Forest**Now** Post-Harvest Regeneration Determination in the Romeo Malette Forest

Project: 9B-2018 - Post-Harvest Surveys from Satellite Capture and Machine Learning

A project funded through the Knowledge Transfer and Tool Development program administered by the Forestry Futures Trust Committee

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Ms. Shelley Vescio
Programs Coordinator
Forestry Futures Trust Committee
Suite 2003 - 1294 Balmoral Street
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Dear Ms. Vescio

We are pleased to submit the final report for the project 9B-2018 *"Post-Harvest Surveys from Satellite Capture and Machine Learning"*. Please find the enclosed document and final progress report.

In the near future, we will schedule some online workshops to present the results and we will send you an invite. As mentioned before, we are also interested in participating any formal knowledge transfer session the Forestry Futures Trust may organize. Please keep us informed.

Please feel to reach if you have any questions or comments.

Yours sincerely,

Peter Young

Executive Summary

This project has used the GSI Platform, ForestNow, to systematically identify the species composition and predict tree attributes which are important to determine adequate regeneration of forest in the Romeo Malette Forest in Ontario. ForestNow uses the power of high-performance computing and machine learning combined with actual ground observations/measurements, LiDAR and satellite data to provide an objective determination of tree species, size and distribution

GSI is pleased to confirm that the results of this project show great promise to help forest managers quantify the regenerating forest. While the results are good, GSI suggest they are not precise enough to assess regenerating areas to the specific minimum thresholds indicated in the Ontario Ministry of Natural Resources and Forestry (OMNRF) regeneration standards.

Though the direct results of this project may not be a full replacement for the current methods of assessing regenerating areas, with some changes in standards, these methods could contribute to a more effective program overall. GSI is more than willing to work with OMNRF staff to align policy and platform outcomes for a common goal of streamlining the assessment of regenerating areas.

We have created an online geographic portal for ease of viewing without the need for specialty software knowledge (e.g. QGIS, ArcMap, etc.). Our portal offers users an easy and intuitive environment to view various prediction results and reference layers much like using Google Earth©.

GSI welcomes the opportunity to work with the OMNRF to apply the methodologies developed from this project to large scale areas of Ontario's forest. GSI now has the capability of processing areas more than 15 million hectares in size in a matter of a couple of months resulting in extremely low cost per hectare.

Overall objectives

The goal was to produce an automated and objective process to quantify key metrics in post-harvest clearcuts necessary to determine how those areas compare against the OMNRF standards. These metrics could include but not limited to species ID, stocking, height, etc. to help determine whether post-harvest area meet the regeneration standards.

Based on discussions with Ontario forestry professionals, the consensus was the post-harvest survey program is expensive and a source of frustration for many forestry managers from both the government and industry. One key issue being OMNRF and industry agreeing on a common method for measuring surveys that is objective and cost effective while ultimately meeting the goal of regeneration to acceptable standards. Commonly, the forest industry conducts these regeneration surveys by visual aerial method (helicopter) which is also considered dangerous. The OMNRF then audits a sub-portion of the survey area by measuring ground plots.

Deliverables

Deliverables are in both raster and vector form. The raster format is pixel-based (10m resolution) which is an excellent format for displaying results and are flexible as it could allow forest inventory analysts to:

1. Calculate zonal statistics for existing forest inventory polygons by summing all pixels that fall within each polygon. For example, a species composition typing label can be calculated (e.g. 60% black spruce / 30% balsam fir / 10% white birch) similar to the outcomes from the traditional photo-interpretation method, or give an average of tree attributes (height, density, stocking, etc.).

2. Auto-delineated polygons by aggregating pixels of similar species composition to create polygons. Since the process is automated, it allows to adjust delineation patterns based on the needs of the application. For example, in an operational application, there may not be the need to separate white and black spruce; however, it may be especially important wildlife habitat purposes. Raster layers allow for ultimate flexibility based on the end-use desired.

GSI has produced raster layers for each attribute measured (tree height, stocking, and density) as well as one layer for each of the species predicted where the sum of all species for each pixel sums to 100% and one composite species layer showing the most dominant species by pixel (refer to Figure 1 for an example).

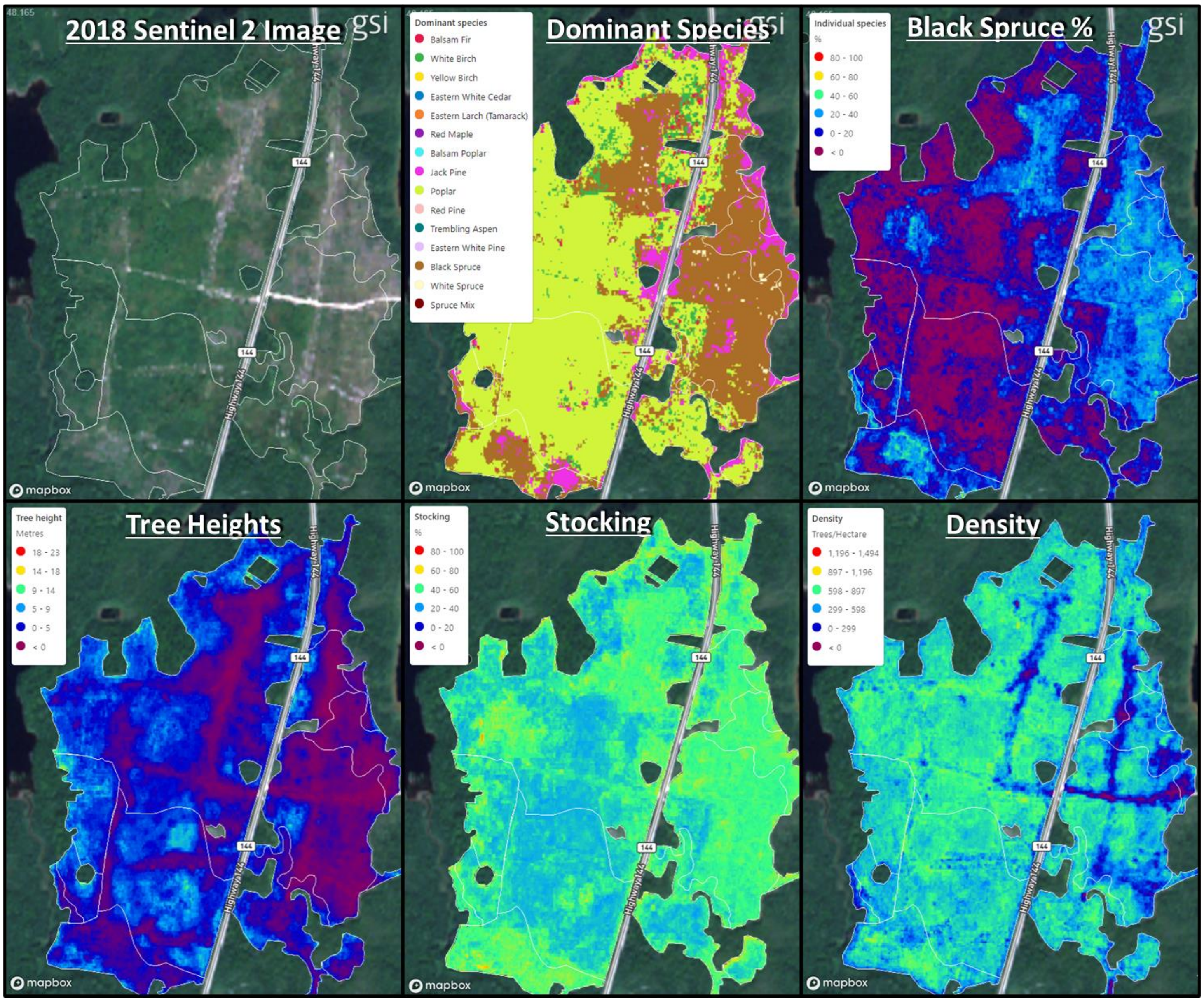

Figure 1. Sample image of a raster showing the each of the 2018 predicted attributes and species (black spruce as an example) of a harvest block within the RMF. A 2018 Sentinel 2 image is also shown for comparison.

In addition, GSI has also calculated the zonal statistics for each harvest block which were subdivided into strata during the aerial survey was done as described above in point #1. Figure 2 shows an example of the predicted stocking ratio on the left and the right image shows the calculated average of the pixels contained within each of the strata polygons (white lines). As you can notice, the prediction coming from the GSI model suggests that this harvest block could be sub-divided differently based on the stocking ratio.

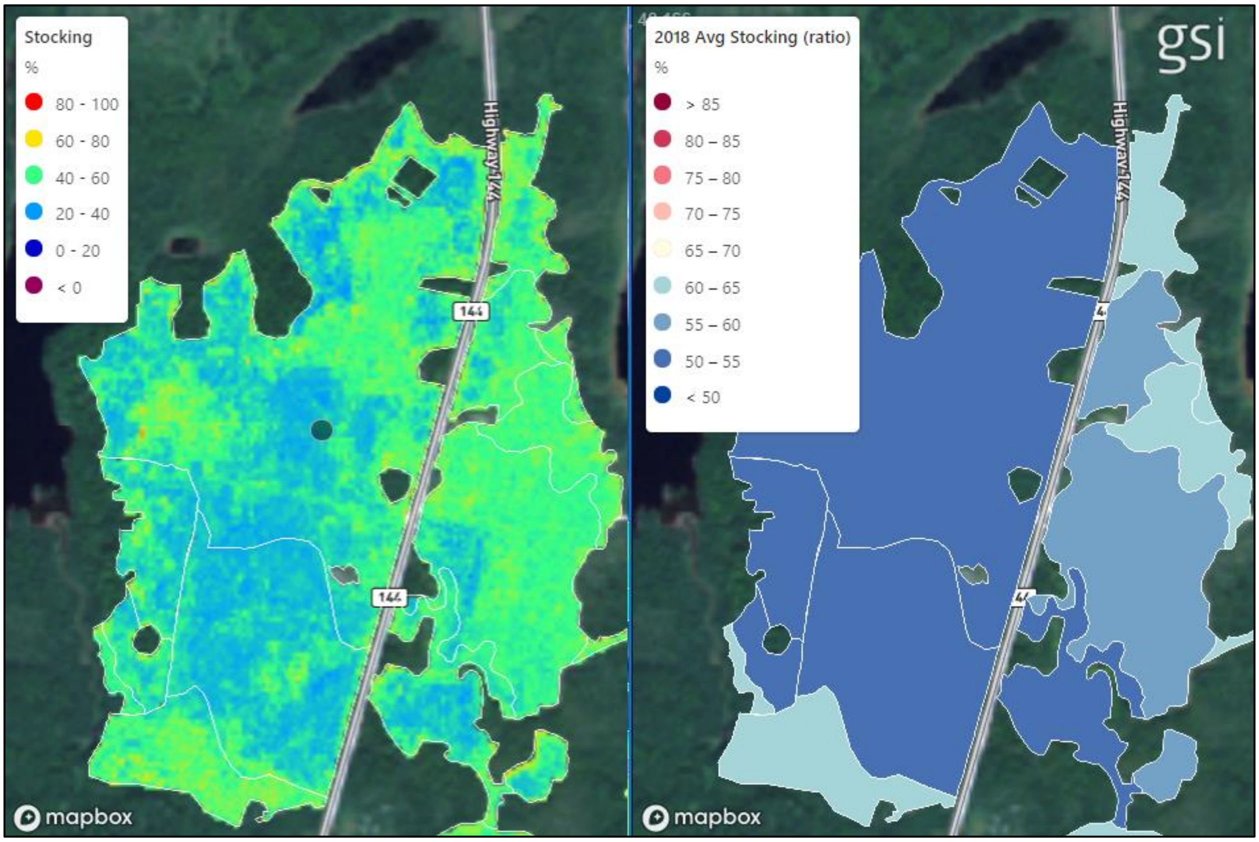

Figure 2. Sample image of the process of calculating average zonal statistics using proportional stocking as an example of a harvest block within the RMF.

Area of Interest

The area of interest (AOI) used in this project is the Romeo Malette Forest (Figure 3).

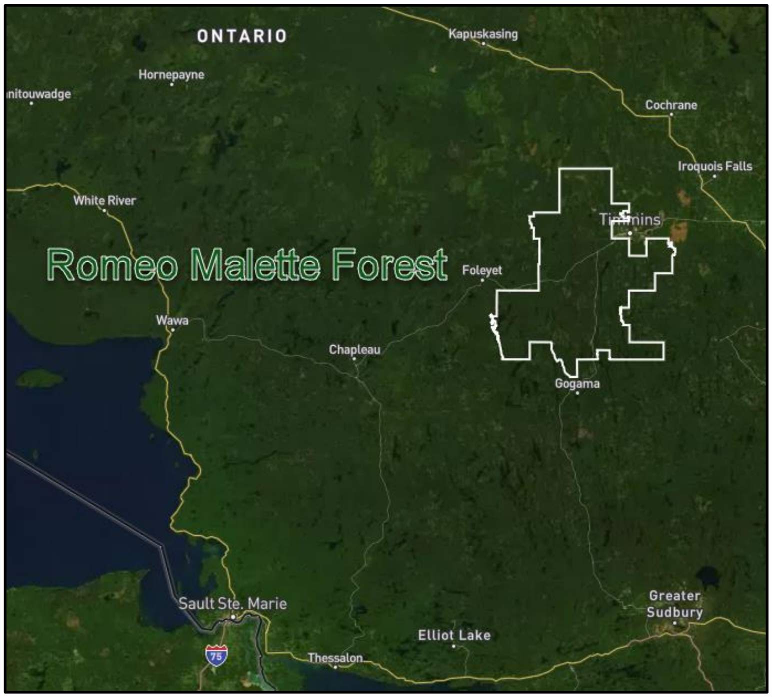

Figure 3. Map showing the area of interest (AOI); the Romeo Malette Forest (RMF).

Romeo Malette Forest, Ontario

The Romeo Malette Forest (RMF) was chosen as suggested by the Ontario Ministry of Natural Resources and Forestry (OMNRF) since there were several concurrent trials occurring on that forest with the acquisition of new single-photon LiDAR. This area was also used as part of two other project carried out by GSI.

Target Audience and Benefits

All forest stakeholders can benefit from having a more accurate and flexible forest inventory which includes annual monitoring recently harvested areas to determine whether the regenerating forest meets the OMNRF's criteria.

- Ontario Ministry of Natural Resources and Forestry (OMNRF)
- Forest Industry Companies

Quantifying the regenerating forest is important for managing and monitoring the forest resource from multiple interests including, but not limited to:

- Timber management for effective sustainable supply for economic gain
- Wildlife and forest community management to maintain healthy populations
- Monitoring the effects of climate change on species presence, establishment and migrating range.

Model Data

Satellite Images

GSI used both reflectance (multi-spectral bands) and synthetic aperture radar (SAR) from various publicly available satellite images (e.g. Sentinel 1 and 2, Modis, Landsat, etc). Reflectance data provides a much broader range of useful data; however, since it cannot penetrate through clouds, its frequency of clear usable scenes can be limiting. GSI has some internal processes to reduce the impact caused by cloud cover by supplementing the model with the use of partially clear scenes. SAR on the other hand, can penetrate through cloud (therefore more frequently reliable); although, this type of data relates to physical structure and is fundamentally different to optical reflectivity measurements.

GSI continuously ingest images throughout the calendar year and as a result, it can detect the unique "phenology signature" by distinct species produced by changing seasons. This phenology is not programed explicitly in the model; rather, it is the machine learning process that combines satellite observations with the training data and makes the correct association. These phenological observations could include:

- The presence of leaves or not on deciduous.
- The timing of new shoots in evergreens and/or bud break on deciduous.
- The color and timing of leaf fall in autumn.
- The color differences in twig bark color amongst deciduous species visible during leaf-off timing.

By adding sample tree attribute elements (height, stocking, density, etc.) as training into the machine learning process, GSI can also quantify those elements as outputs.

Training Data

The primary source for the training data was the Ontario Ministry of Natural Resources and Forestry; specific data used was as follows:

- Lidar Point Cloud: Captured in 2018 using Single Photon (~25 points/m2).
- Lidar-based CHM model (0.5m x 0.5m): Produced by the Ministry
- Ministry/Industry's Free-to-Grow (FTG) survey results: A shapefile with the approved FTG status on younger regenerating areas. Data is provided at the polygon-level with averaged tree attributes such as species composition, height, stocking.

Methodology

Approaches

Milestone 1 - 2018 Recognition of Post-Harvest Forest Condition Using LiDAR and FTG Surveys

The approach used by GSI to generate our raster layer predictions is based on a regression method which involves training with examples of known conditions or measurement such as ground survey data at specified locations or tree attributes derived from LiDAR survey data. The training data is then fed into the system along with satellite imagery for the same locations within an acceptable timeframe inline with the training data.

This regression approach is more effective and flexible compared to an alternate approach which is a classification-based analysis. Regression provides a precise quantitative approach where it predicts a continuous range of data, such as the proportion of all species across the entire composition mixture (e.g. values of 0-100% per species). By quantitative, it also means that any two pixels can have separate continuous values along mathematically comparable scale. Alternatively, classification analysis uses categorical data that represent forest qualities, but any two pixels with different values do not exist along a mathematically comparable scale. This means GSI's results can be validated on a pixel-by-pixel basis using the training data with standard "goodness of fit" statistical tests such as R-squared, root mean square error (RMSE) and mean absolute error (MAE). Classification analysis is limited to confusion matrices and binary diagnostic tests, such as sensitivity, specificity, positive predictive value, and negative predictive value.

In the case of species composition, GSI has used the species composition label assigned at each post-harvest survey area used in the training. Using GSI's unique machine learning model that is based on multivariate output regression, where the output (one layer for each species) sums all predictions to equal 100% for each pixel. This means that the machine learning process can model percentages without over or under prediction. We then used this model with satellite data to develop a pixel-level individual species estimate.

Alternatively, classification predicts based on a dominance approach so only assigns each pixel a qualitative label representing a class rather than continuous values. This method is effective in forest conditions where there is a low species diversity; however, is problematic in conditions of high species mixtures such as the RMF where it could significantly under-represent minor species components. The other downfall of a classification analysis is that this method is a qualitative labelling of a category and because categorical data is not quantitative, some mathematical assumptions must be defined to compensate and develop a usable outcome for estimating species composition at a stand level.

Milestone 2 - Replicate 2018 post-harvest analyses in 2015, 2016 and 2017

The work for Milestone 1 was based on processing data specifically for 2018. The aim for Milestone 2 was to repeat this processing for earlier years; however, given the absence of adequate Sentinel-2 images in 2015, it was not possible to generate results that year.

The processing for each year was a replication of the processing originally performed for 2018, comprising:

- Remapping all input imagery (satellite data for specific year, lidar-derived target data and polygon-derived target data) to the same projection and scale
- Training using only satellite data from 2018
- Predicting using satellite data for specific year

Since the training was done on 2018 images to match the vintage of the LiDAR, it does not make sense to validate results from other years in the same way as was done for Milestone 1 (2018). Rather, the validation becomes a question of how attributes and species predictions compare year-to-year under expected natural stand growth and dynamics. For example, species composition would not be expected to change drastically unless through a major disturbance (natural or human) while height would be expected to gradually increase.

Quantitative Validation

Validation of results is a crucial step to proving the accuracy of the results and the most important factor is the independence of the validation. With machine learning, it is important not to train and validate on the same data directly. When a machine learning model trains with pixels directly overtop a ground observation, it tends to “over-fit” at that particular location; therefore, when validating on those over-fitted pixels, the results will typically show a very “high” accuracy. Those results; however, are not a proper representation of accuracy due to the lack of independence between the training and validation steps.

GSI believes in the true characterization of the accuracy of the results; therefore, we employ methods best suited for the purpose of the machine learning processing. The validation method differs depending on the tree attribute being measured.

Since we have a relatively small number of surveyed harvest blocks to train with, reserving a significant subset for validation only, would reduce the model’s ability to accurately train with. As a result, we use a K-Fold test which is common in machine learning where the test uses all the training samples while still validating against 100% of the same samples in an independent fashion. The test separates the total dataset into different subsets where it trains on one subset and validates with the other one. Then we run a K-Fold analysis with the sample data using GSI’s developed automated procedures where we cycle through a different reserved validation subset until all samples have been validating against.

In this project we used K=2 test which means that the training data was split into two random halves, with one half used for training and the other used for validation, then these roles were switched, giving an independent predicted value for each sample which was based on training *not* using that sample. The results are summarised in the Results’ section.

Please note that validation based on training against polygons, the results are likely to be coarser in resolution at a pixel-level prediction; however, still reasonable at a polygon-level where the values of the pixels contained within are averaged for each polygon. Statistics for each species and attribute are presented in the Results section.

Results

Portal

An online geographic display portal has been setup for viewing key results. The portal format allows for easy viewing by anyone with no need for specialty software knowledge (e.g. QGIS, ArcMap, etc.). Our portal offers users an easy and intuitive environment to view various result and reference layers much like using Google Earth (refer to Figure 4 for example setup).

The layers are presented in the following manor:

Base Maps

These are for reference purposes:

- Sentinel 2: A 2018 satellite image from the ESA Sentinel 2 constellation and is one of the images used in the stack for analysis.
- Areas of Interest: This is an outline of the harvest blocks where GSI predicted the regenerating forest. These are areas that were harvested between 2005-2013; therefore, between 5-13 years since harvest.

Predicted

These are the predicted layers produced from the machine learning output for tree attributes (height, stocking, and density) and species composition.

The raster layers are presented for Milestones 1 (2018) and the polygon with average zonal statistics are presented for Milestones 1 and 2.

Training

These layers represent the data that was used in the training of the machine learning process to produce the predicted layers.

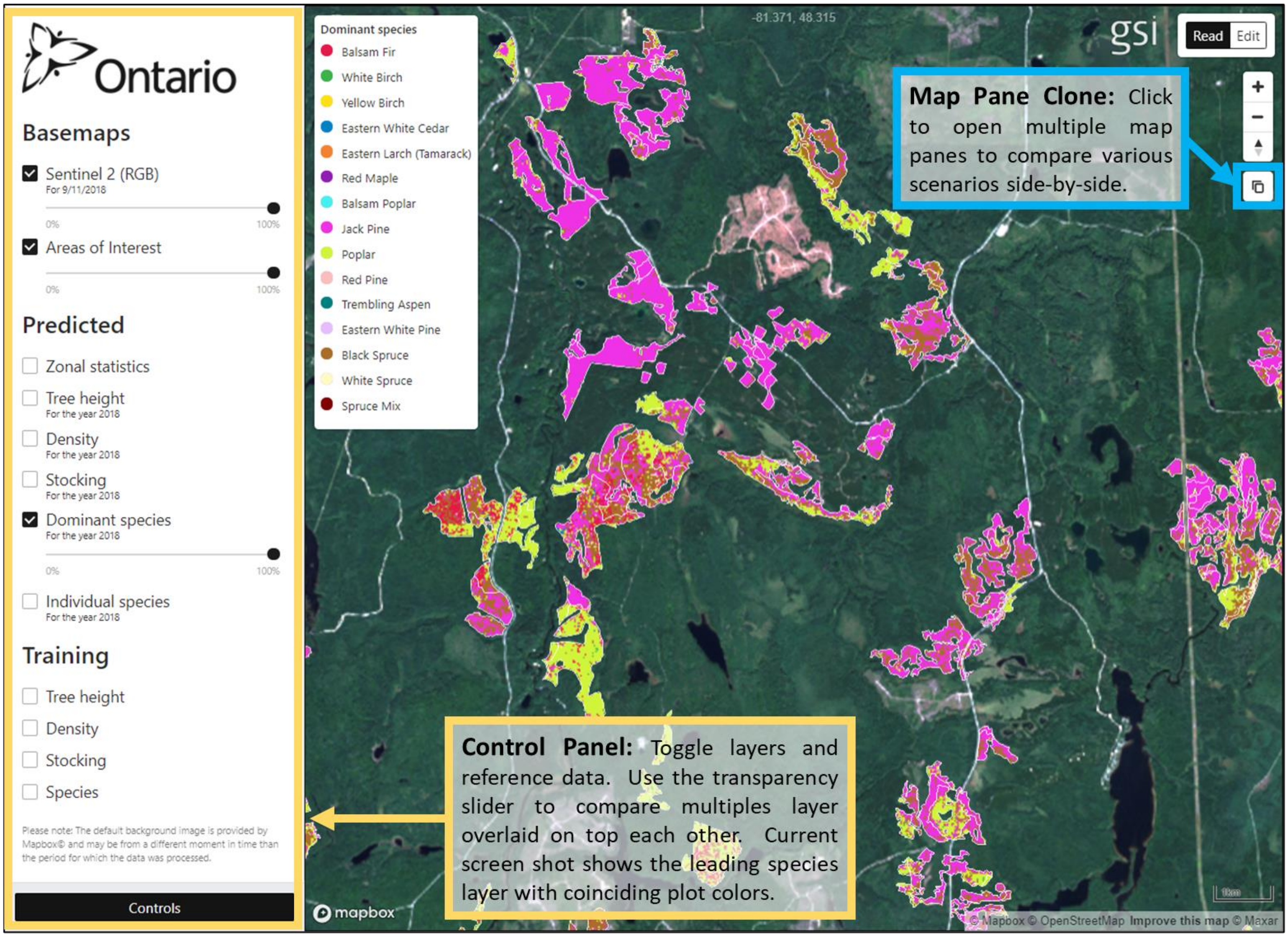

Figure 4. Screen capture of the GSI portal available for viewing. Dominant species layer is shown as an example; though, multiple options can be toggled on/off and overlaid using transparency for comparison of layers.

The site can be accessed by request through contacting GSI at the following link: https://www.surfaceintelligence.com/contact

Milestone 1

Accuracy of Attributes

Table 1 shows the results from the K-Fold Test (K=2) completed on the predicted results for each of the attributes modelled. Stocking ratio and tree heights have excellent results as supported by the higher R-squared.

Density had lower accuracy statistics than those reported below. We did not have plot-based density data to initially calibrate the LiDAR-derived density (tree count) data in our tree identification algorithm. We conjecture that the tree crown identification algorithm requires additional tuning for shorter trees, but we were unable to complete any tuning without plot-based density data. Therefore, we do not report accuracy statistics for remote sensing-derived density, because the lidar derived training data was not validated. We did however perform a visual inspection of the predicted density heat maps and they show a clear relative pattern of low density in sparse areas increasing to higher densities in full cover areas.

Table 1. Accuracy statistics of the tree and stand attributes predicted on the RMF.

Tree/Stand Attribute	Rsq	RMSE	MAE
Stocking Ratio (0-100%)	74.8%	6.1%	4.2%
Tree height (m)	77.4%	3.06	2.04

Rsq = R-squared (= correlation coefficient squared) where values can range from 0-100%, where 0% shows no correlation and 100% shows a perfect 1:1 correlation.

RMSE = Root Mean Square Error (= square root of average of the squared value of all differences between measured value and predicted value for all samples), where the value shown in the table is in the same units as the attribute itself.

MAE = Mean Absolute Error (= average of all absolute values of difference between measured value and predicted value for all samples).

Accuracy by Species

Table 2 shows the accuracy and frequency of available training data available for species training. Results range from relatively high to low depending on the species which is clearly linked to training abundance for a given species.

Table 2. Accuracy statistics of the tree and stand attributes predicted on the RMF.

Species	Rsq	RMSE	MAE	Number of pixel available for training
Poplar	68%	17.3%	10.3%	3,005
Black Spruce	58%	22.0%	16.9%	10,426
Eastern Cedar	25%	8.2%	4.0%	2,252
Jack pine	20%	11.6%	7.3%	898
Balsam Fir	18%	11.6%	8.9%	3,821
Eastern Larch (tamarack)	15%	9.9%	6.1%	2,804
White Birch	6%	3.7%	2.5%	815
White Spruce	1%	2.3%	1.4%	482

Milestone 2

Overall, Milestone 2 results show a clear pattern of consistent results which adds confidence that the GSI process is effective for a year-on-year continual type of application. This is due to the fact GSI stacks its data cube with multiple images from across the year instead of relying on any one single image. The multiple-image approach helps stabilize predictions across years by normalizing elements such as atmospheric conditions.

Assessment of Attribute Results

All three attributes have results that are reasonable to expect in the sense that there are no major differences between years and the differences are generally in line with expected natural forest dynamics (Figure 5).

- Average Top Height (m): Shows increasing tree height from year-on-year which is expected for trees in this stage of growth. The two between-year intervals are significantly different; however, on average seems to be within a reasonable trend overall. In addition, it is worth noting that the density may be influenced the overall height averages. Given that density is increasing over time, it is plausible that overall height is lagging because new smaller trees are continuously establishing and keeping the average height lower.
- Density (tree/hectare): Stand density is showing as gradually increasing over time. This trend seems reasonable for stands of this age (5-8 years old) as canopy closure may still not be at 100%.
- Proportional Stocking (%): Of the three attributes, this is the only one where there is no consistent trend across the years; however, the differences between years are minimal and likely all within an error of margin.

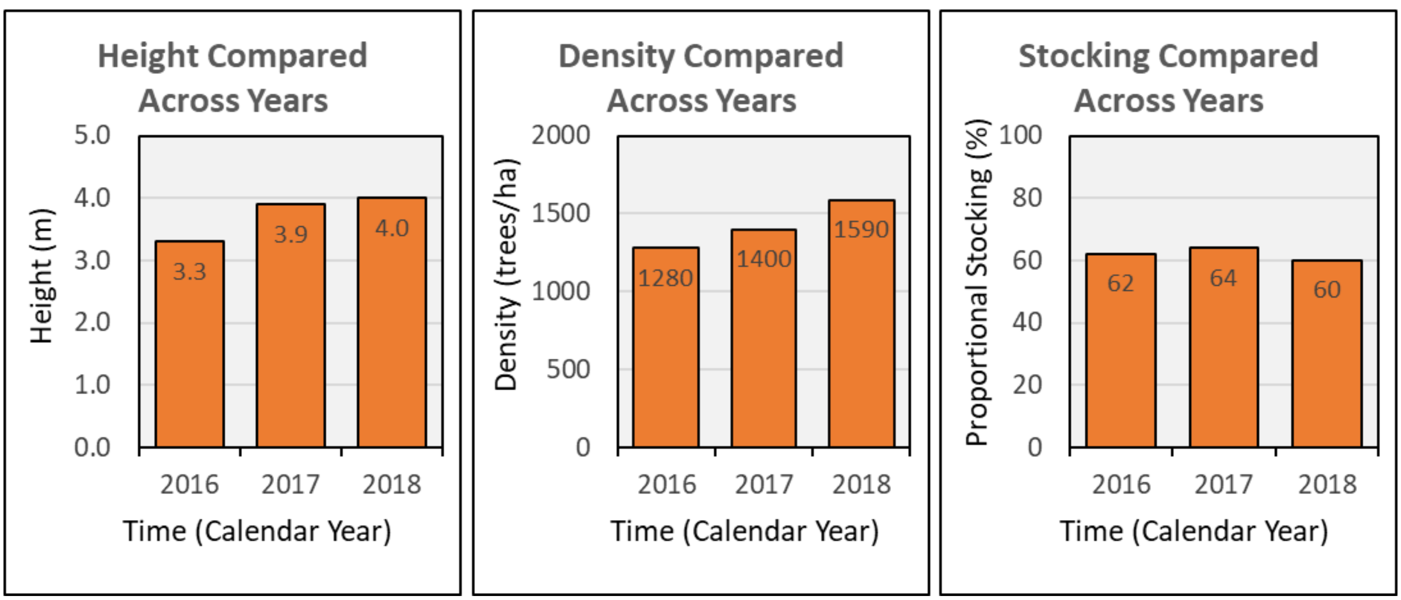

Figure 5. The comparison of overall predicted tree attributes (average height, stand density, and proportional stocking) across three years for all areas of interest within the Romeo Malette Forest.

Assessment of Species Results

Each of the species present in the training dataset were predicted for the years 2016 and 2017 in order to compare their overall distribution across the areas of interest for the RMF. The results clearly show a relatively consistent distribution with no significant differences in any species across each year (Figure 6).

This result again supports the notion that the GSI methodology provides consistent results from training on images from a specific year (2018) and predicting images from other years.

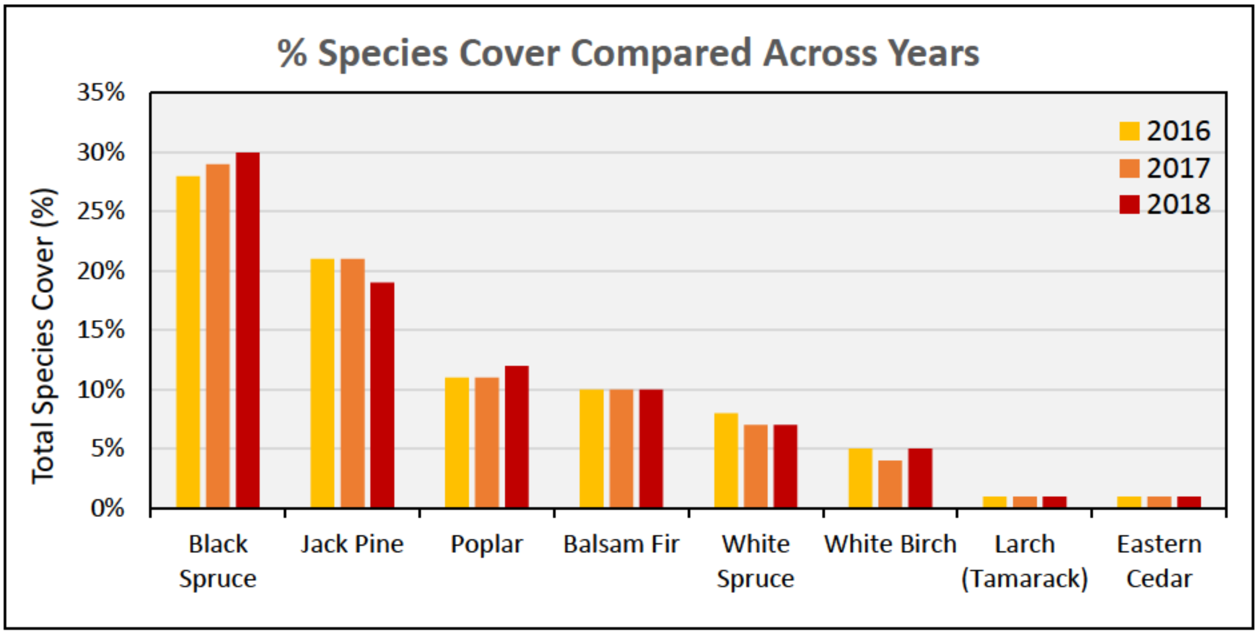

Figure 6. The comparison of each species' overall coverage across the three years for all areas of interest within the Romeo Malette Forest.

Conclusion

GSI believes the results presented from this project have the potential to be incorporated at least in part into current OMNRF monitoring process. GSI results are relatively consistent from year-to-year which is required to provide an annual satellite remote sensing solution.

However, the GSI process as tested during this project may not be robust enough to be a full replacement to the current process where some of the tolerances required to declare a stand free-to-grow, may not be detectable at the expected time of survey. When this project was executed, GSI was limited to process single Sentinel-2 tiles at a time; therefore, had limited amount of training data. GSI can now process 15+ tiles (~15 million hectares) in a single instance which opens the window for including more diverse training sets taking entire eco-regions in a single model for improved outcomes and flexibility.

Regardless of this new capability, the flexibility of the GSI methodology could be directly incorporated into a modified survey approach where the results from the predictions are used to class regenerating areas into a priority ranking using a risk-based approach. By calculating the zonal statistics from the regression results, GSI could provide levels of confidence on individual harvest blocks to bucket them into risk classes based on OMNRF rules.

GSI has also recently developed a robust and configurable auto-delineation process which could be used to sub-divide harvest blocks into strata which can be quantified as described above for each delineated sub-harvest section.

As was noted earlier, there were clear differences between the previously delineated areas from the FTG surveys versus the patterns from the GSI-predicted results which suggests those results can offer an opportunity for improving/automating the delineation process. GSI would use its auto-delineation process to group sub-sections of similar species composition in conjunction with other tree attributes such as tree size (DBH/height), total basal area, canopy closure, etc. This function can be tailored to individual clients' needs depending merging/splitting criteria and priority ranking of each attribute. This methodology is well suited for combining the predicted results of each attribute and species/species-groups to compare against a regenerating standard.

GSI has provided the full raster layers (pixelized) and summarized data for of each harvest blocks analysed to the OMNRF and invites them to fully scrutinize the results. We look forward to an opportunity to discuss their findings.

GSI would welcome the opportunity from the OMNRF to apply the methodology developed here to large scale areas of Ontario's forest. GSI now has the capability of processing areas more than 15 million hectares in size in a matter of a couple of months resulting in extremely low cost per hectare.

Thank you

We wish to thank the Forestry Futures Trust for the funding to proceed with this project. We would also like to thank the *Ontario Ministry of Natural Resources and Forestry* and *Rayonier Advanced Materials – Forest Management* and several other organizations that contributed the necessary data and expertise for GSI to do its analysis. This project would not have been possible without them.