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Optimal harvest cluster size with increasing opening costs for harvest sites☆

Paulo Borges [a,*], Annika Kangas [a,b], Even Bergseng [a]

[a] Department of Ecology and Natural Resource Management, Norwegian University of Life Sciences, P.O. Box 5003, NO-1432 Aas, Norway
[b] Natural Resources Institute (Luke), Economy and Society Unit, P.O.BOX 68, FI-80101 Joensuu, Finland

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ABSTRACT

In strategic level planning, the harvest levels are often obtained by maximizing NPV of the forest area. The resulting harvests within each planning period are then typically scattered over the area. In practical forestry, clustering harvests is seen as important, but tools for planning harvest clustering applicable for practical level planning are largely missing. In previous studies, clustering harvests has been seen as an objective in itself rather than means to save costs. It has thus not been possible to define an optimal level for clustering in order to maximize the NPV. In this study, clustering is carried out by minimizing the total opening costs (TOCs) for harvest sites. TOC is defined as a fixed cost for one contiguous harvest cluster. It consists of e.g. transferring the machines to the harvest site, waiting time for the machinery and workers due to the transfer, delineation of the harvest site and administrative work required for each harvest site. Our results show that with small opening cost, it is optimal to follow the strategic level plan, while as the opening cost increases it is optimal to make larger and larger harvest clusters. The clustering also affects the treatments carried out: with high opening costs the harvests in some stands will be postponed for 10 years or more, or the treatment may change from the strategic level optimum.

1. Introduction

In strategic level planning, harvest levels are typically obtained by maximizing NPV of the forest area. The resulting harvests within each planning period are then most likely scattered over the forest area. In practical forestry, clustering of harvests is desirable. Although there are plenty of tools designed for clustering the harvests available, tools designed for the scale needed (for several hundred thousands of stands) are largely missing (Laamanen and Kangas, 2011; Kangas et al., 2014). The importance of such clustering may increase in the future, as many forest organizations start using laser-scanning based micro stands as management unit rather than traditional stands in their planning systems (Packalén et al., 2011).

Clustering harvesting activities in forest planning can be motivated by the potential savings in operational costs associated with the logistics of machinery needed to perform harvesting activities and administrative tasks related to opening a new harvesting site (Öhman and Eriksson, 2010). The costs of moving machinery may be high and it is therefore important to plan (at the tactical level) in which region of the forest area the machinery should be placed at any given time. On the other hand, clustering of harvests will introduce economic loss as the optimal timing of treatments from the strategic level plan are not followed and harvests are performed either too early or too late for the stands in question. The losses arising from not following the strategic level plan may be higher for stands with high site index than for the stands with poor site index. This will affect a forest level analysis of the profitability of clustering.

Finding the optimal number of clusters of harvest activities (harvest sites or openings) in a forest landscape must take into account the neighboring relationships among the forest stands. The idea is that each harvest site is a contiguous set of stands being the optimal number and the combined size of the clusters controlled by the cost of one harvest site. This neighborhood can be defined based on the vicinity of the stands. However, in a real-life problem it could be defined to account for the accessibility of the stands: the stands accessible from a given forest road are neighbors even if they have no common border, but stands that have a common border but are not accessible from the same forest road should not be defined as neighbors. The problem becomes challenging since the potential number of clusters that can be formed over the forest landscape could be extremely large (see e.g. Borges et al., 2015; Goycoolea et al., 2009; McDill et al., 2002), and especially so if the a maximum size (area) of a harvest site is not specified.

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* Corresponding author.
E-mail address: paulo.borges@nmbu.no (P. Borges).

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Most of the studies carried out so far have applied heuristic algorithms. The harvest clustering problems have been solved by introducing spatial goals into the optimization problem, for instance by maximizing the proportion of boundaries between cells harvested at the same time or minimizing the perimeter of contiguous harvest areas (e.g. Heinonen et al., 2007; Lu and Eriksson, 2000; Öhman and Lämås, 2003; Öhman and Eriksson, 2010; Pukkala et al., 2009).

Moreover, the applications typically deal with fairly small areas, especially the applications of exact optimization methods. With heuristic methods, especially methods such as decentralized cellular automation method (Pukkala et al., 2009), larger areas have been dealt with. Even larger areas can be dealt with using the hierarchic planning approach (Kangas et al., 2014). However, the performance of computers and optimization algorithms is increasing all the time and therefore possibilities of using exact methods for such complicated problems will improve in the future.

In most studies carried out so far, clustering harvest activities has been an objective in the problem (see e.g. Öhman and Eriksson, 2010), and giving more weight to clustering will increase the size of openings in the forest. Assuming the plan without the clustering goals or constraints is economically optimal, increasing the weight of harvest clustering (either as a goal or as a constraint) will result in larger economic losses due to diminished value growth. The weights are based on the idea that the clustering is an important goal (e.g. environmental goal) rather than a mean to reduce costs. Therefore, an analysis showing what would be the optimal level of clusters is still missing. Such an analysis requires that both the gains and losses due to clustering can be calculated in monetary terms.

The aim of this research is to focus on how the cost of opening new harvesting sites affects the clustering of harvesting activities. The opening cost (OC) is defined as a fixed cost for one contiguous harvest cluster. It reflects the costs of transferring forest machines to the harvest site, the delineation of the harvest site and administrative work required for each harvest site and other costs possibly related to the opening. We solve the problem using a branch-and cut algorithm method (see e.g. Martins et al., 2004). We analyze how the opening costs affect the number of openings and the average size of opening area, net present value of the forest (NPV) and also the effect of clustering on the actual optimal treatment for stands. We will also analyze the effect of forest structure on the profitability of clustering. The research is based on hypothetic forest data.

2. Material and methods

2.1. Experimental design

To provide data for the analysis, we constructed three artificial forest landscapes, more specifically three forest structures referred to as young (the age distribution weighted towards young stands), even (uniform age distribution) and old (the age distribution weighted towards old stands) due to the age structure of the forest. We apply three realizations of each forest type, nine forests in total (from now called data sets). Each data set consists of 400 stands distributed over a grid of 20 × 20 cells. The area of each cell equals one ha. The data sets were generated based on 8990 sample plots from the Norwegian national forest inventory (NFI). Sample plots were chosen with respect to productivity, stocking density and stand age in order to represent a wide range of forest conditions in Norway. The grid configuration and the area assigned to each cell prevent effects of MU size and number of neighbors per MU on the results. The neighborhood considered between the MUs was such that if any two MUs share a border or a single point they are consider as neighbors. This definition of neighborhood was selected, as the stands are simulated, but the neighborhood can be defined according to the needs of the problem at hand.

For each NFI plot a set of treatment schedules were simulated by the growth simulator GAYA (Gobakken, 2003; Hoen and Eid, 1990). The simulator takes as input a set of MUs (plots) and a set of rules which define how and when forest treatments may be applied. The output provides detailed information on common forest state variables (e.g. standing volume) as well as treatments (e.g. harvested volumes) and corresponding economic values (incomes and costs) for all periods in each treatment schedule. In addition, the NPV based on an infinite planning horizon, i.e. after the initial simulation period, is provided for each treatment schedule by adding the value of the ending inventory. This is calculated by projecting forest growth for the ending inventory according to preset forest treatment rules and then calculating the net present value of the projected growth. The preset forest treatment rules are based on a series of simulations and optimizations to be near optimal. The value of the ending inventory is thus not optimized in the same manner as for the treatment in the analysis period itself.

In this study the following treatments were allowed; natural regeneration and planting, pre-commercial thinning, conventional thinning and final harvest. This means that not only final harvests contribute to the volume harvested in a period but also conventional thinnings. Simulations were performed for 12 5-year periods. A 3% discount rate was applied. The number of treatment schedules for each data set is shown in Table 1.

2.2. The strategic model

The strategic model maximizes NPV. Only one treatment schedule was allowed within an MU. This model also account for a sequential flow of the harvested volume over the entire time horizon with a maximum variation between consecutive planning periods. Thus, the mathematical formulation was as follows:

$$\text{Max} \quad \text{NPV} \tag{1}$$

Subject to

$$\sum_{k \in TS_i} y_{ik} = 1, \forall i \in N \tag{2}$$

$$\sum_{i \in N} \sum_{k \in TS_i} A_i npv_{ik} y_{ik} - \text{NPV} = 0 \tag{3}$$

$$\sum_{i \in N} \sum_{k \in TS_i} hv_{ikt} y_{ik} - HV_t = 0, \forall t \in T \tag{4}$$

$$(1-\alpha) HV_t \leq HV_{t+1}, \forall t \in T\ \{|T|\} \tag{5}$$

$$(1+\alpha) HV_t \geq HV_{t+1}, \forall t \in T\ \{|T|\} \tag{6}$$

$$y_{ik} \in \{0,1\}, \forall i \in N, \forall k \in TS_i \tag{7}$$

$$\text{NPV} \geq 0 \ \text{ and } \ HV_t \geq 0, \forall t \in T \tag{8}$$

where, N is the set of MUs, T is the set of planning periods, TS_i is the set of treatment schedules of MU$_i$. The A_i is the productive area of MU$_i$, npv_{ik} is the NPV associated with MU$_i$ when treated by treatment schedule k, vh_{ikt} is harvest volume in planning period t when treatment schedule k is applied in MU$_i$. The HV_t is the total harvest volume in planning period t.

Table 1
Number of treatment schedules for each data set within a forest structure.

No. treatment schedules			
Dataset	Forest structures		
	Young	Even	Old
F1	13,795	16,334	17,439
F2	15,903	15,555	16,259
F3	14,056	16,191	18,214