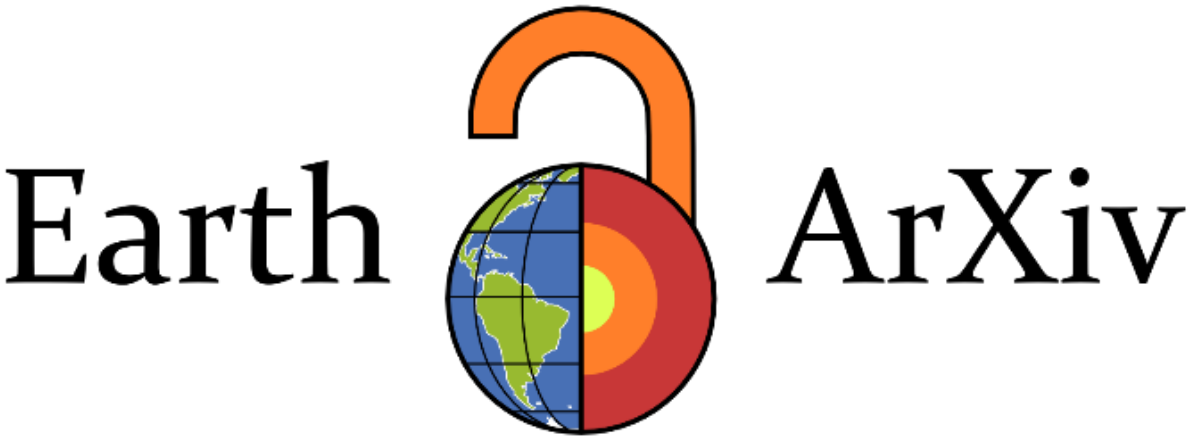

GEDIMetrics: a QGIS plugin for accessing and integrating multi-product GEDI spaceborne LiDAR data

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Abstract

NASA's Global Ecosystem Dynamics Investigation (GEDI) provides near-global, high-resolution 3D LiDAR observations of forest vertical structure. However, GEDI products are distributed as independent HDF5 files organised by beam, requiring ad-hoc workflows for data discovery, quality filtering, spatial subsetting, and footprint-level alignment across products. Existing tools either target a single product, require programming expertise, or operate outside common GIS environments. Here, GEDIMetrics is presented as an open-source QGIS plugin that integrates the full GEDI processing chain for four products focused on forest vertical structure: canopy height (L2A), vertical canopy structure (L2B), aboveground biomass density (L4A), and waveform structural complexity (L4C). The plugin implements a five-stage pipeline: granule discovery via the NASA CMR API, authenticated download, variable extraction with quality filtering, spatial subsetting, and multi-product merging using the shot_number identifier, with export to GeoPackage and GeoParquet. Its core contribution is the automated footprint-level fusion of these products into a single analysis-ready dataset through a graphical interface, without scripting. GEDIMetrics was tested across two contrasting forest ecosystems (~100 km² each): a temperate mixed forest in northeastern France and a humid tropical rainforest in Madre de Dios, Peru. The plugin is freely available through the QGIS Plugin Repository and on GitHub.

Keywords: Earth observation, GEDI, GIS, forest structure, remote sensing, waveform lidar

1. Introduction

Forests are key carbon reservoirs and critical regulators of the global climate system (FAO 2025), while their three-dimensional structure underpins carbon storage and dynamics, biodiversity, habitat quality, and sustainable forest management across scales (Goetz and Dubayah 2011). Conventional approaches, such as ground-based inventories and airborne laser scanning (ALS), provide high-accuracy measurements but are logistically constrained, costly at large scales, and spatially discontinuous, often requiring multisource data integration (Næsset et al. 2011; Coops et al. 2023; Meng et al. 2026). Satellite remote sensing provides consistent, large-scale observations; however, optical and radar data are limited in their ability to directly resolve vertical forest structure and typically require LiDAR data for structural characterization (Pardini et al. 2019). Spaceborne missions (e.g., ICESat-2) have extended LiDAR observations to high-

latitude and boreal regions (Markus et al. 2017), while NASA's Global Ecosystem Dynamics Investigation (GEDI) represents a major advance in the detailed characterization of forest vertical structure at near-global scale (Dubayah et al. 2020a).

Mounted aboard the International Space Station (ISS) since 2018, GEDI provides near-global sampling of forest structure between 51.6°N and 51.6°S through billions of laser waveforms, known as footprints, delivering detailed information on vegetation vertical structure across multiple data products (Dubayah et al. 2020a; Hakkenberg et al. 2023). Level 2A product provides canopy height and ground elevation metrics (Dubayah et al. 2020b), Level 2B characterises vertical canopy structure (e.g., canopy cover, plant area index, foliage profiles) (Dubayah et al. 2021), and Level 4A delivers aboveground biomass density (AGBD) estimates derived from globally calibrated models(Dubayah et al. 2022). The Level 4C product provides footprint-level estimates of the Waveform Structural Complexity Index (WSCI), a metric describing three-dimensional canopy structural complexity derived from machine-learning models trained on collocated GEDI and airborne LiDAR data (De Conto et al. 2024). Together, these products support a wide range of ecological and environmental applications, including forest carbon mapping, biodiversity assessment, natural disturbance monitoring, and the calibration and validation of satellite-based vegetation models (Vogeler et al. 2023; De Conto et al. 2024; Torresani et al. 2026). However, integrating these complementary datasets remains technically challenging, as they are distributed as independent HDF5 files organised by each beam and require alignment via the *shot_number* identifier alongside specialised workflows for data access, download, spatial subsetting, and filtering, posing a barrier for many users in ecology, forestry, and geospatial analysis.

Several tools address individual components of the GEDI processing workflow but lack end-to-end integration. NASA's EarthData Search portal supports data discovery and download but does not perform subsetting, filtering, or cross-product integration (NASA 2026). Programmatic solutions such as rGEDI (Silva et al. 2020), and pyGEDI (Serna and Hernandez-Serna 2020) enable flexible programmatic processing but require coding expertise and do not provide unified workflows for multi-product analysis. Unified workflow frameworks such as GEDI-Data-Resources (ref https://github.com/nasa/GEDI-data-resources) and GEDI-Pipeline (Corado and Godinho 2025) introduce automation layers and simplified execution pipelines, enabling stable and reproducible large-scale GEDI data retrieval through a single command-line or Jupyter-based execution (Kluyver Thomas et al. 2016). However, these frameworks do not provide a graphical user interface (GUI) suitable for non-programming users.

Other tools address specific tasks such as scalable database management or geolocation correction (Vangi et al. 2023; Corado et al. 2025; Besnard et al. 2025), yet none are designed for interactive, GIS-based analysis. Within the QGIS ecosystem, the most widely used open-source GIS platform globally (Graser et al. 2025), numerous plugins exist for optical and SAR data processing (Congedo 2021; Martinoli et al. 2026). Recent developments such as the GEDI-Pipeline QGIS Plugin (https://plugins.qgis.org/plugins/gedi_pipeline_plugin/) introduced graphical access to the GEDI data workflow, lowering the technical barrier associated with command-line execution. However, the plugin does not support integrated multi-product merging, advanced filtering operations or unified analysis of GEDI structural and biomass products.

In this paper, GEDIMetrics is presented as an open-source plugin for QGIS (3.4 or higher) that addresses this gap by integrating the full GEDI data processing chain into a single graphical workflow. The plugin implements a modular pipeline comprising granule discovery, data download, spatial subsetting, quality filtering, and multi-product merging based on the shot_number identifier, followed by export to standard geospatial formats (e.g., GeoPackage, GeoParquet). Its core contribution lies in the automated fusion of the L2A, L2B, L4A, and L4C GEDI data products into a single analysis-ready dataset for GIS-based

vegetation analysis. The structure of this paper is organised as follows: Section 2 presents the technical background of GEDI data products; Section 3 describes the architecture, processing pipeline, and user interface of GEDIMetrics; Section 4 describes the case study; Section 5 presents the results; Section 6 discusses the methodological contribution, implications, and limitations; and Section 7 concludes.

2. GEDI spaceborne lidar data

GEDI data products are generated through a hierarchical processing chain from full-waveform LiDAR observations acquired from the ISS (Fig. 1). Each laser footprint (~25 m diameter) is spaced approximately 60 m along-track and captures the vertical distribution of returned energy, from which canopy height, vertical structure, biomass, and structural complexity metrics are derived at four processing levels (Table 1). All products are distributed as HDF5 files organised by beam group and require alignment via the *shot_number* identifier to enable cross-product integration. This data architecture, combined with the independent distribution of each product and the application of product-specific quality filters, introduces technical challenges for routine multi-product analysis. The joint use of L2A, L2B, L4A, and L4C enables integrated assessments of vegetation structure and biomass, supporting applications such as biomass modelling, disturbance detection, and validation of large-scale mapping products yet practical implementation remains constrained by the complexity of accessing, processing, and merging these datasets.

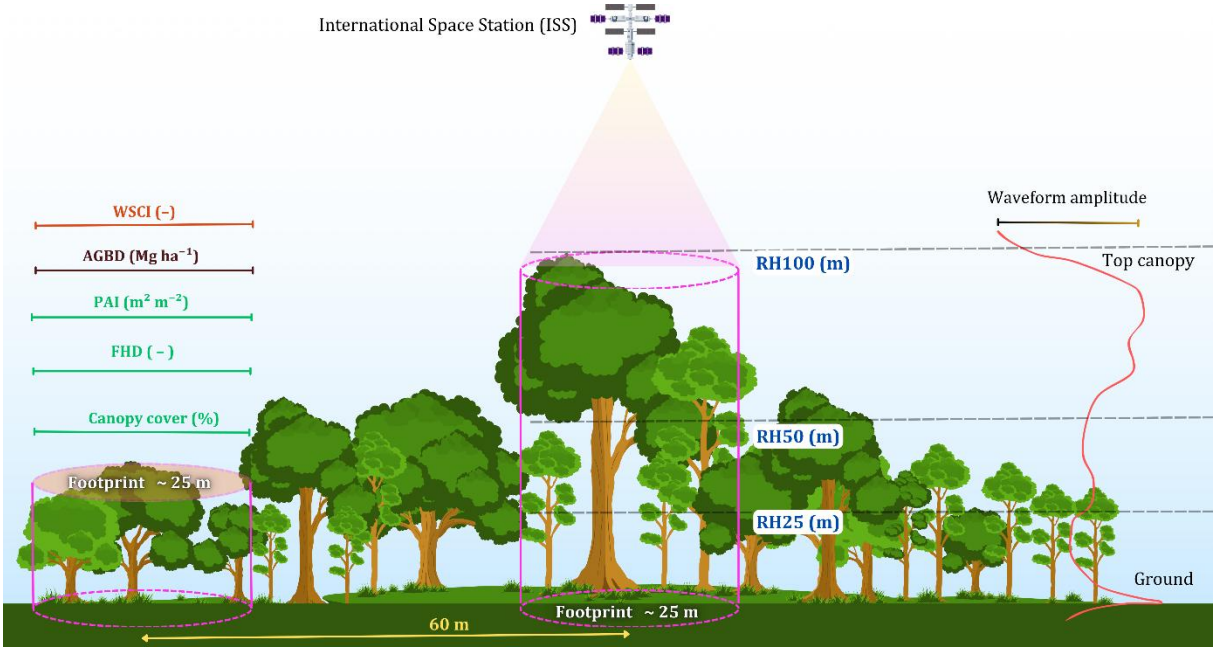


Figure 1. Figure 1. Conceptual representation of GEDI full-waveform LiDAR measurements and derived forest structural metrics. GEDI laser footprints (~25 m diameter), spaced ~60 m along-track, sample the vertical distribution of vegetation structure. L2A metrics (relative height, i.e., RH25, RH50, RH100), L2B metrics (plant area index, PAI; foliage height diversity, FHD; and canopy cover), L4A metrics (aboveground biomass density, AGBD), and L4C Waveform Structural Complexity Index (WSCI) are illustrated.

Table 1. Summary of GEDI data products supported by GEDIMetrics. For each product, the table lists the primary thematic domain, key variables available for extraction, associated quality flags used for filtering, and the original data reference.

Product	Domain	Key variables	Quality flags / filters	Reference
GEDI02_A (L2A)	Canopy height and ground elevation	RH0–RH100, elev_lowestmode, elev_highestreturn, selected_algorithm	quality_flag, degrade_flag, sensitivity	(Dubayah et al. 2020b)
GEDI02_B (L2B)	Vertical canopy structure	cover, PAI, FHD, PAI_z, PAVD_z (vertical profile)	l2b_quality_flag, degrade_flag, sensitivity, surface_flag	(Dubayah et al. 2021)
GEDI04_A (L4A)	Aboveground biomass density	AGBD, AGBD_se, AGBD_prediction, l4_quality_flag	l4_quality_flag, degrade_flag, sensitivity, selected_algorithm	(Dubayah et al. 2022)
GEDI04_C (L4C)	Structural complexity	WSCI, WSCI_se	l4c_quality_flag, degrade_flag, sensitivity	(De Conto et al. 2024)

3. Design and implementation

3.1. Architecture and workflow

GEDIMetrics is implemented as a QGIS plugin in Python 3, compatible with QGIS versions 3.4 or higher. It follows a modular pipeline architecture comprising five sequential stages: orbit discovery, data download, subsetting, multi-product merging, and export. Each stage is encapsulated in an independent module and coordinated by a central pipeline controller, enabling flexible execution, error handling, and partial re-processing. Download operations are executed asynchronously to prevent the QGIS interface from becoming unresponsive during large data retrievals.

The workflow is configured through a graphical interface, where users specify target GEDI products (L2A, L2B, L4A, L4C), temporal range, region of interest (ROI), variables, quality filters, and output format. The system requires the NASA CMR (Common Metadata Repository) API (Application Programming Interface) to identify relevant granules and retrieves them via authenticated access to NASA EarthData. Each granule is then processed through variable extraction, quality filtering, and spatial clipping to the user-defined ROI. Product-specific outputs are integrated into a single dataset through a *shot_number* based join and exported to standard geospatial formats (Fig. 2).

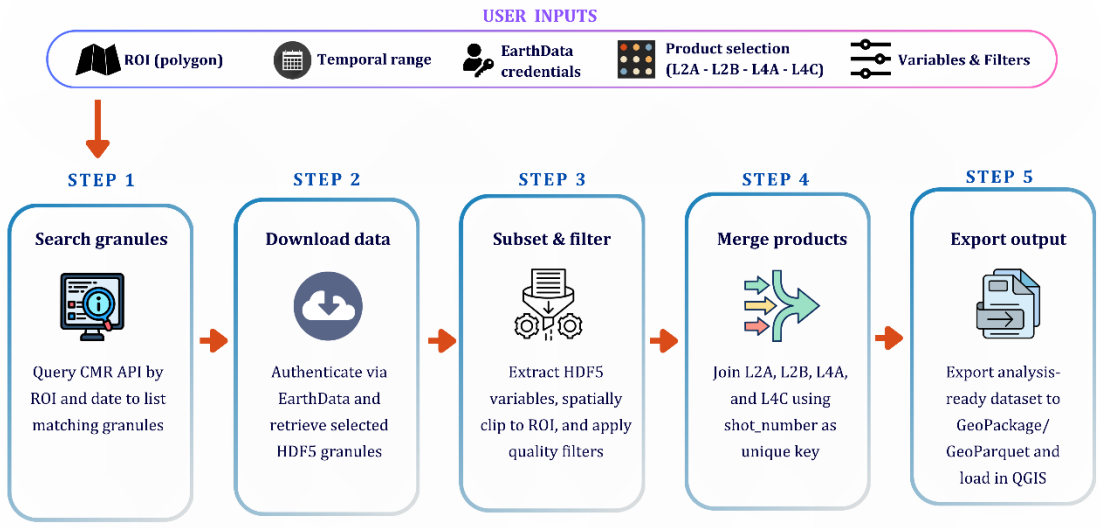


Figure 2. GEDIMetrics workflow illustrates the five-stage pipeline: granule discovery via CMR API, data download from EarthData, subsetting and quality filtering of HDF5 data, multi-product integration using shot_number, and export to GIS-compatible formats.

3.2. Data Processing and Integration

GEDI granules are stored in HDF5 format, with data organised by eight beam groups (four full-power and four coverage beams). The subsetting stage iterates over all beams within each granule, extracting user-selected variables together with essential metadata: coordinates, shot_number, acquisition time, and quality flags (Fig. 3). Spatial filtering is performed in two stages: an initial bounding-box pre-filter based on coordinate ranges for computational efficiency, followed by precise point-in-polygon clipping against the user-defined ROI using Shapely geometric operations. This two-stage approach substantially reduces processing time for large granules covering areas much wider than the target region.

The principal methodological contribution of GEDIMetrics is the automated, footprint-level integration of L2A, L2B, L4A, and L4C data using the shot_number identifier as a unique key (Fig. 3). Because each product undergoes independent processing and considering that data availability may differ across products due to variations in temporal coverage, algorithm convergence, or quality criteria, the number of retained footprints is generally not identical across products. To solve this, merging is performed sequentially using L2A as the base product, with configurable join strategies: an inner join retains only footprints present in all selected products, ensuring cross-product consistency, while an outer join preserves maximum spatial coverage at the cost of null values for missing fields. The resulting dataset contains one row per footprint, in which canopy height metrics (from L2A), vertical structure descriptors (from L2B), biomass estimates (from L4A), and structural complexity indices (from L4C) are aligned at the individual shot level (Fig. 3).

The merged dataset is exported in GeoPackage format for direct use within QGIS and other GIS environments, or in GeoParquet format for large-scale programmatic workflows in Python (https://www.python.org/ or R (https://cran.r-project.org/) languages. Output files include embedded metadata recording the processing configuration: selected products, temporal range, ROI geometry, applied quality thresholds, merge strategy, plugin version, and processing timestamp, ensuring full reproducibility. GeoPackage merged output are automatically loaded into the active QGIS project.

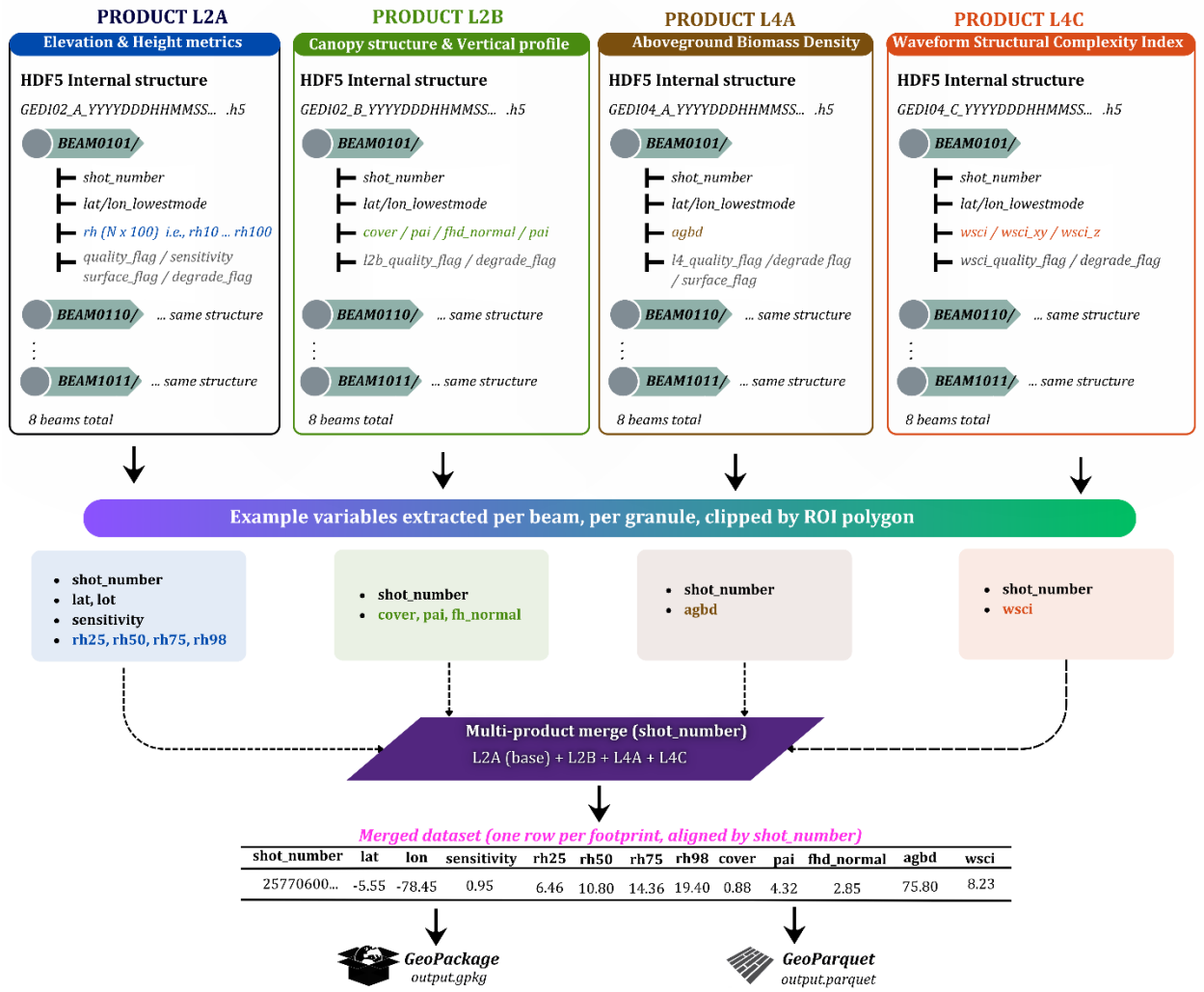


Figure 3. Multi-product GEDI data processing and integration workflow. Variables are extracted per beam from L2A, L2B, L4A, and L4C HDF5 granules, spatially clipped to the user-defined region of interest, and merged at the footprint level using the shot_number identifier. The resulting dataset contains one row per footprint with variables from all selected products, exported in GeoPackage or GeoParquet format.

3.3. User Interface and quality filtering

The GEDIMetrics graphical interface provides an integrated environment for configuring all processing parameters without requiring programming expertise. The plugin is accessible through the QGIS Plugin Manager (Fig. 4a) and is organised into five tabbed panels.

The General panel (Fig. 4b) allows users to select one or more GEDI products to download and merge (L2A – Canopy Height, L2B – Canopy Cover, L4A – Biomass, L4C – Structural Complexity), the product version, a temporal range with start and end dates, and the region of interest defined by a polygon layer loaded in the active QGIS project. An option to restrict processing to selected features within the polygon layer is provided, together with a recurring months filter for seasonal analyses.

The Variables panel (Fig. 4c) enables per-product variable selection through dedicated sub-tabs. For L2A, users can select individual relative height percentiles (RH10 to RH100) and auxiliary variables such as elev_lowestmode, elev_highestreturn, sensitivity, selected_algorithm, and solar_elevation. Equivalent

selection interfaces are provided for L2B (e.g., cover, PAI, FHD), L4A (e.g., AGBD, AGBD_se), and L4C (e.g., WSCI, WSCI_xy, WSCI_z). A set of base fields: shot_number, latitude, longitude, beam, and delta_time are always included in the output to ensure spatial referencing and traceability.

The Filters panel (Fig. 4d) controls quality constraints applied after subsetting. Product-specific quality flags are configurable as minimum thresholds (default ≥ 1 for quality_flag, l2b_quality_flag, l4_quality_flag, and wsci_quality_flag). A global minimum beam sensitivity threshold (default ≥ 0.90) can be applied selectively to any combination of products through individual checkboxes, following the criterion proposed by Potapov et al., (2021) for broad-scale applications; users may increase this value for specific ecosystem types, such as ≥ 0.96 for temperate forests (Rajab Pourrahmati et al. 2023) or higher for dense tropical canopies (Oliveira et al. 2023). Degraded footprints are excluded by default (degrade_flag = 1), and surface type filtering allows restriction to land, water, or all surface types.

Additional tabs provide configuration for the output format (GeoPackage or GeoParquet) and EarthData authentication credentials. Real-time feedback is provided through a progress indicator and logging panel visible in the main interface, enabling transparent execution monitoring.

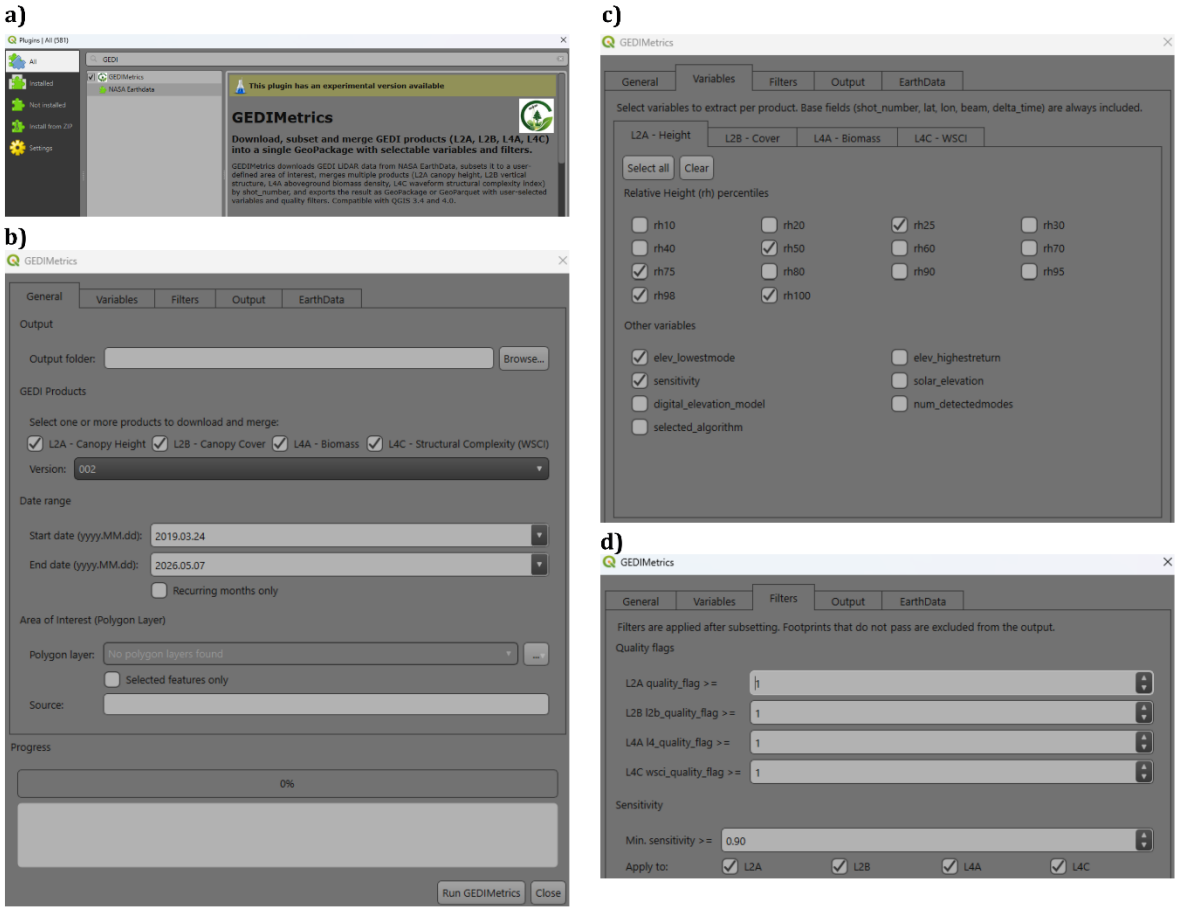


Figure 4. GEDIMetrics graphical user interface. (a) Plugin installation through the QGIS Plugin Manager. (b) General panel for product selection (L2A, L2B, L4A, L4C), version, temporal range, and region of interest configuration. (c) Variables panel showing per-product variable selection (L2A relative height percentiles and auxiliary metrics illustrated); (d) Filters panel for quality flag thresholds, beam sensitivity, degradation exclusion, and surface type filtering.

3.4. Software availability and requirements

GEDIMetrics is distributed as an open-source plugin through the official QGIS Plugin Repository (listed as GEDIMetrics experimental version), enabling direct installation via the Plugin Manager or manually from the ZIP archive available at https://github.com/AlexanderCotrinaS/gedi-metrics-qgis. The current release (v1.0.2) is compatible with QGIS 3.4 or higher and is released under the GNU General Public License v3.0 (GPL v3). A permanently archived version is deposited at Zenodo (DOI: pending).

GEDIMetrics requires several Python libraries: h5py (HDF5 access), pandas and geopandas (tabular and spatial data), shapely and fiona (geometry and file I/O), rtree (spatial indexing), and pyarrow (GeoParquet export). Libraries pre-installed with QGIS (numpy, requests, PyQt5) require no additional action; the remaining dependencies are automatically installed on first launch, or manually via pip if needed. On Windows, installation via the OSGeo4W distribution is strongly recommended, as it provides pre-compiled geospatial binaries (GDAL, GEOS, PROJ) that resolve common dependency conflicts; in that case, dependencies can be installed through the OSGeo4W Shell using pip install h5py geopandas pyarrow. A valid NASA EarthData account (https://urs.earthdata.nasa.gov) is required for data access.

4. Case study

4.1. Study areas

The performance of GEDIMetrics was evaluated across two contrasting forest ecosystems within the GEDI sampling domain (Fig. 5): a temperate mixed forest in northeastern France, and a humid tropical rainforest in the Peruvian Amazon, covering approximately 100 km² each study area. These sites were selected to represent distinct structural, climatic, and ecological conditions, ensuring coverage of a broad range of canopy complexity and biomass regimes, as well as differing GEDI acquisition characteristics.

The temperate study area (Fig. 5a) is located in northeastern France (~48.6°N, 6.6°E). According to the Copernicus Land Monitoring Service Dominant Leaf Type (European Environment Agency 2024), the forest composition is predominantly broadleaved, although smaller coniferous patches are also present within and around the main forested area. Compared to the tropical site, GEDI observations at this location benefit from improved ground return detection due to lower canopy density and deciduous canopy gaps; however, the higher latitude results in lower footprint density, requiring broader temporal windows for adequate data acquisition.

The tropical study area (Fig. 5b) is located in the Madre de Dios Department, southeastern Peru (~13.0°S, 70.0°W). The site partially overlaps the Tambopata National Reserve and its designated buffer zone, a region where intact tropical forest is under increasing pressure from illegal gold mining and associated deforestation (Caballero Espejo et al. 2018; Pacsi et al. 2026). This context makes the area particularly relevant for monitoring forest structural degradation using active remote sensing tools. The site is characterised by dense, multi-layered tropical canopies with high species diversity. From a GEDI perspective, this environment presents challenging acquisition conditions: dense canopies attenuate the laser signal, reducing ground return detection and increasing uncertainty in waveform-derived metrics. These characteristics make the site well suited for evaluating quality filtering performance and footprint retention under low-sensitivity conditions.

4.2. Processing configuration

For both study areas, GEDI data were acquired using GEDIMetrics with the following configuration: products L2A, L2B, L4A, and L4C, version 002, temporal range from 2019-03-24 to 2023-04-01, and a global minimum beam sensitivity threshold of 0.90 (Potapov et al. 2021). All other quality filters were

applied at default settings (quality_flag ≥ 1, degrade_flag excluded, surface_flag = land; Table 1, Fig. 4d). Footprints were spatially clipped to each study area polygon and merged using an inner join to retain only footprints with data across all selected products.

To focus the analysis on forested areas, a post-processing mask was applied using the annual forest/non-forest classification from the Joint Research Centre (JRC) Global Forest Cover product (Bourgoin et al. 2024). Only footprints falling within pixels classified as forest were retained for subsequent analysis, excluding non-forest land covers such as agricultural fields, water bodies, and cleared areas. This step ensures that the integrated GEDI metrics correspond exclusively to forested conditions, enabling meaningful comparison of structural and biomass variables across the two contrasting sites.

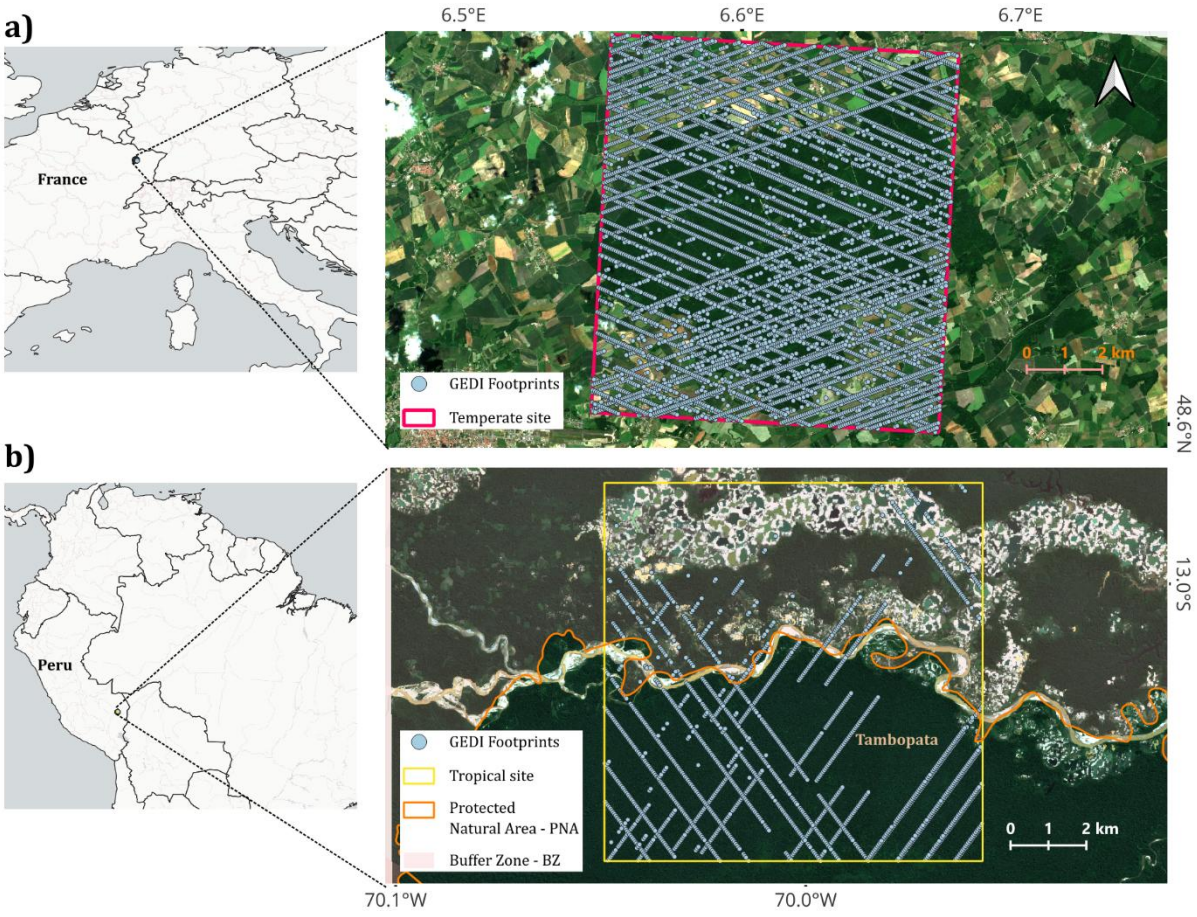


Figure 5. Location of the two study areas used to evaluate GEDIMetrics. (a) Temperate site in France (~48.6°N, 6.6°E), covering approximately 100 km² of mixed temperate forest. (b) Tropical site in the Madre de Dios Department, southeastern Peru (~13.0°S, 70.0°W), encompassing approximately 100 km² partially overlapping the Tambopata National Reserve (PNA) and its buffer zone (BZ). Blue dots represent GEDI footprints retrieved and processed by GEDIMetrics. Background imagery: Sentinel-2 scenes from July 2022.

5. Results

5.1. Data acquisition and footprint retention

GEDIMetrics was used to acquire and process GEDI data for both study areas using the full available temporal range (March 2019 – March 2023), product v2, and default quality filtering parameters (quality_flag ≥ 1, degrade_flag excluded, surface_flag = land, sensitivity ≥ 0.90). Footprints lacking valid coordinates were excluded, and a JRC forest/non-forest mask (Vancutsem et al., 2021) was applied to restrict the analysis to forested areas. Table 3 summarises the acquisition outcomes and per-product footprint availability for both sites.

Despite comparable ROI areas (~100 km²), the temperate site yielded substantially more granules and forested footprints than the tropical site (96 vs. 23 granules; 5,939 vs. 1,712 footprints), reflecting the higher GEDI revisit frequency at mid-latitudes due to ISS orbital geometry. Product-level availability differed markedly between sites: L2B retention was moderate in the temperate site (60.8%) but nearly absent in the tropical site (0.9%, n = 16), whereas L4A showed the inverse pattern (7.2% vs. 87.2%). These asymmetries indicate that product-level data availability is strongly site-dependent and cannot be assumed from L2A footprint counts alone.

Table 3. GEDI data acquisition and footprint retention for the temperate and tropical study areas. Quality filtering was applied with default thresholds (sensitivity ≥ 0.90, quality_flag ≥ 1, degrade_flag excluded, surface_flag = land). Product-level counts represent footprints with valid (non-null) values for each product's key variable after forest masking; percentages are relative to the total forested footprints at each site.

Parameter	Temperate (France)	Tropical (Peru)
Acquisition		
Granules identified	96	23
Raw data volume (GB)	~184	~80
Footprint filtering		
Total footprints (from plugin)	11,071	2,291
With valid coordinates	10,497	1,944
After JRC forest mask	5,939	1,712
Valid footprints per product		
L2A – Canopy Height	5,939 (100%)	1,712 (100%)
L2B – Canopy Cover	3,609 (60.8%)	16 (0.9%)
L4A – Biomass	430 (7.2%)	1,493 (87.2%)
L4C – Structural Complexity	4,940 (83.2%)	621 (36.3%)

5.2. Forest structure and biomass characterization

Table 4 presents summary statistics for key GEDI-derived variables at each study site. Height percentiles RH50, RH75, and RH98 were selected as representative descriptors of canopy vertical structure; lower percentiles (e.g., RH25) were excluded due to frequent negative values arising from terrain estimation artefacts in waveform processing.

The tropical site exhibited consistently taller canopies than the temperate site across all height percentiles (RH98: 24.05 ± 6.55 m vs. 18.86 ± 7.21 m). Height variability was greater at the temperate site (RH98 SD = 7.21 m) compared to the tropical site (SD = 6.55 m). Aboveground biomass density was higher at

the tropical site (157.49 ± 118.35 Mg ha^{-1}) than at the temperate site (139.51 ± 79.89 Mg ha^{-1}), with the tropical distribution showing a wider range (0.00–2,884.04 Mg ha^{-1}) and right-skewed shape. Structural complexity (WSCI) was also higher at the tropical site (10.24 ± 0.72 vs. 9.60 ± 0.59). The distribution of height percentiles and biomass values across both sites is shown in Fig. 6.

Table 4. Summary statistics of GEDI-derived forest structural and biomass variables for forested footprints at each study site. Values are reported as mean ± standard deviation, with sample size (n) per product. L2B metrics at the tropical site (n = 16) should be interpreted with caution. Variables RH50, RH75, and RH98 were selected as representative height percentiles following standard GEDI analysis practice.

Variable	Unit	Product	Temperate (n)	Temperate (mean ± SD)	Tropical (n)	Tropical (mean ± SD)
RH50	m	L2A	5,939	3.56 ± 5.29	1,712	11.28 ± 5.60
RH75	m	L2A	5,939	9.99 ± 6.48	1,712	16.93 ± 6.24
RH98	m	L2A	5,939	18.86 ± 7.21	1,712	24.05 ± 6.55
cover	—	L2B	3,609	0.31 ± 0.20	16*	0.44 ± 0.27
pai	m^2 m^{-2}	L2B	3,609	0.91 ± 1.07	16*	1.47 ± 1.27
fhd_normal	—	L2B	3,609	2.85 ± 0.48	16*	2.85 ± 0.31
agbd	Mg ha^{-1}	L4A	430	139.51 ± 79.89	1,493	157.49 ± 118.35
wsci	—	L4C	4,940	9.60 ± 0.59	621	10.24 ± 0.72

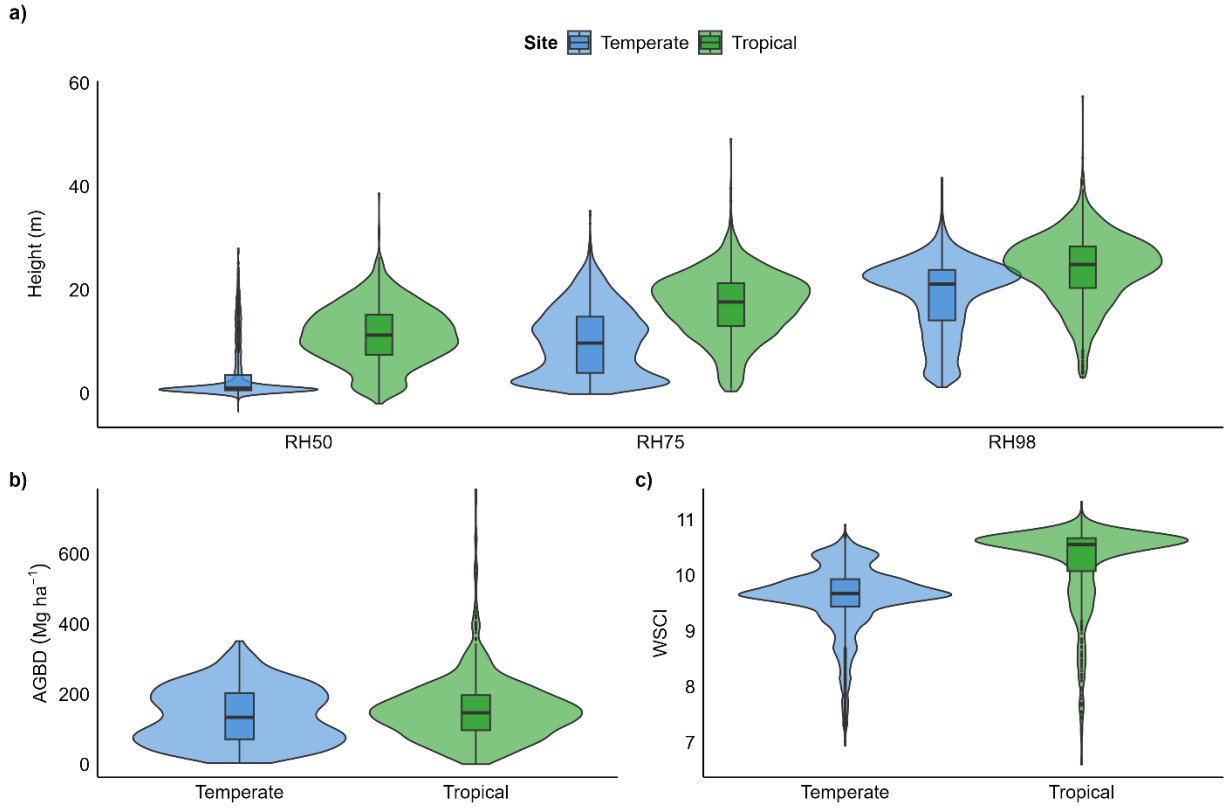


Figure 6. Distribution of GEDI-derived forest structural variables for forested footprints at the temperate (blue) and tropical (green) study sites. (a) Relative height percentiles (RH50, RH75, RH98) from L2A. (b) Aboveground biomass density (AGBD) from L4A. (c) Waveform Structural Complexity Index (WSCI) from L4C. Violin plots show the probability density of each distribution; embedded boxplots indicate the median, interquartile range, and outliers.

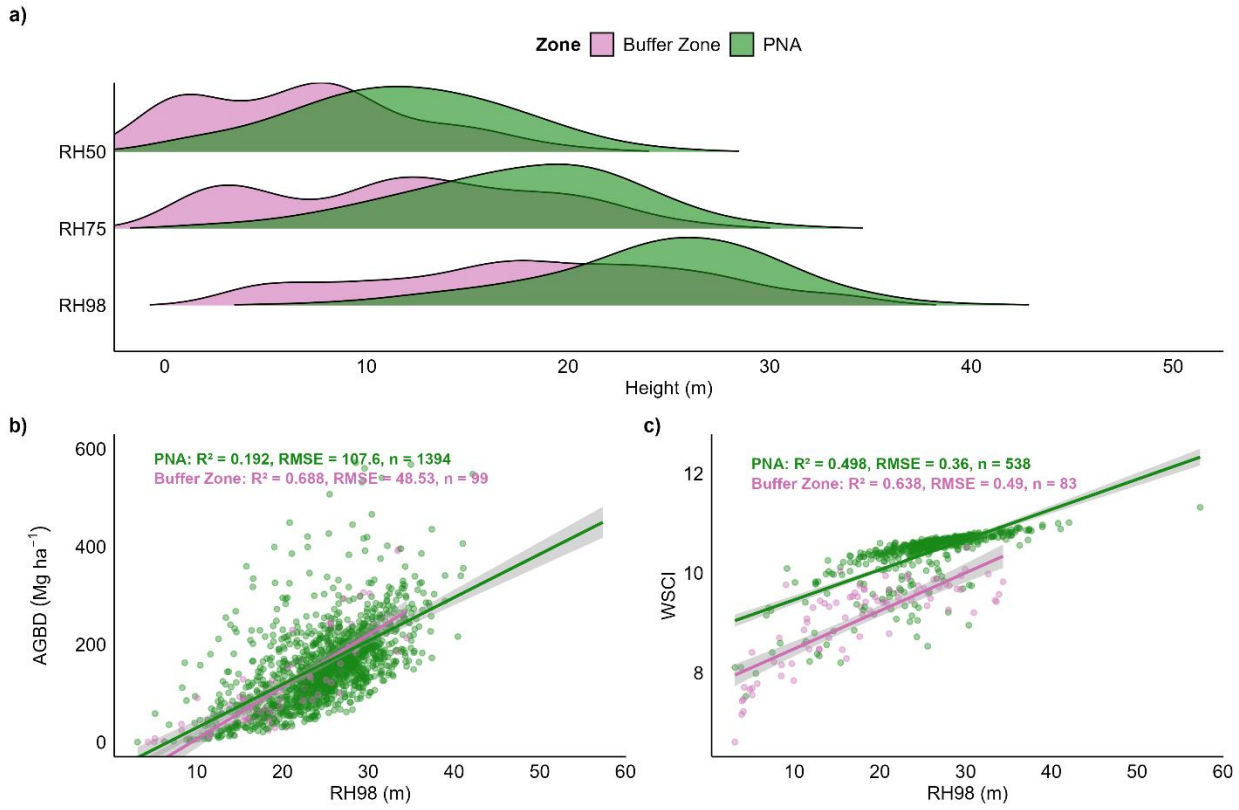
5.2.1. Forest structure inside and outside protected area

Footprints at the tropical site were classified according to their location within the Tambopata National Reserve (PNA, n = 1,536) or its surrounding buffer zone (BZ, n = 176). Table 5 and Fig. 7 summarise the results.

Forested footprints within the PNA exhibited consistently higher values across all evaluated variables compared to the buffer zone (Table 5). Canopy height differences were most pronounced at upper percentiles (RH98: 24.68 ± 6.06 m in PNA vs. 18.48 ± 7.94 m in BZ), while AGBD was 38% higher inside the reserve (160.41 vs. 116.34 Mg ha^{-1}). WSCI also showed clear separation between zones (10.42 ± 0.51 vs. 9.09 ± 0.82). Linear relationships between RH98 and both AGBD and WSCI were positive in both zones (Fig. 7b, c), with the buffer zone showing higher R^2 values (AGBD: $R^2 = 0.69$; WSCI: $R^2 = 0.64$) compared to the PNA (AGBD: $R^2 = 0.19$; WSCI: $R^2 = 0.50$), though based on substantially smaller sample sizes (n = 99 and n = 83, respectively).

Table 5. GEDI-derived forest structural and biomass variables for forested footprints inside the Tambopata National Reserve (PNA) and its buffer zone (BZ) at the tropical study site. Values are reported as mean ± standard deviation.

Variable	Unit	Product	PNA (n)	PNA (mean ± SD)	BZ (n)	BZ (mean ± SD)
RH50	m	L2A	1,536	11.78 ± 5.42	176	6.89 ± 5.26
RH75	m	L2A	1,536	17.51 ± 5.89	176	11.82 ± 6.88
RH98	m	L2A	1,536	24.68 ± 6.06	176	18.48 ± 7.94
agbd	Mg ha^{-1}	L4A	1,394	160.41 ± 119.73	99	116.34 ± 87.38
wsci	—	L4C	538	10.42 ± 0.51	83	9.09 ± 0.82



316

317 **Figure 7**. GEDI-derived forest structural differences between the Tambopata National Reserve (PNA, green) and its
318 buffer zone (BZ, purple) at the tropical study site. (a) Density ridgeline plots of relative height percentiles (RH50,
319 RH75, RH98) from L2A showing the shift toward taller canopies inside the reserve. (b) Relationship between
320 canopy height (RH98) and aboveground biomass density (AGBD, L4A) with linear regression fits and statistics per
321 zone. (c) Relationship between canopy height (RH98) and waveform structural complexity index (WSCI, L4C).
322 Shaded areas indicate 95% confidence intervals.

323 **5.2.2. Seasonal variation in canopy structure at the temperate site**

324 To assess the capacity of the GEDI dataset to capture phenological dynamics, footprints at the temperate
325 site were classified into vegetative (April–October, n = 2,668) and non-vegetative (November–March, n =
326 3,271) periods. Table 6 presents the results for L2A height percentiles and L2B canopy structure metrics.

327 Canopy cover and plant area index showed clear seasonal differences, with higher values during the
328 vegetative period (cover: 0.37 ± 0.27 vs. 0.27 ± 0.12; PAI: 1.32 ± 1.58 vs. 0.68 ± 0.48), consistent with
329 the presence of deciduous foliage. In contrast, canopy height (RH98) remained stable across seasons
330 (18.93 ± 7.41 vs. 18.79 ± 7.03 m), confirming that height metrics are largely insensitive to phenological
331 state. Foliage height diversity (fhd_normal) showed no seasonal variation (2.85 in both periods). The
332 most pronounced seasonal signal was observed in RH50, which increased from 1.27 ± 1.75 m in the non-
333 vegetative period to 6.36 ± 6.66 m during the vegetative period, reflecting the increased interception of
334 laser energy by mid-canopy foliage.

Table 6. Seasonal comparison of GEDI-derived canopy height and structure variables at the temperate study site. Vegetative period: April–October; non-vegetative period: November–March. L2B metrics (cover, PAI, fhd_normal).

Variable	Unit	Product	Vegetative (n)	Vegetative (mean ± SD)	Non-vegetative (n)	Non-vegetative (mean ± SD)
RH50	m	L2A	2,668	6.36 ± 6.66	3,271	1.27 ± 1.75
RH75	m	L2A	2,668	11.44 ± 7.27	3,271	8.81 ± 5.48
RH98	m	L2A	2,668	18.93 ± 7.41	3,271	18.79 ± 7.03
cover	—	L2B	1,308	0.37 ± 0.27	2,301	0.27 ± 0.12
pai	m^2 m^{-2}	L2B	1,308	1.32 ± 1.58	2,301	0.68 ± 0.48
fhd_normal	—	L2B	1,308	2.85 ± 0.50	2,301	2.85 ± 0.48

6. Discussion

6.1. Methodological contribution and positioning within existing tools

The principal contribution of GEDIMetrics is an automated process of footprint-level fusion of L2A, L2B, L4A, and L4C products through the shot_number identifier within a unified GIS environment. This multi-product integration approach builds on the processing logic originally proposed by (Corado and Godinho 2025), extending it from a command-line pipeline to an interactive graphical workflow embedded in QGIS. The tool addresses a long-standing operational bottleneck: users must currently navigate independently distributed HDF5 files across several GEDI products organised by beam, each with product-specific quality logic and filtering (Dubayah et al. 2020a; De Conto et al. 2024) and align footprints across software environments before any analysis can begin. Through its graphical interface, GEDIMetrics removes this requirement, allowing users to select products, variables, quality thresholds, and join strategies without scripting, lowering the barrier for non-programming users. Direct export to GeoPackage and GeoParquet makes outputs usable in GIS and interoperable with Python and R workflows, supporting reproducible and open-source forest analysis workflows in line with broader FAIR-oriented (Findability, Accessibility, Interoperability, and Reusability) data management and open-science practices (Wilkinson et al. 2016; Atkins et al. 2022).

GEDIMetrics complements existing tools, each addressing a different segment of the GEDI workflow. Libraries such as rGEDI (Silva et al. 2020), pyGEDI (Serna and Hernandez-Serna 2020), and GEDI-Pipeline (Corado and Godinho 2025)enable flexible scripted processing but require coding expertise and do not natively produce multi-product datasets. NASA's EarthData Search supports discovery and download but lacks quality filtering, or product integration (NASA 2026). The gediDB Python package (Besnard et al. 2025) offers scalable TileDB-based querying of pre-ingested L2A–L4C data but lacks an interactive GIS interface accessible to users with limited coding experience, while geolocation correction methos such as GeoGEDI (Schleich et al. 2023) and GEDICorrect (Corado et al. 2025) address the complementary problem of improving GEDI footprint positional accuracy and could be coupled with GEDIMetrics in extended workflows. Within the QGIS plugin ecosystem, GEDIMetrics is among the first tools designed for spaceborne LiDAR data processing. Its outputs can be directly combined with optical remote sensing data acquired through other QGIS plugins (e.g., Semi-Automatic Classification Plugin; (Congedo 2021)) or cloud-based platforms such as Google Earth Engine (Gorelick et al. 2017), positioning GEDIMetrics as a user-friendly, GIS-integrated entry point for multi-source analysis.

6.2. Multi-product integration: implications and applicability

The case study, conducted across two geographically distinct areas (~100 km² each), exposes a fundamental constraint of GEDI-based analysis. Considering that GEDI is mounted on the ISS, footprint distribution is governed by ISS orbital geometry rather than a regular repeat-pass scheme, producing markedly uneven spatial and temporal coverage (Dubayah et al. 2020a): the temperate site in France yielded 96 granules, compared to only 23 granules at the tropical site in Peru over a comparable temporal range. Beyond acquisition volume, the amount of usable information varies substantially depending on applied filters and product-specific quality criteria, as demonstrated by the contrasting retention rates observed between the temperate and tropical sites for L2B canopy structure and L4A biomass. These asymmetries are shaped by the analytical decisions that GEDIMetrics makes explicit through its interface: join strategy, quality thresholds, and beam sensitivity, which can be adjusted according to vegetation density or analysis scale (e.g., (Rajab Pourrahmati et al. 2023; Oliveira et al. 2023)). By exposing these choices through a graphical interface rather than embedding them as fixed defaults, GEDIMetrics makes methodological decisions transparent and reproducible, regardless of the study area or ecosystem under analysis.

The plugin's versatility was illustrated through two contrasting examples: comparative analysis of forest structure inside and outside the Tambopata National Reserve in the Peruvian Amazon, a region affected by gold-mining-driven deforestation (Asner et al. 2013; Caballero Espejo et al. 2018), and detection of seasonal variation in canopy structure at the temperate site. Similar workflows can be extended to other forest-monitoring applications where integrated structural and biomass information at the footprint level is required. The applicability of such analyses will depend on study area size, ecosystem characteristics, and GEDI footprint availability, which varies substantially between regions due to ISS orbital coverage and could be complemented with ICESat-2 data in boreal and high-latitude regions (Duncanson et al. 2026).

6.3. Limitations and future development

GEDIMetrics depends on authenticated access to NASA EarthData and the stability of the CMR API. Institutional firewall restrictions are partially mitigated by the plugin's support for personal access tokens as an alternative to standard credentials. Processing is currently single-machine and sequential, which can result in long execution times for large ROIs; however, the modular pipeline architecture facilitates future implementation of parallelised downloads and batch processing of multiple non-contiguous areas. Installation requires careful handling of geospatial and HDF5 dependencies (h5py, geopandas, shapely, fiona, rtree), which can conflict with other QGIS Python environments. On Windows systems, the OSGeo4W distribution provides a self-contained environment that resolves these conflicts, and future releases will aim to simplify dependency management across platforms. GEDI footprint geolocation uncertainty (~10 m at 1σ for v002; (Tang et al. 2023)) is not currently corrected within the plugin, but its modular design allows straightforward integration with external correction tools such as GeoGEDI (Schleich et al. 2023) and GEDICorrect (Corado et al. 2025).

The current release targets four GEDI products focused on forest vertical structure (L2A, L2B, L4A, L4C), providing a solid foundation for uncoming extensions. Development priorities include polygon-level summary statistics, retention diagnostics quantifying footprint loss at each filtering stage, and in-plugin visualisation of vertical foliage profiles available through L2B variables (e.g., pai_z, cover_z, pavd_z). Looking further ahead, GEDIMetrics could evolve toward a hybrid local–cloud workflow. NASA EarthData increasingly supports cloud-native data discovery, and STAC-based cataloguing is being adopted across the EarthData datasets. Integration with cloud-hosted archives such as gediDB

(Besnard et al. 2025) would allow large-scale data retrieval to be delegated to remote infrastructure while GEDIMetrics preserves its role as an accessible, GIS-integrated analysis front-end.

7. Conclusions

GEDIMetrics integrates the full GEDI processing chain: granule discovery, authenticated download, variable extraction, quality filtering, spatial subsetting, and multi-product merging into a single graphical workflow within QGIS, accessible to non-programming users. Its core contribution is the automated footprint-level fusion of L2A, L2B, L4A, and L4C products through the shot_number identifier, producing analysis-ready outputs in GeoPackage and GeoParquet formats interoperable with Python and R workflows. Users interactively select products, variables, quality thresholds, and join strategies, replacing multi-step custom scripting with a transparent and reproducible procedure.

The plugin was tested across two contrasting forest ecosystems: temperate mixed forest in northeastern France and humid tropical rainforest in Madre de Dios, Peru, spanning different canopy conditions, footprint availability, and quality-flag retention behaviour. The case study confirmed functionality and effective multi-product data availability. The workflow can be extended to other forest-monitoring applications where integrated structural and biomass information at the footprint level is required. GEDIMetrics is freely distributed through the official QGIS Plugin Repository and on GitHub under the GNU General Public License, with planned extensions toward parallelised processing, cloud-native data access, and broader product support.

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