Operational Implementation and Cost Analysis of a LiDAR inventory in Boreal Ontario

Murray Woods
Southern Science & Information
OMNR – North Bay
Regional Delivery through Partnerships

Partnerships

**FPInnovations:** CWFC, Forest Ops., Wood Prod., Pulp&Paper

**CFS:** Luther, Leckie, Gougeon, Wulder, Beaudoin

**Universities:** UBC, Queen’s, Nipissing, Sherbrooke, UQAM, Laval, Sir Wilfred Grenfell

**Provinces:** BCMoFR, ASRD, OMNR, MRNF-QC, NLDNR, NBDNR

**Industry:** West Fraser, Tembec, Foothills G&Y, Corner Brook P&P, J.D. Irving

**Funding partners:** GEOIDE, OCE, FQRNT, ACOA, AIFI, NSERC

... inventory systems that support Value Chain Optimization by allowing us to send the right wood to the right markets, at the right time!
Advanced Forest Resource Inventory Technologies
TEAM AFRIT

Doug Pitt
Dave Nesbitt
Margaret Penner
Forest Analysis Ltd.
Kevin Lim
Lim Geomatics
Paul Treitz
Dave Etheridge
Jeff Dech
Don Leckie
François Gougeon
Implementation and Cost Analysis of a LiDAR inventory

- LiDAR 101
- LiDAR Derived Inventory Primer
- Current LiDAR Inventory Success Stories
- Operational Decision Support Tools – AFRIDS
- Operational Economics
- Enhancements to Next Generation Inventories
“Active” remote sensing technology; transmit & receive ~35,000 - 500,000 pulses of NIR laser light per second

Discreet System - Each pulse can produce multiple returns (up to 4)

GPS provides the exact X-Y-Z position of each return
LiDAR Technology

Historical Reason for Acquiring LiDAR Data

Ground Hits -> DTM
LiDAR Technology

Vegetation Hits Only

Ground Hits -> DTM
Airborne-LiDAR

- High Resolution DTM
- Hazard mapping
- Floodplain/risk mapping
- Landform Classification-ELC
- Agricultural Land mapping
- Geological Mapping
- Open pit mining
- Coastal/Shoreline Mapping
- Predictive Hydrology
- Urban Modeling
- Woodlot Extraction
- Transmission Line corridors Forest Engineering
- Corridor/Right-of-way Mapping
- Wetlands/Riparian areas
- Habitat modeling
- Forest Inventory
Field Sampling

- Cruising generally not occurring in Boreal forests
- Very “light” 1%-2%
- Expensive
- Only provides information on sampled sites – extrapolated
- Need to do for the next stand…and the next…
Field Sampling vs. 100% Enumeration

- 100% enumeration of the landbase with LiDAR measurements of vertical structure
- permits the use of regression estimators to scale PU estimates to groups of PUs, Stand, Block or Forest
LiDAR offers more than a DTM
Additional forest inventory information contained in point cloud data
Focus of AFRIT is “Area” based modeling NOT “Individual Tree”
Prediction Unit = 20m X 20m (400m²)
LiDAR Derived Inventory – Pairing with Ground Data

Field Plot Measurement
LiDAR Derived Inventory – Statistical Predictors

- Derived for each ground field plot
  LiDAR point cloud

- Statistical
  - Mean, Standard Deviation, Absolute Deviation, Skew, Kurtosis

- Percentiles
  - Deciles (p10 … p90) and Maximum Height
    - A decile is any of the 9 values that divide sorted data into 10 equal parts with each part representing 1/10th of the sample or population.

- Density
  - d1 … d9
    - Range of heights divided into 10 equal intervals.
    - Cumulative proportion of returns starting from the lowest interval.
  - Da : Number of first returns divided by all returns.
  - Db : Number of single returns divided by all returns.
  - Dv : Number of first returns classified as non-ground divided by all returns.
  - CC : Crown Closure (percent canopy) based at various Z thresholds.
  - VCI: Vertical Complexity Index, etc.
Study Sites

Boreal Forest MU

- Romeo Malette Forest
  ~630k ha

- Hearst Forest
  ~1.3 M ha
LiDAR Derived Inventory

LiDAR predictive Models for:

- Height (AVG, Top)
- QMDBGH
- Volume (GTV, GMV)
- Basal area
- Biomass
- Density*
- Sawlog Volume
- Close Utilization Volume
- Dom/Codom Ht
- Mean Tree GMV
- Size Class Distributions

* Derived from DBHq & BA
LiDAR Derived Inventory – 400m² Surfaces

**Top Height**
- Top Height = 17.2 ± 0.2 m

**Average Height**
- Average Height = 12.8 ± 0.3 m

**Basal Area**
- Basal Area = 20.2 ± 1.0 m² ha⁻¹

**QMDBH**
- QMDBH = 14.8 ± 0.3 cm

**Gross Total Volume**
- SUMGTV = 144.3 ± 8.1 m³ ha⁻¹

**Gross Merchantable Volume**
- SUMGMV = 102.1 ± 6.3 m³ ha⁻¹

**Biomass**
- Biomass = 85087.3 ± 4374.0 Kg ha⁻¹

**Density**
- Density = 1187 stems ha⁻¹

1 Density was calculated from Basal Area and QMDBH and confidence intervals were not calculated.
LiDAR Information can add more value to our rich image and inventory interpretation.
Enhanced Modeling Approaches

Regression

\[ y = e^{b_0} \cdot x_1^{b_1} \cdot x_2^{b_2} \cdot \ldots \cdot x_5^{b_5} \]
Enhanced Modeling Approaches

Regression

\[ y = b_0 + b_1 x_1 + b_2 x_2 \]

\[ y_1 = b_0 + b_1 x_1 + b_2 x_2 \]

\[ y_2 = b_0 + b_1 x_1 + b_2 x_3 \]

\[ \vdots \]

\[ y_p = b_0 + b_1 x_2 + b_2 x_3 \]

\[ y = e^{b_0} \cdot x_1^{b_1} \cdot x_2^{b_2} \cdot \ldots \cdot x_5^{b_5} \]

RandomForest

Option for hundreds to thousands of trees
SUR vs. RandomForest - Predicted vs. Observed

SUR Regression Model

RandomForest
LiDAR Derived Inventory

LiDAR vs. RandomForest Models – CV (% of mean) by Forest Type

- **Dom/Codom HT CV Comparison by Model Type**
  - Coefficient of Variation
  - Forest Type: SB, SF, SP, PJ, IH, LC, MWC, MWH

- **Merch BA CV Comparison by Model Type**
  - Coefficient of Variation
  - Forest Type: SB, SF, SP, PJ, IH, LC, MWC, MWH

- **GMV CV Comparison by Model Type**
  - Coefficient of Variation
  - Forest Type: SB, SF, SP, PJ, IH, LC, MWC, MWH

- **DBHq CV Comparison by Model Type**
  - Coefficient of Variation
  - Forest Type: SB, SF, SP, PJ, IH, LC, MWC, MWH

- **SUR**
- **RandomForest-Regression**

For each 400m²
LiDAR Derived Inventory

LiDAR vs. RandomForest Models – CV (% of mean) by Forest Type

Dom/Codom HT CV Comparison by Model Type

Merch BA CV Comparison by Model Type

GMV CV Comparison by Model Type

DBHq CV Comparison by Model Type

DBHq RMSE (+/-) Comparison by Model Type

+/- cm

0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0

Forest Type

SUR

RandomForest-Regression

SB

SF

SP

PJ

IH

LC

MWC

MWH

Forest Type

Coefficient of Variation

0% 5% 10% 15% 20% 25%
RandomForest LiDAR derived Inventory Surfaces

LiDAR Predicted GMV Raster

Advantages of RandomForest
- doesn't rely on an existing polygon inventory
- no separate forest-type models to statistically build
- very quick to implement
- custom application of LiDAR predictions for each 20m x 20m

LiDAR Predicted Dbhq Raster

Disadvantages of RandomForest
- black box – “loss of control”
- Critical that extremes of forest conditions are sampled as input
Value Added – RandomForest 1st-cut Stand Polygons

LiDAR Predicted GMV Raster

LiDAR Predicted Dbhq Raster

Photo Interpreted Stand Boundaries

Photo Interpreted Stand Boundaries
LiDAR Derived Inventory – 400m$^2$ Surfaces

Pockets of species within a typed stand
LiDAR Derived Inventory – Size-Class Distributions

Density and Volume by 2cm Diameter Classes

Black Spruce Validation Data – Aggregated by VCI class
LiDAR Derived Inventory – Size-Class Distributions

Density and Volume by 2cm Diameter Classes

Mixedwood Validation Data – Aggregated by VCI class
Harvested 2008, 35ha (PJ)
Plan Volume 4,669m³
LiDAR Volume 7,543m³
Scaled Volume 7,733m³
LiDAR Within 2%!

12 of the 43 blocks sampled fell within 5%, Clearcut System
LiDAR Derived Inventory – RMF Block Validation

Harvested 2007, 91ha (PO)
Plan Volume 9,943m³
LiDAR Volume 13,258m³
Scaled Volume 12,340m³
LiDAR Within 8%

14 of the 43 blocks sampled fell within 5-15%, Wildlife Retention
Harvested 2009, 197ha (SB/LA)
Plan Volume 24,152m³
LiDAR Volume 16,606m³
Scaled Volume 13,238m³
LiDAR Within 25%

Inventory issues
- Sp Comp
- Age
- resultant Site Class
- resultant Yield Curve

Residual Sb
AFRIDS Advanced Forest Resource Inventory Decision Support System
AFRIDS Advanced Forest Resource Inventory Decision Support System
Forest Unit: SB1
Area: 45 ha

AFRIDS Advanced Forest Resource Inventory Decision Support System
AFRIDS  Advanced Forest Resource Inventory Decision Support System
Improving planning decisions by using Enhanced Forest Inventory (EFI)

Sébastien Lacroix, FPInnovations
Murray Woods, OMNR
Chad St-Amand, Tembec
Lino Morandin, Tembec
Pierre Bédard, FPInnovations
Joseph Nader, FPInnovations
Doug Pitt, CWFC
Objectives

- Are LiDAR-enhanced inventories leading to better forest management decisions?
- What are the cost savings associated with enhanced decision making?
### Approach – Volume Comparison

- LiDAR provides better volume prediction (statistically tested)
  - Yield Curve: **14.5%**
  - LIDAR: **5.4 %**

#### Difference from harvested volume (scaled)

<table>
<thead>
<tr>
<th>Yield Curve</th>
<th>LIDAR</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Yield Curve</strong></td>
<td><strong>LIDAR</strong></td>
</tr>
<tr>
<td>BW</td>
<td>SP</td>
</tr>
<tr>
<td>208</td>
<td>12%</td>
</tr>
<tr>
<td>214</td>
<td></td>
</tr>
<tr>
<td>216</td>
<td>-2%</td>
</tr>
<tr>
<td>220</td>
<td>14%</td>
</tr>
<tr>
<td>244</td>
<td>-9%</td>
</tr>
<tr>
<td>245</td>
<td>-2%</td>
</tr>
<tr>
<td>246</td>
<td>-2%</td>
</tr>
<tr>
<td>251</td>
<td>6%</td>
</tr>
<tr>
<td>252</td>
<td>9%</td>
</tr>
<tr>
<td>254</td>
<td>-1%</td>
</tr>
<tr>
<td>256</td>
<td>1%</td>
</tr>
<tr>
<td>257</td>
<td>7%</td>
</tr>
<tr>
<td>259</td>
<td>1%</td>
</tr>
<tr>
<td>275</td>
<td></td>
</tr>
</tbody>
</table>

**10 % & under**

**greater than 10 %**
### Approach – Volume Comparison

- LiDAR provides better volume prediction (statistically tested)
  - **Yield Curve:** \(14.5\%\)  
  - **LIDAR:** \(5.4\%\)

#### Difference from harvested volume (scaled)

<table>
<thead>
<tr>
<th>Yield Curve</th>
<th>BW</th>
<th>SP</th>
<th>PJ</th>
<th>PO</th>
</tr>
</thead>
<tbody>
<tr>
<td>208</td>
<td>12%</td>
<td>10%</td>
<td>0%</td>
<td>-22%</td>
</tr>
<tr>
<td>214</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>216</td>
<td>-2%</td>
<td>33%</td>
<td>3%</td>
<td>-34%</td>
</tr>
<tr>
<td>220</td>
<td>14%</td>
<td>-15%</td>
<td>0%</td>
<td>1%</td>
</tr>
<tr>
<td>244</td>
<td>-9%</td>
<td>34%</td>
<td>-12%</td>
<td>-14%</td>
</tr>
<tr>
<td>245</td>
<td>-2%</td>
<td>9%</td>
<td>-1%</td>
<td>-6%</td>
</tr>
<tr>
<td>246</td>
<td>-2%</td>
<td>20%</td>
<td>-1%</td>
<td>-17%</td>
</tr>
<tr>
<td>251</td>
<td>6%</td>
<td>33%</td>
<td>6%</td>
<td>-45%</td>
</tr>
<tr>
<td>252</td>
<td>9%</td>
<td>55%</td>
<td>1%</td>
<td>-66%</td>
</tr>
<tr>
<td>254</td>
<td>-1%</td>
<td>4%</td>
<td>10%</td>
<td>-12%</td>
</tr>
<tr>
<td>256</td>
<td>1%</td>
<td>-6%</td>
<td></td>
<td>5%</td>
</tr>
<tr>
<td>257</td>
<td>7%</td>
<td>-17%</td>
<td></td>
<td>9%</td>
</tr>
<tr>
<td>259</td>
<td>1%</td>
<td>0%</td>
<td></td>
<td>-1%</td>
</tr>
<tr>
<td>275</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>LIDAR</th>
<th>BW</th>
<th>SP</th>
<th>PJ</th>
<th>PO</th>
</tr>
</thead>
<tbody>
<tr>
<td>208</td>
<td>2%</td>
<td>-6%</td>
<td>0%</td>
<td>3%</td>
</tr>
<tr>
<td>214</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>216</td>
<td>-16%</td>
<td>6%</td>
<td>1%</td>
<td>8%</td>
</tr>
<tr>
<td>220</td>
<td>0%</td>
<td>-11%</td>
<td>4%</td>
<td>7%</td>
</tr>
<tr>
<td>244</td>
<td>-10%</td>
<td>2%</td>
<td>2%</td>
<td>5%</td>
</tr>
<tr>
<td>245</td>
<td>0%</td>
<td>5%</td>
<td>1%</td>
<td>-6%</td>
</tr>
<tr>
<td>246</td>
<td>0%</td>
<td>5%</td>
<td>1%</td>
<td>-6%</td>
</tr>
<tr>
<td>251</td>
<td>1%</td>
<td>11%</td>
<td>5%</td>
<td>-17%</td>
</tr>
<tr>
<td>252</td>
<td>4%</td>
<td>23%</td>
<td>2%</td>
<td>-29%</td>
</tr>
<tr>
<td>254</td>
<td>1%</td>
<td>-4%</td>
<td>0%</td>
<td>4%</td>
</tr>
<tr>
<td>256</td>
<td>2%</td>
<td>-1%</td>
<td></td>
<td>-1%</td>
</tr>
<tr>
<td>257</td>
<td>2%</td>
<td>-5%</td>
<td></td>
<td>3%</td>
</tr>
<tr>
<td>259</td>
<td>-3%</td>
<td>-2%</td>
<td></td>
<td>5%</td>
</tr>
<tr>
<td>275</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**10 % & under**

**greater than 10 %**
Comparison of 2 scenarios

1. **Actual cut over – ACTUAL**
   - Area harvested within approved plan

2. **Redesign blocks within proposed plan – LIDAR**
   - New harvest planning using LiDAR for area similar to initial plan
   - Validated by Tembec FRM
   - Stay within approved 5 year harvest blocks
Approach – Cost Analysis: Scenarios

Actual harvested area, obtained using digital imagery - ACTUAL
Approach – Cost Analysis: Scenarios

Actual harvested area, with LiDAR predicted DBHq - **ACTUAL**
Approach – Cost Analysis: Scenarios

Actual harvested area, with LiDAR predicted GMV - ACTUAL
Approach – Cost Analysis: Scenarios

Redesign plan, based on full suite of LiDAR data products – LIDAR

Removed area of less GMV from Scenario
Approach – Cost Analysis: Scenarios

Proposed ‘NEW’ road network, takes advantage of LiDAR scenarios

Road segments not required and removed from modeling
Approach – Cost Analysis Categories

Three groups of cost items:

A. Inventory acquisition and processing - 6 items

B. Forest operations – 20 items

C. Mill - 4 items
## B. Forest Operations Cost Analysis

<table>
<thead>
<tr>
<th>Cost Category</th>
<th>Savings</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Forest management plan (FMP) revisions</td>
<td>N/A</td>
</tr>
<tr>
<td>• Better wood allocation at the planning stage</td>
<td>$0.13 m³</td>
</tr>
<tr>
<td>• Budget forecast</td>
<td>$0.02 m³</td>
</tr>
<tr>
<td>• Decrease of Forest and Mill Inventory</td>
<td>$0.07 m³</td>
</tr>
<tr>
<td>• Better freshness on the wood products</td>
<td>$0.09 m³</td>
</tr>
<tr>
<td>• Feller-buncher productivity (m³/ha)</td>
<td>$0.08 m³</td>
</tr>
<tr>
<td>• Full-tree productivity (m³/stem)</td>
<td>$0.19 m³</td>
</tr>
<tr>
<td>• Skidding productivity</td>
<td>$ ????</td>
</tr>
<tr>
<td>• Wood cutting optimization</td>
<td>$ ????</td>
</tr>
<tr>
<td>• Wood damage on immature wood</td>
<td>$ ????</td>
</tr>
<tr>
<td>• Wood delivery logistics</td>
<td>$ ????</td>
</tr>
<tr>
<td>• Floating costs</td>
<td>$0.05 m³</td>
</tr>
<tr>
<td>• Block layout</td>
<td>$0.05 m³</td>
</tr>
<tr>
<td>• Handling productivity</td>
<td>$0.02 m³</td>
</tr>
<tr>
<td>• Better road location &amp; design</td>
<td>$0.01 m³</td>
</tr>
<tr>
<td>• Road construction</td>
<td>$0.43 m³</td>
</tr>
<tr>
<td>• Road maintenance</td>
<td>$0.03 m³</td>
</tr>
<tr>
<td>• Silviculture funds</td>
<td>$0.06 m³</td>
</tr>
<tr>
<td>• Silviculture cost</td>
<td>$0.02 m³</td>
</tr>
<tr>
<td>• Indirect costs</td>
<td>$0.15 m³</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>$1.40 m³</strong></td>
</tr>
</tbody>
</table>
Results: Actual vs. LiDAR Scenario

Three groups of cost items:

A. Inventory acquisition and processing - 6 items $ - 0.10 m³

B. Forest operations – 20 items $ 1.40 m³

C. Mill - 4 items $ 0.30 m³

Savings $ 1.60 m³

X 500,000 m³ / year = $ 800,000 / year

Payback = 1.3 years

*Tembec’s LiDAR acquisition 50% of what was modeled so payback was achieved in the first year !!!
Ongoing Enhancements

- Site Productivity - Wet Areas Mapping – Predicted Texture
  Clement Akumu, John Johnson, Peter Uhlig, Sean McMurray, Dave Etheridge
  Paul Arp, Jae Olivie - UNB

Using the Cartographic Depth-to-Water Index to Locate Small Streams and Associated Wet Areas across Landscapes
  Barry White, Jae Ogilvie, David M.H. Campbell, Douglas Hiltz, Brian Gauthier, H. Kyle Chisholm, Hua Kim Wen, Paul N.C. Murphy, and Paul A. Arp
Ongoing Enhancements

- Site Productivity - Wet Areas Mapping – Predicted Texture

Clement Akumu, John Johnson, Peter Uhlig, Sean McMurray, Dave Etheridge
Paul Arp, Jae Olivie - UNB

Depth to Water table Raster
Environmental input variables:
- Elevation (10m)
- Slope (%)
- Surface shape (Curvature)
- Mode of deposition (NOEGTS)
- Landcover
- Slope Position from TPI
  - (macro window = 1km)
  - (medium window = 500m)
  - (micro window = 20m)
- Wetness Index
Ongoing Enhancements

• Fibre Analysis – Jeff Dech, Bharat Pokharel, Megan Smith, Art Groot
Ongoing Enhancements

- ITC – Individual Tree Classification
Ongoing Enhancements

- **ITC – Individual Tree Classification**

  ![Jack Pine DBH Graph](image1)

  ![Black Spruce DBH Graph](image2)
Ongoing Enhancements

• Rapid technology evolution
  – Discrete LiDAR ➔ Full Waveform ➔ Increased density
  – SGM Pixel-correlation methods expanding
  – New acquisitions on PRF to pursue next generation inventories – crown attributes – species - stem form – tree quality – fibre properties
Future Directions

- Focus shifting towards individual tree modeling
Future Directions

- LiDAR Species Classification…from Low to High Density

$n = 346$ plots; 86 used for validation:

<table>
<thead>
<tr>
<th>Actual %</th>
<th>HWD</th>
<th>MWH</th>
<th>MWC</th>
<th>CON</th>
</tr>
</thead>
<tbody>
<tr>
<td>HWD</td>
<td>91</td>
<td>4</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>MWH</td>
<td></td>
<td>100</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MWC</td>
<td>9</td>
<td>9</td>
<td>82</td>
<td></td>
</tr>
<tr>
<td>CON</td>
<td></td>
<td></td>
<td></td>
<td>96</td>
</tr>
</tbody>
</table>

Predicted %

Prediction for each $400m^2$
Future Directions

- LiDAR Species Classification…from Low to High Density

<table>
<thead>
<tr>
<th>No. Classified trees</th>
<th>At</th>
<th>Ms</th>
<th>Pj</th>
<th>Pw</th>
<th>Total</th>
<th>OA</th>
<th>KA</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. Validation trees</td>
<td>139</td>
<td>8</td>
<td>29</td>
<td>11</td>
<td>187</td>
<td>74.3%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>87</td>
<td>4</td>
<td>13</td>
<td>114</td>
<td>76.3%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>23</td>
<td>2</td>
<td>120</td>
<td>3</td>
<td>148</td>
<td>81.0%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>8</td>
<td>5</td>
<td>89</td>
<td>112</td>
<td>79.4%</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>182</td>
<td>105</td>
<td>158</td>
<td>116</td>
<td>561</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA</td>
<td>76.3%</td>
<td>82.8%</td>
<td>75.9%</td>
<td>76.7%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Error matrix of classification

Baoxin Hu
Dept. of Earth and Space Science and Engineering
York University, Toronto, Canada
An Exciting Future ahead

- New eFRI is setting a new benchmark for inventories
- LiDAR has the ability to complement eFRI information
  - add spatial resolution of metrics - additional values
- Opportunity to develop scalable inventory information to ensure:
  - forest sustainability
  - linkage between strategic & operational planning
  - maximizing value – “right wood to the right mill at the cheapest cost”
  - spatial habitat modeling, product quality, etc.
- Software tools are available and expanding
- Economics of acquiring LiDAR datasets are being realized by industry and Gov’t
- New and expanded technologies offer exciting future opportunities
Thank you

Questions?

Contact information:

murray.woods@ontario.ca  dpitt@nrcan.gc.ca

705 475-5561  705 541-5610
Extra Slides
## A. Acquisition & Processing Cost Analysis

<table>
<thead>
<tr>
<th>Cost Comparison Items</th>
<th>Cost paid by</th>
<th>Actual</th>
<th>LiDAR</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Data acquisition &amp; processing costs</strong></td>
<td></td>
<td>$/ha</td>
<td>$/ha</td>
</tr>
<tr>
<td>LiDAR data acquisition</td>
<td>Tembec</td>
<td>-</td>
<td>1.00*</td>
</tr>
<tr>
<td>LiDAR processing</td>
<td>Tembec</td>
<td>-</td>
<td>0.45</td>
</tr>
<tr>
<td>Lidar validation plots</td>
<td>Tembec</td>
<td>-</td>
<td>0.15</td>
</tr>
<tr>
<td>Photo acquisition</td>
<td>Govt</td>
<td>0.46</td>
<td>0.46</td>
</tr>
<tr>
<td>Photo processing and interpretation</td>
<td>Govt</td>
<td>0.44</td>
<td>0.44</td>
</tr>
<tr>
<td>Traditional inventory plots</td>
<td>Govt</td>
<td>0.40</td>
<td>0.40</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>$1.30</td>
<td>$2.90</td>
</tr>
</tbody>
</table>

Conversion from $/ha to $/m³ based on annual area and harvest levels

- $0.08 m³
- $0.18 m³

*RMF LIDAR acquisition cost about $0.50/ha
### C. Mill Cost Analysis

<table>
<thead>
<tr>
<th></th>
<th>Savings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sawmill scheduling</td>
<td>N/A</td>
</tr>
<tr>
<td>Wood purchase</td>
<td>$0.11 m³</td>
</tr>
<tr>
<td>Wood net value - sawmill productivity</td>
<td>$0.12 m³</td>
</tr>
<tr>
<td>Lumber Value</td>
<td>$0.07 m³</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>$0.30 m³</strong></td>
</tr>
</tbody>
</table>
Soil moisture will in first choice be assessed in rough outline by estimation of groundwater level.