## Appendix S1

Table S1. LiDAR survey details. Data from the 2014 campaign were only used to compute topographical variables and not forest height (P95) since no clear-cuts were surveyed during this campaign.

| Year of acquisition | 2012 | 2014 | 2016 |
| :--- | :--- | :--- | :--- |
| Period of the year | July to August | June to July | July to November |
| LiDAR technology | Optech ALTM 3100A | Riegl LMS-Q680i | Optech ALTM Galaxy |
| Impulse frequency | 100 Hz | $87-160 \mathrm{~Hz}$ | $300-350 \mathrm{~Hz}$ |
| Scanning frequency | 52 Hz | $52-64 \mathrm{~Hz}$ | 52 Hz |
| Flight altitude | 950 m | 800 m | 1200 m |
| Flight speed | $77 \mathrm{~m} \cdot \mathrm{~s}^{-1}$ | $51 \mathrm{~m} \cdot \mathrm{~s}^{-1}$ | $72 \mathrm{~m} \cdot \mathrm{~s}^{-1}$ |
| Wipe angle | $\pm 19^{\circ}$ | $\pm 30^{\circ}$ | $\pm 24^{\circ}$ |
| Mean point density | 6.6 points. $\mathrm{m}^{-2}$ | 3.2 points. $\mathrm{m}^{-2}$ | 8.5 points. $\mathrm{m}^{-2}$ |
| \% of the study area | $18 \%$ | $5 \%$ | $77 \%$ |

Table S2. Generalized variance inflation factor (GVIF) analysis. GVIF analysis (Fox and Monette 1992) is analogous to classical variance inflation factor (VIF) analysis but allows calculation of GVIF for categorical variables, where values can be compared with values of continuous variables after correcting for differences in degrees-of-freedom (Df). The transformation that permits the comparison of categorical and continuous variables is $\mathrm{GVIF}^{(1 /(2 \times \mathrm{Dff})}$. To apply a classical threshold of VIF $<10$, $\mathrm{GVIF}^{(1 /(2 \times \mathrm{Dff}))}$ should be less than $10^{(1 /(2 \times \mathrm{Df}))}$. The selection column indicates variable rejection after applying a threshold equivalent to VIF > 10, while all displayed values for accepted variables are smaller than an equivalent VIF threshold of 5 .

|  | GVIF | Df | GVIF $\left.^{(1 /(2 \times \text { Df })}\right)$ | Selection |
| :--- | :--- | :--- | :--- | :--- |
| Age | 1.9615 | 1 | 1.4005 | YES |
| Potential vegetation | 1.5855 | 2 | 1.1221 | YES |
| Surface deposits | 1.6953 | 2 | 1.1411 | YES |
| Sylvicultural scenarios | 1.1617 | 1 | 1.0778 | YES |
| Slope | 1.3901 | 1 | 1.1790 | YES |
| Degree-days | 13.3901 | 1 | 3.6592 | NO |
| TWI | 1.3077 | 1 | 1.1435 | YES |
| Elevation | 11.6518 | 1 | 3.4135 | NO |
| Aspect | 1.0553 | 7 | 1.0039 | YES |

Table S3. Growth rates observed in 23 individual black spruces remeasured between 1974 and 2015 ( t 1 and t 2 ) in 59 permanent plots located in a 20 km radius of our study area. We only retained dominant or co-dominant black spruces aged between 10 and 50 years ( Age $_{t 1}$ and Age $_{t 2}$; estimated with dendrochronology) to compare these growth rates with the results obtained in our model. Values in columns of height at $\mathrm{t} 1, \mathrm{t} 2$, and $\Delta$ are in meters.

| t1 | t2 | Agetı | Aget2 | Heighttı | Heightt2 | $\boldsymbol{\Delta}$ Years | $\boldsymbol{\Delta}$ Height | Growth rate (cm.year ${ }^{\mathbf{- 1}}$ ) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1974 | 1980 | 37 | 43 | 6,7 | 7,7 | 6 | 1 | 16,7 |
| 1999 | 2015 | 28 | 44 | 10,6 | 13,4 | 16 | 2,8 | 17,5 |
| 1999 | 2015 | 28 | 44 | 9,9 | 12,7 | 16 | 2,8 | 17,5 |
| 1999 | 2015 | 26 | 42 | 9,3 | 13,3 | 16 | 4 | 25,0 |
| 1999 | 2015 | 32 | 48 | 13,6 | 16 | 16 | 2,4 | 15,0 |
| 1999 | 2015 | 29 | 45 | 7,3 | 9,9 | 16 | 2,6 | 16,3 |
| 1999 | 2015 | 25 | 41 | 7,2 | 9,6 | 16 | 2,4 | 15,0 |
| 1999 | 2015 | 24 | 40 | 7 | 9,9 | 16 | 2,9 | 18,1 |
| 1999 | 2015 | 28 | 44 | 8 | 11,1 | 16 | 3,1 | 19,4 |
| 1999 | 2015 | 28 | 44 | 8,4 | 10,9 | 16 | 2,5 | 15,6 |
| 1999 | 2015 | 23 | 39 | 7,9 | 11 | 16 | 3,1 | 19,4 |
| 1999 | 2015 | 32 | 48 | 8,6 | 11,3 | 16 | 2,7 | 16,9 |
| 1974 | 1980 | 25 | 31 | 8,8 | 10,8 | 6 | 2 | 33,3 |
| 1974 | 1980 | 33 | 39 | 7,9 | 8,6 | 6 | 0,7 | 11,7 |
| 1974 | 1980 | 37 | 43 | 9,1 | 9,8 | 6 | 0,7 | 11,7 |
| 1974 | 1980 | 39 | 45 | 8,8 | 9,3 | 6 | 0,5 | 8,3 |
| 1974 | 1980 | 30 | 36 | 10,4 | 11,2 | 6 | 0,8 | 13,3 |
| 1974 | 1980 | 30 | 36 | 9,1 | 10,2 | 6 | 1,1 | 18,3 |
| 1974 | 1980 | 30 | 36 | 7,9 | 8,7 | 6 | 0,8 | 13,3 |
| 1974 | 1980 | 35 | 41 | 8,2 | 9,1 | 6 | 0,9 | 15,0 |
| 1974 | 1980 | 38 | 44 | 10,1 | 11 | 6 | 0,9 | 15,0 |
| 1975 | 1980 | 31 | 36 | 8,8 | 10,5 | 5 | 1,7 | 34,0 |
| 1990 | 2001 | 33 | 44 | 8,9 | 12,7 | 11 | 3,8 | 34,5 |

$0 \quad 1 \quad 2 \mathrm{~km}$

Potential vegetation


Figure S1. Illustration of data from forestry maps used in our model for three logged sectors (i.e., rows 1 to 3 ) in our study area. The first column shows the 1:20000 polygons (minimum size of 4 ha ) identified as clearcuts, overlayed upon the $20 \mathrm{~m} \times 20 \mathrm{~m}$ raster of canopy height model (LiDAR P95). The second and third columns illustrate the spatial distribution of categorical variables (i.e., surface deposits and potential vegetation) extracted from forestry maps.


Figure S2. Semi-variogram obtained with 10.000 randomly selected pairs of $20 \mathrm{~m} \times 20 \mathrm{~m}$ pixels (for each distance class) in the logged sectors of the canopy height models (P95 in meters). The red vertical bar shows the 250 m minimum distance retained to select pixels of the training and validation datasets.


Figure S3. The age-height relationship established for 65000 black spruce trees that were measured as part of the permanent plot inventory network maintained by the provincial government of Quebec. The black line shows the 95th percentile that marked an aberrant height threshold for each age class.


Figure S4. Correlation matrix between continuous and categorical variables; Pearson's $r$ is specified for each pair of variables. Latitude has been added to the list of variables to obtain information on the effect of the south-north gradient of the study site. The cell color depicts the strength of correlation; $\left(^{*}\right)$ indicates relationships where $p<0.05$.


Figure S5. Model uncertainty across age classes in the validation dataset. Observed and predicted values for each age class (A) and residuals (observed - predicted values; B) in the validation dataset. Random forest absolute (C) and relative standard deviation (D) in the prediction of the validation dataset (see the Methods section for details).


Figure S6. The proportion of deciduous trees in the pixels of the training dataset. The Laurentian Forestry Centre (Canadian Forest Service) established the proportion of deciduous trees with a Random Forest classification of the territory based on Landsat images between the provinces of Ontario and Newfoundland and Labrador ( $30 \mathrm{~m} \times 30 \mathrm{~m}$ raster), and more than 10 k inventory plots from the Ministère de la Forêt et des Farc of Québec.

