**Dissertationes Forestales 257**

# Improving forest management planning by means of airborne laser scanning and dynamic treatment units based on spatial optimization

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Academic dissertation

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# ABSTRACT

The use of airborne laser scanning (ALS) has enhanced forest inventory during the last decades due to the increasing capability of lasers to describe the three-dimensional structure of forests. This research focuses on the integration of ALS-based forest inventory into forest planning when the aim is to create dynamic treatment units (DTUs). In this approach, the management units are not fixed and predefined. They are temporary and formed by aggregating fine-grained inventory units. Management objectives and forest dynamics are the drivers of that aggregation process.

The research was conducted in two pine forests in Castilla y León (Spain) in which ground and ALS data were collected. This PhD thesis reviews four manuscripts concerning the implementation DTU (studies I and III), the implications of using alternative forest inventory units (FIU) in two types of problem formulations (studies I, III and IV), and the impact of plot positioning errors on the whole planning process starting from the sampling stage and ending with decision-making (study II). In all studies, growing stock attributes were estimated with ALS statistics, while diameter distributions and stand dynamics models developed in permanent plots were used to predict growing stock attributes. The alternative management schedules developed during the simulation phase aimed at maximizing a utility function composed of non-spatial (study III) and spatial objective variables (all studies).

The findings of this work highlight the good performance of irregular types of FIU and the benefit of using segmentation techniques when the aim is to generate compact DTUs. The use of spatial optimization improved the spatial layout of forest plans at a minor cost compared to non-spatial formulations. The use of spatial goals and spatially explicit harvest cost functions enhance the aggregation of FIUs. Heuristic-based optimization methods were effective when solving spatial combinatorial problems.

This PhD shows how the combination of ALS-based methods, widely used in forestry practice and spatial optimization contribute to the development of forest management planning methods.

**Keywords**

Heuristic optimization, treatment scheduling, precision forestry, decision-making.

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Joensuu, September 2018

# LIST OF ORIGINAL ARTICLES

This PhD thesis consists of an introductory review followed by four research articles. These papers are reproduced with the permission of the publishers.

I. Pascual A, Pukkala T, Rodríguez F, de-Miguel S (2016) Using Spatial Optimization to Create Dynamic Harvest Blocks from LiDAR-Based Small Interpretation Units. Forests 7(10): 220.
https://doi.org/10.3390/f7100220

II. Pascual A, Pukkala T, de-Miguel S (2018) Effects of plot positioning errors on the optimality of harvest prescriptions in spatial forest planning based on ALS data. Forests 9(7): 371.
https://doi.org/10.3390/f9070371

III. Pascual A, Pukkala T, de-Miguel S, Pesonen A, Packalen P (2018) Influence of size and shape of forest inventory units on the layout of harvest blocks in numerical forest planning. Submitted manuscript.

IV. Pascual A, Pukkala T, de-Miguel S, Pesonen A, Packalen P (2018) Influence of timber harvesting costs on the layout of cuttings and economic return in forest planning based on dynamic treatment units. Forest Systems 27:1.
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# AUTHOR’S CONTRIBUTION

In all papers, data analysis and optimization were performed together with Prof. Timo Pukkala, main supervisor in the research. Mr. Adrián Pascual was the main author and mainly responsible for all calculations and analyses, except for the stages involving ALS-based segmentation and the definition of nano-segmentation in articles III and IV.

The research ideas in all articles were developed jointly by the authors who also contributed to various stages of the analyses and writing the articles, thereby improving the final quality of the papers of this PhD thesis.

# TABLE OF CONTENTS

# ABBREVIATIONS

| | |
|---|---|
| 3D | three-dimensional |
| ABA | area-based approach |
| AIC | Akaike's information criterion |
| ALS | airbone laser scanning |
| BAL | basal area of trees larger than the subject tree |
| CA | cellular automata |
| CC | cut-cut |
| CNC | cut-noncut |
| CHM | canopy height model |
| CV | coefficient of variation |
| dbh | diameter at breast height |
| DTM | digital terrain model |
| DTU | dynamic treatment unit |
| FF | final felling |
| FNF | final felling-non final felling |
| FIU | forest inventory unit |
| G | basal area |
| GI | growth index |
| GIS | geographic information systems |
| GPS | global positioning system |
| h | tree height |
| $H_o$ | dominant height |
| INS | inertial navigation systems |
| IP | integer programming |
| ITD | individual tree detection |
| LiDAR | light detection and ranging |
| MIP | mixed integer programming |
| N | stand density |
| NFI | national forest inventory |
| OF | objective function |
| RelValInc | relative value increment |
| $R^2$ | total explained variance |
| RMSE | root mean square error |
| RS | remote sensing |
| SA | simulated annealing |
| SI | site index |
| SUR | seemingly unrelated regression |

# 1 INTRODUCTION

## 1.1 Remote sensing and laser scanning in forest inventory

Collecting information on the status of forest resources is the basis for developing environmental policies and setting management goals (World Bank 2008). These two decision-making processes are driven by indicators and statistics that can be computed at different scales, from municipality to national level (McRoberts et al. 2009). In the case of forest inventories, computing population totals by measuring all existing trees for a given area of interest is such a prohibitively-expensive and time-consuming task that statistical inference and sampling designs are necessary (Schreuder et al. 1993). These sampling schemes of forest inventory aim at collecting trustworthy information, from which one can compute unbiased and high-precision estimates (Saarela 2015). For this purpose, nationwide projects such as National Forest Inventories (NFI) have been conducted during decades (Gschwantner et al. 2016). Relying purely on ground-based measurements to build robust estimators implies the use of massive resources, which can be reduced if auxiliary information is integrated in the statististical inference process (Tomppo et al. 2008).

The rapid development of remote sensing (RS) technologies since the 1900s has progressively increased the possibilities in earth-observation science (Yang 2013). The integration of passive RS sensors (i.e. sensors that measure the reflected radiation, usually sunlight, from an object) dates back to 1920s when image analysis was firstly used for forestry applications (Packalen 2009). The improvement in passive RS has been exponential and the LANDSAT programme is a great example that has been widely and effectively used for e.g. land-use classification (Hansen and Loveland 2012). However, when it comes to quantitatively describe the structure of elements above the ground, active RS sensors (i.e. sensors that emit energy and receive the reflected energy), and airborne laser scanning (ALS) in particular, have been proved to be the best option when estimating growing stock attributes (Vauhkonen et al. 2014).

The term ALS refers to a LiDAR (Light Detection and Ranging) sensor onboard an aircraft that captures the information while flying across the area of interest. The strength of ALS-based methods compared to passive sensors is the possibility to straightforwardly derive georeferenced point clouds (Maltamo et al. 2009). The three-dimensional (3D) structure of the forest canopy can be described due to the capability of laser pulses to pass through small canopy openings. Using the constant speed of light, the measured time between a laser pulse is emitted and received can be expressed in distance from the aircraft to the scanned objects (Wehr and Lohr 1999). The synchronised use of Global Positioning System (GPS) and Inertial Navigation Systems (INS) made it possible to record the position and the orientation of the sensor in every moment along the flight. Most ALS instruments used in forestry applications are capable of recording several echoes for each emitted pulse if the laser encounters objects that light can partly penetrate. As a result, a 3D-point cloud can be generated as the x, y and z coordinates of all echoes are registered.

The classification of echoes (i.e. identification of the elements the laser encounters while passing through canopies such tree branches or ground in the end) is a crucial step when processing ALS point clouds. There are alternative methods to accomplish this filtering process (Hyyppä et al. 2002). In all cases, echoes classified as ground echoes are used to build the digital terrain model (DTM) of the bare earth and then, the DTM is used to convert the heights of other echoes to above-ground heights. As a result, echoes classified as first echoes form a canopy height model (CHM): a spatially-continuous layer that is highly correlated with vegetation height (Coops et al. 2004).

The estimation of growing stock attributes using ALS data can be done in two ways: at area or at tree level. The area based approach (ABA) computes statistics on echoes height distribution such as height percentiles, or statistics related to canopy density (e.g., proportion of echoes above a certain threshold) for a certain region like sample plots' area (McGaughey 2015). The ABA is the most common approach in the forestry literature due to its accuracy at estimating area-based attributes such as dominant height, basal area or growing stock volume (Næsset 2002; Vauhkonen et al. 2014). Alternatively, individual tree delineation methods (ITD) rely on identifying tree attributes directly from the 3D point cloud, recognising local maxima before delineating forest canopies using segmentation algorithms (Vauhkonen 2010). Point cloud density and forest conditions act as constraints when conducting ITD, which is computationally more demanding and it requires an accurate positioning of all trees (Kaartinen et al. 2012).

In both methods, the spatial relationship between ground observations and remotely sensed data is essential. In the ABA approach, the position of trees inside field plots is not needed as growing stock attributes are computed at area level. However, the locations of plot centres are highly important when computing ALS statistics at the plot level: echoes within a certain radius are only considered when computing the information. Usually, the radius is the same as used in the sample plots of the training data. Therefore, plot positioning errors can affect the relationship between ALS statistics and growing stock attributes using the ABA (Hasegawa et al. 2007; Gobakken and Næsset 2009). There are few examples in which the impact of errors in ALS-based forest inventory has been traced further, from forest inventory to decisions supported by forest planning (Mäkinen et al. 2010; Islam et al. 2012). Moreover, the implications of plot positioning errors during field operations in the achievement of forest management goals remain unexplored when using ABA. The relevance of positioning errors when performing ITD is more important as, usually, all trees within a plot are measured and referenced from the centre of the plot. When the x and y coordinates of each tree are available, the correlation between the position of detected and measured trees is high in suitable conditions (Vauhkonen et al. 2012).

Construction of models, and their application to support formal statistical inference, is a natural step in nearly all scientific disciplines including RS (McRoberts et al. 2014). At this point in forest inventory, the accuracy of ALS-based estimates can be even better than in the traditional and expensive stand-level inventory methods (Packalen 2009). In modern ALS-based forest inventory, growing stock attributes measured in the field can be estimated using

ALS statistics by means of alternative modeling techniques such as regression modeling (e.g. Næsset 2002) or non-parametric methods (e.g. Maltamo et al. 2006). Once model relationships are built and estimates evaluated in terms of statistical indicators, these models are used to predict growing stock attributes using the continuous coverage of ALS data.

The integration of ALS-based methods into forest management planning is a timely research topic (Saad 2017) oriented to enhance decision-making when present state information is available (i.e. forest inventory). The following step is to define the size and shape of the forest inventory units (FIUs) for predicting growing stock attributes.

### 1.2 Delineation of forest inventory units from airborne laser scanning

Another important asset of ALS-based methods is the possibility to improve the precision when delineating FIUs while increasing their spatial resolution (White et al. 2016). In this regard, ALS-based segmentation has been used to delineate FIUs: using e.g. the CHM expressed as spatially-continuous layers of interpolated information at a certain cell size (Fig. 1), segments of different size can be produced by clustering cells (Mustonen et al. 2008). Several methods have been proposed to conduct object-based segmentation using ALS data (Koch et al. 2014). The idea is to compose homogeneous segments by minimizing the standard deviation of vegetation height among cells inside each segment while maximizing the difference in mean vegetation height between adjacent segments. The outcome is a tessellation of segment units that is adjusted to edges between forest patches while recognising the presence of discontinuities across a forest area (Fig. 1).

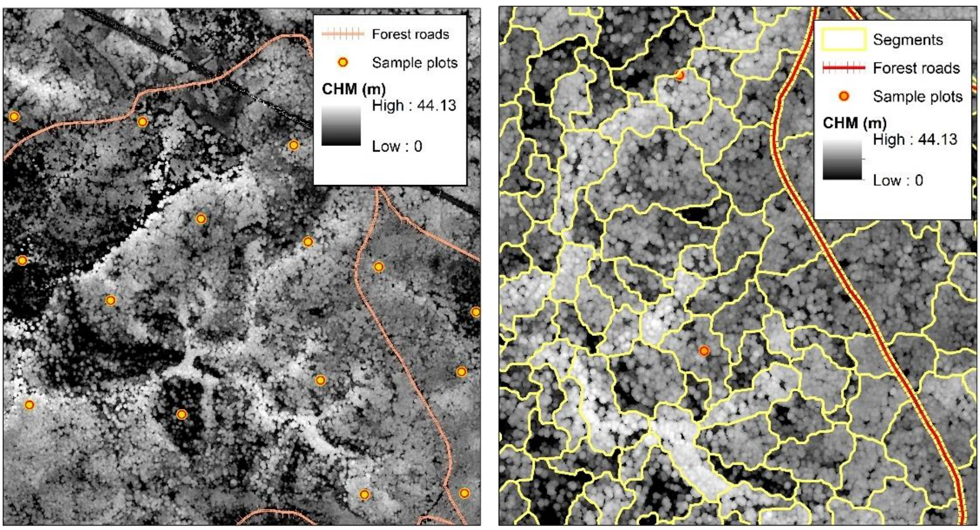



Figure **1**. Left: Partial view of the study area (articles III and IV) showing sample plot locations, forest roads and the canopy height model (CHM). Right: Spatial layout of segments used as forest inventory units.

When forest management planning fully relies on ALS-based segmentation, the estimation of growing stock attributes is postponed after segmentation at study area level is available, so the arrangement of plots aims not only to cover the whole area of interest as much as possible, but also capture the spatial variability of the computed ALS statistics for the area. The sampling design can acknowledge the presence of different strata and arrange the distribution of plots accordingly. In this way, stratum-specific models can be improved as well as their predicting capability when estimating growing stock attributes (Hawbaker et al. 2009).

Segmentation methods are computationally more demanding than alternative straightforward approaches. The adjustment of segments according to stand borders is a clear advantage compared to procedures that use a regular grid of cells. The use of square cells (Valbuena et al. 2016) or hexagons (Heinonen and Pukkala 2007) are straightforward alternatives to generate FIUs. Previous research showed how segments tend to be more homogenous than grid cells in terms of growing stock attributes, and follow better existing irregular stand boundaries (Hyvönen et al. 2005). The spatial variation in biophysical factors such as site quality, together with the effect of forest management prescriptions, often result in spatially heterogenous forest landscapes formed by smaller forest patches with homogenous forest attributes and structure. The control parameters of algorithms used in segment-based tessellation can be tuned-up to provide multiple levels of resolution for alternative forest management problems. One of these problems is how to define stands or management units. A forest stand is a geographically contiguous vegetation patch whose site type and growing stock attributes are homogeneous (Koivuniemi and Korhonen 2006). The use of fine-grained segmentation in forest areas, with practical considerations such as road proximity or site access, eases the delineation of stand boundaries, the basic units of forest management.

The contribution of ALS-based methods to forest inventory is clear. Translating the advances in forest mensuration and inventory during the last decades into further stages can contribute to a more efficient management of forest resources. The use of that information adds more value to the achieved outcomes of ALS-based forest inventory and enhances forest management planning.

### 1.3 Theory and applications of decision making in forest planning

The aim of forest planning is to provide support for forestry decision-making by proposing management alternatives and evaluating their consequences with three aims: maximize the achievement of goals, minimize unwanted outcomes and minimize deviations from goals (Pukkala 2002). For this, forest planning needs to estimate the preferences of the owner or multiple stakeholders that can have different objectives concerning the use of forests during a certain period of time (Diaz-Balteiro and Romero 2008). To find the optimal allocation of timber production factors is a complex task that involves the recognition of the multiple spatial and temporal scales (McDill 2014). Some decisions are more important, or strategic, than operational decisions regarding e.g. the harvests of an annual cutting plan. Therefore, forest management planning needs to be flexible and adjustable to the scale of the problem. From tree- to landscape-level, forest planning requires the use of optimization methods to maximize the use of forest resources. However, practical forest planning is not only preference analysis and optimisation. Inventory, data management, calculation, computer simulation and numerical optimization all play important roles in the decision-making process.

The scope of this PhD thesis can be classified as forest level planning according to the spatial scale and as strategic or tactical according to the temporal scale. For a general forest planning problem at forest- and landscape-level, the afore-said decision-making steps chronologically work as follows (Pukkala 2002): once forest inventory at present-state is available and growing stock attributes are computed for all foest inventory units (FIUs) (i), different treatment alternatives are generated for each FIU. Growing stock attributes are predicted using models for stand dynamics under alternative management options and e.g. the volumes of timber assortments, amounts of non-wood forest products and ecosystem services are calculated (ii). Then, the combination of treatment schedules is searched to maximize an objective function that expresses the achievement of management objectives selected by the stakeholders (iii). Numerical optimization methods are used to find an exact solution, or approximate solutions of the problem formulation within the feasible region (iv). The proposed solution is evaluated as candidate solution, which is implemented in case stakeholders acknowledge the proposed solution has fulfilled their initial expectations (v). The following flowchart (Fig. 2) illustrated the described decision-making process in forest planning.

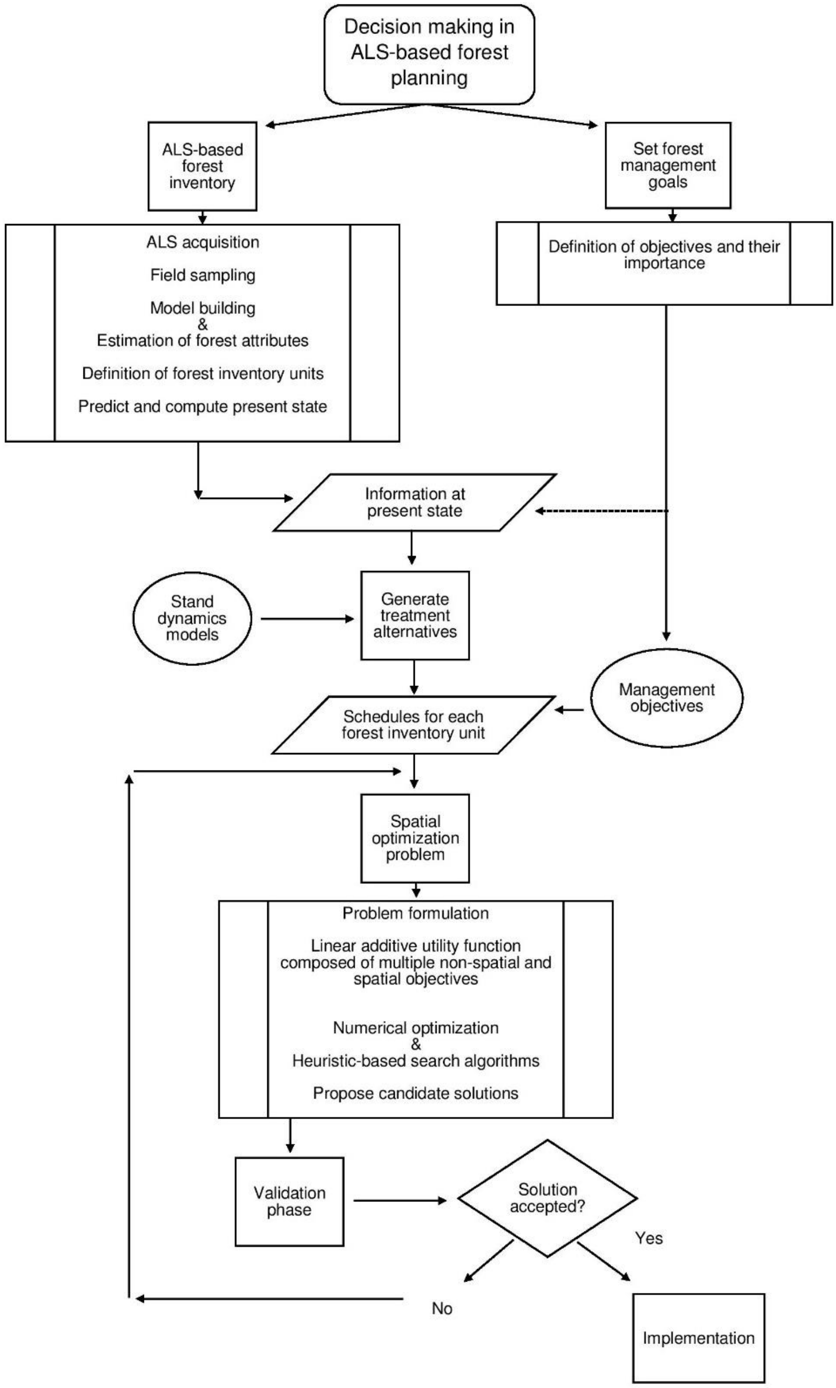



Figure **2**. Decision-making flowchart in the presented PhD thesis integrating ALS-based forest inventory into forest management planning.

A typical setting in strategic forest planning is a forest area divided into a set of management units, or stands, each of them having several treatment alternatives. The selection of treatment alternatives for each management unit aims to fulfill the management goals proposed by the stakeholders and they are included in the problem formulation (Kangas and Kangas 2002). In the early days when the first forest plans were developed, the goal was the provisioning of timber while ensuring the perpetuity of the forests (Evelyn 1664). This challenge was overcome by controlling the harvested area or the harvested volume in each period (Davis et al. 2001). These first simple regulation problems devoted to maximizing timber production are usually considered as single-objective despite the fact that even-flow harvesting is another objective in traditional regulation methods (Pukkala 2002). Environmental and economic concerns have led to important modifications in forest planning models increasing their multi-objective dimension compared to first management plans (Baskent and Keles 2005). For instance, ensuring timber harvesting targets while meeting wildlife habitat conservation (Weintraub and Bare 1996; Kurttila 2001) or improving connectivity along the planning period (Öhman 2001) are two examples of multi-objective complexity that forest planning must address today. In these forest- and landscape-level problems, the selection of one treatment alternative for a given FIU depends not only on stand-level information for that unit, but also on decisions regarding neighbouring units. In this regard, proximity or adjacency constraints among FIUs matter (Murray, 1999). Information regarding the position and relative location of all units, area and perimeter of each FIU and shared boundary between FIUs are examples of the variables needed to transform non-spatial solutions into improved spatially explicit solutions for a given problem in forest planning. The widespread implementation of geographic information systems (GIS) for forestry applications eased the calculation of the afore-said information (Pukkala 2002) and, hereby, forest problems on e.g. perimeter boundary minimization (Toth and McDill 2008), clustering and dispersion of units (Heinonen et al. 2007; Öhman and Eriksson 2010), or connectivity (St.John et al. 2016) have been formulated.

The inclusion of ALS-based methods increases the need for spatial problem formulations and feeds existing models with fine-grained inputs. For instance, the impact of edge-effects when composing harvest blocks or management units is a suitable field of research in which to test the likely improvement of ALS-based inputs compared to existing solutions (Zeng et al. 2007; Ross and Tóth 2016). The capability of ALS data to detect vegetation gaps and discontinuities is a good reason to decrease the size of calculation units. However, increasing the spatial resolution of FIUs increases the complexity of the planning problem: more treatment alternatives and candidate solutions need to be evaluated due to the increment in the number of FIUs. Therefore, the use of fine-grained data leads to a larger solution space (Heinonen 2007) and therefore, greater computational effort in numerical optimization.

### 1.4 Optimization techniques in forest management planning

Two optimization approaches have been used over the last decades to solve spatial forest management problems: mathematical optimization and meta-heuristic techniques (Borges et al. 2014a). Linear programming (LP) is a mathematical optimization method that is used to provide exact solutions to traditional harvest-scheduling models (Kurttila 2001) using the simplex method (Murray and Snyder 2000). A linear program is the problem formulation for minimizing or maximizing a linear objective function of the decision variables, $x_1$, ... $x_n$, subject to linear equality or inequality constraints. In this approach, the relationships between decision variables, objective and constraining variables are always linear. To overcome this restriction, alternative problem formulations and constraint relaxations need to be adopted to acknowledge the presence of non-linear relationship in harvesting models that deal with spatial and adjacency constraints (Lockwood and Moore 1993; Tóth and McDill 2008).

Transforming LP models into integer programming (IP) and mixed integer programming (MIP) formulations overcame the issue, and practical spatially explicit models have been widely developed during last decades (Pasalodos-Tato et al. 2013). Both IP and MIP formulations can provide exact solutions to complex combinatorial problems. Cutting plane methods or the branch and bound algorithm can addressed spatially constrained forest planning problems (Boston and Bettinger 1999; Crowe et al. 2003). However, the major constraint of these exact methods is that the solution space increases at a disproportionately greater rate when using many calculation units (Lockwood and Moore 1993). As a result, heuristic solutions have been regarded more feasible to achieve approximate solutions (i.e. solutions within the feasible region but likely not the optimal) at a reasonable computational cost (Reeves and Beasley 1993).

Heuristic optimization has been used in a great variety of spatially explicit problems in forest planning in general (Bettinger et al. 2003) and harvest-scheduling formulations in particular (Boston and Bettinger 2002). In fact, heuristic search methods are being used more and more in forest planning (Pukkala and Kurttila 2005). The main drawback of heuristics' performance is that their efficiency is highly related to the control parameters that drive the searching process. In this regard, previous studies have shown how this tuning process can be optimized as well (Jin et al. 2016), so that nearly optimal solutions for very complex formulations can be found (Pukkala and Heinonen 2006; Heinonen 2007). Several search algorithms have been used in spatial problems: the good performance of simulated annealing (Borges et al. 2014b), tabu search, hero or genetic algorithm (Pukkala and Kurttila 2005) has been reported.

In this context, the possibility to use fine-grained data from ALS-based forest inventory as calculation units in spatial optimization better finds its allocation under the heuristic-based approach. However, the afore-described searching algorithms still do not cope well when tens of thousands units are involved: the search becomes tedious and the optimization might stop prematurely before finding a nearly optimal solution (Pukkala et al. 2009). Especially interesting is the good performance of heuristic approaches that decompose the problem formulation to shorten optimization time. Decentralized computing methods like cellular automata (CA) (Von Neumann 1966) and the reduced cost method (Pukkala et al., 2009) have improved the spatial layout of the achieved solutions in spatial forest planning methods for a huge searching space scenario (Mathey et al. 2007). Their efficiency is related to the fact that they maximize management goals at the stand-level (or any other FIU) while simultaneously considering global constraints (e.g. sustained-flow of cuttings along a period plan). The development of heuristic optimisation techniques should acknowledge the integration of fine-grained ALS-based FIUs when addressing complex spatial formulations (Heinonen 2007). An example is the aggregation of fine-grained units into treatment units. Nowadays, we refer to this forest planning approach as dynamic treatment units (DTUs).

### 1.5 Dynamic treatment units

The use of DTUs leads to the abandonment of the traditional concept in which management units, also referred to as stands or compartments, are regarded as fixed units that do not evolve in space and time (Pukkala et al. 2014). The recognition of stand boundaries as permanent units is a constraint that ignores the effect of stand dynamics or harvesting prescriptions on growing stock attributes. The first experiences on dynamic treatment units (Holmgren and Thuresson 1997) already suggested a change of paradigm in forest planning methods but did not reach the practical and operational level (de-Miguel et al. 2013).

Previous studies on DTU have addressed the performance of grid cells of different size when used as FIU and calculation units in forest planning (e.g. Packalen et al. 2011). However, until what extent the size and shape of FIUs affect the efficiency of spatial optimization remains partly unexplored. In this regard, the use of segmentation units derived in ALS-based forest inventory requires of a greater computational effort compared to straightforward approaches relying on regular-shaped units (Heinonen et al. 2007). This effort might be compensated when assessing the performance of segmentation in forest planning. The hypothesis is that segment units can precisely adjust their boundaries to existing forest edges and discontinuities, which does not happen when raster cells are used.

Although spatial goals have been used to define management units when maximizing timber production (Öhman 2001), it may be more meaningful to pursue spatial objectives indirectly, for instance via the effect of the location and size of the resulting management units. The arrangement of management units and the spatial layout of forest roads across the area of interest have a great impact on forest planning efficiency, especially from the economic point of view (Bettinger et al. 2003). In this regard, studies in the context of spatially explicit forest planning have been conducted (e.g., Augustynczik et al. 2016), but little attention has been paid to the spatial variability of harvesting costs depending on forwarding distance. Previous research in Spain developed functions for calculating the harvesting costs as a function of distance to road, slope of the terrain and growing stock attributes (Solano et al. 2007). If these models are fed with ALS-based information, the estimation of harvesting costs would be more precise as, by using ALS data, terrain features can be derived and biophysical attributes predicted. The possibility to compute ALS information to produce a fine-grained DTM eases the detection of horizontal discontinuities when predicting growing stock attributes. As a result, the spatial variability of harvesting costs can be precisely estimated.

### 1.6 Opportunities and strategic challenges in Spain

The implementation of DTU-based planning systems in Spain is a great opportunity to extend the usability of ALS data. At this moment, the whole country has been scanned at least once. Despite the non-forestry motivation of the project, existing experiences on the use of low-density ALS data have reported good results when estimating growing stand attributes (García et al. 2010). In fact, ALS-based forest inventory using the ABA approach is the business as usual forest inventory method in both local and large-scale projects. The division of forests into management units implies the need to compute present state information at that scale. Usually, management units are predefined and do not change along time. In this regard, forest management would get benefit from using ALS data to correct and adjust the boundaries of existing management units if the purpose is to maintain those. In this way, the improvement in the estimation of forest attributes is not undermined by incorrect boundary delineation when computing total and average values for a given unit of interest.

In view of the relevance of ALS methods in Spain, it would be interesting to maximize its utility when combined with the expertise forest managers and researchers have in growth and yield modelling (Bravo et al. 2012). Reducing the uncertainty in forest planning is highly related not only to the accuracy of present state information, where ALS data can enhance the process, but also on the accuracy and realism of stand dynamics and growth models that are used to predict growing stock attributes. The rich literature on stand dynamics modelling is possible due to intensive field measuring campaigns led by the NFI project. With the completion of the 4$^{th}$ NFI currently in progress, there will be three records for all permanent sample plots that are systematically distributed across the country. Models developed between the 2$^{nd}$ and 3$^{rd}$ NFI can be updated in the short-term for a better description of stand dynamics. This is a promising opportunity to broaden the range of existing modelling datasets by adding new models on forest ecosystem services and non-wood forest products. Indeed, this scenario seems the right context where to implement dynamic forest planning solutions not only in Spain, but also in Europe and especially in the Mediterranean region where forests are so multi-functional today. In fact, policy-making on the use of forests is targeting the efficient use of forest-based resources as one of the key points for the agenda (EFI 2010). The multi-objective functionality of forests is also demanded and for that, big expectations are allocated on how modelling and optimization techniques can be used for the purpose (de-Miguel, 2014).

This thesis aims at supporting the change of paradigm on how forest management units are conceived in forest planning. Modern forest planning needs to be flexible and multi-objective, and for that purpose, implementing DTU-based solutions is a good strategy that this PhD thesis aims to reinforce. Based on the management objectives of today and precise 3D information, this work shows how to develop flexible and dynamic solutions in spatial forest planning.

## 1.7 Objectives of the PhD thesis

This PhD thesis aims at addressing several of the aforementioned research goals concerning the use of enhanced ALS-based forest inventory and its implications when forest planning is conducted under the DTU approach.

Specifically, the objectives of this PhD thesis are to:

i. Implement a DTU-based planning while testing the performance of existing stand boundaries comparing to the use of fine-grained cells (study I).

ii. Evaluate the robustness of solutions achieved in DTU-based planning acknowledging the presence of plot positioning errors during field operations following the ABA approach (study II).

iii. Assess the implications of transforming classic non-spatial regulation problems into spatially explicit harvest-scheduling solutions testing FIU types of different size and shape (study III).

iv. Integrate spatially-dependent harvesting cost functions into the problem formulation (study IV).

# 2 MATERIALS AND METHODS

## 2.1 Materials

### *2.1.1 Study area*

The study areas selected for the research are Mediterranean pine forests located in the provinces of Soria and Burgos (Castilla y León, Spain) close to the Iberian Mountain System. Two study sites were used in this PhD thesis, henceforth referred to as Forest #76 (studies I-II) and Forest #89 (studies III-IV). Both forests are similarly managed in terms of land rights and forest management legislation (i.e. revenues are shared among surrounding municipalities while forest management is carried out by regional forest service under the legislation of the regional government) although both areas differ in terms of size, species and other biophysical information:

- Forest #76: The area selected for this study is around 200 ha (UTM30N coordinates: 479786 - 478042 West-East; 4635486 – 4633630 South-North), consisting of even- and uneven-aged stands of Scots pine (*Pinus sylvestris* L.) and Maritime pine (*Pinus pinaster* Ait.). The understory was mainly composed of natural regeneration of pines and patches of Spanish oak (*Quercus pyrenaica* Willd.). The study area mainly includes dense forests that are managed using instructions for even-aged management. The effects of previous harvesting operations were observed within the boundaries of the site. A bunch of scattered forest patches used as seed source were left in the treated areas.

- Forest #89: The area selected for this study was 1,059 ha (UTM30N coordinates: 488633 – 493468; West-East; 4625282 - 4631225 South-North). The forest is a mixture of dense and sparse stands of *Pinus nigra* Arn. with scattered presence of *P. pinaster* Ait. as a secondary species. Stands are managed following even-aged silviculture. The area is splitted by a main road while secondary forest tracks cross the area and define study area boundaries except for the south-western limit, where the steep Rio Lobos canyon defines the limit. About 1% of the area is steeper than 35%, which is regarded in forest management practice as the threshold for timber harvesting. The area is highly valuable for its recreational use.

Forest management in the two studied areas is oriented towards the production of timber, the driver of regional economy during last decades (González-Olabarria et al. 2012). The demand has shifted from construction-oriented sawlogs to thinner timber assortments while woodfuel has highly increased its value. The importance of non-wood products, especially edible mushroom species has continued gaining social and economic relevance in the region (Martínez-Peña et al. 2012). For instance, the area was recognised as International Model Forest Network member in 2006 due to its multi-functionality and the responsible use of forests by rural communities. Conversion of classical regulations into more multi-objective management planning by e.g. integrating more forest products, ecosystem services or spatial goals, is a real need that forest managers of the area must acknowledge.

### *2.1.2 Sampling designs, field measurements and ALS point clouds*

A network of 160 circular sample plots, 44 in Forest #76 and 116 in Forest #89 all with a radius of 12.6 metres (500 $m^2$), was established to be used as training data when estimating growing stock attributes. Sample plots were systematically placed in the field aiming to cover the whole extent of both forest areas. In Forest #76, the clear-cut areas in the southern part and forest areas in the proximity of perimeter boundaries (also for Forest #89) were left out from the sampling design because they were outside the coverage of the available ALS data. The field work was carried out during autumn 2010 using satellite positioning equipment (Trimble R6 Global Navigation Satellite System) with differential correction to precisely determine the position of all plot centres. The accuracy of the positioning equipment made it possible to match ALS statistics and training data, a key step in the ABA approach.

On each plot, all trees with diameter at breast height (*dbh*) >7.5 cm were callipered and the heights of all trees were measured using Vertex III hypsometer. In addition, the ages of 44 trees, a dominant tree in each plot, were measured. The proportion of each pine species in each plot was used to divide Forest #76 into two strata: the Pinaster stratum (i.e. pure *P. pinaster* stands) and the Mixed stratum (i.e. mixed *P. sylvestris* and *P. pinaster* stands). For the case of Forest #89, a single *P. nigra* stratum was used. The following additional stand and tree level variables were computed in the data preparation process in both cases: stand basal area (*G*), dominant height ($H_o$), mean diameter at breast height (*dbh*) and stand density (*N*). These tree- and stand-level variables were needed in the forest planning system used in the research to simulate stand dynamics using growth and yield models. Information on the growing stock attributes measured on field plots is presented in Table 1.

Table **1**. Summary information of the sample plots used for the training data in Forest #76 (studies I-II) and Forest #89 (studies III-IV).

| Measured growing stock attributes | Studies I-II | | | Studies III-IV | | |
|---|---|---|---|---|---|---|
| | Min | Mean | Max | Min | Mean | Max |
| Diameter at breast height (*dbh*, cm) | 10.0 | 28.7 | 55.7 | 7.5 | 19.8 | 64.2 |
| Tree height (*h*, m) | 7.1 | 14.6 | 22.0 | 2.1 | 11.1 | 27.0 |
| Number of trees (*N*, trees $ha^{-1}$) | 260.0 | 656.0 | 1440 | 60.0 | 714.1 | 2000 |
| Stand basal area (*G*, $m^2$ $ha^{-1}$) | 12.9 | 42.9 | 72.1 | 1.3 | 25.9 | 56.5 |
| Dominant height ($H_o$, m) | 10.7 | 16.7 | 21.8 | 6.1 | 15.3 | 27.0 |
| Stand age (yr) | 33.0 | 58.7 | 78.0 | 23.0 | 61.4 | 132.0 |

Both study areas were scanned on April 28th 2010 using the ALS60 II laser scanning system. The two ALS datasets were scanned under the same flight conditions and sensor specifications, with a scan angle of ±12 degrees, and from an altitude of 1,200 m above ground level. This resulted in a nominal pulse density of 2 pulses $m^{-2}$ and a footprint size of 26 cm. Overall, 20 flight strips were needed to scan both areas.

### *2.1.3 Data for modelling stand dynamics*

A set of models for both study areas were developed using data from the 2nd and 3rd National Forest Inventory (NFI) of Soria and Burgos provinces. Models were developed at tree level. The model set consisted of the following models: (i) diameter-increment; (ii) survival; (iii) height-diameter relationship and (iv) ingrowth. The ingrowth model consisted of two sub-models, one predicting the number of trees per hectare that pass the 7.5-cm limit and the other predicting the mean diameter of ingrowth trees at the end of the 10-year period. Tree growth and survival were modelled as a function of competition, tree size, and site quality. The same set of models was used for studies I and II, including specific-models for mixed pine forests and for pure *P. pinaster* forests; while stand dynamics models for *P. nigra* were used in studies III-IV. The models are presented in studies I and III.

### *2.1.4 Cartography and information on harvesting costs*

The use of compartments when creating DTUs was tested in Forest #76. Forest compartments (i.e. calculation units in the so-called traditional forest planning) were defined as the overlay of the two layers: stands layer (13 management units currently used in operational forest management and defined by local managers) and vegetation unit layer (17 polygons). As a result, 68 compartments were defined and used as FIUs in study I. A grid of square cells was used as a benchmark to assess the performance of compartments in DTU-based planning (study I).

Existing harvesting cost functions (Equations 1 and 2) developed under similar conditions as the forest areas were used in study IV. Felling costs (including debranching and cross-cutting) and forwarding costs to the nearest forest road were calculated using ALS-derived information on slope and the predicted *dbh* of each harvested tree. In study IV, these spatially explicit cost functions (Fig. 3) were used with segments aiming at testing the implications of income-oriented instead of production-oriented management. The harvesting cost functions were as follows:

$$C_{felling} = e^{(3.406 - 0.568 \ln(d) + 0.01\, Slope)} \qquad (1)$$

$$C_{forwarding} = e^{(4.396 - 0.110\, d + 0.012\, Slope + 0.002\, Distance)} \qquad (2)$$

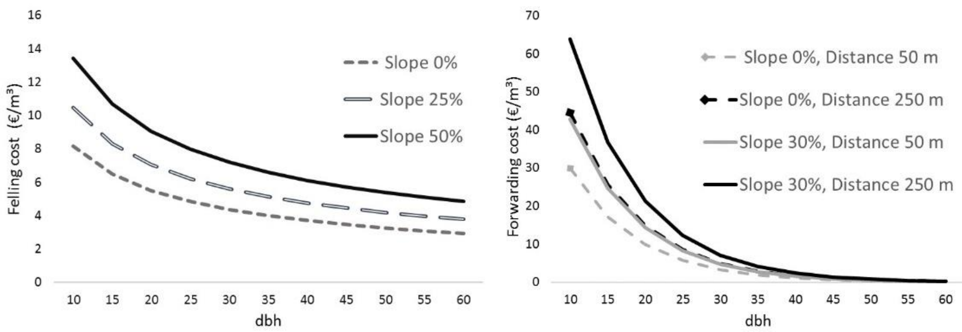



Figure **3**. Felling cost as a function of *dbh* and slope (left); and forwarding cost as a function of *dbh*, slope and distance to road (right).

where $C_{felling}$ is felling cost (€/m$^3$), $C_{forwarding}$ is forwarding cost (€/m$^3$), *d* is *dbh* of the harvested tree (cm), *Slope* is the average slope of the stand (%), and *Distance* is distance to road (m). The distance from a segment to the nearest forest road was computed along the surface of the terrain considering the slope. The slope was calculated from ALS data as the mean slope of the segment.

## 2.2 Methods

### *2.2.1. Methods to conduct ALS-based forest inventory*

In this PhD thesis, ALS data was used to estimate growing stock attributes at plot level (all studies), to define segment-based FIUs (studies III and IV) and to estimate harvesting costs (study IV). In all cases, the starting point was the processing of both ALS points clouds. The objective was to derive the CHM and DTM and then, compute the ALS statistics first for the circular sample plots and then for each FIU. First, ALS points were classified to ground points and other points using the approach explained by Axelsson (2000). After this filtering step, a DTM raster with a cell size of 1 m was created by computing the average elevation of all ground points within the cell. Then, non-ground echoes were re-scaled to above-ground heights by subtracting DTM elevation from these non-ground ALS echoes. As a result, an interpolated 1-m$^2$ CHM was created by searching the highest ALS echo from the centre of each pixel within a radius of 1.6 m. Empty pixels were filled by the average value of non-empty neighbouring pixels.

The benefit of using ALS point clouds to estimate growing stock attributes has been widely shown (e.g. Vauhkonen et al. 2014). In this work, the peformance of the ABA method was tested using the circular field sample plots. The measured coordinates of sample plots centres were used to create a buffer of 12.6 m in order to compute ALS statistics at the plot level. The ALS statistics can be divided into height, density and intensity metrics

(McGaughey 2015). Echoes whose height was less than 2 metres were not considered when computing ALS statistics to separate trees from the shrub layer. Percentiles of the height distribution of the pulse data ($h_5$,... $h_{100}$) were computed for echoes classified as first echo as well as proportions such as the ratio between first echoes *versus* ground echoes in each plot. In studies II, III and IV, only height percentiles and the proportions were computed while, in study I, intensity metrics of non-ground echoes were also computed and tested as predictor candidates when fitting models.

### *2.2.2. Methods to simulate plot positioning errors*

The ABA has been widely used to estimate growing stock attributes based on ALS statistics due to the high correlation between measured stand characteristics and ALS-based statistics (e.g. Vauhkonen et al. 2014). In this ABA method, the measured plot centre positions are assumed to be correct and ALS statistics are computed based on the measured position. However, the accuracy of GPS equipment and study site conditions might result in deviations of different magnitudes between measured and real position of sample plots in the forest (Hasegawa et al. 2007).

To evaluate the impact of positioning errors on forest inventory and forest planning, the coordinates of field plots were altered by introducing normally distributed errors simulating the occurrence GPS positioning errors. Three normal distributions of mean zero and standard deviation of 2.5, 5 or 10 m were generated using R software (R Core Team 2016). For each standard deviation, a random displacement was drawn for each plot from the normal distribution. The direction of the displacement was also random, uniformly distributed between 0 and 360°. In study II, this process was repeated 20 times for each of the three standard deviations, leading to 60 sets of plot locations, in addition to the case with no plot positioning errors (i.e., Reference inventor as shown in Fig. 4).

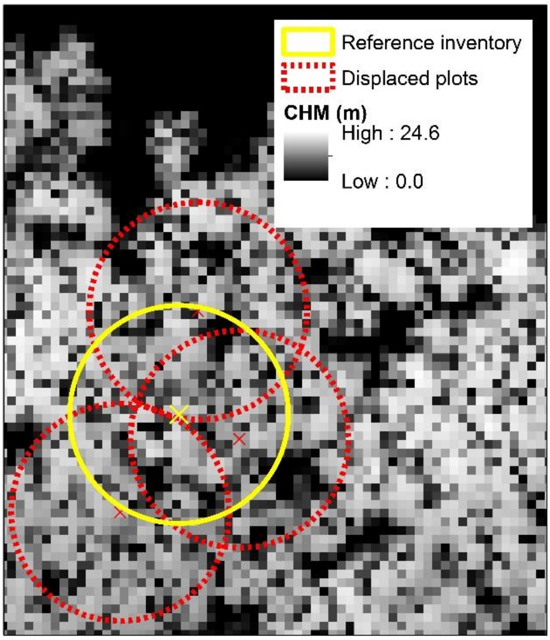



Figure **4**. Example of a sample plot showing the variation of the canopy height model (CHM) in the background. By displacing the measured position in the field (Reference inventory), positioning errors (displaced plots) were simulated.

*2.2.3. Methods to predict the diameter distribution of trees*

The prediction of growing stock attributes at plot-level based on individual-tree growth models required the use of diameter distribution models to assess how e.g. $N$ or $G$ is distributed among tree diameter classes inside each plot. Based on the good results of previous studies (e.g. Palahi et al. 2006), the following two-parameter Weibull density function was used:

$$f(d) = \frac{c}{b}\left(\frac{d}{b}\right)^{c-1} \exp\left(\left(\frac{t}{b}\right)^{c} - \left(\frac{d}{b}\right)^{c}\right) \quad (t \leq d \leq \infty, t, c, b > 0) \qquad (3)$$

where $t$ is the truncation point (7.5 cm), $b$ is the scale parameter, $c$ is the shape parameter and $d$ is *dbh*. The function is truncated at 7.5 cm because this was the lowest measured diameter in the plots. The parameters of the Weibull density function were estimated by fitting the distribution function to the diameter distribution data of each plot using maximum likelihood method. Therefore, for each of the 160 field plots, a pair of $b$ and $c$ values was computed. In study I, the information was computed separately for *P. pinaster* and *P. sylvestris.* That distinction was not considered in study II due to the similarity of both distributions (checked in study I) and the small proportion of stands where *P. sylvestris* was the main species in

Forest #76. In studies III-IV, *b* and *c* Weibull parameter values were computed only for *P. nigra*, the only species in that study area.

### 2.2.4. Methods to estimate growing stock attributes

In this PhD thesis, regression analysis was the method used to build plot-level models for estimating growing stock attributes. The forest planning system required the estimation of dominant height ($H_o$), stand basal area ($G$) and number of trees ($N$). Linear and non-linear regression were used. Stepwise variable selection methods were used to pick the best predictors from the initial set of ALS statistics that also included variable transformations: square root, logarithm and square of the response and predictor variables were evaluated. After that, predictors were selected for each of the models to predict $H_o$, $G$ and $N$. This selection mechanism was based on authors' expertise in study I while the stepwise model construction procedure (Venables and Ripley, 2002) was also considered and used in studies II, III and IV. Models for dominant height ($H_o$) included only one predictor except in study I. The stepwise method was iteratively applied until models for stand density ($N$) and stand basal area ($G$) comprised three predictor variables. The fitting mechanism was further improved in study II, by testing the Seemingly Unrelated Regression (SUR), which enhances the fitting process as previous research has shown (Maltamo et al. 2007). Models for $N$ and $G$ included a common predictor variable ($FC_1$: the proportion of first echoes above 2 meters among all echoes)

A set of models to predict parameters *b* and *c* of the Weibull density function was presented in study I. These models were built using region-specific ground data collected in similar conditions as the study area. The prediction of *b* relied on growing stock attributes and site elevation, while prediction of *c* was based on *b* and mean quadratic diameter. These models were finally used in studies I and II after testing the performance of the SUR method to simultaneously estimate both growing stock attributes and Weibull parameters. The SUR-based models for *b* and *c* showed less predicting capability than the region-specific models finally used.

### 2.2.5 Methods to delineate forest inventory units

The CHM was used in studies III-IV to create FIUs of different size and shape. Object-based segmentation was carried out using a 1-m cell size CHM as input. Two sets of segments of different size were produced by tuning-up the parameter values that drive the multiresolution segmentation. Two fine-grained segmentation of different size were produced: large segments (3.59 ha) and small segments (1.65 ha). With the aim of predicting growing stock attributes on the same scale as model estimates, segments were divided into sub-units that are referred to as nano-segments. A grid of 22.36-m-side cells and the two set of segments were used to create the corresponding nano-segments following the method presented in

Pippuri et al. (2013). The outcome is a segment unit divided into prediction units of about the same size as the field plots but without mixed cells at the borders of segments. As a result, nano-segments never crossed segment boundaries, which prevented the creation of mixed calculation units, i.e., units that included parts of two dissimilar stands. These nano-segments can be squared-shape if located near the centre of the segment, or irregular if located close to the edge. In the latter case, nano-segments were adjusted to the original irregular boundary of the segment (Fig. 5). Alternatively, a grid of square-shaped cells was created in all four studies using the whole extent of both ALS datasets. In all cases, the cell size was 500 $m^2$ (side 22.36 m) i.e. equal to the area of the field sample plots. Overall, four types of FIU were assessed in this research, considering the nano-segments as preliminary interpretation units: compartments (study I), large segments (studies III and IV), small segments (study III) and square cells (all studies).

The same procedure followed to compute ALS statistics at the plot-level was used to obtain ALS statistics for each FIU. In this way, growing stock attributes were predicted wall-to-wall for each FIU. In the studies involving segmentation, ALS statistics were computed at nano-segment level and then used to predict growing stock attributes for each nano-segment. Then, the information was upscaled to obtain predictions at segment level. For the case of cell grids and compartments, ALS statistics and predictions were directly computed on the same scale.

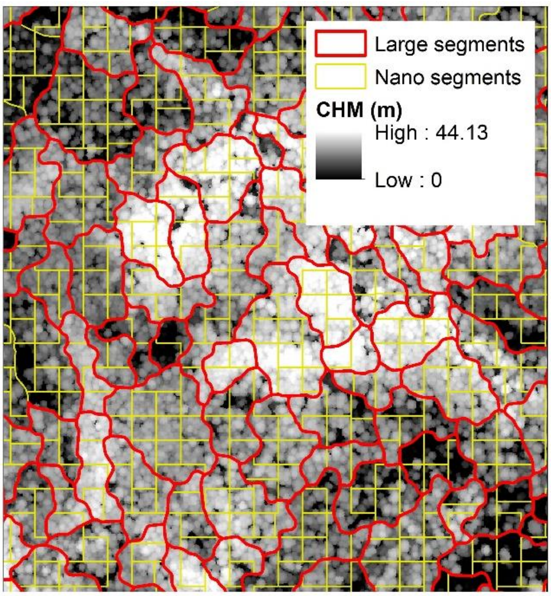



Figure **5**. Delineation of large segments (red boundaries) and the corresponding nano-segments (yellow boundaries) showing the canopy height model (CHM) in the background.

*2.2.6 Methods to derive management instructions and treatment schedules*

Models for stand dynamics were applied over a set of FIUs in order to define the instructions for economically optimal management. Growing stock attributes were predicted from present state to 5 years ahead to compute relative value increment (*RelValInc*). The stumpage prices of different timber assortments (i.e. sawlogs, pulpwood and firewood) were used for the purpose. This information was obtained from Spanish forestry experts and official records on timber purchasing prices in the region. Then, a regression model showing *RelVaInc* as a function of site index (*SI*), mean diameter ($D_{mean}$), and stand basal area (*G*) was fitted for the set of FIUs.

Regression modeling was used to develop instructions for economically optimal management. The instructions showed e.g. the *G* at which thinning should be conducted for a given *SI* or the $D_{mean}$ at which final felling should be done for a given *SI* (Fig. 6). In this PhD thesis, the 2% threshold was used when considering whether a FIU was financially mature for cutting. These calculations were carried out using the Monte forest vers. 6.0 planning software (Palahi et al. 2004) to compute *RelValInc* while R software (R Core Team 2016) was used to fit the regression model for *RelValInc.*

The simulation instructions were used as follows: if the $D_{mean}$ of a given FIU was higher than the final felling diameter of the instruction, seed tree cut was simulated followed by the removal of seed trees in the following period. Otherwise, *G* was compared to the thinning basal area (i.e. *G* at which cutting is proposed for a certain *SI*), and a thinning treatment was simulated if the *G* was higher than in the instruction. To generate several treatment alternatives for each calculation unit, final felling diameter and thinning basal area values of the instruction were multiplied by three constants: 0.7, 1.0 and 1.3. Three thinning intensities were simulated: light (21% reduction in stand basal area), moderate (30%) and heavy thinning (39%).

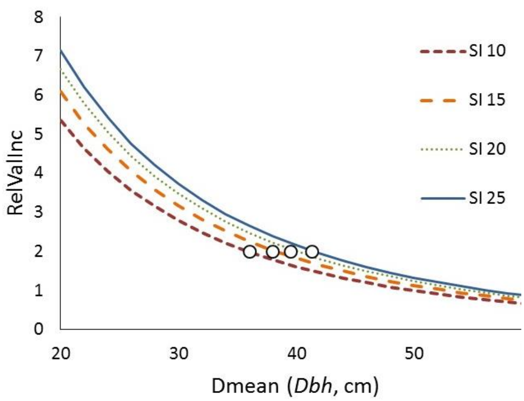



Figure **6**. Relative value increment as a function of site index (*SI*) and mean *dbh* (*Dmean*) in Forest #76 when stand basal area (*G*) is set at 25 m² $ha^{-1}$. The dots indicate the *dbh* at which the relative value increment was below 2%.

The decisions on cuttings constitute a tree-branch scheme that progressively increases in complexity as the number of periods and number of FIUs increase. In all studies, three period plans of different length were considered (10 years each in studies I-II and 20 years each in studies III-IV). Each combination of multipliers (0.7, 1.0 and 1.3 for thinning intensity, thinning *G* and clear felling *Dmean*) was applied with 8 different settings concerning whether cutting was allowed or not during a certain n-year period (from 000 = no cuttings to 111 = cutting allowed during every period). Overall, 216 simulations were done for each FIU for even-aged forestry. In study I, 72 simulation rules schedules were applied (9 x 8) to simulate uneven-aged management. The number of treatment schedules increased with decreasing size of the tested types of FIU. In Forest #76, a total of 864,864 schedules for all cell units were simulated while, in Forest #89, the sets of FIUs resulted in 60,581 (large segments), 129,641 (small segments) and 460,417 (cells) different schedules.

### *2.2.7 Management objectives and definition of problem formulations*

The selection of schedules was oriented to maximizing a utility function composed of the identified preferences. In this PhD, the management objectives of classical regulation plans were included in the problem formulations: maximizing timber production was proposed in all studies while promoting its achievement under even-flow timber harvesting. The harvesting of 7,500 (study II), 10,000 (study I) and 50,000 $m^3$ (studies III-IV) in each period plan was required and translated into management objectives that acted as constraints (i.e. the targets were always met at the end of the optimizations).

In study IV, timber production-oriented planning was compared with income-oriented planning plans that maximized or minimized the net income. For that, spatially explicit harvesting costs (Fig. 6) were computed and then net income in each period was calculated. The plan that minimized net income worked as the lower bound to assess the performance in economic terms of forest management oriented to maximizing timber production.

The spatial layout of the resulting DTUs matters when it comes to managing forest efficiently. In this regard, the DTUs should to be large enough, compact and round-shaped. In this way, forest management becomes more efficient (Tóth and McDill 2008). Previous studies have shown the contribution of spatial objective variables to the purpose (Heinonen and Pukkala 2004; Packalen et al. 2011). The following spatial objective variables were used in all studies:

- Maximization of the proportion of cut–cut borders of adjacent FIUs (*CC*).
- Maximization of the proportion of cut–cut borders of adjacent FIUs that are prescribed as final felling (*FF*).
- Minimization of the proportion of cut–non-cut borders of adjacent FIUs (*CNC*).
- Minimization of the proportion of cut–non-cut borders of adjacent FIUs that are prescribed as final felling (*FNF*).

The clustering of FIUs to conform compact DTU layout was pursued via these variables: *CC* and *CNC* variables aimed at aggregating all cuttings, while *FF* and *FNF* specifically aggregated final fellings to prevent isolated FIU prescribed as final felling from appearing within a DTU where only thinning is prescribed. Spatially explicit formulations were used in all studies, while non-spatial formulation was only tested in study III with the aim of comparing non-spatial and spatial problem formulations with three alternative types of FIU.

### *2.2.8 Methods to conduct optimization in forest planning*

The utility theoretic approach, which has been successfully applied in multi-objective forest planning (Pukkala and Kangas 1993), was followed in this PhD thesis. Management objectives are first evaluated separately, one by one, and then aggregated in a linear additive utility function that describes the overall utility of the alternatives (Kangas and Kangas 2002). The multiple management objectives are weighted to express priorities. Numerical optimization methods were used to maximize the total utility of the afore-described forest planning problems. In this PhD thesis, global search heuristic and decentralized heuristics algorithms were used.

In studies I-II, preliminary tests on heuristic-based optimization revealed the better performance of simulated annealing (SA) compared to Hero and tabu search, in line with previous studies (Pukkala and Kurttila 2005). In the light of those tests, SA was used to solve the numercial optimization problem using compartments (study I) and cells (studies I-II). The forest inventory datasets were 4,434 cells in study I and 4,004 cells in study II. According to the literature (Mathey et al. 2007; Pukkala et al. 2009), spatially explicit harvest-scheduling problems might become too complex when thousands of FIUs are involved. In this regard, preliminary tests in studies III-IV showed that SA-based optimizations became incomplete and poor in terms of the achieved spatial layout of DTUs when using cell data (22,879 cells and 460,000 treatment schedules). To overcome problem complexity, cellular automaton (CA) was used in studies III and IV due to its reported efficiency when tackling combinatorial problems of such a complexity (Heinonen and Pukkala 2007).

**Simulated annealing**

Simulated annealing (SA), as other heuristic optimization algorithms, generates initial solutions that are gradually improved by making local changes (moves). In this PhD thesis, a move consisted on the reassignment of a management prescription to two FIUs at the same time. The adjustment to two management units during one move of the heuristic is considered a "change" version of a 2-opt process (Caro et al. 2003) as opposed to an "exchange" version of a 2-opt process (Bettinger et al. 1999). In either event, from a heuristic point of view, a 2-opt procedure was implemented.

The schedule for each FIU included in the current solution was replaced by a randomly selected alternative schedule. Then, the move was accepted if the objective function (*OF*) value improved; otherwise, it was accepted with the following probability:

$$p = exp^{\frac{(OF_{Candidate} - OF_{Current})}{T}} \tag{4}$$

where $OF_{Current}$ is the *OF* value of the solution before implementing the move, $OF_{Candidate}$ is the *OF* value after the move, and *T* is 'temperature' which affects the probability of accepting candidate solutions poorer than the current solution. The temperature was decreased toward the end of the search, which means that the probability to accept inferior moves also decreased. Several candidate moves were produced at each temperature. Preliminary tests and publications (Pukkala and Kurttila, 2005; Jin et al. 2016) were used to find a set of optimal values for the control parameters.

In studies I and II, the planning problems were formulated as a linear additive utility function:

Maximize

$$\text{OF} = \sum_{i=1}^{I} a_i u_i(q_i) \tag{5}$$

subject to

$$q_i = Q_I(\mathbf{x}) \qquad i = 1, \dots, I \tag{6}$$

$$\sum_{k=1}^{N_n} x_{kn} = 1 \qquad n = 1, \dots, N \tag{7}$$

$$x_{kn} = \{0,1\} \tag{8}$$

where *OF* is the objective function, *I* is the number of management objectives, $a_i$ is the importance (weight) of management objective *i*, $u_i$ is the sub-utility function for objective *i* and $q_i$ is the value of objective *i*. $Q_i$ is an operator that calculates the value of objective *i*, **x** is a vector of binary decision variables ($x_{kn}$) that indicate whether FIU *n* is treated according to schedule *k*, and *N* is the number of alternative treatment schedules for FIU *n*. All sub-utilities are scaled to the same range [0-1]. Preliminary single-objective optimization tests were used to compute the maximum possible values for the spatial objective variables and set the weights at which the layout of DTUs was compact. For that, more weight was given to *CNC* and *FNF* in order to minimize the number of isolated cells treated with thinning or final felling. For instance, the OF and sub-utility functions used in study II were as follows:

$$OF = 0.18 \left(\frac{V_{2047} - V_{min}}{V_{\max}}\right) + 0.09\, u_1\,(R_1) + 0.09\, u_2\,(R_2) + 0.09\, u_3(R_3) + 0.04\left(\frac{CC}{Max\ CC}\right) + 0.235\left(1 - \frac{CNC}{Max\ CNC}\right) + 0.04\left(\frac{FF}{Max\ FF}\right) + 0.235\left(1 - \frac{FNF}{Max\ FNF}\right) \qquad 9)$$

where $V_{2047}$ is the growing stock volume at the end of the 30-year plan, $V_{max}$ and $V_{min}$ are the largest and smallest ending volume for the whole forest after 30 years ($m^3$), $u_i$ is the sub-utility function for harvested volume during period $i$; $R_1$, $R_2$, $R_3$ are the harvesting targets in each period (7,500 $m^3$ all in study II) while *Max CC*, *Max FF*, *Max CNC*, and *Max FNF* are the values of the spatial objective variables (defined in section 2.2.7) in the preliminary single-objective optimizations.

**Cellular automata**

The CA method described in Heinonen and Pukkala (2007) was used to solve a two-phase optimization problem including management objectives at FIU-level (local function) and global goals at study area level. The following parameters control the progress of the optimization: initial mutation probability, a change parameter for mutation probability, initial innovation probability, a change parameter for innovation probability and total number of iterations. The CA searching process was as follows: the system generates the initial solution by a random assigment of one of the simulated schedules to each FIU (same as in SA). Then, for each FIU, a random number is drawn from a uniform 0-1 distribution. A mutation takes place if the random number is smaller than the current mutation probability. Otherwise, innovation occurs if the random number is smaller than the current innovation probability. The probability of mutation depended on the initial probability, total number of iterations, and current iteration number. When innovation occurs (i.e. an improvement in the utility), the schedule which maximizes the following local OF is selected for a given FIU:

$$OFL_{jk} = \sum_{i=1}^{I} w_i u_l\left(q_{ijk}\right) \qquad j = 1, \dots, n_k \tag{10}$$

where $OFL_{jk}$ is the *OF* value of schedule $j$ of FIU $k$, $I$ es the number of objectives, $w_i$ is the weight of objective $i$ in the local OF, $u_i$ is a priority function for objective $i$, $q_{ijk}$ is the quantity of objective variable $i$ in schedule $j$ of FIU $k$, and $n_k$ is the number of alternative management schedules in FIU $k$. Once the local optimization phase is completed, a global priority function (Eq. 11) was added to the algorithm resulting in a function including a local and a global component (Eq. 12):

$$OFG = \sum_{l=1}^{L} v_l p_l(g_l) \tag{11}$$

$$OF = \frac{a_k}{A}\, OFL_{jk} + \, b\, OFG \qquad j = 1, \dots, n_k \tag{12}$$

where *OFG* is the function global priority, $L$ is the number of evaluated objectives, $v_l$ is the weight of objective $l$, $p_l$ is a piority function for objective $l$, $g_l$ is the quantity of objective $l$, $a_k$ is the area of FIU $k$, $A$ is the total area, $b$ is the weight of the global priority function *OFG*.

In this PhD thesis, spatial objective variables and the main goal of the problem formulations (*M*) were included in the local optimization phase (Eq. 13). The M objectives were maximizing timber production (studies III and IV) and maximizing or minimizing net income (study IV). In the global phase (Eq. 14), the *M* objective was included also in the global objective function together with the global harvesting constraints. As an example, the problem formulation used in study IV to maximize timber production is presented:

$$OFL = 0.36\, s \frac{M}{Mmax} + 0.04\, CC - 0.24\, CNC + 0.08\, FF - 0.28\, FNF \tag{13}$$

$$OFG = 0.25\, p_1\, (R_1) + 0.25\, p_2\, (R_2) + 0.25\, p_3\, (R_3) + 0.25\, p_4\, (M) \tag{14}$$

$$OF = \frac{a}{A}\, U + bP \tag{15}$$

where *M* is the growing stock volume at the end of the 60-year plan, $M_{max}$ is the largest per hectare value of the principal objective variable *M* among all schedules of all segments; *CC*, *CNC*, *FF*, *FNF* are the aforesaid spatial objective variables used in all studies; $R_1$, $R_2$, $R_3$ are the total harvested volume to be cut in each of the three 20-year periods, *a* is the area of the given segment and *A* is the sum of the area of all segments in Forest #89. Once local optimization phase was completed, the global phase started increasing *b* proportionally to the average size of FIUs in every iteration until the global utility (*OFG*) was 0.999.

### *2.2.8 Assessment of ALS-based inventory and DTU-based planning*

Model selection in the estimation phase was based on the following criteria and metrics: statistical significance (p-value $< 0.05$) of model parameters, normality and homogeneity of variance of the residuals checked visually from Q–Q and scatter plots, simplicity, robustness and precision. Model selection was supported by the following goodness-of-fit statistics: coefficient of determination or total explained variance ($R^2$), root mean square error (RMSE) and Akaike's information criterion (AIC). All statistical analyses were carried out using R software (R Core Team, 2016). In study II, the variation in model relationships when altering plot coordinates was measured also through model coefficients. Model predictions were used to evaluate the effect of plot positioning errors (study II) and the effect of using alternative types of FIU when computing the inventory information at present state (study III). For both studies, mean values and standard deviations of predicted growing stock attributes were compared.

In the forest planning stage, the achieved values of non-spatial and spatial objective variables were used to compare forest plans in all studies. The spatial arrangement of the resulting DTUs was evaluated in the following terms: mean size of all DTUs, number of isolated FIUs prescribed either as final felling or thinning or the number of DTUs larger than a certain area threshold. In all cases, the spatial layout of DTUs was displayed for a visual assessment. The area - perimeter ratio (AP) was also used to compare forest plans when alternative types of FIU were used. Two smoothing procedures were used in studies I-III to correct the edge effect of cells before making the comparison cells *versus* segments, and cells *versus* segments in terms of AP ratios. The AP ratios were computed at two levels in study III: considering all prescriptions together and only harvest blocks composed of final fellings. Other indicators such as the standard deviation of basal area predictions within each DTU (study I), optimization time (study III), changes in the location of DTUs (studies III-IV) and their proximity to forest roads (IV) or the mean diameter of harvested trees (study IV) were used. The information was computed for each plan period and for the whole planning horizon.

The influence of plot positioning errors in forest planning (study II) was further evaluated using inoptimality losses (Eid 2000): the optimal solutions for the forest inventories containing plot positioning errors were used with the inventory free of positioning errors. In this way, the deviation between bad (i.e. decisions made based on the erroneous datasets) and good decisions (i.e. no simulated errors, true coordinates) are evaluated when the prescriptions are applied to the good dataset. The impact was measured in terms of utility and timber production losses. In the same study II, the degree of reliability of the decisions made in forest planning was evaluated by counting how many times the same FIU was prescribed similarly as in the inventory free of positioning errors.

# 3 RESULTS

## 3.1 Estimation of growing stock attributes

The estimation of growing stock attributes using ALS statistics was carried out twice in Forest #76 (studies I and II) and once in Forest #89 (study III). In all cases, the models were highly accurate and precise $H_o$ and $G$ ($R^2$ around 0.9 and 0.8-0.7, respectively). On other side, poorer fitting statistics were observed, as expected, when estimating the relationship between $N$ and ALS statistics.

The use of SUR modeling when predicting both growing stock attributes and diameter distribution models was evaluated in study II. The goodness of fit of the model for parameter $b$ was considerably high ($R^2$ = 0.97, RMSE = 1.008 for *P. pinaster*, and $R^2$ = 0.94, RMSE = 1.645 for *P. sylvestris*) and reasonably good for parameter $c$ ($R^2$ = 0.45, RMSE = 1.607 for *P. pinaster*, and $R^2$ = 0.64, RMSE = 0.856 for *P. sylvestris*). The performance of SUR was worse for parameter $b$ ($R^2$ = 0.77, RMSE = 2.036 combining both species) than the presented models in study I. Finally, the SUR method was only used to estimate growing stock attributes of interest and not for diameter distributions.

## 3.2 Testing compartment-based DTU solutions (study I)

Traditional compartments of forest #76 were nearly as efficient as grid-based planning when maximizing timber production. However, the achieved solutions differed according to the distribution of treatments (Table 2) and their spatial layout (Fig. 7). For instance, the number of DTUs was 33 for cell-based planning and 5 when using compartments. The average size of compartment-based DTU was 5 times larger than when using cells. The computed AP value was 0.007 for compartments and 0.011 for cells. The standard deviation of predictions for $G$ within each DTU was 11.7 $m^2$ $ha^{-1}$ for cells and 15.0 $m^2$ $ha^{-1}$ for compartments. Forest compartments resulted in larger and more compact DTUs than fine-grained square cells.

Table **2**. Treatment area (ha) in study I for each period and for the whole planning horizon when using compartments and when using cells.

| Treatment | Period 1 | | Period 2 | | Period 3 | | Total | |
|---|---|---|---|---|---|---|---|---|
| | Cell | Comp | Cell | Comp | Cell | Comp | Cell | Comp |
| Light thinning | 32.8 | 40.0 | 52.3 | 17.2 | 56..5 | 18.4 | 141.7 | 75.6 |
| Moderate thinning | 16.9 | 36.4 | 16.7 | 12.2 | 19.5 | 0.0 | 53.1 | 48.6 |
| Heavy thinning | 0.7 | 0.0 | 1.8 | 11.7 | 0.3 | 10.5 | 2.8 | 22.2 |
| Seed tree cut | 30.1 | 23.1 | 39.0 | 32.9 | 9.3 | 21.5 | 78.4 | 77.5 |
| Remove overstory | 0.0 | 0.0 | 4.9 | 0.0 | 32.2 | 32.9 | 37.1 | 32.9 |
| Total | 80.5 | 99.5 | 114.7 | 74.0 | 117.9 | 83.3 | 313.3 | 256.8 |

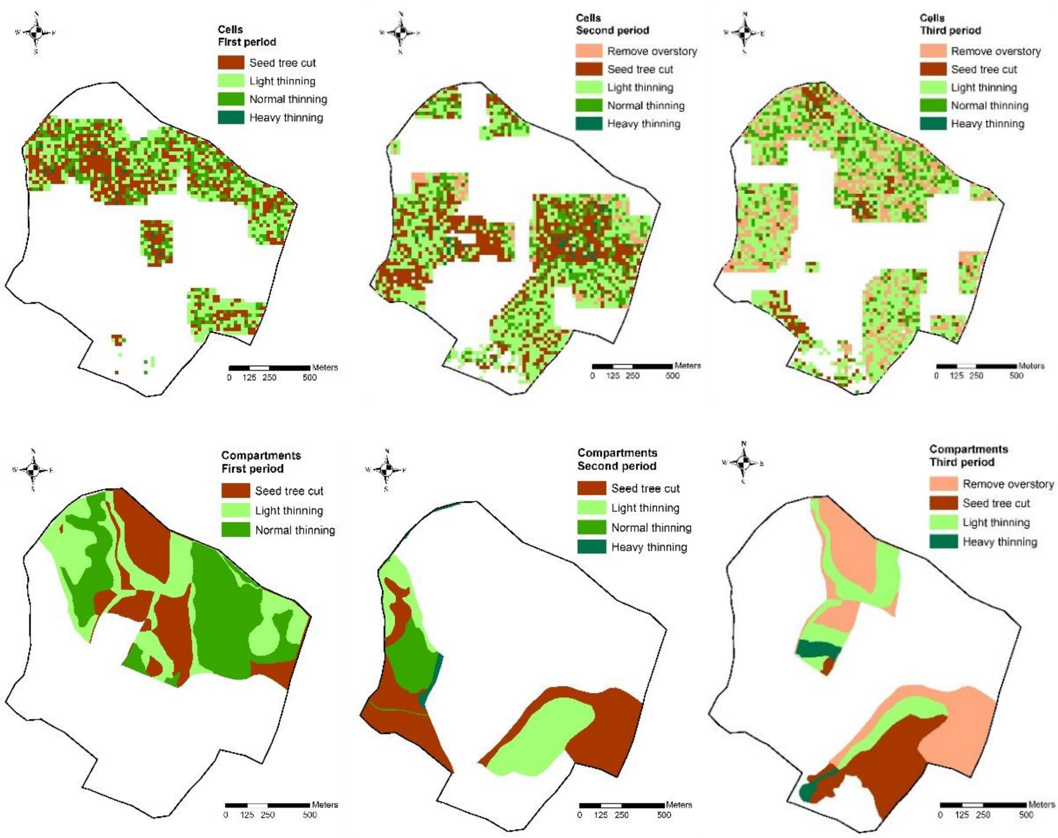



Figure **7**. Treatment units when using cells (above) and when using compartments (below) for the three 10-year periods of the planning horizon defined in study I.

### 3.3 Impact of plot positioning errors (study II)

The prediction capability of models when estimating growing stock attributes decreased as the simulated errors in plot positions became greater (Table 3). The proportion of explained variance ($R^2$) progressively decreased from 0.56 (for *N*), 0.85 (*G*) and 0.91 ($H_o$) down to 0.31 (*N*), 0.73 (*G*) and 0.85 ($H_o$), when the standard deviation of plot positioning error increased from 0 to 10 m. Model coefficients and intercepts were compared to verify the observed worsening effect as the spatial mismatch between ground measurements and ALS statistics increased. When model predictions at cell level were assessed, higher values of growing stock information were obtained with erroneous plot centre coordinates (Table 4). For instance, the overestimation in total growing stock volume reached 10.5% for the greatest standard deviation of displacements (10 m). The between-cell standard deviation of predicted *N* and *G* tended to decrease with increasing plot positioning error, which was an expected result.

Table **3**. Effect of plot positioning errors on the estimation of stand variables as described by root mean squared error (RMSE %) and adjusted $R^2$. Reference is the case free of plot positioning errors.

| Displacement | Number of trees (tree $ha^{-1}$) | | Stand basal area ($m^2$ $ha^{-1}$) | | Dominant height (m) | |
|---|---|---|---|---|---|---|
| | RMSE (%) | $R^2$ | RMSE (%) | $R^2$ | RMSE (%) | $R^2$ |
| Reference | 25.6 | 0.56 | 14.6 | 0.85 | 4.6 | 0.91 |
| 2.5 m | 26.9 | 0.47 | 15.3 | 0.82 | 4.6 | 0.91 |
| 5 m | 28.8 | 0.39 | 16.2 | 0.80 | 4.9 | 0.90 |
| 10 m | 30.9 | 0.31 | 18.6 | 0.73 | 6.9 | 0.85 |

Table **4**. Effect of plot positioning errors on the prediction of growing stock attributes: stand density (*N*), stand basal area (*G*) and growing stock volume (*V*). Mean values and standard deviations (*Std*) among replications were calculated using the 60 datasets containing positioning errors. The inventory free of plot positioning errors (Reference) is also presented. For the case of *N* and *G*, the standard deviation between cells was also computed ($Std_{cells}$).

| Displacement | *N* predictions | | | *G* predictions | | | *V* predictions | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std | $Std_{cells}$ | Mean | Std | $Std_{cells}$ | Mean | Std |
| Reference | 546.5 | - | 298.6 | 34.9 | - | 20.4 | 345.1 | - |
| 2.5 m | 549.6 | 11.5 | 291.7 | 34.8 | 0.1 | 20.2 | 345.2 | 4.0 |
| 5 m | 562.9 | 22.5 | 278.9 | 35.2 | 0.4 | 19.9 | 348.3 | 6.8 |
| 10 m | 626.9 | 57.9 | 261.1 | 36.5 | 1.2 | 18.5 | 361.4 | 10.5 |

The achieved values for non-spatial and spatial objective variables at the end of the optimization run showed the clear impact of positioning errors on the achieved volume at the end of the planning period. The coefficient of variation of this variable, standard deviation divided by the computed average value, was only 0.24% when repeating the runs (10 times) with the inventory free of positioning errors. However, the values increased to 1.44, 2.44 and 4.81%, respectively, for positioning errors having standard deviations of 2.5, 5 and 10 m respectively. On the other hand, the observed variability of spatial objectives variables made it to detect a worsening effect when comparing plans.

The assessment on how reliable the assignment of treatment prescriptions was in the presence of positioning errors showed that 75.7, 75.4.5 and 74.7% of all prescriptions, including no-treatment, were assigned in the same way as in the *Reference inventory* (i.e. inventory free of plot positioning errors) for the case of 2.5-, 5- and 10-meter displacement, respectively (Fig. 8). The inoptimality loss in timber production progressively increased when solutions based on forest inventories that contained positioning errors were applied to the case free of them (Table 5). Also, the loss in total utility followed the same increasing pattern and reached 3.35% for the largest displacement tested.

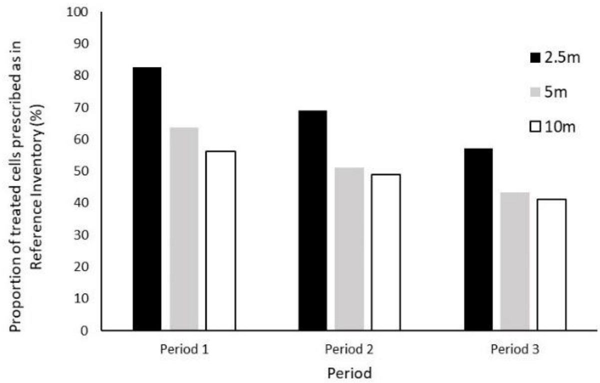



Figure **8**. Proportion of cells prescribed in the same way as in the *Reference inventory* (i.e. free of plot positioning errors) for the three 10-year periods and the three simulated levels of plot positioning errors tested in study II.

Table **5**. Effect of applying the optimization solutions based on inaccurate forest inventory data to the case free of errors (Reference) in terms of ending volume ($V_{2047}$) and total harvest along the plan. The results show the mean value of 20 replications for each positioning error tested in study II. Losses in utility and loss in timber production (yield loss) are also presented

| | $V_{2047}$ ($m^3$ $10^3$) | Harvests ($m^3$) | Yield loss ($m^3$) | Yield loss (%) | Total utility | Utility loss (%) |
|---|---|---|---|---|---|---|
| *Reference* | 55.25 | 22,500 | | - | 0.885 | - |
| 2.5 m | 54.01 | 23, 705 | 36 | 0.42 | 0.860 | 2.82 |
| 5 m | 53.71 | 23,968 | 109 | 1.26 | 0.858 | 2.99 |
| 10 m | 53.61 | 23,713 | 406 | 4.68 | 0.855 | 3.35 |

### 3.4 Assessing the benefit of using spatial optimization (study III)

The assessment of forest plans developed using non-spatial and spatial optimization was done when using large segments, small segments and square cells as FIUs. In study III and for each FIU type, one problem was formulated aiming at maximising timber production at even-flow of cuttings (*NonSpatPlan*). Another problem increased the number of management objectives up to six with the inclusion of spatial objective variables (*SpatPlan*).

The results showed an increment in timber production with decreasing segment size (Table 6). Cell-based planning was the least efficient FIU type at maximizing timber production in *NonSpatPlan* and also in *SpatPlan* formulation. In all cases, the inclusion of spatial objective variables reduced the achieved ending volume at the end of the forest plan: the difference in timber production was 5.6% for large segments, 6.3% for small segments and 7.1% for cells. The computational cost of using cells was about ten times higher than with small segments.

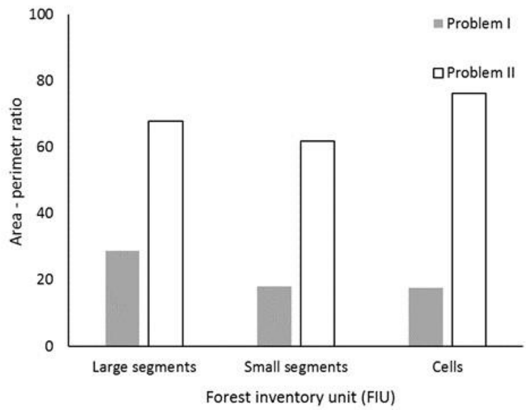
Table **6**. Timber production and time consumption in the optimization for the three types of forest inventory unit (FIU) assessed in study III. Values for non-spatial formulations (*NonSpatPlan*) and spatially explicit formulations (*SpatPlan*) are presented.

| FIU | NonSpatPlan Production ($m^3$ $ha^{-1}$) | Solution time (s) | SpatPlan Production ($m^3$ $ha^{-1}$) | Solution time (s) |
|---|---|---|---|---|
| Large segments | 154.1 | 91 | 145.4 | 225 |
| Small segments | 159.1 | 367 | 149.0 | 894 |
| Cells | 153.6 | 3,117 | 142.2 | 8,636 |

Compared to non-spatial problems, spatial optimizations took about 2.4 times more computing time with segments and 2.7 times more with cells. In *SpatPlan*, the optimization time with cells was 38 times longer than with large segments and 10 times longer than with small segments. The difference in time consumption decreased to 6.1-fold (cells vs. large segments) and 4.1-fold (cells vs. small segments) when the time consumed for segmentation was added. The time for simulating alternative treatment schedules for the FIUs was directly proportional to the number of FIUs, i.e., 7.8 times longer for cells than large segments, 2.2 times longer for cells than small segments, and 3.6 times longer for small segments than large segments.

According to the AP values, the use of large segments aggregated all cuttings most efficiently (higher AP ratio) in *NonSpatPlan*, followed by small segments and cells (Fig. 9). The AP values increased 2.4-, 3.4- and 4.4-fold for large segments, small segments and cells, respectively, from *NonSpatPlan* to *SpatPlan* when all cuttings were assesed. Therefore, the benefit of spatial optimization increased as FIUs decreased in size. As a result, small segments planning was the most efficient approach in *SpatPlan*. The same pattern was observed when only considering final fellings: the improvement of AP ratios was 2.1-, 2.5- and 3.7-fold respectively. In this case, harvest blocks composed of large segments were the most efficient both in *NonSpatPlan* and in *SpatPlan*. In the *NonSpatPlan*, the size of harvest blocks was always the largest when using large segments. However, in the *SpatPlan*, spatial optimization made it possible to narrow the gap between small and large segments (Table 7) even though large segments remained as the most efficient alternative.

The mean size of harvest blocks was 6.1 times larger in *SpatPlan* as compared to *NonSpatPlan* for large segments, 8.9 times for small segments and 22.8 times for cells. In all cases for *SpatPlan*, the size of harvest blocks increased from the first period onwards. The number of harvest blocks was clearly lower in *SpatPlan* than in *NonSpatPlan*. In non-spatial problems, all plans had scattered harvest blocks, mostly when cells were used (Fig. 10). Moreover, the plans started to differ more after the first 20-year period in the spatio-temporal allocation of treatments and in terms of prescriptions type. Solutions for segment-based planning included more area devoted to final fellings while cell-based planning relied more on thinning prescriptions to reach the proposed harvesting targets. In *SpatPlan*, the spatial layout and distribution of treatments were very similar for the three types of FIU tested.



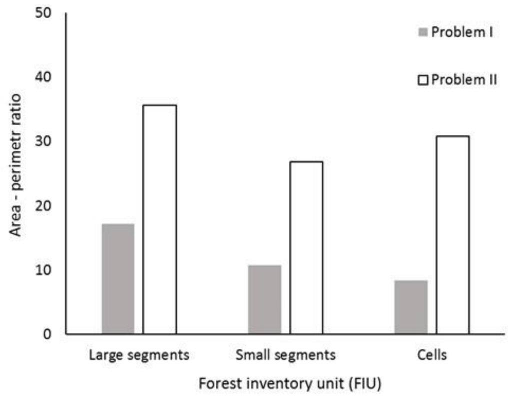




Figure **9**. Area - perimeter ratio (AP) in *NonSpatPlan* (non-spatial formulation) and *SpatPlan* (spatially explicit formulation) for the three types of forest inventory unit (FIU) tested in study III when considering all cuttings (above) and specifically for the case of final fellings (below). The greater the AP value, the better the aggregation and compactness in the resulting dynamic treatment units.

Table **7**. Mean harvest block size (ha), number of harvest blocks greater than 0.5 (in brackets) for the three types of forest inventory unit (FIU) tested in study III. The results are presented for each 20-year period and for the whole planning period.

| | Large segments | | Small segments | | Cells | |
|---|---|---|---|---|---|---|
| | *NonSpatPlan* | *SpatPlan* | *NonSpatPlan* | *SpatPlan* | *NonSpatPlan* | *SpatPlan* |
| Period 1 | 2.7 | 5.1 | 1.2 | 3.7 | 0.4 | 4.1 |
| | (133) | (57) | (281) | (81) | (802) | (88) |
| Period 2 | 3.7 | 16.6 | 1.7 | 18.5 | 0.5 | 19.8 |
| | (132) | (30) | (294) | (27) | (920) | (26) |
| Period 3 | 1.4 | 25.7 | 1.0 | 30.8 | 0.6 | 41.8 |
| | (189) | (26) | (351) | (22) | (782) | (16) |
| All | 2.1 | 12.9 | 1.3 | 11.4 | 0.5 | 11.9 |
| periods | (453) | (113) | (926) | (130) | (3,554) | (130) |

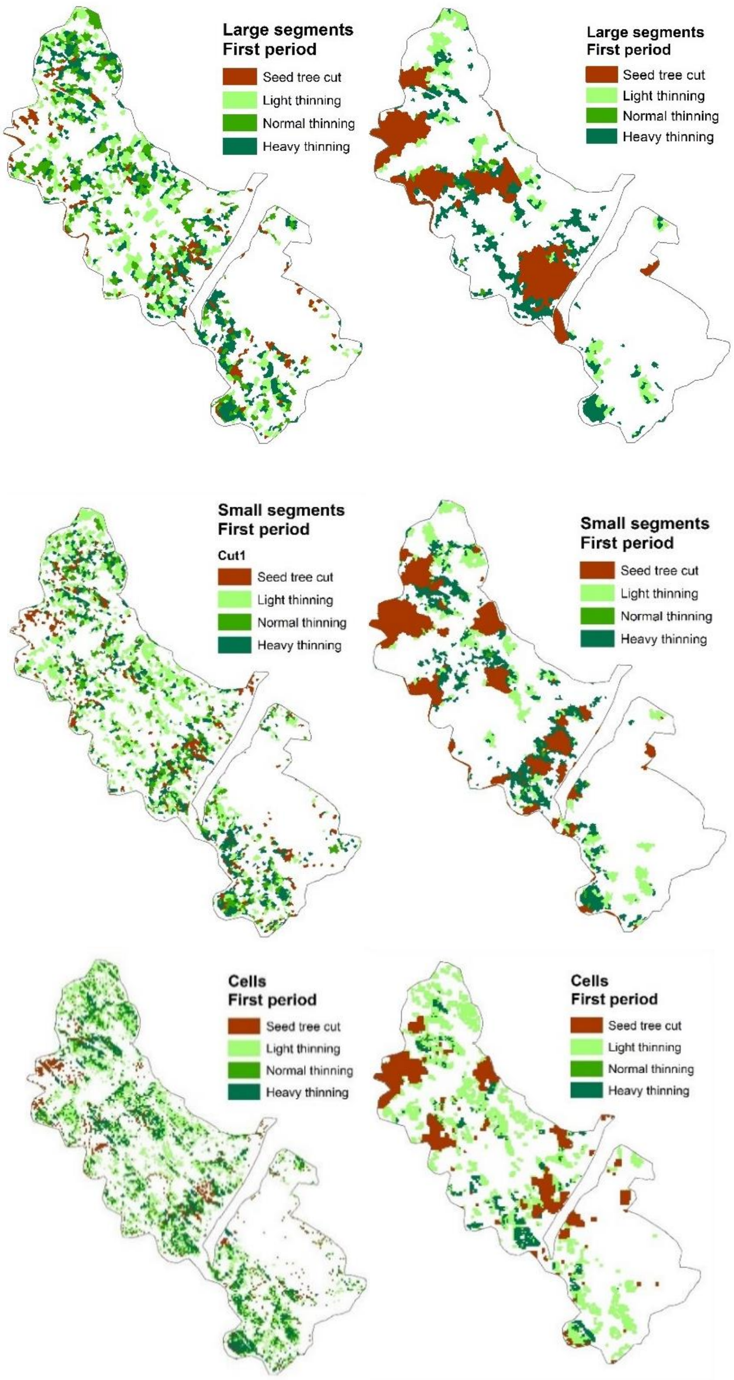



Figure **10**. Spatial layout of dynamic treatment units (DTU) for *NonSpatPlan* (non-spatial optimization, left) and *SpatPlan* (spatial optimization, right) when using small segments and cells as forest inventory units (FIUs). The presented maps correspond to the first of the three 20-year pleriods used in studies III-IV.

### 3.5 Income- versus production-oriented planning (study IV)

Three forest formulations, including the same spatial objective variables and weights, were tested in study IV. The planning horizon was 60 years (three periods of 20 years each). The harvest target of 50,000 was always met in the three following cases:

- *MaxPro*: Maximization of standing volume at the end of the plan
- *MaxNetInc*: Maximization of net income during the plan
- *MinNetInc*: Minimization of net income during the plan

The plans were ranked according to the total net income and ending volume at the end of the 60-year plan (Fig. 11). *MaxNetInc* resulted a clearly higher net income (6.24 million €) than *MaxPro* (5.67 million €) and *MinNetInc* (5.56 million €). In terms of timber production, *MaxPro* accumulated the most standing volume at the end of the plan (260,507 m$^3$) followed by *MinNetInc* (249,395 m$^3$) and *MaxNetInc* (246,776 m$^3$). The stumpage values of the standing growing stock volume at the end of the plan were 14.15, 13.05 and 13.67 million € respectively in *MaxPro*, *MaxNetInc* and *MinNetInc*.

The location of prescriptions was visually assessed by displaying the resulting DTU (Fig. 12). The motivation for using *MinNetInc* plan was to set the lower bound when assessing the economic performance of *MaxPro* plan. In *MaxNetInc*, DTUs tended to be more clustered along the road network during the second and third periods when comparing to the *MaxPro* plan. In the second period, more segments were prescribed as seed tree cut in the *MaxNetInc* than in the *MaxPro* plan, as income-oriented plan preferred cuttings where the harvesting cost per cubic meter was low (harvested trees were large). The spatial layout of the harvest blocks showed an increasing level of compactness in the *MaxNetInc*, while, in the *MaxPro*, prescriptions were more scattered and less compact than in *MaxNetInc* and *MinNetInc*.

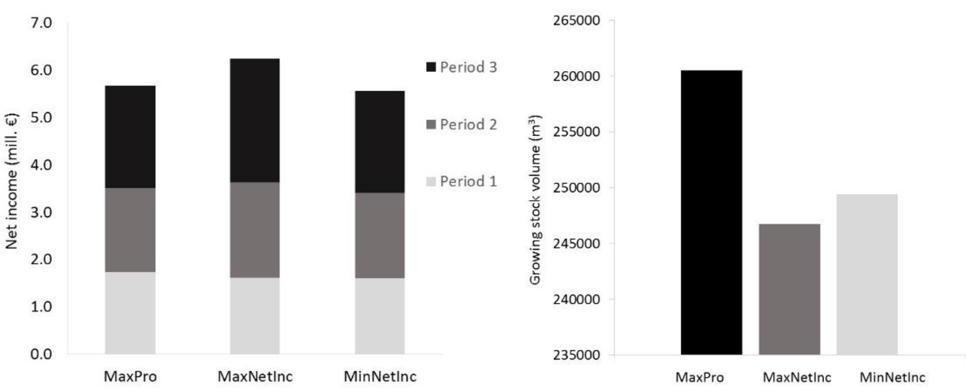



Figure **11**. Accumulated net income (left) and standing growing stock volume at the end of the plan (right) computed for each period and problem formulation (*MaxPro*: maximization of timber production; *MaxNetInc*: maximization of net income and *MaxNetInc:* minimization of net income in each period). Note that the y axis of the right-hand-side diagram is cut.

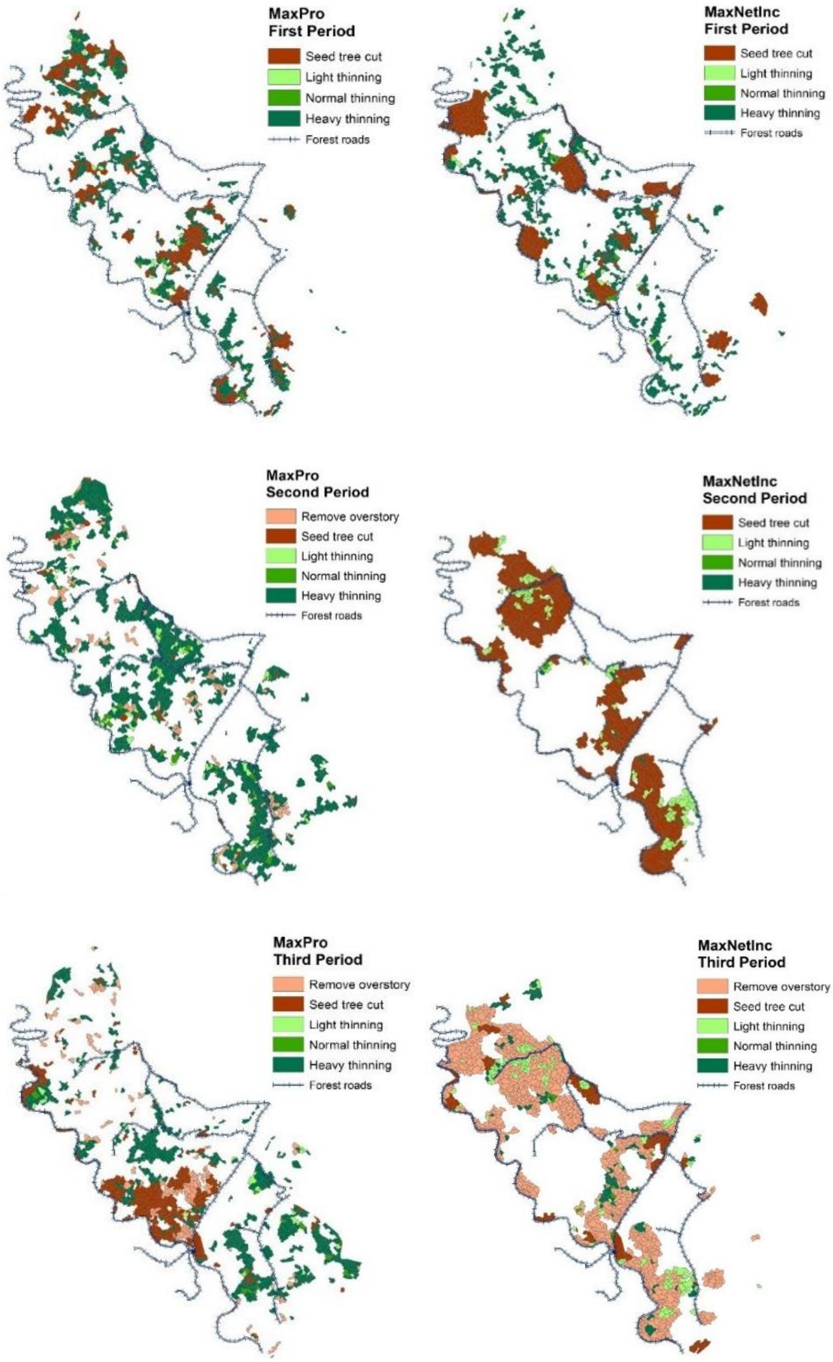



Figure **12.** Spatial layout of dynamic treatment units (DTU) when the aim is to maximize timber production (left) and net income (right) in each period of the plan.

The observed differences in the allocation of prescriptions were further assessed by comparing the mean diameter of the harvested trees and forwarding distance on *MaxNetInc* and *MaxPro* (Fig. 13). The mean distance to road of all cuttings was 253.9 m in *MaxPro* and 168.8 m in *MaxNetInc*. In the first period, the scatter plots were very similar. The size of the harvested trees considerably increased in *MaxNetInc* during the second and third period. In the second period, cuttings prescribed in *MaxNetInc* were located close to forest roads (600 m maximum), while in *MaxPro* cuttings were prescribed up to 1,300 m from the nearest road.

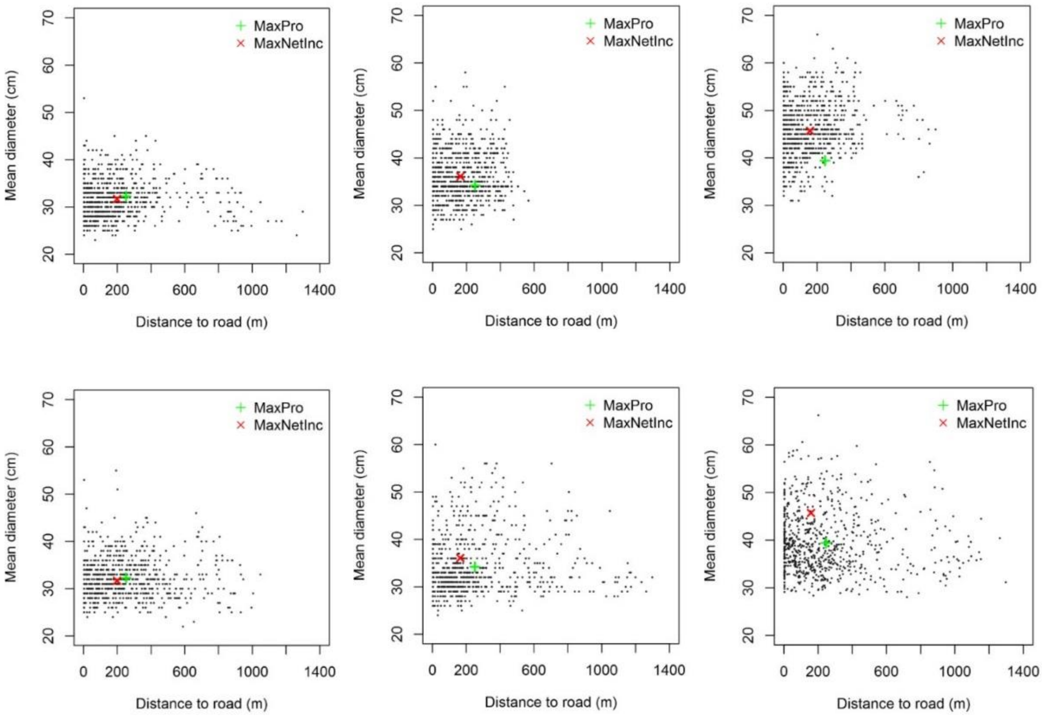



Figure **13**. Distribution of mean diameter of harvested trees and distance to road for *MaxNetInc* (maximization of net income; above) and for *MaxPro* (maximization of timber production; below). The green (+) and red (x) marks show the mean distance to road and the overall mean diameter of trees in the prescribed cuttings for *MaxPro* (+) and *MaxNetInc* (x). The results are presented from the first to the third period (from left to right).

# 4 DISCUSSION

The studies developed throughout this PhD thesis show how ALS data can be used in forest inventory and forest management planning. During the last decades, much effort has been devoted to precisely capture the 3D forest information with both aerial and terrestrial scanning with the purpose of improving the estimation of growing stock attributes. At this point, ALS-based inference in forest inventory is a well-established and mature discipline of both scientific and practical importance (Vauhkonen et al. 2014). Although there is an extensive literature concerning the use of ALS in forest inventory under different approaches and experimental designs, there is a lack of studies that extends the use of ALS data further than the inventory stage. Filling that gap was one of the motivations of this PhD.

In forestry, it is quite common among technicians and researchers to associate the density of ALS point clouds as the parameter of reference when assessing the goodness of ALS information. In this PhD thesis, the two study areas (Forest #76 and #89) were scanned at a higher density (2 points $m^{-2}$) than what is publicly available in Spain (0.5-point $m^{-2}$ density nationwide and 1-point $m^{-2}$ in some areas in the North). There is a trade-off between ALS point cloud density and both ALS acquisition and processing costs. The implications of using low-density ALS data in these four studies would have partially affected the findings. On one hand, the estimation of growing stock attributes might not be so much affected when estimating area-based variables (e.g. Gobakken and Næsset 2008; García et al. 2010). On the other hand, the quality of the CHM will decrease and this has a direct impact on the delineation of FIUs using segmentation techniques. This limitation might be overcome if segmentation is based on additional high-resolution sources such as aerial images (Pekkarinen 2002) that are more accessible than higher density ALS datasets at this moment. In this regard, spectral and texture metrics derived from aerial images can provide meaningful information in forest inventory (Mustonen et al. 2008). In this work, the performance of alternative types of FIU was assessed in study I (compartments *versus* cells) and study III (segments *versus* cells).

In study I, compartments were defined aiming to simulate the business as usual procedure in practical forest planning in the area. This process resulted in non-homogeneous compartments in terms of forest attributes, which were assumed homogeneous in the calculations. When forest compartments were assessed using the CHM as a background, a high variation of CHM information was observed. This most probably led to overestimated growth predictions because, if a compartment is composed of sparse and dense patches, their average growth is less than the growth of an average patch of a homogeneous compartment (this is because of the non-linear relationship between stand density and growth). The use of compartments results in losses in the information gained by ALS-based inventory, as management units are not defined according to stand-level information but are based on predefined boundaries. Therefore, it may be assumed that the pixel-based DTU approach was more precise in terms of growth predictions and more accurate than the compartment-based alternative. Therefore, reducing the variation of CHM information within a given FIU and adjusting the boundaries of FIUs to the irregular border of forest stands were two key challenges that motivated studies III and IV.

In study III, a multi-resolution segmentation method was used to delineate FIUs. Two sets of segments were created for Forest #89. An additional step presented in Pipurri et al. (2013) was used to divide segments into nano-segment units of almost equal size. In this way, the outer boundary of nano-segments and segments followed the irregular boundary of forest patches which is a clear advantage compared to gridding approaches using FIUs of regular shape (e.g. Valbuena et al. 2016). These regular cells might be located in the transition zone between two forest patches of different characteristics, or between forest and non-forest area. Creating a regular grid of cells of certain size is a more straightforward approach than doing segmentation and, in this way, one ensures all cells are equal in size, which is the optimal situation when predicting growing stock attributes wall-to-wall. In grid-based planning (studies I, II and III), the area of grid cells was the same as the sample plots. In this way, growing stock attributes were predicted at the same scale as they were fitted. In segment-based planning, the nano-segment step mitigate the effect of the fact that segments are irregular in shape but also in size. Nano-segments were not equal in size (study III) but they adjust to natural boundaries. In segment-based planning, growing stock attributes were predicted at nano-segment level and the predicted information was computed at segment level.

The results of study III were rather encouraging. The achieved solutions in non-spatial forest problems (study III) add more value to the use of segmentation. The spatial layout for segments in *NonSpatPlan* showed fewer isolated FIUs as compared to cells, which had a poor layout with much dispersion between DTUs. It would be unrealistic to accept, in practical forestry, the *NonSpatPlan* plan based on cells. Opposite to using square cells, relying on ALS-based segmentation leads to some spatio-temporal clustering of forest treatments even without the use of spatial objective variables in optimization. Therefore, segmentation may be regarded as a method to conduct preliminary or first-stage aggregation of cuttings. In all cases, the solutions for *SpatPlan* (i.e., including spatial goals) improved the formation of compact harvest blocks by promoting the spatio-temporal clustering of both cells and segments, which is in line with previous studies (Lu and Eriksson 2000; Tóth and McDill 2008).

According to the improvement of forest plans from *NonSpatPlan* to *SpatPlan*, the expected cost of spatial optimization by increasing the number of management objectives (Baskent and Keles 2005) was highly compensated for. For instance, timber production in cell-based planning decreased by 4.9% but the layout of DTU greatly improved according to the values of the AP ratio, especially for DTUs in which final felling was the only prescription. The impact was 6.3% and 7.8% for small and large segments, respectively. Hereby, these results corroborated previous studies that linked the achieved solutions in forest planning to the size and shape of FIU types, and to the definition of spatial constraints (Murray and Weintraub 2002). The assessment of segment-based planning pointed out, in line with previous studies (Heinonen et al., 2007), the increment in timber production due to decreasing the size of FIUs. The reason is that the smaller the size, the more FIUs to cover the same area and more combinations of treatments can be tested during the optimization.

Study IV tested the shift from production-oriented forest management (*MaxPro*) to income-oriented management (*MaxNetInc*). The economic return of the *MaxPro* plan was very close to that of *MinNetInc*, the worst possible scenario in economic terms. This means that forest management for maximal timber production was very costly. The case of *MaxPro* is the typical scenario in public forests in the study region, in which the management is not evaluated in economic terms. Both approaches reflect the supply (forest service and local municipalities) and the demand (timber companies): one side cares about forest perpetuity and a reasonably steady flow of revenues, while the other seeks for the financial returns from the harvests. In public forests, timber companies purchase, usually through public bids, for the right to harvest in certain areas proposed by the forest service. Even when the purpose of the management is not entirely income-oriented, the financial efficiency of the plan should be addressed. Indeed, the differences between *MaxPro* and *MaxNetInc* plans showed that the degree of clustering of FIUs composing a DTU may partly depend on the main objective of the forest plan and not only on spatial objective variables included in the formulation specifically for that purpose.

The integration of harvesting costs into problem formulation (Solano et al. 2007) contributes to not only management objectives, but it also reinforces the clustering of management prescriptions, reducing the fragmentation of the forest. Although the clustering of DTU was pursued in study IV for all three management plans, the integration of harvesting cost equations contributed to a better clustering of treatment units. Additional spatial constraints may be considered to prevent the DTUs from becoming too large and not conforming with country-specific forest management regulations (Murray 1999; Tóth and McDill 2008). Previous research on spatial forest planning problems have relied on indirect methods such as external data to assign harvesting costs to each calculation unit (Augustynczik et al. 2016; Öhman et al. 2011). By using full-coverage ALS data, we were able to estimate the spatial variation in harvesting costs across the study area.

The studies of this PhD thesis were based on numerical optimization using heuristic-optimization algorithms. Both heuristic methods used met the global constraints (i.e. harvesting targets in each period) while creating compact and round-shaped DTUs. Although SA was tested in all studies, it was finally implemented only on studies I and II. SA resulted inefficient at creating compact harvest blocks when tested in the cell-based problem including spatial goals (*SpatPlan* in study III). At that point, the performance of decentralized heuristic approaches was tested. The CA-based optimization was successfully implemented and the decomposition of the forest planning problem resulted in good solutions, in accordance with previous studies (Heinonen and Pukkala 2007; Mathey et al. 2007), that were achieved in less than 3 hours in all cases. Although the achieved solutions using CA were considered as satisfactory, there might room for improvement due to the inability of heuristics to find the global optimum with certainty (Bettinger and Boston, 2017).

The use of heuristics in forest planning problems was needed due to the inability of mathematical programming methods to cope with spatial and adjacency constraints when tens of thousands of units are involved. This is exactly the context of this PhD: maximize the usability of ALS data from forest inventory to forest planning using fine-grained data precisely delineated. Spatial and adjacency constraints have been successfully addressed for small problems (Baskent and Keles, 2005) but heuristic optimization is still regarded as the optimization method when dealing with operational and practical forest problems of today. IP or MIP techniques have substantial limitations (directly related to problem size) when applied to large combinatorial problems (Bettinger et al. 2003; Pukkala et al. 2009). However, recent advances using those exact methods are offering solutions in the context of spatially constrained forest planning problems (Yoshimoto and Asante 2018).

The driving force of the widespread use of ALS data in forest inventory has been the possibility to reduce costs while improving the estimation of growing stock attributes. Previous studies have evaluated the consequences of altering plot coordinates when estimating growing stock attributes (Gobakken and Næsset 2009). In line with previous studies, a decreasing capability of models to predict growing stock attributes was observed when increasing the simulated displacement in plot coordinates. Increasing the error in plot positions resulted also in the estimation of more homogeneous forest structure throughout the study area. The effect of positioning errors in further stages than forest inventory has received less attention in research and this made it difficult to compare and evaluate the results obtained in study II. In fact, previous research on the effect of forest inventory errors on forest management planning (Islam et al. 2012) did not explicitly consider errors arising from the uncertainty in plot positioning due to limited GPS accuracy.

The differences in terms of utility and timber production between 0-, 2.5- and 5-m standard deviations of displacement error were very small and the average timber production loss with 10 m standard deviation was just 406 $m^3$ for 30-year planning horizon. The decline in timber production was previously related to inventory errors by Eid (2000). The proportion of FIUs prescribed as final felling decreased in the presence of simulated positioning errors as suggested in Borders et al. (2008). Islam et al. (2012) linked errors in forest inventory information to an increment in the prescribed area. In study II, no clear pattern was detected when computing the mean treated area using the 60 replications. However, increasing positioning error resulted in timber production losses as well as in increasing variability in terms of treated area, despite the mean treated area remained similar. The impact of positioning error was clear in the non-spatial objective but not in the spatial ones. With the aim of assessing the influence of heuristic optimization on the achieved solutions, the inventory free of positioning errors was repeated ten times. The lack of variation of spatial objectives variables in these runs made it not possible to detect a worsening effect when comparing plans. The impact of positioning errors on the reliability of prescriptions in Forest #76 was difficult to detect when maps were displayed although the rate of reliability of prescriptions progressively decreased along the plan. The findings of study II are in accordance with previous studies regarding the implications of inventory errors on the spatio-temporal allocation of forest treatments (Mäkinen et al. 2010).

The impact of plot positioning errors might be stronger in a more heterogeneous forest, especially if there is variation within short distance. Particularly, in fragmented forest areas with considerable spatial variability in stand structure, plot positioning errors may have greater impact on forest management planning as compared to the rather homogeneous stand structures of Forest #76. In light of the rather low impact of positioning errors, one can regard the use of expensive GPS system not worthwhile if cheaper professional GPS devices speed up field work, reduce costs and result in nearly similar performance as e.g. devices with sub-metric precision in theory. Nevertheless, further research could be devoted to increase the number of factors assessed in study II, for instance by testing alternative sampling designs in more sparse forest and heterogeneous areas using different scanning configurations. A deeper understanding on the matter is required to validate this first experience (study II) that links errors in plot positioning with their impact on solutions for the DTU approach. To minimize the uncertainty in solutions in forest planning when forest inventory relies on ALS data deserves further research. For instance, the selection of predictor variables when modeling forest attributes might consider the stability of ALS statistics when computed at plot level, acknowledging the occurrence of plot positioning errors as authors of study II assessed. The best possible model might not be the most convenient if the selected ALS statistics showed variation when altering plot coordinates. For instance, one promising approach to mitigate the impact of positioning errors is to combine ITD and ABA methods to improve the adjustment of sample plots boundaries to the detected tree canopies (Packalen et al. 2015). Although uncertainty is inherent to forest planning with e.g. the use of growth models, or assumptions regarding timber assortment prices and market preferences, reducing the uncertainty when estimating the initial attributes of forests would be a true step forward.

All studies have been developed using sample plots as ground data, ALS statistics as auxiliary information while the set of growth and stand dynamics models were based on NFI plots. The inputs for the presented DTU-based planning are quite easy to collect: growth and yield models in Spain are available (Bravo et al. 2012), ALS datasets are also becoming increasingly available and ALS-based inference can reduce the sampling effort (Maltamo et al. 2007). For the case of Spain and the study areas, the presented set of growth models allows for scientific forest management in large areas of mixed pine forests in Central and East Spain. These models can be used to simulate alternative scenarios with the aim of developing multi-objective forest planning optimization. In this regard, DTU-based planning could be more multi-objective by the recognition of more than one forest-based products when defining the optimal management instructions. The presented studies could be used as a benchmark when broadening the multi-objective scope of plans based on DTUs. For instance, by including edible fungi production when developing management instructions or promote the minimization of risk due to wildfires (González-Olabarria and Pukkala 2011). Indeed, the presented methodology is likely to be improved by recent developments in the field of remote sensing. For instance, the use of hyper-spectral ALS might improve the efficiency of the ABA as the estimation of growing stock attributes becomes species-specific and, as a result, both diameter distribution and growth models can be applied to a more detailed information at present state.

The four studies that compose this PhD thesis, together with this summary dissertation, contribute to increasing the scientific knowledge concerning the integration of ALS data into forest management planning. The PhD thesis also provides further insight into several methodological issues relevant to ALS-based forest inventory concerning, for instance, the use of alternative types of FIU and the impact of positioning errors when solving spatial forest planning problems. The combination of fine-grained information in forest inventory and advanced heuristic optimization methods resulted in good solutions when composing DTUs. The relevance of this work is in line with existing policy strategies regarding the efficient use and management of forests.

The main aim of this PhD thesis was to spread the possibilities of DTUs when combined with ALS data for its implementation in forest planning practice. The widespread use of ALS data, growth and yield modeling and the use of spatial optimization offer good opportunities to solve complicated forest planning problems.

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