Forest planning utilizing high spatial resolution data

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Abstract

This thesis presents planning approaches adapted for high spatial resolution data from remote sensing and evaluate whether such approaches can enhance the provision of ecosystem services from forests. The presented methods are compared with conventional, stand-level methods. The main focus lies on the planning concept of dynamic treatment units (DTU), where treatments in small units for modelling ecosystem processes and forest management are clustered spatiotemporally to form treatment units realistic in practical forestry. The methodological foundation of the thesis is mainly airborne laser scanning data (raster cells 12.5x12.5 m^2), different optimization methods and the forest decision support system Heureka. Paper I demonstrates a mixed-integer programming model for DTU planning, and the results highlight the economic advances of clustering harvests. Paper II and III presents an addition to a DTU heuristic from the literature and further evaluates its performance. Results show that direct modelling of fixed costs for harvest operations can improve plans and that DTU planning enhances the economic outcome of forestry. The higher spatial resolution of data in the DTU approach enables the planning model to assign management with higher precision than if stand-based planning is applied. Paper IV evaluates whether this phenomenon is also valid for ecological values. Here, an approach adapted for cell-level data is compared to a schematic approach, dealing with stand-level data, for the purpose of allocating retention patches. The evaluation of economic and ecological values indicate that high spatial resolution data and an adapted planning approach increased the ecological values, while differences in economy were small. In conclusion, the studies in this thesis demonstrate how forest planning can utilize high spatial resolution data from remote sensing, and the results suggest that there is a potential to increase the overall provision of ecosystem services if such methods are applied.

Keywords: cellular automata, forest decision support systems, forest ecosystem services, heuristics, mixed-integer programming, remote sensing, retention forestry, spatial optimization

Skoglig planering med rumsligt högupplöst data

Sammanfattning

Denna avhandling presenterar ansatser för skoglig planering anpassade för rumsligt högupplösta data från fjärranalys och utvärderar huruvida sådana ansatser kan öka leveransen av skogliga ekosystemtjänster. De presenterade modellerna jämförs med konventionella skogliga planeringsansatser med data och beslut på beståndsnivå. Avhandlingen fokuserar främst på dynamiska åtgärdsenheter (dynamic treatment units (DTU)), där skötsel av små enheter klustras för att formera åtgärdsenheter. Metodologiskt baseras avhandlingen främst på data från flygburen laserskanning (rasterdata med 12.5x12.5 m^2 upplösning), olika optimeringsmetoder och det skogliga beslutsstödsystemet Heureka. Studie I presenterar en heltalsmodell för DTU-ändamål och resultaten understryker ekonomiska förtjänster i att klustra avverkning. Studie II och III presenterar ett tillägg till en befintlig heuristisk modell för DTU utvärderar dess utfall. Resultaten visar att lösningar kan förbättras om fasta kostnader modelleras direkt istället för indirekt samt att högre ekonomiska värden kan genereras med DTU, eftersom ansatsen kan bestämma optimal skogsskötsel med högre precision än beståndsbaserad planering. Studie IV utreder om det sistnämnda gäller även för andra värden än ekonomiska och presenterar en ansats baserad på högupplöst data för att allokera områden för generell hänsyn. Utvärderingen av ekonomiska och ekologiska värden indikerar att högupplösta data och en anpassad planeringsansats ger högre ekologiska värden än traditionell ansats, medan skillnaderna i ekonomiskt utfall är små. Sammanfattningsvis visar studierna i denna avhandling hur högupplösta data från fjärranalys kan användas tillsammans med rumsligt explicita planeringsmodeller och resultaten antyder att det finns möjligheter att överlag öka leveransen av ekosystemtjänster från skogar om sådana metoder utnyttjas.

Nyckelord: cellulär automata, fjärranalys, generell hänsyn, heltalsprogrammering, heuristik, rumslig optimering, skogliga beslutsstödsystem, skogliga ekosystemtjänster

Dedication

To my grandparents Elsy, Verner, Margareta, and Kjell,
who lived by and with the forests of Västerbotten.

Contents

List of publications

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

I. Wilhelmsson P., Sjödin E., Wästlund A., Wallerman J., Lämås T., Öhman K. (2021). Dynamic treatment units in forest planning using cell proximity. Canadian Journal of Forest Research, 51(7):1065–1071, https://doi.org/10.1139/cjfr-2020-0210

II. Wilhelmsson, P., Lämås, T., Wallerman, J., Eggers, J., Öhman, K. (2022). Improving dynamic treatment units forest planning with cellular automata heuristics. *European Journal of Forest Research*, 141(5): 887-900, https://doi.org/10.1007/s10342-022-01479-z

III. Wilhelmsson, P., Wallerman, J., Lämås, T., Öhman, K. Dynamic treatment units in forest planning improves economic performance over stand based planning. (manuscript)

IV. Wilhelmsson, P., Lundström, J., Wallerman, J., Lämås, T., Öhman, K. Utilizing high-resolution in long-term forest planning for cost effective promotion of biodiversity in retention forestry. (manuscript)

The contribution of doctoral student Pär Wilhelmsson to the papers included in this thesis is documented as follows:

I. Conducted parts of the analysis and wrote the manuscript with support from the co-authors.

II. Developed the research idea, wrote the code, conducted the analysis and wrote the manuscript with support from the co-authors.

III. Developed the research idea, wrote the code, conducted the analysis and wrote the manuscript with support from the co-authors.

IV. Developed the research idea together with the co-authors, prepared parts of the data, conducted the analysis and wrote the manuscript with support from the co-authors.

Abbreviations

ALS	Airborne laser scanning
CA	Cellular automata
DU	Description unit
DSS	Decision support system
DTU	Dynamic treatment unit
EC	Entry cost
IL	Inoptimal loss
LP	Linear programming
MIP	Mixed-integer programming
NFI	National forest inventory
NPV	Net present value
TU	Treatment unit

1. Introduction

Ecosystem services are defined as the human or environmental benefits from e.g. forests, directly or indirectly (MEA, 2005). Forest ecosystem services comprise, among other things, the production of merchantable timber, sequestration and storage of carbon, species habitat, and recreational values. The goals of forestry are thus to achieve preferred combinations of ecosystem services. The activity of forest planning aims at specifying where, when and how to conduct management activities to align the provision of ecosystem services with landowner's, stakeholders', or society's goals. Forest planning research aims to develop and evaluate models applicable to solving forest planning problems, as well as investigate the provision of ecosystem services over space and time, given different management scenarios. The research summarized in this thesis focuses on forest planning utilizing high spatial resolution data, made available by advances in remote sensing techniques and increased computer capacity, to store huge data sets as well as perform large and complex calculations. High spatial resolution data describing forests' present state and projected development, combined with improved optimization procedures, enables higher precision forest management compared to traditional approaches. Thus, the employment of these data and methods offers a potential for increased efficiency in the utilization of forest resources. This potential is one of the incentives for the present research.

1.1 Forest planning

Documentation of systematized forest planning exist from the century shift at year 1800 (af Ström, 1822; Cotta, 1804; Hartig, 1795). These early ideas were based on the periodic block system, in which the rotation age and total area of forest determines an annual area for forest treatments such as final felling. The reasoning was that employing this strategy will eventually achieve an even age-class distribution and thereby even flow of timber over time. The term "rotation age" implies even-aged forestry (time between two subsequent final fellings) but the same principle to obtain an even flow of timber can be applied in continuous cover forestry, where the term "cutting cycle" is used for the interval between two selection fellings. Forest research has proposed several other methods for decision making on how and when trees ought to be harvested. Such methods can be characterized by the level of which they operate: tree-level, stand-level or forest-level.

Operating at the arguably finest level relevant for forest management (Bettinger et al., 2016), tree-level planning deals with decision making concerning the harvest for individual trees, see e.g. (Pascual and Guerra-Hernández, 2022; Vauhkonen and Pukkala, 2016).

Stand-level planning deals with finding the optimal timing and manner of silvicultural treatments for an individual forest stand (Bettinger et al. 2016). The concept of stands has been an important concept in the facilitation of forest planning for a very long time (af Ström, 1822; Faustmann, 1849; Nilsson et al., 2012). O'Hara and Nagel (2013) cites the American Dictionary of Forestry (Helms, 1998) to note that stands, in a silvicultural sense, are "contiguous groups of trees sufficiently uniform in age-class distribution, composition, and structure and growing on a site of sufficiently uniform quality". Forest planning has often utilized stands as the smallest unit for the collection and storage of data, as well as modelling of ecosystem processes such as growth and mortality. When forest planning is conducted, stands are usually assumed homogeneous in terms of tree layer and site characteristics, and the delineation is then considered rigid over time (Davis et al., 2005; Nelson and Brodie, 1990; Ståhl et al., 1994). An important feature of stands is that they are large enough to be managed individually and without further spatial consideration, e.g. of the management of nearby stands. Quite naturally these assumptions are simplifications (Holmgren and Thuresson, 1997), as within-stand variations occur (Ståhl, 1992). Historically, stands have been delineated by interpretation of analogous and (later) digital aerial images (O'Hara and Nagel, 2013). It is also possible to delineate stands in an automated fashion from remote sensing data (Jia et al., 2020; Olofsson and Holmgren, 2014; Pascual and Tóth, 2022; Pukkala, 2021; 2020).

The largest spatial scale, which this thesis concerns, is forest-level planning. It aims to align forest management on the property-level with the goals by defining a set of potential management alternatives for all stands and deciding the best combination of management alternatives for all stands (Yoshimoto et al., 2016). The advantage of forest-level planning is that it enables the pursuit and satisfaction of forest-level goals such as the appropriate size of adjacent areas for final felling or annual yield from the entire forest. Such goals are unlikely to be satisfied if planning deals with trees or stands in an isolated manner (Wikström, 2000).

Forest planning problems are recognized as complex and ill-structured due to long time-horizons, the complex production system of forests, multiple goals and the various ways to manage forests. As a measure to cope with these, the practice of dividing forest planning problems into sub-problems in a hierarchy is widely acknowledged by large-scale forest owners (Bettinger et al., 2016; Borges et al., 2014; Duvemo et al., 2014; Eyvindson et al., 2018; Kangas et al., 2015; Martell et al., 1998; Nilsson et al., 2012; Ulvdal et al., 2022; Weintraub and Cholaky, 1991). The literature offers the nomenclature of long-, medium- and short-term planning (Borges et al., 2014; Nilsson, 2013) but we will adhere to the stages as strategic, tactical and operational planning (Bettinger et al., 2016; Ulvdal et al., 2022). Although occasionally questioned in research (Eriksson et al., 2014; Tittler et al., 2001), the hierarchical approach is widely accepted among forest organizations. While the exact scope, horizon and outputs of each phase in the hierarchy are not strict, here follows a general outline of them. Strategic planning investigates the long-term (typically coinciding with the length of one rotation, i.e., ca. 100 years in a boreal setting) pursuit of management goals. The highest sustainable timber yield or highest economic yield in terms of NPV are typically the core answers sought from strategic planning. The tactical planning phase aims at geographically allocating the management activities to meet the output of the strategic planning, for the coming 3-10 years. The operational planning is typically conducted monthly and has the shortest time scope, usually 3-6 months. Here, the planning is involved with logistics and the scheduling of management treatment in the specific stands selected in the tactical planning. Two properties are clear here. First is the routine of repeating a planning phase with a time interval shorter than the planning horizon of the phase. This serves as an adaptation to an intricate system afflicted with uncertainties with regard to, e.g., markets, models and natural disturbances. Second, the sequential, top-bottom structure provides an environment in which a forest organization can allow top-down steering. The planning problem itself is also broken down into sub-problems, which decreases its complexity. Relating to stands, the strategic planning process can be carried out in different ways and characterized by the coverage, origin and resolution of the data. Strategic planning as conducted by industrial forest owners in Sweden has long been dominated by the strata-based approach (in the form of sample-based planning, see Jonsson et al., 1993). Here, a stratified sample (with regards to age, standing stock, productivity etc.) of the stands representing the forest is selected and surveyed in the field in an objective manner. The optimal management over time is then found for each stratum, thus answering strategic questions regarding what harvest levels are sustainable over time, thinning and fertilization regimes, and the extent and characteristics of retention and other environmental concerns. The alternative to the strata-based approach is area-based planning (Ulvdal et al., 2022). Here, the entire geographical extent of the forest is represented by stands in a so-called wall-to-wall data, and the optimal management is decided for all stands. The approaches come with different drawbacks and advantages. The strata-based approach is unable to deal with explicitly spatial issues (Daust and Nelson, 1993), since geographical relations are unknown. Furthermore, the strata of stands may be skewed if sampling is not conducted with due diligence in the strata-approach. A drawback of the area-based approach is that the stand register data used to conduct the analysis often have low or unknown quality (Duvemo et al., 2014) and application of stands drastically increases the size and complexity of the planning problem.

1.2 Decision support systems

Tools often employed to deal with complex forest planning problems are forest decision support systems (DSSs), which facilitates the employment of sophisticated methods for determining location, timing and manner of forest management activities. Several definitions exist in the literature regarding what a DSS is. The following definition, describing both the functional and technical nature of existing forest DSSs is suggested by Vacik and Lexer (2014): “computer-based tools which provide support to solve ill-structured decision problems by integrating database management systems with analytical and operational research models, graphic display, tabular reporting capabilities and the expert knowledge of scientists, managers and decision makers to assist in specific decision-making activities”. Forest DSS can be classified as simulating or optimizing. Simulating systems use a set of management rules to simulate a single future management alternative for each stand, and project the resulting output from and development of forests. Optimizing systems also incorporate management rules in order to, firstly, generate a set of potential management alternatives for each stand in the forest. Secondly, the optimizing system uses user set goals, constraints and optimization techniques to find the best possible combination of stand management alternatives. The papers in this thesis are involved with evaluating and developing new methods for forest DSS of the optimizing kind.

A large number of forest DSSs exist internationally (Borges et al., 2014; Packalen et al., 2013; see also a compilation of systems on www.forestdss.org). Until quite recently, forest management focused on the pursuit of economic goals, e.g. timber production. An example of this can be found in the documentation of the Forest Management Planning Package (Jonsson et al., 1993): “in forest management, the goal is to achieve the highest possible yield”. However, introduced in the 1960s in the US (e.g., The Multiple Use Sustained Yield Act, passed in 1960, see also (Hoogstra-Klein et al., 2017) for the European context), a more holistic view with the acknowledgement of the multi-functions of forests has had an increasing impact on the development of forest DSS (Nordström et al., 2019). The pillars of sustainability are now widely acknowledged as economic, social and biological (see e.g. United Nations (1992)). Additionally, their role in climate change mitigation and adaptation has been added to the list of functions forests are expected to fulfill (European Union, 2018). The concept of sustainability is now central in forest management (Hahn and Knoke, 2010) and has reached global acknowledgement among governments, industry and communities (MacDicken et al., 2015). Aspects of participatory planning involving forest owners, indigenous people, communities are also to be added (Nilsson et al., 2016). Furthermore, forest planning problems may include elements of uncertainty such as natural disturbances and changing markets (Pasalodos-Tato et al., 2013). Altogether, the aspects that forest planning problems now deal with, have added to the complexity that DSS are expected to handle. This results in a wider scope of forest management issues, which Vacik and Lexer (2014) identify as important drivers of DSS development, alongside advances in models, methods, and technology. The latter two are of particular relevance for this thesis, namely methodological and technological advances in remote sensing and in optimization.

1.3 Optimization in forest planning

1.3.1 Exact solution methods

An influential solution method for decision support in forestry, often used in different DSS is linear programming (LP) (Kaya et al., 2016; Weintraub and Romero, 2006), a milestone for which was the simplex algorithm (Dantzig, 1951). The application of LP to a decision problem is based on four assumptions: proportionality, additivity, divisibility and certainty (Bettinger et al., 2016). LP can solve planning problems given that involved functions are linear, a goal function is stated, and a set of constraints is formulated as equalities or inequalities. The method allocates management alternatives in time and space using mathematical theory and guarantees optimality. Combined with its robustness and ability to solve large problems, the method has been implemented in forest planning for decennia all over the world (Davis and Johnson, 1987; Dykstra, 1984; Kilkki, 1985). Specific LP formulations for forest planning were proposed by Johnson and Scheurmann (1977), presenting the so-called Model 1 and Model 2. Model 1 has had a great influence on Swedish forestry, with implementations in the widely used Heureka DSS (Wikström et al., 2011) and former Forest Management Planning Package (Jonsson et al., 1993), the latter after the implementation of the JLP optimization routine (Lappi, 1992). Model 1 uses a set of potential alternatives for each management unit, with the associated growing stock, age, yield etc., over the entire planning horizon. Model 2 on the other hand, reallocates the area of management units that are harvested within a given time period into specific strata – containers for management units – which are then used for further calculations. While Model 1 is arguably easier to set up and Model 2 may demand fewer constraints, McDill et al. (2016) show that Model 1 performs better for problems with a few time periods whereas Model 2 is more efficient in solving problems with many time periods.

The simple and robust nature of LP formulations also has limitations. A problem may not satisfy the four assumptions demanded for the application of LP, which calls for other solution methods. Due to the fact that non-integer decision variables are needed, LP is unable to deal with spatially explicit problems. Such planning problems have been imposed by, e.g., legislation (Bettinger and Sessions, 2003; Dahlin and Sallnäs, 1993) and motivated by sociological and ecological aspects (Öhman and Eriksson, 2002) or economic incentives (Borges et al., 2017). This shortcoming of the LP optimization method has motivated the use of mixed-integer programming (MIP) and heuristics. A planning problem is classified as MIP if one or more of the variables in the model are defined as integer (including binary), which is necessary when dealing with spatial problems. Here, the simplex algorithm used for solving LP problems is no longer applicable. MIP has been applied in spatial forest planning, with the advantage of managing spatiality and the ability to produce solutions where the maximum distance from the true optima is known. Efforts have improved the well-known slow solution times of MIP algorithms (Constantino et al., 2008; Goycoolea et al., 2005; Toth et al., 2012). Still, as reported by Bettinger et al. (2009), the drawbacks of LP and or MIP involve of a) the inability to deal with non-linear relationships, b) slow solution times, and c) limitations on the number of constraints which has led researchers to turn to heuristics to solve forest planning problems.

1.3.2 Heuristics

Heuristics are solution methods often characterized as optimization techniques, although they are not exact solution methods. These approaches use the power of computers to search the solution space of a problem according to some logical principle. Heuristics are able to provide solutions within a reasonable time, but do so without providing certain knowledge of the quality of an acquired solution, i.e. there is no guarantee that the optimal solution is found and the distance from the optimum of a solution is unknown. Where LP and MIP may be described as solving an approximation of the problem in an exact manner, heuristics may solve a more exact form of the problem approximately. Heuristics applied in forest planning research include, but are not limited to, simulated annealing (Lockwood and Moore, 1993), tabu search (Murray and Church, 1995), genetic algorithm (Lu and Eriksson, 2000), threshold accepting (Dueck and Scheuer, 1990), reduced cost method (Hoganson and Rose, 1984), and cellular automata (Strange et al., 2001), the latter being the heuristic used in this thesis.

1.4 Remote sensing and high spatial resolution forest data

Over the recent decades, methodological advances in remote sensing, i.e. techniques for measuring forest metrics from platforms such as satellites, aircrafts and drones using sensors like radar (Persson and Fransson, 2014), cameras (Bohlin et al., 2017), and laser (Axelsson et al., 2018), has revolutionized the data available for forest planning and DSS. Specifically, airborne laser scanning (ALS, see Næsset, 2002) has become widely used for forestry applications. Early experiments performed in 1970s in the Soviet Union found that trees could be measured using lasers and the conclusion was made that devices could be attached to aircrafts to remotely measure forests (Nelson, 2013). The working principle of ALS techniques is that if the position of the sensor, the angle and timing of an emitted light pulse, the time it takes for the light pulse to return to the sensor as it is reflected by an object, and the speed of light is known, a 3D point cloud can be generated. If a laser is mounted on an aircraft, the vertical distribution metrics of the produced 3D point cloud are useful for measuring the tree canopy. In the area-based approach for remote sensing (Næsset, 2002) regression analysis is conducted to find a correlation between the ALS data metrics and georeferenced field plot data with measurements of e.g. tree height, diameter, and biomass (Holmgren, 2004). The elaborated models are then applied on the ALS data for the area of interest, enabling representation of forests by fine-grained raster cells. Thus, instead of relying on stand-level data as in the past, it is now possible to describe the forest (e.g. variables such as tree species distribution, height, volume, etc.) at the raster cell level, i.e. areas that are, for example, 12.5x12.5 m^2. The accuracy of this procedure is on stand level comparable (Nilsson et al., 2017) or superior (Persson et al., 2022) to that of traditional subjective field surveys. The routine has been applied to produce forest data for entire landscapes in, among other places, Scandinavia (Breidenbach et al., 2020; Kotivuori et al., 2016; Nilsson et al., 2017), Switzerland (Waser et al., 2017) and North-America (White et al., 2013). These strides made in remote sensing have opened new possibilities for forest planning. High-resolution and wall-to-wall data has historically been expensive and difficult to obtain and store but has now arrived and are utilized by forest and forestry related decision-makers and stakeholders.

1.5 Dynamic treatment units

The combined advances in remote sensing, forest DSS and optimization techniques have opened possibilities for a more flexible and dynamic handling of treatment units in forest planning compared to the traditional stand-based approach. In a new approach, typically named dynamic treatment unit (DTU) planning, the concept of spatially and temporarily rigid stands are not used. Conventional stands are relatively large areas (normally 1-20 ha), used as both the smallest unit for data storage and modelling of ecosystem processes (description units), and as units for modelling and scheduling treatments (treatment units). DTU planning instead maintains a high spatial resolution of forest data through the planning process, and each treatment unit consists of many small description units temporarily clustered into areas of comparable sizes as traditional stands. The advantage of DTU planning is that the solution space is increased, and treatment units are formed as a result of the goal function, rather than by the pre-defined and fixed stands (Heinonen and Pukkala, 2007; Holmgren and Thuresson, 1997). Additionally, DTU planning facilitates the establishment of new plans when conditions change (shifts in prices, stakeholder’s goals, and policy or when natural disturbances occur) compared to stand-based planning, since the formation of treatment units are, to a lesser extent, the result of stand delineation. However, an application in the optimization process of forest planning of the non-spatial Model 1 to high-resolution description units would result in small, scattered treatment units not realistic in practical forestry. Thus, spatially explicit solution methods such as MIP or heuristics are necessary in DTU planning. While MIP models have been applied in spatial forest planning for decades with so-called area-restriction models and unit-restriction models (Augustynczik et al., 2016; Goycoolea et al., 2005; McDill et al., 2002; Toth et al., 2012) for solving problems connected to limiting the contiguous areas of final felling areas, the use of MIP is rare in the DTU planning literature (although see (Öhman, 2001; Pascual and de-Miguel, 2022), possibly due to concern with long solution times (see e.g. Augustynczik et al. 2016; Borges et al. 2017). Instead, various heuristics have been applied, including threshold accepting (Heinonen et al., 2007), reduced cost (Heinonen et al., 2018; Packalen et al., 2011; Pukkala et al., 2009), genetic algorithm (Lu and Eriksson, 2000), simulated annealing (de Miguel Magaña et al., 2013), and cellular automata (Heinonen and Pukkala, 2007; Mathey et al., 2007; 2005; Pascual et al., 2019; 2018).

However, even if the are many studies about DTU planning the core question of whether DTU planning results in more efficient use of forest resource compared to stand based approaches has rarely been addressed. One exception is a study by Holmgren and Thuresson (1997). They found when solving a tactical planning problem of one period, that compared to plans produced based on the stand approach, DTU plans have higher NPV due to lower inoptimal loss from suboptimal decisions caused by the spatial resolution of data. Another important finding was that optimal allocation of treatment units change when timber prices changes. The authors noted that while the findings on inoptimal loss were relevant, methodological differences between the DTU model and the stand based model limited conclusions on the supposed superiority of DTU. Nevertheless, the findings (Holmgren and Thuresson, 1997) support the reasoning that DTU planning should enable a “more efficient utilization of the production potential” of the forest (Heinonen et al., 2007). The economic output of DTUs compared to stands were highlighted when Heinonen et al. (2007) found that a higher amount of harvest (timber volumes) can be maintained for a given total area of old forest or vice versa, if DTU planning is applied instead of stand-based planning. In their study, different spatial objectives were investigated, similar to other DTU studies. Common boundary length has been used for this purpose (Heinonen et al., 2007; Heinonen and Pukkala, 2007; Pascual et al., 2019, 2018), as has been the number of description units in the proximity with common management or properties (Heinonen et al., 2018; Holmgren and Thuresson, 1997; Mathey et al., 2007). These are ways to model the incentive to cluster management and e.g. old forest, due to economic, social and ecological advantages. Another possibility would be to directly model the economic incentive to cluster by including a full mapping of treatment units and applying the fixed cost directly to each of them.

1.6 Retention forestry

The general reasoning among DTU researchers, namely that a high-resolution description of the forest should enable better decisions, is founded on optimization theory. Increasing the solution space will lead to equal or improved solutions. This phenomenon is not specific to economics but is valid in a biodiversity context as well. This is relevant for the allocation of retention patches in retention forestry (RF). RF is a strategy to balance conflicting goals in forest management by retaining or creating forest structures at the time of harvest (Gustafsson et al., 2012) to achieve a significant level of continuity in forest structure, complexity and composition (Lindenmayer et al., 2012), and securing biological legacies (Mori and Kitagawa, 2014). Furthermore, RF increases the social acceptability of forestry (Putz et al., 2008; Ribe, 2005) and enhances aesthetic values (Shelby et al., 2005). RF was introduced in parallel in both North America (under the name New Forestry, see Franklin (1989)) and Northern Europe during the 1980s and 1990s (Simonsson et al., 2015). This reached full scale implementation when certification schemes became widespread (Gustafsson and Perhans, 2010) and RF is now practiced on several continents (e.g. Europe (Gustafsson and Perhans, 2010; Kuuluvainen et al., 2019; Shorohova et al., 2019), South America (Pastur et al., 2009), Australia (Baker and Read, 2011), and North America (Palik and D'Amato, 2019)) and is applicable in both even-aged and un-even aged forest management systems (Gustafsson et al., 2019). Similar to how DTU planning aims at achieving higher efficiency in forest resource use, one may identify a potential to increase the ecological function of retention patches if the decision of where to allocate these structures is based on high-resolution data, increasing the solution space and allowing for higher precision forestry.

2. Thesis objectives

The objective of this thesis is to develop methods applicable to forest planning with high spatial resolution data and evaluate the potential gains of such data and methods, as compared to conventional practices, with respect to the provision of ecosystem services. The main focus lies on the planning approach of dynamic treatment units.

Here follows a list of the aim of the respective papers:

Paper I: The objective of this paper is to provide a method applicable to DTU planning problems based on an exact solution method, MIP. The aim is also to provide added flexibility in the formation of treatment units, by regarding adjacent areas as included in the treatment unit, not only immediately adjacent ones.

Paper II: The objective of this paper is to improve a heuristic method applied to DTU planning problems in the literature. The heuristic is cellular automata and the paper adds a third phase to an existing algorithm. In this added phase, direct ECs are calculated in high detail, rather than estimated using spatial proxy variables.

Paper III: The objective of this paper is to evaluate whether the DTU approach to forest planning can lead to a more efficient use of the forest resource in economic terms, compared to the traditional stand approach. This is conducted by solving a spatial planning problem where ECs are applied to treatment units.

Paper IV: The objective of this paper is to present an approach to utilize high spatial resolution data and spatially explicit planning tools for the allocation of retention patches in long-term forest planning. The approach is in a case study compared to a schematic stand-based allocation of retention patches with regard to the resulting provision of economic and ecological ecosystem services.

3. Materials and methods

The following section offers an overview of the methodology of the papers (summarized in Table 1), the geographical location of the analysis areas (see Figure 1) as well as a description of the materials and methods used in two or more papers. For materials and methods used in specific papers, see their respective subsections and chapters.

Table 1. Summary of forest data, solution methods, and decision support systems used in the papers included in the thesis

Paper	DU type	Avg size (ha)	Analysis area (ha)	No of DUs	Solution method	Decision support systems
I	Cells	0.015625	56	3587	MIP	Heureka, external solver
II	Segments	0.28	1192	4218	CA	Heureka, external solver
III	Cells	0.015625	4479	286553	CA	Heureka, external solver
	Segments	0.27	4477	16477	CA	Heureka, external solver
	Stands	5.2	4477	861	LP	Heureka
IV	Cells	0.015625	9250	591759	LP	Heureka, Zonation
	Stands	5.43	9250	1702	LP	Heureka

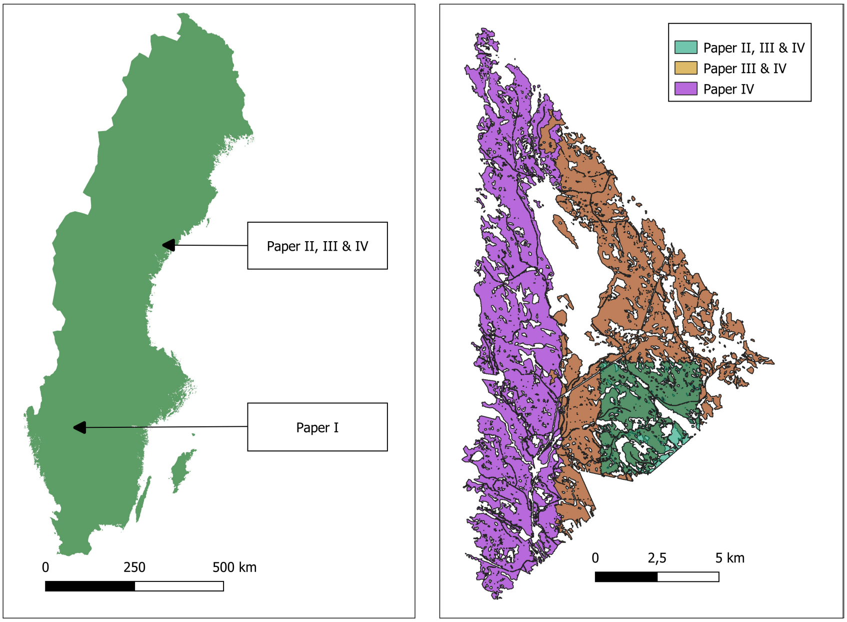

Figure 1. Locations of analysis areas for the papers in the thesis. Paper I in the county of Västra Götaland and Paper II-IV in the county of Västernorrland.

3.1 Remote sensing data (I-IV) and the estimation of the initial state on segment- and stand-level (II-IV)

Remote sensing was a crucial source of data for the estimation of the initial state of the forest in all four papers. The Swedish Land Survey and the Swedish University of Agricultural Sciences (SLU) cooperates to conduct a nationwide ALS which is then combined with NFI plots to output estimations for Swedish forests. The compiled 12.5x12.5 m^2 raster data are available in open-access, provided by The Swedish Forest Agency (SFA) (SFA, 2022a; see also Nilsson et al., 2017). This source provided all papers included in the thesis with raster data on Lorey's mean height, diameter, basal area and volume, which on the plot-level (10m radius) has relative root mean square errors of 9.8-11.2%, 16.4-17.1%, 20.4-26.7%, and 19.2-25.1%, respectively (Nilsson et al., 2017). Estimations of soil moisture class was also provided by SFA (SFA, 2022a). Moisture classes are given in a 5-graded scale of dry, mesic, mesic-moist, moist, and wet. The moisture map is based on digital terrain indices and machine learning technique as presented by Ågren et al. (2021).

In papers II-IV, besides raster data, forest data in the form of traditional stands and/or segments were also used. Segmentation algorithms merge similar, small units into larger units by some spatial principle (see, e.g., Olofsson and Holmgren, 2014). For details on the stand data and two segmentation algorithms forming segments used in Paper II and Paper III, see their respective subsection. After applying the segmentation algorithm, the following routine was applied to estimate segment- or stand-level data (i.e., covering an area of more than a single 12.5x12.5 m^2 raster cell) (summary in Table 2). First, each cell (containing data records for all values necessary for further analysis) was converted into centroids (i.e., point data). Second, an intersection analysis GIS associated each centroid by their geographical location to a segment or stand. Finally, variable-specific metrics (e.g., mean, median, or most frequent) of the centroids intersecting each segment or stand as defined in Table 2 were set to represent each description unit.

Table 2. Summary of forest variables used for import to Heureka PlanWise and the statistical metrics used to compute the initial state of description units (papers II – IV).

Forest attributes	Data sources for estimation in cells	Statistical metrics for estimation in segments and stands
Lorey's mean height (m)	Skogliga grunddata[1]	Median
Tree diameter (cm)	Skogliga grunddata[1]	Median
Volume (m^3 ha^{-1})	Skogliga grunddata[1]	Median
Basal area (m^2 ha^{-1})	Skogliga grunddata[1]	Median
Volume spruce (%)	SLU Forest Map[2]	Mean
Volume pine (%)	SLU Forest Map[2]	Mean
Volume broadleaves (%)	SLU Forest Map[2]	Mean
Site index species (pine or spruce)	Closest matching NFI plot	Most frequent
Site index	Closest matching NFI plot	Most frequent
Vegetation type	Closest matching NFI plot	Most frequent
Mean age (yrs)	Closest matching NFI plot	Median
Soil moisture class	Soil moisture map[3]	Most frequent

[1] Derived from airborne laser scanning (SFA, 2022a), see also Nilsson et al. (2017).

[2] Derived from satellite imagery (SLU, 2022a), see also Wallerman et al. (2021).

[3] Derived from airborne laser scanning, see Ågren et al. (2021).

3.2 Heureka PlanWise (I-IV)

The Heureka PlanWise software (Wikström et al., 2011) was used in all four papers in the thesis. The Heureka forest DSS, developed at SLU, contains a suite of software. PlanWise is one of four applications in the Heureka system, applicable to different scales with respect to geographical range and stakeholder involvement. PlanWise has a widespread use in research, education and commercial forestry. While it is applicable to forest-level planning problems, PlanWise is designed to find the optimal forest management on the estate-level. In principle, PlanWise consists of two modules; a simulation module and an optimization module. The core of the simulation module, shared with the other applications in the Heureka system handling forest dynamics, is a set of models for the prediction of, e.g., growth, mortality and ingrowth. For growth there are both empirical and process-based models and mortality there are deterministic as well as stochastic models to choose from for projecting future tree-layer state.

PlanWise lets the user define a forest management framework with both the selection of forest management system (even-aged, uneven-aged and unmanaged) as well as settings for regeneration, pre-commercial thinning, thinning, selection felling, final felling, fertilization, nature conservation efforts, etc. Given the framework, the system software generates a set of potential treatment programs (TPs) for each description unit. A TP is a sequence of treatments (or non-treatments) over the planning horizon (the timeframe that is set by the user), which is divided into five-year periods. A typical planning horizon used in boreal forest contexts is 100 years, i.e. a rotation period. In the optimization module, the user defines the objective function and a set of constraints for steering the selection of TP for each planning unit, following the form of Model 1. Thus, PlanWise finds the combination of the description unit specific TPs that best fulfills the objective while also satisfying the constraints. Depending on the definition of variables in the problem, LP or MIP is applied as solution method. Finally, the system offers functionality for reporting numerous result variables, e.g. harvest yield, amount of old forest or standing stock.

The use of Heureka PlanWise differed among the papers in this thesis. In all papers, PlanWise was used to project calculate the initial forest state, to generate TPs, and to simulate forest management with the projected future state of the forest given the TP. The simulations generated TPs within the even-aged management system in all papers. The optimization module in Heureka PlanWise was used in papers III and IV. LP in the form of Model 1 (Johnson and Scheurman, 1977) was applied. The decision variable of Model 1 assigns a specific TP out of the potential ones to each treatment unit or to shares of treatment units. For details on objective function and constraints, see the subsections for respective papers.

3.3 Mapping of treatment units (I-III)

The geographical delineation of treatment units is a central concept in papers I-III, the concept being based on defining a neighborhood for each description unit (DU). Two DUs are considered neighbors if their closest points are within a specified maximum distance, referred to as neighborhood distance. In practical forestry, treatment units do not necessarily need to be coherent. To reflect this in our models, we mapped the treatment units with the following routine: Two DUs are part of the same treatment unit (TU) as long as they are interconnected in the same network of neighbors where the same type of treatment coincides in time. Equivalently, in a specific time period, two treatment units are distinctly separate if no DU in one TU is neighbor to any DU in the second TU (see Figure 2).

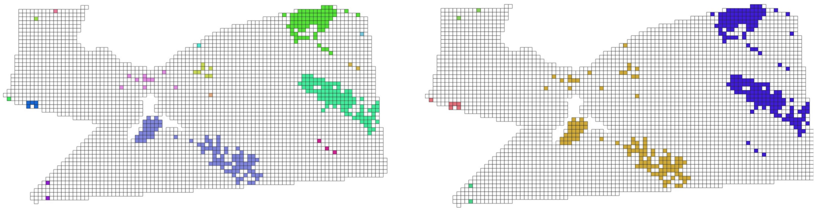

Figure 2. Mapping of treatment units in papers I-III. Consider all colored 12.5x12.5 m^2 cells scheduled for final felling in a given period. Each color mark distinct treatment units, as mapped with a 50 m neighborhood distance (left) and mapped with a 200 m neighborhood distance (right). Note that both maps show the same landscape and management plan.

3.4 Cellular automata (II-III)

Papers II and III applied cellular automata (CA) as solution method. The CA heuristic is an iterative search algorithm first introduced by von Neumann (1966). In its generic form, a CA consists of a grid of cells, each cell with a finite number of states. Cells change states over the progression of the algorithm, subject to rules that depend on a utility function and the states of the neighboring cells, which belong to a subset of cells typically adjacent to or within a defined distance from the subject cell. To my knowledge, CA was introduced in natural resource management research when Strange et al. (2002, 2001) applied it to allocate different land uses. In a forest planning setting, a cell corresponds to a DU (a cell, segment or stand), whose states are assigned TPs. The spatiality of the presented CA model lies in the calculation of entry cost (EC), which is the fixed costs associated with conducting treatments like thinning or final felling. EC represents preparatory measures, e.g, fieldwork, road maintenance, moving machinery and personnel, and administrative work (Borges et al., 2017). The EC is shared among nearby DU with the same type of treatment coinciding in time. By considering each contiguous cluster as part of the same treatment unit and applying the EC to each defined treatment unit, the model is incentivized to cluster treatments in time and space, and DTUs being formed as a result (see Figure 3). This process corresponds to what Mathey et al. (2007) refers to by claiming that in CA, large-scale patterns emerge due to local spatial rules. Another useful property of CA is that different spatial scales can be integrated (Mathey et al., 2007). CA is a decentralized system which means that the entire system does not have to be calculated anew when changes occur in a single cell, and this leads to faster solution times (Pukkala et al., 2014, 2009). CA has been applied in DTU planning several times in the past decades (Heinonen and Pukkala, 2007; Mathey et al., 2007, 2005; Pascual et al., 2019, 2018).

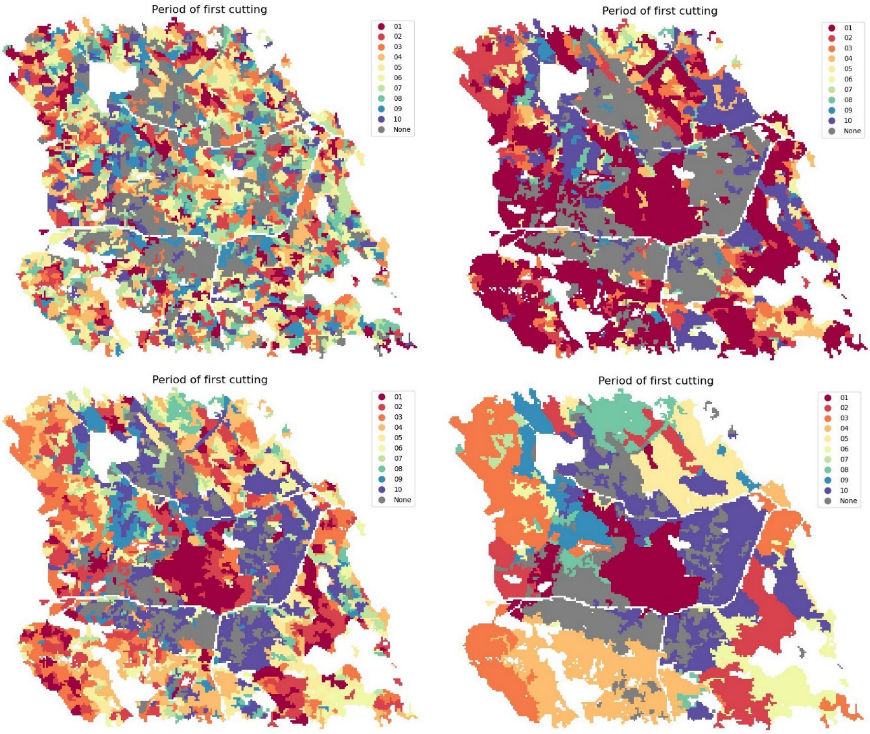

Figure 3. Visualization of how cellular automata clusters treatments over its phases for an example landscape of 1521 segments. Top left: randomized starting plan. Top right: end of local phase. Bottom left: end of global phase. Bottom right: end of final phase.

In the DTU planning literature (Heinonen and Pukkala, 2007; Mathey et al., 2007, 2005; Pascual et al., 2019, 2018), CA consists of two phases where the output plan from the first, local phase, is used as input in the second, global phase. The output of the global phase represents the solution to the problem. Each phase ends after a fixed set of iterations or by using a stopping criterion.

Starting from a state where all DU have a randomly selected TP among the available ones, the local phase aims to generate a local-level optimized plan, under simplified assumptions. Such local-level optimization does not guarantee the satisfaction of forest-level goals however (Wikström, 2000). Therefore, the global phase introduces consideration to such constraints, here total yield (harvest level). The algorithm used in papers II and III is inspired by previous works (Heinonen and Pukkala, 2007; Mathey et al., 2007; Strange et al., 2002, 2001. We have, however, added a third phase in the algorithm, the "final phase". Here, DTUs are mapped in a high-detail manner and explicit, fixed ECs associated with harvest operations are included in the utility function, while maintaining consideration to the harvest level. This has not been implemented in earlier studies found in the literature and is the main contribution of Paper II. While the local and global phases use a fixed moving window to define neighbors and cluster treatments under simplified assumptions (local phase), as well as refine the solution to include forest-level goals (global phase), the final phase conducts calculation of EC where the exact extent of every TU is mapped (see Figure 4 and subsection 3.3). In Paper II, three different neighborhood distances (closest points) were used – 1 m (which corresponds to immediate adjacency using units no smaller than 12.5x12.5 m^2), 50 m and 200 m. In Paper III, two neighborhood distances were used – 1 m and 49 m.

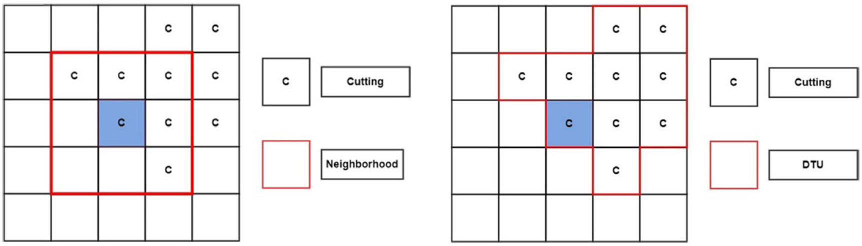

Figure 4. Visual representation of the spatial scope of the local and global phase (left) and the final phase (right) of the CA algorithm of papers II-III. Consider the grid a representation of a forest, as managed in a certain period. In the local and global phase, the blue marked cell will be charged as a share of a downscaled EC proportionate to the number of cells within the neighborhood scheduled for the same treatment. In the final phase, the full extent of the treatment unit is mapped, and the full-scale EC is divided among the DUs constituting the DTU.

The different spatial scopes of the phases have implications for the calculation of EC. Especially for short neighborhood distances, only a small subset of those cells in the neighborhood may share the EC in the local and global phases. For this reason, the EC was scaled down by multiplying it with a factor of 0.02, the factor chosen after trial runs. When the final phase starts, the full EC is charged from each DTU.

One of the main drawbacks with heuristics is that they may not guarantee optimal solutions, and distance to the global optima for a given solution is unknown. Therefore, mechanisms may be included in efforts to prevent algorithms from getting stuck in local optima (e.g. n-opt moves (Bettinger et al., 1999) and search reversion (Bettinger et al., 2015)). Therefore “mutation” and “innovation” are included as probability events in CA. Mutation refers to an event when a random DU is selected for a DU from the available TPs, without regard for the utility function. Innovation refers to selecting the best TP according to the utility function. There is also a probability of leaving a DU unchanged but updating the utility of the current TP (Figure 5). The algorithm used in papers II and III processes over a fixed number of predefined iterations, where all DUs undergo innovation or mutation, or are left unchanged according to probabilities set by the user (in the papers presented here 90%, 5% and 5%, respectively). The final phase ends with a single iteration where all DUs are innovated to avoid the final plan from containing scattered treatments as the result of mutation.

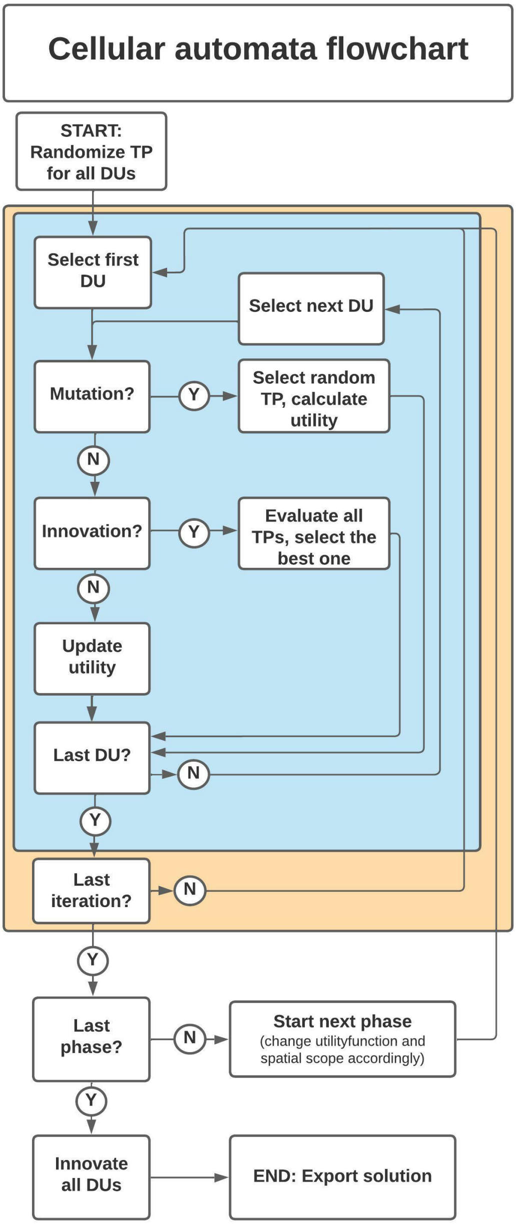

Figure 5. Conceptual flowchart of the cellular automata heuristic used in papers II and III. The blue area marks events within the same iteration and the orange area marks the events within the same phase.

3.5 Further material and method details on included studies

3.5.1 Paper I

The paper presents an MIP model applied to solve a planning problem of 50 years with a DTU approach. The analysis area consists of 3587 12.5x12.5 m^2 DUs, representing a small forest of 56 ha, which approximately corresponds to the average size of non-industrial private forest estates in Sweden (Haugen et al., 2016). The analysis area in Paper I is located in southern Sweden (see Figure 1). The growing stock is dominated by Norway spruce (*Picea abies*, 84.1%) and the rest consists of Scots pine (*Pinus sylvestris*, 5.6%) and a mix of broadleaf trees (alder (*Alnus incana*), willow (*Salix caprea*), and rowan (*Sorbus aucuparia*), 10.3%).

ALS data were used for import to Heureka PlanWise where, firstly, estimation of the initial state of the forest was made. Site index was calculated as the mean of two existing forest plans and tree species distribution (as represented by percentages of the growing stock) was collected from one of the plans. Age was not available in neither ALS data nor the plans, thus an approximation was made. The site index and age were assumed correct and using an iterative method, the age between 0 and 200 years that best matched height development functions (Johansson et al., 2013), was chosen. Secondly, even-aged forestry was simulated in all DUs, including the treatments soil preparation, planting, pre-commercial thinning, thinning and final felling. The site index dependent minimum allowed final felling age was set to match that of Swedish legislation and the upper limit was 30 years above the legal minimum limit. A TP without treatments was also simulated for all DUs. The simulations generated 42 957 potential TPs in total for the 3587 DUs, resulting in an average of 11.98 per DU. The real interest rate was set to 3%.

The model decides forest management by assigning TP to all DUs within the forest. The goal function maximizes NPV from future forest management under an infinite time horizon while satisfying constraints on the total harvested volume in each of the 10 five-year time periods, as well as the spatial allocation of harvest activities under the first three five-year time periods. The constraint on harvested volume is defined such that the total harvest must not decrease from one period to the next one, which in combination with the goal function of maximum net present value, typically leads to a reasonably even flow of harvest over time. The spatial constraint guarantees that a minimum proportion (a, set to 90% in cases 1-4) of cells treated with thinning or final felling in a given time period is considered clustered. A DU *i* is clustered when thinning or final felling occurs in DU *i* as well as in a minimum number of cells (*T*) with the closest distance of their perimeter within specified a distance (*r*) from the centroid of DU *i* in the same time period (see Figure 6).

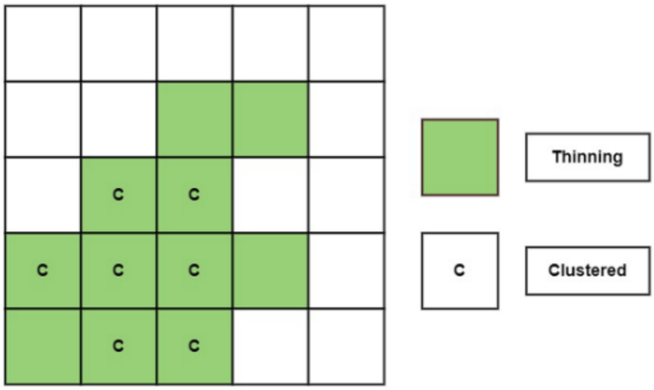

Figure 6. Classification of clustered DU in Paper I. Consider the grid a representation of a forest. Green cells mark the DUs that are scheduled for thinning in period *p*. Given a radius of 12 m and a *T*-value of 4, thinning must occur in at least 4 of the closest 9 neighbors (including DU *i*) for DU *i* to be classified as clustered. C-marked DUs show DUs that are clustered given the stated settings. The parameter *a*, used to constrain the model with regards to clustering, represent the share of the green cells that must be clustered in a feasible solution.

The paper consists of five case studies, where the value of r and T varies (see Table 3). Case 0 is a reference case where the spatial constraint was not included in the optimization. The motive for using different values on r and T was to demonstrate flexibility in the creation of spatial layouts of thinning and final felling and quantify the economic effects of varying degrees of clustering. For the full mathematical notation of the MIP model, the reader is referred to the published paper (Wilhelmsson et al., 2021).

Table 3. Settings for the five cases analyzed in Paper I.

Case	**Radius (*r*, m)**	**Neighbors within radius *r***	**Neighbors required for 'clustered' status (*T*-value)**
0 - reference	n/a	n/a	n/a
1	12	9	3
2	12	9	5
3	30	25	5
4	30	25	10

NPV from costs and income from future forest management is presented in the different cases. To include not only the income of future forest management but also quantify the gains of clustering treatment units, we further analyze the economic performance of the case studies by performing a post-optimization mapping of DTUs, in line with the routine described in the subsection Mapping of treatment units (I-III). The cases are evaluated by mapping using two different neighborhood distances – 50 m and 100 m, respectively. Thus, individual DTUs representing thinning or final felling are identified, and each of them are charged 10 000 SEK in EC. We also report the number of individual DTUs in the periods the spatial constraint was active (periods 1-3), the harvested volume, and the solution times of the MIP model. All cases were solved using a branch-and-bound algorithm with a tolerance gap of 0.1%. The problem was formulated using AIMMS and solved using CPLEX version 12.7 on a PC with 64-bit Windows 10, a 3.4 GHz Pentium 4 processor, and 16 GB of RAM.

3.5.2 Paper II

The heuristic CA algorithm presented above is applied to a DTU planning problem in Paper II. The heuristic solves a planning problem for a forest represented by segments. The segmentation procedure used for forming segments is based on ALS data (Nilsson et al., 2017) and performed in two steps, segmentation and minimization of within-segment deviation. Starting from a grid with 12.5x12.5 m^2 cells, the segmentation algorithm (a region growing method, see Grilli et al. (2017)) merges adjacent cells or segments by considering their similarity with regards to five forest attributes - the basal area, Lorey's mean height, proportion of growing stock of pine, spruce, and broadleaves, respectively. The region-growing model repeats merging until the smallest difference between two merging-candidates (cells or segments) is larger than a user-set value. The second step in the segmentation routine deals with limiting the size of the largest segments, as they may have grown very large when merged. Here, an MIP model selects segments from a set of possible ones by minimizing the sum of standard deviation within segments, while two constraints are satisfied – (1) each cell must belong to a segment and (2) the maximum size of segments must not surpass the user-set limit, here set to 1 ha. The segmentation resulted in 4218 segments with an average size of 0.28 ha.

The analysis area, owned by the industrial forest company SCA and located in mid-Sweden some 30 km northwest of Sundsvall, encompasses 1192 ha. The average productivity is 4.9 m^3 ha^{-1} $year^{-1}$ and the average age is 58 years. The forest is comprised of Norway spruce (*Picea abies*, 49% of the growing stock), Scots pine (*Pinus sylvestris*, 30%), and birch (*Betula pubescens* and *Betula pendula*, 19%). A larger dataset (forest area) was available, and the area used for the paper was selected with a reasonably even age class distribution in mind. The estimation of the initial state of each segment, as required for import to Heureka PlanWise, was carried out in accordance with Table 2. The generation of TPs for all DUs was also conducted using PlanWise. In total, 53 473 TPs were generated for an average of 12.7 TPs per DU.

The main contribution of Paper II is the added final phase in the CA algorithm. DUs change treatment programs over three phases, for a predefined number of iterations, which in turn processes all DUs one time. DUs are processed (with innovation, mutation or no change) one at a time and the TPs of all other DUs are considered fixed when the evaluation of a subject DU's TPs is conducted. The evaluation is carried out with respect to the utility function. The utility function is the NPV from future forest management for an infinite time horizon, including a fixed EC within the planning horizon (10 five-year periods). The contribution to NPV from harvest in a specific TP and period, including ECs, is multiplied with a factor relating to the distribution of harvested volume over time and a user set harvest goal. Henceforth, the factor is referred to as the harvest coefficient. The harvest coefficient takes on a value between 0 and 1, depending on the harvested volume in each period due to the selection of a certain TP for the current DU. Thus, the harvest coefficient is specific for the DU i, TP j, and period p, and is denoted $u_{i,j,p}$. The harvest coefficient $u_{i,j,p}$ takes the value

1	if $h_p \leq t_p$
$1 - (h_p - t_p) / (1.1 * t_p - t_p)$	if $t_p < h_p \leq 1.1 * t_p$, and
0	if $1.1 * t_p < h_p$

where *hp* is the harvested volume in period *p* and *tp* is the target volume in period *p*. The consequence of defining the harvest coefficient as such and including it in the utility function, is that the utility of actions that lead to overharvest (more than the set harvest goal) will be punished in proportion to the surplus of harvest, and the utility of serious overharvest (exceeding more than 110% of the harvest goal) will be set to 0. If all TPs have the utility of zero, the model will select the TP without thinning or final felling, and overharvest is thereby prevented. The harvest coefficient is included in the global and final phases.

When evaluating the utility of TPs for a given DU, the EC is distributed among the DUs constituting the DTU in proportion to their respective area. This design aims to prevent a scenario where a treatment in a small DU with low total income would be regarded as not economically viable, while the rest of the DUs constituting the DTU would still be scheduled for cutting and thus, EC would be charged.

The CA model was run in asynchronous (sequential) mode, which in general terms means that when the changing of state occurs for a cell in the system, knowledge of the rest of the system is perfectly up to date. In the specific case of Paper II, it means that the DTUs are all mapped anew when the calculation of utility occurs. The opposite is synchronous (parallel) mode, where the system acts upon information that may be outdated, since it is only updated at the start of an iteration (see Paper III).

Two properties of heuristics motivate further investigation of solutions: the element of chance, here caused by DUs changing TP in a random manner when mutation occurs, and the fact that the distance from the global optima is unknown. Bettinger et al. (2009) suggest a six-level framework for the validation of heuristics with regards to variation in solutions. Corresponding to level two in the presented framework, spread in NPV and utility function value were reported. We also report the impact of this randomness by investigating how consistently the CA selects TPs for each DU when run repeatedly. “Stability” refers to how consistently TPs were selected by the CA and Table 4 offers an example of how stability was computed. The average stability is reported for each analysis with 20-40 repeated runs.

Finally, solutions found by the CA algorithm are compared with solutions for a similar problem, formulated and solved with LP technique.

Table 4. Example of how stability is computed for three DUs given six repetitions and the selected TPs.

	Repetition							
DU no.	1	2	3	4	5	6	Most frequent TP	Stability (%)
1	TP_{12}	TP_{12}	TP_{13}	TP_{12}	TP_{13}	TP_{12}	TP_{12}	67
2	TP_{25}	TP_{23}	TP_{24}	TP_{21}	TP_{23}	TP_{24}	TP_{23}, TP_{24}	33
3	TP_{34}	TP_{31}	TP_{34}	TP_{34}	TP_{34}	TP_{34}	TP_{34}	83
							Avg	61

Paper III

Paper III evaluates the economic performance of the DTU planning approach, compared to the traditional stand approach, when maximizing the NPV including EC while maintaining an even harvest flow over time. The CA presented in Paper II is applied in eight different cases (see Table 5) on a 4478 ha forest area, each case with its combination of neighborhood distance allowed when forming DTUs and planning approach. Planning approaches are distinct with respect to (1) the type of DU - data used for storing information and modelling ecosystem processes and forest management, as well as (2) the solution method applied to solve the planning problem. Cases 1a and 1b use the CA model to conduct DTU planning on cells (12.5x12.5 m^2) as DUs. Cases 2a and 2b use the same CA model but use segments as DUs. Suffixes a and b refer to the neighborhood distances used; 1 and 49 m, respectively. Cases 3-1a, 3-1b, 3-2a and 3-2b use stands as DUs and an LP model is applied to solve the planning problem (Table 5). Each stand case name starts with “3-“ and ends with the name of the DTU approach solution it is compared to.

Table 5. Summary of Paper III cases and their respective datasets, the solution methods applied and the neighborhood distance used when mapping treatment units.

Case	DU type	Avg size (ha)	Solution method	Neighborhood distance (m)
1a	Cells	0.015625	CA	1
1b	Cells	0.015625	CA	49
2a	Segments	0.27	CA	1
2b	Segments	0.27	CA	49
3-1a	Stands	5.2	LP	1
3-1b	Stands	5.2	LP	49
3-2a	Stands	5.2	LP	1
3-2b	Stands	5.2	LP	49

The cell data are compiled from the sources in Table 2. In this dataset, the analysis area is represented by 286 553 cells for which Heureka PlanWise generated 10.25 million TPs in total. The cell data were also used to estimate the initial state of the forest for the other two datasets used – segments and stands.

Segments were formed by merging cells into segments with an iterative segmentation algorithm originally intended for the delineation of stands based on single-tree data (Olofsson and Holmgren, 2014). For methodological reasons (described below), segments were not allowed to cross the borders of stands. Thus, there is an association between each segment and the stand it was formed within (Figure 7). The procedure resulted in 16 477 segments with an average size of 0.27 ha. The initial state of the forest in each segment was derived from the cells, in accordance with Table 2.

Stand borders (polygons) were collected from a stand register provided by the forest owner, the industrial company SCA. Practitioners such as SCA manually delineate stands and update borders e.g. in conjunction with forest operations, by interpretation or processing of remote sensing data, or simply when personnel visit nearby stands. An important property of the stand delineation is that the quality and date may be unknown and may vary greatly between stands within the same dataset, as is the case with our stand data. Stand registers typically contain data needed for forest management, such as height and standing stock, but only the stand borders were used in this research. The estimation of forest attributes was performed as shown in

Table 2. In total, 861 stands represented the forest, for an average size of 5.2 ha, which can be considered typical for mid-Swedish forestry.

Table 6. Summary of the initial state of the three datasets representing the same forest in Paper III. Note how the routine to estimate e.g. age results in different results for cells and stands.

	Cells	**Segments**	**Stands**
No. of DU	286 553	16 477	861
Avg DU size (ha)	0.015625	0.27	5.2
Total area (ha)	4477.4	4477.9	4479.5
Initial growing stock (m^3 ha^{-1})	205	209	212
Age (yrs, mean)	66.8	61.9	60.7
Initial productivity (m^3 ha^{-1} yr^{-1})	4.31	4.41	4.68

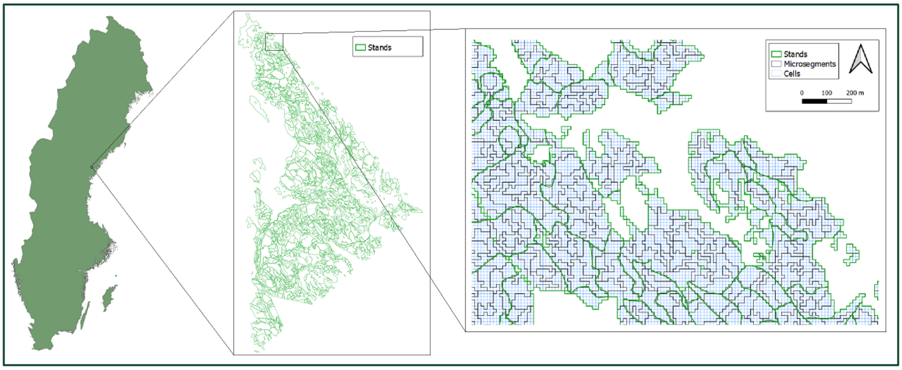

Figure 7. Overview of the location of the analysis area, and the three datasets used in Paper III. The three datasets cover the same area, and the right map displays stands (green), segments (black) and cells (blue).

The CA heuristic presented in Paper III was applied in cases 1a, 1b, 2a, and 2b. In comparison to Paper II the design was modified in four ways:
1) the harvest coefficient from Paper II was not used since it did not guarantee an even flow of harvest but only prevented overharvest. Instead, the utility function used to evaluate TPs includes a penalty to deviations from a stated harvest goal, formulated such that its impact is near 0 in the first iteration, and increases exponentially towards 1 over the global phase. The mathematical notation of the harvest penalty is

$$F \; = 0.05 * (\frac{i}{I})^2 \sum_{p=1}^{P} (T - h_p)^2$$

where

F is the harvest deviation penalty,

i is the current iteration of the global phase,

I is the total number of iterations in the global phase,

T is the harvest goal, and

h_p is the harvest in period p.

The constant of 0.05 was set after a set of trial runs.

2) the EC was linearly progressive – contrary to the constant in Paper II – over the iterations in the final phase, reaching its full scale only in the last iteration of the final phase, including the final iteration when all DUs are innovated.

3) the EC was distributed among the DUs in a DTU in linear proportion to the income from harvesting each DU – contrary to Paper II, where it was distributed in linear proportion to the area of each DU. After changes 2 and 3, the mathematical notation of the EC in the final phase is

$ec_i = EC * (k/K_f) * n_i / N$

where

ec_i is the EC charged from DU i,

EC is the base EC of 10 000 SEK,

k is the current iteration of the final phase,

K_f is the total number of iterations in the final phase,

N is the total income from the DTU that includes DU i,

n_j is the income from the treatment (thinning or final felling) in DU j.

4) the CA was applied in synchronous (parallel) mode meaning that the mapping of DTUs occurred only at the beginning of each iteration – contrary to asynchronous (sequential) mode, which means that DTUs are mapped at the time of e.g. innovation for a cell or segment, as in Paper II.

The motive for change 2-4 was to deal with specific challenges with complexity and runtime encountered when solving the problem using cell data. Change 2 and 3 was specifically aimed towards mitigating the effect of switching the simplified calculation of EC as in the local and global phase to the detailed calculation as in the final phase. When applied to cell data in trial runs, the CA design used in Paper II produced output from the global that the full mapping conducted in the final phase considered as small, scattered, and non-profitable. The changes in EC calculation enables a transition where DTUs are gradually made larger and larger under an increased incentive to cluster treatments.

The harvest goal was set by solving a long-term planning problem on the stand data, where NPV from forest management under an infinite time horizon was maximized under two constraints – (1) that the growing stock after 100 years must be equal to or greater than that of the initial state and (2) that all periods must have the exact same amount of harvest (m^3). This analysis found that a sustained harvest level of 129 979 m^3 was possible for the forest, which set the harvest goal for the CA model.

The CA was applied to the planning problems using the cell data in cases 1a and 1b and the segments in cases 2a and 2b, suffixes a and b referring to neighborhood distances of 1 m and 49 m, respectively. The goal function maximizes the NPV from future forest management including an explicit inclusion of the ECs. Each case results in, among other things, estimations of NPV, allocations of DTUs, and a harvest level over time. The harvested volume from each of the four cases 1a, 1b, 2a, and 2b was used as input to the corresponding stand approach cases 3-1a, 3-1b, 3-2a, and 3-2b. The latter cases were solved using LP where the goal function was to maximize the NPV from future forest management, but without any calculation of EC, since it is not possible to perform the same type of mapping as conducted in the DTU analyses. The LP model also had a constraint, which stated that each case must have the same harvested volume in each period as a corresponding DTU solution. This means that case 3-1a was forced to have a periodical harvest profile equal to that of case 1a, and so on. The motive for this design is that it is not possible to use the formulation of harvest deviations as the sum of deviations squared in a LP model. There were some variations in initial state caused by the preparation of data (see Table 6). To mitigate this source of error and estimate inoptimal loss from rough spatial resolution of decisions and forest data, the TPs of each stand in stand approach cases were applied by force on the cells associated with the stand to finalize case 3-1a and 3-1b and the corresponding was performed on segments in case 3-2a and 3-2b. Since this is a spatial process, the assignment of treatment programs must be binary. Thus, the decision variable in the solution found with LP, $x_{i,j}$, which was continuous in the solving of the problem and represents the share of each DU i that is treated with TP j, was rounded to the nearest binary number. The analysis is finalized by mapping the treatment units in cases 3-1a, 3-1b, 3-2a, and 3-2b, with the neighborhood distance used in their corresponding DTU case. Next, EC is charged from each treatment unit using the same neighborhood distance as the corresponding DTU approach cases. This enables an appliance of the management that is found using stands as DUs, onto the corresponding DUs with higher spatial resolution, and estimations of potential gains or losses in economic terms are possible.

3.5.3 Paper IV

Paper IV compares methods for the allocation of retention patches in forest planning, distinct in their usage of decision support systems and spatial resolution of data, and evaluates the resulting provision of economic and ecological ecosystem services. The two approaches compared are hereafter called the cell approach and the stand approach. The paper also evaluates the potential effects of allocating the retention patches by considering the present attributes of the forest and as well as considering the possible development of forest attributes over 100 years, given no management of the retention patches.

The analyzed area spans 9250 ha north of Sundsvall, Sweden (Figure 1). The data foundation of the paper was polygons in a systematic 12.5x12.5 m^2 grid, cell attributes compiled from various remote sensing raster data sources, listed in Table 2. The non-productive areas (estimated mean annual increment of below 1 m^3 ha^{-1} yr^{-1}) were excluded before analysis. Two variables needed for the analyses were not included in these data – distribution between deciduous species and the amount of deadwood. The distribution between birch (79.8%) and other deciduous trees (here aspen, alder, willow, and rowan (20.1%)) in each cell was set as proportionate to the regional estimates of NFI plots (SLU, 2022b). Deadwood was estimated using an imputation technique using 1710 NFI plots from productive, non-protected areas within Västernorrland county, surveyed 2017-2021. Lorey's mean height and the tree diameter in each cell was normalized against the standard deviation in each dataset. The same computations were conducted for the NFI plots before the imputation step. The deadwood of the closest matching NFI plot, with regards to the Euclidean distance in the two-dimensional space of standardized variables mentioned, was applied to each cell. This statistical technique is also known as kNN (Tomppo et al., 2008). If two or more NFI plots were best matches, a random plot was drawn from this subset.

Using Heureka PlanWise for the entire process, the stand approach conducts a schematic allocation of retention patches by assigning a share (10 or 20%, respectively) of each stand's area as retention. Stand polygons were provided by the forest owner, the industrial forest company SCA. The stand data provided by SCA contained parameters for e.g. tree height, stand age, species distribution etc. but stand attributes from the forest owner's stand register were not used, only the geographical shape of the stands (5.43 hectares in average size) was used in the paper. The present state of each stand, after defining retention patches, was estimated by compiling metrics for the cells in each stand, in accordance with Table 2. Forest attributes were described using stand-level mean values. Before the simulation of treatment programs, retention patches were drawn in a schematic manner as rectangles around the centroid of each stand using the built-in tool in Heureka PlanWise. The retention patch inherited the data from the original stand and since the spatial distribution attributes within the stand was not known, the stand and the retention patch were identical in terms of tree height, standing stock etc. before simulation of forest development began. Therefore, the stand approach represents a routine for allocating retention patches based on data with lower spatial resolution compared to the cell approach. After retention patches were established, PlanWise was used to simulate forest management in all stands according to their respective management regime. Retention patches were left unmanaged for the entire planning horizon of 100 years, and a set of even-aged forestry TPs was simulated in each of the original stands (retention patches excluded). Finally, to produce a long-term forest plan, management was decided for all stands by maximizing NPV such that the harvest yield did not decrease from one period to the next (for periods 1-20).

The cell approach used data with high spatial resolution, namely cells in 12.5x12.5 m^2 format, as well as the stand polygons provided by SCA, and combined Heureka and the Zonation conservation planning tool (Moilanen, 2007) to allocate retention patches. The cell data were imported to Heureka PlanWise and forest development was then simulated under two management regimes: even-aged forestry, and no management. Retention indicators in raster data format was compiled from projections in the Heureka simulation – NPV (given even-aged forestry and a 3% discount rate) was used as indicator of the economic value of a cell. Indicators for biodiversity (given no management) were deadwood (m^3 ha^{-1}), volume of deciduous trees

(m^3 ha^{-1}), number of large trees (minimum diameter of 35 cm for deciduous trees and 45 cm for conifers) (stems ha^{-1}), and mean age. These five indicators were compiled in two sets of raster files. The first set of raster files was based on the present state in the forest (albeit NPV is estimated for all future income and costs under an infinite time horizon), used in cases named "Present" (see Table 7). The second set of raster files was based on the future development of the retention indicators – as average values over the coming 100 years given no management – and used in cases named "Future" in Table 7. To indicate that cells with low potential income from forestry are preferable for retention, the NPV raster file was multiplied by -1.

In the next step, the data records in all the raster files were normalized such that,

$$x_{ki} = y_{ki} / z_k$$

where

x_{ki} is the normalized value of indicator *k* in cell *i*,

y_{ki} is the absolute value of indicator *k* in cell *i*, and

z_k is the highest absolute value of indicator *k* in the entire landscape of 591 759 cells.

The produced raster files were imported to the Zonation tool, used in the cell approach to allocate retention patches. The Zonation algorithm starts by selecting the entire landscape for retention, and removes raster cells by their priority for retention, until no cells remain. Only edge cells were eligible for removal in the study. The algorithm outputs raster data containing values between 0 and 1 for each cell where a value close to 1 indicates that the cell has a high priority for retention. Zonation offers different algorithms for conducting the priority ranking. The additive benefit function was used, which ranks cells based on the weighted sum of overlapping data records across all raster files for the subject cell, thus promoting a high sum. Zonation was run four times, with different boundary length penalties for retention patches and temporal scope of input files, resulting in four priority files. Including boundary length penalty enables clustering of retention patches. Each output file was used to delineate retention patches of two extents – the raster cells with the highest priority, their accumulated area corresponding to 10% and 20% of the total area, respectively. The cases are summarized in Table 7.

Table 7. Overview of cases in Paper IV. Temporal scope refers to how the Zonation input raster data were compiled - either by present state or by future development of biodiversity indicators.

Case	Case name	Temporal scope	Border length penalty	Retention level (%)
1	Present, 10	Present	0.000	10
2	Present, spatial, 10	Present	0.250	10
3	Future, 10	Future	0.000	10
4	Future, spatial, 10	Future	0.250	10
5	Stands, 10	n/a	n/a	10
6	Present, 20	Present	0.000	20
7	Present, spatial, 20	Present	0.250	20
8	Future, 20	Future	0.000	20
9	Future, spatial, 20	Future	0.250	20
10	Stands, 20	n/a	n/a	20

When the retention patches for a case had been decided, all cells marked for retention were merged into a multi-polygon, which was clipped with the stand polygons in GIS. The result is a set of case-specific stands, each assigned for either even-aged forestry (hereby referred to as production stands, where 0% retention level is applied) or retention (hereby referred to as retention stands, where the entire stand is left unmanaged). The initial state of both production and retention stands was then estimated in terms of stand-level values as defined in Table 2. In some rare cases, when a stand (had been separated from the retention patch as identified by Zonation, formed a narrow shape and) did not intersect with any centroids, the cell polygons were buffered with -1 meters, and metrics were computed for the buffered cells intersecting with the stand. Next, the forest data were imported into Heureka PlanWise, where forest management was simulated following the same principle as the stand approach. A single, no-management treatment program was simulated in retention stands and a set of even-aged forestry TPs was simulated in production stands. Finally, the optimal combination of treatment programs for all stands was found (in the same way as in the stand approach) by maximizing the NPV subject to a constraint that guarantees a non-declining harvest yield over the 20 periods that constitute the planning horizon. Thus, (while the resulting cell approach DUs may be as large as the original stands) the cell approach utilizes high resolution data to allocate retention patches, and differences in the provision of economic and ecological ecosystem services emerge, when compared to the stand approach.

Heureka can evaluate the amount of suitable habitat for different species within a forest landscape. A habitat model converts the stand data to raster format and evaluates the structure in each cell along with the nearby area, demanding a specified amount of preferred structures for a given species. We selected Hazel grouse (*Bonasa bonasia*) and Siberian jay (*Perisoreus infaustus*) as example species. We also added a fictitious species. The amount of suitable habitat for each species is reported in the results.

The provision of economic and ecological value was estimated for each case with a normalized overall score. Economic score was established by dividing the NPV of each case with the highest NPV of any case, resulting in values between 0 and 1. The ecological performance of the forestry in each case was evaluated using habitat models and biodiversity indicators corresponding to Sweden's environmental goals called Living forests (Swedish Environmental Protection Agency, 2022). These include forest with high abundance of dead wood[1], old deciduous forest[2], and abundance of large trees[3], respectively. Since biodiversity indicators develop over time, the ecological score was computed with the following routine. We compute the average of periodical values of each biodiversity indicator (periods 1-20 included) for all cases. Second, we normalize the average value of each indicator by dividing the case specific average value with the highest average value observed for any case for the given indicator, resulting in case specific values between 0 and 1. Finally, we take the average values of biodiversity indicator indices, which ranges from 0 to 1 and establish the biodiversity score of a case. The total score for a case is the sum of the economic score and the biodiversity score.

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[1] Stands where dead trees with a minimum diameter of 20 cm constitute at least 20 m^3 ha^{-1}.

[2] Stands with a mean minimum age of 80 years where deciduous trees constitute least 30% of the basal area.

[3] Stands with at least 60 large trees (counting only deciduous trees with minimum diameter of 35 cm and conifers with a minimum diameter of 45 cm).

4. Results

4.1 Applying an MIP model to DTU forest planning problems (Paper I)

Paper I presents an MIP model for DTU planning application. Economic output in plans found with the spatial constraint active (cases 1-4) generally indicate that spatial clustering of treatments is beneficial if ECs are applied. Without mapping DTUs and charging ECs, cases 1-4 resulted in decreased NPV compared to the reference case (case 0), see Table 8. Additionally, a higher T-value for a given radius resulted in lower NPV without ECs.

Table 8. Summary of the economic results. NPV decrease represents the relative decrease in NPV for each case compared to the best case for the given neighborhood distance.

	Case				
	0	**1**	**2**	**3**	**4**
Radius (m)	n/a	12	12	30	30
T-value	n/a	3	5	5	10
	No EC, no post-optimization mapping of DTU				
NPV (SEK ha^{-1})	80 204	80 146	80 132	80 196	80 070
NPV decrease (%)	0.00	0.07	0.09	0.01	0.17
	Including EC, 50 m neighborhood distance				
NPV (SEK ha^{-1})	75 256	74 239	76 656	74 599	77 581
NPV decrease (%)	4.28	4.31	1.19	3.84	0.00
No. of DTUs (p 1-3)	40	40	24	38	17
	Including EC, 200 m neighborhood distance				
NPV (SEK ha^{-1})	78 005	77 972	78 093	78 285	78 447
NPV decrease (%)	0.56	0.61	0.45	0.21	0.00
No. of DTUs (p 1-3)	15	15	14	13	11

When mapping of DTU was included and ECs charged accordingly, the reference case (case 0) had the second lowest NPV using both neighborhood distances (Table 8). Case 4 had the highest NPV, with the other cases showing a decrease in NPV of up to 4.31% and 0.61%, respectively. Case 4 also had the lowest number of treatment units for both neighborhood distances.

Comparison of cases with a given radius shows that an increased T-value resulted in higher NPV when ECs were included, in contrast to the ECs being excluded.

The solution times varied, where the reference case (without any spatial constraints) was solved the fastest (2.2 s) and case 4 was the slowest (2552 s). The variation in harvested volume was negligible, ranging from 6.31 to 6.32 m^3 ha^{-1} $year^{-1}$.

Visual inspection of harvest activity spatial layout (see Figure 8) indicates that treatments units were the most compact in case 2, where 5 of 9 or 55.6% of neighboring cells need to be harvested within a given time period, as well as the subject cell, for the subject cell to be classified as clustered. This case had the highest degree of clustering, compared to case 0 (reference, no clustering), case 1 (3 of 9 or 33.3% cells needed), case 3 (5 of 25 or 25% cells needed) and case 4 (10 of 25 or 40% cells needed).

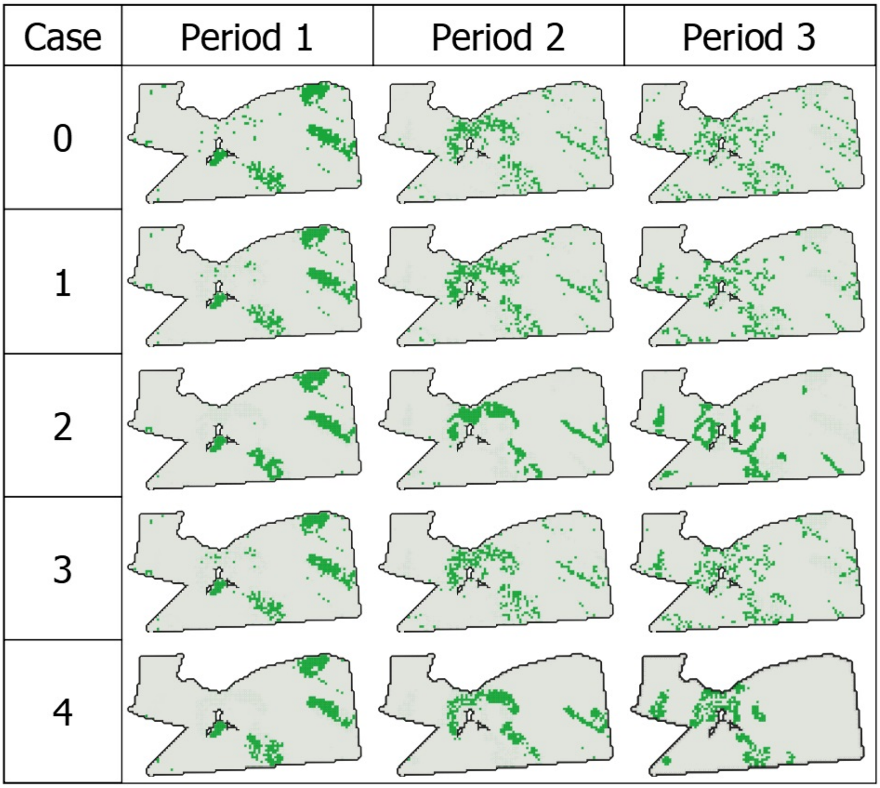

Figure 8. Layout of harvest activities (green) in the 56 ha analysis area (Paper I).

4.2 The advantages of directly quantifying the economic incentive to cluster treatments (Paper II)

Paper II aims to improve an existing CA heuristic for DTU planning by adding a third phase to the algorithm, where treatment units are mapped in high detail. The added phase in the algorithm increased both the utility (1.5-32.2%) and NPV (3.6-33.8%) (see Table 9). These estimations are based on a mode of the algorithm where a full EC is calculated (along with the associated high-detail mapping of DTUs) in parallel to the simplified mapping and downscaled EC that guides the search process in the global phase. The lion's share of the improvement presented in the Delta-column (representing the improvements on NPV and utility in the final phase) took place in the first few iterations of the final phase, with some contributions in the last iteration, where all DUs are innovated. The model produced results with consistency, as indicated by the average stability of 87% for all analyses, as well as the coefficients of variations (all below 0.0161).

Table 9. Results for repeated runs of the algorithm in Paper II. Delta represents the increase in utility and NPV (the latter in SEK) from the end of the global phase to the end of the (added) final phase.

		Global phase	Final phase				
Neighbor-hood distance		**Avg (M)**	**Avg (M)**	**Delta (%)**	**SD (k)**	**Coeff. of variation**	**Stability (%)**
1[1]	Utility	37.3	49.9	32.2	80.4	0.0161	87
	NPV	38.5	51.0	33.8	65.1	0.0013	
50[1]	Utility	47.5	53.1	11.7	15.6	0.0029	87
	NPV	48.9	53.5	9.2	60.8	0.0011	
200[2]	Utility	51.0	51.7	1.5	61.1	0.0118	87
	NPV	52.5	54.4	3.6	45.4	0.0008	

[1]40 repetitions; [2]20 repetitions.

Utility, NPV, and harvested volume increased with increased neighborhood distance, see Table 10. In contrast, the number of DTUs decreased with increased neighborhood distance. The average size of DTU was between 2.04 and 12.7 ha, depending on neighborhood distance.

Table 10. Basic results for the three cases in Paper II.

Neighborhood distance	Utility (M)	NPV (MSEK)	Avg DTU size (ha)	No of DTUs per period	Harvested volume (m^3 ha^{-1} yr^{-1})
1	50.3	50.9	2.04	49.6	7.4
50	51.2	53.4	5.90	19.4	8.1
200	53.9	54.4	12.7	9.8	8.3

4.3 The provision of economic values as a result of different planning approaches (Paper III)

Paper III aims to compare the economic performance of plans produced with the model for DTU planning presented in Paper II with a conventional stand approach planning procedure. Plans found with the DTU approach consistently outperformed plans produced with the stand approach. The NPV of stand approach plans was 2.7-5.2% lower than the corresponding DTU plans (Table 11). Most of the differences between DTU approach plans and stand approach plans were the result of lower IL, even though EC were also lower in the DTU approach plans.

Table 11. Economic summary of results for the eight case studies. Estimations of NPV includes IL and EC, which are both discounted using a 3% rate (Paper III).

Case	Data	Neighbor-hood dist. (m)	NPV (Rel.)	NPV (SEK ha^{-1})	IL (SEK ha^{-1})	EC (SEK ha^{-1})
1a	Cells[1]	1	1.000	45898	4338	1459
3-1a	Stands & cells[2]	1	0.963	44222	5850	1662
1b	Cells[1]	49	1.000	47425	3446	822
3-1b	Stands & Cells[2]	49	0.948	44972	5829	894
2a	Segments[1]	1	1.000	47422	4402	1077
3-2a	Stands & Segments[2]	1	0.973	46133	5166	1602
2b	Segments[1]	49	1.000	48212	3965	742
3-2b	Stands & segments[2]	49	0.972	46846	5158	898

[1] Solution found with CA heuristic.

[2] Solution found with LP and management of each stand applied to underlying cells or segments.

The small differences in EC between the planning approaches were also reflected in small differences in the total number of treatment units between comparable plans. The average size of treatment units was between 3.28 and 6.60 ha over all cases (Table 12). The total area to total perimeter ratio (A:P ratio) revealed that stand approach plans consistently had more compact treatment units than plans produced with the DTU solution method, particularly for DTU plans based on cells. The spatial patterns of treatment units are visualized in Figure 9 and Figure 10, where the varying degree of compactness can be seen. Finding DTU solutions was time consuming using cells (286 553 DU and 10.25 M TP), with the planning model requiring up to 4 days, 21 hours and 37 seconds. Using segments, solutions were found within 43 minutes (excluding the time for the segmentation) and the stand-based solutions were found within 7 seconds (excluding the time for post-optimization mapping of treatment units).

Table 12. Spatial metrics for treatment units in the case studies. A:P ratio represents compactness and is computed as the total area of treatment units (m^2) divided by the total perimeter of treatment units (m).

Case	**Data**	**No of TUs**	**No of TUs < 0.25 ha**	**Avg TU area**	**A:P ratio**
1a	Cells	1211	707	3.29	15.7
3-1a	Stands & cells	1383	468	3.28	29.2
1b	Cells	706	534	6.10	6.0
3-1b	Stands & Cells	738	71	6.17	29.4
2a	Segments	974	210	4.27	24.0
3-2a	Stands & segments	1363	447	3.34	29.9
2b	Segments	657	134	6.60	17.2
3-2b	Stands & segments	741	71	6.16	29.9

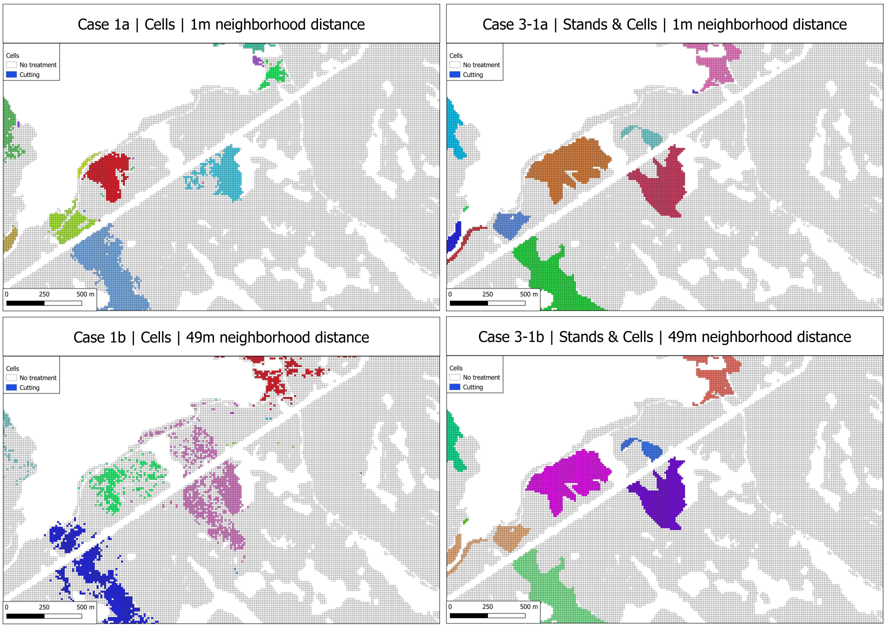

Figure 9. Maps showing the treatment units (distinct colors mark distinct treatment units) in period two in a subarea of the forest analyzed. Cell based plans, with the DTU approach plans to the left and stand approach plans to the right (Paper III).

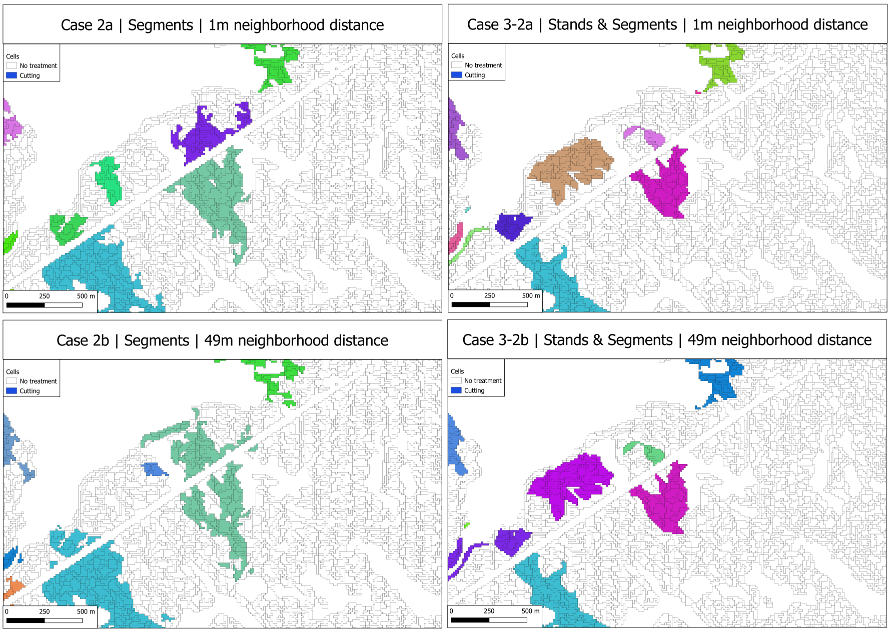

Figure 10. Maps showing the treatment units (distinct colors mark distinct treatment units) in period two in a subarea of the forest analyzed. Segment based plans, with the DTU approach plans to the left and stand approach plans to the right (Paper III).

4.4 The provision of ecological values as a result of different approaches to allocating retention (Paper IV)

Figure 11 displays the retention patches as allocated in the different cases. The clustering in spatial cases is clear from visual inspection, as is the schematic allocation of the stand approach.

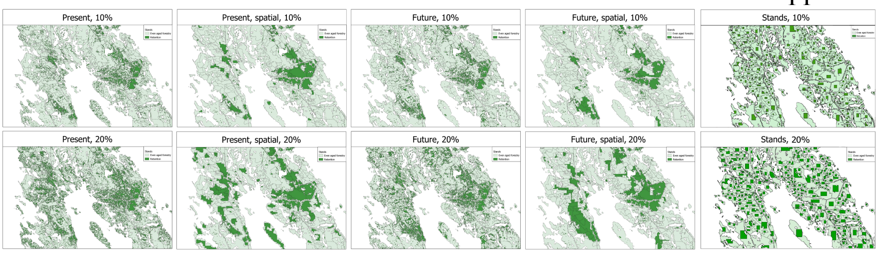

Figure 11. Allocation of retention patches in a northern part of the analysis area for the 10 cases of Paper IV. Top row: 10% retention level. Bottom row: 20% retention level.

The spatial cell approach case based on future development of forest attributes with a retention level of 20% received the highest total score, indicating the highest overall provision of ecosystem services (Table 13). This case was by a clear margin the best for biodiversity, recording the highest normalized average value for four of the six indicators that constitute the biodiversity score. While this case was the second worst for the economic outcome, the differences in economic score were much smaller than those for biodiversity score. The results of Table 13 indicate that the economy deteriorated, and the biodiversity improved when the retention level increased from 10% to 20% for all cases. The stand approach cases provided the lowest total score, but the highest scores for forest with abundance of deadwood and habitat for Siberian jay.

Table 13. Metrics for the estimation of ecosystem services provision in Paper IV. Biodiversity indicators are a derivative from mean values for periods 1-20 (rows 2-7). For rows 8-10, economic score is equal to NPV (row 1) and biodiversity score is the average of indicators in rows 2-7. Total score is the sum of economic and biodiversity scores. For a detailed clarification on the computations, see subsection of *Material & methods.* Bold figures indicate the highest values for each indicator.

	10% retention					20% retention				
	Present	Present, spatial	Future	Future, spatial	Stands	Present	Present, spatial	Future	Future, spatial	Stands
1. NPV	**1.00**	**1.00**	0.99	**1.00**	0.99	0.85	0.83	0.84	0.85	0.88
2. Forest with abundance of deadwood	0.81	0.80	0.82	0.81	0.86	0.94	0.88	0.92	0.91	**1.00**
3. Forest with abundance of large trees	0.24	0.27	0.57	0.33	0.07	0.35	0.45	**1.00**	0.56	0.13
4. Old, deciduous forest	0.56	0.42	0.66	0.56	0.22	0.68	0.48	**1.00**	0.77	0.30
5. Habitat for Hazel grouse	0.91	0.92	0.93	0.93	0.87	0.96	0.94	**1.00**	**1.00**	0.95
6. Habitat for Siberian jay	0.82	0.84	0.81	0.83	0.86	0.94	0.95	0.91	0.95	**1.00**
7. Habitat for fictitious species	0.79	0.65	0.82	0.79	0.19	0.78	0.68	**1.00**	0.87	0.35
8. Economic score	**1.00**	**1.00**	0.99	**1.00**	0.99	0.85	0.83	0.84	0.85	0.88
9. Biodiversity score	0.69	0.65	0.77	0.71	0.51	0.77	0.73	**0.97**	0.84	0.62
10. Total score	1.69	1.65	1.76	1.71	1.50	1.62	1.56	**1.81**	1.69	1.50

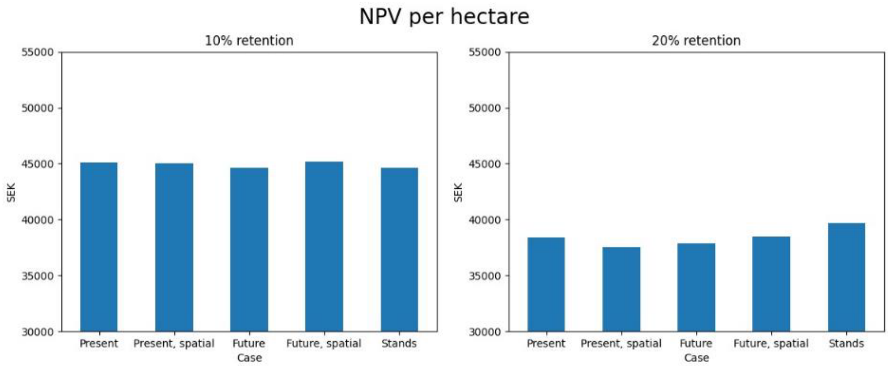

Figure 12. Net present value given a 3% real interest rate.

Increasing the retention level from 10 to 20% resulted in a consistent decrease in NPV (see Figure 12). Comparison across other types of cases (stand and cell approach cases, spatial and non-spatial cell approach cases, etc.) did not show consistent differences.

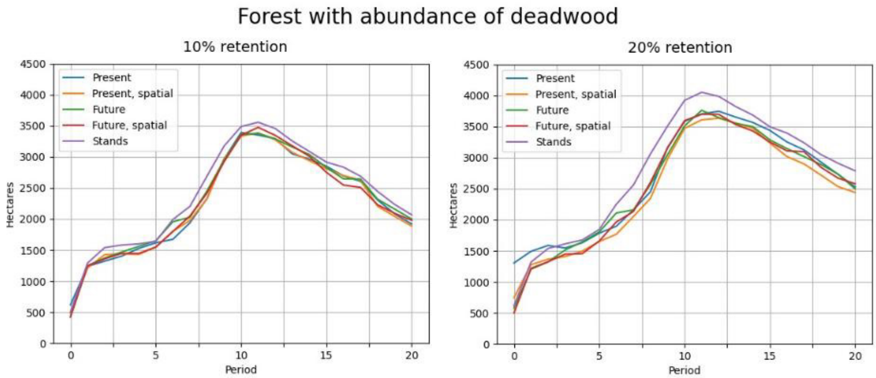

Figure 13. Area of forest where the amount of deadwood exceeds 20 m^3 ha^{-1}. In accordance with Sweden's environmental goals, only downed or standing trees with a minimum diameter of 20 cm are included.

Quantities in Figures 13-15 correspond to indicators of Sweden's environmental goals Living forests. All cases had an increase in forest with abundance of deadwood from the initial values, with peaks in period 11 or 12 (Figure 13). Figure 13 also shows that the area of forest with an abundance of dead wood was largest in the stand approach cases, which is also visible in Figure 11.

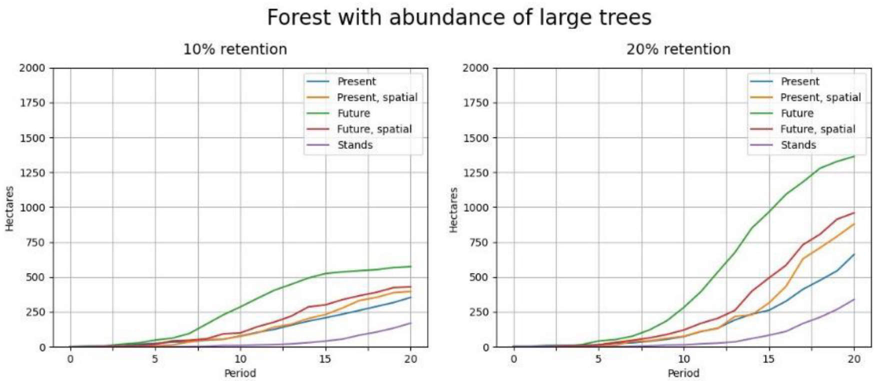

Figure 14. Area of forest where the number of large trees exceed 60 stems per hectare. The minimum diameter in breast height is 45 cm for conifers and 35 cm for deciduous trees, as per the definition in Sweden's environmental goals.

All cases had a very low amount of forest with an abundance of large trees in the initial state (Figure 14), and this forest type gradually increased over time. Cell approach cases based on the future outperformed the other cases with respect to this environmental goal, and the stand approach cases provided the least amount of this forest type with a clear margin. The differences between spatial and non-spatial cell approach cases were ambiguous.

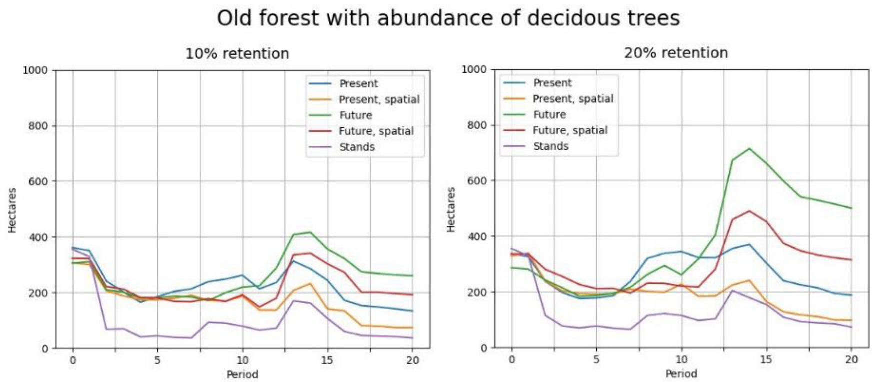

Figure 15. Area of old, deciduous forest. In accordance with Sweden's environmental goals, the mean stand age must be at least 80 years and broadleaves must constitute at least 30% of the stand's basal area.

Old forest with an abundance of deciduous volume declined in early periods in all cases (Figure 15). This forest type recovered back up to the initial levels only in cell approach cases based on future forest attributes and with 20% retention level. The non-spatial cell approach cases provided more old forest with abundance of deciduous trees than its spatial counterpart, and the stand approach cases consistently had the smallest area of this forest type through the entire analysis period.

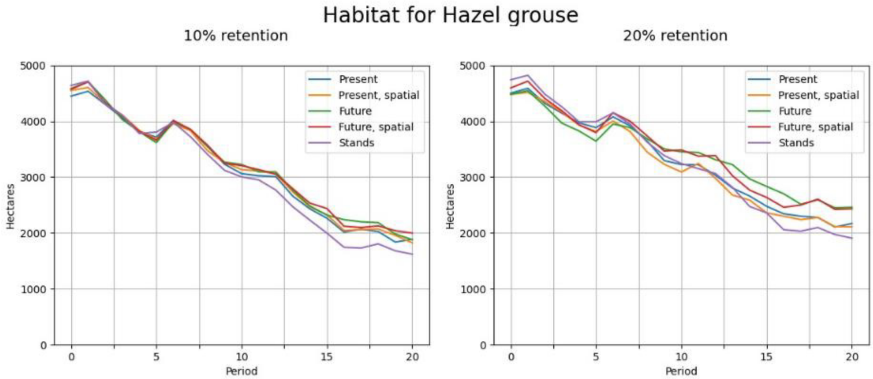

Figure 16. Area of forest suitable for Hazel grouse (*Bonasa bonasia*). The habitat model demands a 20% share of the nearby 100 ha of forest with a tree species mix of spruce and deciduous trees, as well as a mean tree age of minimum 20 years. For further details on the habitat model, see Paper IV manuscript.

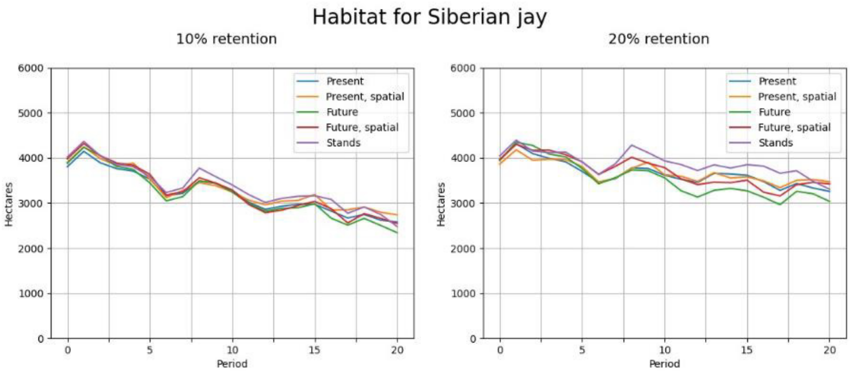

Figure 17. Area of forest suitable for Siberian jay (*Perisoreus infaustus*). The habitat model demands that a 50% share of the nearby 200 hectares are dominated by conifers and having a minimum age of 30 years. For further details on the habitat model, see Paper IV's manuscript.

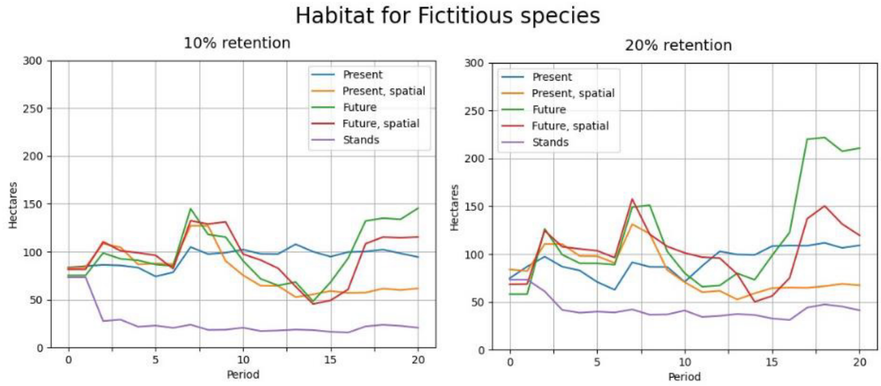

Figure 18. Area of forest suitable for the fictitious species. The habitat model demands a 25% share of the nearby 3.14 hectares being minimum 100 years of age, with abundance of deciduous trees. For further details on the habitat model, see Paper IV manuscript.

Table 13, Figure 16 and Figure 17 show that the habitat area for Hazel grouse and Siberian jay declined over time in all cases, and the differences between cases were relatively small. In general, the stand approach provided the most habitat for Siberian jay among the different cases while, on the other hand, this approach provided the least habitat for Hazel grouse (Figure 16 and Figure 17, respectively). The habitat model for our fictitious species, which emphasizes old forest in a small nearby area (100 m radius), indicated that the stands approach consistently provided the smallest amount of suitable habitats (Figure 18). The Future cases, with some exceptions, provided the largest areas of suitable habitat (Table 13).

5. Discussion & conclusions

5.1 The efficiency of forest ecosystem services provision

The main research topic in this thesis is how to use high spatial resolution forest data in long-term forest planning and whether such data used with adapted planning methods can increase forests' provision of ecosystem services. The emphasis lies on economic values and the DTU planning approach, compared to stand-based planning. One of the essential results is found in Table 11, indicating that DTU planning based on small DUs can outperform stand based planning in economic terms. The explanation for this outcome has earlier been hypothesized by forest planning researchers: DTU-planning should lead to "more efficient utilization of the production potential of the forest" (Heinonen et al., 2007). From an optimization-theoretical standpoint, DTU planning using small DU represents an increase of the solution space when compared to larger stands, which may only result in equal or better solutions (Lundgren et al., 2010). From a forest management standpoint, the explanation is that high spatial resolution data allows models to find management activities better adapted for the local conditions of the forest. This is indicated by Table 11, showing that most of the NPV increase when DTU planning was applied came from a lower IL. This result is a reiteration of the findings made by Holmgren and Thuresson (1997). While papers I-III focus on possible economic gain from the use of DTU, the principle of better solutions due to a larger solution space is general, and not exclusive to monetary qualities. The possible gains in ecological values from planning based on high-resolution data and adapted planning methods were evaluated in Paper IV. Similar results appeared, as an indication was given of a higher potential for the provision of ecosystem services when the overall score of cell approach cases outperformed the stand approach cases consistently (Table 13). Differences in economic score were small or ambiguous between cell approach and stand approach cases. The difference in overall score was instead caused by a clear increase in biodiversity score for cell approach cases. The presented cell approach is a sequential routine where the Zonation-algorithm (a heuristic of sorts) was enabled to cherry-pick the most valuable areas for biodiversity. Thus, locally adapted forest management increased the provision of ecosystem services.

To elaborate on an increased solution space, we return to the example of DTU planning. In short, this planning approach may result in higher precision when performing forest activities, compared to stand based planning. Note the expression "may result" and not "will result", because while an increased solution space should lead to better solutions, DTU planning also warrants a shift away from traditional solution methods such as LP to MIP or heuristics, with their respective challenges thereby inherited. For MIP, the main concern is long solution times, which was highlighted in Paper I as solution times grew rapidly when the problems increased in size, and again in Paper III with the huge cell data. Research results show a potential to reduce solution times in MIP, see e.g. Constantino et al. (2008), Könnyű and Tóth (2013), McDill and Braze (2001), and Toth et al. (2012). The challenge for heuristics is (not limited to but includes) consistently searching the solution space in a relevant and efficient enough manner for better solutions to be found. The design of heuristics must consider the specifics of the problem that is to be solved, and appropriate techniques and parameter settings may both reduce run times and improve solutions (Bettinger et al., 2015, 1999).

Forest planning must somehow deal with spatial aspects for plans to be relevant (see e.g. the unrealistic harvest plans of Case 0 and Case 3, Figure 8). Perhaps not obviously, the delineation of stands is a technique for managing this. Pascual et al. (2019) noted that use of segments, compared to cells, is a form of spatiotemporal clustering even if no spatial constraints are included when forming treatment units. The same thing can be said about stands, which together with LP have been serviceable for solving forest planning methods for a long time (Davis and Johnson, 1987; Dykstra, 1984; Johnson and Scheurman, 1977; Kilkki, 1985), during a period when high resolution forest data have been difficult and expensive to obtain, to store and to use in analysis. Helms (1998) defines silvicultural stands for silvicultural practices as

> a contiguous group of trees sufficiently uniform with regards to attributes and site properties.

A key word here is “sufficiently” which I argue is determined by whether the unit is appropriate for uniform management which, in turn, is dependent on the goals of the forest owner or stakeholder as well as technical and economic factors. This is an argument for establishing the goals first and delineating stands second. Also, as Holmgren and Thuresson (1997) suggest, the optimal allocation of treatment units change when outside factors such as timber prices change. This is similar to how Borges et al. (2017) find that the optimal allocation of harvests is subject to road opening costs. Thus, there are motives to update forest plans and TU (stand) borders when factors such as prices or policies changes. Such revision actions may be facilitated if high-resolution data and spatial planning models are utilized.

Regardless of how spatiality is handled in forest planning, there should be no doubt that ecosystem processes have spatial dependency, e.g., the growth, ingrowth and mortality of trees is a function not only of the tree itself, but also its surroundings (Larocque, 2016). Forests’ provision of ecosystem services is also spatially dependent (e.g., forest operations are more cost-efficient when clustered (Borges et al., 2017), and in cases protection of fewer and larger areas is considered better (Ranius et al., 2022) in comparison to many small areas). An increase in spatial resolution of forest data will increase the need for spatial planning models in forest planning even more. This is highlighted in Paper I, when plans without spatial constraints were outperformed when including ECs (Table 8), and in Paper IV, when spatially explicit approaches to the allocation of retention patches provided more suitable habitat for some species (Table 13).

5.2 The presented cellular automata heuristic

The presented CA model is inspired by the literature (Heinonen and Pukkala, 2007; Mathey et al., 2007, 2005; Pascual et al., 2019, 2018; Strange et al., 2002, 2001), where it has proven successful in solving spatial forest planning problems and forming DTU. The model here added a phase to the algorithm

(Paper II) and was evaluated for the purpose of generating forest plans with DTU and compared to a planning approach based on stands and LP (Paper III). Limitations in these studies motivate critically highlighting the model. Parameterization was given only smaller efforts, which is typically a concern for heuristics (Bettinger and Boston, 2017), e.g., the main result from Paper II, the increase in utility function and NPV over the final phase of the CA algorithm, is highly dependent on parameterization (and design). If clustering would have been further incentivized in the local and global phase by downscaling the full EC with a larger factor (than 0.02), the input into the final phase would likely have included larger treatment units, and the improvements on utility and NPV during the final phase would likely have been smaller. The parameters needed for our model also include probabilities for innovation and mutation, and a scalar for EC. The probabilities (0.9 for innovation, 0.05 for mutation and 0.05 for no change in papers II and III) were initially influenced by the literature and finalized after trial runs. Contrary to previous works, where progressive and decreasing probabilities for innovation and mutation have been used (Heinonen and Pukkala, 2007; Strange et al., 2002), our probabilities were constant over the iterations. The EC scalar of 0.02 in the local and global phase was set after inspecting the data and finding that some treatment programs of very small DUs would never be considered economically viable given the simplified mapping of DTUs in these phases of the algorithm. Such behavior would cause the algorithm to refrain from forming treatment units in the local and global phases and risk getting stuck in local optima. Since heuristics are sensitive to parameterization and no analyses were carried out on the matter, our CA may potentially provide better solutions if parameterization is done more thoroughly.

On this topic, one might add that modelling the ECs directly rather than by spatial proxy variables, reduces the need for parameterization and expert-knowledge in users. The design of the harvest coefficient used in Paper II specifically aimed at preventing the model to choose treatment programs where harvests would be conducted just outside the planning horizon, thus resulting in a moderate NPV but without being charged with an EC. Finally, since results showed that the harvest coefficient of Paper II did not achieve an even harvest flow, we decided to change it for Paper III. The harvest volume deviation penalty of Paper III punishes not only overharvest, but also low harvest activities. The mapping of treatment units and EC was used to explicitly quantify the economic gains of spatiotemporal clustering, instead of applying spatial proxy variables, e.g. common border (Pascual et al., 2019, 2018; Pukkala et al., 2014). As argued by Heinonen et al. (2018), the use of adjacency constraints in spatial forest planning may lead to unwanted outcomes when narrow objects such as roads or mires separate nearby stands. Results indicate that the high-detail mapping of DTU improved solutions (Table 9) but at a considerable computational burden. In order to generate more compact treatment units, it may be relevant to combine the direct quantification of costs with use of spatial proxy variables, e.g. the common border between simultaneously treated and adjacent units. Heuristics aims to provide “high quality solutions in shorts amount of time” (Bettinger et al., 2002) for large and combinatorial problems. Therefore, the solution times displayed in the studies are arguably underwhelming. Inclusion of stop criteria may be relevant here, especially since the utility function culminated after only a few iterations in each phase.

5.3 Uncertainties

The research in this thesis relies heavily on the accuracy of remote sensing techniques to estimate forest attributes and forest DSS for projecting forests’ future attributes and provision of ecosystem services. The key aspects of the methodological foundation of these techniques deserve further discussion. As previously noted, the ALS data prevalent in the papers have accuracy on stand level similar to or higher than forest data collected in field survey with objective methods (Nilsson et al. (2017) compares the results from their study with e.g. Ståhl (1992)). Note that all papers presented in the thesis used estimations for much smaller areas than stands, for which the accuracy is lower. The plot (circular, with 5-10 m radius) level relative RMSE for predictions on stem volume, basal area, mean tree height and mean tree diameter are 19.2-22.2%, 20.4-21.3%, 9.8-11.2%, and 16.4-17.1%, respectively, for the different geographical regions in the data (Nilsson et al., 2017). The accuracy is higher on the stand-level, where the corresponding metrics are 17.2-22.0%, 13.9-18.2%, 5.4-9.5%, and 8.7-13.1%, respectively. To fill the gaps of the datasets compiled from remote sensing sources, imputation techniques were applied. By matching a DU with an NFI-plot subject to the shortest Euclidean distance in an n-dimensional space, missing data records for e.g. site index (papers II-IV) and deadwood (Paper IV) were applied to the data. This routine provides datasets that should at best be regarded as serviceable for case studies. However, the accuracy in terms of estimating the true state of the actual forest analyzed in the papers is unknown. Therefore, the absence of the mentioned quantities represents a source of error in the papers.

The projections in Heureka PlanWise were based on a set of empirical models to estimate e.g. growth. The growth models are created and validated using NFI plot data, which means that historical trends in managed forests are extrapolated into the future, which is associated with numerous uncertainties. The expected effects of climate change include increased growth (SOU, 2007), and research has concluded that such changes have already impacted how trees grow in Swedish forests (Appiah Mensah, 2022). Moreover, disturbance regimes are expected to change with a changing climate (SOU, 2007), whose stochastic properties are more difficult to model. While Heureka offers indices for some disturbances, e.g. wind throw, such events do not occur in the modelling environment used to estimate the effects of forestry in this thesis.

Furthermore, even-aged management dominates Swedish forestry (only 728 000 ha, or ~3% of the productive forestland is managed with continuous-cover forestry, (SFA, 2022b)) where treatment units are several hectares in size on average (3.8 ha for final fellings during 2021, (SFA, 2022b)). The analyses in all papers produced management plans where edge effects (between mature forest and regeneration areas) are very likely more prevalent than in practical forestry (see Table 12, where A:P ratios were higher for DTU plans based on cells, and Figure 9 and Figure 10, where this effect is visible). Application of the empirical models of Heureka (which are created and validated in the context of Swedish forestry) in solutions with more prevalent edge effects are thus extrapolations. The studies may have underestimated some effects, including i) skewed growth between young and mature forests and hampered regeneration due to competition, and ii) increased risk of e.g. wind throw (Zeng et al., 2004) on the mature stands, both due to larger areas under edge effects. Also, iii) increased costs in harvest operations due to lower efficiency in less compact harvests.

5.4 DTU planning – possibilities and challenges in Sweden

Modern remote sensing techniques are today operational in several countries and produce high-resolution wall-to-wall data for forests on national level (Breidenbach et al., 2020; Kotivuori et al., 2016; Nilsson et al., 2017; Waser et al., 2017; White et al., 2013). Given the possibility to combine remote sensing data with segmentation algorithms, such as in papers II and III, means that the door for automation of stand delineation is wide open. Nevertheless, some pieces of the puzzle of full implementation of automated forest plans may still be missing. While remote sensing can deliver estimations for parameters connected to tree phenology, forest DSS may need more information to reliably project development of forests and to quantify ecosystem services. For the example of Heureka PlanWise, site index and mean age is used in growth models, and deadwood is an important indicator for biodiversity, all of which are currently lacking in the available remotely sensed data (see SFA (2022a). Concerning site index and age, research has suggested bitemporal ALS to estimate site index age-independently (Noordermeer et al., 2018), and estimations of age would thereafter be obtainable as a derivative of height and site index. Yet another possibility for well-organized foresters with large amounts of data would be to combine data from various sources (e.g. remote sensing and stand register data) in so called data assimilation (Kalman, 1960; Lindgren et al., 2017). However, as long as these data are lacking for Swedish forests, this is a challenge for Swedish practitioners that fully rely on remote sensing data for conducting forest planning.

The classical hierarchy of strategic-tactical-operational planning has dominated historically (Jonsson et al., 1993) and still does (Ulvdal et al., 2022) among large forest-owning companies in Sweden. Ulvdal et al. (2022) reports that sophisticated methods are largely only applied in the strategic planning stage, in the so-called strata-based approach. Fully relying on remote sensing data, the segmentation of DU and spatial models in forest planning would be a paradigm shift for Swedish forest practitioners. It is also not clear where high-resolution data and spatial methods best fit into the conventional planning hierarchy (and the papers in this thesis do not specifically deal with this aspect). Potentially, it might induce the merging of some levels in the hierarchy, such as the merging of the strategic and tactical levels. The burdens of large datasets and long computation times are, however, an argument for full introduction of high-resolution data and spatial planning models in the later stages of the planning process, when harvest levels are set, geographical areas smaller and planning horizons shorter. Such a trade-off between level of detail and complexity is nothing new in forest planning, where techniques for dealing with complexity are already relevant (Bettinger et al., 2016; Borges et al., 2014; Duvemo et al., 2014; Eyvindson et al., 2018; Kangas et al., 2015; Martell et al., 1998; Nilsson, 2013; Weintraub and Cholaky, 1991). Finally, the solution methods available in forest DSS may be a challenge. While the Heureka DSS provides functionality for LP and MIP but not heuristics, an international outlook shows that heuristics can be used to solve forest planning methods. Either by forest DSS with integrated optimization modules using heuristics (e.g. Pukkala, 2004) or by using forest DSS to generate management alternatives, and solving the planning problem in an external software (e.g. Öhman and Eriksson (2002)).

The effects of shifting planning approaches may transcend beyond the provision of ecosystem services, the modelling of which was the basis for analyses in this thesis. Cost-plus-loss analysis (see, e.g., Duvemo et al., 2014) provides an economic framework for estimating the cost of an inventory method and its data. The main principle here is that the inventory cost consists of two components: the cost of obtaining the data, and the cost from inoptimal decisions. This relates to Swedish forest organizations' reasoning behind the choice of strata-based planning (over area-based planning) for the strategic planning phase. Strata-based planning entails costs for assembling the data through sampling and field survey, but planners estimate that the gains in inoptimal loss from more reliable data makes the approach preferable to the area-based approach that would depend on the uncertain quality of the stand register (Ulvdal et al., 2022). This thesis concerns the possible improvement on decisions, but not the cost for data collection.

5.5 Conclusions

The main aim of this thesis is to develop methods applicable to forest planning with high spatial resolution data and to evaluate if there are potential gains in provision of ecosystem services when such planning approaches are applied. The results are presented from four studies where

ALS data and the forest DSS Heureka were employed. Overall, the results in this thesis suggest that the provision of ecosystem services from forests can be improved, if high spatial resolution data is utilized with spatial planning models. This thesis demonstrates suggestions on how to utilize the vast amounts of data produced by remote sensing to improve planning of forest management.

Paper I confirms that there is an economic need to cluster treatments in time and space if high spatial resolution data is used as basis for forest planning and fixed costs for harvest operations are included. The study also successfully solved a DTU problem with an exact solution method. Such models have often been discarded in DTU context for the sake of long solution times but progress on this issue has been made and MIP models may gain relevance in the future. Paper II shows that there is a potential to improve solutions by modelling the economic incentive to cluster directly, by explicitly mapping treatment units and applying fixed costs accordingly. However, the mapping process in papers II and III was a considerable computational burden. Paper III addresses the core question of the argued superiority of DTU planning that several DTU researchers adhere to. The results indicate that the economic performance of forestry may improve if DTU planning replaces stand-based planning, due to lower inoptimal loss and ECs in forest management and an increased solution space. Paper IV focuses on the allocation of retention patches in forestry. The results indicate that there is a potential to improve the ecological values of forests if retention patches are allocated by using an adapted and high-detailed approach, compared to the stand-based approach.

5.6 Future research

The research in this thesis largely focuses on the planning approach of DTUs. Papers II and, in particular Paper III, suggests that stand-based planning entails more suboptimal forest management than DTU-planning due to the spatial resolution of data and decisions inherited from stands. While this research focuses on the spatial resolution of forest planning, it might be the case that a higher temporal resolution of decision making in forestry may enhance provision of forest ecosystem services. This topic is an opportunity for future work.

Most previous work on DTUs have studied economically oriented problems (although see Heinonen et al. (2007) for a multi-objective setting). Except for paper IV, the papers of this thesis are no exception. The main aim of the studies was to provide insights on whether a more efficient use of the forest resource is achievable with DTU planning. The choice of focusing on economic value was motivated by the fact that economy is relatively straightforward to quantify, whereas ecological and social values are more challenging in this regard. Future efforts may provide further insights on how to model and promote economic, ecological and social values in the DTU approach.

The hierarchy of forest planning in larger organizations is established, constituted by the strategic, tactical and operational stages. DTU planning may deal with long time horizons and the question of harvest level over time, which are characteristics of strategic planning. At the same time, the DTU approach focuses on the geographical allocation of treatments, which is typically dealt with in the tactical stage. Future research may investigate how and where in the planning process it is proper to utilize DTU planning and high spatial resolution data.

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Popular science summary

The aim of forest planning is to suggest the location, timing and manner of forest management activities. Activities are carried out in order to provide us with benefits from forests – forest ecosystem services (e.g. timber production, sequestration and storage of carbon, conservation of threatened species, and promotion of recreational values). Forest planning is performed to fulfill the goals of the forest owner, stakeholders, or society. The traditional planning approach is based on stands. A stand is a geographically defined area where the height, diameter, and species distribution of trees is homogeneous. The stand is considered uniform and to be managed uniformly. In principle, stands should also be of sufficient sizes, such that conventional forestry can be carried out in the stand without regard to the management of nearby stands. Stands are the smallest unit for modelling both ecosystem processes such as growth and mortality. The stand-based approach has dominated forest planning in both Sweden and internationally, and its use has so far been appropriate. Forest data with a higher spatial resolution has historically been difficult and expensive to obtain, store, and use in analyses.

Advances in remote sensing techniques have changed this. Today, forest data with significantly higher spatial resolution can be obtained by e.g. airborne laser scanning. The capacity of computers has increased manifold, enabling storage of large datasets and extensive calculations. Altogether, this opens possibilities for forest planning that were not realistic some decades ago. By using modern technology, a higher spatial resolution description of forests is now widely available. Thereby, there is a potential for high precision forestry where the best action is taken at the right place at the right time. Unfortunately, the traditional forest planning models are not applicable on high spatial resolution data, if the plans produced are to be realistic.

Spatial considerations in planning models are necessary to cluster harvest activities or conservation of valuable habitat. In this thesis, such planning models are presented and evaluated. This thesis presents models, adapted for high spatial resolution data produced with remote sensing techniques. The models handle spatial aspects and enable improved forestry compared to traditional planning models.

The thesis is comprised of case studies for forests in southern (Paper I) and central (Papers II-IV) Sweden, where airborne laser scanning has been utilized to estimate the current state of the forest. The decision support system Heureka has been applied to project the development of the forests and the provision of ecosystem services over time, given different management alternatives. Moreover, different optimization methods have been used to decide optimal management

The importance of including spatial aspects in planning models is highlighted in Paper I, which presents an optimization model for clustering of harvest operations. The resulting forest management is compared to that suggested with traditional methods. The study shows that there are economic gains from clustering harvests when fixed costs associated with e.g. moving machinery to the site are included in the calculations of economic value. Paper II presents an alternative model to solve problems similar to that of Paper I. The presented model in Paper II directly (instead of indirectly) quantifies the economic incentive to cluster harvests. The model is an adaptation to a previously presented one. The addition to the algorithm improved the economic performance of forestry in the case study. Paper III is a further evaluation of the model presented in Paper II. The study investigates whether the planning algorithm better achieves economic goals when high spatial resolution data is used, compared to a traditional approach that uses stand-based data. The results indicate that higher economic values are created when the optimal forest management is decided using high spatial resolution data and spatial planning models. The reason for this is that the forest management can be adapted after the local properties of the forest (e.g. growing stock and site productivity) to a higher extent than when applying stand-based planning. Another explanation is that the number of potential management alternatives available is larger when conducting high spatial resolution planning. Thereby, it is likely that a better combination of management alternatives can be found. This line of reasoning is valid for other goals of forestry than the economic ones. Therefore, Paper IV aims to evaluate the gains in economic and ecological values if high spatial resolution data and a spatially explicit planning model are combined to allocate retention patches. Retention forestry means that patches of forest are retained for the long-term at the time of harvest, to mitigate harvests' negative effects on ecological and social values. The results suggest that ecological values can be promoted with adapted planning approaches, while the economic values were similar to that of plans produced based on stand-based planning.

The results in this thesis suggest that utilization of high spatial resolution and adapted planning models can increase the provision of ecosystem services from forests. There are clear possibilities to conduct practical forest planning as demonstrated in the papers. Such data is already widely available and remote sensing techniques will likely provide estimations of more forest attributes in the future. A challenge for planners of large-scale forestry lies in the adaptation of well-established forest management planning routines. This comprehensive and hierarchical process involves several people and deal with long time horizons in an uncertain future.

Populärvetenskaplig sammanfattning

Den skogliga planeringsprocessen syfte är att utse var, när och hur olika skogliga åtgärder ska utföras. Åtgärderna - alternativt inga åtgärder - görs för att skogen ska bidra med en rad ekosystemtjänster, alltså sådant som vi på något sätt har nytta av (t.ex. produktion av virke, inlagring och lagerhållande av kol, bevarande av hotade arter och främjande av rekreationella värden). Planeringen görs för att på bästa sätt möta skogsägarens, andra intressenters eller samhällets mål med skogsbruket. Den traditionella planeringsansatsen bygger på att skogen hanteras som ett antal enskilda bestånd. Ett bestånd är ett geografiskt avgränsat område där skogen är homogen vad gäller egenskaper som trädens höjd, stamdiameter och blandningen av trädslag. Beståndet antas vara så likformigt så att det kan skötas på enhetligt sätt. För att bedriva ett konventionellt skogsbruk ska bestånden vara så stora så att de kan skötas – med tanke på flyttkostnader för maskiner m.m. – utan hänsyn till vad som sker i närliggande bestånd. I planeringsprocessen är bestånden den minsta enheten för modellering av ekosystemprocesser som tillväxt, inväxning och mortalitet. Beståndsansatsen har varit dominerande både i Sverige och internationellt och har så här långt varit ändamålsenlig. Data om skogen med en bättre detaljeringsgrad än på beståndsnivå har hittills varit svåra och dyra att såväl inhämta, lagra som att använda i analyser.

Framsteg inom fjärranalysen har nu förändrat förutsättningarna. Idag kan skogsdata inhämtas med en betydligt högre detaljeringsgrad än på beståndsnivå via bland annat flygburen laserskanning. Dessutom har kapaciteten i datorer ökat mångfaldigt vilket gör att data kan lagras utan större ansträngning och omfattande beräkningar kan göras på kort tid. Sammantaget ger detta nya möjligheter för skoglig planering, möjligheter som inte fanns för ett par decennier sedan. Genom att nyttja modern teknik kan beskrivningen av skogen ges en högre rumslig detaljering än det traditionella beståndet vilket ger fler valmöjligheter när det gäller att bestämma skogens framtida skötsel. I allt högre grad kan rätt åtgärd utföras på rätt plats vid rätt tidpunkt. Skogsbruket kan därför planeras med högre precision jämfört med det traditionella förfarandet baserat på data om bestånd. En nackdel är dock att de traditionella metoderna som används för att lösa skogliga planeringsproblem inte kan användas på högupplösta data om resultatet, dvs själva planen, ska vara realistisk. För att hantera t.ex. stordriftsfördelar i avverkningar, eller för att bevara habitat för arter, behöver man ta hänsyn till hur olika åtgärder eller olika skogstyper fördelas rumsligt i landskapet. I denna avhandling presenteras och utvärderas sådana planeringsmodeller, som anpassats till de högupplösta data som dagens fjärranalystekniker kan leverera. Modellerna kan också hantera rumsliga aspekter och sammantaget gör de det möjligt att bedriva skogsbruket på ett bättre sätt i jämförelse med tidigare planeringsansatser.

Avhandlingen utgörs av fallstudier för skogar i södra (Studie I) och mellersta (Studie II-IV) Sverige, där data från flygburen laserskanning använts för att skatta skogens tillstånd idag. Beslutsstödsystemet Heureka har använts för att skatta skogens utveckling samt utfallet av ekosystemtjänster över tid givet olika typer av skötsel av skogen. Även olika optimeringsmetoder har använts för att bestämma optimal skötsel givet olika mål.

Vikten av att inkludera rumsliga aspekter i planeringsmodeller visas i Studie I där en ny optimeringsmodell för att aggregera åtgärder i tid och rum presenteras. Planen som är resultatet av den nya optimeringsmodellen jämförs med en plan framställd med en traditionell optimeringsmodell. Om fasta kostnader förknippade med t.ex. maskinflytt inkluderas så visar studien att det finns ekonomiska vinster med att klustra avverkningar (samla dem rumsligt) när planeringen utförs med högupplöst data. Studie II presenterar en alternativ optimeringsmodell för att lösa problem som liknar det Studie I fokuserar på. Medan tidigare studier har representerat den rumsliga problematiken med stordriftsfördelar indirekt, så presenterar Studie II en ansats för att direkt hantera ekonomiska faktorer och styra klustring av avverkningar i tid och rum. Ansatsen är en vidareutveckling av en befintlig ansats. Det tillägg som gjordes i planeringsalgoritmen förbättrade planerna med avseende på ekonomi, vilket visades i en fallstudie. Studie III är en utvärdering av planeringsmodellen från Studie II. I studien undersöks om modellen kan hitta skogsskötsel som bättre uppfyller ekonomiska målsättningar, jämfört med en traditionell optimeringsmodell baserad på beståndsdata. Utvärderingen indikerar att högre ekonomiska värden skapas när optimal skogsskötsel bestäms med hjälp av högupplösta data och rumsliga planeringsmodeller. Orsaken är att planeringsmodellen i högre grad kan anpassa skogsskötseln efter lokala förhållanden, såsom markens bördighet, virkesförråd, etc. En annan orsak är att antalet möjliga handlingsalternativ ökar för optimeringsmodellen att välja mellan. En bättre kombination av handlingsalternativ kan därmed hittas, jämfört med när traditionella data och planeringsansatser används. Resonemanget är allmängiltigt och gäller inte enbart för ekonomiska värden. Studie IV syftar därför till att presentera och utreda nyttan i ekonomiska och ekologiska termer av en modell för planering av generell hänsyn baserat på högupplösta data. Generell hänsyn innebär att man av naturvårdsmässiga skäl undantar enskilda träd eller mindre skogsområden från skogsbruk. Resultaten visar att de ekologiska värdena kan höjas med anpassad planering, medan de ekonomiska värdena blev ungefär desamma jämfört med en traditionell planeringsansats.

Sammantaget visar studierna i avhandlingen att högupplösta data från fjärranalys tillsammans med rumsliga planeringsmodeller kan göra det möjligt att öka mängden av ett flertal ekosystemtjänster från skogen. Det finns också bra förutsättningar för att använda de nya typerna av data och planeringsmodeller i praktiskt skogsbruk. Redan idag används fjärranalysdata i stor utsträckning i skogsbruket och möjligheterna ökar i framtiden. Vad som utgör en utmaning för det storskaliga skogsbruket är att bestämma var i den etablerade och hierarkiska planeringskedjan dessa typer av data och analyser bäst hör hemma. Det rör sig om en lång beslutskedja från att bestämma mål till att genomföra skogliga åtgärder, det engagerar många människor och behandlar långa tidshorisonter i en osäker framtid.

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A warm thank you to my family. My mom Britt-Marie and dad Erik always provided a safe and loving family environment for me and my sisters during our upbringing. The support you gave in my childhood made me enjoy school, which has been incredibly useful since I have spent more or less my entire life in education. Special thanks to my sisters Maja and Sara. Your motherhoods and kids inspire me to be a more responsible and mature person. Finally, thank you to my girlfriend Anna, for putting up with me not only during the period of heavy work that is now behind me but in everything we go through together.

P.S. I declare disappointment in my dog, Ava. Your contributions in this work were subpar.

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ARTICLE

Dynamic treatment units in forest planning using cell proximity

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Abstract: In forest management planning, the dynamic treatment unit (DTU) approach has become an increasingly relevant alternative to the traditional planning approach using fixed stands, due to improved remote sensing techniques and optimization procedures, with the potential for the higher goal fulfillment of forest activities. For the DTU approach, the traditional concept of fixed stands is disregarded, and forest data are kept in units with a high spatial resolution. Forest operations are planned by clustering cells to form treatment units for harvest operations. This paper presents a new model with an exact optimization technique for forming DTUs in forest planning. In comparison with most previous models, this model aims for increased flexibility by modelling the spatial dimension according to cell proximity rather than immediate adjacency. The model is evaluated using a case study with harvest flow constraints for a forest estate in southern Sweden, represented by 3587 cells. The parameter settings differed between cases, resulting in varying degrees of clustered DTUs, which caused relative net present value losses of up to 4.3%. The case without clustering had the lowest net present value when considering entry costs. The solution times varied between 2.2 s and 42 min 6 s and grew rapidly with increasing problem size.

Key words: dynamic treatment units, mixed integer programming, optimization, remote sensing, spatial forest planning.

Résumé : En planification de la gestion forestière, l'approche par unité de traitement dynamique (UTD) est devenue une alternative de plus en plus pertinente à l'approche de gestion traditionnelle fondée sur des peuplements fixes. Cela est rendu possible grâce à l'amélioration des techniques de télédétection et des procédures d'optimisation et offre la possibilité d'une meilleure réalisation des objectifs des activités forestières. Avec l'approche par UTD, on ignore le concept traditionnel de peuplements fixes et les données forestières sont conservées dans des unités à grande résolution spatiale. Les opérations forestières sont planifiées en regroupant les cellules pour former des unités de traitement pour les opérations de récolte. Cet article présente un nouveau modèle avec une technique d'optimisation exacte pour former les UTD en planification forestière. Comparativement à la plupart des modèles précédents, ce modèle vise à augmenter la flexibilité en modélisant la dimension spatiale en fonction de la proximité des cellules plutôt que de leur contiguïté. Le modèle est évalué à l'aide d'une étude de cas comportant des contraintes de flux de récolte sur un domaine forestier situé dans le sud de la Suède, représenté par 3587 cellules. L'ajustement des paramètres différait selon le cas, ce qui se traduit par différents degrés de regroupement d'UTD, causant des pertes de valeur actualisée nette relative allant jusqu'à 4,3 %. Le cas qui ne comporte aucun regroupement avait la plus faible valeur actualisée nette lorsqu'on considère les coûts d'entrée. Le temps requis pour trouver la solution variait de 2,2 s à 42 min 6 s et augmentait rapidement avec l'augmentation de la taille du problème. [Traduit par la Rédaction]

Mots-clés : unités de traitement dynamiques, programmation partiellement en nombres entiers, optimisation, télédétection, gestion forestière spatiale.

Introduction

In forest management planning, the concept of stands has been of central importance for a long time (e.g., af Ström 1829). In this context, a stand is a geographically confined area of forest suited for common forest management due to the stand being uniform with respect to site conditions, tree layer state, economic factors, age, or timber extraction properties. In a planning process based on the stand approach, the stands act as description units (DUs), which we define as the smallest unit for storing forest data, modelling ecosystem processes, and simulating treatments. Treatment units (TUs) on their part are defined as geographically confined areas scheduled for forest operations (Holmgren and Thuresson 1997). A TU can be composed of one or more DUs. Typically, stands act as both DUs and TUs in planning processes and forest operations (Bettinger et al. 2009). While stand borders may be changed over time in practical forestry, they are often permanent during the entire planning horizon in the analysis (Nelson and Brodie 1990; Ståhl et al. 1994; Davis et al. 2001). For decades, the delineation of stands has been conducted by aerial photo interpretation in combination with field surveys. Applications of forest planning typically use the stand approach and offer a powerful model for

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long-term forest planning, which is able to solve large problems. However, there are drawbacks to the stand approach. Despite the intent to delineate stands into homogeneous units, variations in tree layer and site properties will occur within stands over time and space (Gunnarsson et al. 1998; Ståhl 1992). Such variation could lead to poor management decisions in planning processes when using stand mean values, compared with an approach that uses data with a higher spatial resolution. Fixed and permanent delineations and stand mean values do not maintain spatial information within the stand, limiting the planning flexibility and utilization of the forest resources (Holmgren and Thuresson 1997).

Until recently, high-resolution data has been difficult and expensive to obtain and store. However, advances in remote-sensing techniques have facilitated new inventory methods. Light detection and ranging (LiDAR) is one such technique. Statistical models can be applied to produce high-resolution data over very large areas (Nilsson et al. 2017; Wulder et al. 2012). Assuming a given total analysis area, using high-resolution data (such as 10 m × 10 m raster cells) instead of stands in forest planning increases the number of description units. This in turn increases the number of decision variables and demands for spatial consideration, since small and isolated harvest units are not realistic. The need for spatial consideration makes the problem hard to solve via linear optimization approaches that are traditionally used in long-term forest planning, e.g., linear programming approaches (Johnson and Scheurman 1977). This facilitates new planning approaches that do not use traditional stands as the basic planning units. An example of this is the dynamic treatment unit (DTU) approach (Holmgren and Thuresson 1997). Here, the concept of stands as 10–20 ha areas fixed over the planning horizon does not exist. Instead, cells corresponding to a very small area (<0.5 ha) act as DUs. The DUs can be systematically patterned (grid, hexagons, etc.) or segmented into microstands. In the planning process, the TUs exist only momentarily and are formed dynamically (hence DTUs) by clustering treatments so that nearby DUs are treated similarly and simultaneously, and most importantly, as a result of the stakeholder's goals. Forest planning based on DTUs has been subject to research for decades (e.g., Holmgren and Thuresson 1997; Heinonen and Pukkala 2007; Pascual et al. 2018). Authors of past studies have argued that the DTU approach facilitates a higher goal achievement, since it is not limited by the rigidity of permanent stands and since dynamically formed TUs will better adapt to the forest's variation in time and space (Holmgren and Thuresson 1997; Heinonen et al. 2007). The traditional stands are typically delineated in such a way that they may be treated regardless of the treatments of neighboring stands. Large stands are economically viable, since the income from harvesting one stand may carry fixed costs associated with said harvesting. This is contrary to the DUs in the DTU approach. In the DTU approach, the utility of a treatment activity, such as final felling or thinning for a small patch of forest (<0.5 ha), is highly dependent upon what treatments are to be conducted in nearby areas. The need to cluster treatments in time and space is therefore apparent in the DTU approach. One solution to the clustering problem is to include a metric for the spatial dimension in the planning problem formulation and subsequent optimization model. Previous DTU planning studies have handled this with various spatial variables. One of the spatial variables used to drive clustering is the conditional shared border (Heinonen and Pukkala 2007; Packalén et al. 2011; Pascual et al. 2018). Conditional shared borders may be defined as the length of a DU's border that is shared with a neighboring DU, often with the condition that neighboring pairs of DUs share a useful property, such as simultaneous treatment or stand age. Another approach is to use indicator variables, which take on a certain value if neighboring DUs share a useful property (e.g., Mathey et al. 2007; Öhman and Lämås 2003). Clustering is driven by letting the spatial variable contribute to the goal function or to include it in a constraint. A drawback for both the shared borders and indicator variables is that the spatial metrics are often defined such that two DUs (cells, pixels, hexagons, and stands) have to be immediately neighboring for the metric to take effect. When forming DTUs, it may be feasible to select DUs that are close but not directly neighboring for simultaneous harvest activity. Heinonen et al. (2018) used a decentralized optimization technique to conduct DTU planning and improved the goal function value by clustering nearby (up to 300 m) DUs rather than demanding immediate adjacency. An exact solution method for spatial planning problems in a forestry and nature conservation setting was presented by Öhman et al. (2011). The aim of the model was not to form DTUs but to consider suitable habitats, including a landscape-scale component, for hazel grouse (*Tetrastes bonasia)* in a harvest scheduling model. However, conceptually this model could also be applied for DTU planning purposes. The model consisted of two parts: suitability assessments of stand-wise conditions and of spatial conditions. In the model, the spatial conditions demanded that a certain percentage of the area within a certain radius from the centroid of a focal stand should fulfill the specified stand conditions. Hence, there were no demands that units had to be immediately neighboring as long as they were within the specified radius.

A drawback with the DTU approach is that the spatial consideration increases the size of the planning problem. If the spatial location of DUs is considered, traditional linear programming with continuous decision variables is not applicable. Instead, various heuristics have been used more frequently to solve DTU planning problems, e.g., simulated annealing (Lind 2000; Öhman and Eriksson 2002; de Miguel Magaña et al. 2013), threshold accepting (Heinonen et al. 2007), cost reduction (Holmgren and Thuresson 1997), reduced cost (Packalén et al. 2011; Pukkala et al. 2009; Heinonen et al. 2018), and cellular automata (Mathey et al. 2007; Heinonen and Pukkala 2007; Pukkala et al. 2009; Pascual et al. 2018). The advantage of heuristic methods is that they can tackle nonlinear relationships and complex problems while solving the problem within reasonable time. However, heuristics may not guarantee an optimal solution. To guarantee optimality, an exact solution method such as integer programming (IP), e.g., with a branch and bound algorithm (Williams 1985; McDill and Braze 2001), must be used. Traditionally, one limitation when using exact solution methods has been the time required for solving complex problems and, connected to this, limitation of problem size. However, past research have improved the performance of such models (Constantino et al. 2008; McDill and Braze 2001; Tóth et al. 2013; Könnyű et al. 2014), which alongside developments in optimization software systems and computer hardware have improved the possibilities for solving large-scale problems within a reasonable time. Unfortunately, even if IP or mixed integer programming (MIP) with a branch and bound algorithm has been used in other types of spatial problems, e.g., in the unit restriction model (URM) and area restriction model (ARM) for solving adjacency problems where the contiguous final felled area is limited (see e.g., Tóth et al. 2013), examples with using IP for DTU problems are rare.

Objective

The objective of the present study is to present a new model for forming DTUs in forest planning, from which the resulting optimization problem can be solved with an exact technique. The model aims to provide increased flexibility when forming the dynamic treatment units by regarding not only immediate neighbors but also nearby DUs (neighbors by proximity). Forest plans elaborated by the model are evaluated by mapping and charging each DTU with a fixed entry cost. For this, a case study of 3587 DUs, representing a 56 ha forest estate in southern Sweden, is used.

Materials and methods

The model for forming DTUs solves a long-term forest planning problem consisting of selecting management actions (e.g., cleaning, thinning, or final felling) for each DU in the study area. The net present value (NPV) for future management activities is maximized, while the harvested volume does not decrease from any one period to the next. The formulation of the optimization model is based on the concept of a treatment program, which is the sequence of treatments from the first planning period to the end of the planning horizon. The planning horizon is composed of ten 5-year periods. The treatments include regeneration, cleaning, thinning, and final felling. Thus, the model is an example of a standard Model I formulation (Johnson and Scheurman 1977), with the addition of the spatial aspects connected to the layout of the harvested DUs. The NPV is calculated for every DU and potential treatment program as the sum of the discounted net income (revenues minus costs) for an infinite time horizon. Revenues and costs for treatments in one DU are not affected by actions taken in surrounding DUs. Other potential economic gains for clustering DUs, e.g., reduced costs for the transport of machinery, are not considered. Therefore, maximizing the NPV without spatial considerations will lead to the selection of DUs for unviable harvesting operations. Consequently, the model includes a demand that a certain proportion of the DUs selected for thinning or final felling in a certain number of planning periods must be defined as clustered. A DU is clustered if the DU itself is selected for thinning or final felling and if a certain number of DUs within the neighboring area are selected for thinning or final felling in the same period. The neighboring area is defined as the number of DUs within a specified radius from the centroid of the DU (Fig. 1). A DU is included in the neighboring area if any part of the DU is within the circle. This formulation for creating DTUs is similar to the optimization model suggested by Öhman et al. (2011) for including hazel grouse habitats in a forest planning problem, in which traditional stands made up DUs and TUs.

The mathematical formulation of the problem is as follows:

$$\text{(1)} \qquad \max\ Z = \sum_{i \in I} \sum_{j \in J_i} N_{ij} x_{ij}$$

Subject to

$$\text{(2)} \qquad h_{ip} \le \sum_{j \in J_i} M_{ijp} x_{ij} \qquad \forall i \in I \quad \forall p \in C$$

$$\text{(3)} \qquad Th_{ip} \le \sum_{l \in L_i} \sum_{j \in J_l} M_{ljp} x_{lj} \qquad \forall i \in I \quad \forall p \in C$$

$$\text{(4)} \qquad \sum_{i \in I} h_{ip} \ge a \sum_{i \in I} \sum_{j \in J_i} M_{ijp} x_{ij} \qquad \forall p \in C$$

$$\text{(5)} \qquad \sum_{i \in I} \sum_{j \in J_i} V_{ijp+1} x_{ij} \ge \sum_{i \in I} \sum_{j \in J_i} V_{ijp} x_{ij} \qquad \forall p \in P-1$$

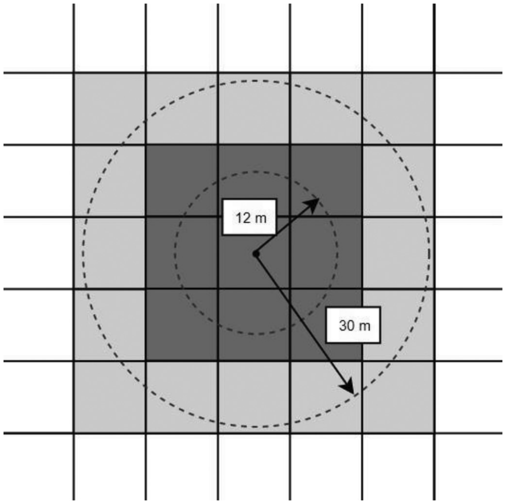
$$\text{(6)} \qquad \sum_{j \in J_i} x_{ij} = 1 \qquad \forall i \in I$$

$$\text{(7)} \qquad h_{ip} = \{0, 1\} \qquad \forall i \in I \quad \forall p \in C$$

x_{ij} = proportion of DU i assigned to treatment program j

h_{ip} = indicator variable that takes the value of 1 if DU i fulfills the definition of being included in a cluster in period p, otherwise 0

Fig. 1. Neighboring area of a focal description unit (DU) as a function of the radius from the central DU's centroid. All DUs with any part inside the specified radius from the centroid of the focal DU were included. Two cases are shown: radius of 12 (with neighboring area in dark grey) and 30 m (with neighboring area in dark grey and grey).



M_{ijp} = parameter that takes the value of 1 if DU i is assigned to a treatment program j that in period p includes thinning or final felling, otherwise 0

M_{ljp} = parameter that takes the value of 1 if DU l and treatment program j in period p consists of thinning or final felling, otherwise 0

I = set of DUs in the landscape

L_i = set of DUs that are included in the neighboring area for DU i

J_i = set of treatment programs for DU i

P = set of periods in the planning horizon

C = set of periods affected by parameter a

N_{ij} = NPV from period 1 to infinity for DU i and treatment program j

V_{ijp} = volume harvested from DU i and treatment program j in period p

T = the minimum number of simultaneously harvested DUs within the neighboring area of a given DU in order for the given DU to be defined as clustered

a = the minimum proportion of all cut (thinned or final felled) DUs that must be defined as clustered

Equation 1 expresses the objective function, i.e., maximizing the NPV for the future forest management of all DUs in the landscape. Equations 2, 3, 4, and 7 are connected to the formation of DTUs. To identify whether a DU is part of a DTU, an indicator variable (h_{ip}) is used. DU i is defined as clustered in period p when h_{ip} takes the value 1. Equation 2 specifies that the variable h_{ip} can only take the value of 1 if DU i is managed with treatment programs that entails final harvest or thinning in period p. Equation 3 ensures that h_{ip} can only take the value of 1 if a minimum total number of DUs within the neighboring area of DU i are managed with treatment programs that consist of thinning or final felling. Both eqs. 2 and 3 must be fulfilled before DU i is defined as clustered and then part of a DTU, which would cause h_{ip} to take the value of 1. Equation 4 ensures that a certain proportion of the DUs selected for thinning or final felling in period p counts as clustered. Equation 7 specifies that the variable h_{ip} can only take the values of 0 or 1. Equation 5 ensures that the harvest volume is always equal to or larger than the previous period during the planning horizon. Finally, eq. 6 ensures that all DUs are assigned a total of one treatment program. Here, it should be noted that there are no demands that x_{ij} should be an integer. This means that parts of a DU could be associated with one treatment program, while other parts could be associated with another program. However, h_{ip} is defined as an integer, which means that a DU can only be defined as clustered if the entire DU is thinned or final felled and there are a certain number of neighboring DUs that are managed with treatment programs that consist of thinning or final felling.

Case study area, forest data, and simulation of treatment programs

The use of the model is illustrated by solving a management problem for a test area consisting of 3587 square DUs (i.e., set I), each 12.5 m × 12.5 m (all productive forest with a mean annual increment of ≥1 $m^3 \cdot ha^{-1} \cdot year^{-1}$) that together represents a 56 ha property in southern Sweden. The growing stock consists of Norway spruce (*Picea abies*, 84.1%), Scots pine (*Pinus sylvestris*, 5.6%), and a variety of broadleaf trees (alder (*Alnus incana*), willow (*Salix caprea*), and rowan (*Sorbus aucuparia*), 10.3%). The forest variables and site characteristics originated from three different sources, namely airborne laser scanning data and two different available forest plans (forest maps and accompanying stand data). Data from these sources were selected and merged into a single dataset, which was used for the subsequent analysis. The volume, basal area, basal area weighted mean stem diameter, and Lorey's mean tree height were collected from nationwide estimations made by the Swedish University of Agricultural Science at the request of the Swedish Forest Agency (Nilsson et al. 2017), which were based on LiDAR data acquired by the Swedish Land Survey. The tree species distribution was collected from one of the available forest plans. The site index was derived as the mean value from the two forest plans. The age was derived using the estimated tree heights, site index, and height development functions (Johansson et al. 2013). The site index and tree heights were assumed to be correct and the best matching age between 0 and 200 years was selected. Other variables necessary for the simulation of treatment programs were collected from the forest plans.

The PlanWise software within the Heureka system (Wikström et al. 2011) was used for the simulation of the initial state and projections of the future forest state for each DU and treatment program. Heureka is a decision support system for forestry, which was developed at the Swedish University of Agricultural Sciences. The initial forest conditions, ecosystem processes, and simulated forest treatments are used to predict the future forest state as well as numerous outcome variables, such as harvested volume, NPV, and amount of dead wood. In the present study, Heureka PlanWise was used to simulate a set of possible treatment programs for each of the 3587 DUs. The forest management system was even-aged forestry. The possible treatments were soil preparation, planting, cleaning, thinning, and final felling. The lowest accepted final cutting age was set according to the Forestry Act of Sweden with respect to the site index for a DU. The maximal final cutting age was set to 30 years above the lowest accepted final cutting age. It was also possible to leave a DU untreated for the entire planning horizon. In total, 42 957 schedules were generated (on average 11.98 per DU). The planning horizon was 50 years. The real interest rate was set to 3%.

Case settings

The model solved five different cases, see Table 1. All cases included a restriction on a nondeclining harvest volume (eq. 5).

Table 1. Summary of the economic results.

	Case 0	Case 1	Case 2	Case 3	Case 4
Radius (m)	NA	12	12	30	30
T value*	NA	3	5	5	10
No entry cost, no post-optimization mapping of DTU					
NPV·ha^{-1} (SEK)	80 204	80 146	80 132	80 196	80 070
NPV decrease	0.00%	0.07%	0.09%	0.01%	0.17%
Including entry cost, DTU breakpoint 50 m					
NPV·ha^{-1} (SEK)	75 256	74 239	76 656	74 599	77 581
NPV decrease	4.28%	4.31%	1.19%	3.84%	0.00%
No. of DTUs (periods 1–3)	40	40	24	38	17
Including entry cost, DTU breakpoint 100 m					
NPV·ha^{-1} (SEK)	78 005	77 972	78 093	78 285	78 447
NPV decrease	0.56%	0.61%	0.45%	0.21%	0.00%
No. of DTUs (periods 1–3)	15	15	14	13	11

Note: Data are the results from the optimization (excluding entry costs) and subsequent mapping of dynamic treatment units (DTUs) (including entry costs). Net present value (NPV) decrease is the relative decrease in NPV for each case compared with the case with the highest NPV for a given breakpoint distance. Entry cost is 10 000 SEK (Swedish krona) for all cuttings.

*T value is the minimum number of simultaneously harvested description units (DUs) within the neighboring area of a given DU for the given DU to be defined as clustered.

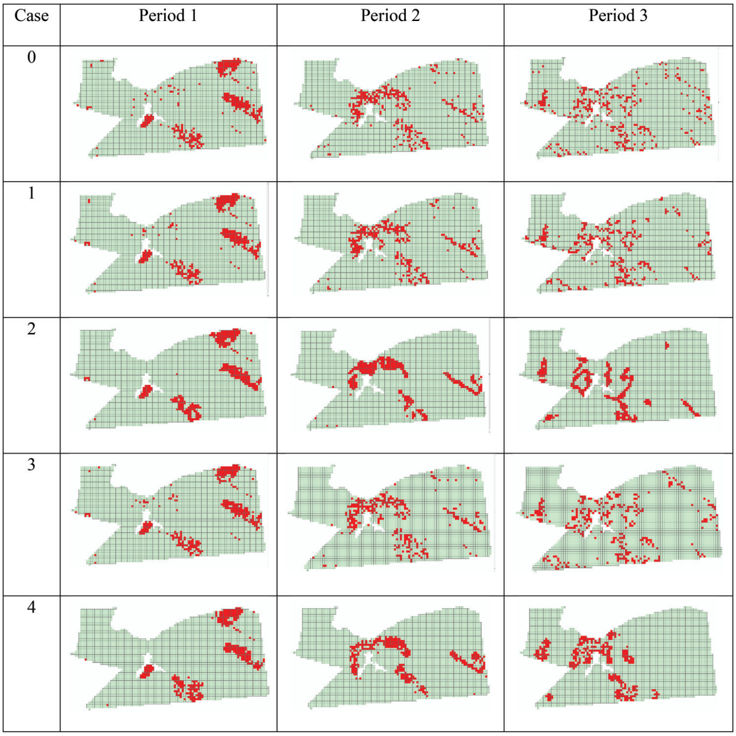
Case 0 acts as a reference with no spatial constraints (eqs. 1 and 5–7 only). Cases 1–4 evaluated the planning problem for different sets of spatial constraints (eq. 1–7). For deciding the neighborhood of a focal DU, all DUs with any part inside a specified radius from the centroid of the focal DU were included (Fig. 1). For cases 1 and 2, the radius was set at 12 m, which resulted in up to nine DUs in the neighboring area for a DU (Fig. 1). Here, the model effectively demands immediate adjacency for a DU to be counted as neighboring to a focal DU. In cases 3 and 4, the radius was increased to 30 m, which increased the number of neighboring DUs to 25 (Fig. 1). These cases include increased flexibility, as DUs are considered to be part of the same DTU as long as they are within the circle, even if they are not immediately adjacent. T defines the number of DUs in the neighboring area that must be harvested simultaneously with the central DU for the central DU to be classified as clustered. Thus, a higher T value demands a higher number of neighboring DUs harvested in the same period as the central DU for the central DU to be considered as clustered. T was set to 3 in case 1, 5 in cases 2 and 3, and 10 in case 4. The motive for using different T values was to demonstrate the increased flexibility when creating spatial layouts with different degrees of clustering of the harvest activities. In all cases, a (the minimum proportion of all cut (thinned or final felled) DUs that must be defined as clustered) was set to 0.9. We aim to provide a model for long-term forest planning where sustainability in harvest yield is maintained. Therefore, P was set to 10 in all cases, i.e., the planning horizon is 50 years in all cases. To reduce the problem size, C was set to 3, i.e., the spatial layout was considered in periods 1–3.

All cases were solved using an exact solution technique involving a traditional branch and bound algorithm (McDill and Braze 2001) with a convergence bound of 0.1%. The optimization model was formulated with the AIMMS software and solved using Cplex version 12.7. Processing was made using a PC with 64-bit Windows 10, a 3.4 GHz Pentium 4 processor, and 16.0 GB of RAM.

Post-optimization mapping of DTUs

The incentive to cluster treatments in time and space in practical forestry comes from reducing fixed forest operation costs. However, the model presented does not quantify the contribution of

Fig. 2. Visualization of harvest activities in the 56 ha case study area (red) for the three periods when the spatial conditions were not active (case 0) and active (cases 1–4). [Colour online.]



clustering to the NPV. In fact, a higher degree of clustering could never increase the NPV defined in the model, since higher clustering is achieved by imposing constraints, which decreases the solution space of the problem. Therefore, a post-optimization mapping of DTUs was conducted with the aim of evaluating the model and the solutions from the optimization for each case. This mapping was conducted as follows. It was assumed that DUs harvested in the same period were part of the same DTU, as long as they were within a certain distance. The rationale for this is that separate areas scheduled for a forest operation but divided by narrow areas (streams, roads, or narrow mires) may be part of the same TU in practical forestry. Two distances, 50 and 100 m, were used as breaking points for when two DUs may no longer belong to the same DTU. The distance refers to a straight line between the closest points of two DUs. For cuttings, a fixed entry cost of 10 000 SEK (Swedish krona) was applied to each DTU, distributed evenly over the DUs, and included in the NPV calculation for each DU. The mapping of DTUs was carried out in periods 1–3 and conducted the same way for cases 0–4.

Results

Without entry costs, cases 1–4 showed a decrease in the NPV compared with the reference case 0 (Table 1). For cases 1–4, the relative loss was <0.2% compared with case 0. Within a given radius, NPVs decreased with increasing T values, that is, case 4 had a lower NPV than case 3 and case 2 had a lower NPV than case 1.

When applying entry costs, case 4 had the highest NPV, which was true for both breakpoint distances. Compared with case 4, the other cases had NPV decreases of up to 4.31% and 0.61% with 50 and 100 m breakpoint distances, respectively. Cases had up to 40 DTUs in periods 1–3 (cases 0 and 1) and the cases with more DTUs had a lower NPV.

Comparing cases with a given radius showed that a higher T value resulted in higher NPVs for both 12 and 30 m radiuses, which is contrary to the outcome when no entry costs were applied. These cases also had a lower total number of DTUs in periods 1–3.

The spatial layout of the harvest activities is visualized in Fig. 2. The figure includes the three periods in which the spatial conditions were active and the DTUs were mapped. In cases with low T values (cases 1 and 3), treatments appear to be scattered. Here, the relaxed spatial restriction allows the model to select scattered DUs from across the study area. Case 2 had the most restricted spatial constraint and visually appears to be the case with the most clustered harvest pattern.

The solution time varied between cases (Table 2). The reference case was the fastest (2.2 s, i.e., without any spatial constraints active), while case 4 was the slowest (2526 s). The variation in the mean harvested volume among the different cases was negligible.

Discussion

In this paper, we present a new modelling approach for forming DTUs in forest planning. The DTU planning approach aims

Table 2. Results concerning the model runtime, harvest, and number of divided description units (DUs).

Case	Radius	*T* value*	Solution time (s)	Average harvest volume ($m^3 \cdot ha^{-1} \cdot year^{-1}$)	No. of divided DUs†
0	0	0	2.2	6.320	3
1	12	3	4.9	6.318	6
2	12	5	211.5	6.314	12
3	30	5	37.9	6.320	10
4	30	10	2526.0	6.308	11

*T value is the minimum number of simultaneously harvested DUs within the neighboring area of a given DU for the given DU to be defined as clustered.

†The "No. of divided DUs" is the number of DUs managed by more than one treatment program.

for more effective utilization of forest resources by increasing and preserving the spatial resolution of decision-making compared with traditional stand approach planning. Past studies have presented several methods aiming to achieve this goal. The current study adds to the collection of methods, with the contribution of increased spatial flexibility as well as the use of an exact solution method. In addition, many forest decision systems are based on exact solution methods, which highlights the need for models such as the one presented here.

The presented model could be used for forming DTUs in forest planning with an exact solution method without demanding that the DUs are immediately neighboring, as long as they are within a given distance from each other. The model enables the decision maker to test a range of plans with different spatial layouts, which may be of interest if operations are not subject to significant fixed costs. The results from the current study also provide some insight into how an exact solution method with proxy variables performs when solving a forest planning problem using a DTU approach. Even while the model does guarantee the optimal solution, the formulated problem is an approximation, which is highlighted when including entry cost a posteriori by performing the post-optimization mapping of DTUs. To find the best parameter settings for a certain forest holding, decision maker, and cell size, it would be necessary to produce several plans with different settings and evaluate them all with the post-optimization mapping. It is of interest to model economic incentives directly to drive clustering of DTUs. Using an MIP methodology, this would be possible by, for example, identifying subareas within the analysis area where all cells scheduled for cutting in a subarea would comprise a DTU. A fixed entry cost would then be applied for each subarea that includes one or more cells scheduled for cutting.

The optimization showed that the reference scenario (no spatial considerations active) had the highest NPV when entry costs were excluded. The aim of applying an entry cost in the postoptimization mapping of the DTUs was to quantify the economic gains from clustering DTUs, which is relevant in practical forestry. The postoptimization mapping showed that the use of spatial clustering increased the NPV when fixed costs were included in the analysis (Table 1). Case 4 had the highest NPV here. The reference case had the lowest and second lowest NPVs, depending upon the breakpoint distance. There was also an association between a higher number of DTUs and lower total NPV. All of this highlights the economic incentive to cluster treatments in time and space when using high-resolution forest data. Forest operations must be conducted on coherent areas with sufficient size for them to be economically feasible. Assumptions were made with regards to how a DTU may and may not be formed. The breakpoint distances of 50 and 100 m refer to a straight line between two DUs and disregard all other relevant information, e.g., obstacles in the terrain or location of roads. Assumptions on how DTUs can be formed can be enhanced by using geographical information in the analysis. Longer distances may also be of relevance. Heinonen et al. (2018) used the reduced cost method (presented by Pukkala et al. 2009) and allowed microstands scheduled for cutting in the same time period to be separated by up to 300 m and still be included in the same DTU.

All cases had an a of 0.9, which means that 90% of all DUs cut (thinned or final felled) in each period must be clustered (and consequently, no more than 10% may be cut but not clustered). However, cases had different radiuses and T values, which resulted in different degrees of clustering. Case 1 had a radius of 12 m, resulting in a nine DU neighborhood, and T value of 3, meaning that three of the nine (33.3%) DUs must be cut simultaneously for the central DU to be clustered. The corresponding percentages for the other cases (apart from case 0, with no spatial considerations active) were 55.6% for case 2 (5 of 9), 20% for case 3 (5 of 25), and 40% for case 4 (10 of 25). This is consistent with the visual interpretations, as the harvest pattern of case 2 appears the most clustered. A high value of a ensures that a high portion of DUs scheduled for treatments have other DUs nearby also scheduled for the same treatment simultaneously, which is desirable from an economic standpoint. Nevertheless, small areas of forest that differ from their surroundings exist, which makes them suited for different management. Therefore, we refrained from setting a to 1. An analysis area with fragmented patches of forest may be suited for lower values of a. C was set to 3 for all cases, meaning that clustering took place in periods 1–3. As DTU planning engages in tasks traditionally dealt with in tactical or operational planning, reducing the problem size is relevant. Heinonen et al. (2018) reduced the temporal solution after the first quarter of the planning horizon. Clustering of DTUs is not irrelevant in the later periods, but the level of detail is more important in the early years of a plan. Setting C to 3 was a way to reduce the size of the problem. Further investigation could have determined the parameter settings that resulted in the highest NPV and the point at which the NPV started to decrease, but no such analysis conducted.

The results raise a few issues that needs to be discussed. The solution time varied between 2.2 and 2526 s, growing with increased degree of clustering. Model runtime is a concern when solving large problems using MIP (Bettinger et al. 1999), and DTU planning is relevant for larger data sets than the one used here. Note, however, that while the analysis area was small, 56 corresponds to an average private owned forest estate in Sweden (Haugen et al. 2016) and the number of DUs — 3587 — is an adequate number. Each DU had an average of 11.98 treatment programs generated resulting in 42 957 treatment programs for the whole case study, which is what affects the problem size (along with constraints). Heinonen et al. (2018) solved a DTU planning problem using a heuristic method. The average runtime of their reduced cost algorithm, about 2000 s on average, was comparable to the runtime for our case 4, but they solved a larger problem (254 823 treatment programs and a higher temporal solution). This highlights the ability of heuristics to produce solutions within reasonable time for large problems, while our model may guarantee a solution within 0.1% of the global optima.

Larger numbers of DUs and treatment programs increase the size of the problem and the solution time. However, a relatively large number of treatment programs is necessary, since variations regarding the timing of the treatments is important when planning a DTU approach, to avoid small, isolated, and expensive harvest operations. Several options are possible to apply the current model on a larger analysis area. It is possible to increase the size of the DUs, for example, by aggregating raster elements into microstands before the simulation of treatment programs, as done by others (Pascual et al. 2018; Heinonen et al. 2018). Moreover, McDill et al. (2002) showed that increasing the tolerance gap in the optimization decreases the solution time while still achieving high objective function values. Heinonen et al. (2018)

decreased the temporal resolution in the later part of the analysis. It is also possible to use geographical information to divide the analysis area into subareas and conduct the DTU planning on each subarea.

The next issue that needs to be discussed is the initial data. In this study, the volume, basal area, basal area weighted mean stem diameter, and Lorey's mean tree height were estimated using linear regression models and LiDAR data, in accordance with Nilsson et al. (2017). The age and site index were calculated in more unconventional ways. The site index was derived in a two-step process. First, the mean of two pre-existing forest plans was calculated for each DU. Second, the resulting raster data were used to provide each DU with the average value of a 5×5 DU grid. Then, the resulting site index was used to estimate the age. An iterative method tested ages from 0 to 200 years, and the best matching tree height development curve (Johansson et al. 2013) was assigned. The purpose of this was not to obtain the true state of the forest but to allow the data to represent the productivity gradient that naturally occurs in the forest in a fictional dataset. This decreases the homogenizing effects of the original stand data for site index and age but is an obvious source of error. It is possible that the solutions are influenced by the site index and age preparation. However, no analysis was conducted to decide whether this was the case.

Conclusion

Here, a model for forest planning using a DTU approach was presented. Past studies have similarly focused on formulating DTUs using a variety of methods. The present study contributed to this collection a model based on true optimization with increased flexibility concerning the spatial dimension, which has the potential to improve goal achievement. Future research is needed for comparing the goal achievement of models using the DTU approach with models using the traditional fixed stand approach. It may also be of interest to model economic incentives directly to drive clustering of DTUs, instead of using proxy variables.

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ORIGINAL PAPER

Improving dynamic treatment unit forest planning with cellular automata heuristics

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Abstract

We present a model for conducting dynamic treatment unit (DTU) forest planning using a heuristic cellular automata (CA) approach. The clustering of DTUs is driven by entry costs associated with treatments, thus we directly model the economic incentive to cluster. The model is based on the work presented in the literature but enhanced by adding a third phase to the CA algorithm where DTUs are mapped in high detail. The model allows separate but nearby forest areas to be included in the same DTU and shares the entry cost if they are within a defined distance. The model is applied to a typical long-term forest planning problem for a 1 182 ha landscape in northern Sweden, represented by 4 218 microsegments with an average size of 0.28 ha. The added phase increased the utility by 1.5–32.2%. The model produced consistent solutions—more than half of all microsegments were managed with the same treatment program in 95% of all solutions when multiple solutions were found.

Keywords Entry cost · Forest planning · High-resolution data · Spatial optimization

Introduction

Forest management planning aims at efficient and sustainable use of the forest resource over time, whether it be for economical, social, biological, or other purposes. In this pursuit, the concept of stands has been used in even-aged forest management planning for a very long time (see, e.g., af Ström 1822; Faustmann 1849; Nilsson et al. 2012). A stand is a delimited area where the forest is homogeneous in some regard, making the whole stand suitable for the same forest management. Stands are typically used as description units (DUs), which we define as the smallest unit for collection and storage of data, and modeling of ecosystem processes. Moreover, stands also act as treatment units as it is the unit used for modeling and planning treatments which on holding level are aligned to fullfil stakeholder goals. An important property of the traditional stand approach is that the stand borders are usually fixed and permanent during the planning horizon in planning processes (Nelson and Brodie 1990; Davis et al. 2001). Furthermore, stands are generally large enough and delineated such that they may be treated individually; spatial clustering of stand management activities is not a prerequisite for practical forestry. This makes linear programming (LP) a suitable and powerful method for solving the resulting optimization problem in forest management planning using the stand approach (see, e.g., Johnson and Scheurman 1977).

The development of remote sensing techniques for data collection has changed and enhanced the conditions for forestry and forest planning (Maltamo et al. 2014). Objective wall-to-wall data with high spatial resolution based on combinations of remote sensing and field surveys are compiled nationwide in, e.g., Finland (Kotivuori et al. 2016) and Sweden (Nilsson et al. 2017). Even if such data may be useful, transforming fine-grained data into stand-wise data will result in loss of information and consequently suboptimal use of the forest resource (Holmgren and Thuresson 1997). An alternative approach to planning forestry based on the stand-wise approach is therefore to utilize dynamic

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treatment units (DTU). DTU planning aims at more efficient use of the forest resource by maintaining high spatial resolution in both the forest data and throughout the planning process. This is attempted by using DUs much smaller than traditional stands and forming DTUs in the planning process by clustering DUs into larger areas in the optimization. Treatments in specific DTUs do not necessarily reoccur. Thus, DTU are dynamic and exist only momentarily in time.

Previous research has studied the concept and performance of DTUs and presented various models for conducting this type of forest planning (e.g., Pascual et al. 2018; Heinonen et al. 2018; Wilhelmsson et al. 2021). The economic incentive to cluster treatments lies in the entry cost for forest operations. The entry cost is defined as the fixed cost associated with a contiguous cluster scheduled for treatment at a specific time point and includes costs for preparatory fieldwork, road maintenance, moving machinery or personnel to the site, and administrative work (Borges et al. 2017). Borges et al. (2017) showed that the entry cost influences the optimal treatment unit size, which has been a concern for past studies concerned with DTU. However, instead of directly modeling the entry cost, most DTU studies have used proxy variables such as conditional common borders in combination with distance from the nearest road (Pascual et al. 2018). Their model tracked the cut-to-cut and cut-to-uncut borders, and metrics were included in the utility function to drive the clustering of treatments.

Forest planning problems with a DTU approach have seldom been solved with exact solution methods (Wilhelmsson et al. 2021), but due to the combinatorial and complex nature of DTU planning, most often solved with heuristics. Pukkala (2009) showed that heuristic methods can successfully handle large spatial problems. This was shown for DTU purposes by Heinonen et al. (2007) and was further highlighted by Pascual et al. (2018). Noteworthy heuristics applied to DTU problems are threshold accepting (Heinonen et al. 2007), reduced cost (Heinonen et al. 2018; Packalén et al. 2011; Pukkala et al. 2009), genetic algorithm (Lu and Eriksson 2000) and simulated annealing (de Miguel and Pukkala 2013; Öhman 2001). One heuristic that has been argued to be particularly well suited for solving forest planning problems in general, and forest planning problems using a DTU approach in particular, is cellular automata (CA). CA was first presented by von Neumann (1966) and introduced in forest planning contexts by Strange et al. (2002). It has been used to solve forest planning problems with a DTU approach in several studies (Heinonen and Pukkala 2007; Mathey et al. 2007; Pascual et al. 2018; Pukkala 2019). In the general form, a CA is constituted of a lattice of cells where each cell may take on a finite set of states. Rules decide how cells may change states, which is dependent on a utility function and spatial relations between the given cell and a subset of the other cells (neighbors). In a DTU forest planning context, a cell in the lattice represents a DU. A state is equivalent to a treatment program (TP), which is a sequence of treatments over the entire planning horizon and the resulting development of the forest. Thus, a CA algorithm forms DTUs by swapping TPs for segments of forest with regard to treatments planned in spatially nearby DUs, clustering treatments in space and time. Mathey et al. (2007) argued that two properties make CA particularly well suited for solving forest planning problems: (1) the way that different spatial scales can be integrated into a CA model, and (2) the way that landscape scale patterns emerge due to local spatial rules determining the change in DU state. While in-depth comparisons with other heuristics are lacking, previous studies have shown potential in CA compared to simulated annealing in computational speed, the number of iterations needed when using stop criteria, and solution quality (Mathey et al. 2007; Heinonen and Pukkala 2007).

This study aims to improve long-term forest planning with a DTU approach using CA by introducing explicit entry costs. The first and second phase of the algorithm is inspired by the literature. However, a third phase is added to the CA algorithm where the economic incentive to cluster treatments is modeled directly by calculating entry costs in high detail for potential DTUs. The approach is applied in a planning problem for a 1 192 ha landscape in northern Sweden where the forest is described with high spatial resolution data using DUs much smaller than the area of traditional stands.

Method

Overview of the cellular automata algorithm

Our approach is based on the CA model presented by Strange et al. (2002), which was improved by Mathey et al. (2007) and Heinonen and Pukkala (2007). The CA evaluated here is a set of DUs representing a forest. The states are (DU specific) TPs. The CA algorithm consists of three phases: local, global and final, each with a number of iterations. The algorithm starts by randomly selecting a TP for all DUs. All phases follow a similar procedure. In each iteration, a random number is drawn from a uniform distribution between 0 and 1 for each DU. Depending on the number, one of three things occur in accordance to probabilities set by the user. The DU is either mutated, innovated, or remain unchanged. A DU being unchanged means that the current TP remains the same. If a mutation occurs, the TP is swapped for a randomly selected one. If innovation occurs, all potential TPs for the DU are evaluated, and the model swaps to the best TP with regard to a utility function stated by the user. DUs are processed in this manner one at a time until all DUs have been processed, at which point the iteration is completed and the next iteration begins by starting over from the first DU. When the predefined number of iterations is done, the phase is completed and the next phase is initiated by starting over from the first DU, meaning that the output plan from a phase acts as starting point for the next phase. What separates the phases from each other is the utility function. This is elaborated below. All DUs are processed until the last DU of the last iteration of the last phase is processed, at which point all DU are innovated one last time. When this is done, the algorithm is complete and the solution exported. A conceptual visualization of the algorithm is shown in Fig. 1.

An essential component of the utility function used here is the net present value (NPV) of a TP, which is calculated by discounting income and costs from different management activities, both within the planning horizon and beyond for an infinite time horizon (Faustmann 1849). In addition to the productivity-based costs for treating a DU, the fixed entry cost is applied to all DTUs within the planning horizon and included in the calculation of NPV. The calculation of entry cost is one of two properties that changes over the phases of the CA algorithm (see Table 1), thus affecting the NPV. A simplified entry cost calculation is conducted in the local and global phases, whereas a higher detail mapping of the DTUs and calculation of entry cost are carried out in the final phase. The other property that changes over the phases is the inclusion of a harvest coefficient. This coefficient is excluded in the local phase but included in the global and final phases. The purpose of the harvest coefficient is to prevent the model from overharvesting, which is a concern when spatiotemporal clustering is beneficial, and the use of NPV may drive the model to harvest large volumes in early periods.

The mapping of DTUs is based on the concept of neighbors. DUs are considered neighbors if the minimum distance between their edges is below a specified distance (neighborhood distance), i.e., neighbors are not necessarily immediately adjacent. In the local phase, the fixed entry cost is calculated using a local scope (see Fig. 2). The entry cost used here is scaled down from a realistic value by multiplying it by 0.02. The local phase is followed by the global phase, which uses the output plan from the local phase as input. Here, the same local scope is used for calculating entry cost, but the utility function is changed to account for harvested volume over time by introducing the harvest coefficient (Fig. 3). coefficient is period-specific and punishes solutions with harvest volumes larger than the harvest target. The resulting plan from the global phase is used as input in the final phase. The final phase, introduced in the current study, maintains consideration to forest level goals using the harvest coefficient but the calculation of NPV changes, as the DTUs are fully mapped in each iteration (see Fig. 4). The complete mapping means that the potential number of

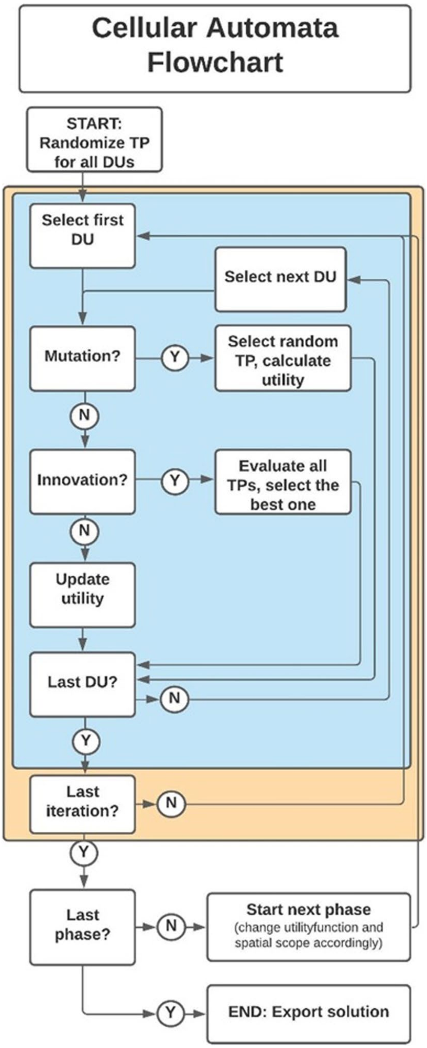

Fig. 1 Conceptual flowchart of the cellular automata approach used in the study

Table 1 How input, output, spatial scope and forest level goals change over the phases over the CA algorithm

Phase	Local	Global	Final
Input	Random start	Plan L	Plan G
Entry cost	Simplified	Simplified	High detail
Harvest coefficient	Not included	Included	Included
Output	Plan L	Plan G	Plan F

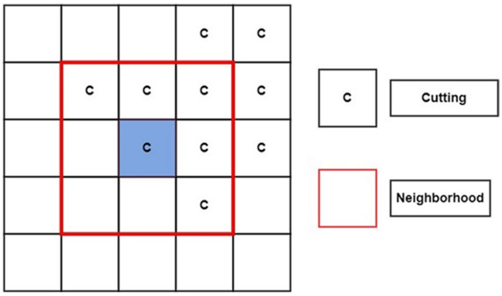

Fig. 2 Consider the lattice a representation of a forest. Treatments in period *p* is shown, where *c* represents cutting. The red square marks the neighborhood of the blue DU. In the local and global phases, $d_{i,j,p}$ represents the number of DUs in the neighborhood of DU *i* (blue) prescribed for the same treatment in period p of treatment program j as the blue DU (including the centering DU itself, here 5). The entry cost $n_{i,j,p}$ is shared equally among the DUs marked with cutting within the neighborhood (see Eq. 3)

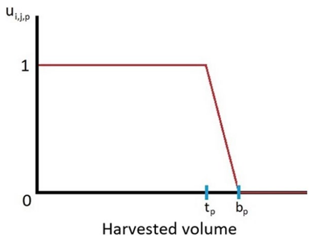

Fig. 3 Graphical representation of the relation between $u_{i,j,p}$, t_p and b_p. The utility coefficient $u_{i,j,p}$ will have a value of 1 between 0 and t_p m^3 harvested volume, at which point it linearly declines toward 0, which it reaches at b_p m^3 harvested volume. For harvests levels even higher, $u_{i,j,p}$ will have a value of 0, considering attempted contributions to the utility function from such harvests as worthless

DUs that constitute the DTU and share the entry cost is increased manyfold. The entry cost is therefore increased to a realistic value to model the true costs as accurately as possible and let that cost drive the clustering. Each phase ends after the predefined number of iterations is completed. In one final iteration, all DUs are innovated in order to remove isolated and small DTUs, which may be the result of chance via mutation. The resulting plan is exported as the solution.

Phases and the spatial rule

Here follows a model formulation for the cellular automata as it progresses over the three phases, as shown in Fig. 1.

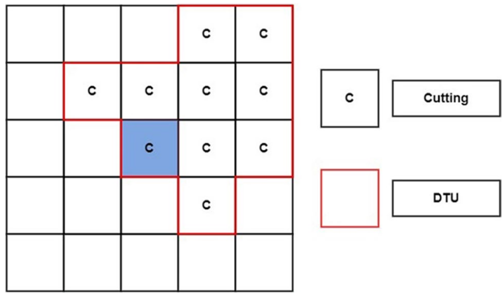

Fig. 4 Consider the lattice a representation of a forest. The lattice shows the treatments in a time period p, where "C" represents cutting. The red shape shows the DTU. In the final phase, the variable D represents the total area of DUs included in the DTU (red area) and a_i represents the area of DU I (blue). The entry cost $n_{i,j,p}$ is distributed among the DUs constituting the DTU in proportion to their area (see Eq. 5)

Local phase: forming simple DTUs

All phases aim to maximize the value of the utility function. In the local phase, it is defined as follows:

$$\text{MaxZ} = \sum_{i=1}^{I} \sum_{j=1}^{J_i} z_{i,j} * x_{i,j} \tag{1}$$

$$z_{i,j} = \sum\nolimits_{p=1}^{P} \frac{g_{i,j,p} - \left(c_{i,j,p} + n_{i,j,p}\right)}{(1+r)^{m_p}} + v_{i,j} \tag{2}$$

where $x_{i,j} = \{0,1\}$, the share of DU *i* managed with TP *j;* m_p = midperiod year of period *p;* $g_{i,j,p}$ = gross revenue in period *p* of TP *j* in DU *i;* $c_{i,j,p}$ = spatially independent cost in period *p* of TP *j* in DU *i;* $n_{i,j,p}$ = entry cost in period *p* of TP *j* in DU *i;* *r* = discount rate; $v_{i,j}$ = terminal value; the discounted value of the forest management beyond the last planning period; *I* = set of DUs; J_i = set of TPs for DU *i*.

The definition of $n_{i,j,p}$ changes over the phases. In the local and global phases, it is defined as

$$n_{i,j,p} = \left(\frac{e}{d_{i,j,p}}\right) \text{if DU } i \text{ has a treatment in period } p, \text{TP} j, \text{ otherwise } 0 \tag{3}$$

where *e* = fixed entry cost; $d_{i,j,p}$ = number of DUs in DU *i*'s neighborhood treated with the same treatment in period *p* as DU *i* in TP *j* in period *p*.

The variable $d_{i,j,p}$ is visualized in Fig. 2. This is what drives clustering in the local and global phase of the CA.

Global phase: introduction of forest level goals

Optimizing the utility function with a local scope does not always lead to solutions that satisfy forest level goals and constraints. Hence, Mathey et al. (2007) introduced the inclusion of forest level goals in a CA model. The present study deals with the flow of harvested volumes over time. In the global phase, the utility function is therefore defined as follows:

$$\mathrm{z}_{\mathrm{i,j}} = \sum\nolimits_{p=1}^{P} \frac{g_{i,j,p} - \left(c_{i,j,p} + n_{i,j,p}\right)}{(1+r)^{m_p}} * u_{i,j,p} + v_{i,j} * w_{i,j} \tag{4}$$

where $z_{i,j}$ = utility of TP j for DU i; $g_{i,j,p}$ = gross income in period p of TP j in DU i; $c_{i,j,p}$ = spatially independent cost in period p of TP j in DU i; $n_{i,j,p}$ = entry cost in period p of TP j in DU i; r = discount rate; $v_{i,j}$ = present value of net revenue from beyond the last planning period (P) to infinity of TP j for DU i; t_p = harvest target in period p; b_p = upper harvest bound in period p; $u_{i,j,p}$ = utility coefficient in period p of TP j of DU i. The parameter takes the value

$$\begin{array}{ll} 1 & \text{if } h_p \le t_p, \\ 1 - \left(h_p - t_p\right) / \left(t_p - b_p\right) & \text{if } t_p < h_p \le b_p, \text{ and} \\ 0 & \text{if } b_p < h_p, \end{array}$$

where h_p is harvested volume in period p; $w_{i,j} = \min\{u_{i,j,p}\}$ of any period p for the given DU i and TP j; m_p = midperiod year of period p.

The inclusion of the harvest coefficient, $u_{i,j,p}$, in the model means that the utility of a TP is lowered if that TP results in overharvesting within the planning period. Thus, while there are no constraints (besides the decision variable $x_{i,j}$ being binary), the inclusion of the harvest coefficient will effectively constrain harvest levels. The parameter $w_{i,j}$ is included since the harvest in each period is connected to the net revenue in each period using the harvest coefficient ($u_{i,j,p}$), when meantime, the NPV from beyond the planning horizon is not connected to any harvest level. $w_{i,j}$ prevents the model from selecting solutions leading to overharvest within the planning horizon in the search for NPV from beyond the planning horizon (terminal value v_{ij}). In such solutions, $w_{i,j}$ will assume the value of 0, which is multiplied with the NPV from beyond the planning horizon. If all TPs available in a DU have the utility of 0, the model will choose the TP without treatments, and overharvest is avoided.

The entry cost is estimated in the global phase using the same spatial scope as the local phase (see Fig. 2).

Final phase: high detail mapping of DTUs

The final phase of the algorithm will maintain the consideration of harvested volumes introduced in the global phase as defined by Eq. 4. What changes is the spatial scope of the calculation of entry cost. Instead of looking only at the window defined by the neighborhood distance around the DU, the model checks if simultaneous treatments are found in a neighboring DU and if so, looks onward into the neighbor's neighbors and so on (into infinity, in theory). Thus, complete mapping of the DTU is conducted, and the entry cost is divided among the DUs constituting the DTU. Stepping stone effects may appear as the model allows separate (non-adjacent) areas to be part of the same DTU as long as all subareas are connected to another subarea according to the definition of neighbor. This change in the definition of entry cost is stated in Eq. 5 and visualized in Fig. 4. Each DU is charged with a share of the entry cost in proportion to its share of the total area of the DTU.

$$n_{i,j,p} = \left(\frac{E}{\frac{a_i}{D}} \right) \tag{5}$$

if DU i has a treatment in period p in TP j, otherwise 0.

where E = constant representing the entry cost; a_i = area of DU i; D = area of the DTU, which DU i is part of in period p for TP j (according to principle shown in Fig. 4).

Note that, the value of D may be high, as the model maps the full area constituting the DTU.

Analysis area, segmentation of DUs, and simulation of treatment programs

The model was evaluated by developing long term plans for a forest of 1192 ha located northwest of Sundsvall, Sweden. The forest is represented by 4218 microsegments, where each microsegment represents a DU with an average size of 0.28 ha. The microsegments are derived from remote sensing data in a two-step process. First, a region growing expansion model (Grilli et al. 2017) merges adjacent and similar 12.5×12.5 m^2 raster elements into possible DUs. Similarity is measured as distance in a 5D space with basal area, Lorey's mean height, proportion of pine, proportion of spruce, and proportion of broadleaves as dimensions. Merging is repeated until the smallest difference between neighboring microsegments is higher than a user defined level. This does not limit the size of segments, however, and they may become very large. Therefore, the second step is carried out using mixed integer programming (MIP). The MIP model selects microsegments from a large set of possible ones generated with the region growing method. The goal function of the MIP model is to minimize the sum of standard deviation within segments. The constraints are (1) each raster element must be assigned to a microsegment and (2) the maximum size of microsegments must not exceed a user defined limit. The MIP solution is the final spatial layout for microsegments (DUs). The wall-to-wall ALS data used for the segmentation were provided by the Swedish Forest Agency and were described by Nilsson et al. (2017).

Initial state

The analysis area forest is comprised mainly of Norway spruce (*Picea abies*, 49% of the standing volume), but also of Scots pine (*Pinus sylvestris*, 30%) and birch (*Betula pubescens* and *Betula pendula*, 19%). The mean productivity is 4.9 m^3 ha^{-1} $year^{-1}$ in the initial state, and the mean age is 58 years. The distribution between age classes is shown in Fig. 5. The case study area was chosen from a larger area, and a reasonably even age distribution was sought after.

Generation of TPs

The generation of TPs for each DU over the 50 years planning horizon was conducted with the PlanWise application in the Heureka decision support system (Wikström et al. 2011). Associated with each TP is a projected state of the DU in each period, including, e.g., growing stock and harvested volume. The core of the Heureka system is a collection of empirical models for projecting stand dynamics, e.g., growth, mortality and yield, in 5 year time steps. Heureka PlanWise generates a set of TPs for each DU within a user-defined forest management framework. The management system was set to even-aged silviculture for all DUs, and the TPs differ with regard to the timing and manner of soil preparation, planting, pre-commercial thinning, thinnings, and final felling. A TP without any treatments was also generated for all DUs. On average, 12.7 potential TPs were generated for each of the 4218 DUs, that is, a total of 53 473 TPs.

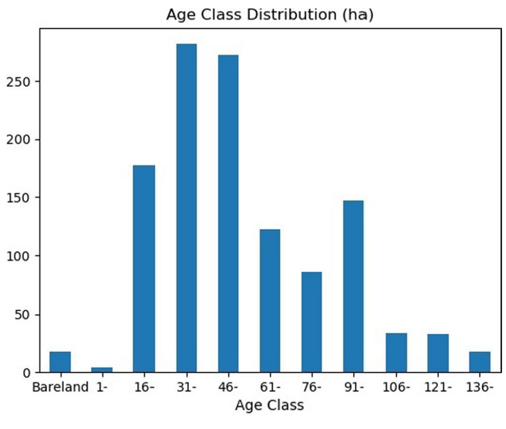

Fig. 5 Initial age class distribution of the analysis area

Model settings and hardware

The cellular automata algorithm for solving the management problem was written in the programming language Python v3.8 using the IDE IntelliJ Pycharm v2019.3.3. The model was run on a Intel Core i7 2.8 GHz computer with 32 GB RAM and 64-bit Windows 10 as operating system. The model was run using three different neighborhood distances; 1 m, 50 m, and 200 m. These are henceforth called "cases." Because of the stochastic nature of the cellular automata algorithm, where optimal solutions are not guaranteed, the solving procedure was repeated 40 times for the 1 m and 50 m neighborhood cases and 20 times for the 200 m neighborhood case. These sets of solutions are henceforth called "analyses."

All cases and analyses used the following parameter settings. Each phase included 50 iterations. The harvest target, i.e., t_p, was set to 50,000 m^3 and the harvest bound, i.e., b_p, was set to 55 000 m^3. The probability of mutation and innovation was set to 5% and 90%, respectively, leaving a 5% probability that the TP for a given DU remains unchanged in an iteration. A discount rate of 3.0% was used for calculating the NPV, i.e., r was set to 0.03.

Model stability

There is an element of chance in the solutions produced since mutation means that a TP is randomly drawn from the set of available ones for a given DU. We investigated the impact of said chance on final plans by studying how consistently the model selected TPs for each DU when the model is run repeatedly. We call the consistency in TP selection "stability" and Table 2 shows how this was investigated.

We describe model stability by reporting descriptive statistics from the column named Stability in Table 6.

Table 2 Example of how stability is measured for three DUs given six repetitions and the selected TPs

DU	Repetition						Most frequent TP	Stability (%)
	1	2	3	4	5	6		
1	TP_{12}	TP_{12}	TP_{13}	TP_{12}	TP_{13}	TP_{12}	TP_{12}	67
2	TP_{25}	TP_{23}	TP_{24}	TP_{23}	TP_{21}	TP_{24}	TP_{23}, TP_{24}	33
3	TP_{34}	TP_{31}	TP_{34}	TP_{34}	TP_{34}	TP_{34}	TP_{34}	83
							Average	61

Stand-based planning with linear programming

The CA solutions were compared with the outcome of long-term planning problems based on the traditional stand approach and solved by LP (Johnson and Scheurman 1977). The same DUs were used in the LP planning problem. Maximum NPV was used as objective function, and the LP problem was solved using the optimization tool available in Heureka PlanWise. Four different solutions were produced using different constraints on harvested volume. One solution had no constraints, and the other three were forced to follow the period-specific harvest profile of each of the three corresponding solutions found with the CA. Note that, the LP solutions do not include entry fixed costs in the manner that the CA does, therefore no clustering is conducted here.

Results

Cases

Table 3 show how utility and NPV increased with higher neighborhood distance. Harvested volume followed the same pattern. The different cases also resulted in different spatial layouts of treatments. The final plans from each case are visualized by showing the treatments and DTUs in the northeast corner of the analysis area in period 2 (Figs. 6, 7, 8). With an increase in the neighborhood distance, the DTUs became larger and fewer but were also more dispersed over the landscape. An example of this can be seen when comparing Figs. 6, 7, 8: The striped

Table 3 Summary of results for the three cases

Neighborhood distance (m)	Utility (million)	NPV (million SEK)	Average DTU size (ha)	No. of DTUs per period	Harvested volume (m^3 ha^{-1} $year^{-1}$)
1	50.3	50.9	2.04	49.6	7.4
50	51.2	53.4	5.90	19.4	8.1
200	53.9	54.4	12.7	9.8	8.3

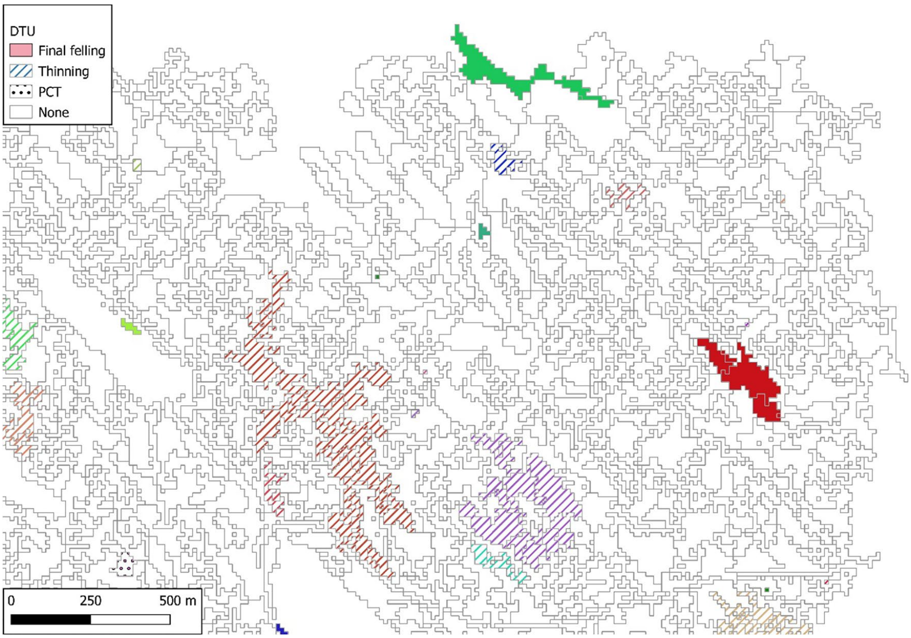

Fig. 6 Spatial layout of DTUs in the second five-year period in the northeast corner of the analysis area, using 1 m neighborhood distance. Filled DUs are scheduled for final felling, striped DUs are scheduled for thinning and dotted DUs are scheduled for pre-commercial thinning (PCT). Individual DTUs are colored the same and non-marked polygons are micro sements (DUs) or non-forest

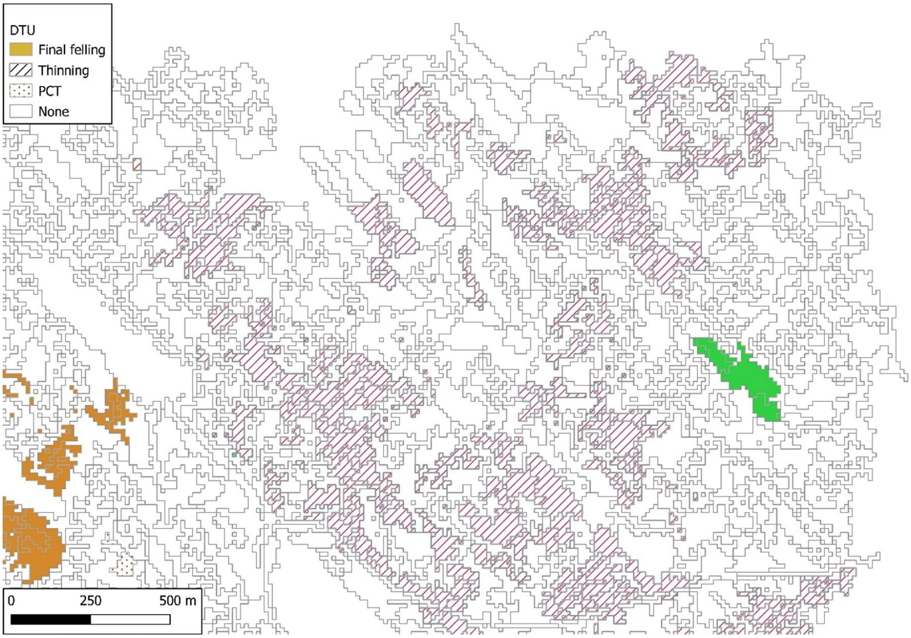

Fig. 7 Spatial layout of DTUs in the second five-year period in the northeast corner of the analysis area, using 50 m neighborhood distance. Filled DUs are scheduled for final felling, striped DUs are scheduled for thinning and dotted DUs are scheduled for pre-commercial thinning (PCT). Individual DTUs are colored the same and non-marked polygons are micro sements (DUs) or non-forest

thinnings in the middle of Fig. 6 are considered separate DTUs when using 1 m neighborhood distance (Fig. 6), whereas the cases with 50 and 200 m, respectively, mapped this area as a single, but dispersed DTU (Figs. 7 and 8). Small, isolated DTUs did occur in all cases (see Fig. 6).

Analysis of the cellular automata algorithm

The final phase contributed to both utility and NPV (see Table 4). Utility increased with 1.5–32.2% and NPV increased with 3.6–33.8% depending on neighborhood distance. The coefficient of variation (standard deviation divided by the mean) varied with neighborhood distance but was 0.0161 or lower for the utility function and 0.0013 or lower for the NPV.

Utility and NPV increased in only the few first iterations of each phase, see Figs. 9, 10, 11, 12. The overall trends were the same for all analyses. Improvements in later iterations were very small. The last iteration of the final phase (innovation of all DUs) made noticeable contributions to both the NPV and the utility function.

Local phase solutions showed clear overharvest in the first period (see Fig. 12, line P1) and a shortage of harvests in the following couple of periods. The introduction of the harvest coefficient in the global phase mitigated this, but the final phase further decreased harvests, i.e., after introducing full entry costs, in some periods (see Fig. 13, lines P2 and P4).

Model runtime

Runtimes increased with longer neighborhood distances, which is logical since the computational burden increases for our model when mapping DTUs that are large in terms of the number of included DUs. The final phase was computationally time demanding, especially so when using 50 and 200 m neighborhoods. The model needed 800–6500 s per plan (repetition) depending on neighborhood distance (Table 5).

Model stability

We investigated the stability of each analysis. On average, the model selected the same TP in ~ 87% of solutions for any neighborhood distance (see Table 6).

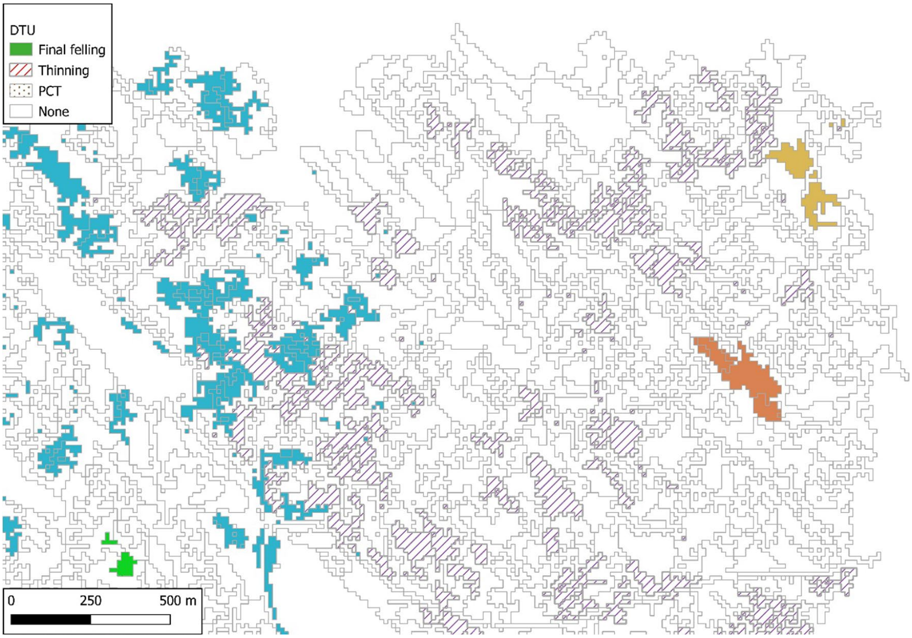

Fig. 8 Spatial layout of DTUs in the second five-year period in the northeast corner of the analysis area, using 200 m neighborhood distance. Filled DUs are scheduled for final felling, striped DUs are scheduled for thinning and dotted DUs are scheduled for pre-commercial thinning (PCT). Individual DTUs are colored the same and non-marked polygons are micro sements (DUs) or non-forest

Table 4 Utility and NPV in the analyses (20–40 solutions). Delta represents changes in solutions achieved by the final phase

		Global phase	Final phase			
Neighborhood distance (m)	Utility or NPV (SEK)	Average value	Average value	Delta	SD	Coeff of variation
1[1]	Utility	37.3 M	49.9 M	32.2%	804 936	0.0161
	NPV	38.5 M	51.0 M	33.8%	65 129	0.0013
50[1]	Utility	47.5 M	53.1 M	11.7%	156 174	0.0029
	NPV	48.9 M	53.5 M	9.2%	60 844	0.0011
200[2]	Utility	51.0 M	51.7 M	1.5%	611,017	0.0118
	NPV	5.25 M	54.4 M	3.6%	45 424	0.0008

[1]40 solutions; [2]20 solutions

Comparison with linear programming

Table 7 shows the NPV and harvested volume when using the heuristic and a traditional LP approach to solve similar planning problems. The relative NPV in solutions found by the CA algorithm (including entry costs) were within 91.4–97.5% of the theoretical maximum found using LP (including neither entry costs nor harvest constraints). Three LP solutions were also found including a constraint stating that the harvest profile had to match the harvest profile from each CA solution. When comparing solutions produced by CA to these LP solutions, the relative NPV from CA then rose to 94.3–98.1%.

Discussion

This study is an attempt to improve forest planning with a DTU approach using a cellular automata algorithm. Clustering treatments is necessary for forest management

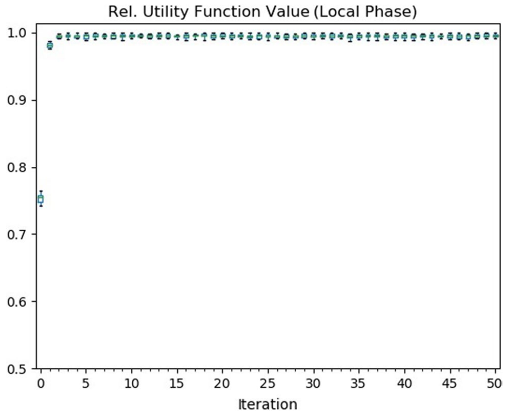

Fig. 9 Utility function values in the local phase, relative to the maximum value in the displayed dataset, for the 50 m neighborhood distance case. Boxplots representing results from the 40 repetitions of the CA algorithm. The utility function changes over phases, hence values are not comparable between Figs. 9, 10, and 11. Iteration 0 showing data from the randomly selected initial plan

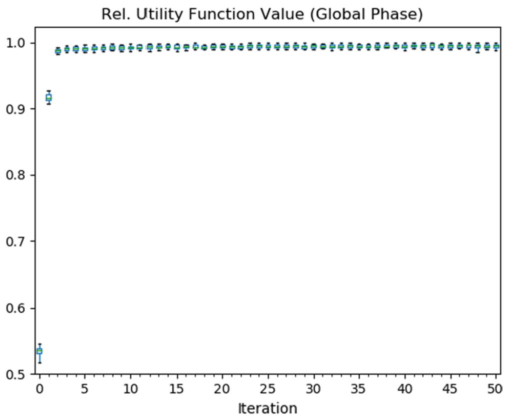

Fig. 10 Utility function values in the global phase, relative to the maximum value in the displayed dataset, for the 50 m neighborhood distance case. Boxplots representing results from the 40 repetitions of the CA algorithm. Utility function changes over phases, hence values are not comparable between Figs. 9, 10, and 11. Iteration 0 showing the solutions produced by the local phase as evaluated by the global utility function

planning when using DUs of high spatial resolution (Heinonen et al. 2018). From an economic standpoint, clustering is needed due to the fixed costs associated with treatments, e.g., for moving harvest machinery. In contrast to comparable studies in the literature, this study explicitly modeled the economic incentive to cluster harvest

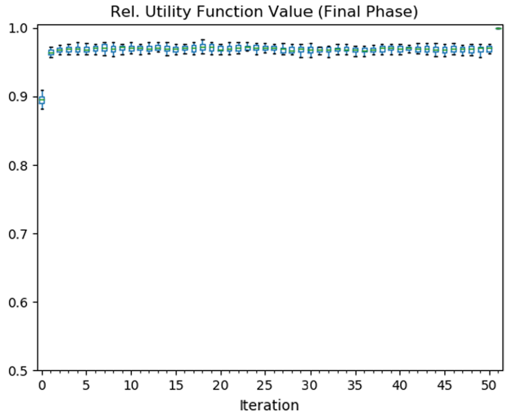

Fig. 11 Utility function values in the final phase, relative to the maximum value in the displayed dataset, for the 50 m neighborhood distance case. Boxplots representing results from the 40 repetitions of the CA algorithm. Utility function changes over the phases, hence values are not comparable between Figs. 9, 10, and 11. Iteration 0 showing the solutions produced by the global phase as evaluated by the final utility function

activities, in a high-detail manner in the final phase of the algorithm.

The model successfully solved the planning problem using different parameter settings and neighborhood distances. The model succeeded in the sense that (i) the plans had clustered treatments (ii) overharvesting did not occur, and (iii) all CA-produced plans (including entry cost) were within 5.7% of the comparable plans found with LP (excluding entry costs). The final phase improved the solutions in terms of both utility function value (1.5–32.2%) and NPV (3.8–32.4%), see Table 4. The model was successful in preventing overharvests compared to the harvest level set by the harvest coefficient. Thus, the effect of including the harvest coefficient was similar to inclusion of a constraint limiting harvest. However, the model did not result in even harvest flow in all periods (Fig. 13), which may be a concern for some forest owners. This may be achieved by decreasing the target volume (variable t_p), possibly in combination with increasing the upper bound (b_p).

A high number of iterations in each phase do not seem to be necessary since the culmination of NPV and utility function values were observed after only a few iterations. Past studies using cellular automata models have had utility culminate later during the iterations (e.g., Pascual et al. 2019), possibly because those models shifted utility weighting linearly over the iterations, whereas our model changes the utility function abruptly when a new phase starts. The final phase was the most time-consuming. The presented model solved the planning problem for 1 192 ha (4218 DUs) in

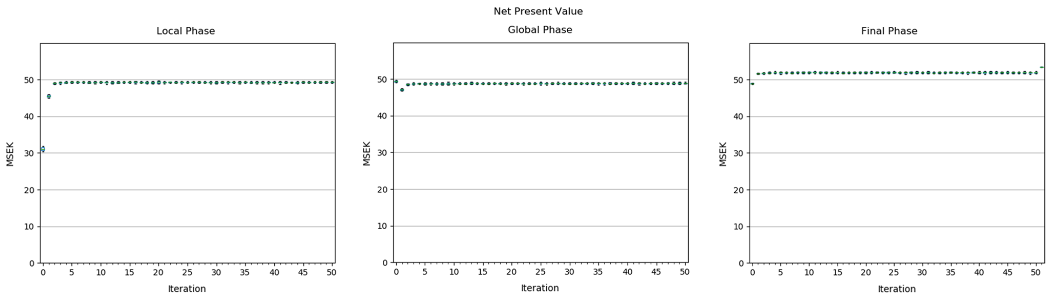

Fig. 12 NPV over all three phases for the 50 m neighborhood distance analysis. Boxplots representing results from 40 repetitions of the CA algorithm. Iteration 0 in the local phase graph marks the NPV of the randomly selected initial plans. Iteration 0 in the global and final phase marks the NPV of the input solution in each phase

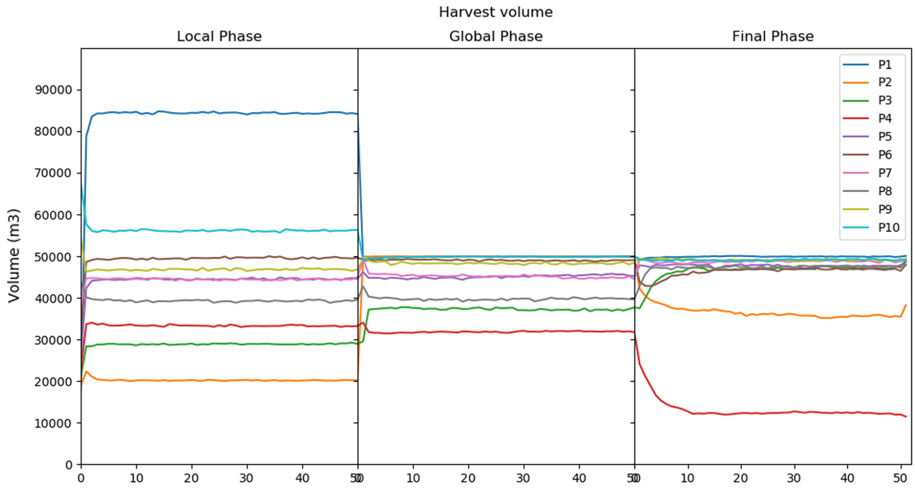

Fig. 13 Harvest profiles for the 50 m neighborhood distance case. Average values for 40 solutions. Global phase introduces the harvest coefficient and the final phase charges each DTU by the full entry cost. Iteration number within each phase on the x axis. P1 – P10 are the ten five year periods over the planning horizon

Table 5 Average values of runtime for different neighborhood distances

Neighborhood distance (m)	Runtime per iteration			Iterations per phase	Repetitions	Avg runtime per repetition (s)
	Local (s)	Global (s)	Final (s)			
1	4.3	4.4	7.9	50	40	830
50	4.4	4.6	29.6	50	40	1855
200	4.5	4.5	121.2	50	20	6510

830–6510 s (Table 5), depending on neighborhood distance. Unfortunately, computation time is not always reported in the literature. Comparisons are possible with the reduced cost model of Heinonen et al. (2018). Their model solved DTU planning problems for a 13 805 ha area (42,606 DUs) with solution times of ~ 2000s (Table 5). Note that, the complexity and computational cost is a result not only of analysis area size and spatial resolution, but also temporal solution, planning horizon, number of treatment units, neighborhood distance, etc. If short solution times is of great

Table 6 For each DU, we investigated which TP occurred the most often in the analyses. The frequency (in percent) of this TP results in a value between 0 and 100 for each DU. This frequency describes the stability in TP assignment, since a value of 100 for a DU shows that the model selected the same TP in 100% of all repetitions for that DU. The table shows descriptive statistics for this frequency for all DUs of the three analyses

Percentile	Stability (%)		
	1 m[1]	50 m[1]	200 m[2]
Min	25	23	25
Median	95	95	95
Max	100	100	100
Average	87	87	87

[1]Average values over 40 repetitions; [2]Average values over 20 repetitions

importance, our model may be improved by adding stopping criteria based on specific utility function values, possibly allowing for finding good solutions in fewer iterations and hence shorter solution times. Regarding runtimes, it has to be stressed that code was not optimized for solution time.

Heuristic models may not guarantee optimal solutions and solutions produced are to some degree the product of chance. Bettinger et al. (2009) suggest a six-level framework for validation of forest planning heuristics, where level six is the highest. Corresponding to level two in this piece of literature, we solve problems repeatedly and report spread in utility function value and in NPV. We also report the model's tendency to select the same TP for an individual DU over a set of solutions. We repeated the solving procedure 40 times for the 1 m and 50 m neighborhood distance and 20 times for the 200 m dito. The coefficient of variation for the utility function value was 0.0161 or lower for all analyses and for NPV the same was true for a value of 0.0013. The stability in TP selection was very similar in the different analyses regardless of neighborhood distance and was relatively high in all analyses—all analyses had an average stability of 87% and a median of 95%. This indicates that the model produces similar solutions over and over when using the same parameters for the same analysis area. This is a mark of quality for the model when nuanced by the comparisons with solutions from LP. Compared to solutions found using LP, the CA produced solutions with relative NPV of 94.3% or higher (Table 7). Bettinger et al. (2009) considers comparisons with optimal solutions generated for similar problems as a high level (five out of six) of validation but our comparison is vague since entry costs play a significant role in the CA but may not be included in the LP. Therefore, we do not consider our analysis as a level five validation. Furthermore, the harvest constraints also differ between the two. The relevance of the comparison lies in the fact that solutions found by LP are always the theoretical optima. Consequently, if the solution found by the CA is close to the solution found by the LP, it indicates that the CA produces high-quality forest plans. Therefore, the comparison was included.

Allowing for longer distances between separate areas within the same DTU increased NPV and utility function value. This is logical since increasing the distance has similarities with the relaxation of a constraint when using an exact solution method and matches the literature (Borges et al. 2017; Heinonen et al. 2018). A wider neighborhood distance allows the model to form more scattered DTU and results in fewer entry costs for a given distribution of treatments in the geography. What the appropriate neighborhood distance is, is however not obvious. The distance should reflect the point at which harvest machinery can no longer move within a harvest area without having transportation assistance by a trailer or similar. This distance is in practice dependent on several factors, many of which were neglected in this study (e.g., water courses, ground conditions, topography, roads). If a very short distance is used, the model will consider many treatments as isolated cuttings,

Table 7 Comparisons of NPV and harvested volume in different CA, and LP solutions. Note that, the LP solutions do not include entry costs in the calculation of NPV. Therefore, even if the selection of TPs was exactly the same in a plan found using LP and a plan found using CA, the CA solution would have lower NPV due to higher costs

Solution	NPV (SEK ha^{-1})	NPV (rel.)	NPV (rel. to corresponding LP solution)	Avg harvest (m^3 ha^{-1} year^{-1})
Linear programming				
No constraints	46 849	100.0	n/a	7.6
1[1]	45 411	96.9	n/a	6.8
50[1]	46 298	98.8	n/a	7.4
200[1]	46 567	99.4	n/a	7.5
Cellular automata				
1[2]	42 804	91.4	94.3	6.8
50[2]	44 851	95.7	96.9	7.4
200[2]	45 699	97.5	98.1	7.5

[1)]Using a constraint stating that the harvested volume in each period must equal the harvested volume from the cellular automata solution with the corresponding neighborhood distance

[2)]Using a utility function promoting even flow of harvested volumes (Fig. 3) and thereby as non-profitable. If a very long distance is used, DTUs are to a more significant extent constituted by small and scattered areas, which the underlying harvest productivity models used in Heureka (Eriksson and Lindroos 2014) are not validated against.

The entry cost is a main component in the model and it was scaled down in the local and global phases. The aim here was that (while a lower detail mapping is conducted in the local and global phases) the effective entry cost charged from single DU would approximately correspond to the effective entry cost charged in the final phase. Furthermore, consideration was taken to the fact that a full entry cost would far exceed the income from thinning very small DU (a single $12.5 \times 12.5 m^2$ grid cell). Using a full entry cost, the model might consider all small DTU as unprofitable, not allowing small DTU to establish in the local and global phase, thus potentially getting stuck in local optima. After reasoning and brief testing, the entry cost was therefore scaled down in the local and global phases by multiplying it by 0.02.

Small DTU occurred in all cases, even though an important aim of the model is to avoid these. The fact that TPs (a sequence of treatments) are evaluated here, rather than individual treatments, is a possible explanation for this. A TP may be considered viable to the model, even though an individual treatment at a specific timepoint in the TP is not. Hence, the model may not guarantee that all treatment in all DUs in a solution are economically profitable, even though NPV was a component in the utility function.

Finally, delineation of forests into microsegments, i.e., the DUs in this study, may be of varying quality and is a source of error for forest planners using such data. Furthermore, the microsegments used here consists of sets of squares, forming straight and perpendicular patterns which in principle is a poor representation of the gradual variations that occur in real forests. As an alternative, remote sensing techniques allow for single tree identification and segmentation algorithms can be employed on such tree level data to form microsegments with more fine tuned borders (e.g., Olofsson and Holmgren 2014). Yet another alternative would have been to use the underlying cells as DUs, at the cost of an even more complex planning problem with many more decision variables. After all, the model for carrying out the segmentation and the model for conducting forest planning are two separate things. The former is not the focus of the study, and therefore, no investigation was conducted on the quality of the microsegmentation.

Conclusions

We conclude that the presented approach is an addition to the set of heuristics applicable to forest planning with DTU. The main contribution of the study is the final phase of the algorithm where the economic incentive to cluster treatments is modeled by calculating entry costs in high detail. The analyses showed that the final phase improves goal function value in solutions. While the magnitude of improvement appears dependent on parameterization in earlier phases of the algorithm and data, modeling a realistic entry cost, instead of using proxy variables, decreases the need for parameterization and expert-usage of decision support systems. While the final phase improved solutions, the phase was also computationally costly. In addition, early culmination of goal function value was observed, which leads us to reason that inclusion of stop criteria may be advisable to reduce solution times. The results also showed that the model produces consistent solutions when a given planning problem is solved repeatedly.

Authors' contributions P.W. developed the method, wrote the code, conducted the analyses and wrote the manuscript. K.Ö., T.L., and J.W. all contributed to the development of the method and provided feedback on the manuscript. J.E. processed and prepared forest data and provided feedback on the manuscript.

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Availability of data The data can be provided on request to the corresponding author PW.

Code availability The code can be provided on request to the corresponding author PW.

Declarations

Conflicts of interest The authors declare that there are no economical nor academical conflicts of interest that could have affected the work in this study.

Consent for publication All authors have given consent for publication.

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