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Predicting quality (AGS/UGS) at the stand, plot and tree levels

Technical Note

Resource Characterization

INTRODUCTION

Decisions on how to manage a forest over time are often done using incomplete information (Eyvindson and Kangas, 2018). In particular, the knowledge of tree quality and vigour is universally lacking although it is crucial to sound forest management.

Modern growth and yield models have been used to alleviate some of those shortfalls but offer no replacement for the ability to identify low quality and vigorous stems which are expected to decline before the next harvesting cycle, and to determine the distribution of wood products (Power and Havreljuk, 2016).

HIGHLIGHTS

- **The determination of tree quality (acceptable growing stock / unacceptable growing stock) is important for silviculture decisions as well as for predictions of growth.**
- **We developed a model to predict tree quality (AGS/UGS) of hardwood species when tree form and risk are unknown, based on ordinary forest inventory and remote sensing variables.**
- **Dendrometric and environmental parameters at the tree level were the best variables to explain variance and showed higher accuracy prediction compared to the LiDAR and image metrics at the plot level.**
- **Results obtained from remote sensing models were more correlated to LiDAR metrics. The addition of spectral and environmental variables on average, decreased the accuracy of purely dendrometric models.**

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Considerable attention must be invested on assessing tree quality, health and vigour in order to determine the right silvicultural regimes. Tree health is an important element of quality and grade but very few jurisdictions systematically characterize trees for those features in their inventory. Vigour takes into account tree health as well as competition for light and other resources.

Tree classification systems such as the ABCD system (Ontario Ministry of Natural Resources (OMNR), 2004); the MSCR system (Boulet, 2007) and the acceptable growing stock / unacceptable growing stock (AGS/UGS) system (OMNR, 2004) have been developed to take into consideration various defects that commonly occur on hardwood trees and impact current and future growing stock (Castle *et al.,* 2017).

For the same reasons, the Northern Hardwoods Research Institute (NHRI) developed a tree classification system based on the integration of metrics for both stem form and vigor (Pelletier *et al.,* 2013). The system was also designed to be compatible with other main stream stem classification approaches such as AGS/UGS.

Unfortunately, and despite its obvious importance, the inclusion of tree quality measures are not universally adopted in many jurisdictions. Our study aims to develop an adaptable model to predict tree quality (AGS/UGS) of hardwood species in absence of tree risk (vigor) and form variables using standard forest inventory and remote sensing variables of stand conditions in order to provide useful information about tree quality to make long-term management decisions. We attempted to predict: (1) tree form; (2) tree risk and (3) (AGS/UGS) of hardwood species.

METHODOLOGY

Data

We used two databases: data1 (446plots/2498 trees) obtained from J. D. Irving Limited and an NHRI database, data2 (637 plots/5683 trees) collected during block planning and other operations. All sampled plots (trees with DBH ≥ 10cm) are in the format of Continuous Land Inventory (CLI), and are situated in northern New Brunswick, Canada.

Two categories of variables were used: calculated dendrometric with available environmental variables; and estimated variables using remote sensing methods (sentinel 2 images and LiDAR).

1. The following dendrometric and environmental variables were obtained or generated for each tree and/or plot levels for data1 and data2:
   - ⇒ Individual tree level: species, DBH (cm), height (m), gross merchantable volume-GMV (m^3/ ha), ratio height/DBH-Ht_DBH (cm), tree form , tree risk and acceptable growing stock-AGS.
   - ⇒ Plot/ stand level: average height (m), average DBH (cm), elevation (m), average gross merchantable volume-GMV (m3/ha), quadratic mean diameter-QMD (cm), density (trees/ha), basal area-BA (m2/ha), percent of acceptable growing stock-AGS (%), percent of form class (% good, % average, % poor), percent of risk class (%good, % poor), aspect, topographic index-TPI, forest unit name-FUNA, soil type, depth water (m), biomass growth index-BGI (FORUS Research, 2016; Hennigar *et al.,* 2016), ecoregion, ecodistrict and ecosite (Hennigar *et al.,* 2016).
2. The remote sensing variables were generated at the plot levels for data2 :
   - ⇒ Sentinel images

     We used four bands (blue, green, red and near-infrared) and the ARVI, EVI, NDVI and VARI index from Sentinel-3 images (10 m x 10 m resolution) obtained in May 2018, July 2018 and September 2018.
   - ⇒ LiDAR

     LiDAR (ALS) data were acquired during the summers of 2017 and 2018 and calculated using the package lidR in R. 56 variables were obtained using this package.

Data analysis

Data was analyzed at two levels: tree level and plot level.

♦ <u>Tree level (qualitative response variable)</u>

Data1 was used to predict tree quality.

1. Form variables were grouped into 3 categories (good: F1, F2; average: F5, F6, F7, F8 and poor: F3, F4) , and risk variables into (good: R1, R2; poor: R3, R4) and AGS/UGS into (1: AGS; 0: UGS),
2. A non-parametric regression model (random forest) was ran with all dendrometric and environmental variables. Then we selected the important variables using the VSURF package in R to be analyzed once again. We thus calculated the out the bag error (OOB), and we generated the confusion matrix to estimate the accuracy of the model using the randomForest package in R.

♦ <u>Plot level (quantitative response variable)</u>

Data2 was used to predict tree quality at the plot level,

1. The percentage of the 3 form categories (% good, % average, % poor) was calculated as well as for the 2 risk categories (% good, % poor) and the percent of acceptable growing stock (% AGS),
2. A non-parametric model, random forest was run with all dendrometric, environmental and remote sensing variables (Lidar and spectral variables (bands and vegetation index)) first, then we selected the important variables using the VSURF package in R to be analyzed once again,
3. Relative Root mean square error (RMSE) and pseudo R-square values were determined respectively using the randomForest package.

All statistical analyses were performed using the R 3.5.1 software (R Core Team, 2018).
Environmental variables were generated using QGIS 3.8.1 software (GIS, 2018).

RESULTS

For the tree level, a confusion matrix and model fit statistics derived from data1 are presented in Table 1.

The random forest model used to predict the tree quality demonstrated excellent prediction, as evidenced by an accuracy of 76% for tree form, 82% for risk and 75% for AGS models.

For the tree form category model, only 5 dendrometric variables (DBH, species, QMD, FUNA, GMV) and one environmental variable (soil) were selected to better explain the variance and predict more accurately form class. The precision of the model was very high, as shown by its error rate-OOB (20% accuracy rate (76%) and confusion matrix (Table 1).

The variables selected for Form models were kept for Risk models and AGS models but 9 dendrometric variables (DBH, Height, ratio Ht_DBH, species, BA, QMD, Density, GMV, and FUNA) and 8 environmental variables (Ecoregion, Ecodistrict, Ecosite, BGI, Soil, Depth to water, Aspect and Topographic index TPI) were added. Predictions of tree risk and AGS are higher, with respectively an error rate OOB (17.11% and 21.18%), accuracy rate (82% and 75%) and confusion matrix (Table 1).

However, when using data2 in order to predict the percent of the 3 categories of form (% good, % average, % poor), the 2 categories of risk (% good, % poor) and the percent of acceptable growing stock (% AGS) using dendrometric, environmental and remote sensing variables, the results obtained with all models are very low and did not explain well the variance.

Table 1. Candidate models, variables selected, error rate (OOB), accuracy and confusion matrix of models estimating from, risk and AGS class using dendrometric and environmental variables.

Candidate models	Variables selected	Error Rate (OOB)	Accuracy	Confusion Matrix			
Form categories	DBH+species+QMD+FUNA+soil+GMV	20.0%	76.0%		**average**	**good**	**poor**
				average	52	41	9
				good	86	536	23
				poor	8	4	9
Risk categories	DBH+height+Ht_DBH+species+BA+ QMD+density+GMV+ecoregion +ecodistrict+ecosite+BGI+FUNA+soil+ depth_water+aspect+TPI	17,11%	82.0%		**good**	**poor**	
				good	530	74	
				poor	55	97	
AGS categories	DBH+height+Ht_DBH+species+BA+ QMD+density+GMV+ecoregion +ecodistrict+ecosite+BGI+FUNA+soil+ depth_water+aspect+TPI	21,18%	75.0%		**0**	**1**	
				0	171	75	
				1	115	381	

The relative Root mean square error (RSME) for the 2 form categories for example (% good, % average) is 17% and 17.3% (Table 2) respectively and the pseudo R-squared of each category is 4% for good class and 11% for average class (Table 2). Moreover, the others selected models of the good risk, poor risk and AGS support the similar low results, with respectively 13 % and 23% of RSME for both risk models and AGS model and with pseudo R-squared inferior or equal to 11% (Table 2).

The relative errors of the models using all variables combined or selected variables did not record any variation. However, the pseudo R-squared decrease when we used selected variables given by the VSURF package (Table 2).Contrary with the form model, selected variables improved the ability of the model to predict good risk, poor risk and AGS, even if the pseudo R-squared did not exceed 11% (Table 2). Because of the low values of pseudo R-squared and the high relative error given by the RMSE for all the models, we did not conduct the prediction and produced a confusion matrix.

Table 2. Candidate models, variables selected, relative RMSE (%) and pseudo R-squared of models estimating from, risk and AGS class using LiDAR, spectral, environmental and dendrometric variables.

Candidate models	Variables selected	Relative RMSE (%)	Pseudo R squared
Good form	All Lidar (56), dendrometric/environmental (15) and spectral variables (103)	17.0%	10.0%
Average form	All Lidar (56), dendrometric/environmental (15) and spectral variables (103)	17.30%	11.0%
Poor form	All Lidar (56), dendrometric/environmental (15) and spectral variables (103)	1,20%	-11.0%
Good risk	6 lidar+1 dendrometric: ipcumzq90+zq85+zq75+zq40+zq15+zmax+GMV	13.0%	7.0%
Poor risk	7 lidar: ipcumzq90+zq85+zq70+zq45+zq40+zq15+zmax	13.0%	10.60%
AGS	4 lidar+1 dendrometric: p1th+zq90+zq95+zq85+FUNA	23.0%	11.0%

DISCUSSION

We undertook the development of a tree quality model to assess the acceptable growing stock / unacceptable growing stock (AGS/UGS) via the prediction of form and risk using various variables.

The results of this study highlighted that the dendrometric and environmental parameters at the tree level were the best variables to explain variance and present a higher accuracy prediction compared to the LiDAR and images metrics at the plot level.

Past works have shown that risk, form and AGS/UGS are very related to dendrometric variables (Castle *et al.,* 2017; Cecil-Cockwell and Caspersen 2015; Pothier *et al.,* 2013). This could be explained by the fact that the NHRI tree classification systems is based on some dendrometric variables such DBH, height, species, and evaluate a wide range of attributes that have implications on hardwood product potential such the GMV variable.

Moreover, environmental variables such as soil, ecoregion, ecosite, BGI were present in the 3 obtained models. They have been shown to be important tree-level attributes for predicting tree quality. This is consistent with previous studies of Baral et al. (2016), which indicated that site quality is also expected to have a role in influencing stem quality and trees were less likely to have defects on higher quality sites.

The implications of remote sensing parameters on stem quality have still not been commonly evaluated. However, different forest characteristics such as: aboveground biomass (Steininger, 2000), basal area (Means *et al.,* 1999), tree crown diameter (Popescu *et al.,* 2003), canopy height (Simard *et al.,* 2011) and canopy structure (Coops *et al.,* 2007) have been successfully derived from satellite images and LiDAR.

Furthermore, forest characteristics derived from remote sensing are mostly related to overstory due to the interference of canopy foliage on the detection of understory vegetation.

Landry et al. (unpublished , 2020) indicate that overstory density (Maltamo *et al.,* 2005; Falkowski *et al.,* 2009; Latifi *et al.,* 2015; Campbell *et al.,* 2018), height (Wing *et al.,* 2012), composition (Naesset, 2005) and canopy cover (Morsdorf *et al.,* 2010) decrease the estimation accuracy of overstory tree characteristics. In our study, the integration of different remote sensing parameters has been shown to be less successful in assessments of tree quality.

Results obtained from remote sensing models were more correlated with LiDAR metrics. Spectral and environmental variables decreased the accuracy of these models. LiDAR is better than images to penetrate through the canopy (Pesonen *et al.,* 2008). Besides, satellite images are more related to canopy cover characteristics than of height (Hudak *et al.,* 2006) highlighting the limitation of Sentitnel-2 imagery.

According to Pearse et al. 2018, Hyde et al. 2006 and Hudak et al. 2006, LiDAR is known to be more accurate than satellite images in estimating forest metrics such as density, biomass and basal area.

CONCLUSION

Few studies have dealt with the question of stem quality from dendrometric and remote sensing data. Results from this study confirmed that dendrometric models have a wide range on stem quality. Explaining differences in stem form, risk and AGS among species is challenging. Remote sensing parameters in previous studies have shown a success in predicting other tree characteristics. Models that included these parameters as covariates demonstrated relatively low precision and predictive incapability, indicating that dendrometric parameters are more considerable and accurate in predicting stem quality classes at the tree level.

Wall-to-wall acquisition of airborne LiDAR took place between 2013 and 2018 in New Brunswick. It is unknown when and if a new cycle will occur in the near future.

In conclusion, this study suggests a new model to predict form and risk class that can be used when the variables were not captured during field inventories, but more is needed to increase accuracy and reduce variance. For the remote sensing model, we suggest to try using satellite images with a higher resolution than Sentinel-2 images, using remote sensing techniques at the tree level and increasing the sample sizes in order to improve the power of the statistical tests.

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