636,090,441	635,707,774	635,614,483	635,269,827
2 no infestation	635,392,857	**637,107,152**	635,957,936	635,555,848	635,438,773	635,059,556
3 low infestation	635,542,884	637,069,077	**636,105,281**	635,677,885	635,523,872	635,086,071
4 medium infestation	635,592,776	637,087,193	636,121,729	**635,720,376**	635,582,326	635,222,753
5 high infestation	635,455,268	637,019,823	635,814,877	635,589,566	**635,548,659**	635,346,586
6 severe infestation	635,452,061	636,695,735	635,689,478	635,580,301	635,586,209	**635,410,438**
Average	**635,344,547**	**637,095,262**	**636,140,048**	**635,520,461**	**635,303,173**	**634,590,450**
Stochastic	**635,364,550**	**637,131,606**	**635,948,961**	**635,629,793**	**635,517,239**	**635,032,471**

Table 7.5 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat18 CAD.

stat18						
AAC equivalent to 0.10% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**31,934,088**	31,990,560	31,950,841	31,937,835	31,934,513	31,926,599
2 no infestation	31,927,111	**32,002,122**	31,949,369	31,929,783	31,926,892	31,916,576
3 low infestation	31,927,784	32,002,224	**31,959,442**	31,930,950	31,928,167	31,917,430
4 medium infestation	31,933,590	32,000,930	31,955,972	**31,938,943**	31,934,286	31,926,217
5 high infestation	31,934,621	31,987,222	31,948,994	31,936,659	**31,934,448**	31,927,260
6 severe infestation	31,930,903	32,001,880	31,947,377	31,933,919	31,934,422	**31,927,966**
Average	**31,911,081**	**32,003,406**	**31,954,940**	**31,918,369**	**31,915,641**	**31,901,708**
Stochastic	**NO RESULT**	**NO RESULT**	**NO RESULT**	**NO RESULT**	**NO RESULT**	**NO RESULT**
AAC equivalent to 0.25% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**79,217,475**	79,356,973	79,265,894	79,224,783	79,213,453	79,199,287
2 no infestation	79,202,544	**79,359,108**	79,248,054	79,211,106	79,200,347	79,177,138
3 low infestation	79,211,436	79,359,942	**79,267,710**	79,223,186	79,216,989	79,198,016
4 medium infestation	79,211,129	79,365,511	79,264,585	**79,224,254**	79,212,977	79,187,749
5 high infestation	79,213,690	79,354,402	79,217,728	79,222,657	**79,221,364**	79,205,039
6 severe infestation	79,210,731	79,352,857	79,232,442	79,214,830	79,216,299	**79,201,564**
Average	**79,165,256**	**79,357,255**	**79,254,843**	**79,182,925**	**79,173,476**	**79,134,370**
Stochastic	**79,212,370**	**79,363,262**	**79,250,373**	**79,195,255**	**79,211,956**	**79,190,975**
AAC equivalent to 0.50% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**157,470,965**	157,752,467	157,590,709	157,482,538	157,477,137	157,425,855
2 no infestation	157,445,623	**157,778,139**	157,536,471	157,466,010	157,441,820	157,387,718

Table 7.5 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat18 in CAD (Continued).

3 low infestation	**157,448,435**	**157,764,338**	157,592,300	**157,478,577**	**157,460,154**	**157,390,518**
4 medium infestation	157,469,875	157,755,400	157,573,869	**157,487,654**	157,474,030	157,418,167
5 high infestation	157,467,758	157,753,897	157,566,265	157,471,884	**157,483,418**	157,427,639
6 severe infestation	157,447,518	157,720,789	157,493,655	157,467,585	157,456,790	**157,432,897**
Average	**157,402,413**	**157,744,706**	**157,581,540**	**157,453,425**	**157,422,320**	**157,294,413**
Stochastic	**157,432,975**	**157,771,762**	**157,518,735**	**157,459,594**	**157,438,954**	**157,402,044**
AAC equivalent to 1% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**312,960,170**	313,656,603	313,106,141	312,957,016	312,945,459	312,867,624
2 no infestation	312,796,563	**313,691,756**	313,054,227	312,879,623	312,522,332	312,697,764
3 low infestation	312,941,793	313,607,866	**313,188,389**	312,974,456	312,931,297	312,802,011
4 medium infestation	312,965,221	313,638,963	313,170,538	**313,010,503**	312,943,650	312,839,191
5 high infestation	312,922,266	313,636,209	313,091,278	312,981,882	**312,963,412**	312,899,362
6 severe infestation	312,897,035	313,489,073	313,022,878	312,964,996	312,955,071	**312,906,556**
Average	**312,816,287**	**313,601,514**	**313,156,377**	**312,838,886**	**312,846,595**	**312,612,206**
Stochastic	**312,857,281**	**313,623,070**	**313,074,247**	**312,904,813**	**312,881,997**	**312,674,624**
AAC equivalent to 2% of initial forest inventory						
For / Solution	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**621,694,119**	623,252,285	622,046,090	621,796,755	621,716,457	621,564,128
2 no infestation	621,487,134	**623,324,933**	622,082,409	621,598,969	621,457,476	621,213,779
3 low infestation	621,740,316	623,286,593	**622,121,127**	621,838,333	621,724,009	621,543,339
4 medium infestation	621,644,521	623,260,189	621,995,735	**621,779,328**	621,708,813	621,599,363
5 high infestation	621,694,438	623,256,965	621,988,185	621,731,979	**621,676,670**	621,556,773
6 severe infestation	621,677,938	623,081,763	621,897,370	621,740,544	621,749,644	**621,605,685**
Average	**621,479,200**	**623,190,722**	**622,211,271**	**621,676,640**	**621,563,672**	**620,935,219**
Stochastic	**621,684,590**	**623,240,904**	**622,096,218**	**621,695,316**	**621,693,451**	**621,507,208**

Table 7.6 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat19 CAD.

stat19						
AAC equivalent to 0.10% of initial forest inventory						
Solution \ For	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**36,194,672**	36,270,606	36,212,332	36,197,805	36,192,420	36,182,980
2 no infestation	36,181,578	**36,284,031**	36,201,309	36,188,911	36,182,696	36,172,408
3 low infestation	36,186,934	36,279,838	**36,213,723**	36,194,226	36,183,587	36,171,979
4 medium infestation	36,191,942	36,280,038	36,206,771	**36,196,274**	36,187,766	36,176,588
5 high infestation	36,190,184	36,280,404	36,208,323	36,193,846	**36,194,982**	36,188,961
6 severe infestation	36,190,352	36,280,923	36,203,486	36,190,950	36,190,678	**36,187,583**
Average	**36,169,364**	**36,273,753**	**36,199,851**	**36,168,812**	**36,175,480**	**36,160,830**
Stochastic	**36,190,411**	**36,279,773**	**36,200,345**	**36,189,553**	**36,189,779**	**36,186,242**
AAC equivalent to 0.25% of initial forest inventory						
Solution \ For	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**89,611,259**	89,898,329	89,691,571	89,638,260	89,591,497	89,563,951
2 no infestation	89,576,644	**89,900,784**	89,644,632	89,603,082	89,557,501	89,522,952
3 low infestation	89,609,082	89,889,571	**89,693,896**	89,639,504	89,580,875	89,551,276
4 medium infestation	89,612,173	89,883,996	89,693,723	**89,644,455**	89,570,499	89,529,082
5 high infestation	89,608,958	89,875,922	89,655,863	89,617,466	**89,610,741**	89,597,794
6 severe infestation	89,602,701	89,892,111	89,645,649	89,616,776	89,606,258	**89,597,130**
Average	**89,600,908**	**89,899,811**	**89,692,876**	**89,632,619**	**89,581,333**	**89,553,160**
Stochastic	**89,550,327**	**89,823,094**	**89,610,031**	**89,570,510**	**89,528,188**	**89,503,436**
AAC equivalent to 0.50% of initial forest inventory						
Solution \ For	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**177,654,911**	178,329,108	177,847,251	177,710,856	177,627,855	177,569,199
2 no infestation	175,432,304	**178,368,779**	177,646,718	177,104,406	174,082,353	172,905,887
3 low infestation	177,562,539	178,308,007	**177,699,203**	177,626,910	177,530,323	177,452,296

Table 7.6 Total profit if implementing the solution of other scenarios, average transition matrix and Two-Stage SP for all AAC per stat19 in CAD (Continued).

4 medium infestation	**177,625,954**	**178,359,563**	**177,784,624**	177,664,741	**177,587,763**	**177,517,921**
5 high infestation	177,638,883	178,264,255	177,717,902	177,657,495	**177,647,670**	177,609,660
6 severe infestation	177,617,850	178,220,304	177,699,106	177,645,859	177,629,869	**177,612,674**
Average	**177,528,025**	**178,355,574**	**177,838,471**	**177,640,399**	**177,350,507**	**177,264,328**
Stochastic	**177,438,276**	**178,230,842**	**177,623,694**	**177,508,773**	**177,377,484**	**177,276,801**
AAC equivalent to 1% of initial forest inventory						
Solution \ For	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**351,915,321**	353,620,265	352,442,970	352,094,539	351,764,703	351,607,235
2 no infestation	346,886,039	**353,734,160**	352,030,776	350,185,400	344,204,139	341,685,166
3 low infestation	351,795,242	353,639,658	**352,217,462**	351,984,689	351,603,572	351,374,760
4 medium infestation	351,871,371	353,723,152	352,352,684	**352,020,687**	351,660,611	351,419,390
5 high infestation	351,857,423	353,600,059	352,234,529	351,979,701	**351,735,156**	351,640,811
6 severe infestation	351,872,854	353,718,278	352,315,328	352,029,307	351,716,537	**351,474,512**
Average	**351,340,728**	**353,600,514**	**352,452,735**	**351,847,356**	**350,995,784**	**350,364,467**
Stochastic	**351,855,575**	**353,730,015**	**352,356,691**	**352,041,411**	**351,697,620**	**351,501,791**
AAC equivalent to 2% of initial forest inventory						
Solution \ For	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
1 datacase	**695,832,278**	700,616,413	697,152,847	696,320,999	695,432,153	694,866,367
2 no infestation	695,384,806	**700,557,253**	697,131,306	696,059,312	694,789,236	694,003,938
3 low infestation	695,526,330	700,431,508	**697,564,706**	696,399,348	694,560,557	693,466,128
4 medium infestation	695,934,215	700,202,173	697,512,937	**696,558,171**	695,250,432	694,488,848
5 high infestation	695,809,034	699,748,573	696,560,059	696,000,235	**695,857,382**	695,680,810
6 severe infestation	695,882,480	700,584,290	697,138,825	696,330,508	695,426,696	**694,714,619**
Average	**694,357,359**	**700,515,200**	**697,493,369**	**695,770,440**	**693,209,072**	**690,852,544**
Stochastic	**695,893,508**	**700,618,290**	**697,183,105**	**696,366,748**	**695,409,648**	**694,815,932**

If we compare how much it will improve the solution of the scenarios with the other scenarios *s*, except for "AVERAGE" and "STOCHASTIC", (see Table 7.1-7.6) for all stats and their respective AAC, we can observe that there are some improvements of the profit as well as worsening of the profit, due to the implementation of the first-stage decision. For instance, if we implement the solution of "2 no infestation" for "6 severe infestation", this will not improve or increase the profit comparing to the other scenarios. Likewise, if we implement solution of "4 medium infestation" for "1 datacase", it will be better than the solution of the "1 datacase" in some cases.

7.3 EVPI and VSS for Applied Case Study

In this section, we will present the results of the EVPI and VSS after obtaining the values of solving when implementing the solution of the average transition matrix and the stochastic solution (see Table 7.7). According to the equations mentioned in Chapter 4, we calculate the EVPI with the difference between the stochastic solution and the expected value of Wait-and-See solutions. For the VSS, we obtained this value with the difference between the recourse solution and the EEV.

We can observe that the values of the EVPI (see Table 7.7) shows us what amount the decision maker will pay for complete and accurate information about the future when trees are infested by SBW with the respective percentage of AAC and if the initial volume of forest stands are different and increase over the years. We can observe that the amount the forest managers will pay for this study or information will be more when the demand is around AAC equivalent to 2% of the initial forest inventory compared to the rest of the other percentages of AAC. However, there are some values that are at a lower cost to pay, like stat16 for AAC equivalent to 0.50% of the initial forest inventory. Therefore, this means that the real information obtained for this case is appropriate with its respective amount percentage of AAC. This information obtained is known or complete when solving the individual scenarios of the deterministic models. This means that forest managers do not need more studies for other parameters as they already have accurate information comparing to the rest of the cases. In conclusion, the higher the EVPI is, the more it will cost the forest managers to get the information needed for solving the optimization models and have more accurate results.

On the other hand, for the VSS of Table 7.7, we can observe what the cost is of ignoring uncertainty by the decision maker during the harvest planning process when dealing with SBW. This means that these values will allow us to compare and see how good or how bad a decision is for the recourse problem (here-and-now decisions) instead of waiting and seeing what will happen and then making a decision. These values of VSS also mean that this will be the possible gain from solving the stochastic model and considering uncertainty in the harvesting planning. When there is no further information about the future or there is more uncertainty and VSS is relevant compared to EVPI, we can observe that because the database obtained from FPInnovations has been forecasted and predicted through some simulation about the SBW population, EVPI is more useful. This is how we evaluate the quality of the solutions, and in the end, it will be the decision maker who will decide if they consider or not the solution of the optimization models considering other factors.

Table 7.7 Expected Value of Perfect Information (EVPI) and Value of Stochastic Solution (VSS) per stat per AAC.

	stat14				
	AAC equivalent to 0.10%	AAC equivalent to 0.25%	AAC equivalent to 0.50%	AAC equivalent to 1%	AAC equivalent to 2%
EVPI	1,964	978	2,564	3,939	27,531
VSS	10,819	5,724	36,718	34,377	76,012
	stat15				
	AAC equivalent to 0.10%	AAC equivalent to 0.25%	AAC equivalent to 0.50%	AAC equivalent to 1%	AAC equivalent to 2%
EVPI	1,397	756	10,822	6,841	407,462
VSS	8,685	27,791	115,448	79,307	1,232,643
	stat16				
	AAC equivalent to 0.10%	AAC equivalent to 0.25%	AAC equivalent to 0.50%	AAC equivalent to 1%	AAC equivalent to 2%
EVPI	207	663	88	46,288	104,813
VSS	12,206	10,793	43,646	11,751	47,528
	stat17				
	AAC equivalent to 0.10%	AAC equivalent to 0.25%	AAC equivalent to 0.50%	AAC equivalent to 1%	AAC equivalent to 2%
EVPI	80	671	6,142	7,378	127,157
VSS	12,769	18,652	27,444	62,574	123,137
	stat18				
	AAC equivalent to 0.10%	AAC equivalent to 0.25%	AAC equivalent to 0.50%	AAC equivalent to 1%	AAC equivalent to 2%
EVPI	NO RESULT	7,574	645	4,129	49,351
VSS	NO RESULT	29,651	57,115	137,358	141,506
	stat19				
	AAC equivalent to 0.10%	AAC equivalent to 0.25%	AAC equivalent to 0.50%	AAC equivalent to 1%	AAC equivalent to 2%
EVPI	1,120	2,520	400	32,304	280,835
VSS	19,409	13,740	111,379	383,648	1,200,236

CONCLUSION

The forest supply chain network can be largely integrated into more processes from harvesting to log terminals, distribution to sawmill and processed into manufacturing wood products. In this research, the focus was only on the wood supply chain part that includes harvesting and transportation to terminals and mills. A Two-Stage stochastic MIP model was proposed for addressing tactical planning in the forest supply chain considering the uncertainty of disturbance events such as insect infestation. These models were applied to a real case study in the North Shore region in the province of Québec (Côte-Nord) and their quality of information analyzed through EVPI and VSS.

The contributions of this project are not only the results given when running the models. In fact, it is the value of the information given by the parameter of percentage value, as it allows better managing forest planning and better controlling inventory (forest stands) by improving it and salvaging it from natural disturbances that can affect the yield and the availability of raw material. Therefore, it will enhance better decision-making to maximize the value chain. Another contribution is the consideration of the impact of infestation on wood supply and forest stands harvest scheduling using advanced optimization techniques such as SP approach. The output is to mitigate the risk of wood supply disruptions on the forest value chain by considering realistic scenarios of the SBW impact in forest stands. However, if we consider other disturbances (e.g. Mountain Pine Beetle in British Columbia) that have similar infestation models, it will be possible to consider the proposed model as generic for other real case problems.

The importance of SP compared to deterministic models is that they give us better solution quality as we consider uncertainty, because we are considering several scenarios. Deterministic models are not enough, as the models use average values in the system parameters while most of the parameters in the forest supply chains are uncertain. Ignoring uncertainty in optimization models may result in non-optimal and/or infeasible solutions for real case studies.

RECOMMENDATIONS

Further research based on this project can be explored and the current mathematical formulation of the harvesting planning problem can be extended to include additional uncertain parameters in the stochastic version to be more comprehensive and realistic. Also, increasing the size of the model, considering changes in the transportation routes, the capacity of sawmills and other factors that are part of the forest supply chain could increase the accuracy of reality, as that could be considered as a full and large integrated forest supply chain model.

Other forest stands physical attributes (e.g. bucking pattern, size, age, colour, dimensions, silviculture practices, and yield), the infestation characteristics (e.g. immigration of the insect, controlling plague factors with insecticides, and climate change), other disturbances like fungal species should be considered for harvesting planning optimization models as the accuracy of information will be better on the rate of transition phases of the SBW. These could allow a better interaction between the SWB life cycle and the population of forest stands by increasing or slowing the defoliation process. With these, the model will likely be more complex and harder to solve, requiring advanced decomposition techniques such as (e.g. L-Shaped or SAA methods).

Moreover, the research project could also be improved if more scenarios are generated and more uncertain parameters (e.g. demand, market price, and fluctuation of costs) are considered. This would be helpful for considering all realization scenarios. Further analysis should be made to improve the model and the results and be applied for other real cases of SBW outbreak. Also, considering the price for the uncertain data provided, this will lead to another extension for price of robustness. In addition, if we consider other decision variables over the planning horizon, this will be another extension of multi-stage SP

APPENDIX I

MOSIM CONFERENCE PAPER 2016: OPTIMIZATION OF HARVEST PLANNING OF FOREST STANDS INFESTED BY SPRUCE BUDWORM USING STOCHASTIC PROGRAMMING BY Zhu Chen, Ouhimmou et Rönnqvist (2016)

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OPTIMIZATION OF HARVEST PLANNING OF FOREST STANDS INFESTED BY SPRUCE BUDWORM USING STOCHASTIC PROGRAMMING

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ABSTRACT: H*arvesting is considered as one of the key critical processes as it provides the primary raw material for different mills in the forest industry. However, due to several natural disturbances such as insect outbreaks, the impact and the effects on the tactical planning of forest supply chain caused by Spruce Budworm (SBW) can be irreversible, creating more susceptibility and vulnerability in trees, and increasing mortality by defoliation. A deterministic MILP model is proposed and extended to a two-stage Stochastic Programming (SP) model to deal with uncertainty related to the severity and propagation of the infestation. The model aims to maximize the market value of the harvested logs considering the occurrence of infestation over all the possible scenarios. The model was implemented in AMPL language and solved with CPLEX solver. Preliminary results show the value of using SP in planning under uncertainty. Such models will have a great impact for better decision making in forest management, reducing costs and loss of trees as SBW can lead to future outbreaks.*

KEYWORDS: *Forest Supply Chain, Spruce Budworm Infestation, Forest Harvesting Planning, Two-Stage Stochastic Programming*

1 INTRODUCTION

In the forest industry, supply chain planning has played a significant role in decision making. Depending on the planning horizon, it can start from the following hierarchical levels: strategic, tactical and operational. However, in tactical planning, it is mostly associated with making decisions about how to treat standing timber on a horizon ranging over several years and can have an impact on the operational level such as annual harvest planning (D'Amours, Ronnqvist et Weintraub, 2008). When making these types of decisions, it will affect the forest supply chain performance that aims to maximize the total profit and/or to minimize total cost. Therefore, harvesting is and has been one of the essential primary processes in the wood supply chain as it considers numerous important decisions such as when and where to cut forest stands. It is the first process for obtaining the raw material in different supply chains of the forest industry as Carlsson D. (2006) explains in his approach.

Troncoso et al. (2015) describe that logs are the raw material for the primary transformation mills that produce final or intermediate products for customers and second transformation mills. Therefore, it is essential to focus more on the harvesting process. However, this process faces uncertainty in forest management as it is not entirely understood and it is unpredictable. It affects the future growth of trees or their yield by windthrows, insect damage, fungi damage, other animals, climate change, air pollution, forest fires, and many other events which are regarded as stochastic disturbances (Lohmander, 2007). Also, these are considered as stochastic parameters which, according to Church (2007), have often been ignored when developing tactical models and the uncertainty can add a significant degree of complexity to modelling forest systems.

Hence, we propose to include, at the tactical planning level, the uncertainty caused by forest insect infestation by Spruce Budworm (SBW) *(Choristoneura fumiferana*) in the province of Québec, Canada. This living organism is a native North American defoliator considered as one of the most harmful forest insects. It causes defoliation, top-kill and tree mortality of specific species. The ability to predict the occurrence period and understand the severity of SBW outbreaks would significantly enhance the capacity of the forest industry to manage forest resources, to mitigate and to minimize the impact of SBW (Gray, Régnière et Boulet, 2000). SBW is hosted by species such as white spruce, red spruce and black spruce (*Picea glauca*) and balsamic fir *(Abies balsamea).* These types of species are important in the forest supply chain due to their high value on the market. Their numerous and extensive applications are diverse, providing different products (e.g. fuel, tools, construction, building materials, furniture making, musical instruments, flooring, and other tools) (Ouhimmou et al. (2008).

There have been several attempts or methods to increase the harvest planning of the hosting tree species as they are essential in the forest value chain. Such efforts are considered to prevent timber losses like commercial thinning that modifies the composition of the trees increasing the defences against diseases and insects by promoting more abundant foliage, but this may affect the quality of the product. With other methods, for instance, the most vulnerable stands are harvested first before outbreaks occur or by salvaging dying trees that have been dead for a short period. Although SBW outbreaks take several years to happen, some of the measures that forest management has taken to face this problem before it occurs is planning, scheduling the harvesting process or scheduling the work and achieving anticipated yields.

The objective of this research is to use an advanced optimization technique that deals with uncertainty, addressing the problem of the tactical planning of harvesting forest stands attacked by SBW. The contributions will be the integration of uncertainty at the tactical planning level of harvesting, using two-stage Stochastic Programming (SP) and comparing it to current practices that ignore such uncertainty.

2 PROBLEM STATEMENT

The main focus of this research consists in the following: harvest schedule planning with insect infestation. This natural disturbance is one of the major issues that forest managers have to deal with, as it causes a great amount of damage to the raw material of the wood supply chain, leading to a significant loss to the forest industry and increased tree mortality that affects the harvesting process, as shown in Figure 2.1. This figure illustrates the defoliation of an individual tree that could host the SBW (synchronized with the SBW life cycle). The line between three and four indicates that starting from there, it would be highly recommended to harvest during these phases. The trees can be harvested once for at least one period (year) as it is necessary to let them grow naturally.

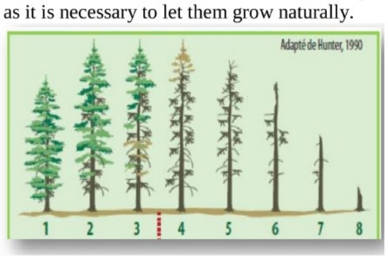

Figure 2.1: Instar or phases of SBW infestation in Balsam Fir taken from Lepage (2014)

Observing Figure 2.2, the research problem has the following characteristics. Starting from the raw material which is obtained in the forest stands (initial inventory), the harvest areas will supply one or many mills with trees according to their required demand. Once it is known which forest stands should be harvested, trees will be processed by removing the leaves and branches. Then, these trees (transformed into logs) will be shipped to any available terminal. The demand will be fulfilled for the final customers and/or stored (e.g. heating plants, sawmills, pulp mills, and panel mills). This allocation, now logs, will be possible through the use of transportation from the terminals.

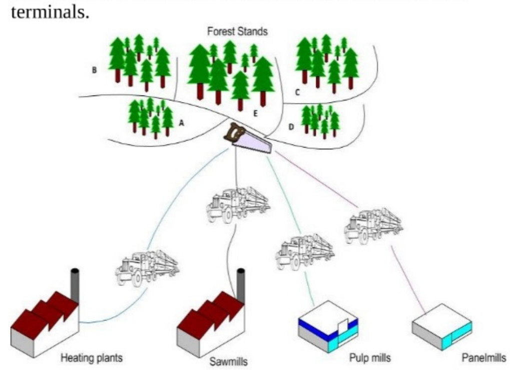

Figure 2.2: Basic harvesting process in the different forest supply chain industries

Also, each volume percentage of trees in the harvest area is in a specific phase of infestation, also called instar of the SBW life cycle (uncertain parameter), shown in Appendix I. These trees can be salvaged, and they have a rank quality corresponding to a price on the market or for sale according to their attributes. Evidently, the higher the quality of the trees, the higher the sale price. For example, in the forest stand "i", some volume percentage "A" is in phase two of the SBW cycle while other volume percentage "B" is in phase five. A decision should be taken by harvesting both amounts "A" and "B", either one of them or none, as "A" takes another several periods for SBW to evolve into the next instars. In contrast, percentage of volume "B" will progressively continue to grow into another random phase or remain in the current phase; or it will be better to harvest both amounts. However, it is required to have the highest quality log as possible, based on the market value shown in Appendix II, in order to reduce the harvesting and processing cost of trees that are severely infested, across the forest supply chain.

The objective is to minimize the costs of damaged harvest areas and the impact of SBW on the entire forest value chain by deciding which harvest area will be better to cut and the right trees to harvest. The decisions should be taken before the SBW outbreak appears, becomes widespread, defoliates and kills as time passes during the planning horizon in most of the forest stands and so, they cannot be salvaged.

As mentioned above, the present state of damage that can affect forest stands can start from the lowest, moderate or high defoliation evolving to an outbreak time. These states can be considered as some of the many or infinite scenarios of defoliation observed in Appendix I. These situations are affected by many types of events that can reduce or increase the dynamic population of SBW and thus make it difficult to make decisions at the moment compared to a mathematical deterministic linear programming (LP) model, as it is uncertain what the outcome of scenarios will be. They can remain in the same phase, or they can evolve into greater or lesser quality, randomly affecting the quality of yield.

3 LITERATURE REVIEW

3.1 OR in Forest Harvesting Planning

First of all, it should be clear what the harvesting process consists of: the trees are cut, and branches are removed (D'Amours, Ronnqvist et Weintraub, 2008), then, the tree is bucked (or cross-out) into logs of specific dimensions and quality. Trees and logs are then transported directly to mills or terminals for intermediate storage. This harvesting operation is part of the procurement process of the wood supply chain at the tactical level, according to the matrix at different hierarchical levels in the pulp and paper industry of Carlsson D; D´Amours S. (2006).

There exist several approaches that have dealt with forest management and harvest scheduling in a deterministic context, and few have dealt with uncertainties like infestation. D'Amours, Ronnqvist et Weintraub (2008) suggested that generally, for harvesting in tactical planning, Mixed Integer Linear Programming (MIP or MILP) and SP methods are better to model as regards decision making about whether, when and where timber should be harvested.

Basic optimization models for forest harvesting consider decisions about which areas to cut, which forest stands should be harvested per period, transportation to industries, which equipment or crews to use and assign or any attributes that can be added or applied to different models depending on the case. Other models consider the bucking process as decision variables like Troncoso et al. (2015) who propose an integrated planning strategy and a generic MIP model to evaluate integrating strategies in the forest value chain by maximizing the Net Present Value of the forest including decisions of bucking pattern. The MIP model is implemented in the modelling language AMPL (2003), and CPLEX 11 is used to solve the model and has been applied for different scenarios in a Chilean case. Another approach like Epstein et al. (2007) includes the basic operational activities related to harvesting, taking into account several characteristics such as quality, length, diameter and delivery. The bucking process tries to obtain as many high-value logs as possible in descending order. The market value will be higher if diameter logs are significantly higher. This approach addresses the total cutting units that should be harvested in each period, technologies and transportation. In the case of SBW, it is similar; if the infestation is higher, the market value of the product is lower, due to the quality. Therefore, these types of problems should be formulated as MIP models as Rönnqvist (2003) suggests, and when obtaining, the outputs of these deterministic models will likely be suboptimal or even infeasible if applied in real life because they do not consider uncertainty.

Contributions like Beaudoin, LeBel et Frayret (2007) for detailed tactical model planning, integrate harvesting decisions with certain log distribution, and mills' aggregated production planning by allowing wood exchanges between companies with a proposed MIP for a five-year horizon planning. It manages the wood flow to extract higher value from the logs processed in the mills, through MonteCarlo sampling and probability distribution function for generating scenarios. Also, a sensitivity analysis was applied to identify the stochastic parameters. Another example of using MIP for harvesting planning can be represented in Karlsson, Rönnqvist and Bergström (2004) who propose a model for an annual harvesting problem, including decisions about harvest areas, allocation of crews and transportation. The model is implemented in AMPL by Fourer, Gay et Kernighan (2003) language solved with CPLEX solver.

However, when it comes to resolving the harvesting models, sometimes it can be complex depending on the model. For example, Jorge R et al. (2003) use a Lagrangian relaxation approach to improving the solution process for machinery location problem between towers and skidders in forest harvesting in an MILP model. Also, Andalaft et al. (2003) introduce a solution approach based on Lagrangian relaxation and a strengthening of the LP formulation, enabling the solution of seventeen forests that are linked by demand constraints at the firm level. This problem was solved considering deterministic demand and price conditions for each period.

3.2 Forest Planning Under Uncertainty

Even though several approaches address harvesting planning, few of them are applied in stochastic optimization. Martell, Gunn et Weintraub (1998) explain that typical uncertainties occur in forestry planning like market uncertainties, natural variations in future growth and yields, the effect of fires or pests, floods, earthquakes, hurricanes, and storms. Martell (2007) suggests that stochastic modelling and optimization will be adequate for managing the forest in case of any occurrence of fire events. For forest management, insect infestation, like fire, is but one of many factors that forest land managers must consider. Therefore, it will be necessary to develop integrated insect/forest management. When talking about SP, it is necessary to consider that instead of solving for every scenario, it allows solving multiple scenarios that the problem can encounter, at the same time. Moreover, Savage, Martell et Wotton (2011) suggest that for reducing uncertainty and risk through forest management planning, some factors should be considered as a test for robustness in harvest scheduling models. The design of policies using SP in forestry planning and logs sorting in forest harvest areas integrated with transportation planning can be anticipated for avoiding shortfalls. As can be seen, for forest harvesting problems, MIP is adequate as Veliz et al. (2015) suggest that harvesting decisions are naturally modelled with binary variables. In this existing approach, it describes the uncertainties involved in their stochastic optimization model considering a tactical planning model developed for a Chilean forest firm making several simplifications.

Most of the previous studies are focused on planning or creating new policies for harvesting and implementing actions before these uncertainties occur, but not for some. An example of this is demonstrated in the Broman, Frisk et Rönnqvist (2006) approach. They designed new supply chain planning operations and transportation after the storm Gudrun had already affected forests in the southern part of Sweden. It is formulated as a two-stage SP with recourse; the penalties or shortages can be considered for dealing with this uncertainty that had already occurred. These actions aimed to harvest most of the damaged forest in a planning horizon; compared to an infested forest, it is similar. MIP will be adequately useful for modelling and solving in the case of SBW outbreaks when it tends to consider that not all harvest areas are healthy for cutting process in each period and these events cannot be controlled (2006).

3.2.1 *Modelling with Stochastic Programming*

When there is not full information or available data of some parameters in the model, these are considered as uncertain. Birge et Louveaux (2011) explain that stochastic linear programs are linear programs in which some problem data may be regarded as uncertain, and these are random variables. Others, such as Dupačová (2002) explains that for modelling two-stage SP, the first-stage decisions consist of all decisions that have to be selected before further information is revealed, whereas the second-stage decisions are allowed to adapt to this information. Stages do not necessarily refer to time periods; they correspond to steps in the decision process.

Several approaches have been applied to many cases using SP for planning problems with uncertainty, such as the production planning that refers to the quality of raw material and cutting patterns of the logs, considering random nature processes yields in sawmill production planning (Kazemi Zanjani, Ait-Kadi et Nourelfath, 2013). This approach considers as the uncertain parameter the yield with a recourse action backorder. The first stage decisions consist in producing and second stage decisions backorder when the demand is not fulfilled. Another example of modelling with SP in forestry can be seen in Shabani et al. (2014), which incorporates uncertainty in a previous model of forest biomass supply chain into a reformulated LP model with a one-year planning horizon. The uncertainty is the availability of biomass into monthly planning. After the reformulation, a two-stage SP model is generated in which scenarios vary between ±20%.

There are many examples of modelling harvesting problems with SP such as Rinaldi et Jonsson (2013) that proposes a model of harvesting decisions of private forest owners. They considered timber price uncertainty under risk-aversion. The SP model analyzes the effect of the information in harvesting decisions. Another example can be seen in Meilby, Strange et Thorsen (2001) that proposed a maximization model of optimal spatial harvesting when forest stands are faced with the risk of windthrows. Another approach to the harvesting process is discussed in Lohmander (2007) who suggests several SP formulations for harvesting problems using stochastic dynamic programming in discrete time with continuous probability density functions of stochastic prices for optimizing the stand level in forest management. Veliz et al. (2015) planned an integrated approach considering both harvesting and road construction decisions in the presence of uncertainty modelled as a multi-stage problem. The scenarios for testing their modelling include uncertainty in timber growth and yield. Also, Mosquera, Henig et Weintraub (2011) find the best plan for harvesting and road construction, given the timber availability and harvest cost, by designing insurance contracts using SP in forestry planning. Another example is explained in Yeh et al. (2015) who proposes an approach to a supply-allocation problem in a timberland system: harvester and manufacturer decision makers who have their own separate objectives to maximize their own profits. Yeh et al. (2015) use two-stage stochastic integer programming considering the penalties, the shortfall, and the excess. The first-stage decisions involve strategic decisions around biorefinery investments, such as location and capacity. The second-stage decisions involve bi-level timberlands.

4 METHODOLOGY

The methodology for addressing this problem will be the following process according to Figure 4.1. First, identify the parameters, variables, and components of the mathematical LP model that are involved in the problem in order to develop and formulate the model for addressing the research problem. Finally, the formulated problem should be validated using any optimization solver and generate data for the parameters.

First, the harvest planning problem is described, and any necessary assumptions or simplifications will be made within the definition of the decision variables, the objective function, and constraints. Then, when all the necessary characteristics are gathered together, the description of the problem will be proposed as a deterministic LP model. Formerly, considering the uncertainty in the harvesting process of forest stands, a two-stage SP with recourse will be used to formulate for the same problem under different scenarios.

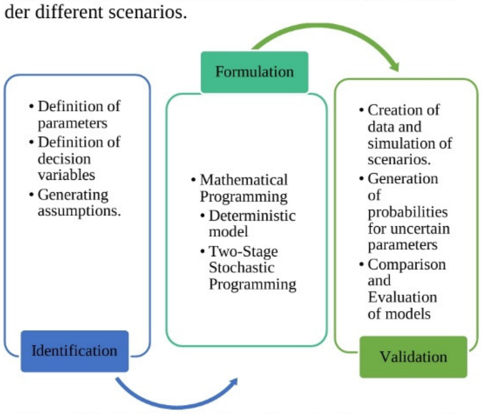

Figure 4.1: Methodology for addressing the process of harvesting of the forest stands.

Then, solvers such as CPLEX compiled in AMPL language will be used to solve the problem for the deterministic LP model. Moreover, a set of independent scenarios that will be required; the two-stage SP can also be solved as a Deterministic Equivalent Model (DEM) mode. Moreover, these scenarios will be run according to the desired planning horizon. Eventually, input data or database collection will be necessary for solving the problem (i.e. information about forest stands and infestation severity). When input data is implemented and processed through the optimization model, solution and evaluation will be shown as an output of the system. The different models will be analyzed, compared and discussed regarding their solution quality.

In SP, the uncertainty can be found on the right-hand side of the constraints or in the objective function. It is well known that some parameters such as market value price, feedstock yield, logistics costs, crop, yield, and demand are considered as stochastic; however, for this research problem, these are deemed to be known; meaning that the process is considered as pull strategy (the harvesting process is driven by the demand of different mills).

4.1 Mathematical Formulation

4.1.1 Assumptions

As mentioned before, all parameters are considered to be known, as well as the market value based on the classification of the quality of the trees according to the infestation phase. The propagation of SBW seems like the fire disturbance which it starts destroying slowly the forest, and if nothing can be recovered from one phase to the other, SBW will continuously evolve until nothing remains. This means that once the tree is dead, the raw material cannot be recovered. However, if these trees are cut before the event occurs, then the infestation will not spread, avoiding outbreaks. Also, it is assumed for this research that the characteristics of the forest stand will not affect the transition phases of the SBW since the age, colour, diameter, and size is assumed to be same in all forest stands. The same applies to road building; it will remain constant and will not suffer changes over the planning horizon.

According to the characteristics of the problem, here is a LP formulation:

A. **Sets**

$i \in I$: forest stands
$j \in J$: industry
$n \in N$: type species tree by forest stands
$q \in Q$: infestation phase of SBW life cycle
$q' \in Q$: infestation phase of SBW life cycle
$t \in T$: period

B. **Parameters**

f_{it} : opening cost of forest stand i in period t
e_{int}: harvesting cost of forest stand i, species n in period t
a_{ijnt}: allocation cost of forest stand i to industry j, species n in period t
d_{jnt} : demand of industry j, species tree n in period t
m_{nqt} : market price value of species n, phase q in period t
l_{inqt-1}: initial inventory of forest stand i, species tree n, phase q in period t
$k_{nqq'}$:percentage of forest stand volume per species n initial and final phase from q to q'

C. **Decision Variables**

x_{inqt}: volume harvested in forest stand i, phase q species n in period t
z_{int}: volume harvested in forest stand i, species n in period t
y_{it}: $\begin{cases} 1, & \text{if forest stand } i \text{ is open in period } t \\ 0, & \text{otherwise} \end{cases}$
l_{inqt} :inventory level of forest stand i, species n and SBW phase q in period t
w_{ijnt} : volume of logs allocated from forest stand i to industry j, species n in period t

D. **Mixed Integer Linear Programming Model**

Maximize $Z= \sum_i^I \sum_j^J \sum_{t=1}^T \sum_q^Q \sum_{q'}^Q \sum_n^N (m_{nqt}x_{iqnt} - a_{ijnt}w_{ijnt} - f_{it}y_{it} - e_{int}z_{int})$ (1)

Subject to:

$l_{inq't} = l_{inq't-1} - x_{inq't} - \sum_q^Q \sum_{q'}^Q (l_{inq't-1} - x_{inq't})(k_{nq'q}) + \sum_q^Q \sum_{q'}^Q (l_{inqt-1} - x_{inqt})(k_{nqq'})$ $\forall i \in I, \forall t \in T, \forall n \in N, \forall q' \in Q, \forall q \in Q$ (2)

$\sum_t^T y_{it} \leq 1 \quad \forall i \in I$ (3)

$\sum_q^Q \sum_n^N x_{inqt} \leq M y_{it} \quad \forall i \in I, \forall t \in T$ (4)

$\sum_q^Q x_{inqt} = z_{int} \quad \forall i \in I, \forall n \in N, \forall t \in T$ (5)

$\sum_i^I w_{ijnt} \leq d_{jnt} \quad \forall n \in N, \forall j \in J, \forall t \in T$ (6)

$\sum_j^J w_{ijnt} = \sum_q^Q x_{inqt} \quad \forall n \in N, \forall i \in I, \forall t \in T$ (7)

$y_{it} \in \{1,0\}, x_{inqt} \geq 0, l_{inqt} \geq 0, w_{ijt} \geq 0 \quad \forall t \in T, \forall i \in I, \forall n \in N, \forall q \in Q, \forall j \in J$ (8)

4.2 Description of Model

First, a deterministic model has to be formulated before the two-stage stochastic model. It is important to mention that when formulating the deterministic model, all the parameters are known, and for two-stage stochastic, one or more parameters are uncertain. The decision variables are considered the following for the problem: the volume harvested (as it is required to know exactly the quantity of trees harvested), the inventory level and volume of logs allocated to the industry according to the demand. Also, another important decision to make is where or which harvest area should be available for harvesting (consider this one as a binary decision as there are only two possibilities).

The main objective function (1) is to maximize the net value obtained from the sale of logs which have a market price according to quality (this quality will be referred to as the phase or instar in which each tree has a defoliation degree) less the costs of opening the area and harvesting or transformation as well as transportation to the terminal and wood allocation, considered as transportation costs. Constraint (2) referred to as the inventory constraint (harvest areas available) which consists of tracking the transition of the SBW evolution considering that the final inventory with the final infestation phase will be equal to the sum of the initial inventory with the previous final phase of infestation less what is cut or harvested with its final phase. It is important to state the fact that the parameter of transition is a time-dependent dynamic probability that consists in the chances that one tree of species *n* will jump to another possible phase or remain in the same state. As this is a balance-flow inventory constraint, not only the final inventory level takes into account the initial inventory less the volume harvested in their last phase of infestation, but also the initial phase infestation for both the original inventory less the volume harvested. This is due to the fact that what it is trying to accomplish is the tracing of the infestation phase. The constraint (3) refers to a total number of harvest areas; which should be a minimum of at least one area collected from each period. The number of harvest areas is also related to the capacity of volume harvested (4), which should not exceed the availability of the area harvested. Because the industries (e.g. sawmills, panelmills, and heating plants) do not consider which state of infestation phase of the SBW the product (log) is presenting, the decision variable x_{inqt} will act as an intermediate variable, another decision variable z_{int} is defined equally to the harvested area (5), but without considering the infestation phase of the SBW, which is why it is strictly equal these two variables. For constraint (6), it consists of supplying or allocating the logs (once the trees are transformed) according to the demand (mills). Also, the volume harvested (7) should be cut only according to what is desired to allocate. Finally, last but not least, constraint (8) states that all decisions variables should be non-negativity.

4.3 Two-Stage Stochastic Programming Model

For this problem, the first-stage decisions will be the opening of the harvest area or forest stands before realizing which trees should be harvested. The second-stage decisions describe the quantity or volume that should be cut as well as the inventory level of the logs and the allocation to each industry. As before, when allocating them through the supply chain, it is necessary to know the information about which areas or forest stands should be opened before performing the harvest operations and activities.

With the previous notation of the deterministic MILP model, an addition of new set of scenarios *S* for each possible realization of scenarios and equal probability of occurrence for those scenarios p^s is shown as the following for the two-stage SP formulation.

$$\text{Maximize } Z = \sum_i^I \sum_j^J \sum_{t=1}^T \sum_q^Q \sum_{q'}^Q \sum_n^N \sum_s^S p^s (m_{nqt} x_{inqt}^s - a_{ijnt} w_{ijnt}^s - e_{int} z_{int}^s) - \sum_i^I \sum_{t=1}^T f_{it} y_{it} \quad (9)$$

Subject to:

$$l_{inq't}^s = l_{inq't\text{-}1}^s - x_{inq't}^s - \sum_q^Q \sum_{q'}^Q (l_{inq't\text{-}1}^s - x_{inq't}^s)(k_{nq'q}^s) + \sum_q^Q \sum_{q'}^Q (l_{inqt\text{-}1}^s - x_{inqt}^s)(k_{nqq'}^s) \quad \forall i \in I, \forall t \in T, \forall n \in N, \forall q' \in Q, \forall s \in S, \forall q \in Q \quad (10)$$

$$\sum_q^Q \sum_n^N x_{inqt}^s \leq M y_{it} \qquad \forall i \in I, \forall t \in T, \forall s \in S \quad (11)$$

$$\sum_q^Q x_{inqt}^s = z_{int}^s \quad \forall i \in I, \forall n \in N, \forall t \in T, \forall s \in S \quad (12)$$

$$\sum_i^I w_{ijnt}^s \leq d_{jnt} \quad \forall n \in N, \forall j \in J, \forall t \in T, \forall s \in S \quad (13)$$

$$\sum_j^J w_{ijnt}^s = \sum_q^Q x_{inqt}^s \quad \forall t \in T, \forall n \in N, \forall i \in I, \forall s \in S \quad (14)$$

$$y_{it} \in \{1,0\}, x_{inqt}^s \geq 0, l_{inqt}^s \geq 0, w_{ijt}^s \geq 0 \quad \forall t \in T, \forall i \in I, \forall n \in N, \forall q \in Q, \forall j \in J, \forall s \in S \quad (15)$$

5 RESULTS AND DISCUSSION

The objective of testing the model is to compare the results and the functionality of the proposed model. In Table 5.1, the following SBW scenarios are introduced according to the different time-dependent dynamic probabilities of the transition matrix of Appendix I. The values for the parameters are tested in the model. Then, it is programmed in AMPL language and solved in CPLEX solver for different infestation scenarios with a certain initial inventory level with seventy five forest stands, five industries to supply, four types of tree species, and seven infestation phases over five periods.

As for the parameters, the data is proposed for validating the model in a congruent way as shown in Appendix II. For example, the market value depends on the transition phase of the SBW. This means the price value will decrease whenever the forest stand goes to the last phase of infestation and increases if there is no probability of infestation. Table 5.1 shows the expected profit value where the deterministic model is solved scenario by scenario and the expected value is calculated. Then, the two-stage SP is solved considering the overall of scenarios. The third column is the average of the scenarios when implementing first-stage solution (when the perfect information is available) for one period in order to allow flexibility in the forest management.

Deterministic model (Scenario by Scenario analysis)	Stochastic Model	Deterministic model-first stage decisions with average scenario	EVPI	VSS
44.66	43.67	44.23	0.99	0.56

Table 5.1: Expected profit of deterministic, stochastic, average scenario, EVPI and VSS in $M.

The quality of solution of the deterministic and stochastic solution is evaluated through the following metrics: EVPI and VSS. The first is known as Expected Value with the Perfect Information. This is the cost that the decision maker is willing to pay for a study of the uncertainty. The second one, VSS (Value of the Stochastic Solution) which is defined as the price or cost that the decision maker pays when uncertainty is not considered. The bounds of these solutions are explained in Escudero et al. (2007). Continuing with Table 5.1, the difference between solving scenario by scenario analysis and solving the model with the two-stage stochastic model is the EVPI, in which is $0.99M. This value is the cost that the decision maker will pay more for perfect information where applying with deterministic is much higher than when solving with a stochastic model as the last one considers all the scenarios. The value of $0.56M explained in the last column of Table 5.1 is the VSS which indicates that if the uncertainty is not considered, that will be the cost that decision maker has to pay for the stochastic solution rather than the mean value solution. This is the difference between the solution of the stochastic model and the expected value of the scenarios when implementing the first-stage solution of the average scenario.

Scenario	Optimal Solution	Stochastic Model	Deterministic model-Average scenario	SM-DM
S1	52.29	52.09	51.88	0.21
S2	51	50.92	50.6	0.32
S3	48.02	47.99	47.59	0.4
S4	45.91	45.86	45.48	0.38
S5	26.07	25.96	25.58	0.38
Expected Value	**44.66**	**44.56**	**44.23**	**0.34**

Table 5.2: Comparison of the different scenarios when solving with a stochastic solution in ($M).

Table 5.2 describes the profit of each scenario of the stochastic and deterministic model (using the average scenario) as well as for the optimal solution. The profit for each scenario is different. The comparison of the profits between using the stochastic model and the deterministic model, the solution of the stochastic model is lower than a deterministic solution as the last one considers all the scenarios rather than per each scenario. Moreover, it can be observed that if the scenario of infestation gets worse, the profit decreases too and vice-versa due to the great loss that forest management could face. This demonstrates that developing and implementing stochastic model reduces the loss and maximizes more the value of the forest taking into account that it also considers all the scenarios. Moreover, the solutions of the first-stage are different from two-stage SP as well as deterministic solution. As for the total quantity of forest stands harvested per period, they are shown in Appendix III and an example of taking into account when to harvest for only one forest stand is observed in Appendix IV.

Last but not least, Table 5.3 shows the profit of each scenario when implementing or fixing the solution of each scenario for one period. This shows that sometimes it can improve the value of the objective function or it can reduce it and/or make it infeasible.

FOR SCENARIO	Solution of scenario				
	S1	**S2**	**S3**	**S4**	**S5**
S1	52.29	52.24	52.14	51.95	51.85
S2	50.9	51.02	50.97	50.82	50.82
S3	47.37	47.83	48.05	47.95	47.95
S4	44.97	45.56	45.87	45.87	45.88
S5	24.49	25.23	25.75	26.07	26.07

Table 5.3: Profit in ($M) of each scenario when implementing each first stage per scenario solution.

There are many situations where one is faced with problems where decisions should be made sequentially at certain periods of time based on information available at each period. That means that if the first-stage decision for the first period is fixed, then this will become the available information for solving the actual period, which will be helpful as it will improve the value of the objective function. This will be an extension of the two-stage SP to a multi-stage SP (Shapiro et Philpott, 2007).

6 CONCLUSION AND FURTHER WORK

In this project, a two-stage stochastic model was proposed for addressing tactical planning in the forest supply chain considering the uncertainty of disturbance events such as insect infestation. The main focus was only on two levels from harvesting to terminals and sawmills. The contributions of this project are the value of the information provided by the parameter of percentage value as it allows better managing forest planning and better controlling the inventory (forest stands) by improving it and salvaging it from natural disturbances that can affect the yield and the availability of raw material. Therefore, it will enhance better decision making and maximizing the value chain.

The importance of SP compared to deterministic models is that it provides better solution quality than others, as uncertainty is considered because several scenarios are taken into account. Therefore, there is an added value in the wood chain. Ignoring uncertainty in optimization models may result in non-optimal and/or infeasible solutions for real case studies.

Potential future extensions of this research could be: adding fewer assumptions for improving the two-stage stochastic modelling, and adding more scenarios, considering more uncertain parameters such as demand and initial inventory that could improve the model. In addition, increasing the size of the model considering other attributes that form part of the forest supply chain could increase the accuracy of reality as that could be considered as a full and large integrated forest supply chain model. Other characteristics such as the bucking pattern, size, age, colour, dimensions, and yield should be considered for the rate of transition phases of the SBW that allow better interaction between the SWB life cycle and the population of forest stands. With these, the model can be more complex and harder to solve and require more advanced decomposition techniques (e.g. L-shaped method and SAA). Further analysis should be made for improving the model and the results and an application made in a real case of SBW outbreak.

7 APPENDICES

FROM/ TO	Low infestation				Medium infestation			
	WS	BS	RS	BF	WS	BS	RS	BF
1//1	0.95	0.82	0.87	0.9	0.68	0.8	0.65	0.58
1//2	0.05	0.15	0.1	0.1	0.32	0.2	0.32	0
1//3	0	0.03	0.03	0	0	0	0.03	0.42
2//1	0.35	0.17	0.22	0	0.15	0.43	0.12	0.11
2//2	0.57	0.49	0.62	0.2	0.7	0.42	0.67	0.61
2//3	0.08	0.15	0.16	0.8	0.15	0.15	0.15	0.21
2//4	0	0.19	0	0	0	0	0.06	0.07
3//1	0	0.09	0.08	0	0.07	0.25	0.07	0
3//2	0.26	0.11	0.35	0	0.45	0.14	0.48	0.11
3//3	0.44	0.32	0.57	0.1	0.38	0.35	0.35	0.34
3//4	0.3	0.26	0	0.9	0.1	0.26	0.1	0.41
3//5	0	0.22	0	0	0	0	0	0.14
4//1	0	0	0	0	0.05	0.08	0	0
4//2	0	0.18	0	0	0.05	0.05	0.05	0.05
4//3	0.36	0.16	0.14	0.36	0.25	0.25	0.25	0.25
4//4	0.24	0.53	0.74	0.24	0.4	0.37	0.37	0.06
4//5	0.4	0.13	0.12	0.4	0.25	0.25	0.25	0.54
4//6	0	0	0	0	0	0	0.08	0.1
5//2	0	0	0	0	0.01	0.04	0.01	0.01
5//3	0.3	0.08	0.09	0.3	0.05	0.05	0.05	0.05
5//4	0.5	0.05	0.21	0.5	0.33	0.33	0.33	0.17
5//5	0.2	0.56	0.5	0.2	0.5	0.47	0.47	0.05
5//6	0	0.18	0.2	0	0.11	0.11	0.11	0.72
5//7	0	0.13	0	0	0	0	0.03	0
6//3	0	0.05	0	0	0	0	0	0
6//4	0.1	0.09	0.1	0.1	0.1	0.24	0.1	0.08
6//5	0.8	0.21	0.05	0.8	0.55	0.3	0.5	0.13
6//6	0.1	0.46	0.82	0.1	0.12	0.24	0.12	0.16
6//7	0	0.19	0.03	0	0.23	0.22	0.28	0.63
7//5	0.8	0.03	0.04	0	0	0	0	0
7//6	0.15	0.84	0.76	0.8	0	0	0	0
7//7	0.05	0.13	0.2	0.2	1	1	1	1

FROM/TO	High Infestation				Severe Infestation			
	WS	BS	RS	BF	WS	BS	RS	BF
1//1	0.68	0.61	0.76	0.62	0.34	0.17	0.27	0.1
1//2	0	0.26	0	0	0	0	0	0
1//3	0.32	0.13	0.19	0.38	0	0	0	0
1//4	0	0	0.05	0	0.66	0	0.5	0
1//5	0	0	0	0	0	0.83	0.23	0.9
2//1	0	0.2	0	0	0	0	0	0
2//2	0.41	0.43	0.33	0.5	0.72	0.83	0.65	0.2
2//3	0.38	0.27	0.45	0.07	0	0	0	0
2//4	0.18	0.1	0.22	0.4	0.14	0	0	0
2//5	0.03	0	0	0.03	0.14	0.17	0.35	0
2//6	0	0	0	0	0	0	0	0.8
3//3	0.35	0.49	0.42	0.34	0.74	0.71	0.58	0.1
3//4	0.42	0.51	0.5	0.41	0	0	0	0
3//5	0.22	0	0.08	0.14	0.26	0	0	0
3//6	0.01	0	0	0	0	0.29	0.42	0
3//7	0	0	0	0.11	0	0	0	0.9
4//4	0.5	0.55	0.68	0.06	0.94	0.4	0.63	0.24
4//5	0.23	0.4	0.29	0.54	0	0.6	0.21	0
4//6	0.27	0.05	0.03	0.25	0.06	0	0.16	0
4//7	0	0	0	0.15	0	0	0	0.76
5//4	0	0.13	0	0	0	0	0	0
5//5	0.78	0.66	0.83	0.07	0.2	0.81	0.92	0.3
5//6	0.1	0.21	0.17	0.72	0.8	0.19	0.08	0
5//7	0.12	0	0	0.21	0	0	0	0.7
6//5	0.1	0	0.08	0	0	0	0	0
6//6	0.83	0.88	0.75	0.2	1	1	1	1
6//7	0.07	0.12	0.17	0.8	0	0	0	0
7//7	1	1	1	1	1	1	1	1

Appendix I: Dynamic Probability of transition of SBW for each scenario per species.

Phase	Market Value			
	WS	BS	RS	BF
1	$ 130.00	$ 100.00	$ 120.00	$ 98.00

2	$ 120.00	$ 85.00	$ 102.00	$ 78.00
3	$ 105.00	$ 67.00	$ 82.00	$ 53.00
4	$ 87.00	$ 47.00	$ 57.00	$ 48.00
5	$ 67.00	$ 22.00	$ 52.00	$ 38.00
6	$ 42.00	$ 17.00	$ 42.00	$ 23.00
7	$ 37.00	$ 7.00	$ 27.00	$ 5.00

Appendix II: Data of Market Value for each species according to the phase of infestation.

Period	1	2	3	4	5	Total
Scenario 1	9	5	6	5	6	31
Scenario 2	7	5	7	9	11	39
Scenario 3	5	7	10	16	25	63
Scenario 4	4	6	11	16	30	67
Scenario 5	4	22	42	4	3	75
Avg Deterministic Model	6	7	9	14	23	59
Stochastic Model	4	15	23	15	18	75

Appendix III: Total number of forest stands harvested for each period.

Scenario	Period				
	1	2	3	4	5
S1	**1**	0	0	0	0
S2	0	0	**1**	0	0
S3	0	**1**	0	0	0
S4	0	0	**1**	0	0
S5	0	0	0	**1**	0
Avg Deterministic Model	0	**1**	0	0	0
Stochastic Model	0	0	**1**	0	0

Appendix IV: Example results of first stage solution of one forest stand.

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APPENDIX II

EXAMPLE DATA OF MARKET VALUE FOR EACH TREE SPECIES PER SBW

INFESTATION PHASE

Table A-II. 1 Example of generated data of Net Value market for each tree species per infestation phase for preliminary validation of model $/m^3$.

Phase	Market Value of Tree Species			
	WS	BS	RS	BF
1	$ 130.00	$ 100.00	$ 120.00	$ 98.00
2	$ 120.00	$ 85.00	$ 102.00	$ 78.00
3	$ 105.00	$ 67.00	$ 82.00	$ 53.00
4	$ 87.00	$ 47.00	$ 57.00	$ 48.00
5	$ 67.00	$ 22.00	$ 52.00	$ 38.00
6	$ 42.00	$ 17.00	$ 42.00	$ 23.00
7	$ 37.00	$ 7.00	$ 27.00	$ 5.00

APPENDIX III

PROBABILITY OF TRANSITION OF SBW FOR EACH SCENARIO PER SPECIES

Table A-III. 1 Transition Matrix of SAB *Sapin Baumier* or *Balsam Fir* for “1 datacase” taken from Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	0%	**50%**	**50%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
2	0%	0%	**50%**	**50%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
3	0%	0%	**40%**	**20%**	**40%**	0%	0%	0%	0%	0%	0%	0%	0%	100%
4	0%	0%	0%	**30%**	**45%**	**25%**	0%	0%	0%	0%	0%	0%	0%	100%
5	0%	0%	0%	0%	**20%**	**30%**	**50%**	0%	0%	0%	0%	0%	0%	100%
6	0%	0%	0%	0%	0%	**35%**	**15%**	**50%**	0%	0%	0%	0%	0%	100%
70	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	0%	100%
71	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	100%
72	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	100%
73	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	100%
74	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%
75	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%

Table A-III. 2 Transition Matrix of EPB *Épinette Blanche* or *White Spruce* for “1 datacase” taken from Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	0%	**50%**	**50%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
2	0%	0%	**50%**	**50%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
3	0%	0%	**40%**	**20%**	**40%**	0%	0%	0%	0%	0%	0%	0%	0%	100%
4	0%	0%	0%	**30%**	**45%**	**25%**	0%	0%	0%	0%	0%	0%	0%	100%
5	0%	0%	0%	0%	**20%**	**30%**	**50%**	0%	0%	0%	0%	0%	0%	100%
6	0%	0%	0%	0%	0%	**35%**	**15%**	**50%**	0%	0%	0%	0%	0%	100%
70	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	0%	100%
71	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	100%
72	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	100%
73	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	100%
74	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%
75	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%

Table A-III. 3 Transition Matrix of SAB *Sapin Baumier* or *Balsam Fir* for “2 no infestation” scenario reproduced and adapted with the permission of FPInnovations and Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
2	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
3	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
4	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
5	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
6	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
70	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
71	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
72	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
73	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
74	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
75	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%

Table A-III. 4 Transition Matrix of EPB *Épinette Blanche* or *White Spruce* for “2 no infestation” scenario reproduced and adapted with the permission of FPInnovations and Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
2	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
3	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
4	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
5	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
6	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
70	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
71	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
72	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
73	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
74	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
75	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%

Table A-III. 5 Transition Matrix of SAB *Sapin Baumier* or *Balsam Fir* for "3 low infestation" scenario reproduced and adapted with the permission of FPInnovations and Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	0%	**90%**	10%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
2	0%	0%	**20%**	**80%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
3	0%	0%	0%	**10%**	**90%**	0%	0%	0%	0%	0%	0%	0%	0%	100%
4	0%	0%	0%	**36%**	**24%**	**40%**	0%	0%	0%	0%	0%	0%	0%	100%
5	0%	0%	0%	**30%**	**50%**	**20%**	0%	0%	0%	0%	0%	0%	0%	100%
6	0%	0%	0%	0%	**10%**	**80%**	**10%**	0%	0%	0%	0%	0%	0%	100%
70	0%	0%	0%	0%	0%	0%	**80%**	**20%**	0%	0%	0%	0%	0%	100%
71	0%	0%	0%	0%	0%	0%	0%	**80%**	**20%**	0%	0%	0%	0%	100%
72	0%	0%	0%	0%	0%	0%	0%	0%	**80%**	**20%**	0%	0%	0%	100%
73	0%	0%	0%	0%	0%	0%	0%	0%	0%	**80%**	**20%**	0%	0%	100%
74	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**80%**	**20%**	0%	100%
75	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**80%**	**20%**	100%

Table A-III. 6 Transition Matrix of EPB *Épinette Blanche* or *White Spruce* for "3 low infestation" scenario reproduced and adapted with the permission of FPInnovations and Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	0%	**95%**	**5%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
2	0%	0%	**35%**	**57%**	**8%**	0%	0%	0%	0%	0%	0%	0%	0%	100%
3	0%	0%	**26%**	**44%**	**30%**	0%	0%	0%	0%	0%	0%	0%	0%	100%
4	0%	0%	0%	**36%**	**24%**	**40%**	0%	0%	0%	0%	0%	0%	0%	100%
5	0%	0%	0%	**30%**	**50%**	**20%**	0%	0%	0%	0%	0%	0%	0%	100%
6	0%	0%	0%	0%	**10%**	**80%**	**10%**	0%	0%	0%	0%	0%	0%	100%
70	0%	0%	0%	0%	0%	**80%**	**15%**	**5%**	0%	0%	0%	0%	0%	100%
71	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	0%	100%
72	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	100%
73	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	100%
74	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	100%
75	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%

Table A-III. 7 Transition Matrix of SAB *Sapin Baumier* or *Balsam Fir* for “4 medium infestation” scenario reproduced and adapted with the permission of FPInnovations and Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	0%	58%	0%	42%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
2	0%	11%	61%	21%	7%	0%	0%	0%	0%	0%	0%	0%	0%	100%
3	0%	0%	11%	34%	41%	14%	0%	0%	0%	0%	0%	0%	0%	100%
4	0%	0%	5%	25%	6%	54%	10%	0%	0%	0%	0%	0%	0%	100%
5	0%	0%	1%	5%	17%	5%	72%	0%	0%	0%	0%	0%	0%	100%
6	0%	0%	0%	0%	8%	13%	16%	63%	0%	0%	0%	0%	0%	100%
70	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%	0%	0%	100%
71	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%	0%	100%
72	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%	100%
73	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	100%
74	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	100%
75	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	100%

Table A-III. 8 Transition Matrix of EPB *Épinette Blanche* or *White Spruce* for “4 medium infestation” scenario reproduced and adapted with the permission of FPInnovations and Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	0%	68%	32%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
2	0%	15%	70%	15%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
3	0%	7%	45%	38%	10%	0%	0%	0%	0%	0%	0%	0%	0%	100%
4	0%	5%	5%	25%	40%	25%	0%	0%	0%	0%	0%	0%	0%	100%
5	0%	0%	1%	5%	33%	50%	11%	0%	0%	0%	0%	0%	0%	100%
6	0%	0%	0%	0%	10%	55%	12%	23%	0%	0%	0%	0%	0%	100%
70	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%	0%	0%	100%
71	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%	0%	100%
72	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%	100%
73	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	100%
74	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	100%
75	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	100%

Table A-III. 9 Transition Matrix of SAB *Sapin Baumier* or *Balsam Fir* for "5 high infestation" scenario reproduced and adapted with the permission of FPInnovations and Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	0%	37%	0%	0%	0%	0%	0%	0%	0%	63%	0%	0%	0%	100%
2	0%	0%	41%	0%	0%	0%	3%	18%	0%	38%	0%	0%	0%	100%
3	0%	0%	0%	26%	0%	10%	22%	42%	0%	0%	0%	0%	0%	100%
4	0%	0%	0%	50%	23%	0%	10%	17%	0%	0%	0%	0%	0%	100%
5	0%	0%	0%	0%	0%	78%	10%	12%	0%	0%	0%	0%	0%	100%
6	0%	0%	0%	0%	0%	0%	10%	83%	7%	0%	0%	0%	0%	100%
70	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	100%
71	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%	0%	100%
72	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	100%
73	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	100%
74	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	100%
75	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	100%

Table A-III. 10 Transition Matrix of EPB *Épinette Blanche* or *White Spruce* for "5 high infestation" scenario reproduced and adapted with the permission of FPInnovations and Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	0%	48%	0%	52%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
2	0%	0%	41%	0%	38%	18%	0%	3%	0%	0%	0%	0%	0%	100%
3	0%	0%	0%	35%	42%	22%	0%	1%	0%	0%	0%	0%	0%	100%
4	0%	0%	0%	0%	50%	23%	0%	27%	0%	0%	0%	0%	0%	100%
5	0%	0%	0%	0%	0%	78%	0%	10%	0%	0%	12%	0%	0%	100%
6	0%	0%	0%	0%	0%	10%	83%	0%	0%	0%	7%	0%	0%	100%
70	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	100%
71	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	100%
72	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%	100%
73	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%	100%
74	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	100%
75	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	100%

Table A-III. 11 Transition Matrix of SAB *Sapin Baumier* or *Balsam Fir* for “6 severe infestation” scenario reproduced and adapted with the permission of FPInnovations and Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	0%	**10%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**90%**	100%
2	0%	0%	**20%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	**80%**	100%
3	0%	0%	0%	**10%**	0%	0%	0%	0%	0%	0%	0%	0%	**90%**	100%
4	0%	0%	0%	0%	**15%**	0%	0%	0%	0%	0%	0%	0%	**85%**	100%
5	0%	0%	0%	0%	0%	**30%**	0%	0%	0%	0%	0%	0%	**70%**	100%
6	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	100%
70	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	100%
71	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	100%
72	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	100%
73	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	100%
74	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%
75	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%

Table A-III. 12 Transition Matrix of EPB *Épinette Blanche* or *White Spruce* for “6 severe infestation” scenario reproduced and adapted with the permission of FPInnovations and Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	0%	**25%**	0%	0%	**66%**	0%	0%	0%	0%	0%	0%	0%	**9%**	100%
2	0%	0%	**20%**	0%	**14%**	0%	0%	**52%**	0%	0%	0%	0%	**14%**	100%
3	0%	0%	0%	**28%**	0%	0%	**42%**	**26%**	0%	0%	0%	0%	**4%**	100%
4	0%	0%	0%	0%	**31%**	**50%**	0%	0%	0%	0%	0%	0%	**19%**	100%
5	0%	0%	0%	0%	0%	**20%**	**65%**	0%	0%	0%	0%	0%	**15%**	100%
6	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%
70	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%
71	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%
72	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%
73	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%
74	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%
75	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	100%

Table A-III. 13 Transition Matrix of EPN *Épinette Noire* or *Black Spruce* for all infestation scenarios reproduced and adapted with the permission of FPInnovations and Charette et al. (2015).

From\To	0	1	2	3	4	5	6	70	71	72	73	74	75	Total
0	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
1	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
2	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
3	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
4	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
5	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
6	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
70	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
71	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
72	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
73	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
74	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
75	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%

APPENDIX IV

TOTAL VOLUME OF INVENTORY FOR EACH STAT

Table A-IV. 1 Total volume (m^3) or inventory of forest stands for each year per infestation phase of SAB data provided by FPInnovations and taken from Charette et al. (2015).

Infestation phase	Total volume (m3) SAB					
	stat14	stat15	stat16	stat17	stat18	stat19
0	71,395,334	71,395,334	71,395,334	71,395,334	71,395,334	71,395,334
1	22,561,618	8,586,304	3,917,273	1,946,299	1,888,690	1,888,690
2	11,860,740	18,274,994	10,707,615	5,827,751	3,191,305	2,024,757
3	1,375,912	8,832,141	16,198,689	13,961,489	10,692,243	6,355,620
4	18,200,643	10,773,943	12,438,324	16,857,219	14,969,558	15,098,297
5	302,198	7,796,006	6,741,256	7,321,128	10,859,198	8,873,551
6	3,359,702	1,128,684	4,756,851	5,909,870	6,516,543	10,007,106
70	2,230,412	2,268,742	632,065	2,936,250	3,706,219	3,869,516
71	860,506	2,230,412	2,268,742	632,065	2,936,250	3,706,219
72	233,695	860,506	2,230,412	2,268,742	632,065	2,936,250
73	87,957	233,695	860,506	2,230,412	2,268,742	632,065
74	564	87,957	233,695	860,506	2,230,412	2,268,742
75	-	564	88,521	322,217	1,182,722	3,413,134
TOTAL	132,469,281	132,469,281	132,469,281	132,469,281	132,469,281	132,469,281

Table A-IV. 2 Total volume (m^3) or inventory of forest stands for each year per infestation phase of EPB data provided by FPInnovations and taken from Charette et al. (2015).

Infestation phase	Total volume (m3) EPB					
	stat14	stat15	stat16	stat17	stat18	stat19
0	6,535,138	6,535,138	6,535,138	6,535,138	6,535,138	6,535,138
1	1,981,077	802,616	585,847	384,570	370,133	370,133
2	1,247,423	1,724,114	970,358	876,379	701,984	485,958
3	157,982	943,149	1,337,676	694,366	612,385	581,566
4	2,114,004	1,124,213	1,464,031	1,852,873	1,228,944	1,192,534
5	38,440	956,567	676,746	745,086	1,139,587	576,316
6	416,189	172,918	642,259	755,877	846,407	1,259,849
70	287,709	231,538	46,661	367,766	409,710	433,084
71	122,845	287,709	231,538	46,661	367,766	409,710
72	41,090	122,845	287,709	231,538	46,661	367,766
73	15,391	41,090	122,845	287,709	231,538	46,661
74	80	15,391	41,090	122,845	287,709	231,538
75	-	80	15,471	56,561	179,407	467,115
TOTAL	12,957,369	12,957,369	12,957,369	12,957,369	12,957,369	12,957,369

Table A-IV. 3 Total volume (m^3) or inventory of forest stands for each year per infestation phase of EPN data provided by FPInnovations and taken from Charette et al. (2015).

Infestation phase	Total volume (m3) EPN					
	stat14	stat15	stat16	stat17	stat18	stat19
0	179,953,417	179,953,417	179,953,417	179,953,417	179,953,417	179,953,417
1	43,460,653	43,460,653	43,460,653	43,460,653	43,460,653	43,460,653
2	19,920,016	19,920,016	19,920,016	19,920,016	19,920,016	19,920,016
3	2,155,150	2,155,150	2,155,150	2,155,150	2,155,150	2,155,150
4	26,623,199	26,623,199	26,623,199	26,623,199	26,623,199	26,623,199
5	372,145	372,145	372,145	372,145	372,145	372,145
6	4,532,938	4,532,938	4,532,938	4,532,938	4,532,938	4,532,938
70	2,534,907	2,534,907	2,534,907	2,534,907	2,534,907	2,534,907
71	879,753	879,753	879,753	879,753	879,753	879,753
72	211,577	211,577	211,577	211,577	211,577	211,577
73	76,024	76,024	76,024	76,024	76,024	76,024
74	589	589	589	589	589	589
75	-	-	-	-	-	-
TOTAL	280,720,369	280,720,369	280,720,369	280,720,369	280,720,369	280,720,369

APPENDIX V

INITIAL VOLUME STATUS OF NORTH SHORE REGION OF QUEBEC (CÔTE-NORD)

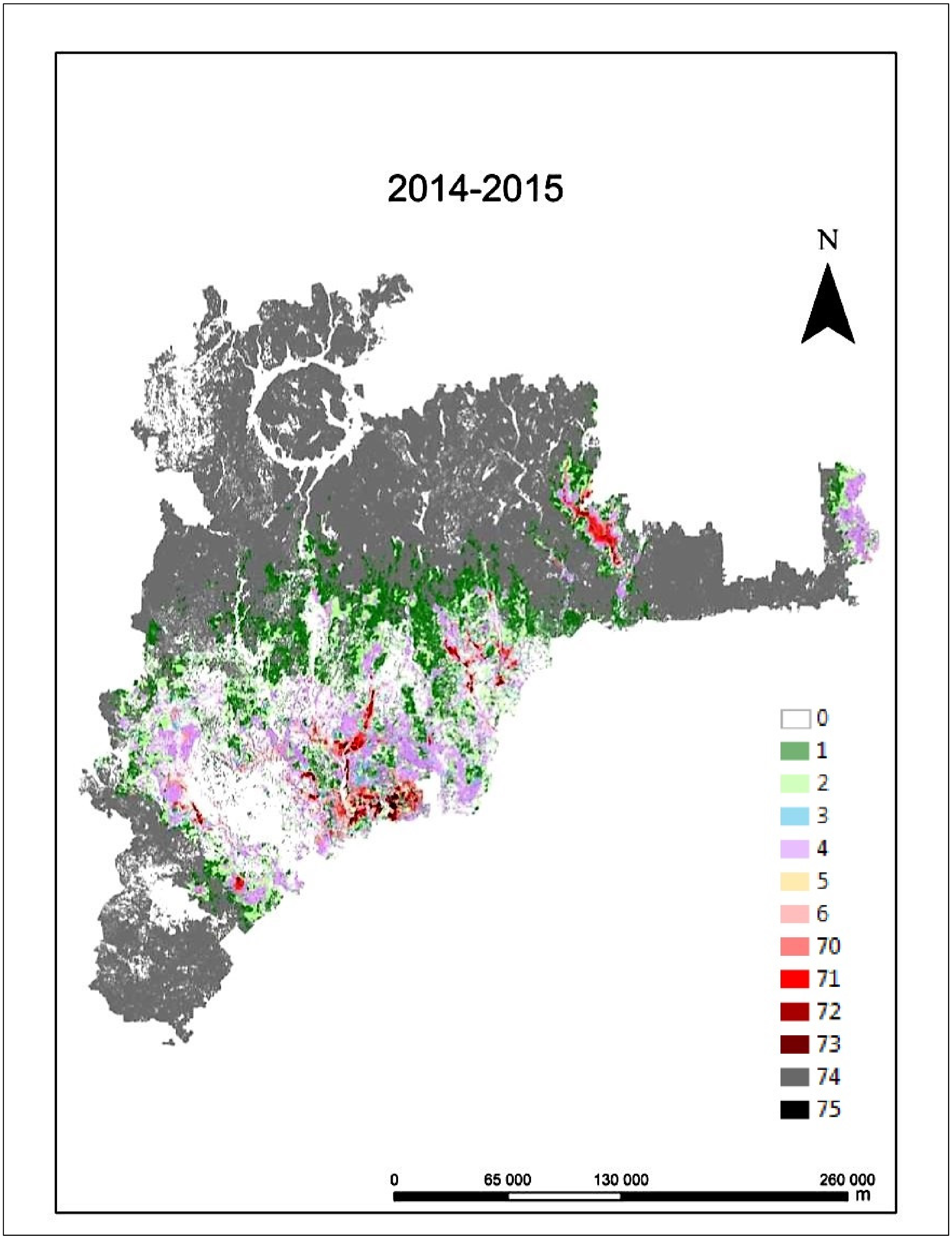

Figure A-V. 1 Cartography Model of the Initial inventory status or stat14 for risk in year 2014-2015 taken from Charette et al. (2015).

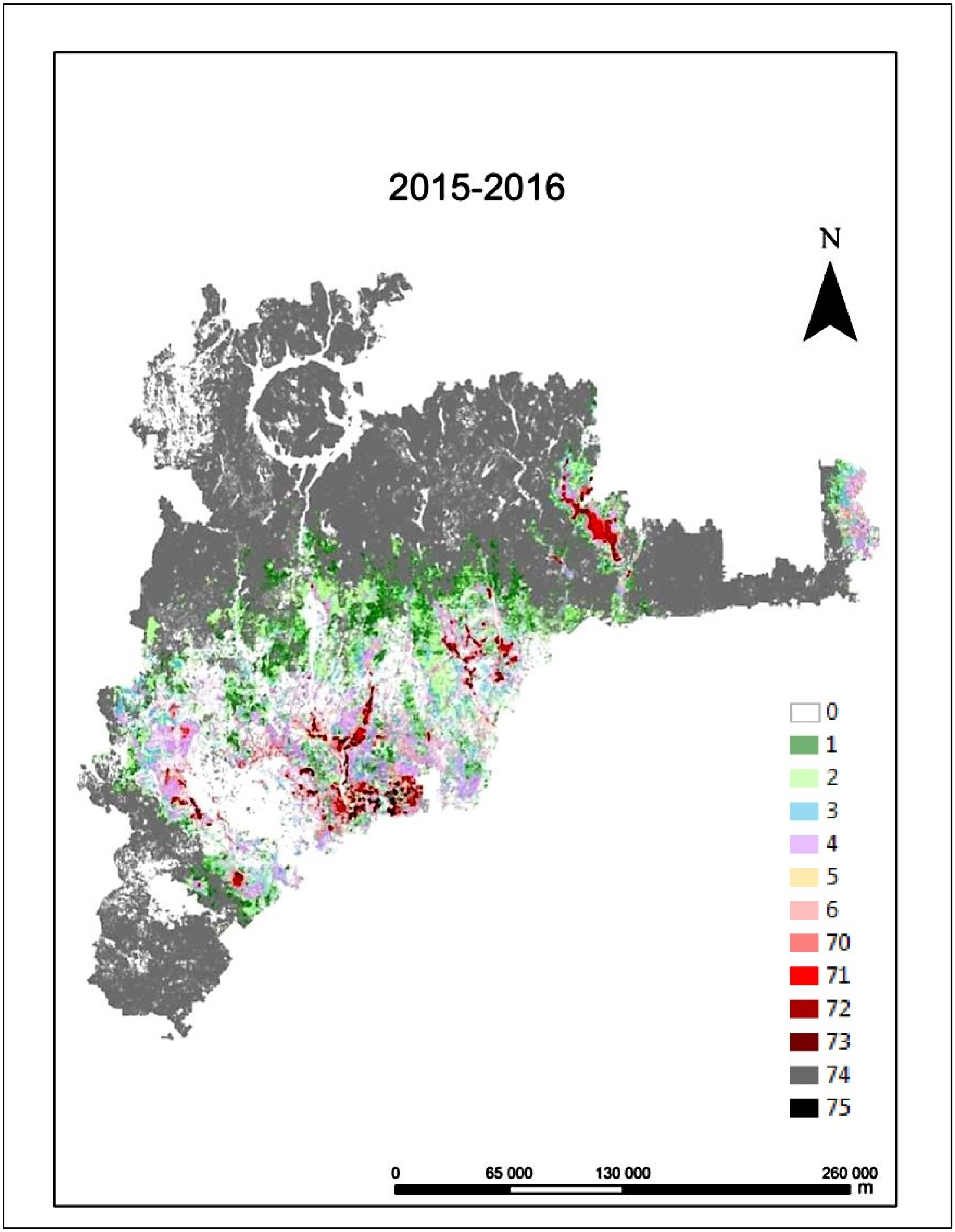

Figure A-V. 2 Cartography Model of the Initial inventory status or stat15 for risk in year 2015-2016 taken from Charette et al. (2015).

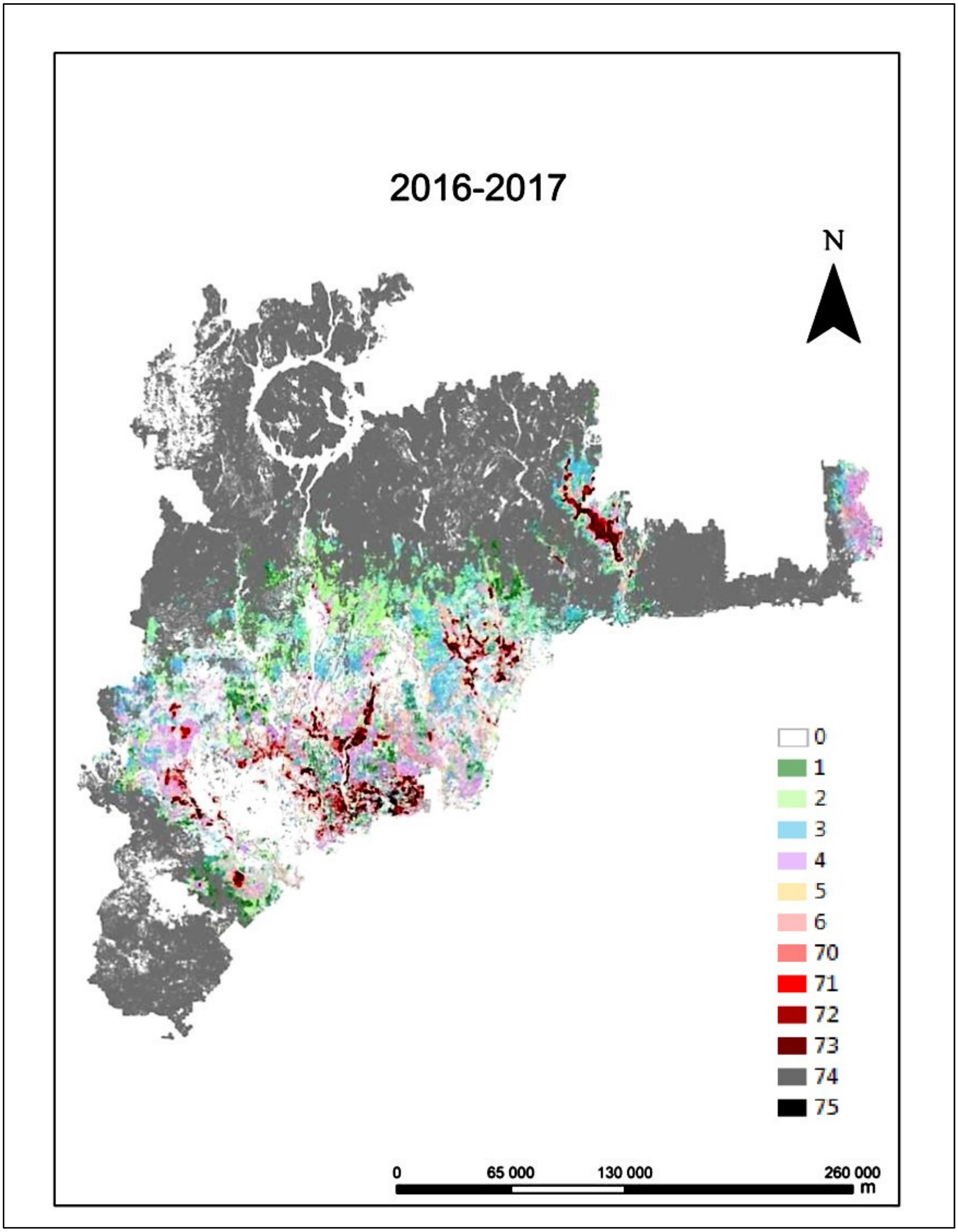

Figure A-V. 3 Cartography Model of the Initial inventory status or stat16 for risk in year 2016-2017 taken from Charette et al. (2015).

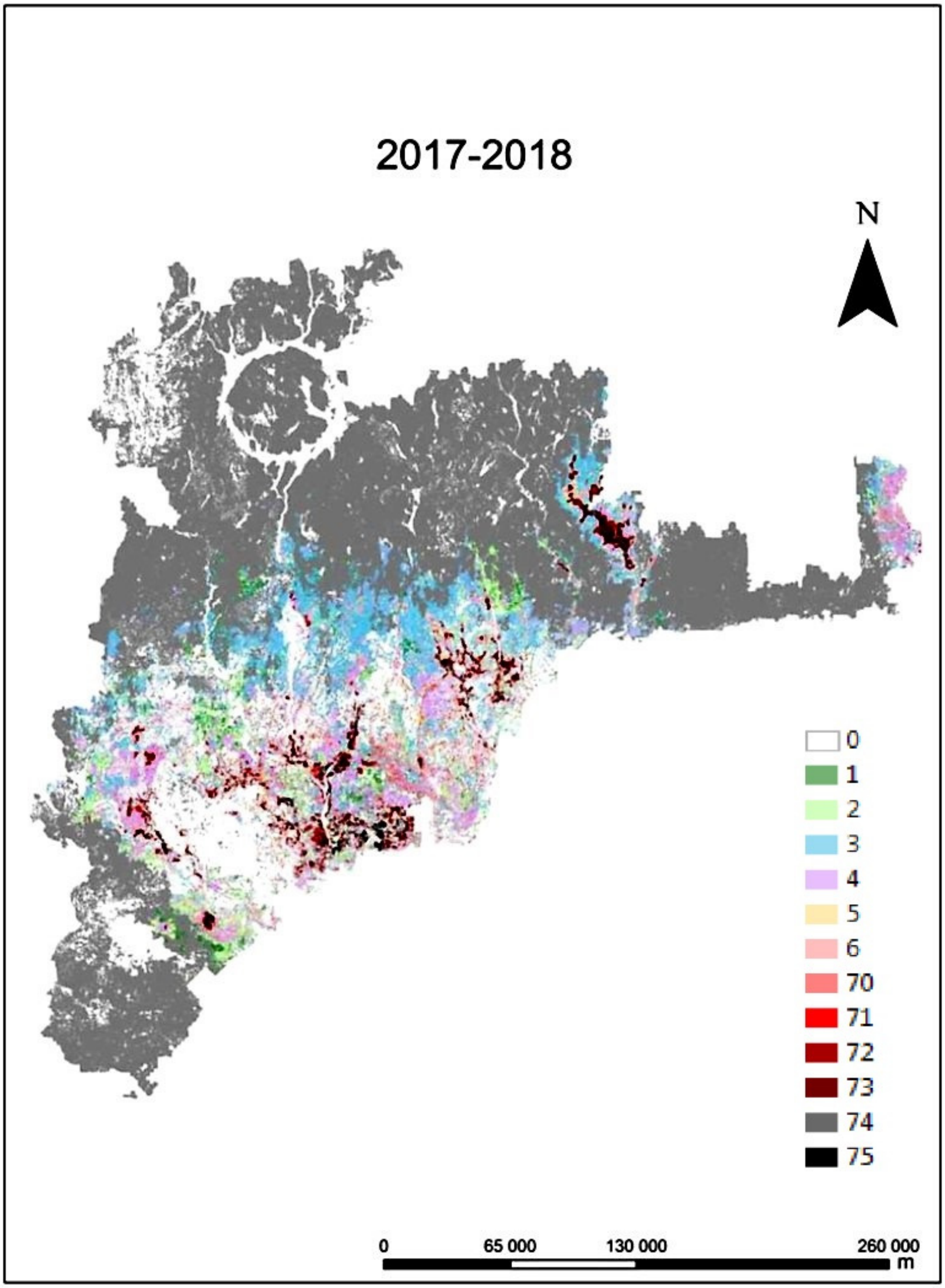

Figure A-V. 4 Cartography Model of the Initial inventory status or stat17 for risk in year 2017-2018 taken from Charette et al. (2015).

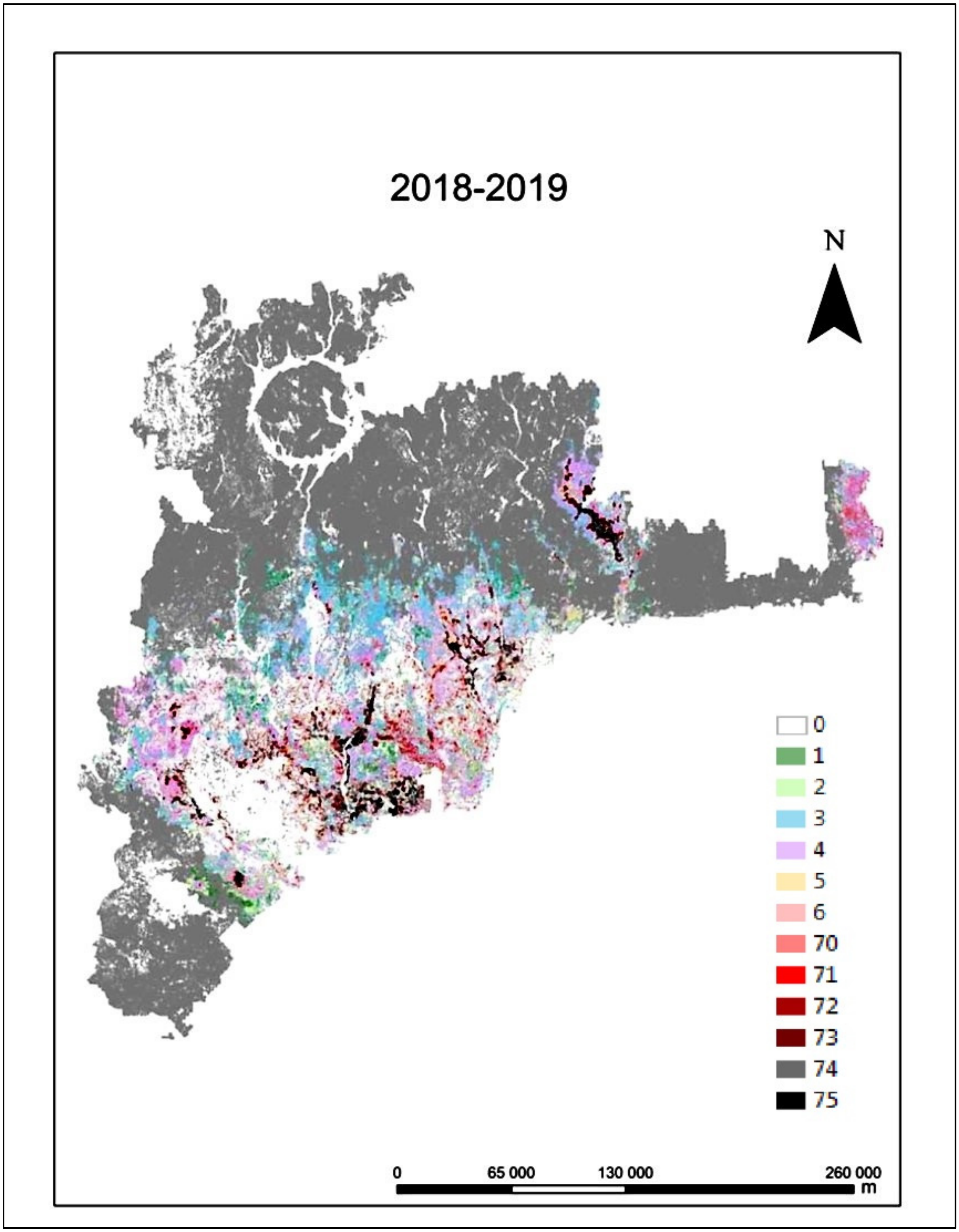

Figure A-V. 5 Cartography Model of the Initial inventory status or stat18 for risk in year 2018-2019 taken from Charette et al. (2015).

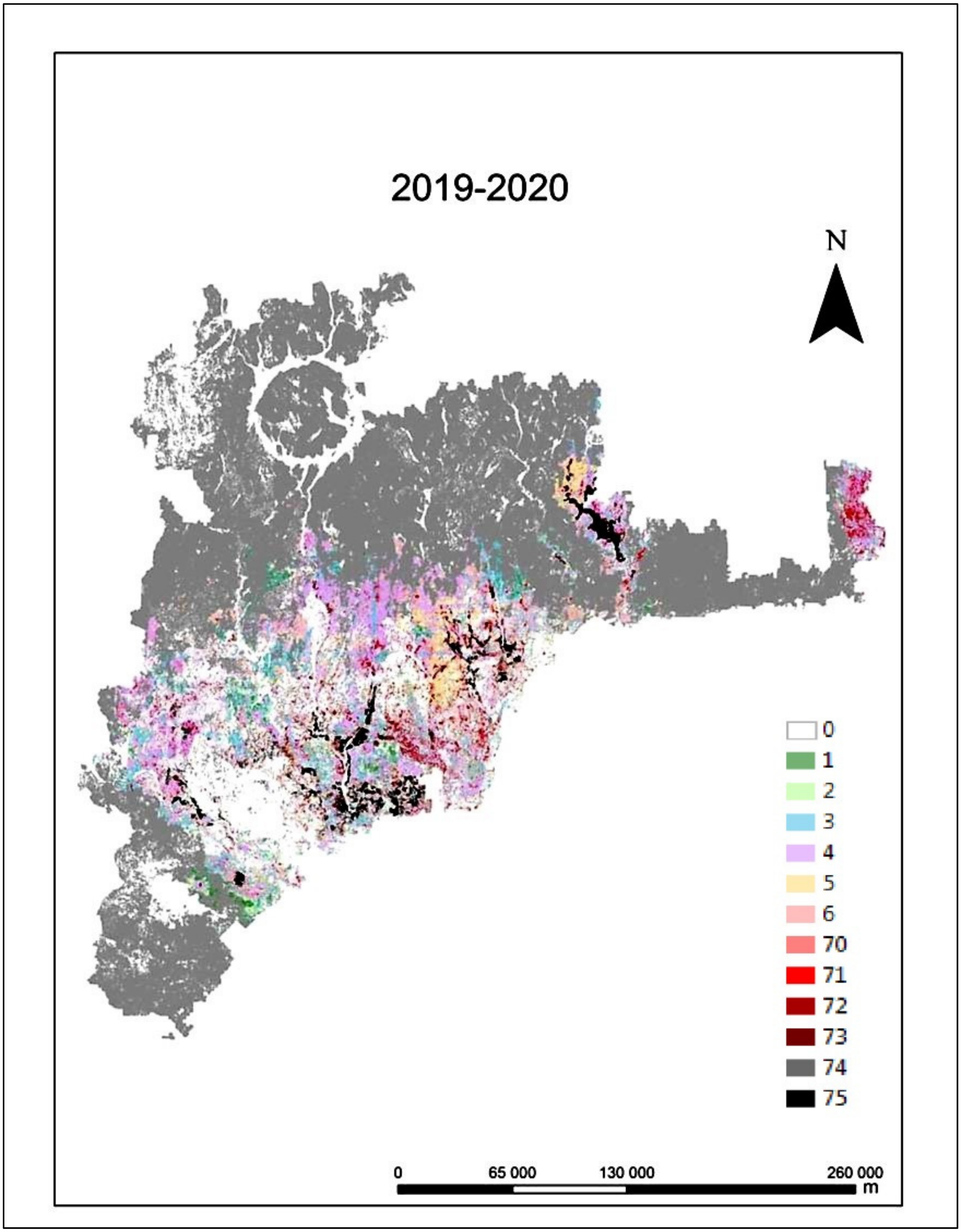

Figure A-V. 6 Cartography Model of the Initial inventory status or stat19 for risk in year 2019-2020 taken from Charette et al. (2015).

APPENDIX VI

ANNUAL ALLOWABLE CUT (AAC) DATA PROVIDED BY FPINNOVATIONS

Table A-VI. 1 Total volume of Annual Allowable Cut (AAC) per stat taken from FPInnovations and taken from Charette et al. (2015).

AAC	Total volume of AAC (m3)					
	stat14	stat15	stat16	stat17	stat18	stat19
0.10%	424,777	472,749	416,690	423,524	414,202	464,654
0.25%	1,061,943	1,181,874	1,041,724	1,058,811	1,035,505	1,161,636
0.50%	2,123,886	2,363,747	2,083,448	2,117,622	2,071,009	2,323,272
1%	4,247,771	4,727,494	4,166,896	4,235,244	4,142,018	4,646,545
2%	8,495,542	9,454,988	8,333,792	8,470,488	8,284,036	9,293,090

Table A-VI. 2 Total volume of Annual Allowable Cut (AAC) per stat per tree species taken from FPInnovations Charette et al. (2015).

	SPECIES	TOTAL VALUE OF AAC (m3) PER SPECIES FOR STAT14				
		0.10%	0.25%	0.50%	1.00%	2.00%
STAT14	SAB	14,567	36,416	72,833	145,666	291,332
	EPN	31,191	77,978	155,956	311,912	623,823
	EPB	1,440	3,599	7,199	14,397	28,794
	SPECIES	TOTAL VALUE OF AAC (m3) PER SPECIES FOR STAT15				
		0.10%	0.25%	0.50%	1.00%	2.00%
STAT15	SAB	14,689	36,723	73,446	146,893	293,786
	EPN	31,191	77,978	155,956	311,912	623,823
	EPB	6,647	16,618	33,236	66,473	132,945
	SPECIES	TOTAL VALUE OF AAC (m3) PER SPECIES FOR STAT16				
		0.10%	0.25%	0.50%	1.00%	2.00%
STAT16	SAB	13,668	34,170	68,340	136,680	273,360
	EPN	31,191	77,978	155,956	311,912	623,823
	EPB	1,440	3,599	7,199	14,397	28,794
	SPECIES	TOTAL VALUE OF AAC (m3) PER SPECIES FOR STAT17				
		0.10%	0.25%	0.50%	1.00%	2.00%
STAT17	SAB	14,427	36,069	72,137	144,274	288,548
	EPN	31,191	77,978	155,956	311,912	623,823
	EPB	1,440	3,599	7,199	14,397	28,794
	SPECIES	TOTAL VALUE OF AAC (m3) PER SPECIES FOR STAT18				
		0.10%	0.25%	0.50%	1.00%	2.00%
STAT18	SAB	13,392	33,479	66,958	133,916	267,831
	EPN	31,191	77,978	155,956	311,912	623,823
	EPB	1,440	3,599	7,199	14,397	28,794
	SPECIES	TOTAL VALUE OF AAC (m3) PER SPECIES FOR STAT19				
		0.10%	0.25%	0.50%	1.00%	2.00%
STAT19	SAB	13,906	34,766	69,531	139,063	278,125
	EPN	31,191	77,978	155,956	311,912	623,823
	EPB	6,531	16,327	32,654	65,309	130,617

APPENDIX VII

TOTAL NUMBER OF FOREST STANDS HARVESTED PER PERIOD PER AAC

Table A-VII. 1 Total number of forest stands harvested per stat and per period for AAC equivalent to 0.10%.

Case	Period	1	2	3	Total
STAT 14	1 datacase	14,971	4,247	1,612	**20,830**
	2 no infestation	15,580	2,606	2,644	**20,830**
	3 low infestation	14,602	4,457	1,771	**20,830**
	4 medium infestation	14,454	4,124	2,252	**20,830**
	5 high infestation	13,081	4,522	3,227	**20,830**
	6 severe infestation	14,557	4,442	1,831	**20,830**
	AVERAGE	**14,541**	**4,066**	**2,223**	**20,830**
	Average Deterministic Model	**16,136**	**4,085**	**609**	**20,830**
	Stochastic Model	**12,592**	**4,594**	**3,644**	**20,830**
STAT 15	1 datacase	14,563	4,047	2,220	**20,830**
	2 no infestation	13,828	3,799	3,203	**20,830**
	3 low infestation	14,353	4,237	2,240	**20,830**
	4 medium infestation	13,924	4,086	2,820	**20,830**
	5 high infestation	12,044	4,827	3,959	**20,830**
	6 severe infestation	16,057	3,875	898	**20,830**
	AVERAGE	**14,128**	**4,145**	**2,557**	**20,830**
	Average Deterministic Model	**14,770**	**5,175**	**885**	**20,830**
	Stochastic Model	**12,270**	**4,357**	**4,203**	**20,830**
STAT 16	1 datacase	13,906	4,312	2,612	**20,830**
	2 no infestation	14,955	2,687	3,188	**20,830**
	3 low infestation	14,299	4,141	2,390	**20,830**
	4 medium infestation	13,430	4,077	3,323	**20,830**
	5 high infestation	12,321	4,596	3,913	**20,830**
	6 severe infestation	13,449	4,565	2,816	**20,830**
	AVERAGE	**13,727**	**4,063**	**3,040**	**20,830**
	Average Deterministic Model	**15,278**	**4,149**	**1,403**	**20,830**
	Stochastic Model	**16,387**	**4,358**	**85**	**20,830**

Table A-VII.1 Total number of forest stands harvested per stat and per period for AAC equivalent to 0.10% (Continued).

STAT 17	1 datacase	13,651	4,049	3,130	**20,830**
	2 no infestation	6,806	3,539	10,485	**20,830**
	3 low infestation	13,892	4,241	2,697	**20,830**
	4 medium infestation	13,041	4,099	3,690	**20,830**
	5 high infestation	12,459	4,479	3,892	**20,830**
	6 severe infestation	7,943	6,031	6,856	**20,830**
	AVERAGE	**11,299**	**4,406**	**5,125**	**20,830**
	Average Deterministic Model	**15,174**	**4,206**	**1,450**	**20,830**
	Stochastic Model	**16,315**	**4,289**	**226**	**20,830**
STAT18	1 datacase	13,622	4,580	2,628	**20,830**
	2 no infestation	16,333	2,827	1,670	**20,830**
	3 low infestation	13,663	4,113	3,054	**20,830**
	4 medium infestation	12,064	4,612	4,154	**20,830**
	5 high infestation	13,810	3,636	3,384	**20,830**
	6 severe infestation	14,107	4,388	2,335	**20,830**
	AVERAGE	**13,933**	**4,026**	**2,871**	**20,830**
	Average Deterministic Model	**15,041**	**4,198**	**1,591**	**20,830**
	Stochastic Model	**NO RESULT**	**NO RESULT**	**NO RESULT**	**NO RESULT**
STAT 19	1 datacase	12,471	4,528	3,831	**20,830**
	2 no infestation	539	20,241	50	**20,830**
	3 low infestation	12,929	4,346	3,555	**20,830**
	4 medium infestation	12,424	4,298	4,108	**20,830**
	5 high infestation	12,552	4,439	3,839	**20,830**
	6 severe infestation	13,901	4,377	2,552	**20,830**
	AVERAGE	**10,803**	**7,038**	**2,989**	**20,830**
	Average Deterministic Model	**14,557**	**4,439**	**1,834**	**20,830**
	Stochastic Model	**15,814**	**4,449**	**567**	**20,830**

Table A-VII. 2 Total number of forest stands harvested per stat and per period for AAC equivalent to 0.25%.

Case	Period	1	2	3	Total
STAT 14	1 datacase	14,934	4,228	1,668	**20,830**
	2 no infestation	15,570	2,622	2,638	**20,830**
	3 low infestation	8,288	6,084	6,458	**20,830**
	4 medium infestation	8,406	5,774	6,650	**20,830**
	5 high infestation	13,022	4,631	3,177	**20,830**
	6 severe infestation	14,432	4,512	1,886	**20,830**

Table A-VII.2 Total number of forest stands harvested per stat and per period for AAC equivalent to 0.25% (Continued).

	AVERAGE	**12,442**	**4,642**	**3,746**	**20,830**
	Average Deterministic Model	**6,650**	**7,563**	**6,617**	**20,830**
	Stochastic Model	**12,701**	**4,522**	**3,607**	**20,830**
STAT 15	1 datacase	16,170	3,505	1,155	**20,830**
	2 no infestation	17,623	2,028	1,179	**20,830**
	3 low infestation	14,290	4,291	2,249	**20,830**
	4 medium infestation	13,839	4,109	2,882	**20,830**
	5 high infestation	11,995	4,860	3,975	**20,830**
	6 severe infestation	13,616	4,890	2,314	**20,820**
	AVERAGE	**14,589**	**3,947**	**2,292**	**20,828**
	Average Deterministic Model	**14,693**	**5,142**	**995**	**20,830**
	Stochastic Model	**12,269**	**4,384**	**4,177**	**20,830**
STAT 16	1 datacase	13,951	4,233	2,646	**20,830**
	2 no infestation	15,575	2,612	2,643	**20,830**
	3 low infestation	14,235	4,216	2,379	**20,830**
	4 medium infestation	13,413	4,067	3,350	**20,830**
	5 high infestation	12,362	4,631	3,897	**20,890**
	6 severe infestation	13,451	4,528	2,851	**20,830**
	AVERAGE	**13,831**	**4,048**	**2,961**	**20,840**
	Average Deterministic Model	**14,402**	**5,200**	**1,228**	**20,830**
	Stochastic Model	**16,356**	**4,358**	**116**	**20,830**
STAT 17	1 datacase	13,626	4,050	3,154	**20,830**
	2 no infestation	15,495	2,682	2,653	**20,830**
	3 low infestation	13,900	4,176	2,754	**20,830**
	4 medium infestation	13,031	4,124	3,675	**20,830**
	5 high infestation	12,527	4,463	3,840	**20,830**
	6 severe infestation	8,206	5,896	6,728	**20,830**
	AVERAGE	**12,798**	**4,232**	**3,801**	**20,831**
	Average Deterministic Model	**15,174**	**4,188**	**1,468**	**20,830**
	Stochastic Model	**16,319**	**4,307**	**204**	**20,830**
STAT 18	1 datacase	13,012	4,266	3,552	**20,830**
	2 no infestation	15,502	2,742	2,586	**20,830**
	3 low infestation	7,793	5,931	7,106	**20,830**
	4 medium infestation	12,724	4,222	3,884	**20,830**
	5 high infestation	12,610	4,424	3,796	**20,830**
	6 severe infestation	8,176	5,791	6,863	**20,830**
	AVERAGE	**11,636**	**4,563**	**4,631**	**20,830**
	Average Deterministic Model	**14,919**	**4,294**	**1,617**	**20,830**

Table A-VII.2 Total number of forest stands harvested per stat and per period for AAC equivalent to 0.25% (Continued).

	Stochastic Model	**16,016**	**4,366**	**448**	**20,830**
STAT 19	1 datacase	12,392	4,564	3,874	**20,830**
	2 no infestation	19,568	798	464	**20,830**
	3 low infestation	12,487	4,780	3,563	**20,830**
	4 medium infestation	11,476	4,883	4,471	**20,830**
	5 high infestation	12,483	4,463	3,884	**20,830**
	6 severe infestation	8,357	5,726	6,747	**20,830**
	AVERAGE	**12,794**	**4,202**	**3,834**	**20,830**
	Average Deterministic Model	**13,497**	**5,573**	**1,760**	**20,830**
	Stochastic Model	**15,806**	**4,527**	**497**	**20,830**

Table A-VII. 3 Total number of forest stands harvested per stat and per period for AAC equivalent to 0.50%.

Case	**Period**	**1**	**2**	**3**	**Total**
STAT 14	1 datacase	14,900	4,259	1,671	**20,830**
	2 no infestation	15,485	2,686	2,659	**20,830**
	3 low infestation	9,243	5,727	5,860	**20,830**
	4 medium infestation	8,376	5,774	6,680	**20,830**
	5 high infestation	7,704	6,186	6,940	**20,830**
	6 severe infestation	14,403	4,515	1,912	**20,830**
	AVERAGE	**11,685**	**4,858**	**4,287**	**20,830**
	Average Deterministic Model	**15,154**	**4,923**	**753**	**20,830**
	Stochastic Model	**13,917**	**907**	**6,006**	**20,830**
STAT 15	1 datacase	14,351	4,103	2,376	**20,830**
	2 no infestation	15,229	2,824	2,777	**20,830**
	3 low infestation	16,059	3,794	977	**20,830**
	4 medium infestation	14,198	4,125	2,507	**20,830**
	5 high infestation	11,869	4,777	4,184	**20,830**
	6 severe infestation	15,763	4,139	928	**20,830**
	AVERAGE	**14,578**	**3,960**	**2,292**	**20,830**
	Average Deterministic Model	**20,299**	**283**	**248**	**20,830**
	Stochastic Model	**12,234**	**4,374**	**4,222**	**20,830**
STAT 16	1 datacase	13,746	4,284	2,800	**20,830**
	2 no infestation	15,539	2,606	2,685	**20,830**
	3 low infestation	14,184	4,176	2,470	**20,830**
	4 medium infestation	13,365	4,084	3,381	**20,830**
	5 high infestation	12,232	4,610	3,988	**20,830**

Table A-VII.3 Total number of forest stands harvested per stat and per period for AAC equivalent to 0.50% (Continued).

	6 severe infestation	7,967	5,951	6,912	**20,830**
	AVERAGE	**12,839**	**4,285**	**3,706**	**20,830**
	Average Deterministic Model	**14,339**	**5,193**	**1,298**	**20,830**
	Stochastic Model	**16,364**	**4,360**	**106**	**20,830**
STAT 17	1 datacase	13,553	4,053	3,224	**20,830**
	2 no infestation	15,608	2,609	2,613	**20,830**
	3 low infestation	7,929	6,105	6,796	**20,830**
	4 medium infestation	12,959	4,130	3,741	**20,830**
	5 high infestation	12,569	4,375	3,886	**20,830**
	6 severe infestation	13,451	4,917	2,462	**20,830**
	AVERAGE	**12,678**	**4,365**	**3,787**	**20,830**
	Average Deterministic Model	**14,190**	**5,264**	**1,376**	**20,830**
	Stochastic Model	**16,214**	**4,350**	**266**	**20,830**
STAT 18	1 datacase	12,941	4,283	3,606	**20,830**
	2 no infestation	15,504	2,703	2,623	**20,830**
	3 low infestation	13,519	4,175	3,136	**20,830**
	4 medium infestation	12,636	4,267	3,927	**20,830**
	5 high infestation	12,564	4,452	3,814	**20,830**
	6 severe infestation	8,173	5,983	6,674	**20,830**
	AVERAGE	**12,556**	**4,311**	**3,963**	**20,830**
	Average Deterministic Model	**20,406**	**186**	**238**	**20,830**
	Stochastic Model	**15,966**	**4,403**	**461**	**20,830**
STAT 19	1 datacase	12,305	4,523	4,002	**20,830**
	2 no infestation	20,518	171	141	**20,830**
	3 low infestation	12,845	4,723	3,262	**20,830**
	4 medium infestation	11,810	4,934	4,086	**20,830**
	5 high infestation	12,469	4,491	3,870	**20,830**
	6 severe infestation	14,186	4,447	2,197	**20,830**
	AVERAGE	**14,022**	**3,882**	**2,926**	**20,830**
	Average Deterministic Model	**18,608**	**370**	**1,852**	**20,830**
	Stochastic Model	**15,755**	**4,513**	**562**	**20,830**

Table A-VII. 4 Total number of forest stands harvested per stat and per period for AAC equivalent to 1%.

Case	Period	1	2	3	Total
STAT 14	1 datacase	8,791	6,075	5,964	**20,830**
	2 no infestation	15,362	2,772	2,696	**20,830**

Table A-VII.4 Total number of forest stands harvested per stat and per period for AAC equivalent to 1% (Continued).

	3 low infestation	14,245	4,319	2,266	**20,830**
	4 medium infestation	8,044	5,975	6,811	**20,830**
	5 high infestation	15,439	4,206	1,185	**20,830**
	6 severe infestation	8,446	6,195	6,189	**20,830**
	AVERAGE	**11,721**	**4,924**	**4,185**	**20,830**
	Average Deterministic Model	**15,013**	**4,994**	**823**	**20,830**
	Stochastic Model	**12,554**	**4,581**	**3,695**	**20,830**
STAT 15	1 datacase	7,052	6,833	6,945	**20,830**
	2 no infestation	14,954	2,888	2,988	**20,830**
	3 low infestation	15,894	3,813	1,123	**20,830**
	4 medium infestation	7,413	6,959	6,458	**20,830**
	5 high infestation	13,778	2,562	4,490	**20,830**
	6 severe infestation	15,534	4,242	1,054	**20,830**
	AVERAGE	**12,438**	**4,550**	**3,843**	**20,831**
	Average Deterministic Model	**14,465**	**5,145**	**1,220**	**20,830**
	Stochastic Model	**6,990**	**6,927**	**6,913**	**20,830**
STAT 16	1 datacase	14,486	3,876	2,468	**20,830**
	2 no infestation	15,471	2,732	2,627	**20,830**
	3 low infestation	14,032	4,216	2,582	**20,830**
	4 medium infestation	12,873	4,446	3,511	**20,830**
	5 high infestation	11,980	4,533	4,317	**20,830**
	6 severe infestation	13,187	5,012	2,631	**20,830**
	AVERAGE	**13,672**	**4,136**	**3,023**	**20,831**
	Average Deterministic Model	**19,114**	**338**	**1,378**	**20,830**
	Stochastic Model	**6,930**	**6,955**	**6,945**	**20,830**
STAT 17	1 datacase	14,128	3,906	2,796	**20,830**
	2 no infestation	15,426	2,730	2,674	**20,830**
	3 low infestation	13,799	4,222	2,809	**20,830**
	4 medium infestation	12,352	4,491	3,987	**20,830**
	5 high infestation	12,408	4,511	3,911	**20,830**
	6 severe infestation	8,062	6,172	6,596	**20,830**
	AVERAGE	**12,696**	**4,339**	**3,796**	**20,831**
	Average Deterministic Model	**14,050**	**5,270**	**1,510**	**20,830**
	Stochastic Model	**16,189**	**4,350**	**291**	**20,830**
STAT 18	1 datacase	12,856	4,341	3,633	**20,830**
	2 no infestation	15,348	2,747	2,735	**20,830**
	3 low infestation	13,435	4,159	3,236	**20,830**
	4 medium infestation	11,955	4,640	4,235	**20,830**

Table A-VII.4 Total number of forest stands harvested per stat and per period for AAC equivalent to 1% (Continued).

	5 high infestation	11,981	4,511	4,338	**20,830**
	6 severe infestation	8,038	6,277	6,515	**20,830**
	AVERAGE	**12,269**	**4,446**	**4,115**	**20,830**
	Average Deterministic Model	**18,936**	**341**	**1,553**	**20,830**
	Stochastic Model	**15,872**	**4,436**	**522**	**20,830**
STAT 19	1 datacase	6,972	6,722	7,136	**20,830**
	2 no infestation	19,940	264	626	**20,830**
	3 low infestation	13,258	4,630	2,942	**20,830**
	4 medium infestation	12,476	4,680	3,674	**20,830**
	5 high infestation	13,037	4,499	3,294	**20,830**
	6 severe infestation	7,854	6,900	6,076	**20,830**
	AVERAGE	**12,256**	**4,616**	**3,958**	**20,830**
	Average Deterministic Model	**18,391**	**459**	**1,980**	**20,830**
	Stochastic Model	**7,068**	**6,820**	**6,942**	**20,830**

Table A-VII. 5 Total number of forest stands harvested per stat and per period for AAC equivalent to 2%.

Case	Period	1	2	3	Total
STAT 14	1 datacase	7,102	6,799	6,929	**20,830**
	2 no infestation	15,150	2,866	2,814	**20,830**
	3 low infestation	15,939	3,933	958	**20,830**
	4 medium infestation	14,678	4,095	2,057	**20,830**
	5 high infestation	12,481	5,592	2,757	**20,830**
	6 severe infestation	6,934	6,980	6,916	**20,830**
	AVERAGE	**12,047**	**5,044**	**3,739**	**20,830**
	Average Deterministic Model	**14,839**	**5,002**	**989**	**20,830**
	Stochastic Model	**7,022**	**6,795**	**7,013**	**20,830**
STAT 15	1 datacase	8,106	6,675	6,049	**20,830**
	2 no infestation	14,361	3,243	3,226	**20,830**
	3 low infestation	8,202	6,297	6,331	**20,830**
	4 medium infestation	7,353	6,923	6,554	**20,830**
	5 high infestation	15,120	3,522	2,188	**20,830**
	6 severe infestation	15,181	4,427	1,222	**20,830**
	AVERAGE	**11,387**	**5,181**	**4,262**	**20,830**
	Average Deterministic Model	**19,403**	**624**	**803**	**20,830**
	Stochastic Model	**7,092**	**6,848**	**6,890**	**20,830**
STAT 16	1 datacase	13,629	4,132	3,069	**20,830**

Table A-VII.5 Total number of forest stands harvested per stat and per period for AAC equivalent to 2% (Continued).

	2 no infestation	15,054	2,940	2,836	**20,830**
	3 low infestation	7,397	7,064	6,369	**20,830**
	4 medium infestation	12,701	4,465	3,664	**20,830**
	5 high infestation	15,577	3,145	2,108	**20,830**
	6 severe infestation	15,434	4,295	1,101	**20,830**
	AVERAGE	**13,299**	**4,340**	**3,191**	**20,830**
	Average Deterministic Model	**18,445**	**477**	**1,908**	**20,830**
	Stochastic Model	**7,015**	**6,983**	**6,832**	**20,830**
STAT 17	1 datacase	13,350	4,043	3,437	**20,830**
	2 no infestation	15,138	2,874	2,818	**20,830**
	3 low infestation	8,134	6,193	6,503	**20,830**
	4 medium infestation	12,214	4,561	4,055	**20,830**
	5 high infestation	11,906	4,662	4,262	**20,830**
	6 severe infestation	13,397	4,954	2,479	**20,830**
	AVERAGE	**12,357**	**4,548**	**3,926**	**20,831**
	Average Deterministic Model	**18,860**	**466**	**1,504**	**20,830**
	Stochastic Model	**7,066**	**6,904**	**6,860**	**20,830**
STAT 18	1 datacase	13,443	4,323	3,064	**20,830**
	2 no infestation	15,132	2,838	2,860	**20,830**
	3 low infestation	7,848	6,880	6,102	**20,830**
	4 medium infestation	12,545	4,639	3,646	**20,830**
	5 high infestation	12,194	4,518	4,118	**20,830**
	6 severe infestation	7,946	6,347	6,537	**20,830**
	AVERAGE	**11,518**	**4,924**	**4,388**	**20,830**
	Average Deterministic Model	**18,801**	**479**	**1,550**	**20,830**
	Stochastic Model	**7,110**	**6,855**	**6,865**	**20,830**
STAT 19	1 datacase	7,183	6,844	6,803	**20,830**
	2 no infestation	14,362	3,319	3,149	**20,830**
	3 low infestation	16,647	2,676	1,507	**20,830**
	4 medium infestation	10,947	4,938	4,945	**20,830**
	5 high infestation	15,456	3,142	2,232	**20,830**
	6 severe infestation	7,362	6,942	6,526	**20,830**
	AVERAGE	**11,993**	**4,644**	**4,194**	**20,831**
	Average Deterministic Model	**17,568**	**746**	**2,516**	**20,830**
	Stochastic Model	**7,036**	**6,910**	**6,884**	**20,830**

APPENDIX VIII

SECOND-STAGE DECISION VARIABLE: INVENTORY OF FOREST STANDS

Table A-VIII. 1 Total market value of the final inventory of stat14 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.10% of initial forest inventory.

SAB 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,749,826,821	8,832,275,924	4,749,901,436	4,749,830,572	4,749,590,139	4,748,656,385
1	189,190,468	-	1,103,027,339	412,815,274	76,643,031	1,513,079
2	1,202,306,811	-	162,208,634	437,424,963	54,727,651	6,349,998
3	1,024,060,610	-	864,518,572	876,208,880	111,218,431	90,288
4	690,585,848	-	1,137,936,377	552,152,775	14,203,223	3,939,827
Total	**7,855,970,558**	**8,832,275,924**	**8,017,592,359**	**7,028,432,465**	**5,006,382,476**	**4,760,549,577**
EPB 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	370,365,963	754,172,048	370,351,755	370,350,436	370,356,421	370,247,938
1	14,175,408	-	97,309,825	82,673,550	12,552,725	1,770,247
2	101,616,207	-	46,370,556	139,252,554	5,151,224	597,751
3	91,084,701	-	111,508,975	50,045,602	31,110,336	204,278
4	67,717,957	-	72,521,672	34,806,975	66,983,654	22,919,139
Total	**644,960,236**	**754,172,048**	**698,062,783**	**677,129,117**	**486,154,360**	**395,739,354**
EPN 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,393,620,893	19,393,620,776	19,393,620,513	19,393,620,677	19,393,620,705	19,393,620,703

Table A-VIII. 2 Total market value of the final inventory of stat14 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.25% of initial forest inventory.

SAB 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,739,315,984	8,817,390,147	4,738,212,552	4,739,321,008	4,739,360,215	4,737,863,468
1	188,992,074	-	1,102,795,543	412,436,485	76,580,581	1,511,861
2	1,200,678,007	-	162,158,422	436,602,501	54,603,780	6,332,765
3	1,022,615,040	-	863,722,553	875,144,644	111,102,293	89,702
4	689,689,135	-	1,136,543,602	551,513,681	14,202,152	3,939,530
Total	**7,841,290,240**	**8,817,390,147**	**8,003,432,672**	**7,015,018,319**	**4,995,849,021**	**4,749,737,326**
EPB 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	369,302,705	752,497,218	369,246,076	369,195,540	369,304,720	369,038,742
1	14,147,009	-	97,035,167	82,510,730	12,511,666	1,767,535
2	101,399,525	-	46,300,941	139,012,097	5,145,497	597,263
3	90,906,741	-	111,388,310	49,970,976	31,042,363	204,198
4	67,602,707	-	72,452,291	34,780,511	66,863,488	22,880,648
Total	**643,358,687**	**752,497,218**	**696,422,784**	**675,469,854**	**484,867,734**	**394,488,386**
EPN 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,361,631,552	19,361,631,227	19,361,630,938	19,361,631,382	19,361,630,957	19,361,630,881

Table A-VIII. 3 Total market value of the final inventory of stat14 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.50% of initial forest inventory.

SAB 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,722,910,150	8,792,730,150	4,727,628,284	4,723,217,696	4,722,663,431	4,719,368,350
1	188,841,900	-	1,101,255,360	411,660,457	76,473,906	1,509,112
2	1,197,876,567	-	161,893,341	434,945,362	54,339,848	6,299,078
3	1,020,112,277	-	860,379,867	872,820,082	110,825,052	89,566
4	687,744,540	-	1,130,574,764	550,030,250	14,202,068	3,939,507
Total	**7,817,485,435**	**8,792,730,150**	**7,981,731,616**	**6,992,673,848**	**4,978,504,305**	**4,731,205,613**
EPB 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	366,960,551	749,730,677	367,119,777	367,092,120	366,942,147	366,930,961
1	14,119,246	-	96,826,784	82,318,782	12,491,653	1,764,522
2	101,244,524	-	46,209,904	138,701,860	5,139,904	596,353
3	90,787,810	-	111,210,405	49,860,535	30,973,101	203,919
4	67,528,379	-	72,339,880	34,748,775	66,757,822	22,835,822
Total	**640,640,510**	**749,730,677**	**693,706,751**	**672,722,073**	**482,304,626**	**392,331,576**
EPN 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,308,661,788	19,308,661,795	19,308,662,515	19,308,661,744	19,308,661,870	19,308,661,685

Table A-VIII. 4 Total market value of the final inventory of stat14 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 1% of initial forest inventory.

SAB 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,689,588,017	8,743,746,329	4,698,535,785	4,692,593,470	4,693,628,572	4,683,466,471
1	188,241,870	-	1,098,024,068	409,910,163	76,219,927	1,504,747
2	1,191,903,064	-	161,406,366	431,801,827	53,905,623	6,257,091
3	1,015,555,876	-	855,868,768	867,993,286	110,371,453	88,445
4	684,202,314	-	1,123,101,704	547,021,404	14,189,276	3,935,958
Total	**7,769,491,141**	**8,743,746,329**	**7,936,936,691**	**6,949,320,149**	**4,948,314,851**	**4,695,252,712**
EPB 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	363,846,439	744,279,154	363,955,156	363,918,930	363,771,341	363,283,655
1	14,008,175	-	96,168,544	81,651,614	12,394,515	1,750,726
2	100,399,918	-	45,899,426	137,622,951	5,072,760	591,127
3	90,096,063	-	110,534,984	49,523,975	30,748,635	203,450
4	67,068,819	-	71,954,314	34,640,958	66,236,629	22,673,484
Total	**635,419,415**	**744,279,154**	**688,512,424**	**667,358,428**	**478,223,879**	**388,502,443**
EPN 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,203,286,780	19,203,287,009	19,203,286,345	19,203,285,944	19,203,285,943	19,203,286,441

Table A-VIII. 5 Total market value of the final inventory of stat14 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 2% of initial forest inventory.

SAB 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,622,652,483	8,646,493,078	4,638,737,968	4,625,633,251	4,624,337,513	4,660,498,650
1	187,295,784	-	1,091,611,578	406,868,113	75,781,426	1,513,537
2	1,180,377,804	-	160,439,496	426,934,494	53,413,238	6,359,236
3	1,007,033,105	-	846,806,695	859,649,933	109,518,789	91,001
4	676,505,245	-	1,110,782,670	541,821,971	14,178,371	3,928,019
Total	**7,673,864,420**	**8,646,493,078**	**7,848,378,406**	**6,860,907,762**	**4,877,229,337**	**4,672,390,444**
EPB 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	358,974,842	733,696,888	359,783,155	359,340,705	358,672,811	361,597,205
1	13,848,028	-	94,912,323	80,174,256	12,247,695	1,773,142
2	98,551,959	-	44,869,910	134,806,639	4,943,559	576,932
3	88,368,064	-	108,351,937	48,470,528	30,341,703	192,157
4	65,669,095	-	70,663,859	34,241,506	65,045,928	22,843,845
Total	**625,411,987**	**733,696,888**	**678,581,184**	**657,033,635**	**471,251,696**	**386,983,281**
EPN 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	18,993,719,260	18,993,719,219	18,993,719,129	18,993,719,095	18,993,719,111	19,020,030,214

Table A-VIII. 6 Total market value of the final inventory of stat15 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.10% of initial forest inventory.

SAB 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,748,298,429	8,832,190,740	4,749,558,535	4,748,692,874	4,748,880,539	4,748,214,106
1	69,828,486		407,239,912	280,789,836	28,296,191	558,628
2	994,613,191		67,390,582	520,795,477	84,842,679	9,847,544
3	959,117,993		995,978,370	735,741,494	74,410,259	596,056
4	761,435,296		1,460,119,311	512,561,011	8,278,963	2,296,499
Total	**7,533,293,396**	**8,832,190,740**	**7,680,286,709**	**6,798,580,692**	**4,944,708,631**	**4,761,512,832**
EPB 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	367,289,713	750,153,825	367,384,463	367,390,720	367,281,264	367,004,839
1	5,371,182		36,840,680	64,915,819	4,750,998	671,557
2	84,211,779		53,873,501	133,730,840	6,969,219	809,969
3	83,075,590		131,825,875	52,945,171	14,104,248	1,264,786
4	70,454,432		83,747,659	37,618,838	56,322,091	11,164,345
Total	**610,402,696**	**750,153,825**	**673,672,178**	**656,601,389**	**449,427,820**	**380,915,496**
EPN 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,393,620,727	19,393,621,381	19,393,620,500	19,393,620,521	19,393,620,916	19,393,621,390

Table A-VIII. 7 Total market value of the final inventory of stat15 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.25% of initial forest inventory.

SAB 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,737,453,582	8,817,182,538	4,739,575,236	4,737,481,453	4,738,308,581	4,736,309,200
1	69,828,517		407,239,437	280,602,241	28,296,158	558,627
2	993,163,182		67,379,450	520,108,212	84,752,185	9,837,382
3	958,019,463		994,407,234	734,824,984	74,358,532	594,254
4	760,137,643		1,458,360,894	511,898,687	8,278,963	2,296,499
Total	**7,518,602,387**	**8,817,182,538**	**7,666,962,251**	**6,784,915,577**	**4,933,994,419**	**4,749,595,962**
EPB 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	362,679,394	742,619,298	363,283,470	363,017,896	362,399,609	362,275,190
1	5,335,759		36,621,581	64,225,820	4,724,077	666,534
2	83,269,572		53,198,918	132,190,104	6,879,107	798,491
3	82,176,673		130,437,437	52,327,273	13,991,254	1,243,053
4	69,728,585		82,940,720	37,423,520	55,722,571	11,072,588
Total	**603,189,984**	**742,619,298**	**666,482,127**	**649,184,613**	**443,716,619**	**376,055,857**
EPN 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,361,630,928	19,361,630,900	19,361,630,947	19,361,630,898	19,361,630,873	19,361,630,881

Table A-VIII. 8 Total market value of the final inventory of stat15 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.50% of initial forest inventory.

SAB 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,719,418,268	8,792,313,955	4,724,141,014	4,720,877,855	4,720,832,709	4,719,161,129
1	69,806,962		407,119,752	280,149,170	28,287,638	558,455
2	991,012,044		67,347,025	518,688,933	84,626,630	9,814,441
3	956,009,480		992,245,576	733,050,963	74,215,443	589,769
4	758,322,770		1,453,170,085	510,507,658	8,278,963	2,296,262
Total	**7,494,569,524**	**8,792,313,955**	**7,644,023,452**	**6,763,274,579**	**4,916,241,383**	**4,732,420,056**
EPB 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	355,567,762	8,792,313,955	357,890,320	356,819,975	354,966,263	354,557,131
1	5,277,427		36,172,429	62,997,422	4,685,170	657,821
2	81,778,547		52,043,859	129,489,296	6,746,742	782,609
3	80,717,199		127,786,425	51,197,974	13,802,484	1,208,668
4	68,436,365		81,326,261	36,899,175	54,705,232	10,924,817
Total	**591,777,300**	**8,792,313,955**	**655,219,293**	**637,403,842**	**434,905,892**	**368,131,046**
EPN 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,308,661,685	19,308,662,074	19,308,661,927	19,308,661,686	19,308,661,693	19,308,662,340

Table A-VIII. 9 Total market value of the final inventory of stat15 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 1% of initial forest inventory.

SAB 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,683,362,427	8,742,918,677	4,695,736,659	4,681,855,270	4,687,668,416	4,679,304,156
1	69,766,794		406,774,051	279,287,018	28,263,405	557,989
2	986,681,640		67,254,993	516,097,249	84,273,474	9,782,116
3	952,152,650		987,447,546	729,746,446	73,914,191	585,116
4	754,765,098		1,441,770,459	507,801,167	8,278,609	2,295,795
Total	**7,446,728,610**	**8,742,918,677**	**7,598,983,709**	**6,714,787,149**	**4,882,398,095**	**4,692,525,172**
EPB 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	343,920,976	706,894,785	346,580,182	344,628,961	342,199,157	340,838,218
1	5,141,041		35,412,408	60,567,984	4,576,732	634,037
2	78,286,047		50,059,928	124,187,813	6,410,146	738,028
3	77,197,259		123,002,281	49,318,069	13,311,503	1,107,513
4	65,399,098		78,398,642	36,044,855	52,218,766	10,539,458
Total	**569,944,421**	**706,894,785**	**633,453,440**	**614,747,681**	**418,716,304**	**353,857,253**
EPN 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,203,285,979	19,203,291,340	19,203,285,931	19,203,285,933	19,203,285,934	19,203,286,154

Table A-VIII. 10 Total market value of the final inventory of stat15 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 2% of initial forest inventory.

SAB 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,603,847,871	8,644,857,990	4,626,102,821	4,606,054,647	4,612,643,076	4,602,344,963
1	69,644,079		405,790,072	277,599,380	28,198,388	556,316
2	980,303,815		67,051,003	511,628,682	83,720,672	9,704,644
3	946,333,185		979,624,535	724,025,892	73,587,463	576,250
4	750,169,456		1,430,392,243	503,563,970	8,278,119	2,294,037
Total	**7,350,298,405**	**8,644,857,990**	**7,508,960,674**	**6,622,872,572**	**4,806,427,718**	**4,615,476,209**
EPB 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	322,988,524	661,763,242	329,974,407	325,695,044	319,115,032	314,857,843
1	4,867,343		33,586,945	55,306,905	4,346,625	594,879
2	71,052,275		45,394,932	112,629,430	5,795,995	667,132
3	70,108,396		111,870,335	44,824,942	12,385,802	959,343
4	59,402,954		71,612,350	33,664,724	47,361,704	9,800,101
Total	**528,419,493**	**661,763,242**	**592,438,968**	**572,121,044**	**389,005,157**	**326,879,298**
EPN 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	18,993,719,083	18,993,726,894	18,993,719,080	18,993,719,893	18,993,719,215	18,993,719,140

Table A-VIII. 11 Total market value of the final inventory of stat16 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.10% of initial forest inventory.

SAB 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,748,287,568	8,832,892,147	4,749,877,044	4,748,391,314	4,748,390,651	4,747,442,112
1	30,578,283		178,332,547	166,401,215	12,391,054	244,626
2	810,865,011		30,817,827	415,430,143	48,428,387	5,620,762
3	849,955,885		981,973,376	598,767,615	93,668,780	1,105,034
4	786,846,260		1,606,717,455	483,523,531	9,617,488	2,667,544
Total	**7,226,533,007**	**8,832,892,147**	**7,547,718,249**	**6,412,513,818**	**4,912,496,360**	**4,757,080,078**
EPB 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	370,326,908	754,172,174	370,419,414	370,365,328	370,375,082	370,219,402
1	3,942,169		27,038,776	55,109,088	3,481,671	490,505
2	70,796,805		49,029,687	118,475,392	3,791,944	440,150
3	73,827,773		128,094,492	53,184,812	11,932,471	1,748,299
4	70,168,820		85,151,220	44,033,505	50,015,696	8,809,011
Total	**589,062,475**	**754,172,174**	**659,733,590**	**641,168,125**	**439,596,865**	**381,707,366**
EPN 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,393,620,514	19,393,620,750	19,393,620,645	19,393,620,528	19,393,620,602	19,393,620,511

Table A-VIII. 12 Total market value of the final inventory of stat16 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.25% of initial forest inventory.

SAB 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,736,673,384	8,818,913,057	4,738,212,552	4,737,601,616	4,737,745,855	4,734,701,969
1	30,578,283		1,102,795,543	166,328,646	12,391,021	244,626
2	810,081,401		162,158,422	414,963,693	48,419,530	5,619,308
3	849,439,546		863,722,553	598,041,389	93,561,931	1,103,844
4	786,020,480		1,136,543,602	482,881,528	9,616,592	2,667,539
Total	**7,212,793,094**	**8,818,913,057**	**8,003,432,672**	**6,399,816,872**	**4,901,734,929**	**4,744,337,286**
EPB 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	369,106,836	752,497,575	369,246,076	369,264,386	369,048,430	369,035,461
1	3,923,090		97,035,167	54,964,952	3,470,544	490,292
2	70,649,582		46,300,941	118,197,610	3,790,478	439,844
3	73,693,910		111,388,310	53,081,155	11,907,129	1,744,747
4	70,068,089		72,452,291	44,000,600	49,952,068	8,794,509
Total	**587,441,507**	**752,497,575**	**696,422,784**	**639,508,703**	**438,168,649**	**380,504,852**
EPN 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,361,630,919	19,361,631,069	19,361,630,938	19,361,630,915	19,361,630,949	19,361,630,955

Table A-VIII. 13 Total market value of the final inventory of stat16 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.50% of initial forest inventory.

SAB 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,718,632,068	8,795,766,486	4,724,638,750	4,719,216,347	4,719,888,384	4,717,615,069
1	30,568,418		178,212,387	166,137,189	12,382,705	244,454
2	808,556,405		30,796,588	414,195,988	48,387,331	5,614,609
3	847,965,297		979,867,246	596,912,378	93,270,082	1,099,002
4	784,573,546		1,598,788,150	481,987,251	9,616,663	2,667,049
Total	**7,190,295,734**	**8,795,766,486**	**7,512,303,122**	**6,378,449,152**	**4,883,545,165**	**4,727,240,183**
EPB 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	366,759,501	749,731,650	367,190,712	367,011,852	366,851,171	366,742,510
1	3,919,054		26,886,074	54,863,427	3,468,293	490,332
2	70,521,223		48,832,151	117,961,029	3,781,015	438,919
3	73,569,679		127,648,728	52,972,282	11,890,318	1,736,202
4	69,957,001		84,884,105	43,962,181	49,836,735	8,786,269
Total	**584,726,458**	**749,731,650**	**655,441,770**	**636,770,772**	**435,827,532**	**378,194,232**
EPN 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,308,661,749	19,308,661,963	19,308,661,726	19,308,661,730	19,308,661,699	19,308,665,203

Table A-VIII. 14 Total market value of the final inventory of stat16 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 1% of initial forest inventory.

SAB 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,680,526,838	8,749,764,587	4,696,041,657	4,684,411,213	4,684,456,811	4,676,742,854
1	30,543,147		178,133,323	165,794,825	12,376,523	244,302
2	806,285,651		30,777,529	412,586,428	48,313,051	5,609,187
3	845,799,111		975,795,046	594,429,094	93,034,693	1,095,274
4	782,422,742		1,589,562,045	479,874,554	9,614,504	2,666,260
Total	**7,145,577,489**	**8,749,764,587**	**7,470,309,599**	**6,337,096,114**	**4,847,795,582**	**4,686,357,877**
EPB 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	363,480,552	744,280,546	363,634,638	363,660,105	362,690,274	363,089,417
1	3,907,570		26,821,604	54,434,888	3,461,279	487,426
2	69,928,147		48,450,542	116,977,054	3,756,407	435,030
3	72,966,133		126,871,976	52,541,537	11,808,428	1,720,247
4	69,324,016		84,393,046	43,802,855	49,531,425	8,741,974
Total	**579,606,418**	**744,280,546**	**650,171,805**	**631,416,440**	**431,247,812**	**374,474,095**
EPN 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,203,286,716	19,203,286,032	19,203,285,959	19,203,286,007	19,203,285,982	19,203,285,941

Table A-VIII. 15 Total market value of the final inventory of stat16 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 2% of initial forest inventory.

SAB 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,607,438,036	8,658,458,211	4,620,260,597	4,611,117,959	4,612,141,288	4,599,420,596
1	30,496,421		177,752,215	165,135,373	12,345,099	243,624
2	800,081,672		30,713,615	409,938,575	48,205,368	5,592,030
3	841,520,242		971,797,952	590,351,064	92,441,380	1,085,209
4	776,602,809		1,582,774,075	476,321,792	9,610,622	2,664,383
Total	**7,056,139,180**	**8,658,458,211**	**7,383,298,455**	**6,252,864,763**	**4,774,743,757**	**4,609,005,842**
EPB 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	357,225,095	733,691,573	358,087,588	358,308,787	356,572,755	356,312,286
1	3,870,781		26,376,065	53,452,634	3,421,230	479,933
2	68,721,625		47,675,669	114,775,286	3,689,630	428,274
3	71,758,055		124,992,413	51,470,941	11,655,442	1,689,876
4	68,191,521		83,186,731	43,223,627	48,662,249	8,615,688
Total	**569,767,077**	**733,691,573**	**640,318,466**	**621,231,276**	**424,001,305**	**367,526,057**
EPN 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	18,993,719,119	18,993,719,624	18,993,720,164	18,993,719,141	18,993,719,577	18,993,719,129

Table A-VIII. 16 Total market value of the final inventory of stat17 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.10% of initial forest inventory.

SAB 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,746,561,009	8,832,369,968	4,749,623,152	4,746,976,891	4,746,987,115	4,745,928,634
1	14,294,451		83,365,236	100,492,192	5,792,454	114,356
2	624,877,609		14,741,207	315,405,771	25,519,714	2,961,913
3	714,170,029		978,812,134	480,102,778	118,263,294	943,192
4	750,918,468		1,620,494,083	425,324,021	13,161,517	3,650,869
Total	**6,850,821,565**	**8,832,369,968**	**7,447,035,813**	**6,068,301,653**	**4,909,724,095**	**4,753,598,963**
EPB 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	370,284,635	754,172,738	370,353,966	370,337,885	370,285,886	370,165,921
1	2,448,056		16,791,213	43,814,330	2,163,420	304,925
2	55,162,424		44,623,842	95,856,915	3,513,325	407,792
3	62,011,230		128,225,233	49,380,544	6,943,352	845,426
4	64,085,420		90,032,323	48,585,881	39,279,718	7,544,891
Total	**553,991,764**	**754,172,738**	**650,026,577**	**607,975,555**	**422,185,700**	**379,268,955**
EPN 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,393,620,639	19,393,621,218	19,393,620,490	19,393,620,504	19,393,620,598	19,393,620,768

Table A-VIII. 17 Total market value of the final inventory of stat17 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.25% of initial forest inventory.

SAB 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,733,417,026	8,817,624,324	4,739,203,162	4,734,368,891	4,734,187,445	4,731,796,786
1	14,294,451		83,365,140	100,440,360	5,792,448	114,355
2	624,265,556		14,740,411	315,118,489	25,516,257	2,961,798
3	713,863,487		978,155,566	479,650,527	118,253,335	942,708
4	750,329,109		1,617,319,471	424,947,143	13,161,517	3,650,869
Total	**6,836,169,628**	**8,817,624,324**	**7,432,783,750**	**6,054,525,410**	**4,896,911,002**	**4,739,466,516**
EPB 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	368,949,631	752,498,003	369,161,495	369,063,421	368,747,914	368,820,932
1	2,437,825		16,721,040	43,717,052	2,163,266	304,728
2	55,050,817		44,535,273	95,665,488	3,510,523	407,727
3	61,908,994		128,049,571	49,307,227	6,933,662	845,104
4	64,001,193		89,923,693	48,562,471	39,257,811	7,534,029
Total	**552,348,460**	**752,498,003**	**648,391,074**	**606,315,659**	**420,613,177**	**377,912,519**
EPN 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,361,630,952	19,361,630,899	19,361,631,060	19,361,630,950	19,361,630,883	19,361,630,939

Table A-VIII. 18 Total market value of the final inventory of stat17 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.50% of initial forest inventory.

SAB 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,712,959,028	8,793,199,953	4,720,836,592	4,714,878,967	4,715,416,295	4,709,388,077
1	14,282,961		83,298,866	100,283,544	5,787,792	114,261
2	622,846,181		14,728,889	314,370,625	25,492,395	2,958,329
3	713,031,814		977,218,832	478,468,167	117,907,976	941,331
4	748,928,249		1,613,025,844	423,941,778	13,160,666	3,650,453
Total	**6,812,048,233**	**8,793,199,953**	**7,409,109,023**	**6,031,943,082**	**4,877,765,124**	**4,717,052,451**
EPB 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	366,649,017	749,730,716	366,909,701	366,763,112	366,503,272	366,524,639
1	2,438,536		16,720,414	43,627,393	2,157,096	304,717
2	54,912,187		44,448,901	95,457,251	3,501,387	406,423
3	61,788,716		127,833,859	49,196,248	6,928,131	842,266
4	63,859,334		89,800,227	48,525,668	39,167,388	7,525,563
Total	**549,647,792**	**749,730,716**	**645,713,103**	**603,569,672**	**418,257,274**	**375,603,608**
EPN 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,308,661,680	19,308,661,763	19,308,661,683	19,308,661,681	19,308,661,688	19,308,661,736

Table A-VIII. 19 Total market value of the final inventory of stat17 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 1% of initial forest inventory.

SAB 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,669,208,286	8,744,672,702	4,686,091,641	4,671,395,550	4,672,625,220	4,663,495,405
1	14,280,727		83,295,913	100,137,308	5,786,682	114,242
2	621,248,830		14,725,896	313,561,766	25,473,910	2,956,900
3	711,996,562		974,979,473	477,181,245	117,652,141	939,372
4	747,397,210		1,603,446,601	422,805,916	13,160,666	3,650,452
Total	**6,764,131,615**	**8,744,672,702**	**7,362,539,525**	**5,985,081,786**	**4,834,698,618**	**4,671,156,371**
EPB 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	362,746,170	744,281,847	363,434,673	363,217,037	362,588,667	362,548,633
1	2,424,698		16,665,041	43,260,855	2,147,727	302,750
2	54,466,618		44,076,799	94,606,987	3,460,135	401,812
3	61,372,924		127,027,105	48,771,534	6,889,247	835,466
4	63,406,602		89,300,748	48,364,522	38,859,787	7,478,450
Total	**544,417,013**	**744,281,847**	**640,504,366**	**598,220,934**	**413,945,564**	**371,567,111**
EPN 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,203,285,972	19,203,286,090	19,203,286,100	19,203,286,004	19,203,286,388	19,203,286,014

Table A-VIII. 20 Total market value of the final inventory of stat17 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 2% of initial forest inventory.

SAB 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,586,274,543	8,648,342,522	4,613,312,576	4,588,968,998	4,587,501,145	4,577,882,598
1	14,294,324		83,274,506	99,721,604	5,784,249	114,161
2	616,842,543		14,714,956	311,546,898	25,368,204	2,938,197
3	708,868,224		971,010,196	474,166,820	117,307,651	930,803
4	743,034,772		1,587,384,366	420,270,063	13,156,747	3,647,981
Total	**6,669,314,407**	**8,648,342,522**	**7,269,696,599**	**5,894,674,384**	**4,749,117,997**	**4,585,513,741**
EPB 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	355,712,263	733,701,076	358,371,343	357,070,211	354,569,407	354,643,500
1	2,406,200		16,485,398	42,505,897	2,129,947	300,024
2	53,607,633		43,251,810	92,916,027	3,386,251	393,753
3	60,410,439		124,855,277	47,828,238	6,812,584	825,244
4	62,437,984		87,900,005	47,776,159	38,318,492	7,383,953
Total	**534,574,519**	**733,701,076**	**630,863,833**	**588,096,532**	**405,216,681**	**363,546,475**
EPN 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	18,993,719,112	18,993,725,609	18,993,719,093	18,993,719,081	18,993,750,187	18,993,719,389

Table A-VIII. 21 Total market value of the final inventory of stat18 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.10% of initial forest inventory.

SAB 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,746,842,409	8,833,079,695	4,749,413,282	4,747,112,268	4,747,141,995	4,746,413,423
1	13,825,271		80,628,982	73,718,007	5,602,332	110,602
2	482,378,644		12,983,467	238,029,596	13,710,485	1,591,444
3	571,616,769		917,989,984	391,815,461	102,111,851	712,205
4	652,678,445		1,536,679,249	363,205,008	11,596,514	3,216,753
Total	**6,467,341,539**	**8,833,079,695**	**7,297,694,963**	**5,813,880,340**	**4,880,163,177**	**4,752,044,426**
EPB 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	370,263,823	754,172,769	370,326,892	370,312,501	370,267,492	370,165,887
1	2,333,840		16,007,810	36,915,297	2,062,877	290,648
2	44,925,251		39,976,874	79,914,978	2,841,459	329,950
3	50,004,632		118,204,740	43,612,454	6,497,566	743,855
4	53,531,642		85,194,602	47,568,689	30,936,587	5,993,600
Total	**521,059,188**	**754,172,769**	**629,710,917**	**578,323,919**	**412,605,981**	**377,523,940**
EPN 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,393,620,526	19,393,621,773	19,393,620,492	19,393,620,495	19,393,620,564	19,393,620,503

Table A-VIII. 22 Total market value of the final inventory of stat18 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.25% of initial forest inventory.

SAB 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,734,435,486	8,817,390,147	4,739,330,368	4,735,073,272	4,735,095,956	4,732,901,879
1	13,825,271		80,628,886	73,671,633	5,602,325	110,602
2	481,878,225		12,983,052	237,763,729	13,707,029	1,591,042
3	571,388,914		917,436,245	391,374,129	102,007,071	712,125
4	652,193,578		1,534,071,693	362,825,433	11,596,514	3,216,753
Total	**6,453,721,474**	**8,817,390,147**	**7,284,450,244**	**5,800,708,196**	**4,868,008,894**	**4,738,532,401**
EPB 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	368,810,990	752,497,218	369,098,403	368,955,148	368,763,941	368,665,813
1	2,324,952		15,937,637	36,841,735	2,056,158	290,647
2	44,869,928		39,903,780	79,784,394	2,838,615	329,696
3	49,955,295		118,048,022	43,538,329	6,488,264	743,873
4	53,456,640		85,097,216	47,542,061	30,912,563	5,987,082
Total	**519,417,805**	**752,497,218**	**628,085,058**	**576,661,667**	**411,059,540**	**376,017,111**
EPN 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,361,631,064	19,361,631,227	19,361,631,050	19,361,630,915	19,361,630,926	19,361,633,094

Table A-VIII. 23 Total market value of the final inventory of stat18 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.50% of initial forest inventory.

SAB 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,713,916,177	8,792,730,150	4,721,689,488	4,715,081,290	4,715,518,440	4,711,628,200
1	13,820,311		80,563,358	73,582,815	5,597,721	110,511
2	481,126,237		12,972,358	237,376,179	13,691,620	1,589,254
3	570,919,474		916,854,691	390,756,925	101,885,461	711,332
4	651,497,342		1,530,058,262	362,323,738	11,595,959	3,216,374
Total	**6,431,279,542**	**8,792,730,150**	**7,262,138,158**	**5,779,120,948**	**4,848,289,200**	**4,717,255,672**
EPB 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	366,362,142	749,730,677	366,771,712	366,618,884	366,227,692	366,216,839
1	2,324,412		15,937,011	36,770,203	2,055,984	290,442
2	44,772,514		39,831,327	79,611,121	2,830,754	328,642
3	49,874,717		117,867,113	43,438,738	6,485,472	742,922
4	53,362,657		84,985,754	47,492,870	30,868,453	5,978,493
Total	**516,696,443**	**749,730,677**	**625,392,917**	**573,931,816**	**408,468,356**	**373,557,339**
EPN 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,308,661,681	19,308,661,795	19,308,661,784	19,308,661,718	19,308,661,729	19,308,661,802

Table A-VIII. 24 Total market value of the final inventory of stat18 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 1% of initial forest inventory.

SAB 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,671,306,988	8,751,618,539	4,689,348,807	4,673,988,279	4,673,661,978	4,668,178,646
1	13,813,893		80,560,405	73,468,152	5,597,567	110,508
2	480,569,674		12,969,852	236,737,276	13,673,799	1,587,185
3	570,245,337		915,101,381	389,750,646	101,784,641	710,331
4	650,983,559		1,520,460,692	361,410,517	11,595,155	3,216,318
Total	**6,386,919,450**	**8,751,618,539**	**7,218,441,137**	**5,735,354,869**	**4,806,313,141**	**4,673,802,988**
EPB 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	362,246,267	744,280,018	363,315,280	362,864,318	361,858,361	361,896,453
1	2,319,349		15,881,291	36,445,030	2,045,453	288,983
2	44,412,737		39,434,436	78,887,694	2,796,135	324,498
3	49,514,750		117,057,071	43,051,447	6,449,189	737,267
4	52,982,553		84,458,030	47,339,053	30,636,744	5,940,765
Total	**511,475,657**	**744,280,018**	**620,146,107**	**568,587,543**	**403,785,882**	**369,187,966**
EPN 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,203,288,505	19,203,286,047	19,203,285,965	19,203,285,942	19,203,286,323	19,203,286,005

Table A-VIII. 25 Total market value of the final inventory of stat18 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 2% of initial forest inventory.

SAB 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,586,836,001	8,662,135,117	4,610,068,057	4,590,056,042	4,589,919,064	4,584,884,050
1	13,820,286		80,537,878	73,275,005	5,596,002	110,477
2	479,445,409		12,961,730	236,050,643	13,622,431	1,579,647
3	568,835,899		911,089,056	388,917,585	101,403,881	706,349
4	649,893,284		1,519,352,285	360,594,381	11,594,026	3,214,427
Total	**6,298,830,880**	**8,662,135,117**	**7,134,009,007**	**5,648,893,656**	**4,722,135,403**	**4,590,494,950**
EPB 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	354,314,525	733,697,147	357,089,093	354,958,362	353,488,803	354,158,385
1	2,296,012		15,713,261	35,951,448	2,028,048	286,677
2	43,754,596		38,849,192	77,791,750	2,705,707	316,681
3	48,796,602		115,395,085	42,703,939	6,351,949	728,761
4	52,354,628		83,354,103	47,077,606	30,114,040	5,862,895
Total	**501,516,364**	**733,697,147**	**610,400,734**	**558,483,105**	**394,688,547**	**361,353,399**
EPN 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	18,993,719,367	18,993,719,163	18,993,719,124	18,993,719,347	18,993,754,040	18,993,753,051

Table A-VIII. 26 Total market value of the final inventory of stat19 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.10% of initial forest inventory.

SAB 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,746,336,818	8,832,728,287	4,747,992,302	4,746,416,595	4,746,562,870	4,746,019,932
1	13,825,271		80,628,982	58,024,003	5,602,332	110,602
2	367,423,727		12,362,811	180,567,394	8,363,459	970,788
3	456,525,059		848,476,712	316,292,997	97,472,965	415,795
4	551,385,410		1,409,692,098	298,694,033	11,661,726	3,234,842
Total	**6,135,496,286**	**8,832,728,287**	**7,099,152,905**	**5,599,995,023**	**4,869,663,352**	**4,750,751,959**
EPB 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	366,732,591	750,243,466	367,084,234	366,853,322	366,681,898	366,640,976
1	2,323,609		15,937,011	31,968,057	2,055,781	290,445
2	38,669,499		33,972,557	68,251,829	1,921,804	223,094
3	43,030,426		106,017,840	37,814,101	6,476,690	738,423
4	45,790,655		78,510,416	42,628,310	27,452,596	5,537,505
Total	**496,546,781**	**750,243,466**	**601,522,058**	**547,515,619**	**404,588,768**	**373,430,442**
EPN 0.10%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,393,620,556	19,393,620,577	19,393,621,543	19,393,620,948	19,393,620,816	19,393,621,096

Table A-VIII. 27 Total market value of the final inventory of stat19 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.25% of initial forest inventory.

SAB 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,733,100,488	8,818,508,264	4,736,590,946	4,733,744,253	4,733,818,118	4,732,015,924
1	13,825,271		80,628,886	57,988,411	5,602,325	110,602
2	367,075,621		12,362,715	180,329,997	8,362,750	970,706
3	456,323,448		848,127,783	315,902,290	97,386,379	415,671
4	551,053,301		1,407,483,028	298,377,478	11,661,726	3,234,842
Total	**6,121,378,130**	**8,818,508,264**	**7,085,193,357**	**5,586,342,429**	**4,856,831,298**	**4,736,747,745**
EPB 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	361,256,192	742,836,336	362,226,303	361,789,108	361,242,091	361,147,326
1	2,307,950		15,824,143	31,554,114	2,037,616	287,919
2	38,169,083		33,536,029	67,329,932	1,889,641	219,755
3	42,522,390		105,024,419	37,291,229	6,409,660	728,005
4	45,227,254		77,866,395	42,357,324	27,092,205	5,479,442
Total	**489,482,869**	**742,836,336**	**594,477,289**	**540,321,707**	**398,671,211**	**367,862,446**
EPN 0.25%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,361,630,891	19,361,630,976	19,361,631,072	19,361,630,876	19,361,630,928	19,361,630,896

Table A-VIII. 28 Total market value of the final inventory of stat19 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 0.50% of initial forest inventory.

SAB 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,711,447,348	8,794,959,449	4,714,113,104	4,711,551,198	4,712,202,989	4,709,373,062
1	13,815,411		80,562,622	57,941,271	5,597,721	110,508
2	366,426,303		12,352,640	180,148,175	8,356,566	969,495
3	455,944,076		847,503,527	315,630,427	97,301,425	415,281
4	550,437,782		1,407,987,944	298,098,587	11,661,403	3,234,541
Total	**6,098,070,921**	**8,794,959,449**	**7,062,519,836**	**5,563,369,659**	**4,835,120,104**	**4,714,102,887**
EPB 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	352,289,568	730,886,422	354,147,797	352,715,230	351,927,249	351,991,249
1	2,287,681		15,657,442	31,042,084	2,025,488	285,586
2	37,438,791		33,011,644	66,147,060	1,832,044	211,879
3	41,711,213		103,600,723	36,890,718	6,336,944	706,344
4	44,510,031		76,941,444	42,104,279	26,588,855	5,417,629
Total	**478,237,284**	**730,886,422**	**583,359,050**	**528,899,371**	**388,710,580**	**358,612,686**
EPN 0.50%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,308,661,810	19,308,661,710	19,308,661,951	19,308,661,681	19,308,661,684	19,308,661,703

Table A-VIII. 29 Total market value of the final inventory of stat19 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 1% of initial forest inventory.

SAB 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,666,844,931	8,748,167,562	4,674,061,904	4,667,844,012	4,666,717,495	4,662,799,203
1	13,815,031		80,560,405	57,871,805	5,597,567	110,508
2	365,701,119		12,351,752	179,743,491	8,351,651	969,417
3	455,573,093		846,095,541	314,979,462	97,161,875	414,896
4	549,737,424		1,404,280,955	297,574,411	11,660,439	3,234,485
Total	**6,051,671,598**	**8,748,167,562**	**7,017,350,557**	**5,518,013,182**	**4,789,489,027**	**4,667,528,510**
EPB 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	337,727,947	707,688,704	341,205,856	338,799,841	335,178,726	332,219,954
1	2,215,774		15,311,021	29,446,837	1,966,661	278,418
2	35,276,878		31,577,663	62,580,049	1,660,216	188,934
3	39,403,045		99,736,908	35,206,404	6,059,637	640,834
4	42,220,172		74,323,415	41,002,902	25,110,849	5,138,742
Total	**456,843,816**	**707,688,704**	**562,154,863**	**507,036,034**	**369,976,089**	**338,466,882**
EPN 1%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	19,203,285,932	19,203,285,934	19,203,286,322	19,203,285,991	19,203,285,990	19,203,290,248

Table A-VIII. 30 Total market value of the final inventory of stat19 of forest stands at the end of the third period for SAB, EPB, and EPN in CAD of AAC equivalent to 2% of initial forest inventory.

SAB 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	4,579,044,307	8,655,281,564	4,601,521,706	4,582,550,476	4,584,284,048	4,571,293,198
1	13,818,428		80,537,878	57,674,480	5,596,002	110,477
2	364,493,537		12,345,605	178,527,645	8,320,806	965,867
3	454,142,898		844,821,977	313,023,077	96,867,592	411,558
4	548,553,896		1,385,437,541	295,707,282	11,660,615	3,232,927
Total	**5,960,053,066**	**8,655,281,564**	**6,924,664,706**	**5,427,482,960**	**4,706,729,063**	**4,576,014,027**
EPB 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	307,824,425	663,309,782	320,772,472	313,355,659	306,822,505	297,243,337
1	2,101,370		14,661,072	26,809,439	1,866,506	263,852
2	31,900,189		28,520,772	56,658,870	1,464,594	159,998
3	35,828,504		90,641,645	31,405,477	5,638,567	544,627
4	38,757,578		68,498,485	37,803,874	22,694,819	4,711,926
Total	**416,412,065**	**663,309,782**	**523,094,446**	**466,033,319**	**338,486,990**	**302,923,741**
EPN 2%						
Phase	**1 datacase**	**2 no infestation**	**3 low infestation**	**4 medium infestation**	**5 high infestation**	**6 severe infestation**
0	18,993,733,410	18,993,727,761	18,993,719,379	18,993,720,057	18,993,719,564	18,993,719,973

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