RC1

The authors present a dataset and accompanying paper on airborne lidar of northern Canadian forests.

Due to the inaccessibility and size of the area, no wall-to-wall laser scanning is available. Instead, transects have been flown that cover all ecozones of Northern Canada. Lidar metrics are available as full dataset or in an abridged version.

The paper describes the data and gives a lot of background information with an exhaustive literature list. The paper does not provide detailed information on each individual metric, but enough information is given so that the metrics can be understood.

The paper is very well-written, I could not find any mistakes or major omissions so I recommend publication as is.

Thank you for the very positive comments. With regards to support information on included metrics: our submission includes two supplements containing individual summaries of each metric, including Supplement A for the full database with 369 metrics and Supplement B for the abridged version with 40 metrics. This additional information will be published alongside the final manuscript. The manuscript also includes the following text:

> ***"In total, 369 point cloud metrics were generated; Table 4 categorizes these metrics by type (for a full list of metrics included in the database, see Supplement A)."***
>
> ***"Given the large number of metrics in the full database (Supplement A), for each year an abridged version of the dataset is also being shared that contains a subset of commonly used metrics for forest inventory (White et al. 2013, 2017; Supplement B)."***
>
> ***"A key advantage of this dataset lies in its flexibility. The inclusion of point cloud metrics from the four combinations of return types and height thresholds (all returns and first returns, > 0 m and > 2 m) supports diverse modeling approaches, including forest inventory, regeneration assessment, and canopy fuel characterization (Table 4, Figure 3, Supplement A, Supplement B)."***
>
> ***"One of the objectives of the NorthForM program is the collection of coincident ALS and ground plot data. As the program progresses, GNSS locations from***

> ***ground plots will be used to clip ALS point clouds to the plot extents. The same suite of 369 metrics described above (Table 4, Supplement A) will then be generated for the ground plot data and made available."***

RC2

The authors present a dataset collected from ALS transects with lidar-derived metrics covering Canada's northern forests. A series of 30 by 30 m lidar metrics was derived to accommodate a wide range of forestry and ecological applications. The manuscript is complete and well-written. However, there are critical aspects missing in order to make the provided datasets useful for a broad community.

Thank you for your comments – they are very much appreciated. Our responses can be found below.

(1) There is no use case demonstrated, illustrating how the provided datasets can be used for "science and application" as the authors stated in the title, such as wildfire fuel mapping, ecosystem monitoring, etc. I think this is an essential aspect of demonstrating how useful this dataset is.

As this is a data paper and not focused on specific applications, we do present in the manuscript examples of how similar data have been used in the past and may be used in the future. Please see the following text from the manuscript:

> ***"Although typically flown in a wall-to-wall configuration, ALS data may be collected as sampled linear transects to extend structural information over remote areas where continuous, wall-to-wall coverage is impractical. Wulder et al. (2012b) described lidar sampling as a cost-effective alternative to wall-to-wall lidar acquisition for large-area forest monitoring. The authors demonstrated that statistically sound sampling and inference methods can enable robust characterizations of forest structure, and that integration of lidar samples with field and satellite data can enhance scalability and precision of estimates. For example, Andersen et al. (2011) presented a methodology for estimating forest biomass over a large area of interior Alaska. The authors used a combination of ground plots and sampled ALS transects to achieve reasonable precision, underscoring the cost-efficiency of integrating partial airborne lidar coverage. Also working in Alaska, Babcock et al. (2018) demonstrated that sparse lidar transects, when fused with field plots and Landsat tree cover in a Bayesian geostatistical framework, can yield wall-to-***

wall biomass maps with quantified uncertainty. Nelson et al. (2012) used an airborne profiling lidar to estimate forest biomass in Norway and found that the results were similar to those obtained through ground surveys. Building on this logic, Margolis et al. (2015) employed a three-phase sampling design combining ground plots, airborne profiling lidar, and ICESat-GLAS satellite lidar data to estimate biomass across the North American boreal forest.

Wulder et al. (2012a) proposed the concept of lidar plots, wherein lidar transect data, augmented by ground plot information, provide sample-based characterizations of forest structure. Lidar plot locations are established within sampled lidar transect swaths at a spatial resolution matching the typical size (area) of tall tree ground plots or the pixel size of medium spatial resolution remotely sensed data (e.g., pixels sized 400-900 m^2). The ALS data are processed to generate a suite of summary statistics or metrics that characterize the point cloud within each lidar plot (e.g., mean height, maximum height, percentiles of height). Using an area-based approach (ABA) (Næsset, 2002; White et al., 2013), a sample of co-located ground plot measurements are then used with the point cloud metrics to generate predictions of inventory attributes of interest such as height, basal area, volume, or biomass, among others. These lidar plots, with associated metrics and attributes, may then be linked to other remotely sensed data (e.g., optical time series) via imputation, enabling the generation of spatially exhaustive and spatially explicit models of forest structure ultimately resulting in maps representing large areas (Coops et al., 2021; Wulder et al., 2012a)

In a proof-of-concept study, Zald et al. (2016) demonstrated how lidar plots could be used as a surrogate for ground plots to map a suite of point cloud height (mean, standard deviation, coefficient of variation, 95th percentile) and cover metrics (percentage of first returns > 2 m, percentage of first returns > mean height), as well as select forest inventory attributes (i.e., Lorey's tree height, basal area, gross stem volume, and total aboveground biomass) for a ~38 million ha forest region in Saskatchewan, Canada for the year 2010 (corresponding to the year of ALS 95 acquisition). Zald et al. (2016) availed upon 1,560 km of lidar transects and a set of 4,340 lidar plots to impute point cloud metrics directly, with the ABA forest attributes carried as ancillary variables in the plot-matching process. Expanding on this approach, Matasci et al. (2018a) employed >25,000 km of lidar transects and 80,687 lidar plots with Landsat surface reflectance composites to produce boreal-wide maps (~552 million ha) of the same point cloud metrics and forest structural attributes as Zald et al.

> ***(2016) for the year 2010. Matasci et al. (2018b) expanded this approach in both space and time, mapping forest structure annually for the entirety of Canada's forested ecosystems (~650 million ha) for each year from 1984 to 2016. Matasci et al. (2018b) availed upon seven different lidar acquisitions and associated lidar plots (n = 84,482) to achieve national, annual maps of forest structure, thereby enabling characterization of structural dynamics in both disturbed and undisturbed forests over the three-decade period considered. Matasci et al. (2018b) also used a completely independent set of lidar plots, derived from separate lidar acquisitions to validate the imputed attributes, both spatially and temporally. Collectively, these studies demonstrate the utility of ALS sampling and lidar plots in generating spatially and temporally rich forest structural information at landscape to continental scales."***

(2) Similarly, 369 lidar metrics have been calculated and provided; however, it remains unclear to users how to select the relevant/useful/robust metrics for different applications. Concrete examples and suggestions/usage notes should be provided on how to potentially best apply the provided lidar metrics.

The 369 metrics are not curated for any specific application; rather our objective was to provide as many potential metrics as possible for any user, thus negating the need for additional processing of the raw ALS point cloud data. We leave it to the user to determine which metrics best suit their application. That being said, we do provide two databases: one with the full suite of 369 metrics, and a second abridged version with a subset of 40 metrics commonly used in forestry applications and identified in best practice guidance (White et al. 2013, 2017). We leave it to users to determine which database best meets their needs, expecting the 40 common metrics are sufficient for most forest applications.

In the manuscript text, we write:

> ***"Given the large number of metrics in the full database (Supplement A), for each year an abridged version of the dataset is also being shared that contains a subset of commonly used metrics for forest inventory (White et al., 2013, 2017a; Supplement B).***

Both databases can be downloaded from Zenodo:

> ***"The 2023 lidar plots and point cloud metrics described here are available at https://doi.org/10.5281/zenodo.16782860 on Zenodo (Bater et al., 2025)."***

(3) The accuracy of the ALS data collection (horizontal and vertical accuracies of points) and the classification accuracy of the point clouds are not provided or evaluated. This is an

important factor to consider in order to know how reliable the datasets and the derived metrics are. Additional evidence needs to be provided.

As we are acquiring data over remote landscapes that lack GNSS base station infrastructure, we did not require ALS vendors to differentially correct their data, nor did we require them to provide survey-based validation of bare-Earth terrain heights, which is typical of ALS acquisitions in more populated areas. Rather, ALS vendors employed precise point positioning (PPP) to post-process ALS return coordinates, with the expectation that they would obtain sub-metre horizontal and vertical accuracies. In the manuscript text, we write:

> ***"The ALS vendors corrected GNSS data using PPP and all reported sub-metre horizontal and vertical accuracies."***

Regarding the accuracy of the point cloud classification, we manually interpreted sampled point clouds to assess quality. We include this information in the manuscript text:

> ***"Point cloud classifications were validated using methods described in section 8.6 of the Canadian lidar acquisition standards (CSA Group, 2025) by randomly selecting 20 x 20 m areas that were then clipped to perform three-dimensional visual checks of the data. Point clouds were also rasterized based on return class (Table 1) and hillshades were generated from the DTMs. Raster surfaces were then visually inspected to ensure specifications were met (e.g., water was properly classified, DTMs were representative of the bare-Earth surface). Similarly, return counts and scan angles were rasterized to ensure transects fell within the specifications for point densities and swath widths (Table 1)."***

More detailed comments are as follows:

1. L23. 15 million 900 m2 lidar plots, what is the point density?

The point density is a minimum of 12 pulses/m^2. Table 1 summarizes the acquisition specifications. We have added this sentence to the abstract:

> ***"Acquisition specifications included minimum swath widths of 500 m (year 2023) or 800 m (2024 and 2025), with a minimum pulse density of 12 pulses/m^2."***

2. L25. The authors mentioned that the chosen 30 by 30 m resolution was to match the medium resolution of Landsat and Sentinel 2, still, I believe lidar metrics with finer

resolution should be considered, given the pulse/point density of ALS data, and it will be more beneficial for a broader user community. There are already country-wide lidar metrics derived from ALS data at 10 m resolution (see references below). 30 by 30 m resolution may be a bit limited in finer scale ecological applications. \

Ref: (1) Assmann, J. J., Moeslund, J. E., Treier, U. A., & Normand, S. (2022). EcoDes-DK15: high-resolution ecological descriptors of vegetation and terrain derived from Denmark's national airborne laser scanning data set. Earth System Science Data, 14(2), 823-844. doi:10.5194/essd-14-823-2022

(2) Shi, Y., Wang, J., & Kissling, W. D. (2025). Multi-temporal high-resolution data products of ecosystem structure derived from country-wide airborne laser scanning surveys of the Netherlands. Earth Syst. Sci. Data, 17(7), 3641-3677. doi:https://doi.org/10.5194/essd-17-3641-2025

We appreciate that rasterization and area-based analyses can be performed at a range of spatial resolutions and that 10 to 20 m is common for natural resources applications. The examples shared represent nations with a terrestrial area that corresponds to less than 0.5%of Canada's land area. We used 30 m because it links directly to national satellite information products available in Canada. The ALS point cloud data will be made publicly available in the near future and users can then generate metrics at any scale they choose. We have updated the manuscript text as follows:

> ***"While ALS derivatives are typically distributed using raster formats (e.g. Assmann et al., 2022; Shi et al., 2025), the layout of the transects (Figure 1) would result in raster surfaces consisting largely of "no data" values. Should a user desire, the point feature classes can be easily rasterized for inclusion in an analysis workflow requiring gridded surfaces. For users interested in leveraging NTEMS datasets (e.g. Hermosilla et al., 2022, 2024; Matasci et al., 2018a), the lidar plots will integrate seamlessly as all data share a common spatial resolution, projection (Table 3), and origin coordinates. Should users prefer to generate metrics at other spatial resolutions, the raw ALS point cloud data will also be made publicly available.***

3. L43-47. Too long for one sentence. Please rephrase.

Thanks for noticing this. The sentence will be rephased as follows:

> ***"It is not entirely fair to compare optical satellite remote sensing and ALS due to their differences in data costs to the end user, the level of detail captured,***

> ***and the intensity and repeatability of collection (Fassnacht et al., 2024). However, ALS provides access to simultaneous measurements of the vertical distribution of vegetation and the underlying terrain morphology (Lefsky et al., 2002), providing critical information on forest complexity and condition that cannot be obtained through other remote sensing methods."***

4. What is the impact of the ALS transects sampling discussed here on areas beyond Canada? It should also be reflected in the Introduction.

To address this suggestion we have added a new paragraph to the discussion:

> ***"Beyond Canada, the ALS transect network provides an example for characterizing vegetation structure over large areas at a relatively low cost. The transects-based approach offers a transferable framework for designing national forest monitoring programs in countries where consistent, high spatial resolution structural data are lacking. By linking ALS measurements to ground plots and satellite observations, the dataset can support regional to global assessments of carbon stocks, disturbance dynamics, and climate-driven change."***

5. L66. It is not clear what "linear samples" mean here.

We rephrased this sentence to read:

> ***"....collected as sampled linear transects to extend....."***

6. L107-108. Please briefly explain how the current study relate/compare to the existing work mentioned here.

The next two sections (*1.1 Motivation* and *1.2 Objectives*) link directly to the literature review preceding these sections.

7. Table 1. What are the horizontal and vertical accuracy of the acquisitions? What are the data volumes?

As we are acquiring data over remote landscapes that lack GNSS base station infrastructure, we did not require ALS vendors to differentially correct their data, nor did we require them to provide survey-based validation of bare-Earth terrain heights, which is typical of ALS acquisitions in more populated areas. Rather, ALS vendors employed precise point positioning (PPP) to post-process ALS return coordinates, with the expectation that they would obtain sub-metre horizontal and vertical accuracies. In the manuscript text, we write:

> ***“Acquisition specifications are summarized in Table 1. Due to the remoteness of the area of interest (Figure 1), the lack of permanent global navigation satellite system (GNSS) base station infrastructure, and the impracticality of setting up ad hoc base stations, precise point positioning (PPP) services were employed to correct ALS return coordinates.”***
>
> ***“The ALS vendors corrected GNSS data using PPP and all reported sub-metre horizontal and vertical accuracies.”***

We address database volumes in the manuscript text:

> ***“For the 2023 ALS transects, 15,353,866 lidar plots were generated within the lidar swaths. The full database including 369 point cloud metrics is 60.2 GB in size, and the abridged version of the database containing a subset of 40 metrics is 7.2 GB. Both versions are shared as SQLite GeoPackages.”***

8. L185. Why remain low points noise (class 7) in the process?

Class 7 (low points – noise) is a valid ASPRS las class and the returns contain useful information, especially for modeling vegetation regeneration. We do remove returns that are below 0 m relative to the DTM. In the text we write:

> ***“Classified lidar point clouds were then normalized to obtain heights above ground, with returns less than 0 m and greater than 100 m being removed.”***

We address height thresholds in the manuscript text:

> ***“As the final products are intended to inform a variety of applications, including forest inventory, regeneration assessment, and wildfire fuels, the metrics were generated in four groups using: (1) all returns above 0 m, (2) first returns above 0 m, (3) all returns above 2 m, and (4) first returns above 2 m. Two height thresholds were used so that models could be created that either consider all vegetation from the ground surface upwards (i.e., ≥ 0 m), or with a focus on overstory structure (> 2 m).”***

9. L204. What is the accuracy of the points classification? For instance, what is the extent of misclassification between ground points and low vegetation points? It is essential for lidar metrics calculation and for deriving further metrics/parameters.

Regarding the classification accuracies, we manually interpreted sampled point clouds to assess quality. We include this information in the manuscript text:

> ***“Point cloud classifications were validated using methods described in section 8.6 of the Canadian lidar acquisition standards (CSA Group, 2025) by randomly***

> ***selecting 20 x 20 m areas that were then clipped to perform three-dimensional visual checks of the data. Point clouds were also rasterized based on return class (Table 1) and hillshades were generated from the DTMs. Raster surfaces were then visually inspected to ensure specifications were met (e.g., water was properly classified, DTMs were representative of the bare-Earth surface). Similarly, return counts and scan angles were rasterized to ensure transects fell within the specifications for point densities and swath widths (Table 1). All raster products were generated using LAStools (version 2.0.4).”***

L221. Are there any data collected in 2025? As in Figure 1 and Table 2, only 2023 and 2024 were listed as acquisition years. This information should be clarified at the beginning.

At the time of writing the 2025 data have now been acquired but will not be delivered by the vendors until 2026.

11. I think Table 5 can be better presented as a Figure. For instance, a land cover map for each ecozone, showing land cover classes and their areas. Lidar plot area can be overlaid with the land cover map with indications of sampling intensity.

While we agree with you that a figure would certainly be more visually impactful, the table is meant to provide raw numbers on sampling intensity broken down by land cover class, lidar plot area, and sampling intensity with the precision that a figure cannot provide.

12. L255. How many of those areas have been selected for validation? And what are the validation results? Why is the area of validation (20 by 20 m) different from the original sample area (30 by 30 m)?

We followed the validation process outlined in the Canadian lidar acquisition standard. The classification validation data are completely unrelated to the 30 x 30 m lidar plots described in the manuscript as they serve different purposes. In the manuscript, we write:

> ***“Point cloud classifications were validated using methods described in section 8.6 of the Canadian lidar acquisition standards (CSA Group, 2025) by randomly selecting 20 x 20 m areas that were then clipped to perform three-dimensional visual checks of the data. Point clouds were also rasterized based on return class (Table 1) and hillshades were generated from the DTMs. Raster surfaces were then visually inspected to ensure specifications were met (e.g., water was properly classified, DTMs were representative of the bare-Earth surface).***

13. L259. How do you rasterize the scan angles, and what is the use of the rasterized layer?

We rasterize the data using LAStools and the surfaces are used for quality control only. We do retain them for future use. We will modify this section to read:

> ***"Point clouds were also rasterized based on return class (Table 1) and hillshades were generated from the DTMs. Raster surfaces were then visually inspected to ensure specifications were met (e.g., water was properly classified, DTMs were representative of the bare-Earth surface). Similarly, return counts and scan angles were rasterized to ensure transects fell within the specifications for point densities and swath widths (Table 1). All raster products were generated using LAStools (version 2.0.4)."***

14. L263. Is this including the volume of the raw point cloud? Why only 2023?

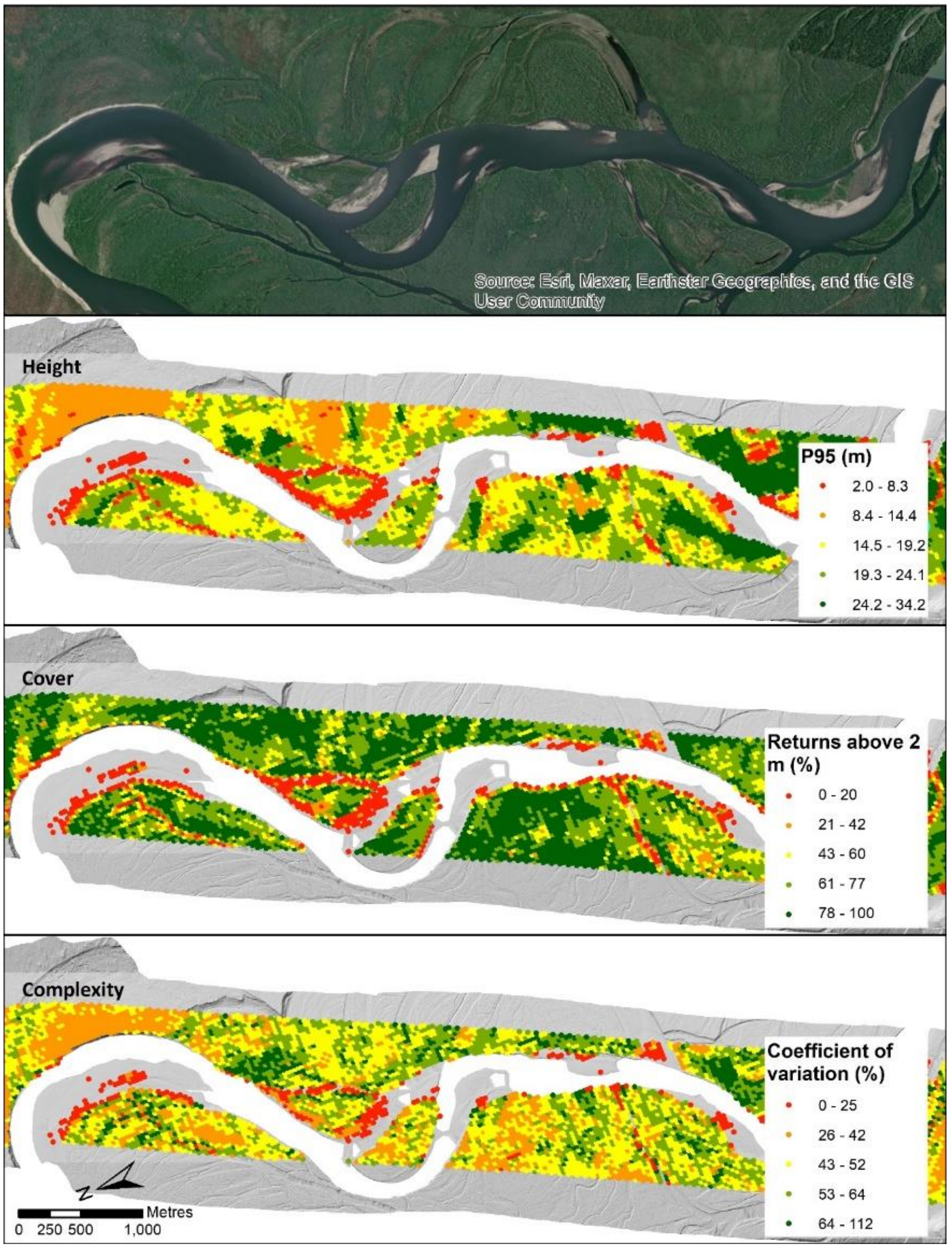
This does not include the volume of the point cloud and includes only the geopackages. We are still processing the 2024 data and have not received delivery of the 2025 data.

15. L269. This may link to the classification of ground points and low vegetation points. It would be helpful to know the quality of such classification.

While we agree that the quality of ground returns is important, the differences seen here are driven by combinations of height thresholds (0 m or 2 m) and return types (all versus first returns).

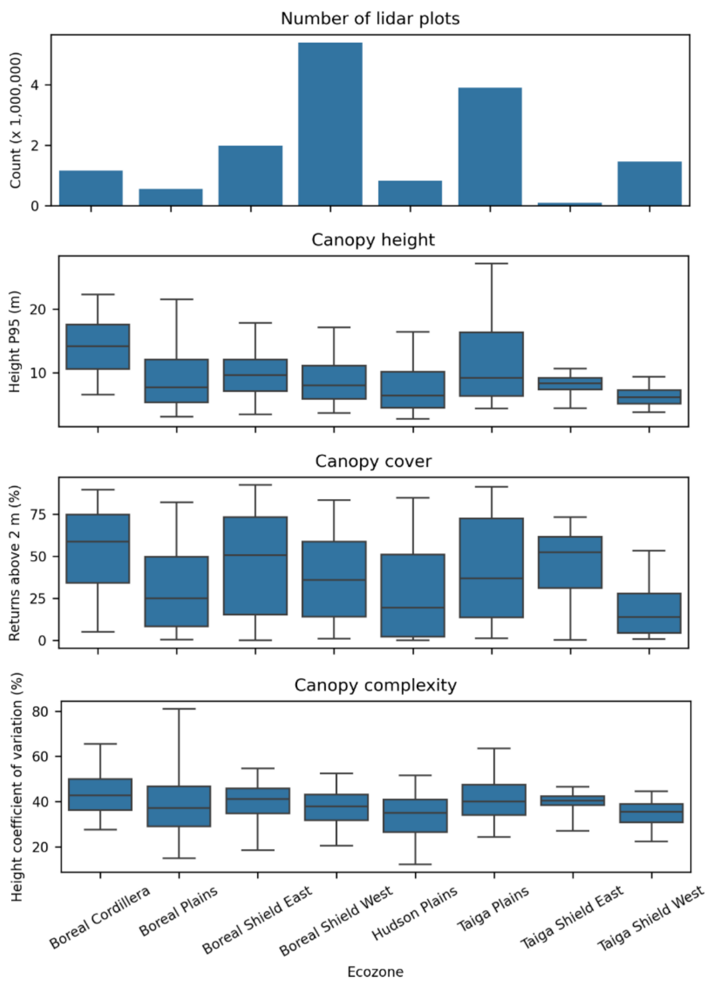
16. Figure 4. Why are there large areas of red color in the water area in the Canopy Cover (the third panel)? Those areas are not shown in the P95 layer, meaning they probably are assigned to the NA value (i.e. no returns observed or masked out as water body)? Then why do those areas occur in the Canopy cover layer, probably having 0 value (which may should be NA)?

You are correct that the canopy cover metrics over water were based on ALS returns that were not masked out. We have modified the figure to remove lidar plots over water (see below).


Source: Esri, Maxar, Earthstar Geographics, and the GIS User Community
Height
P95 (m)
2.0 - 8.3
8.4 - 14.4
14.5 - 19.2
19.3 - 24.1
24.2 - 34.2
Cover
Returns above 2 m (%)
0 - 20
21 - 42
43 - 60
61 - 77
78 - 100
Complexity
Coefficient of variation (%)
0 - 25
26 - 42
43 - 52
53 - 64
64 - 112
N
Metres
0 250 500 1,000

17. Figure 5. The y-axis label of 1e6 for the number of lidar plots seems wrong. The purpose of showing this figure is not very well-explained in the caption and in the main text.

We have removed the 1e6 (see below).



The purpose of the figure is to demonstrate that different vegetation metrics can be summarized at the ecozone level, and by extension vegetation attributes (e.g. biomass) related to those metrics. In the text we write:

> ***"The data can also be analyzed at regional scales (Figure 5) to contribute to population estimates of attributes such as volume or biomass (Andersen et al., 2011; Margolis et al., 2015)."***

18. Figure 7. Please elaborate on the multidecadal NTEMS satellite information products. And what are the main things shown in this figure? Can information such as how many plots were repetitively disturbed by fire be included in the figure?

For additional clarity we have expended upon what is shared in the Figure 7 caption, which now reads: *"Figure 7. Comparison between lidar plots and multidecadal NTEMS*

satellite information products, including land cover class (excluding water) and number of plots disturbed by wildfire (Hermosilla et al, 2016; 2022)."

Examining how many plots were repeatedly disturbed is beyond the scope of this particular paper. In general, multiple disturbances at the same site are relatively rare (Hermosilla et al. 2019). It therefore follows that plots are unlikely to be disturbed multiple times, noting that this can be checked using the NTEMS disturbance time series outputs (https://opendata.nfis.org/mapserver/nfis-change_eng.html)

Hermosilla, T. et al. (2019). Prevalence of multiple forest disturbances and impact on vegetation regrowth from interannual Landsat time series (1985–2015). Remote Sensing of Environment, 233. 111403. doi: 10.1016/j.rse.2019.111403.

We summarize NTEMS in the manuscript text:

> ***"These methods build upon earlier work by the National Terrestrial Ecosystem Monitoring System (NTEMS), which was developed to monitor Canada's forested ecosystems on an annual basis using consistent, nationally available datasets (White et al., 2014; Wulder et al., 2024). The NTEMS relies primarily on medium spatial resolution satellite data (initially solely Landsat, now augmented with Sentinel 2) time series, integrated with ALS transects and ground plots, to generate national information products characterizing disturbance, land cover, and forest structure (Hermosilla et al., 2016). The first national lidar transect dataset was collected in 2010 to support NTEMS product development (Hopkinson et al., 2011; Wulder et al., 2012a), and subsequent work has shown that combining these data sources enables spatially comprehensive estimates of both forest structure and derived attributes (Matasci et al., 2018a, b; Zald et al., 2016)."***

We also elaborate on Figure 7 in the main text:

> ***"Figure 7 provides distributions of 2023 lidar plots for land cover and year of recent wildfire disturbance (1985 - 2022). For the 15,353,866 plots, the dominant land cover type (Hermosilla et al., 2022),excluding water, was coniferous (46%), followed by wetland (17%), shrubs (11%), mixedwood (9%), wetland-treed (8%), broadleaf (4%), exposed/barren land (3%), herbs (1%), bryoids (0.3%), rock/rubble (0.04%), and snow/ice (0.001%). . Moreover, 19% of plots were disturbed by wildfire (Hermosilla et al., 2016) between 1985 and 2022 (Figure 7)."***

19. L320. Can a use case be demonstrated here?

We have updated this sentence to include citations that will lead the reader to examples of use cases:

> ***"The design and implementation of the acquisitions can address both scientific and operational needs, with particular relevance to wildfire fuel mapping (Andersen et al., 2005; Martin-Ducup et al., 2025; Riaño et al., 2003), forest inventory (Reutebuch et al., 2005; Wulder et al., 2008), carbon accounting (Andersen et al., 2011; Babcock et al., 2018), and ecosystem monitoring (Bolton et al., 2015; Matasci et al., 2018b).***

We also present specific examples of how similar data have been used in the past and may be used in the future. Please see the following text from the manuscript:

> ***"Although typically flown in a wall-to-wall configuration, ALS data may be collected as sampled linear transects to extend structural information over remote areas where continuous, wall-to-wall coverage is impractical. Wulder et al. (2012b) described lidar sampling as a cost-effective alternative to wall-to-wall lidar acquisition for large-area forest monitoring. The authors demonstrated that statistically sound sampling and inference methods can enable robust characterizations of forest structure, and that integration of lidar samples with field and satellite data can enhance scalability and precision of estimates. For example, Andersen et al. (2011) presented a methodology for estimating forest biomass over a large area of interior Alaska. The authors used a combination of ground plots and sampled ALS transects to achieve reasonable precision, underscoring the cost-efficiency of integrating partial airborne lidar coverage. Also working in Alaska, Babcock et al. (2018) demonstrated that sparse lidar transects, when fused with field plots and Landsat tree cover in a Bayesian geostatistical framework, can yield wall-to-wall biomass maps with quantified uncertainty. Nelson et al. (2012) used an airborne profiling lidar to estimate forest biomass in Norway and found that the results were similar to those obtained through ground surveys. Building on this logic, Margolis et al. (2015) employed a three-phase sampling design combining ground plots, airborne profiling lidar, and ICESat-GLAS satellite lidar data to estimate biomass across the North American boreal forest.***
>
> ***Wulder et al. (2012a) proposed the concept of lidar plots, wherein lidar transect data, augmented by ground plot information, provide sample-based***

characterizations of forest structure. Lidar plot locations are established within sampled lidar transect swaths at a spatial resolution matching the typical size (area) of tall tree ground plots or the pixel size of medium spatial resolution remotely sensed data (e.g., pixels sized 400-900 m2). The ALS data are processed to generate a suite of summary statistics or metrics that characterize the point cloud within each lidar plot (e.g., mean height, maximum height, percentiles of height). Using an area-based approach (ABA) (Næsset, 2002; White et al., 2013), a sample of co-located ground plot measurements are then used with the point cloud metrics to generate predictions of inventory attributes of interest such as height, basal area, volume, or biomass, among others. These lidar plots, with associated metrics and attributes, may then be linked to other remotely sensed data (e.g., optical time series) via imputation, enabling the generation of spatially exhaustive and spatially explicit models of forest structure ultimately resulting in maps representing large areas (Coops et al., 2021; Wulder et al., 2012a).

In a proof-of-concept study, Zald et al. (2016) demonstrated how lidar plots could be used as a surrogate for ground plots to map a suite of point cloud height (mean, standard deviation, coefficient of variation, 95th percentile) and cover metrics (percentage of first returns > 2 m, percentage of first returns > mean height), as well as select forest inventory attributes (i.e., Lorey's tree height, basal area, gross stem volume, and total aboveground biomass) for a ~38 million ha forest region in Saskatchewan, Canada for the year 2010 (corresponding to the year of ALS acquisition). Zald et al. (2016) availed upon 1,560 km of lidar transects and a set of 4,340 lidar plots to impute point cloud metrics directly, with the ABA forest attributes carried as ancillary variables in the plot-matching process. Expanding on this approach, Matasci et al. (2018a) employed >25,000 km of lidar transects and 80,687 lidar plots with Landsat surface reflectance composites to produce boreal-wide maps (~552 million ha) of the same point cloud metrics and forest structural attributes as Zald et al. (2016) for the year 2010. Matasci et al. (2018b) further extended this approach in both space and time, mapping forest structure annually for the entirety of Canada's forested ecosystems (~650 million ha) for each year from 1984 to 2016. Matasci et al. (2018b) availed upon seven different lidar acquisitions and associated lidar plots (n = 84,482) to achieve national, annual maps of forest structure, thereby enabling characterization of structural dynamics in both disturbed and undisturbed forests over the three-decade period considered.

> ***Matasci et al. (2018b) also used a completely independent set of lidar plots, derived from separate lidar acquisitions to validate the imputed attributes, both spatially and temporally. Collectively, these studies demonstrate the utility of ALS sampling and lidar plots in generating spatially and temporally rich forest structural information at landscape to continental scales."***

20. L331. Here I am missing a bit more concrete suggestions for using the 369 metrics derived. For instance, giving guidance on how to select the most relevant metrics/metric types for different ecological applications (with use cases and examples).

We believe that providing in-depth advice on how users select metrics for use as predictor variables for modelling is beyond the scope of this paper. To reiterate, we do include two versions of the database, including an abridged version with 40 metrics commonly found in the literature that are useful for modelling vegetation-related attributes, particularly for forest inventory applications.

We have updated this section to read:

> ***"The decision to use first returns or all returns may be guided by examining performance diagnostics from predictive models (Arumäe and Lang, 2018; Bater et al., 2011). White et al. (2013, 2017a) provide advice on model development for enhanced forest inventories, and the methods described and citations therein can inform a wide range of applications related to ALS and ecology."***