Integrated Remote Sensing Studio

Characterizing non-stand replacing (NSR) disturbances using bitemporal airborne laser scanning (ALS) data

SILVA21

UBC

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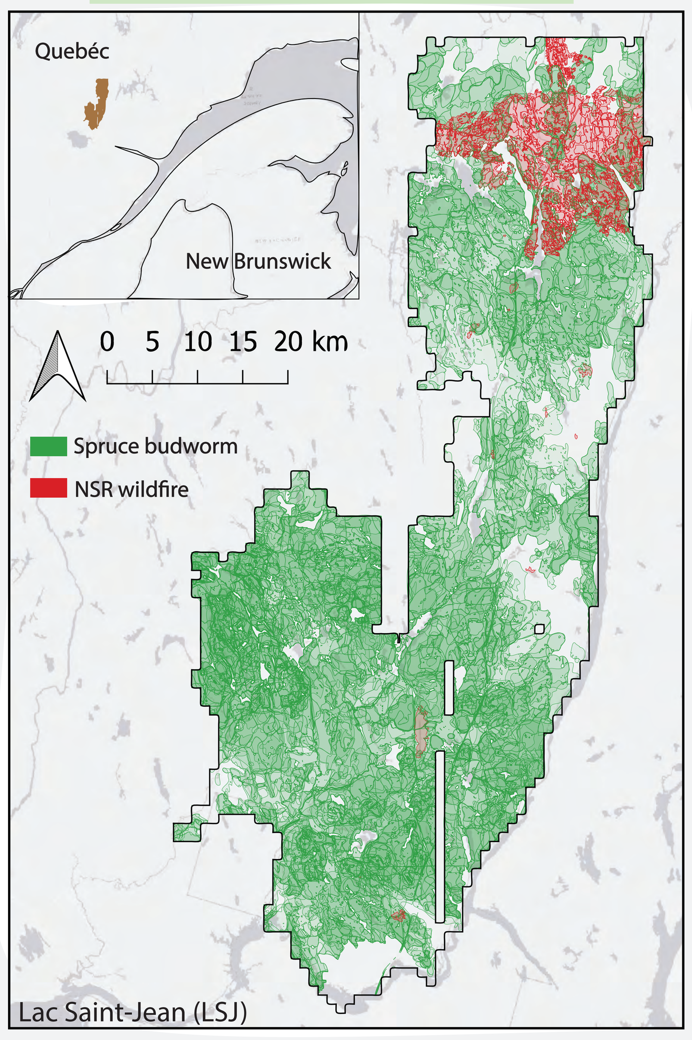
Introduction and Study Area

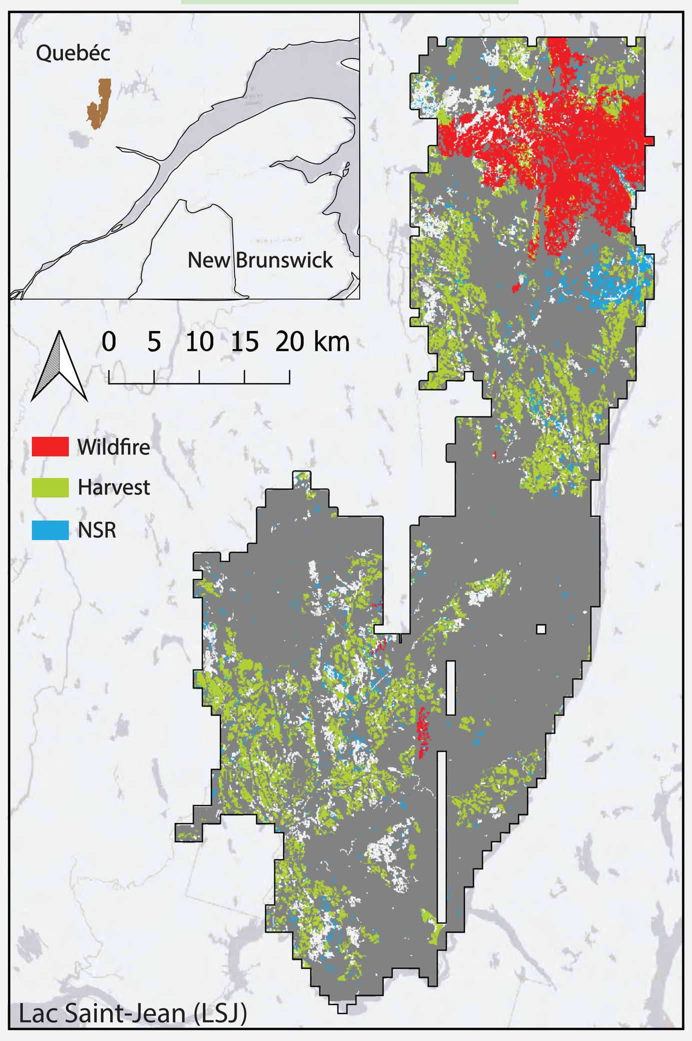
What ALS-derived metrics are most sensitive to detecting changes in forest structure associated with NSR disturbances?

- Natural disturbances shape forest structural, compositional, and functional dynamics.
- NSR are difficult to detect with traditional inventory approaches because of the subtle and long-term effects on the forest structure.
- ALS allows to investigate forest structural modifications at a fine scale over time.
- To detect NSR disturbances, we developed a change detection framework based on Forest Resource Inventory (FRI) data, Landsat time series, and a bitemporal ALS dataset.
- The study area is Lac Saint-Jean, Quebec, Canada. A mixedwood boreal region characterized by a mixture of Black Spruce, White Spruce, Balsam Fir, Trembling Aspen, and Birch spp.

FOREST RESOURCE INVENTORY

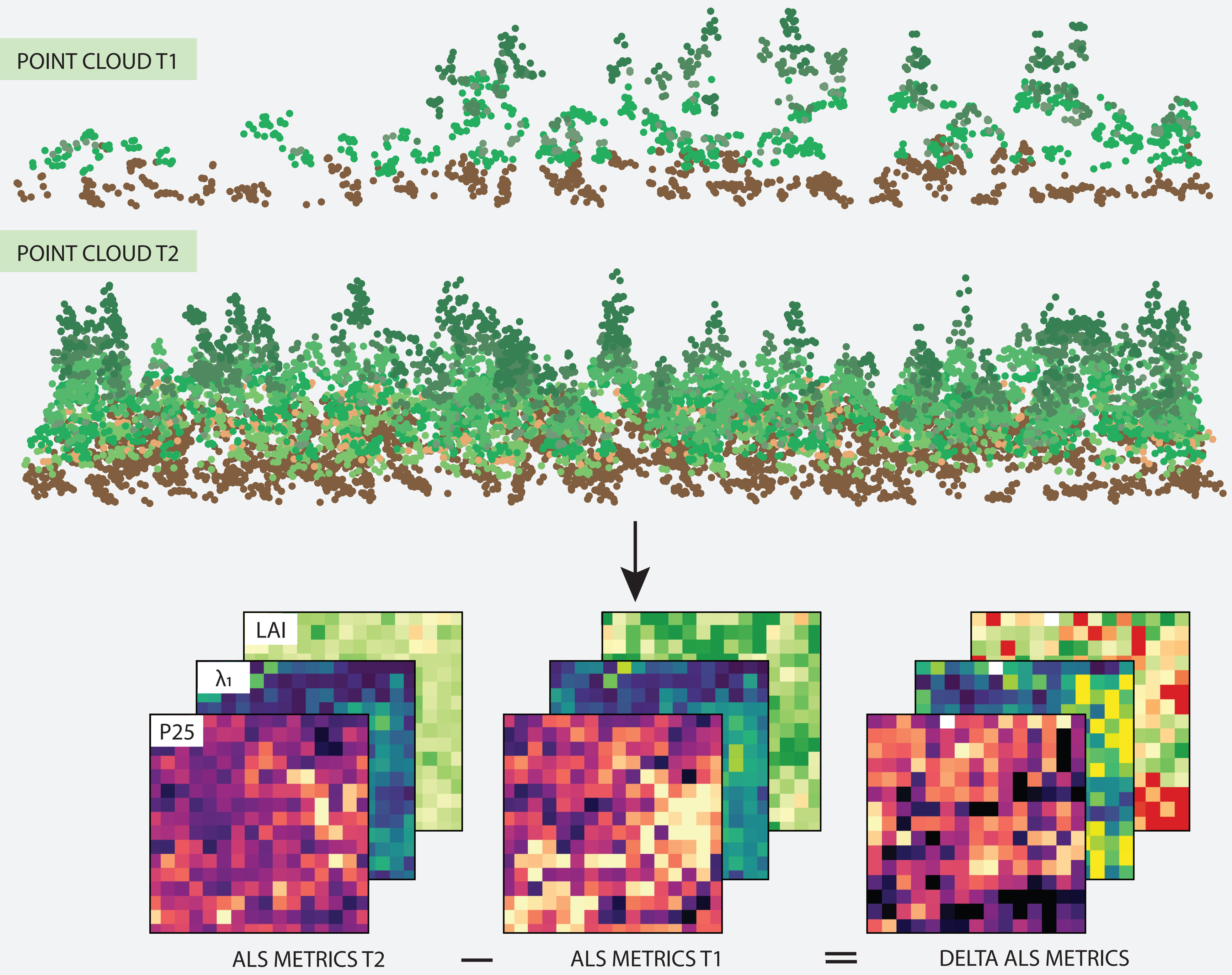


LANDSAT TIME SERIES



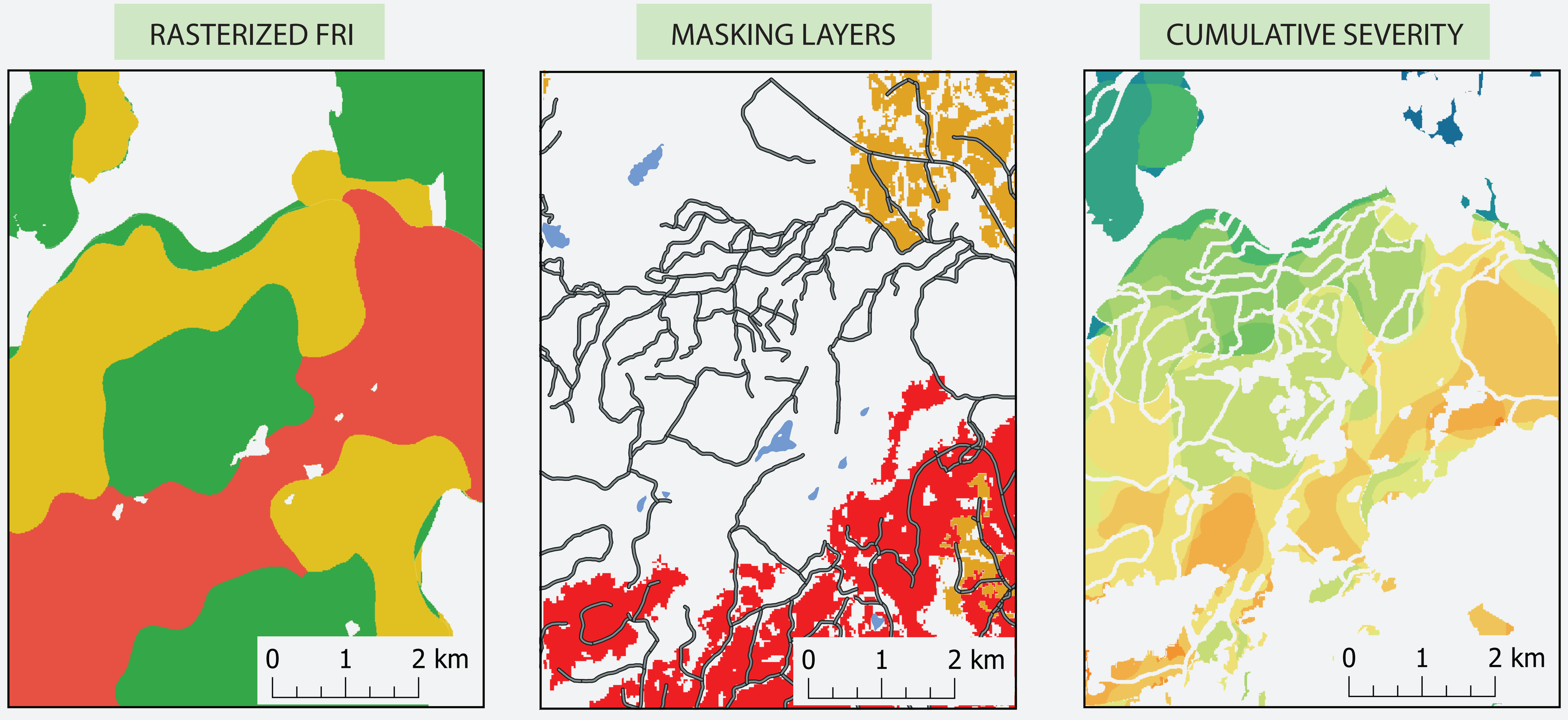
Bitemporal ALS Processing

- Wall-to-wall ALS coverages in 2014 and 2020 with different system specifications were used (e.g. point density, frequency, flight altitude).
- To reduce systematic data inconsistencies and noise, both point clouds were harmonized and a set of 14 uncorrelated (Pearson < 0.9) metrics were estimated for both epochs.
- ALS metrics were rasterized to 10 m and included (i) standard metrics such as height percentiles (e.g. 25th percentile, p25), cumulative height, canopy cover, gap fraction at 5 m, Leaf Area Index (LAI), and (ii) eigendecomposition metrics (e.g. largest eigenvalue, λ_1).



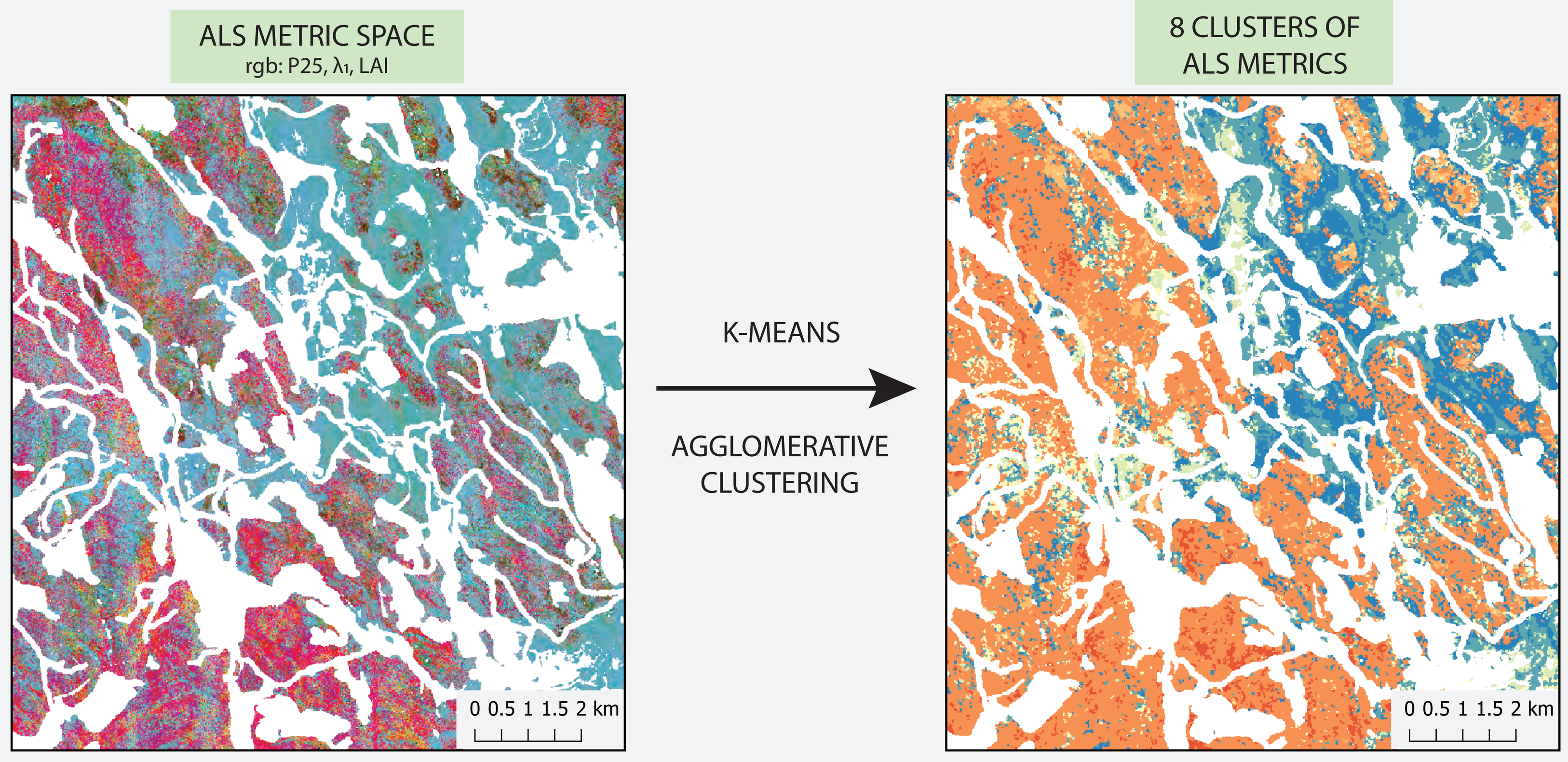
Combining FRI & Landsat

- Annual occurrences of forest disturbances from the FRI were rasterized to 10 m and summed to produce a cumulative severity map.
- Landsat time series were used to mask large-scale disturbances, roads, and harvesting based on a Composite2Change approach (Hermosilla et al., 2016), as well as plantations and deciduous stands with a 20 m buffer.



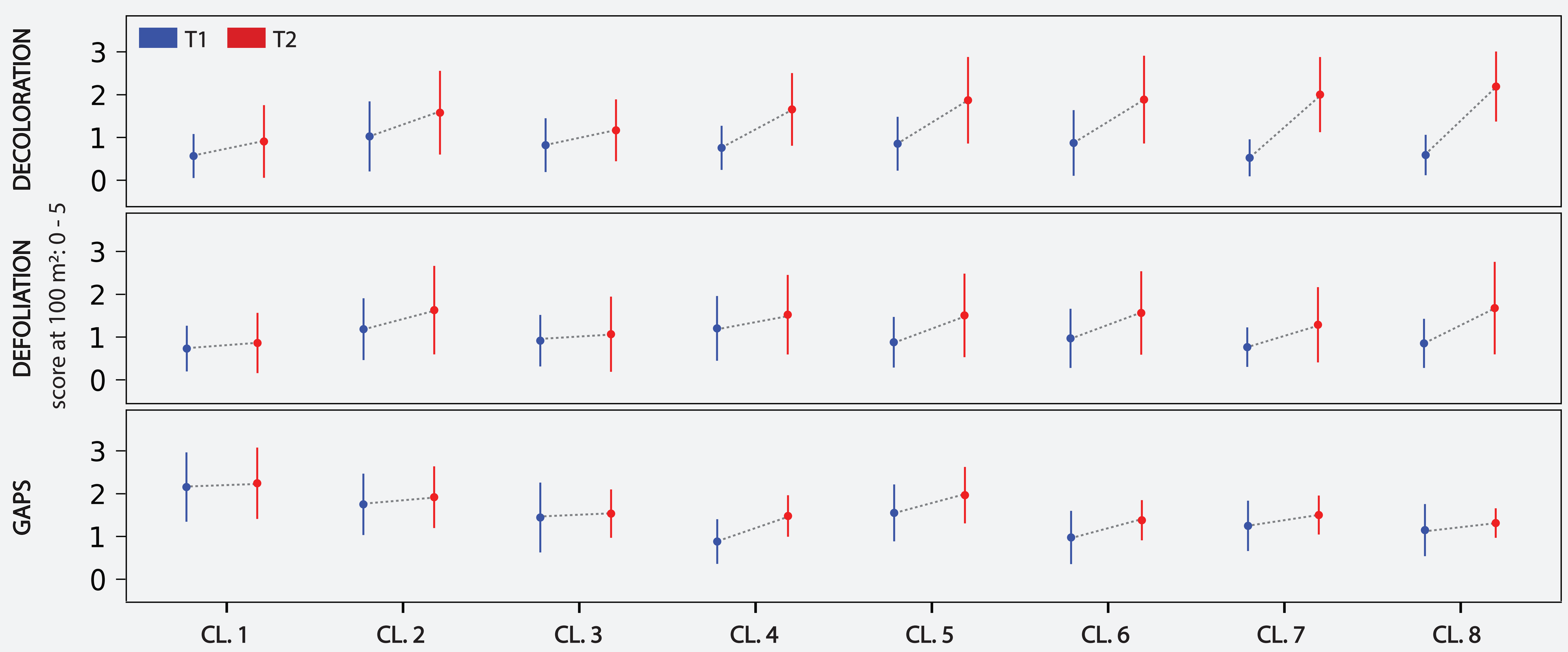
Data Clustering

- To identify pixels with similar response patterns to certain NSR disturbance severities, a two-stage clustering approach was conducted (Coops et al., 2020) using the delta ALS metrics.
- An initial k-means pass was run to generate 100 pre-clusters, followed by a multivariate agglomerative clustering to reduce the clusters to a numerically significant number based on the Manhattan distance and Ward's linkage.

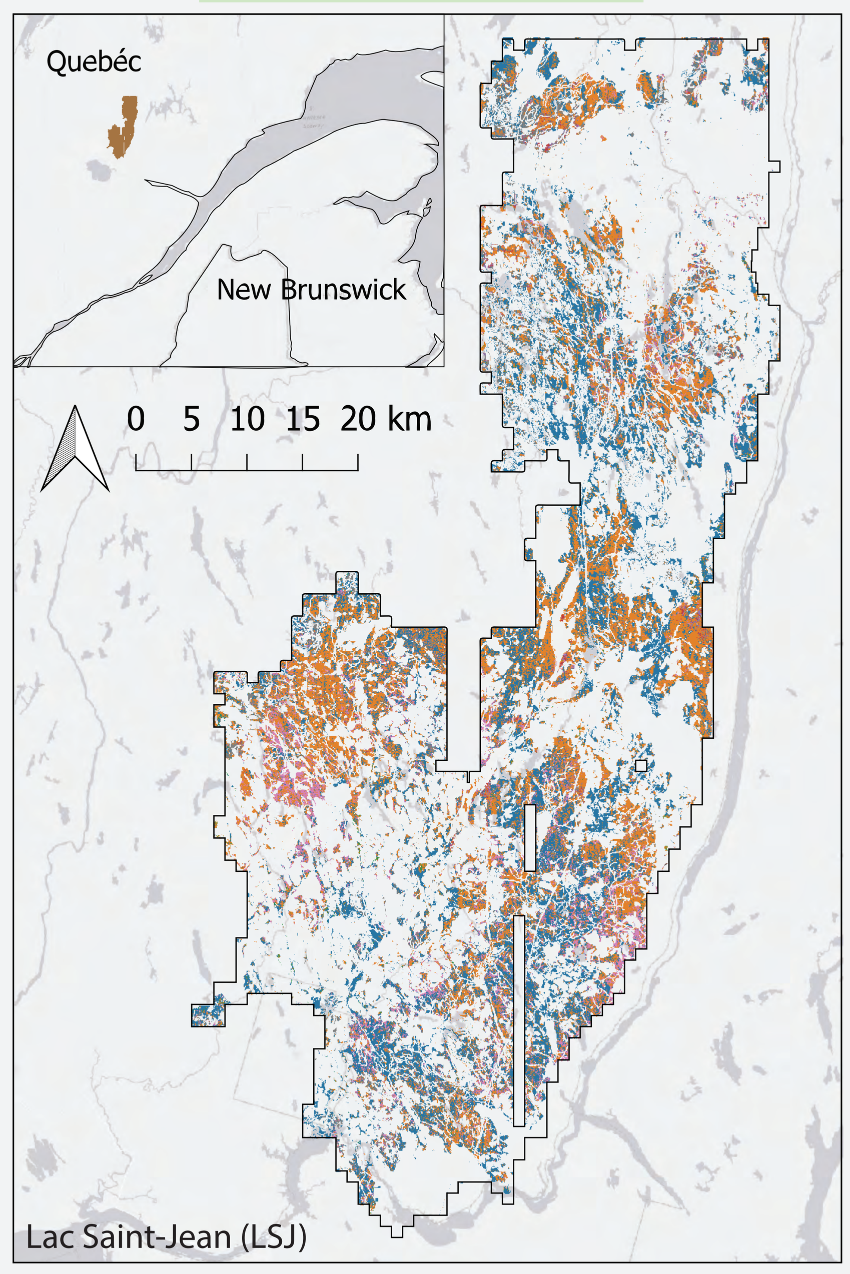


Clustering Validation and Discussions

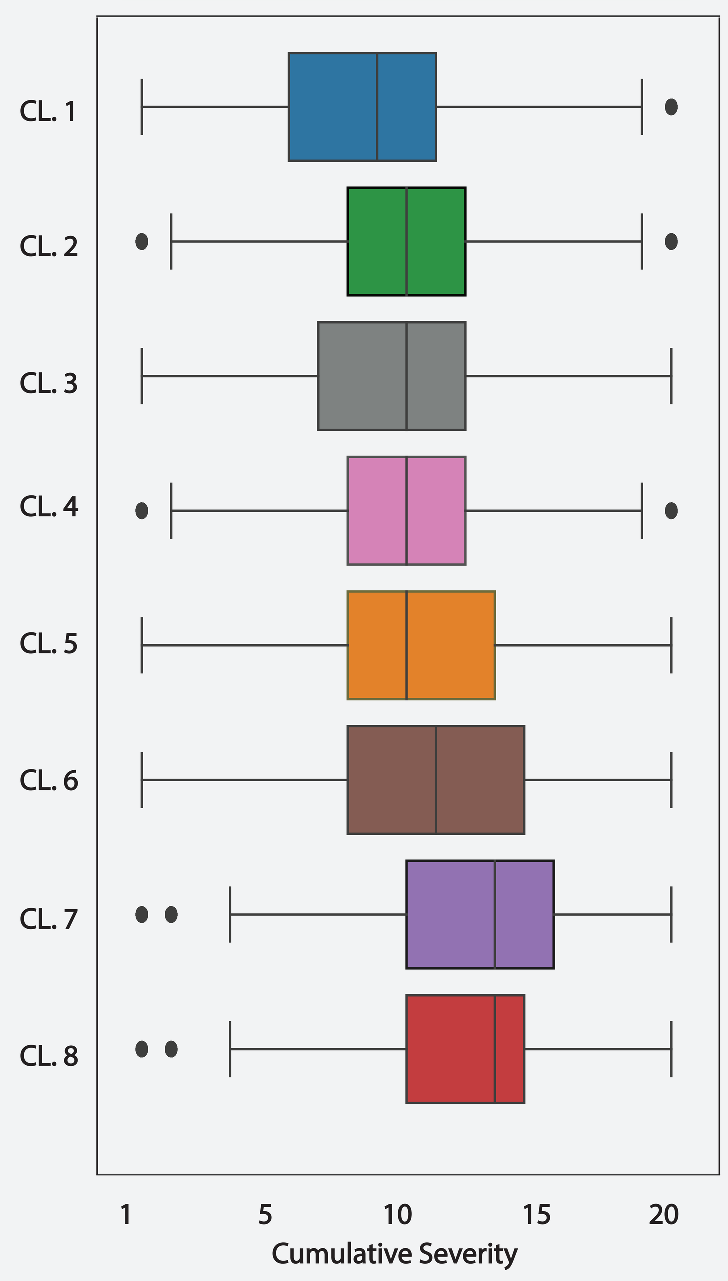
- To validate the clustering, a network of 70 plots per cluster at 2 different sizes (100 m², 900 m²) was established using a stratified random sampling approach (Goodbody et al., 2023).
- Each network location was visually inspected for signs of decoloration, defoliation, and gaps through interpretation of two aerial imagery acquired in 2012 and 2020 in the LSJ region. A 0-5 score was assigned for each indicator.
- To assess cluster uniqueness for each individual ALS metric and cumulative disturbance severity, a Kruskal-Wallis and a Dunn's post-hoc tests were conducted.
- A Random Forest model was trained on a subset of clustered data, which resulted in an overall accuracy of 68%.
- Cluster 8 represented the highest cumulative severity and showed the greatest change in decoloration, defoliation, and gaps, followed by clusters 7 and 6. Low severity clusters 1 and 2 showed the smallest change over time. In general, gap dynamics were relatively stable over time and across clusters.



CLUSTER DISTRIBUTION



CUMULATIVE SEVERITY by CLUSTER



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