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RESEARCH

Maximizing the economic benefit for cable yarding timber harvesting operations by spatially optimizing tree selection

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Abstract
The efficiency of forest logging operations can be strongly affected by the layout of the harvesting pattern, which is usually based on silvicultural constraints and technical feasibility. Specifically, individual tree volume and the spatial distribution of trees significantly impact the overall harvesting performance. Spatial optimization of tree selection at the forest stand level may improve timber harvest efficiency by maximizing key performance indicators, such as the economic benefit, under given operational and silvicultural constraints. In this study, we applied two harvesting operation-optimization approaches based on integer programming for uphill cable yarding operations in mountain areas, including tree selection and load maximization. The first approach involves tree selection based on single tree harvest, while the second one performs tree selection based on tree clusters harvest per work cycle. As input elements a productivity model, derived by time-motion study with a Mounty MT50-2 and individual tree parameters extracted from high-resolution airborne laser scanning data, were prepared. Single tree information was further rated by financial value, and subsequently combined with the productivity model, allowing a detailed breakdown of operational costs. The results showed that optimizing the tree selection while respecting the allowable cut timber volume established in the harvesting plan can improve the efficiency of forest operations. The cluster approach was shown to be more efficient in terms of economic benefit compared to the actual selection, with an increase of 24.94%. However, the single tree approach resulted in a decrease of economic benefit compared to the actual selection, with a decrease of 22.85%.

Keywords Forest operations · Cable yarding · Spatial optimization · Tree selection · Airborne laser scanning

Introduction

Forest ecosystems provide several goods and services depending on forest type, location, and management, including wood and non-wood products, recreational areas, and carbon sequestration (Blattert et al. 2018). Because of their location, mountain forests often provide additional services such as protection from potential hazard events like avalanches and rockfalls (Dorren et al. 2004). Active forest management is essential for preserving these provisions in the long term (Bürgi et al. 2018). However, this means that even forests that are not economically profitable for timber harvesting and show high logging costs must be managed to meet their service target (Bont and Church 2018). This

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problem is evident in mountain forest areas, where forest operations are usually carried out with cable yarding systems that are inherently expensive due to the considerable time required for cable rigging before timber extraction (Holzfeind et al. 2018). New decision support tools based on optimization concepts may help to cope with the general lack of competitiveness of timber harvest in mountain areas and reduce harvesting costs.

When it comes to optimizing forest planning and harvesting, two modeling approaches can be used: meta-heuristic techniques and mathematical programming (Borges et al. 2014; Heinonen et al. 2007). Heuristic search is highly effective in finding optimized solutions, even when dealing with a large number of harvest units (Pukkala et al. 2009) and multiple decision variables (Mathey et al. 2007). Heuristic algorithms such as cellular automata and simulated annealing can find local optimal solutions. This results in an inevitable degree of uncertainty when compared to exact methods (Jin et al. 2016). On the other side, integer programming (IP) formulations are a way to solve complex combinatorial problems with precision. Over the past few decades, spatially explicit models based on IP have been extensively developed (Tato et al. 2013). However, these exact methods suffer from a significant limitation: when the problem complexity increases, the solution space grows at an exponentially faster rate (Lockwood and Moore 1993). Specifically, the potential presence of non-linear components in elaborate physical or biological effects models, and the requirement of several integer decision variables due to spatial constraints could make it difficult to solve problems using conventional mathematical programming methods (Bettinger and Kim 2008). Nonetheless, it has been observed that linearization procedures and the use of idle constraints can simplify the problem and make optimal solutions feasible even when there are many decision variables (Tóth et al. 2012).

Since the late 1970s, various contributions, including practical applications, have been made to optimize the cable road layouts. Dykstra and Riggs (1977) developed a comprehensive theory to support the design process for setting up cable yarders and efficiently allocating cutting equipment. The primary objective was to minimize costs while allocating cable roads and harvesting specific forest units. The model was tailored to clear-cutting conditions and worked with predefined fixed cable length. Following, Chung (2003) and a subsequent study by Chung et al. (2004) presented an effective model that tackled the problem of optimizing cable logging and constructing a network of forest access roads by providing multiple heuristic approaches. Even in these cases, it was assumed that the cutting process met clear-cutting conditions. Later, Bont et al. (2014) introduced the Parallel Multi Length Option (PaMLOC) and the Cascading Multi-Length Option Cable Road (CaMLOC), two new harvesting layout models based on IP for cable yarder technology specifically designed for central European forest management. Unlike the model proposed by Dykstra and Riggs (1977), the two new formulations could handle variable-length cable road layout alternatives. However, PaMLOC and CaMLOC had some limitations. For one, addressing problems for the actual size of forest stands with these models required a significant amount of time and computational effort. Another critical point was the neglect of silvicultural and ecological aspects for effective mountain forest management. The first issue was solved by Bont and Church (2018) who developed two optimization model solutions based on location set covering: the set-covering model (SCM) and the bounded set-covering model (BSCM). Finally, a multi-objective optimization approach was able to both minimizing the harvesting costs and reducing the negative impacts on the remaining forests. It was designed by Bont et al. (2019) who introduced a separate objective function to account for the unfavorable ecological situations.

Although previous research has significantly contributed to improving the efficiency of cable-based timber harvesting operations, it has solely focused on optimizing cable road layout and the forest access network. An optimization approach aimed to improve the efficiency of cable-based harvesting operations based on tree-selection has not been yet developed. This is likely because the optimization models were formulated using input data mainly based on area-based units as given with square grid cells. On the contrary, several studies have developed tree selection optimization models for forest planning based on single tree forest inventory units, which can be considered suitable for forest operations performed with ground-based systems. For instance, Petteri et al. (2020) introduced a tree selection method that identifies the financially mature trees by considering the spatial distribution of the harvested trees. The algorithm is based on cellular automata and account each tree as a cell. Pascual (2021) presented a multi-objective model for single tree selection based on mixed integer programming (MIP) approach that, starting from four single-objective functions, delivers three multi-objective solutions while integrating spatial and economic goals. In this view, optimization models for single tree selection for a cable yarding harvesting scenario could provide new information to improve the performance of forest operations in mountain areas.

The aim of this study is to present two formulations of IP optimization models for single tree selection (STS) and tree cluster selection (TCS) suitable for cable-based harvesting systems that maximize the economic benefit of forest operations. The proposed models were tested on an actual cable yarding worksite for which an efficiency prediction model was developed first and later converted into a productivity model for yarding and processing operations. This was necessary because existing productivity models did not match the site and machine characteristics given. Moreover, this allowed to compare the actual observations from the worksite with the two presented models in terms of harvesting productivity and financial profit directly. To achieve this objective, we developed an inventory based on individual tree detection (ITD) from airborne laser scanning (ALS) data to determine the attributes and locations of individual trees. Using this information, we performed a tree clustering inventory by implementing a hierarchical clustering algorithm to establish an input layer for the TCS model.

Materials and methods

Cable yarder unit

In this study, a Mounty MT50-2 (Mounty 5000) truck-mounted tower yarder by Konrad Forsttechnik GmbH was employed. This yarder is equipped with a 14.2 m high tower and has a 800 m skyline capacity. It is fitted with a KFT MT24 crane, combined with a Woody 60 processing head. Finally, the motorized carriage Liftliner LL40-1 (Konrad Forsttechnik GmbH), and radio-chockers were used for hauling operations (Appendix A).

Study site and cable road layout

The study site is located in the Volleneggli forest in the municipality of Entlebuch (WGS84 coordinates: 46.973872597, 8.131242894, 1128 m a.s.l.) in the Finsterwald district of Canton Lucerne. The forest is owned by the Canton of Lucerne and managed by the State Forest Enterprise Lucerne (Switzerland). The harvest has taken place in an uneven-aged mixed forest stand mainly composed of Norway spruce (*Picea abies* H. Karst.), silver fir (*Abies alba* Mill.), and European beech (*Fagus sylvatica* L.). The forest stand has an average height of the dominant trees of 30 m and a canopy cover of the uppermost layer between 50 % and 70 %. The forest is managed according to the continuous forest cover principle and its primary function is protection against flooding. The harvest unit covers 3.6 ha and is characterized by an average slope gradient of 40 %.

This study focused on one multi-span cable road working in a 2-cable line uphill yarding configuration (skyline and mainline). The cable road was 440 m long and three to four meters wide. Two intermediate supports were set up to achieve a minimum ground clearance of seven meters. The maximum tensile force at loaded skyline (T_{max}) applied at the highest point was 189 kN. A 1/5 load factor was used to get the maximum permissible payload, resulting in 37.8 kN. After deducting the approx. 1050 kg of the carriage, the maximum load that could be attached was 27.5 kN. The working crew comprised two members, a yarder operator and a choker setter, both equipped with remote controls to operate the carriage. A third operator was involved in initial felling operations, skyline installation, and relocation of the processed logs at the forest road. All the selected trees were motor manually felled before the skyline installation. Most trees were hauled as full trees except for those that exceeded the maximum payload, which were cross-cut first. Trees were delimbed, bucked, and sorted in piles by the processor at the landing site.

Study preparation

Each felled tree was marked with an unique numerical ID spray painted at the stump and additionally at breast height (DBH) level. The ID was incremented by 10 at the stump and by 1 at the DBH to prevent overlapping in case of cross-cut during logging operations, where a new digit was needed for the same tree. For each tree the species and DBH were recorded. Total height was measured for 45 trees to develop a representative height curve of the forest stand within the harvest area.

For the site documentation and to derive the tree positions, a DJI Matrice 300 RTK drone was used to record a georeferenced orthophoto of the harvesting area. This allowed to set up a field survey project in QField®Android app, where the orthophoto was used as a base map to identify each tree hauled during the logging operations. In addition, a point vector layer was created to collect the farthest chocker set position from the cable road for each work cycle. This led to a more accurate lateral yarding distance information necessary for the productivity model input.

Time and motion study and data analysis

For data collection 190 work cycles were observed between July 7th and July 10th 2022. The related time study was based on video recordings using three digital video cameras simultaneously (Drift®, Ghost-X) with a field of view of 140°. One camera was mounted on the carriage, one inside the machine's cabin, and the third carried by the researcher using a shoulder-mounted support. A synchronization of the camera's clock time was carried out every morning by a dedicated app for mobile phones. The position of the carriage was recorded using a Huawei U9200 smartphone equipped with the GPS Logger application at a frequency of 1 Hz. StanForD 2010 data were also collected at the end of the harvesting operations. Each work cycle was divided into the following elements: 1) lifting the empty hook to the carriage (lifting empty); 2) moving the empty carriage from landing to the loading site (outhaul); 3) lowering the hook and approaching the logs (pulling out); 4) hooking the logs (hooking); 5) pulling in the load to the cable road and lifting it (pulling in); 6) moving the loaded carriage back to the landing (inhaul); 7) lowering the load and detaching the hook (unload); 8) securing the load with the processor (securing); 9) gripping and swinging the logs for subsequent operations (grip-swing); 10) processing the logs (processing); 11) piling the logs (piling); 12) operational, technical and personal delays (delays). The hoisting functions 'lowering the hook to the ground' and 'lifting the load,' as defined by Heinimann et al. (2001) were coupled with the closest work elements, 'pulling out' and 'pulling in,' respectively, due to the difficulty of separating the two pairs of work elements precisely. IDs of the harvested trees and the farthest chocker point position were collected for each work cycle. We assumed that yarding efficiency is a function of yarding distance (YD), lateral yarding distance (LD), load volume (Vol), number of extracted stems per load (Nr_{STEM}), and slope gradient (SL). In addition, the efficiency of roadside slashing depends on the volume processed (Vol) and the number of processed logs (Nr_{LOG}). An overall yarding and processing efficiency model was developed considering all the previous explanatory variables. The yarding distance and the slope gradient were computed between the cable yarder and carriage positions at the loading site. The lateral yarding distance was determined as the shortest distance from the furthest chocker point and the skyline. StanForD 2010 data were used to compute load volume as the sum of individual harvested tree volume and the number of logs produced per work cycle.

The efficiency model was developed using multiple linear regression methods. A first examination of the significance of the independent variables was conducted through bivariate correlation analysis. A stepwise backward regression procedure was adopted to model the variability of forest operation efficiency as a function of the selected variables. Independent variables were considered significant at $p < 0.05$. Studentized residual distribution was checked to assess the normality assumption, while homoscedasticity was visually verified checking the residual plot and by using the *Non-constant Variance Score test* (NCVtest) for a double check. In case of assumption violation, square root and logarithm transformations were tested on both response and explanatory continuous variables, as appropriate. InfluencePlot function from the Companion to Applied Regression (car) package (Fox and Weisberg 2018) in R was used to detect potential outliers according to the Cook's distance. The *variance inflation factor* (VIF) was used to check the absence of multicollinearity. The goodness-of-fit of linear models was finally tested through the *Akaike Information Criterion* (AIC) by comparing different model configurations. All statistical analyses were performed with R (R Core Team 2022). Forest operations efficiency (time per m^3) was computed based on net productive system time (PSH_0) by excluding all delay times. As the productivity model was derived, delays up to 15 min (PSH_{15}) were considered by applying a conversion factor of 0.8 (Stampfer 2003).

Forest stand unit inventory

The harvesting area for applying the optimization models was defined using a 35 m buffer on both sides of the skyline profile. The buffer size was determined according to a rule of thumb for which the width of a cable road should be limited to a tree length, generally approximated to 30 m (Bont et al. 2014). We added 5 ms more to ensure the inclusion of border trees. This resulted in a total area of 3.4 ha (Fig. 1a), where we conducted a forest stand unit inventory by performing ITD using the Airborne LiDAR Data Manipulation and Visualization for Forestry Applications (lidR) package in R (Roussel et al. 2020). ALS data used in this study were acquired through a survey conducted between 2019 and 2020 by the Swiss Federal Office of Topography. The LiDAR dataset exhibits an average point density of 15–20 points per square meter (pt/m^2), ensuring comprehensive coverage of the study area. Additionally, the data possess a planimetric accuracy of ± 20 cm and an altimetric accuracy of ± 10 cm, guaranteeing reliable and precise three-dimensional information. To perform the ITD, a first ground classification was carried out through cloth simulation filtering (CSF) based on the algorithm developed by Zhang et al. (2016). Afterwards, the point cloud was normalized by applying the "kNNIDW" algorithm, which integrates the K-Nearest Neighbors method with Inverse Distance Weighting (IDW) for spatial interpolation. The resulting normalized point cloud was used to detect single tree tops with a local maximum filter (LMF), able to find tree tops without needing a raster layer. The LMF was employed by setting up a dynamic size window that varies according to the point height. Expressly, the dynamic size window was set to relate any point below 2 ms to a window size of 3 ms, while points above 20 ms were equated to a window size of 5 ms. A non-linear function was finally adopted to compute the window size for all the points belonging to the 2–20 ms range as follows:

$$y = 2.6 \cdot \left(-\left(e^{-0.08\cdot(x-2)}\right) - 1\right) + 3 \quad (1)$$

where y is the window size and x is the point height. The dynamic size window was implemented with a minimum height value set to 15 ms, below which no point was considered a local maximum. Thereafter, a canopy height model (CHM) was generated using the point-to-raster algorithm in the lidR package (Fig. 1b). The CHM was employed to execute the individual tree segmentation algorithm (Dalponte and Coomes 2016) to identify individual trees and compute their crown metrics (Fig. 1c). All the parameter settings used in lidR are provided in Appendix B. In total, 557 trees were detected over the selected harvesting area. Data on DBH and tree height collected during the field survey were used to estimate DBH for all the detected trees. The volume for

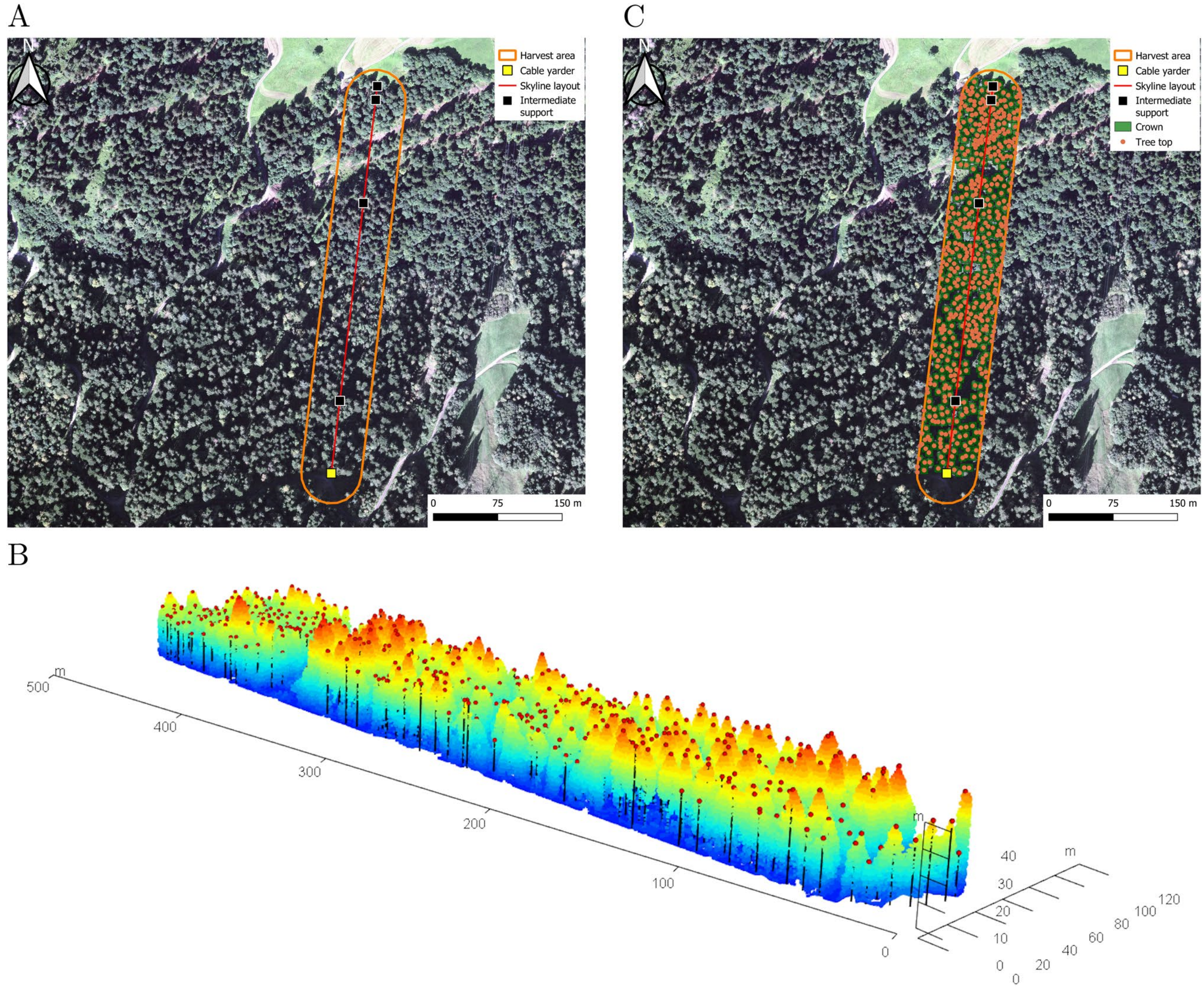


Fig. 1 Overview of the harvest area used to implement the optimization models (**A**). The point cloud shows the trees identified by the LMF using the lidR package (**B**). C shows the identified tree tops and the relative canopy metrics derived from ALS Swiss data (Swisstopo, Swiss Federal Office of Topography)

each tree was estimated by using the implementation of the BDAT Tree Taper Fortran Functions (rBDAT) package in R, which includes the last version of the Fortran program library BDATPro developed by the Forest Research Institute Baden-Württemberg for the German national forest inventory (Kublin 2003). The package allows the calculation of diameter at different heights, tree heights, volume, and biomass for the main European tree species. The estimated volume was rescaled to obtain a more plausible value of timber volume at the roadside, that could be comparable with the actual harvest. The rescaling operation was performed with the following linear regression equation:

$$Vol_t = 0.01346 + 0.66013 \cdot Vol_e \tag{2}$$

where Vol_t is the timber volume achievable from a single tree after being processed (bark included) and Vol_e is the estimated volume with rBDAT (*adjusted* $R^2 = 0.78$, $RSME = 0.63$). The regression is based on a dataset of 234 trees for which the timber volume data from the StanForD 2010 and the estimated volume with rBDAT are provided. The same dataset was further used to develop a Poisson regression to estimate the number of logs retrievable per single tree after being processed at landing based on tree height:

$$a = e^{(0.255152+0.033797 \cdot h)} \tag{3}$$

where a is the number of logs and h is the tree height. For each additional meter in tree height, there is a 3 % increase in the number of logs (ratio of the residual deviance to the residual degrees of freedom = 0.33). Following, the tree's financial value was computed as the sum per each log based on the Swiss timber price list provided by the Statistical Service of Swiss Agriculture (Agristat) for the bimonthly period following the harvesting operation. Finally, all trees with a volume greater than 3.1 m^3 were divided into two or three separate virtual trees whose sum of volume and number of pieces reflected the values of the original tree. This was performed to simulate the cross-cutting for relatively large trees that cannot be fully loaded because exceeding the maximum payload for the skyline configuration under analysis. In this regard, a density conversion factor of 0.906 $t \cdot m^{-3}$ (Starke and Geiger 2022) was used to estimate the volumetric threshold to simulate the cross-cut.

Trees spatial aggregation for cluster selection

In addition to the inventory of forest stand units, we generated a set of potential tree clusters within the harvest area to allow for multiple tree selection per work cycle. To generate tree clusters we employed the hierarchical clustering algorithm (HCA) provided by the Scikit-learn library (Pedregosa et al. 2011) in Phyton. The HCA works by considering each tree as an individual cluster. The algorithm finds the most closely related clusters and combines them into a new cluster during each iteration. This process continues until a predetermined stopping criterion is met such as, in our case, a maximum distance threshold. There are several connection methods which can be used to determine the similarity or dissimilarity between clusters, such as 'complete,' 'single,' and 'average.' These methods indicate how the distance between two clusters is computed based on the distances between their individual points. In our analysis, we used the 'complete' connection method, which merges clusters based on the maximum distance between any two points in the clusters. We first computed the pairwise distances between all treetop points using the Euclidean distance metric. Later, these distances were converted into a distance matrix, which was used as input to the clustering algorithm. We run the algorithm several times by setting an increasing distance threshold each time by 0.5, starting from 0.5 ms up to 35 ms, and specifying that clusters should be formed by merging points within this distance threshold. In this way, a dataset of 13701 tree clusters was created out of the 557 potentially harvestable trees. The number of clusters decreased as the threshold distance increased during each iteration of the HCA. This was because more trees were included in the same cluster. For example, when the threshold distance was 0.5 m, the number of clusters was equal to the number of trees and each cluster included only one tree. When the threshold distance was increased to 2 m, 545 clusters were created and for a distance of 5 m, 431 clusters were created. The last iteration with a threshold distance of 35 m generated only 35 clusters. The tree cluster dataset was then filtered to remove the duplicates, namely the clusters including the same trees. The final set of tree clusters used as input for the optimization models consisted of 1159 clusters.

Problem conceptualization

Our models aim to define a selection of trees that maximizes the marginal economic return of the forest operation. We developed two IP optimization models. The first optimizes the marginal return by selecting trees according to a single-tree selection (STS) where a single tree is hauled and processed for each work cycle. The second one performs the optimized tree selection considering potential tree clusters (TCS), where multiple trees per cycle can be combined as one single load. In setting the STS model, we indicate with N the set of trees (i) detected with ALS. The decision variable is represented by the 0-1 binary variable x_i. If tree i is selected, $x_i = 1$; otherwise, it is 0. To ensure that the selected trees are distributed evenly over the entire harvest area, while constraints on the amount of volume to be harvested are applied, two equally sized sub-areas ($SubA_1$, $SubA_2$) are created to enforce a balanced volume removal. In this regard, we established a removal range of 12.5−17.5 % of the initial standing volume V in both $SubA_1$ and $SubA_2$. Furthermore, we set constraints based on the DBH of the trees to promote selection that aligns with the actual harvest using two predefined DBH ranges and set minimum proportions to be respected for these ranges: at least 65 % of the selected trees must have a DBH equal to or less than 41 cm; at least 25 % of the selected trees must have a DBH greater than 41 cm. To specify the TCS model, a further set of work cycles representing tree clusters (w) was denoted with C. In this model, the decision variable is represented by the 0-1 binary variable y_w. If cycle w is selected, $y_w = 1$; otherwise, it is 0. We also incorporated constraints similar to those in the STS model to establish a volume removal range equally distributed across $SubA_1$ and $SubA_2$ and to respect the proportions of trees to be selected according to DBH ranges. When dealing with cycles w that contained trees i both in $SubA_1$ and $SubA_2$, we assigned them to either $SubA_1$ or $SubA_2$ in order to balance the total available standing volume between the two sub-areas as evenly as possible. Moreover, we set the cycle volume threshold (v_w) at 3.1 m^3 to respect the maximum payload of the harvesting system under investigation. A further constraint was defined to prevent more than one cycle containing the same tree from being selected. This constraint specifies that the total number of cycles including tree i that can be selected should be equal to or less than 1.

Problem formulation

STS optimization model

Set:

$N=$ tree set indexed by i;
$A_1=$ subset of trees in sub-area $SubA_1$;
$A_2=$ subset of trees in sub-area $SubA_2$;
$D_1=$ subset of trees with DBH ≤ 41 cm;
$D_2=$ subset of trees with DBH > 41 cm;

Decision variable:

$x_i=1$ if tree i is harvested; 0 otherwise;

Accounting variables:

$N_h=$ number of all trees harvested;
$v_i=$ merchantable volume of tree i (m^3);
$V=$ total standing volume in N (m^3);
$p_i=$ economic value of tree i (CHF);
$c_i=$ logging cost (variable cost) of tree i (CHF);
$f=$ fixed cost of cable system set-up and dismantling (CHF);

Objective function:

The objective function maximizes the total profit by selecting the trees with the highest economic value and subtracting the logging costs from the revenue. The fixed cost is subtracted from the objective function to account for the cost of skyline set-up and dismantling:

$$\max \sum_{i=1}^{N}\left[(p_i-c_i)\cdot x_i\right]-f \quad \text{(CHF)}$$

Constraints:

1. Harvested trees accounting $\forall i\in N$

$$\sum_{i\in N} v_i x_i = N_h;$$

2. Harvesting level equally distributed in both sub-areas $SubA_1$ and $SubA_2$ in the 12.5–17.5 % of the initial standing volume

$$0.125V \leq \sum_{i\in A_1} v_i x_i \leq 0.175V;$$
$$0.125V \leq \sum_{i\in A_2} v_i x_i \leq 0.175V;$$

3. Minimum proportion of selected trees according to DBH ranges $\forall i\in N$

$$\frac{\sum_{i\in D_1} x_i}{\sum_{i\in N} x_i} \geq 0.65;$$
$$\frac{\sum_{i\in D_2} x_i}{\sum_{i\in N} x_i} \geq 0.25;$$

4. Assignment control $\forall i\in N$

$$\sum_{i\in N} x_i \leq 1;$$

5. non-negativity and integrality of the binary variable

$$x_i \in \{0,1\};$$

$$p_i, c_i, v_i \in \mathbb{R}^+ \quad \forall i\in N$$

6. *TCS optimization model*

Set:

$N=$ tree set indexed by i;
$C=$ working cycle set indexed by w;
$Q_w=$ set of trees included in cycle w;
$A_1=$ subset of cycles in sub-area $SubA_1$;
$A_2=$ subset of cycles in sub-area $SubA_2$;
$D_1=$ subset of trees with DBH ≤ 41 cm;
$D_2=$ subset of trees with DBH > 41 cm;

Decision variable:

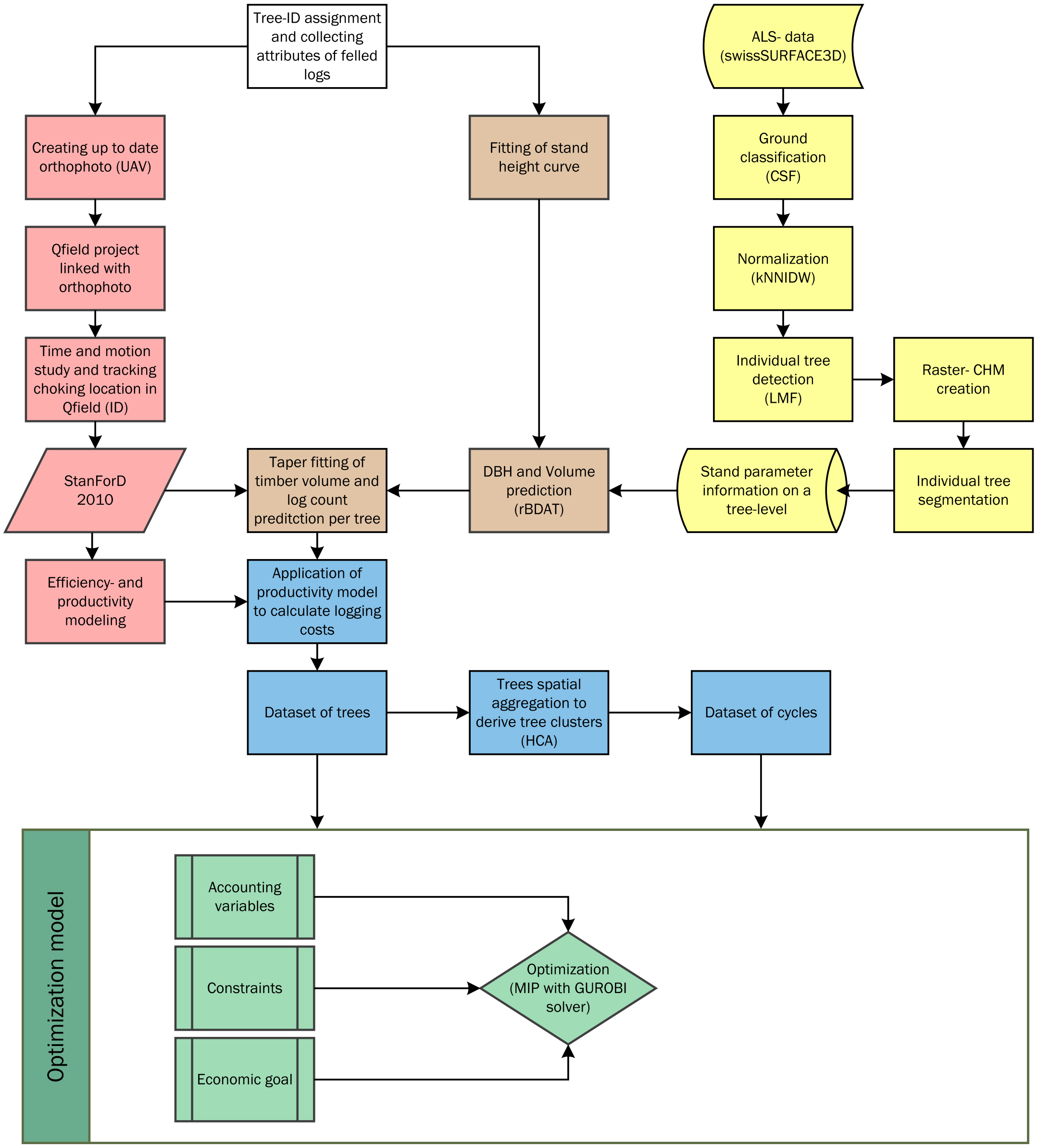
$y_w=1$ if cycle w is done; 0 otherwise;

Accounting variables:

$C_h=$ number of selected work cycles;
$N_w=$ number of trees in cycle w;
$N_{w,D_1}=$ number of trees in cycle w categorized under D_1;
$N_{w,D_2}=$ number of trees in cycle w categorized under D_2;
$v_w=$ volume logged with cycle w (m^3);
$V=$ total standing volume in N (m^3);
$p_w=$ economic value of timber logged with cycle w (CHF);
$c_w=$ logging cost (variable cost) of cycle w (CHF);
$f=$ fixed cost of cable system set-up and dismantling (CHF);

Objective function:

The objective function maximizes the total profit by selecting the work cycles with the highest economic value (given by the tree or the sum of trees harvested) and subtracting the logging costs from the revenue. The fixed cost is



Tree-ID assignment and collecting attributes of felled logs
ALS- data (swissSURFACE3D)
Creating up to date orthophoto (UAV)
Fitting of stand height curve
Ground classification (CSF)
Qfield project linked with orthophoto
Normalization (kNNIDW)
Time and motion study and tracking choking location in Qfield (ID)
Individual tree detection (LMF)
Raster- CHM creation
StanForD 2010
Taper fitting of timber volume and log count preditction per tree
DBH and Volume prediction (rBDAT)
Stand parameter information on a tree-level
Individual tree segmentation
Efficiency- and productivity modeling
Application of productivity model to calculate logging costs
Dataset of trees
Trees spatial aggregation to derive tree clusters (HCA)
Dataset of cycles
Optimization model
Accounting variables
Constraints
Economic goal
Optimization (MIP with GUROBI solver)

◂**Fig. 2** Workflow of the methodology adopted to optimize tree selection for improved cable yarding. The efficiency and productivity model development steps are listed in red, the ITD steps based on ALS-data are listed in yellow, the steps taken to derive DBH, timber volume and number of logs per each individual tree are represented in brown, the operations carried out to gather the logging cost for each individual tree and the spatial aggregation for getting tree clusters are shown in blue, and the components considered to develop the optimization models are listed in green

subtracted from the objective function to account for the cost of the skyline skyline set-up and dismantling tasks:

$$\max \sum_{w=1}^{C} \left[(p_w - c_w) \cdot y_w \right] - f \quad \text{(CHF)}$$

Constraints:

7. Work cycles accounting $\forall w \in C$

$$\sum_{w \in C} v_w y_w = C_h;$$

8. Harvesting level equally distributed in both sub-areas $SubA_1$ and $SubA_2$ in the 12.5−17.5 % of the initial standing volume

$$0.125V \leq \sum_{w \in A_1} v_w y_w \leq 0.175V;$$

$$0.125V \leq \sum_{w \in A_2} v_w y_w \leq 0.175V;$$

9. Minimum proportion of selected trees according to DBH ranges across the selected cycles $\forall w \in C$

$$\frac{\sum_{w \in C} N_{w,D_1} \cdot y_w}{\sum_{w \in C} N_w \cdot y_w} \geq 0.65;$$

$$\frac{\sum_{w \in C} N_{w,D_2} \cdot y_w}{\sum_{w \in C} N_w \cdot y_w} \geq 0.25;$$

10. Maximum payload per work cycle $\forall w \in C$

$$y_w \cdot v_w \leq 3.1 \quad (\text{m}^3);$$

11. Shared trees exclusion $\forall w \in C$

$$\sum_{w \in C | i \in Q_w} y_w \leq 1;$$

12. Assignment control $\forall w \in C$

$$\sum_{w \in C} y_w \leq 1;$$

13. non-negativity and integrality of the binary variable

$$y_w \in \{0, 1\};$$

$$p_w, c_w, v_w \in \mathbb{R}^+ \quad \forall w \in C$$

14.

Constraints (6) and (14) state accounting variables as positive real. For both IP models, the harvesting costs for yarding and processing operations were determined through the productivity model developed with the time study (shown later in the results). The model proposed by Lemm et al. (2019) was integrated into the cost calculation to account for the felling activity. Finally, the cable system set up and dismantling were accounted for by multiplying the time needed for the installation (≈ 10 h) by the machines and operators' hourly costs as provided by HeProMo (Pedolin et al. 2017).

The IP problems were formulated in a Python environment using the Python-MIP package (Santos and Toffolo 2020) and by setting up GUROBI software 10.0.1 as solver engine. The operation was performed with a computer-i7 10510U central processing unit, 2.30 GHz, with 16 GB of random-access memory.

The research methodology is synthesized in Fig. 2.

Results

Time consumption

Over the 190 work cycles observed, we selected 177 to be effectively used to develop the efficiency model. The remaining 13 cycles were unsuitable because they lacked independent variable parameters. In the course of the selected 177 work cycles, 298 m^3 of timber were extracted and processed at the roadside. The average yarding distance was moderate (198 m), while the average lateral yarding distance was 1/3 of the maximum permissible distance, which is traditionally 30 m (average height of a mature tree) in Alpine areas. Following the full tree method, shorter lateral yarding distances are typical due to technical feasibility and to avoid damage to remaining standing trees (Stampfer 2003). The slope gradient of the cable road was on average (24.9 %) lower than the slope of the harvesting area. The mean payload transported was 1.68 m^3, corresponding to 1.5 tons, which is lower than the system's maximum load capacity. Only in few cases the maximum payload was exceeded (Table 1). On average, the number of stems extracted per load and the number of logs produced per cycle were 2 and 5.17, respectively.

The total work time (TWT) accounted for 1801 min, while delays shorter than 15 min were 178 min. Therefore, the productive work time (PWT) was 1623 min or 27 PSH_0, representing 90.1 % of the TWT. In yarding operations, inhaul, hooking the logs, and lifting the load consumed most of the PWT. At the roadside, processing the stems into logs and grip-swinging were the most

Table 1 Descriptive statistics of independent variables

Parameter	Unit	Mean	Median	SD	Min	Max
Terrain slope	%	24.94	22.68	8.19	16.20	51.95
Yarding distance	m	198.74	204.08	96.21	10.44	352.70
Lateral yarding distance	m	10.78	9.87	7.07	0.22	31.42
Stems per load	n	2.08	2.00	0.99	1.00	6.00
Load volume	m^3	1.68	1.63	0.61	0.27	3.78
Number of processed logs	n	5.17	5.00	2.65	1.00	14.00

Table 2 Descriptive statistics of time consumption elements, efficiency and productivity

Activity/Parameter	Unit	Mean	Median	SD	Tot	% on TWT
Lifting empty	Min	0.18	0.17	0.09	32	1.8
Outhaul	Min	0.75	0.75	0.42	132	7.3
Pulling out	Min	0.73	0.72	0.27	129	7.2
Hooking	Min	1.24	1.15	0.63	219	12.2
Pulling In	Min	0.92	0.82	0.41	162	9.0
Inhaul	Min	1.44	1.40	0.66	254	14.1
Unloading	Min	0.39	0.37	0.18	69	3.9
Securing	Min	0.29	0.27	0.20	8	0.4
Grip swing	Min	1.07	1.02	0.65	190	10.6
Processing	Min	1.69	1.65	0.71	299	16.6
Piling	Min	0.73	0.58	0.56	129	7.2
PWT	Min	9.17	9.13	1.79	1623	90.1
Delays < 15 Min	Min	1.63	0.88	2.53	178	9.9
TWT	Min	10.17	9.98	2.70	1801	/
Efficiency	Min PSH0 m^{-3}	6.50	5.57	4.09	/	/
Productivity	m^3 PSH0^{-1}	11.50	10.78	4.82	/	/

time-consuming operations. When grouped, operations performed at the roadside consumed 38.5 % of the total PWT, while lateral yarding operations took 31.4 %. Transportation and hoisting functions took 23.8 % and 6.2 % of the PWT, respectively. The average time consumption per cycle was 9.16 ± 1.79 min, corresponding to an average efficiency of 6.5 ± 4.09 min PSH_0 m^{-3} and an average productivity of 11.5 ± 4.82 m^3 PSH_0^{-1} (Table 2).

Efficiency and productivity models

To develop the efficiency prediction model, we adopted a stepwise regression approach that checks the contribution of each predictor variable every time a variable is added or deleted. The analysis showed that only Nr_{STEM} had a non-significant impact on the response variable among the selected predictors. Moreover, we adopted an inverse square root transformation for the response variable not to violate the normality assumption. Finally, two data points were excluded from the model development as they were identified as outliers. These data points were initially detected as influential points based on their Cook's distance values (0.12, 0.3, threshold = 0.02) and standardized residual (−2.5, 2.47). These observations corresponded to two logging cycles that displayed significantly higher efficiency than the average. Upon conducting a video analysis, it was discovered that these were incomplete cycles because the trees had not been processed after being transported to the landing. Therefore, these data points were excluded from the model to ensure its accuracy. All the model coefficients and detailed statistics are reported in Table 3, while the residual plot and the Q-Q plot can be found in Appendix C. The resulting prediction model is the following:

$$\text{Eff} = \frac{1}{\left(\beta_0 - \beta_1 \cdot \text{YD} - \beta_2 \cdot \text{LD} - \beta_3 \cdot \text{SL} + \beta_4 \cdot \text{Vol} - \beta_5 \cdot \text{Nr}_{\text{LOG}}\right)^{2.5}} \quad (4)$$

where:

Eff = efficiency of cable yarding system, min PSH_0 m^{-3}
YD = yarding distance, m
LD = lateral yarding distance, m
SL = slope gradient, %
Vol = load volume, m^3
Nr_{LOG} = number of processed logs, [ ]

Table 3 Model statistics, parameter estimates, and test statistics for cable yarding efficiency model

Cable yarding system efficiency				
Predictors	Estimates	Std. Error	t-Value	*p*
(Intercept)	0.33	0.03	12.705	<0.001
YD	−0.0002	0.00005	−4.728	<0.001
LD	−0.0017	0.0004	−4.176	<0.001
SL	−0.0013	0.0006	−2.280	0.024
V	0.13	0.005	26.831	<0.001
Nr_{LOG}	−0.005	0.001	−5.176	<0.001
Observations	175	RSE	0.037	
R^2 / R^2 adjusted	0.837 / 0.833	F-value	174.1	
AIC	−648.524	*p*-value	< 2.2e−16	
NCVtest				
X^2	2.467235	*p*-value	0.11624	
VIF				
YD 2.678	LD 1.117	SL 2.772	V 1.057	Nr_{LOG} 1.014

The efficiency model can be converted into a productivity model by Eq. 5, as proposed by Varch et al. (2021). We adopted a conversion factor of 0.8 (Stampfer 2003) to account for delay times less than 15 min:

$$Prod = \frac{60}{(Eff \cdot k)} \tag{5}$$

where:

$Prod$ = productivity of cable yarding system, $m^3\ PSH_{15}^{-1}$
Eff = efficiency of cable yarding system, min $PSH_0\ m^{-3}$
k = delay factor, where k = 0.8

As expected, productivity increases as the load volume increases while decreasing as all the other parameters increase since they involve a more significant investment of time in timber yarding and processing. However, independent variables such as YD, LD, and SL affect the overall harvesting system performance differently. By setting a standard Vol = 1.68 m^3 and Nr_{LOG} = 5.17, for a fixed terrain slope of 24.9 % and lateral yarding distance of 10.8 m, the productivity shows an average decline of 5.6 % for every additional 50 m in yarding distance. Furthermore, the slope of the terrain also plays a significant role in the productivity levels of the harvesting system. Our analysis shows that productivity decreases by an average of 7.37 % for every 10 % increase in terrain slope (Fig. 3a). At a given yarding distance and terrain slope, the lateral dragging distance greatly affects productivity. On average, the productivity decreases by 4.94 % for every 5 m increase in lateral yarding distance (Fig. 3b). Based on our model analysis, we have found that when hauling and processing the same volume and number of logs, working at lower lateral distance, even at larger slope gradient, is more beneficial than harvesting at lower slope but at farther distances (Fig. 4).

Optimization models

Both IP-formulated problems were resolved successfully. The computational time for the STS model was 0.52 s, whereas the TCS model took 2.5 s to find the optimal result. The STS and TCS models showed differences in their estimates compared to the actual observations of 190 work cycles (Table 4). With the optimization, the number of cycles increases by 1.05 % in STS and decreases by 27.37 % in TCS. Following, we noticed a decrease in the number of trees harvested for the STS model and an increase for the TCS model. These changes were almost identical in proportion to the actual site. The former had a decrease of 17.95 %, while the latter had an increase of 17.09 %. After analyzing the average DBH of the selected trees, it was observed that

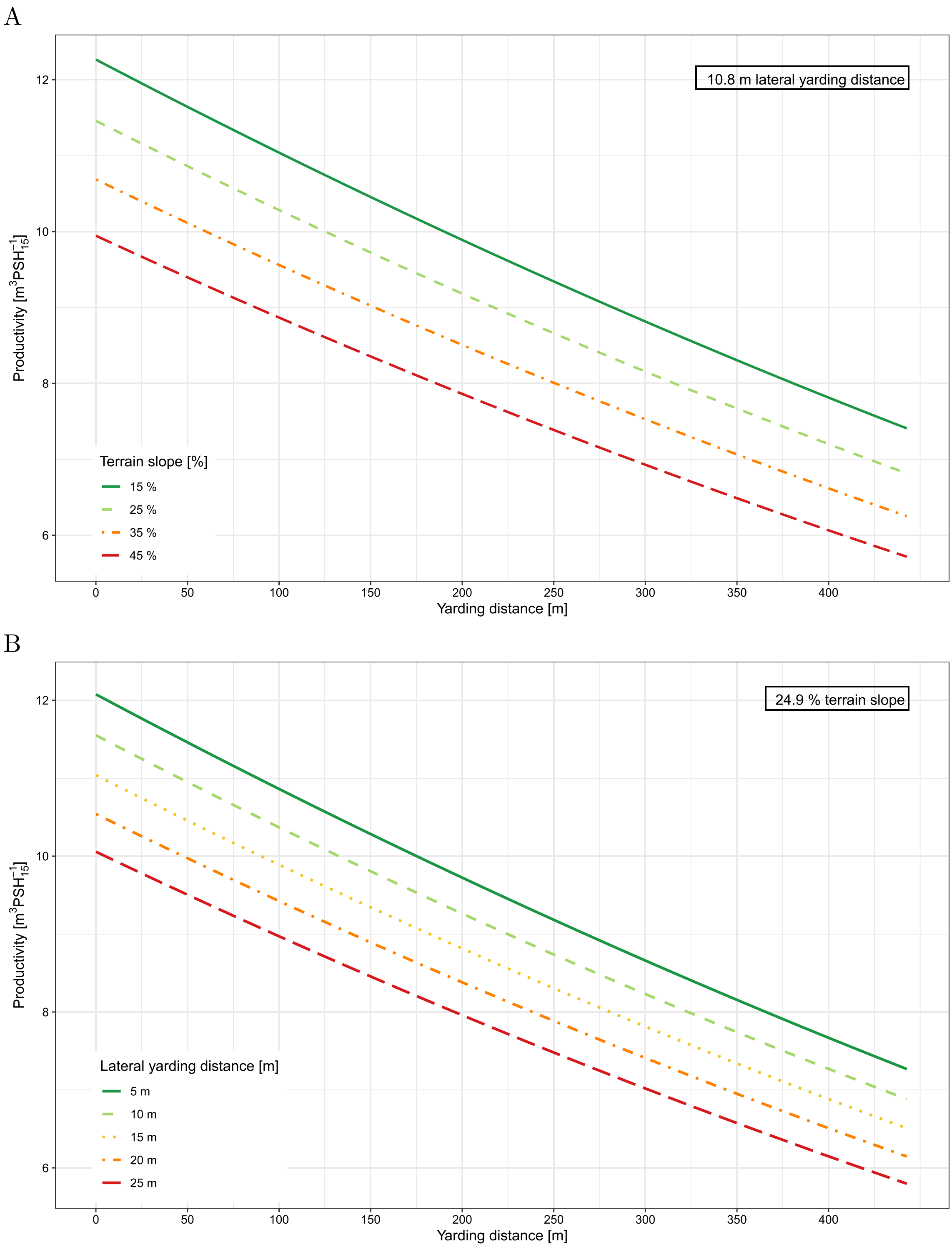


Fig. 3 Yarding and processing productivity as a function of yarding distance and terrain slope for LD = 10.8 m, Vol = 1.68 m^3, and Nr_{LOG} = 5.17 (**a**). Yarding and processing productivity as a function of yarding distance and lateral yarding distance for SL = 24.9 %, Vol = 1.68 m^3, and Nr_{LOG} = 5.17 (**b**)

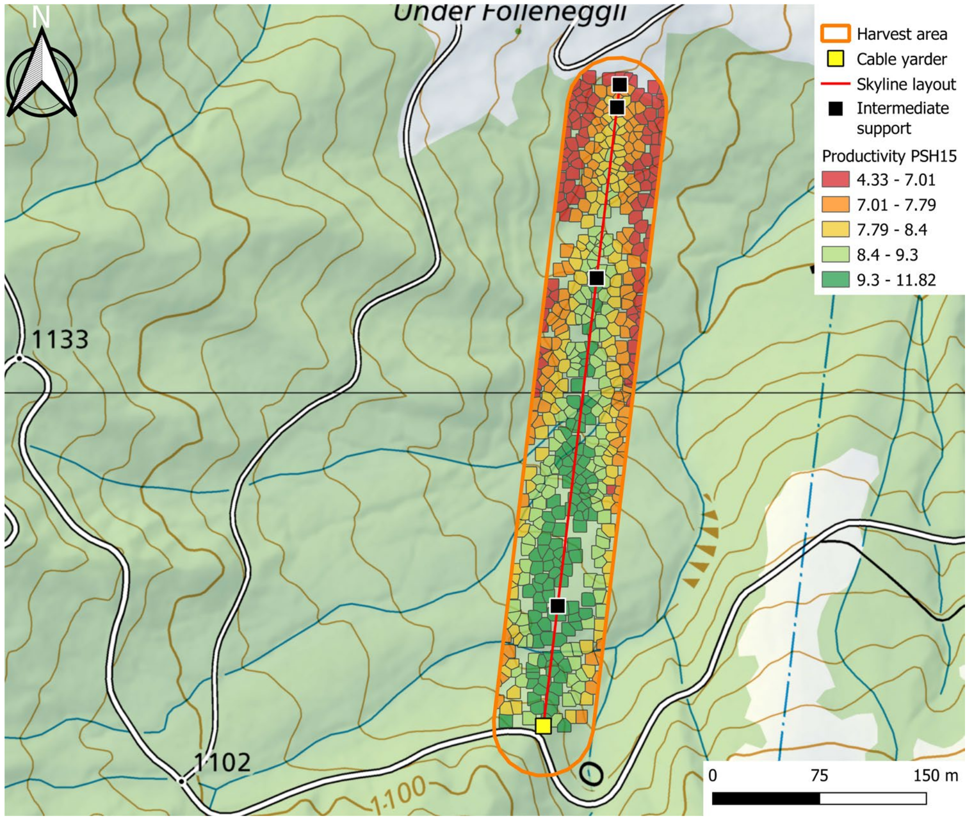


Fig. 4 Yarding and processing productivity as a function of yarding distance, terrain slope, and lateral yarding distance for Vol = 1.68 m^3 and Nr_{LOG} = 5.17 applied at single tree level

Table 4 Comparison of the results of STS and TCS models with actual worksite observations

Parameter	Unit	Worksite	STS	TCS
Work cycles	n	190	192	138
Harvested trees	n	234	192	274
Average DBH	cm	35.8	42.3	36.1
Harvested volume	m^3	301.74	302.09	302.16
V_{harv}/V_{tot}	%	34.95	34.99	35.00
Number of logs	n	875	745	938
Revenue	CHF	26715	26729	26750
Installation cost	CHF	5390	5390	5390
Logging costs	CHF	13677	15439	11804
Average productivity	m^3 PSH_{15}^{-1}	10.54	9.41	12.68
Economic profit	CHF	7648	5900	9556

the STS model chose larger trees compared to the actual selection (+ 18.15 %), while the TCS model selected trees that were more consistent with the actual selection (+ 0.83 %). The worksite reported 875 processed logs, while the STS and TCS models predicted 745 and 938, respectively. The difference between the actual logs and those calculated by the STS (−14.86%) is due to the fact that fewer trees were selected to achieve the same harvest volume. On the opposite, the number of processed logs estimated by the TCS shows a smaller positive gap (+7.2 %). This indicates that the TCS tree selection solution is more in line with the actual harvesting plan by choosing a larger amount of smaller and medium sized trees. Financially, the actual revenue from the worksite was CHF 26,715 as similarly predicted by both the models. The cable system installation cost computed for the worksite throughout HeProMo reflected a total cost (mounting and demounting) of CHF 5,390. The same was imposed for both the IP models as fixed cost. An additional divergence can be observed for the logging costs (felling, yarding and processing costs): the worksite incurred costs of CHF 13,677, while the STS and TCS models estimated costs at CHF 15,439 (+12.88 %) and CHF 11,804 (−13.69 %), respectively. The logging costs difference is mainly reflected by the discrepancy in productivity. Upon comparing the STS model to the actual worksite, we note a 10.72 % decline in productivity. On the other hand, switching to the TCS model results in a 20.3 % boost in productivity. The economic profit from the actual worksite was CHF 7,648. In comparison, the STS model projected a 22.85 lower financial return, while the TCS model showed a 24.94 % higher financial return.

In addition, the harvested volume distribution trends indicate that the STS model focuses on shorter to mid-range yarding distances, with a peak in number of selected

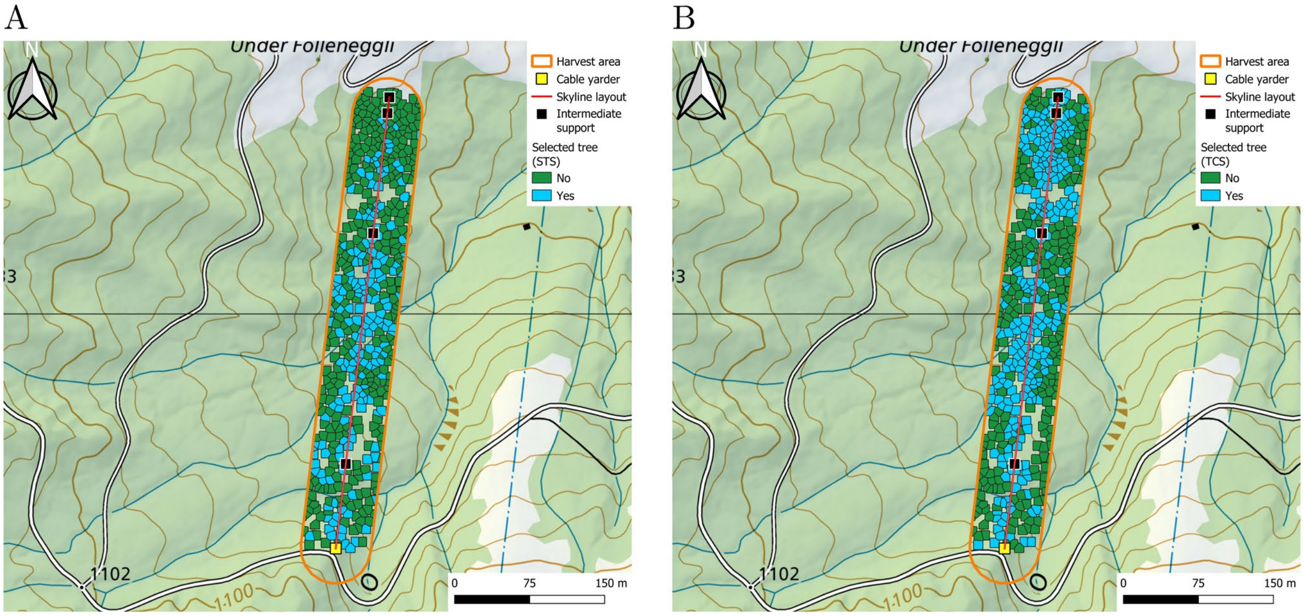


Fig. 5 Tree selection for STS optimization model (**a**) and TCS optimization model (**b**)

trees at mid-ranges before dropping off. Specifically, 24.46 % of the volume is harvested within the first 100 m, 21.70 % between 100 and 200 m, 28.18 % between 200 and 300 m, 22.56 % between 300 and 400 m, and only 3.09 % over 400 m. On the other hand, the TCS model maintains the level of harvested volume more constant throughout the harvest area. The model selects trees for a 19.06 % volume proportion within 100 m of yarding distance. The harvested volume increases to 27.05 % in the second range, between 100 and 200 m, to decrease again to 20.03 % in the third distance range between 200 and 300 m. It maintains a steady volume through to the 300–400 m range (18.77 %) decreasing slightly at the longest yarding distances (> 400 m) with a harvested volume proportion of 15.09 %. This indicates that tree density also plays a key role in tree selection when the optimization model groups small and medium-sized trees within the same working cycle.

Discussion

We have proposed two novel approaches for selecting trees for cable-based timber harvesting planning in steep terrain. Both problems are formulated as single-objective optimization problems that aim to maximize the economic marginal return of forest operations. These problems are solved by IP algorithms. Our approach involves developing a productivity model from a real case study that can be used along with the ITD forest inventory as input for the optimization problems. Finally, we compared the IP model's performance with actual worksite observations to detect the potential of improvement for cable-based harvest planning and operations (Fig. 5).

The yarding and processing productivity for a cable yarding system could be explained by load volume, yarding distance, lateral yarding distance and the average slope gradient (Stampfer 2003; Lindroos and Cavalli 2016). Unlike this study, Schweier et al. (2023), as well as Varch et al. (2021), adopted the average load volume as explanatory variable, which is the result of the averaged load volume divided by the number of trees hauled per cycle. This approach allows taking into account the number of trees per cycle without adding another variable to the prediction model. However, in our case, we decided to use the real load volume and the number of logs that can be retrieved to better account for processing time. We think that a real load volume-based productivity model is more suitable for optimization algorithms at the individual tree level. Following, we observed that under the given site conditions, increasing the load volume per work cycle can enhance the performance of the harvesting system. However, slope also plays a key role in productivity variation. Given the same distances and volumes, we have noticed that the model tends to favour those trees that have easier accessibility in terms of the steepness of the terrain. This can be clearly seen in Fig. 3 where, in the section of the harvesting area close to the landing, the trees at the boundary of the area show a lower productivity (yellow-orange colour) than the trees that present the same LD but are further away in terms of YD (light green colour) due to a lower slope of the yarding path. In comparison, the average productivity of 11.5 m^3 PSH_0^{-1} achieved by the investigated cable yarding system was the same reported from Stampfer (2003) for the Syncrofalke with an average load volume of 0.89 m^3, an average yarding distance of 178 m and an average lateral yarding distance of 5 m. In this case, the lower load volume per cycle was compensated by the shorter transport distances. Similar comparison can be made with the study of the Syncrofalke 3t carried out by Papandrea et al. (2023), that reported an average productivity of 15.20 m^3 PSH^{-1} with an average load volume of 1.23 m^3, an average yarding distance of 67.44 m and an average lateral yarding distance of 14.78 m. This shows how the yarding distance can have a significant impact on the overall harvesting performance with a cable yarding system.

Two optimization models were set up: STS involves a single-tree harvest operation while TCS involves multi-tree harvest operations per work cycle. To enable the selection of multiple trees in the TCS formulation, we generated a set of potential tree clusters based on increasing distances among trees using hierarchical clustering analysis. Both STS and TCS were tested on the same harvest area where the operation performance of the cable yarding system was investigated. They were designed by applying the same silvicultural constraints that guided the actual selection process, taking into account the maximum wood volume that could be harvested and the diameter distribution of the selected trees.

Our major finding was that both the IP models achieved positive economic benefits. However, the TCS model proved to be more efficient than the STS model. This can be observed through a comparative analysis of the models' outputs with the actual harvest data. Specifically, the TCS model demonstrated greater economic benefit for a given volume collected, while the STS model showed comparatively lower economic benefit. The basis for this outcome rested on the TCS model ability to gather more trees per cycle, which is a common practice in cable yarding operations. This possibility enabled optimal utilization of smaller trees to maximize the payload. Moreover, despite the TCS model showing a larger number of work cycles than the actual timber harvest, it presented higher productivity and lower logging costs, highlighting the relevance of maximizing the payload. It is important to keep in mind that comparing the outputs of two models with the actual harvest requires considering yarding distances, which have a direct impact on productivity levels and logging costs. It is important to note that the models are based on distances calculated from the standing position of the trees. However, in reality, the distances to be covered could be potentially different since the felled trees may move from a few to several meters from their original position, especially when working on steep slopes (Wimer et al. 2007). From a silvicultural perspective, the TCS model appears to be more plausible than the STS model. When comparing the average DBH of the tree selection results, we can observe that the TCS model is very close to the actual value, deviating by only 0.3 cm. On the other hand, the STS model shows a larger deviation of 6.5 cm, indicating that it mainly focuses on selecting medium and large-sized trees penalizing small trees. Additionally, although both models exhibit an even distribution of the selected trees throughout the harvesting area, only the TCS model has a considerable portion of the harvested volume in the last section of the cable road (> 400 m). It can be concluded that the volume of the trees is the primary factor in selecting trees using the STS method. On the other hand, the TCS method is influenced greatly by the availability and proximity of trees of all sizes, which helps in achieving better payload optimization. However, maximizing the marginal economic return of timber harvesting differs from the typical objective of silvicultural operations in mountainous areas, where functions such as direct protection against natural hazards or mitigation of climate changes are prioritized over the productive aspect (Price et al. 2011). It is evident that even TCS, despite being closer to a real harvest plan, requires finer gradation based on silviculture criteria to be adopted in mountain environments. A crucial aspect to consider is the size of the gaps generated by the tree selection. The individual gap should not be more than 20 ms long along the steepness slope direction if the forest must provide reliable protection against rockfall (Berretti et al. 2006). At the same time, the gap size should be large enough to allow sufficient light and warmth to reach the ground for seedlings to grow and survive (Ott et al. 1997). According to Haberl (2020), a gap length of one mature tree (around 30 ms) and a gap width of half of a mature tree (around 15 ms), oriented obliquely relative to the cable road, could achieve good results. Hence, in order to improve the optimization model, provision could be made to include different silvicultural treatments aimed at different management objectives, such as carbon sequestration or protection against natural hazards. In addition, an improved model should also consider medium- and long-term forest planning, optimizing multiple interventions over a longer period by adding a tree growth model (Bugmann and Seidl 2022). In this regard, a multi-objective tree selection could be implemented through a mixed integer programming (MIP) model to enable a trade-off of different objective functions, as similarly done by Pascual (2021). In fact, our results suggest that even if the inclusion of these objective functions would lead to a considerable lowering of the harvesting economic benefit, the optimization model could still improve the efficiency of the harvesting system investigated by simultaneously achieving several forest management goals. Likewise, environmental targets could also be the subject of optimization. With the emergence of CanBUS systems, data on the fuel consumption and CO_2 emission of forest machines have become increasingly accessible (Cadei et al. 2021; Bacescu et al. 2022), showing possibilities to integrate new environmental functions in the optimization process. For instance, such information could be used to set up the TCS model to derive a tree selection that would minimize the CO_2 emission of cable yarding harvesting activity. This would have a significant influence on the eco-friendliness of forest operation, as it would reduce their environmental impact. A MIP model set up in this way could enable the practitioners to make more informed decisions that benefit both the environment and the financial aspect.

A final consideration to improve the model performance is related to the accuracy and truthfulness of the forest inventory input layer. Public ALS data provide valuable information source on individual tree characteristics of a forest stand. However, despite the high-resolution of ALS data for Swiss territory, the detection of the dominated tree layer may fail because of the tree crown overlap (Lindberg et al. 2010). The next model formulations could take advantage of the improvements achieved in ITD through the use of terrestrial laser scanning (TLS) platforms (Seifert et al. 2010) and more recently with mobile laser scanning devices (Tupinambá-Simões et al. 2023). The new lidar technology could indeed provide further information from the detection of standing trees, such as clear identification of dominated trees and reliable number and type of retrievable logs (Alvites et al. 2021).

Conclusion

The proposed optimization models for tree selection in cable-based harvest planning scenario are simple formulations which consider tree attributes and spatial distribution to maximize economical goal. TCS showed a more plausible and efficient tree selection compared to STS. TCS is easy to adopt by adjusting the harvest volume, the maximum payload per work cycle and the DBH ranges. Future studies will focus on TCS improvement based on silviculture criteria to enable to consider different management scenario and ecosystem services.

Appendix A

See Table 5.

Table 5 Technical parameters of the Mounty MT50-2 truck-mounted tower yarder, Woody 60 processing head and Liftliner LL40-1 carriage

Parameter	Value
Tower yarder	
Power	331kW / 450 hp
Tower height	14.2 m
Skyline winch	Ø 22 mm / 800 m
Pulling force	120 kN
Mainline winch	Ø 12 mm / 800 m
Pulling force	47 kN
Haul-back winch	Ø 11 mm / 1600 m
Pulling force	40 kN
Crane type	MT24
Crane lifting torque	220 kNm
Range	9.9 m
Processing head	
Delimbing diameter	8–65 cm
Max. grapple opening	120 cm
Feed force	35 kN
Weight	1450 kg
Operating pressure	300–350 bar
Chain speed	40 m/s
Length of the saw guide bar	820 mm
Max. cutting diameter	680 mm
Carriage	
Weight	1050 kg
Skyline diameter	Ø 18 mm / 22 mm
Engine power	55 kW
Winch pulling force	40 kN
Wire rope	Ø 11 mm / 100 m

Source: https://www.forsttechnik.at/en/

Appendix B

See Table 6.

Table 6 Parameter settings for each function used in lidR to perfrom ITD and individual tree segmentation

Process	Function	Algorithm	Parameters
Ground classification	classify_ground	Cloth simulation filtering algorithm	Default
Point cloud normalization	normalize_height	"kNNIDW" algorithm	Default
ITD	locate_trees	Local maximum filter algorithm	ws = Eq. 1 hmin = 15 shape = “circular” ws_args = “Z”
CHM	rasterize_canopy	Point-to-raster algorithm	res = 0.5 subcircle = 0.2
CHM post-processing smoothing	focal	/	fun = median
Individual tree segmentation	segment_trees	“dalponte2016”	Default

Appendix C

See Figs 6 and 7.

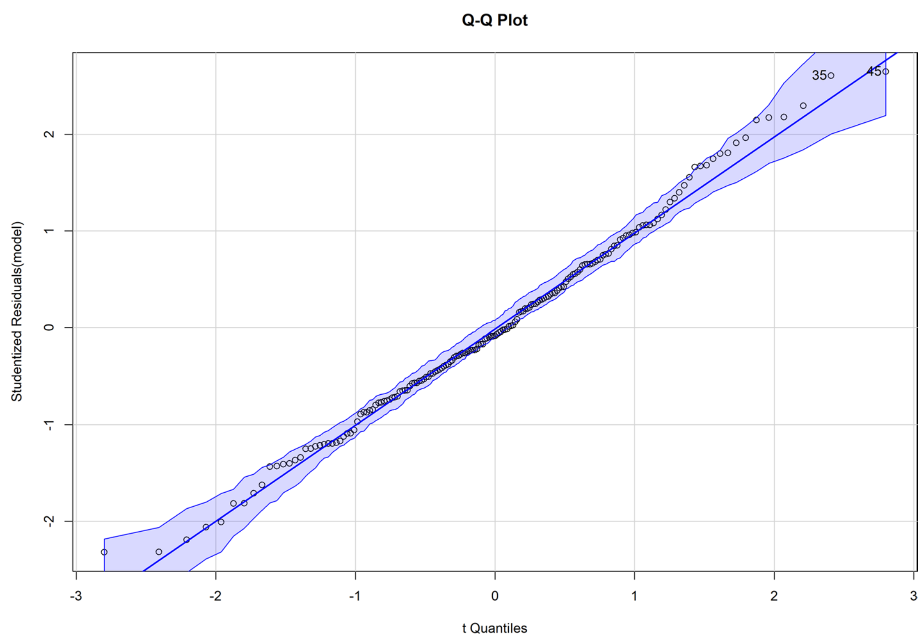


Fig. 6 QQ plot of the efficiency model

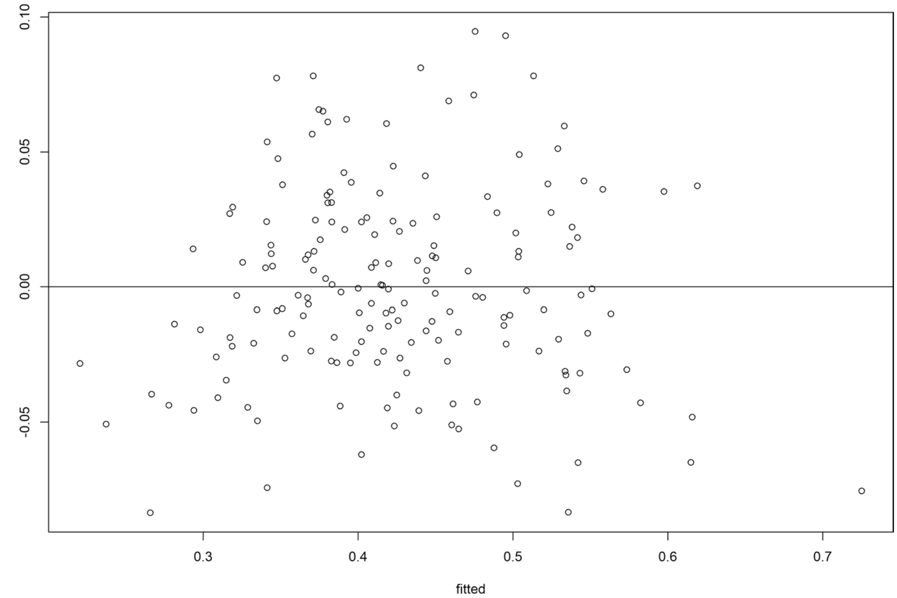


Fig. 7 Residual plot of the efficiency model

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Author Contributions FS: conceptualization, methodology, formal analysis and investigation, writing - original draft preparation, writing - review and editing. MS: conceptualization, methodology, formal analysis and investigation, writing - review and editing, supervision. PD: methodology, writing - review and editing. PT: methodology, writing - review and editing. EL: writing - review and editing, supervision. MZ: conceptualization, writing - review and editing, funding acquisition, resources, supervision.

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Data availability The time-study dataset and the ITD forest inventory dataset are stored at Univeristy of Padova and are available for public use at the following link https://researchdata.cab.unipd.it/id/eprint/1085. The Digital Object Identifier (DOI) of the datasets is: 10.25430/researchdata.cab.unipd.it.00001085. If the above link is no longer functional, please contact Francesco Sforza at francesco_sforza@hotmail.com, and he will send you the datasets directly.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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