Multi-objective forest planning at tree-level combining mixed integer programming and airborne laser scanning

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ABSTRACT

The development of forest planning at tree-level is nowadays feasible due to the advances in laser scanning. Tree-level data remains still not fully utilized in the context of tree selection mechanisms and harvest-scheduling models. Using spatial optimization with tree-level data can shift the situation. The research presented a decision-support model set based on mixed integer programming (MIP) to select trees based on economical and spatial goals. Trees were represented as polygons to conduct spatial optimization and account for perimeter boundary minimization while establishing adjacency constraints. The proposed model framework method was tested in a Stone pine (Pinus pinea L.) stand of almost 4400 trees in Spain where individual tree detection with airborne laser scanning data was conducted. The MIP-based tree selections were presented using different priorities for single and multi-objective optimizations to demonstrate the potential of spatial goals to make forest management planning more efficient when controlling the spatial arrangement of solutions. The results showed the general MIP formulation is feasible and all presented combinatorial problems reached global optimality fast. The use of MIP formulations to schedule tree-level decisions has positive cascading effects towards operational forest planning while expanding the current frontiers of tree-level forest planning based on heuristic optimization.

1. Introduction

Forest inventories employing Airborne Laser Scanning (ALS) data have become common in many countries (Maltamo et al., 2014; Næsset et al., 2004; Wehr and Lohr, 1999; White et al., 2016). The ALS-based forest inventory methods are typically categorized into two groups: the area-based approach (ABA) (Næsset, 2002) and individual tree detection (ITD) (Hyvypää et al., 2001; Koch et al., 2006). The implementation of tree-level forest inventory is not as consolidated as area-based implementations (Maltamo et al., 2014), but ITD methods are gaining relevance supported by sophisticated ALS-based scanning platforms (Duncanson et al., 2014; Seifert et al., 2010; Vauhkonen et al., 2012). The effectiveness of the ITD is reinforced in sparse forest ecosystems in which the presence of multi-layered forest structures does not restrict the capability of the lasers to detect dominant trees and segment large tree canopies (Kukunda et al., 2018; Pascual, 2019). Standard tree detection methods perform well at describing dominant tree canopies despite using low-density point clouds (Hyvypää et al., 2001; Koch et al., 2006). The estimation of tree attributes and their precise spatial locations using lasers represent a relevant stream of data from which to continuously support forest management planning and silvicultural operations (Bettinger and Tang, 2015; Vauhkonen, 2020).

Tree selection models have been developed using ground data before contemporary ALS-based forest inventory methods became available (e.g., Seifert et al., 2010). The question of which trees to cut has always remained as an important question for a forester (Pukkala et al., 2015). The drivers of the tree selection methods can recognize species composition (Bettinger and Tang, 2015), the financial maturity of the harvests (Vauhkonen and Pukkala, 2016), stem quality attributes (Knoke et al., 2006) or adjacencies between trees (Wing et al., 2019; Packalen et al., 2020). The latter represented a recent shift in the perspective of tree-level forest planning as it pioneered on the recognition of the spatial distribution of the standing trees but also of the harvested trees. Controlling the spatial location of harvested trees is a
timely and important combinatorial problem aligned with the increasing importance of diversity and ecological indexes to characterize forest ecosystems (Nishikawa, 1996; Pomerening, 2006; Hui et al., 2011). Guide curve methods and discounting have traditionally driven the financial analyses used as criteria for harvesting trees and stands (Davis and Johnson, 1987). However, tree selection models based on financial drivers can turn into multi-objective solutions when spatial and ecological variables join the financial principles as part of decision-making models. Consequently, decisions (treatments) could simultaneously respond to maximize revenues while integrating ecosystem services or spatial patterns such as fire spread risk (Palma et al., 2007). For instance, proximity between tree canopies at different stage of development can favor fire propagation from the undergrowth and regeneration layer (ground fires) up to forest canopies. Treatments could be used to simultaneously reduce fire risk while obtaining revenues from forests (Wei, 2012). The wall-to-wall tree-level data derived from laser data can support tree selection strategies by making spatial variables available and so spatial optimization methods (Pascual, 2018).

To undertake and implement forest management decisions in such detailed spatial scales increases the combinatorial possibilities (Pukkala et al., 2009). In forest optimization, complex combinatorial problems represent a dilemma as they can be numerically solved under heuristics algorithms such as cellular automata (Pukkala et al., 2009) or by using exact optimization methods such as linear programming (LP) or mixed integer programming (MIP) when feasible (Weintraub and Murray, 2006). Heuristic search is advised when the number of decision variables is very large that can turn spatial problems into overwhelming sizes for the feasible region (Mathey et al., 2007). Heuristic search is fast and effective at finding solutions even when dealing with thousands of low-scale forest units (Pukkala et al., 2009). However, the proximity of the solutions to the global optimum and the need of parametrization are always a source of uncertainty when evaluating the goodness of the solutions achieved with heuristics compared to exact methods (Jin et al., 2016). The search of best bounds in spatial forest problems with MIP optimization is not always feasible. The number of decision variables and the non-linearity of the problem are properties to consider before using an MIP approach under global optimality. The use of lazy constraints and linearization procedures can reduce problem complexity in such a way that global optimal solutions become realistic despite using large pools of decision variables (Tóth et al., 2012). Arguably, the preference for heuristics might result inefficient compared to exact MIP solutions. The scale of tree-level applications can help to overcome the restrictions on the number of decision variables while paving the way to develop tree selection formulations based on MIP optimization in tree-level forest planning. To date, the use of exact optimization methods in tree-level forest planning remains unexplored. The aim of the study is to present a set of tree selection models considering four single-objective optimizations and three multi-objective examples. The models show the shift from single- to multi-objective optimization while integrating spatial and economic goals derived from tree-level inventory data and growth models. All problems are framed under MIP optimization, which is a novelty in tree-selection methods compared to existing solutions based on heuristic algorithms.

2. Material and methods

2.1. Training area

The study area is the public forest #50 owned by the municipality of Portillo (province of Valladolid) and managed by the Forest Service of Castilla y León (Spain). The training area is patch of a large forest ecosystem (Calama and Montero, 2004) composed on monospecific stands of Stone pine trees (Pinus pinea L.). There are stands in all stages of development and tree spacing varies with the site and the management history. The Stone pine forests are managed under a multi-objective approach in which timber and nut production are the two main drivers of forest management decisions. The occurrence of severe forest fires in the region is scarce and forest fires can be easily controlled since the terrain is relatively flat. Guidelines on fire risk control in the region target undergrowth and biomass accumulation control at the forest edges near to transited paths and entry points to the area. The training area is a representative case of Mediterranean pine forests on which to reinforce the use of cuttings to create more fire-resistant forest ecosystems.

2.2. Forest inventory at tree level

Laser surveys from the National Program of Aerial Orthophotography of Spain were used to conduct individual tree detection (ITD). Digital terrain maps (DTM) and canopy height models (CHM) were derived to calculate the above-ground elevation of ALS pulses. As a guide for the reader, the author recommends the papers from Wehr and Lohr (1999) to understand the principles of ALS and the interpretation 3D point clouds under a forestry perspective. The CHM was used to detect tree top locations and heights (seeds) to be used in the delineation of tree canopies using a CHM-dependent region-growing method as explained in Packalen et al. (2020). The training area was reduced to a 42.3-ha forest patch on which tree spacing was larger (more space between trees as shown in Fig. 1) so the site-specific effectiveness of ITD is outstanding (i.e., more than 95% of measured trees were detected with ITD) as documented in previous studies in the region (Pascual, 2019; Blázquez-Casado et al., 2019). Tree measurements (3 4 4) collected across public forest #50 on diameter at breast height (DBH) and height were used to estimate and predict DBH for all tree heights detected across the forest patch. The measured ground positions and tree heights were associated to the detected positions from ALS data considering a 3-m threshold in the 3D Euclidean space (Vauhkonen et al., 2012). The forest inventory dataset comprised tree coordinates (eastings and northings), detected tree height (m), detected canopy size ($m^2$) and the predicted DBH (cm) for all 4,305 trees identified in the 42.3 ha of the forest patch.

2.3. Growth and yield modeling to calculate value increment

Growth models on stone pine forests in Spain from Calama and Montero (2004, 2005) were used to compute site index and to predict height and DBH growth over the next 5 years. The valuation of each tree in economic terms was conducted at present state and after 5 years after predicting growth keeping timber assortments and prices constant in the assessment. The valuation of trees was based on the models presented by Pasalodos-Tato et al. (2016) for the species in the region, which scaled tree value based on DBH and tree height attributes without acknowledging the effect of stem quality variables on assortment prices. As a result, the relative value increment (RVI, €/m$^3$) was calculated for all trees (Davis and Johnson, 1987; Pukkala et al., 2015). From the financial accounting viewpoint, the cost of felling trees whose RVI is high is financially detrimental considering potential revenues in the following periods while risking future forest management actions in case revenues converged towards profitability minimums. The driving mechanism and logic of tree selection under financial optics are to promote the removal of trees whose RVI tends to zero and to preserve those trees about to reach the jump in price (i.e., tree value increases when reaching the minimum DBH requirements of the next assortment). The distribution of DBH estimates at present state provides insights on the proportion of trees likely to increase their value. The exercise applies for the case due to the expected slow growth of Stone pines over the 5-year interval used to calculate RVI (Calama and Montero, 2004).

2.4. Tree-level polygons to conduct spatial optimization

The geospatial attributes of the tree-level forest inventory included polygons (tree canopies) whose centre point provided the casting and...
northing of each tree. The information is not wall-to-wall yet as there are gaps between canopies. Adjacencies and spatial goals cannot be formulated in the present format. As a result, and as presented in Packalen et al. (2020), trees were conceptualized as polygons (regions) representing a single tree. Tree regions were the result of implementing a DBH-weighted voronoi tessellation accounting for the effect of tree

![Forest Ecology and Management](https://example.com/forest-ecology-and-management.png)

**Fig. 1.** General overview of the training area (Forest #50, a) and the forest patch used to list tree-level data. The latter is presented using the orthophotograph in the background (b) and the canopy height model (CHM) derived with ALS data (c).

![Forest Ecology and Management](https://example.com/forest-ecology-and-management.png)

**Fig. 2.** Display of tree regions showing the canopy height model (CHM) derived from ALS (a) and adding the detected tree heights (b). As a showcase, the tree values for detected trees (4,305) are presented using the derived tree regions across the Stone pine forest patch (c).
size (i.e., predicted DBH) and tree spacing when delineating the size of the regions. The edge between two adjacent trees was closer to the smallest tree DBH estimate (Fig. 2). The largest area and longest perimeter for a tree region computed in the training dataset were 938 m² and 123 m, respectively. The approach of considering trees as if they were segmented allowed the computation of adjacencies and polygon neighboring relationships, which are needed to propose spatially-explicit and multi-objective solutions (Weintraub and Murray, 2006).

The formulation of a spatial problem requires from adjacency relationships, the relative position of all calculation units, and both their size and perimeter (Weintraub and Murray, 2006). The pairwise adjacencies were calculated considering two cells are adjacent when sharing an edge. The number of pairwise adjacencies was 12,848. The maximum value of the shared border between two regions was 26 m. The set of adjacencies formed the basis of the presented MIP optimization model parametrized to harvest trees considering financial drivers and new spatial objectives to be addressed in the next generation of tree selection optimization models.

2.5. Spatial objectives on canopy connectivity and safety during firefighting

The suppression of forest fires benefits from the facilitation of firefighting conditions using proper safety zones across landscapes. As Butler (2014) showed, the link between forest structure and safety conditions during firefighting operations is close as expressed with the Safe Separation Distance Score (SSDS), which an estimation of the optimality of the forest during firefighting operations depending on tree height and site conditions. The SSDS as presented in Butler (2014) can be derived from tree level data as follows:

\[
SSDS = 8 \times H_{tree} \times \Delta,
\]  

(1)

where \(H_{tree}\) is tree height and \(\Delta\) is the slope-wind correction factor. The general recommendations on the use of the SSDS in Campbell et al. (2017) suggest setting the value of 1.5 for the latter as the training area is very flat with low-speed winds. The mean value of SSDS was 121.5, ranging from 17.7 to 197.8. The selection of trees during cuttings can target tree regions with low SSDS as a mechanism to create a more safety forest environment for firefighters. The segmented canopies and adjacencies can describe the multi-layered relationships or pairwise relationships. From the fire risk perspective, it is relevant to avoid ground fires to reach canopies so tree selection can focus on selecting young trees for which the sum of height differences between a given tree and the set of adjacencies for the given tree is low and minimizes the risk of the fire spreading up. From a fire connectivity perspective, the size and height gap between adjacent trees can be used to promote the selection of trees with large canopies and surrounded (tree grouping) by trees at the same stage of development. As a result, tree selection could break the continuity among the tree canopies resulting in worse conditions for bottom-up canopy fire spread. The average height gap between adjacent trees was 1.75 m.

2.6. Problem conceptualization

To specify the spatial MIP optimization model that drives the selection of trees, let \(T\) denote the set of trees (i) detected with ALS. The set \(E\) is defined as the pairwise list of adjacent relationships between all \(i \in T\). According to the objective of the MIP model, the model decides whether a given tree \(i\) is cut or not. Let the 0–1 binary variable \(x_i\) represent the decision variable. If it should, \(x_i = 1\); otherwise it is 0. To account for timber-flow constraints, we allow fluctuation on the cuttings \(V_c\) in the range of 20–25% of the initial standing merchantable volume \(V\) (Equation 2). The selection of trees was implemented by means of four objectives: i) perimeter boundary minimization (SO-1), ii) relative value increment (SO-2) and when minimizing iii) height gap (SO-3) and iv) the SSDS after cuts (SO-4).

• SO-1: Spatial optimization was conducted when aggregating cuttings based on perimeter \(p_i\), the array of adjacencies across the \(E\) set and the shared boundary \(b_{ij}\) between adjacent units \(i\) and \(j\) when both \(x_i\) and \(x_j\) are harvested. Equations 4 and 5 linearize the cross-product between the two binary variables using \(\epsilon_ij\) as auxiliary binary variable for linearization: \(\epsilon ij\) turns the value of 1 if both trees \(i\) and \(j\) are harvested.

• SO-2: The selection of trees responded to financial maturity of the cuttings by minimizing the relative value increment (RVI) of harvested trees \(x_i/1\) and leave standing those showing high potential for growing in value.

• SO-3: Cuttings were concentrated on pairwise tree relationships on which the height gap between adjacent trees is small to fragment the connectivity between canopies.

• SO-4: SSDS values were computed using \(h_i\) for all \(T\) set. The coefficients SSDSi were used to drive the selection \(x_i/1\) on trees presenting low values for SSDS.

2.7. Problem formulation

Sets

\[T = \text{tree set indexed by } i; E = \text{set of pairwise tree adjacencies trees indexed by } ij;\]

Decision variables:

\[x_i = \text{if tree } i \text{ is cut; 0 otherwise;}\]

Accounting variables:

\[a_i = \text{area of the polygon comprising tree } i; A = \text{sum of all } a_i \text{ in } T;\]

\[p_i = \text{perimeter of the polygon comprising tree } i; P = \text{sum of all } p_i \text{ in } T;\]

\[b_{ij} = \text{shared perimeter boundary between trees } i \text{ and } j \text{ as defined in } E;\]

\[T_c = \text{count of all trees cut; } V_c = \text{associated harvested volume for } T_c;\]

\[h_i = \text{height of tree } i;\]

\[\text{V_merc} = \text{merchantable volume of tree } i; V = \text{total growing stock volume in } T;\]

\[\text{RVI}_i = \text{relative value increment for tree } i;\]

\[\text{SSDS}_i = \text{Safe Separation Distance Score computed for tree } i;\]

Auxiliary variables for linearization:

\[\epsilon ij = 1 \text{ if } x_i = x_j = 1, 0 \text{ otherwise;}\]

Model:

The following single-objective problem formulations were proposed:

(SO-1) [perimeter boundary minimization]

\[\min \sum_i p_i + \sum_i p_j - \sum_{ij \in E} b_{ij} x_i x_j\]

(SO-2) [maximization of value after cutting]

\[\min \sum_i x_i V_c\]

(SO-3) [minimise the absolute height gap between harvested trees]

\[\min \sum_i |h_i x_i - h_j x_j|\]

(SO-4) [maximise the Safe Separation Distance Score of uncut trees]

\[\min \sum_i x_i \text{SSDS}_i\]
\[ \sum_{i \in T} v_i x_i = T_i; \]

\[ V_i \leq 0.25V; V_i \geq 0.20V; \]

\[ \sum_{i \in T} x_i \leq 1; \]

\[ (4) \text{ [perimeter accounting] where } x_i x_j \text{ is replaced by } \epsilon_{ij} \text{ for linearization} \]

\[ (5) \text{ [linearization of } x_i x_j \text{ ] } \forall i,j \in T, \]

\[ \epsilon_{ij} \leq x_i; \epsilon_{ij} \leq x_j \]

2.8. Combining single-objective optimizations in CPLEX

The MIP problems were solved in CPLEX optimization software (IBM ILOG CPLEX, 2020) in a computer-i5 44605 central processing unit, 2.90 GHz with 8 GB of random-access memory. The shift from single-objective optimizations to a multi-criteria approach was carried out in the 12.9 version of CPLEX, which eases the development of multi-objective problems accounting for priorities, weights and absolute and relative tolerances. The user can define multiple objectives for a single problem, and combine them as a hierarchy, through blending, or with combinations of both. With the priority hierarchy structure in CPLEX 12.9, the solutions when adding new objectives to the formulation can be controlled attending to degree of priority assigned to the objectives. The branch-and-bound algorithm first conform the feasible region for the most important objective and then it constrains the region by selecting the best bound for the next objective in priority without violating the previous feasibility. The results from the single-objective optimization SO 1–3 showed more than one feasible solution from which to built-up multi-objective problems. The effect of spatial optimization in SO-1 improves the efficiency of forest management but at the same time the financial perspective is certainly required. To ease the understanding of priorities, three models are presented using the symbol \( \sum \).

\[ \epsilon \]

\[ V \]

\[ c_{ij} \]

\[ T \]

\[ W \]

\[ x \]

\[ 0 \]

\[ 1 \]

\[ i,j \]

\[ SO-1 \]

\[ SO-2 \]

\[ SO-3 \]

\[ MO-1 \]

\[ MO-2 \]

\[ MO-3 \]

\[ W(2) \]

\[ W(3) \]

\[ W(0) \]

\[ SO-1 \]

\[ SO-2 \]

\[ SO-3 \]

2.9. Model assessment and tree selection outcomes

The completion of the optimizations was the first diagnosis to validate the new MIP formulation. The results were computed for SO 1–4 and MO 1–3 accounting for the listed variables including relative value increment or SSDS among the harvested and preserved trees. The effect of tree selection of forest biophysical attributes such as DBH, merchantable volume and tree height were assessed for the seven configurations of the MIP model. The financial assessment of the plans was based on RVI and the distribution of tree values in the inventory. The implications of spatial optimization were assessed in terms of the effective perimeter calculated as the sum of all tree region perimeters prescribed for cutting but subtracting the shared boundary length in case two adjacent regions are both to be harvested. The number of clusters (tree grouping) and their size was computed as follows: the shared boundary between two tree regions prescribed for cutting was dissolved to generate multi-parts harvest blocks. In the absence of connectivity between cuttings, the isolated tree regions to be harvested were considered as independent harvest blocks without imposing constraint on their minimum size. The spatial arrangement of the multi-part harvest blocks was displayed to benchmark their spatial location to the initial conditions of the forests and to illustrate the shift in detail when scaling and shifting priorities from MO-1 to MO-3 formulations. The research methodology is synthesized in Fig. 3.

3. Results

3.1. Optimization and tree biophysical attributes

The set of problems were all feasible and solved in less than 30 s considering a 0.01% gap in optimality. The scale of the problems reached 16,801 decision variables and 24,984 linear constraints for the more complex problems SO-1 and MO-1. The dynamic search in CPLEX MIP optimization was efficient based on the balance between current and best possible bounds. The progress of the runs were fast despite the progressively increase in the computational time when adding multiple hierarchy levels by means of the priority score: the optimization times for MO-1 (i.e., three levels) and MO-3 (i.e., one level) were 28.7 and 2.1 s, respectively. The results for the pairs i) MO-3 and MO-4, and ii) SO-1 and MO-1 are presented separately despite reaching the same values as later explained in the discussion.

The results of tree selection optimization were compared based on tree attributes. The distributions for DBH, tree height and tree merchantable volume were rather similar in the four SO optimizations (Table 1). The size of the trees and the driving force of the selection showed the expected differences. Large trees are preferred under for the financial perspective resulting in less tree cuts (SO-2). When accounting for spatial goals, the number of tree cuttings increased to maximise the shared boundary between tree polygons as presented in later sections. The size of the harvested trees was the smallest for problems SO 3–4. The results for the three multi-objective formulations showed how tree selection progressively increased the size of harvested trees when increasing the importance of financial goals in the hierarchical structure of the MIP model first, followed by the integration of SO-3 formulation focusing on minimizing the adjacent tree height differences.

3.2. Financial analyses and management revenues

The value for harvested trees under SO-2 formulation were the lowerst in terms of tree value and RVI (Fig. 4). The selection of trees under SO-1 increased the RVI of harvested trees by 22% while decreasing harvested tree value by 37.5%. The highest values were observed for SO 3–4 plans for which ignored economic goals when scheduling decisions on tree removals. The relative value increment of the remaining trees was rather constant in the 22–23 € tree\(^3\) range. The addition of financial goals from MO-1 to MO-2 pushed down the mean RVI in tree cuttings by 19%. The distribution of tree value was not affected under the multi-objective plans MO 1–3 while RVI remained in the 12–13 € tree\(^1\) interval for the three multi-objective plans.

3.3. Spatial goals and decision maps

The contribution of spatial goals as defined in SO-1 maximized the
Fig. 3. Research workflow of the presented tree-level optimization conducted from individual tree detection.

Table 1
Assessment of the seven MIP optimizations considering tree-level attributes for preserved and harvested trees, for which the number of cuttings and total harvested merchantable volume is presented.

<table>
<thead>
<tr>
<th>MIP problem</th>
<th>DBH (cm)</th>
<th>Tree height (m)</th>
<th>Tree merchantable volume (m$^3$ tree$^{-1}$)</th>
<th>$V_c$ (m$^3$)</th>
<th>$T_c$ (tree)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cut</td>
<td>Uncut</td>
<td>Cut</td>
<td>Uncut</td>
<td>Cut</td>
</tr>
<tr>
<td>SO-1</td>
<td>39.6</td>
<td>34.3</td>
<td>12.17</td>
<td>9.8</td>
<td>0.702</td>
</tr>
<tr>
<td>SO-2</td>
<td>42.6</td>
<td>34.0</td>
<td>13.11</td>
<td>9.7</td>
<td>0.866</td>
</tr>
<tr>
<td>SO-3</td>
<td>35.4</td>
<td>34.9</td>
<td>10.3</td>
<td>10.1</td>
<td>0.501</td>
</tr>
<tr>
<td>SO-4</td>
<td>35.4</td>
<td>34.9</td>
<td>10.3</td>
<td>10.1</td>
<td>0.501</td>
</tr>
<tr>
<td>MO-1</td>
<td>39.6</td>
<td>34.27</td>
<td>12.17</td>
<td>9.79</td>
<td>0.702</td>
</tr>
<tr>
<td>MO-2</td>
<td>41.28</td>
<td>34.2</td>
<td>12.43</td>
<td>9.77</td>
<td>0.735</td>
</tr>
<tr>
<td>MO-3</td>
<td>41.77</td>
<td>34.17</td>
<td>12.54</td>
<td>9.76</td>
<td>0.748</td>
</tr>
</tbody>
</table>

$V_c =$ Harvested merchantable volume in cubic meters; $T_c =$ number of harvested trees.
clustering of tree regions (Table 2). The effective perimeter of multi-part harvest blocks decreased the total tree regions perimeter by 85% in SO-1 and MO-1 (best solution spatially), by 39% for SO-2 and by 19% for problems SO 3–4. The opposite trend was observed for number of harvest blocks which drastically increased from MO-1 to 13- and 45-fold, respectively. Within the multi-objective set, the achieved reduction rates for the effective perimeter were 75 and 71% for MO-2 and MO-3, respectively, a worsening effect compared to the incumbents SO-1 and MO-1. The same pattern was observed the number of harvest blocks: the addition of more objectives damaged the achieved compactness when solutions were purely based on perimeter boundary minimization.

The small effect of tree selection on the height distribution for the preserved trees limited the impact on reducing the SSDS values. For the average initial score of 121.5 for each tree, the values after the optimization for the preserved ranged from 116.9 (SO-2) to a maximum of 120.9 as expected for the SO 3–4 formulations.

Fig. 4. Average of tree value increment in 5-years (a, € tree⁻¹) and initial tree value (b, € tree⁻¹) after completing the optimizations. The results are presented for cut and preserved (uncut) trees and for the seven problem MIP formulations.

Table 2
Assessment of the seven MIP optimizations considering the balance between perimeter for tree regions and their effective value for harvests after aggregating tree regions based on adjacencies. The count and mean size of multi-part harvest are shown.

<table>
<thead>
<tr>
<th>MIP problem</th>
<th>Tree perimeters (m)</th>
<th>Effective harvest perimeter (m)</th>
<th>Harvest blocks area (m²)</th>
<th>Harvest block (uds)</th>
<th>Block mean size (m²)</th>
<th>Block mean perimeter (m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SO-1</td>
<td>18,232</td>
<td>2,555</td>
<td>36,754</td>
<td>9</td>
<td>4,083</td>
<td>283.9</td>
</tr>
<tr>
<td>SO-2</td>
<td>20,717</td>
<td>12,708</td>
<td>59,297</td>
<td>121</td>
<td>490</td>
<td>105</td>
</tr>
<tr>
<td>SO-3</td>
<td>32,286</td>
<td>25,984</td>
<td>83,627</td>
<td>405</td>
<td>207</td>
<td>64.1</td>
</tr>
<tr>
<td>SO-4</td>
<td>32,286</td>
<td>25,984</td>
<td>83,627</td>
<td>405</td>
<td>207</td>
<td>64.1</td>
</tr>
<tr>
<td>MO-1</td>
<td>18,232</td>
<td>2,555</td>
<td>36,754</td>
<td>9</td>
<td>4,083</td>
<td>283.9</td>
</tr>
<tr>
<td>MO-2</td>
<td>18,035</td>
<td>4,353</td>
<td>38,092</td>
<td>22</td>
<td>1,731</td>
<td>197.8</td>
</tr>
<tr>
<td>MO-3</td>
<td>17,906</td>
<td>5,137</td>
<td>37,678</td>
<td>32</td>
<td>1,171</td>
<td>160.3</td>
</tr>
</tbody>
</table>

A. Pascual
objective optimizations confirmed the increasing level of the dispersion among the harvest blocks from SO-1 to SO-4 (Fig. 5). The spatial arrangement of harvest blocks when accounting for perimeter boundary minimization correlated with the tree value clusters presented in Fig. 2. The shift in multi-objective plans showed how the compact harvest blocks in MO-1 were affected by new decisions under MO 2–3 inducing fragmentation inside large harvest blocks and producing irregular perimeters (Fig. 6).

4. Discussion

The main outcome of the paper is that the tree-level optimization is feasible under mathematical programming by means of MIP and the use of simple but effective formulations capable to control the spatial arrangement of decisions under multi-objective frameworks. Large arrays of decision variables do not necessarily risk the feasibility of the problem solution if the relationships between the set of inequalities and equations remain sufficiently linear, as the presented tree selection mechanism. The incumbent and global optimum solutions were found for all MIP problems at low computational effort. The results reinforced the potential of exact methods to improve earlier developments based on heuristic rules.

The goal of the tested problems tackles a very important decision in forest management planning: which trees to cut and which to preserve. A binary decision that has become more challenging under the multi-objective framework in forest planning nowadays. The research showed how to combine a set of four objectives to conduct tree-level forest planning under several priorities. Single-objective optimizations are useful to define the feasible region and to benchmark the results of the multi-objective solutions. The problems SO 1–4 showed different spatial arrangements. The use of spatial objective variables certainly made harvesting economically feasible when accounting for operational practicalities during the harvests: the more compact the treatment units are, the higher the productivity during machinery logging operations. The main outcome of SO-2 model is that financial assessment can be based on a very simple calculation regarding value increment (Pukkala et al., 2015). There are more factors to consider when accounting for the economics of harvesting, but the use of spatial goals to promote harvest blocks of certain size and compactness can further support the return of revenues (Pascual et al., 2019). The level of dispersion between harvest blocks was minor in MO-1 while it became important for SO-2 for which the driver of the selection was profitability. The strategy to give more priority to spatial goals was a good decision: large-scale homogenous harvest blocks can be fragmented, and the boundaries shifted for a better search of the best bound.

Controlling the exact number of harvest blocks might be a request from the side of forest practitioners, but the harvest-flow, the initial conditions of the area and the projected growth challenge the development of a general formulation. The path algorithm (McDill et al., 2002; Tóth et al., 2012) seems a relevant implementation to develop further studies on tree-level forest planning aiming to account for all possible combinations of tree regions above or below a given area threshold. The underlying principle of the path algorithm is to boost the degree of implementation of the solutions when dispersion is high in the solutions. Some of the harvest blocks (isolated tree regions) displayed in SO-2 plan and a very few of them in SO-1 might not be regarded as feasible in practical operations. The path method then creates an intermediate calculation unit between forest inventory units and forest management units, but the additional complexity might pay off when accounting for technical guidelines to implement decisions. Further research will explore the performance of the path method under the tree-level scope once MIP has been proved solid at solving the presented SO and MO problems.

The study area was ideal for the optimal application of individual tree detection methods (Pascual, 2019). The performance of ITD in other forest ecosystems might not be as outstanding as in Stone pine forests,
and therefore high-dense ALS and fine-grained imagery could be the vectors to detect tree positions and derive tree regions (Duncanson et al., 2014; Kukunda et al., 2018). Spatially explicit methods to manage forest ecosystems under a multi-objective approach are on high demand as the next generation of tree-level forest mapping applications is evolving fast from airborne and terrestrial laser scanning (TLS) platforms to mobile personal laser scanning (Seifert et al., 2010; Liang et al., 2014; Sankey et al., 2017). The increasing capability of the scanners and the decreasing costs are both pushing the development of tree-level forest mapping forward, creating room for timely and important enhancements in coming studies on tree-level decision-making (Seifert et al., 2010). The integration of flexible TLS could help to improve the estimation of tree value accounting from branches and form factors, which greatly impact the economics of forest management in other ecosystems more devoted to timber revenues (Knoke et al., 2006). Stem variables become less significant in Stone pine forests in the region as timber assortments are less valuable than cone production. The contribution of TLS to enhance taper functions for the species and to improve the economics of the management might not compensate in the area unless used with ALS data to better detect of tree crown attributes affecting cone yield.

The forest inventory data in this paper was the same as in Packalen et al. (2020) but the optimization method was completely different. The harvesting targets were slightly different and therefore the benchmarking of the formulations is not completely unbiased. The locations of the cuttings remained similar when using spatial goals (MO-1) and the more clustering alternatives defined as “clear cut” and “tree group”. The number of harvest blocks was 5 versus 9 in the presented MIP-based solutions considering the difference of 30 m³ between both harvesting targets (60 trees considering the average tree merchantable volume of 0.49 m³ tree¹). The size of the combinatorial problem using MIP might be not large enough to challenge the optimality of the heuristic search. Once, the novel MIP formulation was tested, validated against similar optimization methods, coming studies will expand the spatial range of tree level applications considering more improvements in the presented formulation. The use of tree regions responded to the important need of producing polygons from which to develop spatial optimization. Under perimeter-boundary minimization (SO 1 & MO 1) the decision of allocating more growing space to larger trees had a strong impact as the driver of the aggregation was the shared boundary.

The results for S0 3–4 showed the collinearity and the minor effect of SSDS as driver of the selection. The marginal decrement of the SSDS values was very as the distribution of tree heights before and after the cuttings remained similar. The case of height minimization can be improved from the fire reduction perspective by assigning fire spread probability depending on the stage of development of the tree, slopes and most frequent wind directional distributions. For the specific case of Stone pines, the removal of large canopies despite being canopy-connected can compromise the production of nuts reducing the level acceptance from forest stakeholders caring about constant annual revenues (Pasalodos-Tato et al., 2016). However, with tree detection and the path algorithm it could be possible to control the extent of the openings. The singularities of the training area could have been further integrated into the planning formulation imposing constraints on the

Fig. 6. Decision maps for the multi-objective optimizations MO-1 (a), MO-2 (b) and MO-3 (c). Tree regions assigned to harvests are shaded in grey color and the detected treetops are presented for the largest harvest block located in Western region of the area.
maximum canopy size or on minimum height thresholds, but the aim was to implement simple constraints to allow the generalization of the tree selection approach based on MIP, a novelty in the field. Multi-objective optimization was successfully conducted using the widely used CPLEX optimization environment (IBM, 2020), which weights priorities between objectives. More levels of hierarchy (scale and weights) could adjust the outcomes even more to match changing preferences and with the guarantee that the solutions are the global optimals in all cases.

The incumbent solutions were found so fast that upscaling the problem to comprise more tree regions seems feasible even with the computing resources used for the study. The optimality gap would decrease faster when involving super-computational capacity in case the problem structure shifts to multi-temporal (i.e., the same binary 0–1 decision for a given tree but along more planning periods) to better undertake operational forestry.

5. Conclusions

The proposed tree selection model pioneered on the use of MIP and multi-objective optimization. A simple and efficient model formulation was presented using four management goals separately and later combined to optimize the selection of trees accounting for economical and spatial goals. The problem formulation was developed with optimization techniques and widely available ALS data, a solid combination that can be straightforwardly integrated into forest management planning to support and enhance tree-level decision-making.

Ethics approval and consent to participate

Not applicable.

Authors’ contribution

The author was responsible for all research tasks ranging from experiment design to scientific reporting of the results.

Consent for publication

Not applicable.

Availability of data and materials

The research data and materials are available from the corresponding author on reasonable request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

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References


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