Smart Silviculture: Enhancing Carbon Sequestration through Optimized Tree Selection

Prof. Mauricio Acuna, Luke **Forest Carbon Vision, Kick-off meeting**



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Source: Ponsse



Presentation's Outline

- 1. Introduction & Context
- 2. The Role of Thinning
- 3. Smart Tree Selection Framework
- 4. Key Decision Parameters
- 5. Optimization Models (Single and Bi-objective)
- 6. Dealing with uncertainty (Stochastic Programming)
- 7. Implementation and Operational Integration
- 8. Policy & Market Relevance
- 9. Conclusions



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Why It Matters in Finland? Forests, Climate, and Policy Goals

- Finland has 75% forest cover; forests play a key role in national climate targets
- Commitment to carbon neutrality by 2035
- Forest thinning is a common management practice
- Climate-smart forestry requires smarter thinning decisions



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Carbon balance of the land use sector

The carbon sinks of forests remained larger than emissions from other land uses until 2020. However, in 2021, the carbon sinks weakened to the extent that the land use sector as a whole became a source of emissions. 2022 data is preliminary. milj. tonnes CO2-ekv.





The Role of Thinning

Traditional Goals and New Challenges

- Purpose: reduce competition, improve growth, increase wind resilience
- Typically based on spacing or DBH thresholds
- Carbon impacts are often not explicitly considered, current thinning practices optimize for growth and timber



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Smart Tree Selection

Data-Driven Decision Making

- Move from rule-based to goal-based decision-making •
- Use optimization to select individual trees for removal
- Objectives: •
 - ✓ Maximize long-term carbon storage
 - ✓ Minimize operational harvesting cost
 - ✓ Maintain or enhance forest productivity



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Key Parameters in Selection What Drives a Good Decision?

Parameters	Role in Optimal Selection	Data Source / Methodology
DBH / Height	Predicts biomass/carbon and growth potential	Field inventory, LiDAR, Harvester head, Growth models from Motti
Species	Affects growth rate, carbon allocation, rotation length	Forest inventory, remote sensing
Crown Class / Dominance	Indicates competitive status, growth trajectory	UAV imagery, expert scoring
Health / Vigor	Impacts survival and carbon storage reliability	Visual inspection, AI-based detection
Harvesting Cost	Affects economic feasibility of thinning operations	Harvester productivity models
Spatial Location	Determines machine access, cluster optimization	GPS, spatial data layers
Stand Structure	Drives ecological stability, affects thinning strategy	UAV + LiDAR analysis
Risk Factors	Accounts for mortality, windthrow, pest damage	Simulation models, historical data



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Optimization Model

Single Objective, Maximizing Long-Term Carbon

Model type: MIP (Mixed-Integer Programming) or Metaheuristics (for large problem sizes)

- Decision Variable: $X_i = \begin{cases} 1, if tree \ i is removed \\ 0, otherwsise \end{cases}$
- Objective Function:

Maximize:

 $\sum_{i=1} (1 - X_i) * CarbonPotential_i$

Subject to: - Stand density & spacing constraints

- Operational feasibility (e.g. terrain, machine limits)
- Optional: Harvest volume targets, budget limits

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Optimization-Based Tree Selection Model



- Binary variable x_i • 1 if tree is removed
- Maximize long-term carbon sequestration
- Constraints
 - Stand density & spacing
 - Operational feasibility
 - Harvest volume targets

Maximize:

- x_i = 1f tree is removed
- $\sum (1-x_i) \cdot \text{CarbonPotential}_i$

CarbonPotential_i

Carbon potential is derived from tree species, DBH, growth projection, mortality risk, and carbon retention lifespan



Optimization Model Single Objective, Maximizing Long-Term Carbon



Forest Ecology and Management Volume 482, 15 February 2021, 118847

How does carbon pricing impact optimal thinning schedules and net present value in Mediterranean pine plantations?

Mauricio Acuna a 1 🔗 🖾 , Rafael Mª Navarro-Cerrillo ^{b 1}, Francisco Ruiz-Gómez ^b, Miguel Lara-Gómez ^c, Javier Pérez-Romero ^d, Mª Ángeles Varo-Martínez ^b, Guillermo Palacios-Rodríguez ^b

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Optimization Model Bi-Objective, Balancing Carbon and Harvest Cost

Bi-objective formulation

Let:

- $-X_i \in \{0, 1\}$: 1 of tree i is removed
- C_i: carbon portential of tree i
- B_i : harvesting cots of tree i

Objective Function:

 $max \{f_1$

ε-constrained method

Optimize one objective, constrain the other:

 $max\{\sum$

Vary ε to trace out the Pareto frontier

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$$(x) = \sum_{i} (1 - X_i) C_i, \quad f_2(x) = \sum_{i} X_i B_i,$$

$$G_i(1-X_i) C_i$$
, subject to $f_2(x) = -\sum_i X_i B_i$,





Pareto Frontier Example

Carbon versus Harvesting Cost



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Dealing with Uncertainty

Building Robust Thinning Plans

Factors: climate variability, pest outbreaks, growth uncertainty, carbon prices

Use of Stochastic Programming (SP)

- First stage: thinning decision (which trees to remove now)
- Second stage: scenario-based decisions adapting to realized conditions
- Adjust thinning intensity
- Modify harvest schedule
- Allocate post-disturbance interventions or carbon reporting corrections



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Decision Variables: •

- x: First-stage decision variables (decisions made before the uncertainty is revealed).
- x_s : Second-stage decision variables for scenario s (decisions made after the uncertainty is revealed for scenario s).
- Objective Function:

$$\min_{x,x_s}\left\{c^Tx+\mathbb{E}_s[Q(x,\xi_s)]
ight\}$$

where $Q(x, \xi_s)$ is the second-stage cost for scenario s:

$$Q(x,\xi_s)=\min_{x_s}\{q_s^Tx_s\mid T_sx+W_sx_s=h_s\}$$

- Constraints:
 - First-stage constraints: Ax = b
 - Second-stage constraints for each scenario $s: T_s x + W_s x_s = h_s$

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Implementation with Finnish Data

Leveraging Existing Data Ecosystems

- Metsään.fi, forest inventory, UAV and LiDAR data
- PREBAS and Motti for carbon and growth modelling
- Harvester APIs (StanForD) for feedback and monitoring



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Integration into Harvester Operations

Decision Support for Operators







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Policy and Market Relevance

Connecting Silviculture with Incentives

- EU Green Deal and biodiversity goals push for climate-smart forestry
- Finland's national forestry strategy encourages sustainable intensification
- Carbon-oriented thinning could be tied to voluntary or compliance carbon markets
- Opportunities for ecosystem service payments and blended finance models



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Conclusions

Key takeaways

- Smart tree selection = better alignment with climate and economic goals
- Optimization enables data-driven thinning
- Next steps: field trials, integration, policy linkage



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