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RESEARCH

Dynamic treatment units in forest planning improves economic performance over stand-based planning

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Abstract
High-resolution, wall-to-wall forest information enables precision-driven decision-making in forest management planning. In a case study we compare planning approaches using such information for solving long-term forest planning problems. The two first approaches are based on dynamic treatment unit (DTU) planning with high-resolution cells (12.5×12.5 m^2) or segments (0.27 ha on average), respectively, solved with a cellular automata heuristics. The third approach is a traditional stand-based approach using stands (5.2 ha on average) and linear programming to solve the planning problem. Fixed costs associated with cutting operations are quantified as each treatment unit is charged with an entry cost of 10 000 SEK. The entry costs are included in the DTU approach while in the stand approach entry costs are applied accordingly in a post-optimization routine. In large, the analyses are based on open-access tools and data provided by Swedish authorities. The traditional stand approach produced plans with 5.2–2.7% lower net present value compared to DTU planning. Most of the differences were caused by greater suboptimal losses in plans produced with the stand approach, but entry costs were also lower in DTU plans. While forestry was less profitable, treatment units were more spatially compact with stands, especially compared to cell-based plans. Therefore, we reason that a combination of modelling of direct costs and use of spatial proxy variables, such as common border length, may be advisable in DTU planning to achieve compact and realistic treatment units. Finally, the results indicate that high-resolution data and DTU planning may better utilize forests' potential of economic production, compared to the traditional stand approach.

Keywords Cellular automata · Entry cost · High spatial resolution data · Optimization · Remote sensing · Spatial

Introduction

Forests provide a wide range of ecosystem services such as carbon sequestration and storage, biodiversity and production of woody products. Forest management activities may enhance the forests' provision of said ecosystem services and forest planning attempts at deciding when, where and how forest management activities should be conducted to best ensure that resources for human and environmental needs are provided. How this planning is conducted is affected by the available data. Today high-resolution, wall-to-wall forest data – i.e., data with full spatial coverage of an analysis area – is widely available in many countries e.g. Finland (Kotivuori et al. 2016), Sweden (Nilsson et al. 2017), Norway (Breidenbach et al. 2020), Switzerland (Waser et al. 2017) and North-America (White et al. 2013). Such data has opened up possibilities for high-precision decision making in forest planning. One planning approach for achieving this is based on using dynamic treatment units

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(DTU). Here, the description unit (DU) – the unit for carrying information about the forest and for modelling ecosystem processes, e.g., a cell or microstand (see e.g. Pascual et al. 2019), is not synonymous to the unit associated with a treatment – treatment unit (TU). This is contrary to the traditional stand approach where the stand fills both these functions. In DTU planning, a treatment unit instead consists of more than one DU. The main property of DTU planning models is the spatiotemporal clustering of treatments to enhance economical, biological, or social values, which is necessary if the resulting plan is to be implementable. The literature contains several studies where models for conducting forest planning with a DTU approach are presented (de Miguel Magaña et al. 2013; Heinonen et al. 2007; Heinonen and Pukkala 2007; Holmgren and Thuresson 1997; Lu and Eriksson 2000; Packalen et al. 2011; Pascual et al. 2018; Pukkala et al. 2009; Wilhelmsson et al. 2021). Additionally, the wider field of spatial forest planning span decades and contains a plethora of models applicable also in DTU planning if modified accordingly (Bettinger and Boston 2017; Constantino et al. 2008; Kašpar et al. 2016; Martins et al. 2014; McDill and Braze 2001; Öhman and Eriksson 2010).

However, even if there are many studies presenting models for DTU planning very few studies actually present the advantages with this kind of planning compared to the traditional stand-based planning. One rare example is a pioneer DTU study by Holmgren and Thuresson (1997) where they solved a tactical planning problem of one period. The problem formulation minimized the sum of inoptimality losses (IL) and entry cost (EC), subject to a minimum amount of harvest volume. The IL of a selected management alternative for a DU is defined as the highest net present value (NPV) of any potential management possible for that DU, minus the NPV of the selected management. An important result of the study was that the IL was higher if planning was based on stands instead of cells. This is in line with subsequent reasoning that DTU planning should lead to '*more efficient utilization of the production potential*' (Heinonen et al. 2007). The other component of Holmgren and Thuresson's (1997) goal function consists of the EC, representing preparatory and logistical costs for conducting a forest operation. The EC is the main economic incentive to cluster treatments and research has shown that EC affects economically optimal forest management (Borges et al. 2017; Öhman and Eriksson 2010; Wilhelmsson et al. 2021). In the DTU model by Holmgren and Thuresson (1997), EC was represented with a spatially dependent variable, calculated by dividing a fixed cost with the area scheduled for cutting within a 80 m radius around a DU if that DU was also scheduled for cutting. However, the problem formulation based on a stand approach did not model EC in the same way as the DTU approach. Therefore, no conclusion was made on the possibly higher utilization of the production potential (in terms of monetary values) with a DTU approach. The production potential of forests using DTU planning and the stand approach, respectively, was addressed by Heinonen et al. (2007). Using a threshold acceptance model (Dueck and Scheuer 1990), the tradeoff between harvest yield and area of old forest was studied. The study found that DTU planning resulted in a larger amount of old forest, while providing a certain supply of harvests, when compared to stand-based solutions.

However, apart from Heinonen et al. (2007) and Holmgren and Thuresson (1997), the literature does not offer direct comparisons between stand-based planning and DTU planning, but highlights various aspects important for DTU planning. Pascual et al. (2018) applied the DTU model presented by Heinonen and Pukkala (2007) to focus on modelling the costs of cuttings in a DTU planning problem. The objective function included spatial objectives (common border metrics), and costs for felling and forwarding derived from slope, distance to roads and stem diameter of trees. The estimation of costs were of the lower spatial order, i.e., associated with the geographical location but not, e.g., neighborhood relations. Additionally, the spatially dependent economic advantages of clustering DTU were not included in the study. Heinonen et al. (2018) modelled the spatial aspect of DTU planning not by adjacency, but by proximity. The presented model, based on the reduced cost heuristic (Pukkala et al. 2009), allowed up to 300 m of uncut forest between subareas of a treatment unit. While economic advantages of clustering were not quantified, the analysis found that longer allowed distances within the same harvest block resulted in more profitable forestry. Similar results were presented by Wilhelmsson et al. (2021), where a mixed-integer programming (MIP) model was presented and the well-known (e.g. Augustynczik et al. 2016; Borges et al. 2017) limitations of MIP models for DTU use was showcased. In summary, efforts have been made in the field of DTU planning and studies have provided models to conduct DTU planning. Investigations on the supposed superiority of DTU planning are, however, lacking since direct and relevant comparisons between planning approaches and the ability of forests to provide economic resources as a result of said approaches, are scarce.

The aim of this study is to evaluate whether DTU forest planning can achieve an economically more efficient use of the forest resource than stand-based forest planning. We measure economic efficiency in forest resource use in terms of NPV, including EC. We also study the IL in forest resource use when decreasing the spatial resolution in the forest data, from raster cells of an average size of 0.0156 ha, or segments of ~0.25 ha, to stand of ~5 ha. The analysis is conducted using forest data from a 4 480 ha mid-Swedish forest landscape.

Material and method

The analytical framework in this study consists of comparisons of different approaches for solving a spatial, long-term planning problem for the case study area. The planning problem aims at finding areas for final felling and thinning over time in order to maximize the NPV given an even flow of harvested timber over time. Three approaches for solving the planning problem are compared:

1. DTU approach, based on high-resolution cells (cases *1a* and *1b*, *a* and *b* referring to maximum allowed distances between DTU subareas).
2. DTU approach, based on segments derived from cells (cases *2a* and *2b*).
3. Stand approach, based on fixed stands, initial stand attributes derived from cells, stand management solutions (thinning, final fellings, etc., in each period) forced on associated cells (cases *3-1a* and *3-1b*), or stand management solutions forced on associated segments (cases *3-2a* and *3-2b*).

Forest data

The ca. 4480 ha forest area used for analysis is situated (at 62.77 N, 17.22 E) outside of Sundsvall in central Sweden (Fig. 1). Areas of non-productive forest (mean annual growth < 1 m^3 ha^{-1} $year^{-1}$) were excluded from the study. The forest data of the study was collected from various remote sensing sources. The Swedish Land Survey, the Swedish Forest Agency (SFA), and the Swedish University of Agricultural Sciences (SLU) collaborates to conduct nationwide airborne laser scanning (ALS) data collection and produce raster maps of forest attributes using the ALS data in combination with reference data from the Swedish national forest inventory. The resulting maps are provided open-access by the Swedish Forest Agency (SFA 2022; see also Nilsson et al. 2017). The maps are raster estimations for Lorey's mean height, basal area weighted mean stem diameter, mean volume per hectare, and basal area per hectare, based on ALS height distribution metrics. Estimations of tree species distribution were retrieved from SLU Forest map (SLU 2022), which is a similar product as the ALS-based maps but utilizing spectral satellite image data and tree height data from national aerial images rather than ALS data. Site index, site index species (pine or spruce), vegetation type, and mean age are compiled using spectral data, by matching satellite image raster cells with georeferenced NFI plots. Soil properties were provided from soil moisture map (SFA 2022) derived from ALS-based digital terrain indices and machine learning (Ågren et al. 2021), in which the forest is classified as dry, mesic, mesic-moist, moist or wet. All of the maps mentioned are raster data in 12.5 × 12.5 m^2 resolution.

The first planning approach uses cell level data. Here, a grid with a total of 286 553 cells of 12.5 × 12.5 m^2 represent the entire analysis area (Table 1). Each cell holds the assembled data from all raster maps, describing the current state of forest attributes (tree height, stem diameter etc.). The cell data was used in cases *1a*, *1b*, *3-1a*, and *3-1b*.

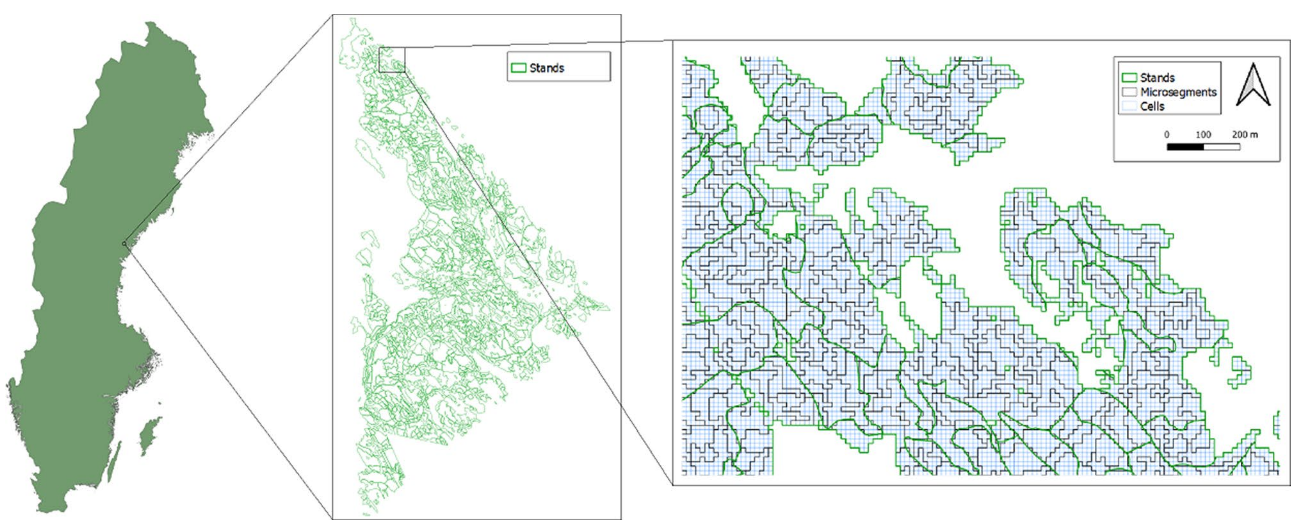

Fig. 1 The analysis area location outside Sundsvall, Sweden (left), overview of the ~4480 ha constituting the analysis area (middle) and the visualization of the three datasets (right). The datasets cover the same area, and the analyses use the association between each stand (green) and the corresponding set of segments (black) or cells (blue)

Table 1 Summary of the initial state of the forest in the three datasets used

	Stands	Segments	Cells
No. of DU	861	16,477	286,553
Avg DU size (ha)	5.20	0.27	0.015625
Total area (ha)	4479.5	4477.9	4477.4
Initial standing stock (m^3 ha^{-1})	212	209	205
Age (mean)	60.7	61.9	66.8
Productivity (m^3 ha^{-1} yr^{-1})	4.68	4.41	4.31

Table 2 Data sources for cells and estimation method for segments and stands. Closest matching NFI plot means that each cell's satellite image data is compared to NFI plots and e.g. the site index of the closest matching NFI plot is assigned to the cell

Forest parameter	Data source for cell level estimations	Statistical metric for estimation in segments and stands
Lorey's mean tree height (m)	Skogliga grunddata [1]	Median
Stem diameter (cm)	Skogliga grunddata [1]	Median
Stem 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 (H100, m)	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 2022). See also Nilsson et al. (2017)

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

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

The second planning approach uses segment level data. This dataset was made by aggregating the cells into segments using an iterative region merging algorithm (Olofsson and Holmgren 2014) and based on the similarity of adjacent regions (cells or cluster of cells). Similarity refers to the Euclidean distance in a 3-dimensional space (Lorey's mean height, basal area weighted mean stem diameter, and proportion of broadleaves (of the standing volume)). The size of segments was equivalent to 1–70 cells, resulting in an average size of 0.27 ha (Table 1). The decision of what segment size to use was based on our subjective judgement. A segment may not cross the fixed stand borders of the stands in the third dataset. Thus, there is a distinct association between each segment and the stand where the segment is located. For each segment, estimation of parameters needed for import to the Heureka system was based on statistical metrics shown in Table 2 for the subset of cells intersecting the segment. The segment data was used in cases *2a*, *2b*, *3-2a*, *and 3-2b.*

The third approach uses stand level data, whose polygons are 5.2 ha on average (Table 1). The industrial forest company SCA owns the forestland and provided the stand borders. Stand borders are established manually and subjectively, in a balancing act between identifying variation in the forest while also creating large enough stands for mechanized forest operations. The borders are typically updated before or after harvest operations, or by interpretation or processing of remote sensing data. Therefore, the quality of stand borders may vary greatly within the same geographical area. This is the case for the dataset used here – the quality of the delineation is unknown. Traditionally, GIS databases containing borders also hold forest data, e.g. mean tree height and volume, together making up a typical stand register. However, only the stand borders were used here. Instead, the estimation of current forest state was derived from the cell data following the routine described in Table 2. The stand data was used in cases *3-1a*, *3-1b*, *3-2a*, and *3-2b.*

Due to the use of three different datasets, small differences occur in Table 1. The differences is caused by the use of median values of the underlying cells when calculating the forest parameters in a stand or segment. Approximately, the forest area spans 4480 hectares where the mean productivity is 4.5 m^3 ha^{-1} and the growing stock (mean of 209 m^3 ha^{-1}) consists of Norway spruce (Picea abies, 51%), Scots pine (Pinus sylvestris, 34%) and birch (Betula pendula and Betula pubescens, 15%).

Cells, segments and stands comprise three datasets with different spatial resolutions, representing the same forest. Thus, there is an association between each stand and the segments at the same location as the stand, and equivalently, between each stand and the cells at the same location as the stand (see rightmost picture in Fig. 1). This association is later used to apply the forest management decided on stand-level onto the associated cells or segments.

Generation of treatment programs

The formulation of the planning problem is based on the concept of treatment programs (TPs), which refers to a sequence of treatments (such as planting, thinning, final felling, etc.) or non-treatments over the discrete time periods constituting the planning horizon. The planning horizon in this study was 50 years, divided into 10 periods of 5 years. The forest decision support system Heureka (Lämås et al. 2023) was used to generate potential TPs and to project forest developments for each DU and TP. The Heureka system, developed by SLU, consists of four applications for forest planning aimed at dealing with different planning questions and scales. Here, we use Heureka PlanWise, which contains models for growth, mortality, etc., and an engine for simulation of TPs. The user defines settings for simulations of forest management and the software then generates the set of potential TPs for each DU. Associated with a TP is the outcome, e.g. NPV, growth, growing stock, and stand age. In all cases and for each DU, a set of potential TPs with different variations of even-aged forestry containing one or zero thinnings before final felling were simulated together with one TP in which no treatments were simulated, i.e. the forest is left unmanaged. To calculate NPVs periodic net revenues were discounted using a 3% real interest rate.

Dynamic treatment unit approach

The DTU approach applied on the high-resolution cells (cases *1a*, *1b*) and the segments (cases *2a*, and *2b*), respectively, uses the heuristic method cellular automata (CA) to solve the planning problem, i.e. find the combination of TP's that maximize NPV while there is an even flow of harvested timber over the planning horizon. The CA used forms treatment units by spatiotemporally clustering of small DU (cells or segments). CA was introduced in forest planning by (Strange et al. 2002) and further developed or used in later studies (Heinonen et al. 2007; Mathey et al. 2005, 2007; Pascual et al. 2018, 2019).

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 utilizing the states of a subject cell and of the neighboring cells. In a typical forestry application, a CA consists of a set of units (e.g. stands) that change TPs subject to spatially dependent rules. If the rules are relevant for the specific planning problem, large scale spatial patterns emerge, and high-quality solutions are provided within reasonable time. An advantage of CA is that as a decentralized heuristic, it evaluates solutions at unit-level. As a consequence, CA may find solutions faster than centralized heuristics that conducts calculations on forest-level (Pukkala et al. 2009, 2014).

In a DTU setting (Heinonen and Pukkala 2007; Mathey et al. 2005, 2007; Pascual et al. 2018, 2019) CA typically consists of two phases where the output plan from the first, local phase, is used as input in the second, global phase. The local phase aims to generate a local-level optimized plan, under simplified assumptions, providing a solution that typically does not satisfy forest level goals. The global phase therefore secures forest level goals and restrictions. To this approach, Wilhelmsson et al. (2022) added a third 'final' phase in which DTUs are mapped in a high-detail manner and explicit, fixed Entry Costs (ECs) associated with harvest operations are included in the utility function, while maintaining consideration to the harvest level.

Our application of CA is based on Wilhelmsson et al. (2022). The spatiality of the model used lies in the calculation of EC, which is the fixed costs associated with conducting treatments like thinning or final felling including preparatory measures. The EC is shared among nearby DU with the same type of treatment coinciding in time and the CA model is thereby incentivized to cluster treatments in time and space.

The CA algorithm uses the set of DU (cells and segments, respectively) that constitutes the analysis area, with the DU's associated set of TPs. Over a predefined number of iterations within each phase, the model changes TPs for all DUs, aiming at spatiotemporal clustering of treatments – thereby creating DTUs. Changing TP for a DU occurs according to probabilities for selecting one of following actions; (1) finding the TP with the highest utility ('innovation'), (2) randomly choosing a TP ('mutation'), or (3) keeping the current TP until next iteration. A spatial utility function that changes over the three phases of the algorithm decides the utility of a TP. The first, local phase has a utility function with simple calculations of EC but has no considerations to harvest levels over time. The second, global phase adds a penalty for solutions in which the harvest deviates from a stated target harvest volume in each period. The harvest penalty is a change in design compared to the presented model (Wilhelmsson et al. 2022), where the mechanism relating to harvest level did not achieve an even harvest flow, but only prevented overharvest. Therefore, we use a penalty function that exponentially punishes solutions with deviations from the stated harvest goal by multiplying it with a penalty weight coefficient. The global phase of the algorithm introduces the harvest penalty. The penalty weight coefficient increases exponentially through the iterations of the global phase, reaching its full magnitude in the last iteration of this phase and maintaining it through the final phase. The penalty is small in the first iteration of the global phase, and increases exponentially towards the end of it. The mathematical definition of the harvest volume deviation penalty is:

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

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,

h_p is the harvest in period p, and

P is the final period.

The constant of 0.05 was set after evaluation of trial runs. This factor is set to scale down the exponential penalty to deviations from the harvest level. Without the coefficient of 0.05, the incentive to match the harvest level became too strong, and the model got stuck in what most likely were local optima.

The third, final phase maintains the ending penalty of harvest deviation from the global phase, which will guide the search process and avoid solutions that severely deviate from the harvest level. The final phase also conducts a refined mapping of treatment unit and adds a full EC of 10 000 SEK, driving clustering as result of high-detail mapping of each DTU.

In order to find a suitable harvest level for the analysis area, a traditional planning problem using the stand data was first solved with linear programming (LP). Here the objective maximized the NPV from future forest management. Two constraints were included. The first stated that the harvest level (m^3) must be the same in all time periods. The second constraint stated that the total growing stock of the forest (m^3) must not be lower at the end of the last (tenth) period, compared to the initial state. This optimization found that a total harvest of 129 979 m^3 in each 5-year period is possible in the analysis area in the long term. Thus, a level of 129 979 m^3 was set as harvest target in the CA model for the DTU approaches using cells and segments, respectively.

To mitigate the complexity of the large planning problem (10.25 M TPs over 286 553 DU for the cell data) and deal with specific challenges encountered along the study, two adaptations were made of the CA model presented in Wilhelmsson et al. (2022). First, the original model is asynchronous (sequential), meaning that the state of all cells is always known before processing a single DU. In the present study, the model was run on synchronous (parallel) mode, meaning that states are updated only between each iteration (which consists of one processing per DU in the analysis area). Second, a different calculation of entry cost in the final phase of the algorithm was used compared to the original version. Testing indicated that if EC was introduced abruptly in the final phase, the model would consider harvest of small DUs as unprofitable unless the DTU was large. Therefore, the present study calculates the EC in a given final phase iteration i as EC*i/I where I is the total number of iterations in the phase. As a result, the effective EC increases over the iterations, reaching its full value of EC at the last iteration of the final phase. Thus, the model is increasingly incentivized to form DTU with realistic sizes. The distribution of EC among DUs is proportionate to the net income of harvest in each DU, whereas in the model by Wilhelmsson et al. (2022), EC was distributed proportionate to the area of each DU. The gradual clustering of treatment units over the phases of the algorithm is visualized in Fig. 2. For full documentation of the model used, see Wilhelmsson et al. (2022).

Stand approach

The third approach uses traditional LP to solve the planning problem. LP is frequently used in forest management planning, often following the Model I form (Johnson and Scheurman 1977). LP is a powerful tool when applicable but can unfortunately not deal with spatial problems such as clustering of treatments (without transforming the problem to an MIP). We used the stand approach to solve planning problems with a Model I in the optimization application of Heureka PlanWise software (Lämås et al. 2023). For each DTU solution produced, we identified a corresponding solution using stands and LP, constituting cases *3-1a*, *3-1b*, *3-2a*, and *3-2b*. The stand solution must have the same harvested volume in each period as the corresponding CA solution. This is achieved by allowing for continuous decision variables in the optimization problem, which in a Model 1 formulation represents the share of each stand's area that is managed with a certain TP. After the TP of each stand is decided, that TP is applied to the cells or segments within the stand (see Fig. 1). Since the procedure of applying the management of a stand onto all cells or segments located within the stand is spatially explicit, the decision variable must be binary. Thus, we rounded the decision variables accordingly, causing some deviations from the harvested volume of the corresponding DTU solution. The resulting management of the cells or segments constitutes a 'stand solution'.

Evaluation of planning approaches

The results from the different approaches are evaluated by spatial metrics (size of treatment units and their area-to-perimeter ratio), harvested volume, NPV, IL, and EC. The calculation of NPV includes EC, which is the fixed cost for logistical preparations, field work and administration associated with a forest operation (Borges et al. 2017) in a Scandinavian context. The analysis is based on charging each treatment unit with such a fixed cost. This is performed endogenously in the DTU approach (cases *1a*, *1b 2a*, and *2b*) since the EC is explicitly included in the model. This is not possible in the stand approach with LP (cases *3-1a*, *3-1b*, *3-2a*, and *3-2b*). Instead, the ECs were calculated in a post-optimization analysis using the neighborhood criteria as in the DTU approach. We define a treatment unit as a coherent area scheduled for cutting at a specific point in time. Cutting includes both thinning and final felling – we assume

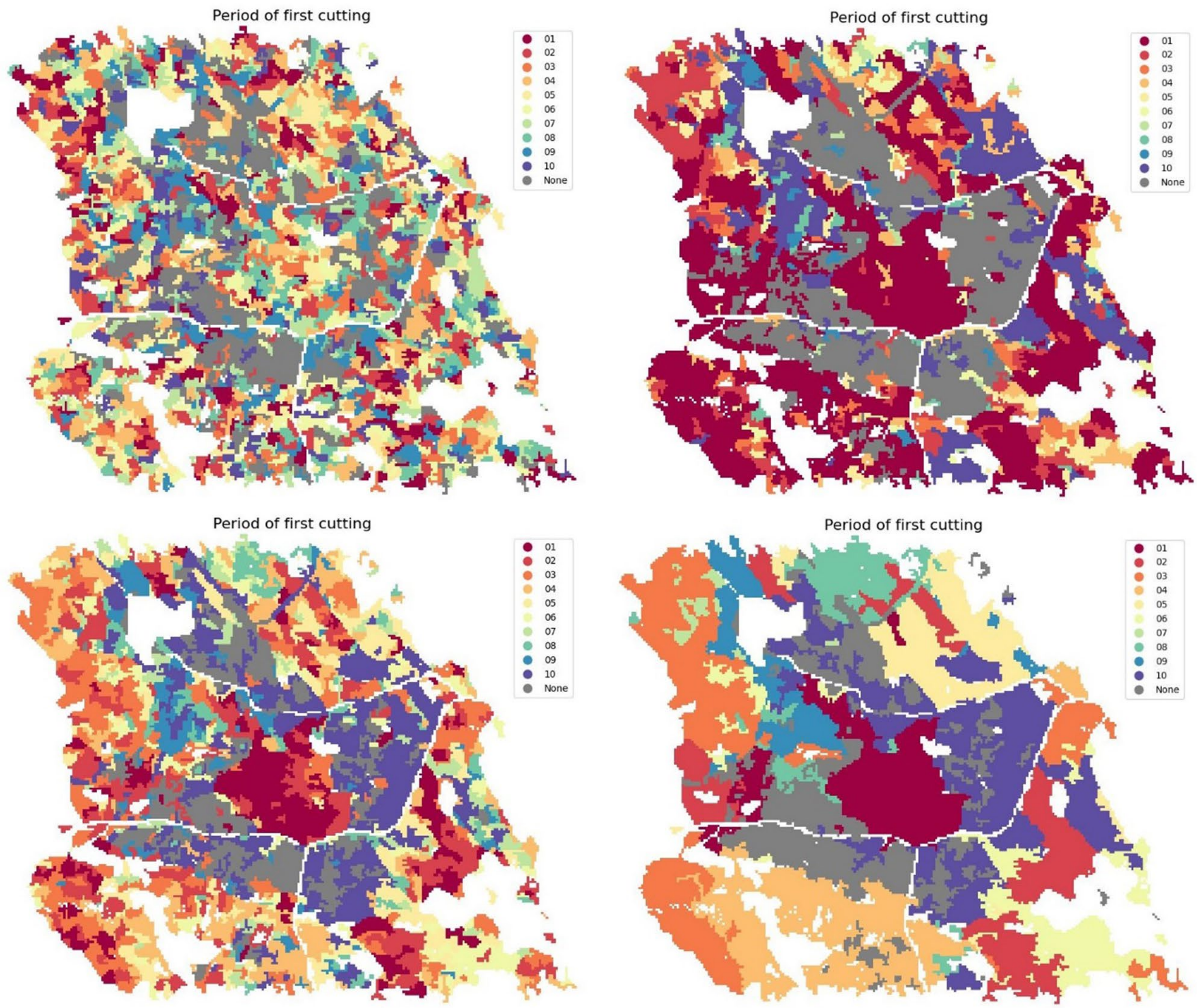

Fig. 2 Visualization of how cellular automata clusters treatments over its phases for an example landscape of 1521 segments. Top left: randomized starting plan. Top right: end of local phase. Bottom left: end of global phase. Bottom right: end of final phase

that the harvest machinery can carry out both treatments if necessary. A treatment unit may be considered coherent even if not all DU constituting it are immediately adjacent. A DTU may consist of several smaller subareas, as long as they are connected according to a neighborhood logic. In this study, two DUs were considered neighbors if the shortest distance between any part of their perimeters was shorter than a specified neighborhood distance. The treatment unit is considered as one and the same as long as all DU in the treatment unit are connected to the other DU by its neighbors, and its neighbors' neighbors (and so on, until infinity). Thus, stepping stone effects may occur, depending on what neighborhood distance is used. Two different neighborhood distances were tested: 1 m (cases with suffix *a*) and 49 m (cases with suffix *b)*.

To summarize the method, we find the optimal management on stand-level using LP, apply it to all cells within the stand, and compare it with management found on cell-level using a DTU heuristic. The comparison includes a fixed cost for all treatment units, which are formed using spatial rules. We repeated the analysis for segments and with two different spatial rules (neighborhood distances) for formation of treatment units. A conceptual overview of the workflow in the study is given in Fig. 3.

The analyses was carried out on a Intel Core i7 2.8 GHz PC with 32 GB RAM and a 64-bit Windows OS.

Fig. 3 Analytical framework of the study. The outputs of the first four rows provide input to the DTU approaches (rows 5–8) and the stand approaches (rows 9–12)

Results

In terms of NPV, the plans found with the DTU approach outperformed the corresponding plans found with the stand approach in all cases (see Table 3). The highest NPV (48 212 SEK ha^{-1}) was found for the planning approach based on segments and a neighborhood distance of 49 m (case *2b*). The higher NPVs for DTU approaches compared to the stand approach were caused mainly by lower IL for the DTU solutions, but DTU solutions also had lower EC. Comparisons between DTU solutions show that plans based on segments outperformed the corresponding cell plans. Regardless if planning was based on cells, segments or stands, allowing a longer neighborhood distance (49 m compared 1 m) increased the NPV by reducing both the EC and IL.

Table 3 Economic summary of results for the eight cases. Net present value (NPV) includes entry cost (EC). A 3% real interest rate is used for calculating NPV, inoptimality loss (IL) and EC

Case	Data	Neighbor-hood distance (m)	NPV (Rel)	NPV (SEK ha^{-1})	IL (SEK ha^{-1})	EC (SEK ha^{-1})
1a	Cells[1]	1	1.000	45,898	4338	1459
3-1a	Stands & cells[2]	1	0.963	44,222	5850	1622
1b	Cells[1]	49	1.000	47,425	3446	822
3-1b	Stands & cells[2]	49	0.948	44,972	5829	894
2a	Segments[1]	1	1.000	47,422	4402	1077
3-2a	Stands & segments[2]	1	0.973	46,133	5166	1602
2b	Segments[1]	49	1.000	48,212	3965	742
3-2b	Stands & segments[2]	49	0.972	46,846	5158	898

[1] Solution found with DTU heuristic

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

Table 4 Geographical analysis of treatment units in each solution. A: P ratio is the average ratio between the total area (A) and total perimeter of the harvested areas (P) over the entire 50 years period (a and b indicate 1 m and 49 m neighborhood distances, respectively)

Case	Data	No of treatment units	No of DTUs < 0.25 ha	Avg DTU (ha)	A: *P* ratio (m^2 m^{-1})
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

Finding DTU solutions using cells (286 553 DUs) was time consuming compared to the stand approach, with the planning model requiring up to 4 days, 21 h and 37 min to find solutions. The segments (16 477 DUs) required 43 min (excluding the time for the segmentation procedure) and the stand-based solution was found within 7 s (excluding the time for post-optimization mapping of treatment unit to calculate EC).

Average areas of treatment units were between 3.28 and 6.60 ha over all cases (which can be considered reasonable for Swedish forestry contexts), see Table 4. There were no clear differences in the number of treatment units between the DTU and the stand-based solutions. However, DTU solutions had a higher number of DTUs smaller than 0.25 ha, thereby the DTU solutions also had some large DTUs. Harvests created by the DTU approach were less clustered, as indicated by their lower A:P ratio. This is visualized in Fig. 4 where e.g. the higher compactness of stand approach case *3-1b* compared to DTU approach case *1b* is visible. Of the DTU solutions, 1 m neighborhood distance resulted in more clustered harvests than 49 m distance (Table 4, A:P ratio and Fig. 6).

The harvested volume was lower in plans produced with the stand approach, see Fig. 5.

Discussion

This study compares the DTU approach and the traditional stand approach by solving a long-term, economically oriented planning problem. The results indicate that DTU planning may enhance forest resource use since the solutions found using DTU resulted in higher NPV than stand-based solutions. The NPV differences between the DTU approach solutions and the stand approach solutions were larger for cell-based plans (3.7–5.2%) than segment-based plans (2.7–2.8%), i.e. when spatial resolution of forest data was increased (Table 3). Thus, our result supports the reasoning that higher resolution data can enable more efficient use of the forest resource.

Previous findings on this topic can be found in Heinonen et al. (2007), where results showed that the production possibility frontier was farther from the origin in plans produced from raster data with their DTU approach. By contrast, when Pascual et al. (2019) used large segments, small segments and cells to solve a DTU planning problem with CA, small segments allowed for the highest amounts of harvested wood (i.e., not cells, which were the smallest). While in theory, higher resolution data should allow more combinations of actions and should enable better plans, the ability of the heuristics to explore solutions might not be efficient enough to entail better plans. While this study (and the papers mentioned above) focus on economic aspects, we claim that the principle of increasing the solution space is just as valid for ecological and social ecosystem services. Thus, high-resolution data may also be of service for other types of forest planning.

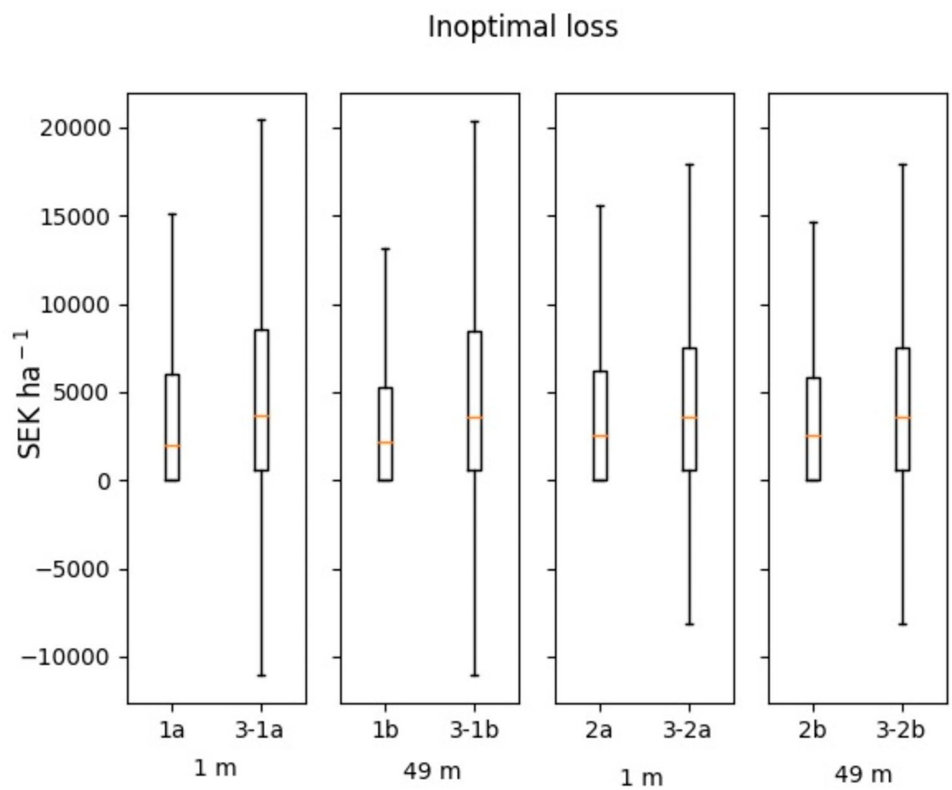

Fig. 4 Boxplots of inoptimality losses for the cells (cases 1x and 3-1x) and segments (cases 2x and 3-2x), respectively. a and b indicate 1 m and 49 m neighborhood distances, respectively

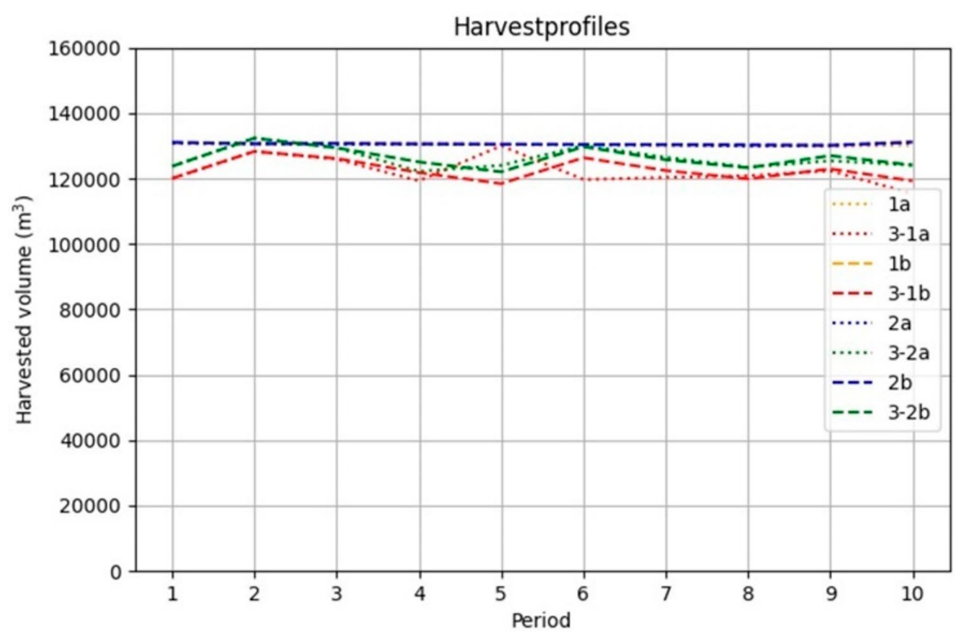

Fig. 5 Harvest profiles for all cases. Cases 1a, 1b, 2a and 2b are very similar as a result of the harvest target set in the CA model. Cases 3-xx varies due to the rounding of the continuous LP decision variable solution to a binary variable

Increasing the neighborhood distance increased NPV in all cases (Table 3). This was expected and logical since it allows a more generous mapping of treatment units and the result matches the literature (Heinonen et al. 2018). We also studied the IL due to the use of different spatial resolution in forest data. Similar to Holmgren and Thuresson (1997) we found that IL was larger when using stands compared to either segments or cells. In terms of forest management, this means that the best silvicultural treatments were carried out at the right place at the right time to a larger extent when using high-resolution data, compared to using stand-level data. Research on this topic by Persson et al. (2022) suggests that improvements on economy and growth may be low in Swedish, even-aged forests. The mentioned study analyzed variable thinning in a simulating study, using 20 stands dominated by either Norway Spruce or Scots pine and scheduled for thinning in the near future by the forest company Sveaskog. The authors reasoned that a larger scale analysis may accentuate the potential of precision forestry, which is possibly what occurred in our analysis. In addition, Fig. 4 shows records of negative inoptimality losses, which in theory should not be possible. The explanation is that the TP found optimal on stand-level was not available in the generated set of TPs simulated in the associated cell or segment.

While performing lower NPV than the DTU approach, the stand approach produced the highest area-to-perimeter ratios (Table 4). Compact treatment units should lead to less downtime and more efficient machine work and thus cheaper cuttings. In turn, this should decrease the NPV gap between stand solutions and DTU dittos. The possible effect of more compact treatment units on NPV is not quantified beyond EC and remains a source of error in this study. Other improvements to the study presented here are possible. While we focus on modelling EC, the cost calculations for harvests could be refined by considerations to road locations (instead, a template distance to road of 200 m was used here). Including distance to road may have a clustering effect on treatment units, see Pascual et al. (2018). Furthermore, in our study we did not have access to site index or age from remote sensing data. Thus, these parameters were estimated by matching spectral data to NFI plots, a method whose uncertainties remain unknown. The quality of the stand delineation provided by the forest company was also unknown and should be regarded as a source of error. Finally, despite our best efforts to compute the metrics for each dataset, there were differences in e.g. age and mean productivity in the initial data that may have affected the results (Table 1).

Although constraints were applied to reach specific harvest levels, the harvest volumes were lower in stand approach solutions, see Fig. 5. We can identify two possible explanations for this. First, Table 1 describes the estimation of initial state of stands and segments. This routine, combined with the differences in initial state reveals that application of TPs found on stand-level on the associated cells or segments, may result in harvest volume discrepancies. Second, the decision variable in the LP Model 1 was rounded to a binary number since assignment of TP for the associated cells or segments must be un-ambiguous. This entails deviations from the harvest target set by the corresponding DTU solution.

Pascual et al. (2019) reasoned that using segments rather than cells represents a clustering prior to optimization. This is what practitioners do in the stand approach – stands are delineated such that they may realistically be managed without further spatial regard. Tactics aimed at reducing complexity are practiced in forest planning, where problems may be large and complex (Bettinger et al. 2016; Borges et al. 2014; Duvemo et al. 2014; Eyvindson et al. 2018; Kangas et al. 2015; Nilsson 2013; Ulvdal et al. 2022). To mitigate complexity in DTU planning problems, it may be advisable to use a lower spatial resolution in the long-term forest planning and introduce high-resolution data in the tactical planning stage. Here, we solved a spatial, long-term planning problem with high-resolution cells which proved costly in terms of time for solving the problem (the DTU model requiring days to finish, nota bene the code was not optimized for fast execution). Information on individual trees provide a potential for even higher spatial resolution then the cell approach and forest planning research on this topic is already ongoing (Packalen et al. 2020; Pascual and Guerra-Hernández 2022; Vauhkonen and Pukkala 2016). Hence, such an increased complexity adds, among others, to the relevance of segmentation models (Olofsson and Holmgren 2014; Pascual and Tóth 2022; Pukkala 2019a, b).

In this study we used CA for solving the planning problem in the DTU approach. Even if there are other methods capable of solving these types of combinatorial problems (Bettinger et al. 2002) CA appeared to be the most expedient choice this time, considering the combined effort of implementing the algorithm and running the problem. The CA model presented in Wilhelmsson et al. (2022) was applied here in a synchronous mode. Specifically, it is the mapping of DTU that is synchronous in the present study. Computing harvested volumes in each period, on its' part, is non-spatial and computationally cheap and was therefore performed after each cell or segment was processed. Still, the important information of DTU area may be outdated but is still acted upon when a DU changes TP. Thus, after the first cell state change in an iteration, the information about the system is somewhat outdated but is still acted upon for the rest of the iteration. This makes the computational cost decrease, with the drawback that oscillatory behavior may occur where the system does not reach a stable state (Mathey et al. 2007). Heinonen and Pukkala (2007) studied both synchronous and asynchronous modes of CA in DTU planning in the same paper and found no significant differences in the goal achievement performance between the two modes.

Finally, the approach for delineation of individual DTU is in our study is based on the concept of neighborhood distance. Like Heinonen et al. (2018), we reason that it is realistic to allow harvest machines to move short distances and resume cutting. However, our modelling resulted in sparse DTU for some combinations of data and neighborhood distance (see cell solution with 49 m neighborhood distance in Fig. 6). Consistent with previous research (Pascual et al. 2019), our results indicated that cell-based planning had less clustered DTU (lower A:P ratio, Table 4) than segments and stands. Combining direct entry costs with use of spatial

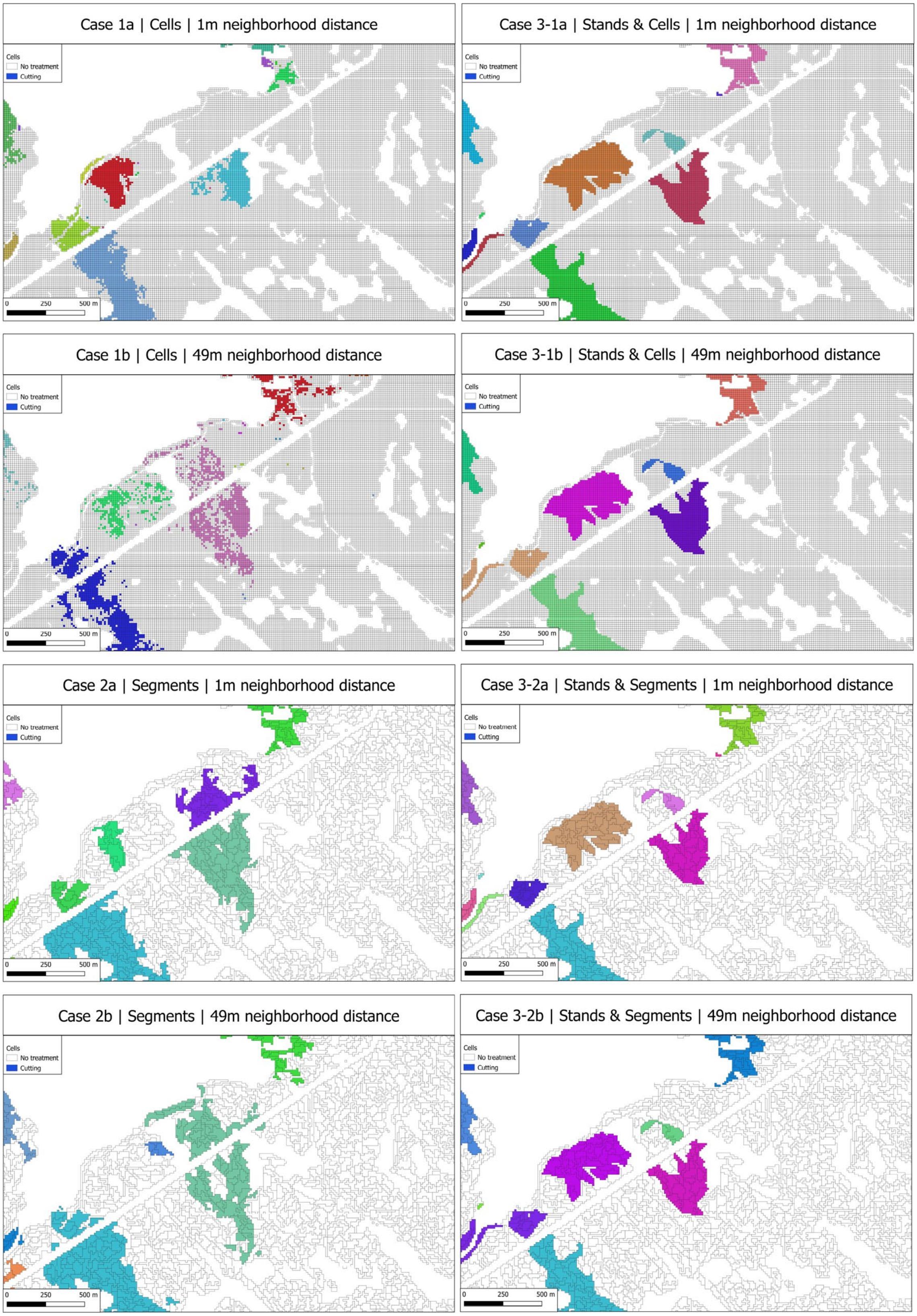

Fig. 6 Maps showing the treatment units (distinct colors mark distinct treatment units) in period two in a subarea of the forest analyzed. DTU approach plans to the left and stand approach plans to the right (a and b indicate 1 m and 49 m neighborhood distances, respectively)

criteria such as common border length (e.g. Packalen et al. 2011; Pascual et al. 2019, 2018; Pukkala et al. 2009) may therefore be desirable to drive compactness of DTU. Moreover, it should be recognized that reducing the spatial size of the planning units generally increase the uncertainty of the data. This is a prominent feature for data inferred from remote sensing-based raster maps, where means inferred from a small number of raster cells show larger errors than means from a large number of cells (Nilsson et al. 2017). Uncertain data can lead the optimization model to identify solutions that are not truly optimal under real-world conditions. The effects of data uncertainty were, however, outside of the scope of this study.

Conclusions

The results in this study suggest that DTU planning facilitates more efficient use of the forest resource in an economical setting compared to traditional stand-based planning. The stand-based plans produced larger and more compact treatment units. However, applying DTU planning and achieving a more fine-tuned allocation of harvest activities in time and space reduced IL and EC and DTU plans outperformed its' stand-based counterparts in terms of NPV. The delineation of treatment unit is based on a maximum distance between subareas of treatment units. Combined with use of data with very high spatial resolution, this may result in sparse treatment units and long solution times. Therefore, use of spatial variables such as common border in combination with direct entry costs may result in more realistic treatment units. Using segments also resulted in more compact treatment units and reduced solution times with orders of magnitude compared to cells. Thus, the study suggests that using segments may reduce solution times greatly while still providing the benefits of DTU planning.

Author 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.

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Data availability The data can be provided on request to the author PW

Declarations

Competing interests The authors declare no competing interests.

References

Ågren AM, Larson J, Paul SS, Laudon H, Lidberg W (2021) Use of multiple LIDAR-derived digital terrain indices and machine learning for high-resolution national-scale soil moisture mapping of the Swedish forest landscape. Geoderma 404:115280. https://doi.org/10.1016/j.geoderma.2021.115280

Augustynczik ALD, Arce JE, Yousefpour R, Lindbeck da Silva AC (2016) Promoting harvesting stands connectivity and its economic implications in Brazilian forest plantations applying integer linear programming and simulated annealing. For Policy Econ 73:120–129. https://doi.org/10.1016/j.forpol.2016.09.007

Bettinger P, Boston K (2017) Forest planning heuristics. Current recommendations and research opportunities for s-metaheuristics. Forests 8(12):476. https://doi.org/10.3390/f8120476

Bettinger P, Graetz D, Boston K, Sessions J, Chung W (2002) Eight heuristic planning techniques applied to three increasingly difficult wildlife planning problems. Silva Fenn 36(2):545. https://doi.org/10.14214/sf.545

Bettinger P, Boston K, Siry JP, Grebner DL (2016) Forest management and planning. Academic, London

Borges JG, Nordström E-M, Garcia Gonzalo J, Hujala T, Trasobares A (2014) Computer-based tools for supporting forest management. Report of Cost Action FP 0804 Forest management Decision Support Systems (FORSYS). Umeå. https://res.slu.se/id/publ/60316

Borges P, Kangas A, Bergseng E (2017) Optimal harvest cluster size with increasing opening costs for harvest sites. For Policy Econ 75:49–57. https://doi.org/10.1016/j.forpol.2016.11.012

Breidenbach J, Granhus A, Hylen G, Eriksen R, Astrup R (2020) A century of National Forest Inventory in Norway. Informing past, present, and future decisions. For Ecosyst 7:46. https://doi.org/10.1186/s40663-020-00261-0

Constantino M, Martins I, Borges JG (2008) A new mixed-integer programming model for harvest scheduling subject to maximum area restrictions. Oper Res 56(3):542–551. https://doi.org/10.1287/opre.1070.0472

de Miguel Magaña S, Pukkala T, Pasalodos Tato J (2013) Dynamic treatment units. Flexible and adaptive forest management planning by combining spatial optimization methods and LIDAR. Sociedad Española De Ciencias Forestales 37:43–48. https://doi.org/10.31167/csef.v0i37.10282

Dueck G, Scheuer T (1990) Threshold accepting: a general purpose optimization algorithm appearing superior to simulated annealing. J Comput Phys 90(1):161–175. https://doi.org/10.1016/0021-9991(90)90201-B

Duvemo K, Lämås T, Eriksson LO, Wikström P (2014) Introducing cost-plus-loss analysis into a hierarchical forestry planning environment. Ann Oper Res 219:415–431. https://doi.org/10.1007/s10479-012-1139-9

Eyvindson K, Rasinmäki J, Kangas A (2018) Evaluating a hierarchical approach to landscape-level harvest scheduling. Can J for Res 48(2):208–215. https://doi.org/10.1139/cjfr-2017-0298

Heinonen T, Pukkala T (2007) The use of cellular automaton approach in forest planning. J Res 37(11):2188–2200. https://doi.org/10.1139/X07-073

Heinonen T, Kurttila M, Pukkala T (2007) Possibilities to aggregate raster cells through spatial optimization in forest planning. Silva Fenn 41(1):474. https://doi.org/10.14214/sf.474

Heinonen T, Mäkinen A, Rasinmäki J, Pukkala T (2018) Aggregating microsegments into harvest blocks by using spatial optimization and proximity objectives. Can J for Res 48(10):1184–1193. https://doi.org/10.1139/cjfr-2018-0053

Holmgren P, Thuresson T (1997) Applying objectively estimated and spatially continuous forest parameters in tactical planning to obtain dynamic, treatment units. For Sci 43(3):317–326. https://doi.org/10.1093/forestscience/43.3.317

Johnson KN, Scheurman HL (1977) Techniques for prescribing optimal timber harvest and investment under different objectives. Discussion and synthesis. For Sci 23(Suppl 1). https://doi.org/10.1093/forestscience/23.s1.a0001.

Kangas A, Eyvindson K, Hujala T, Kangas J, Kurttila M (2015) Decision support for forest management. Managing forest ecosystems. Springer International Publishing, London. https://doi.org/10.1007/978-3-319-23522-6

Kašpar J, Marušák R, Bettinger P (2016) Time efficiency of selected types of adjacency constraints in solving unit restriction models. Forests 7(5):102. https://doi.org/10.3390/f7050102

Kotivuori E, Korhonen L, Packalen P (2016) Nationwide airborne laser scanning based models for volume, biomass and dominant height in Finland. Silva Fenn 50(4):1567. https://doi.org/10.14214/sf.1567

Lämås T, Sängstuvall L, Öhman K, Lundström J, Årevall J, Holmström H, Nilsson L, Nordström E-M, Wikberg P-E, Wikström P, Eggers J (2023) The multi-faceted Swedish Heureka forest decision support system. Context, functionality, design, and 10 years experiences of its use. Front Global Change 6:1163105. https://doi.org/10.3389/ffgc.2023.1163105

Lu F, Eriksson LO (2000) Formation of harvest units with genetic algorithms. For Ecol Manag 130(1–3):57–67. https://doi.org/10.1016/S0378-1127(99)00185-1

Martins I, Ye M, Constantino M, da Conceição Fonseca M, Cadima J (2014) Modeling target volume flows in forest harvest scheduling subject to maximum area restrictions. TOP 22:343–362. https://doi.org/10.1007/s11750-012-0260-x

Mathey A-H, Krcmar E, Vertinsky I (2005) Re-evaluating our approach to forest management planning: a complex journey. Forestry Chron 81(3):359–364. https://doi.org/10.5558/tfc81359-3

Mathey A-H, Krcmar E, Tait D, Vertinsky I, Innes J (2007) Forest planning using co-evolutionary cellular automata. For Ecol Manag 239(1–3):45–56. https://doi.org/10.1016/j.foreco.2006.11.007

McDill ME, Braze J (2001) Using the branch and bound algorithm to solve forest planning problems with adjacency constraints. Sci 47(3):403–418. https://doi.org/10.1093/forestscience/47.3.403

Nilsson M (2013) Knowledge in the forest planning process. Diss. Swedish University of Agricultural Sciences. Acta Universitatis Agriculturae Sueciae 2013:31. https://res.slu.se/id/publ/40499

Nilsson M, Nordkvist K, Jonzén J, Lindgren N, Axensten P, Wallerman J, Egberth M, Larsson S, Nilsson L, Eriksson J, Olsson H (2017) A nationwide forest attribute map of Sweden predicted using airborne laser scanning data and field data from the National Forest Inventory. https://doi.org/10.1016/j.rse.2016.10.022

Öhman K, Eriksson L (2010) Aggregating harvest activities in long term forest planning by minimizing harvest area perimeters. Silva Fenn 44(1):457. https://doi.org/10.14214/sf.457

Olofsson K, Holmgren J (2014) Forest stand delineation from lidar point-clouds using local maxima of the crown height model and region merging of the corresponding voronoi cells. Remote Sens Lett 5(3):268–276. https://doi.org/10.1080/2150704X.2014.900203

Packalen P, Heinonen T, Pukkala T, Vauhkonen J, Maltamo M (2011) Dynamic treatment units in eucalyptus plantation. Sci 57(5):416–426. https://doi.org/10.1093/forestscience/57.5.416

Packalen P, Pukkala T, Pascual A (2020) Combining spatial and economic criteria in tree-level harvest planning. Ecosys 7:18. https://doi.org/10.1186/s40663-020-00234-3

Pascual A, Guerra-Hernández J (2022) Spatial connectivity in tree-level decision-support models using mathematical optimization and individual tree mapping. For Policy Econ 139:102732. https://doi.org/10.1016/j.forpol.2022.102732

Pascual A, Tóth SF (2022) Using mixed integer programming and airborne laser scanning to generate forest management units. J Res 33:217–226. https://doi.org/10.1007/s11676-021-01348-2

Pascual A, Pukkala T, De-Miguel S, Pesonen A, Packalen P (2018) Influence of timber harvesting costs on the layout of cuttings and economic return in forest planning based on dynamic treatment units. Syst 27(1):e001. https://doi.org/10.5424/fs/2018271-11897

Pascual A, Pukkala T, De-Miguel S, Pesonen A, Packalen P (2019) Influence of size and shape of forest inventory units on the layout of harvest blocks in numerical forest planning. Eur J Res 138:111–123. https://doi.org/10.1007/s10342-018-1157-5

Persson M, Trubins R, Eriksson LO, Bergh J, Sonesson J, Holmström E (2022) Precision thinning. A comparison of optimal stand-level and pixel-level thinning. Scand J Res 37(2):99–108. https://doi.org/10.1080/02827581.2022.2044902

Pukkala T (2019a) Optimized cellular automaton for stand delineation. J Res 30:107–119. https://doi.org/10.1007/s11676-018-0803-6

Pukkala T (2019b) Using ALS raster data in forest planning. J Res 30:1581–1593. https://doi.org/10.1007/s11676-019-00937-6

Pukkala T, Heinonen T, Kurttila M (2009) An application of a reduced cost approach to spatial forest planning. Sci 55(1):13–22. https://doi.org/10.1093/forestscience/55.1.13

Pukkala T, Packalén P, Heinonen T (2014) Dynamic treatment units in forest management planning. In: Borges JG, Diaz-Balteiro L, McDill ME, Rodriguez LCE (eds) The management of Industrial Forest plantations. Springer Netherlands, Dordrecht, pp 373–392. https://doi.org/10.1007/978-94-017-8899-1_12

SFA (2022) Skogsstyrelsen karttjänster. https://www.skogsstyrelsen.se/sjalvservice/karttjanster/geodatatjanster/oppna-data/ Accessed 23 Sept. 2022

SLU (2022) SLU Forest Map. Department of Forest Resource Management, Swedish University of Agricultural Sciences. https://www.slu.se/en/Collaborative-Centres-and-Projects/the-swedish-national-forest-inventory/foreststatistics/slu-forest-map/about-slu-forest-map/ Accessed 22 Dec. 2018

Strange N, Meilby H, Thorsen BJ (2002) Optimization of land use in afforestation areas using evolutionary self-organization. Sci 48(3):543–555. https://doi.org/10.1093/forestscience/48.3.543

Ulvdal P, Öhman K, Eriksson LO, Wästerlund DS, Lämås T (2022) Handling uncertainties in forest information: the hierarchical forest planning process and its use of information at large forest companies. Forestry 96(1):62–75. https://doi.org/10.1093/forestry/cpac028

Vauhkonen J, Pukkala T (2016) Selecting the trees to be harvested based on the relative value growth of the remaining trees. Eur J Res 135:581–592. https://doi.org/10.1007/s10342-016-0956-9

Wallerman J, Axensten P, Egberth M, Janzén J, Sandström E, Fransson J, Nilsson M (2021) SLU Forest Map. Mapping Swedish forests since year 2000. In: 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, 11–16 July 2021, Brussels, Belgium https://doi.org/10.1109/IGARSS47720.2021.9554458

Waser LT, Ginzler C, Rehush N (2017) Wall-to-wall tree type mapping from countrywide airborne remote sensing surveys. Remote Sens 9:766. https://doi.org/10.3390/rs9080766

White J, Wulder M, Vastaranta M, Coops N, Pitt D, Woods M (2013) The utility of image-based point clouds for forest inventory: a comparison with airborne laser scanning. Forests 4(3):518–536. https://doi.org/10.3390/f4030518

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

Wilhelmsson P, Lämås T, Wallerman J, Eggers J, Öhman K (2022) Improving dynamic treatment unit forest planning with cellular automata heuristics. Eur J Res 141:887–900. https://doi.org/10.1007/s10342-022-01479-z