

Article

Cross-Platform Mapping of Aboveground Carbon Storage Using MLS, UAV LiDAR, GEDI, and Sentinel-2 in a Romanian Mountain Forest

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Abstract

Forest landscapes used for recreation also provide climate-regulating services that are often absent from spatial planning. We mapped aboveground biomass density (AGBD) and aboveground carbon storage in the Postavaru-Piatra Mare mountain landscape near Braşov, Romania, using a cross-platform remote-sensing workflow. MLS point clouds from 16 plots served as an independent plot-level reference, UAV LiDAR acquired at 70, 120, and 150 m provided airborne comparisons, and GEDI L4A samples, Sentinel-2 predictors, and terrain variables were modelled in Google Earth Engine using Random Forest (RF) and Gradient Boosted Trees (GBT). GBT achieved $R^2 = 0.34$ and RMSE = 106.42 Mg ha⁻¹, whereas RF achieved $R^2 = 0.33$ and RMSE = 107.45 Mg ha⁻¹. These values indicate limited explanatory power; accordingly, the resulting 25 m maps are interpreted as landscape-scale screening products rather than operational stand inventories. Against MLS, RF produced an RMSE of 79.05 Mg ha⁻¹ and GBT 82.58 Mg ha⁻¹, while UAV estimates were positively biased at all tested flight heights. Mean carbon density peaked at 1200–1400 m and was highest in coniferous forest, whereas broadleaved and tree-cover classes contributed the largest total stock because of their larger area. The RF and GBT estimates differed by 2.3% in aggregated study-area carbon stock. Aboveground carbon storage was the only ecosystem service quantified. The resulting maps should be interpreted as landscape-scale screening layers and as ecological inputs for future studies integrating trail, visitor-use, participatory-mapping or perception data; they do not quantify cultural ecosystem services.

Keywords: aboveground biomass density; carbon storage; multi-platform LiDAR; MLS; UAV LiDAR; GEDI; Sentinel-2; Google Earth Engine; mountain forests; ecosystem services

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1. Introduction

Forests provide provisioning, regulating, and cultural ecosystem services. Climate regulation, biodiversity support, and soil and water regulation arise from ecological processes, whereas recreation, learning, aesthetic appreciation, and sense of place emerge through interactions between people and landscapes [1,2]. European ecosystem-service

frameworks therefore distinguish ecological service capacity from the benefits actually experienced by users [3–5]. Cultural ecosystem services cannot be inferred from carbon stocks alone. They usually require social evidence such as visitor surveys, participatory mapping, mobility data, or perception studies [4–10]. Nevertheless, spatial maps of regulating-service capacity can form one ecological input to such assessments. Aboveground carbon storage is directly relevant to climate mitigation and conservation [11–15], while its spatial distribution can be overlaid with future evidence on access and use. The present study therefore treats carbon storage as the measured service and the regulating–cultural link as a prospective GIS integration.

Remote sensing and GIS make biomass patterns spatially explicit and comparable across management units. Google Earth Engine supports repeatable processing of large remote-sensing archives [16]. GEDI provides footprint-scale vertical-structure and AGBD information, while Sentinel-2 supplies continuous spectral observations [13,17,18]. These products nevertheless differ in footprint, temporal support, and sensitivity to terrain and canopy saturation. No single platform resolves all forest components. MLS captures stems and lower-canopy structure at plot scale; UAV LiDAR provides high-resolution canopy observations; GEDI samples vertical structure from space; and Sentinel-2 and terrain data permit wall-to-wall scaling. Previous studies have fused spaceborne LiDAR with optical, radar, and terrain predictors [19–24], but fewer have explicitly compared the direction and magnitude of error across terrestrial, airborne, and spaceborne estimates in complex peri-urban mountain forests. Optical and SAR data have also been combined for forest biomass estimation [25]. Furthermore, while previous studies have evaluated the impact of different UAV fly altitudes on vegetation monitoring [26,27], documenting the trade-offs between point density and structural precision, their integration into multi-platform ecosystem service frameworks remains underexplored. A second unresolved issue is how to translate cross-platform evidence into GIS-ready service layers without conflating measured regulating services with unmeasured cultural benefits.

Cross-platform validation is especially important in mountain terrain. Canopy heterogeneity, optical saturation, geolocation error, slope, and plot-to-footprint mismatch can all alter biomass estimates [20–22,28]. UAV-MLS comparisons likewise show that top-down and ground-based point clouds emphasize different structural components [29,30]. Consequently, model accuracy alone is insufficient; the direction of sensor-specific bias and the representativeness of validation plots must also be evaluated.

The forests surrounding Braşov, especially the Postavaru-Piatra Mare landscape, form a peri-urban mountain belt with steep elevation gradients, mixed and coniferous stands, protected habitats, and intensive recreation infrastructure. Romanian peri-urban forest research also shows that cultural benefits are best assessed through direct visitor evidence rather than ecological proxies [10]. The landscape is therefore well suited to test carbon mapping while maintaining a clear boundary between quantified regulating-service capacity and future cultural-service assessment. The objective of this study was to map and evaluate aboveground carbon storage in the Postavaru-Piatra Mare landscape. Specifically, we aimed to: (i) map AGBD and aboveground carbon storage from GEDI, Sentinel-2, terrain variables, RF, and GBT; (ii) compare mapped AGBD with MLS and UAV LiDAR estimates; (iii) summarize carbon storage by elevation, forest type, and land cover; (iv) quantify the model and carbon-factor sensitivity available from the present data; and (v) define how the carbon layers could be combined with future visitor and perception data without claiming direct cultural ecosystem-service measurement.

The novelty of this study does not lie in the independent use of MLS, UAV LiDAR, GEDI or Sentinel-2, which are established technologies. Rather, it lies in: (i) evaluating the direction and magnitude of disagreement among ground-based, airborne and spaceborne biomass estimates in a steep peri-urban mountain forest; (ii) examining UAV flight-height

effects within the same cross-platform comparison; and (iii) translating the resulting estimates into GIS-ready, screening-level carbon-service layers while maintaining a clear distinction between measured regulating-service capacity and unmeasured cultural ecosystem services.

2. Materials and Methods

2.1. Study Area and Ecosystem-Service Context

This study was conducted in the Postavaru-Piatra Mare Massif, south and southeast of Braşov, Romania (Figure 1). Elevation ranges from approximately 600 m near the urban fringe to almost 1800 m in the higher mountain sector. The landscape includes steep slopes, forested terrain, mixed beech-fir stands at mid elevations, coniferous forests in colder upper zones and lower-elevation areas affected by fragmentation and human access. The Romanian Carpathians are characterized by pronounced climatic and topographic gradients, which influence forest structure, species distribution and productivity [31].

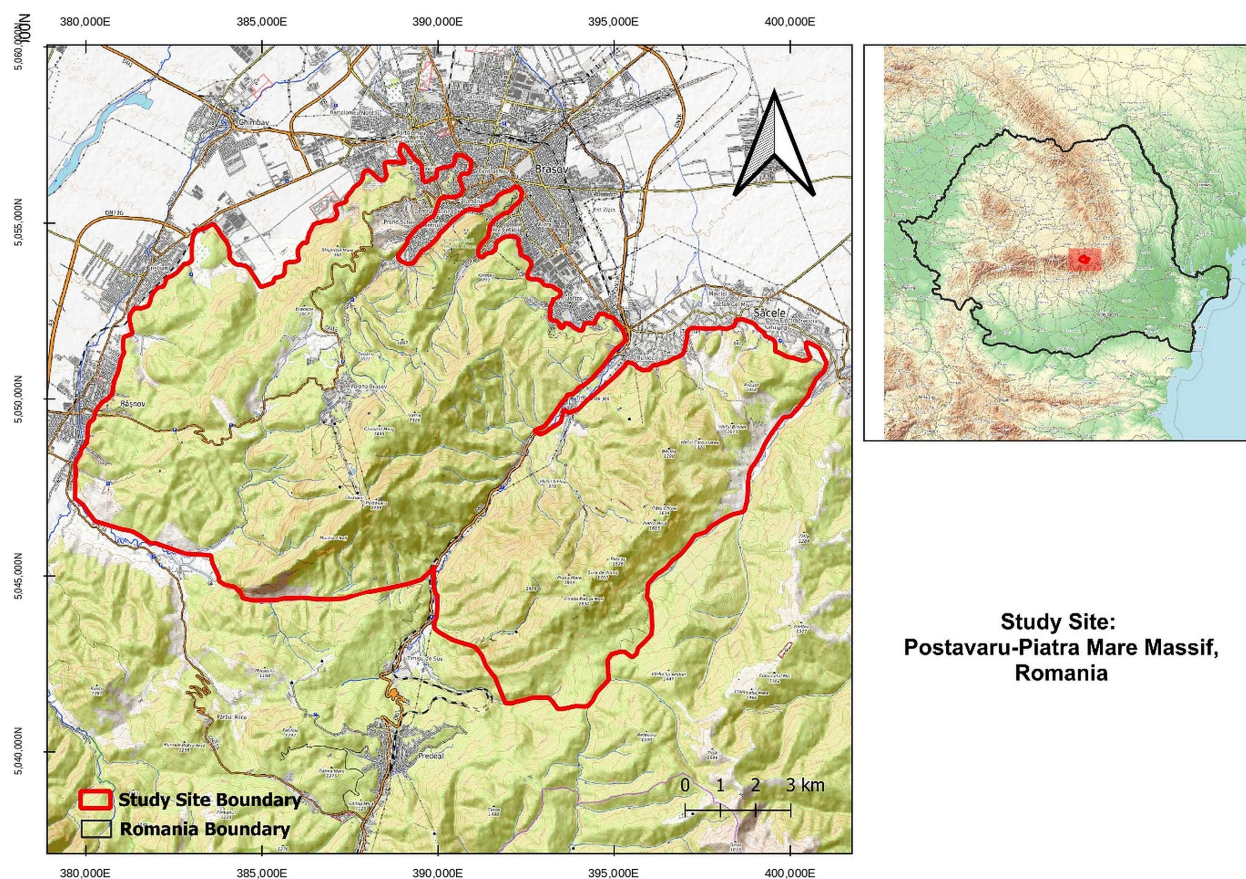


Figure 1. Location of the Postavaru-Piatra Mare study area in relation to Braşov, Romania. The main panel shows the study boundary, local topography, a north arrow, and a 0–3 km scale; the inset locates the study area within Romania. The red box in the inset indicates the approximate location of the study area within Romania.

The study quantified aboveground carbon storage as a regulating ecosystem service. Recreation, scenic experience, and outdoor education occur in the same landscape, but their supply, demand, and realized use were not measured. Carbon maps are therefore

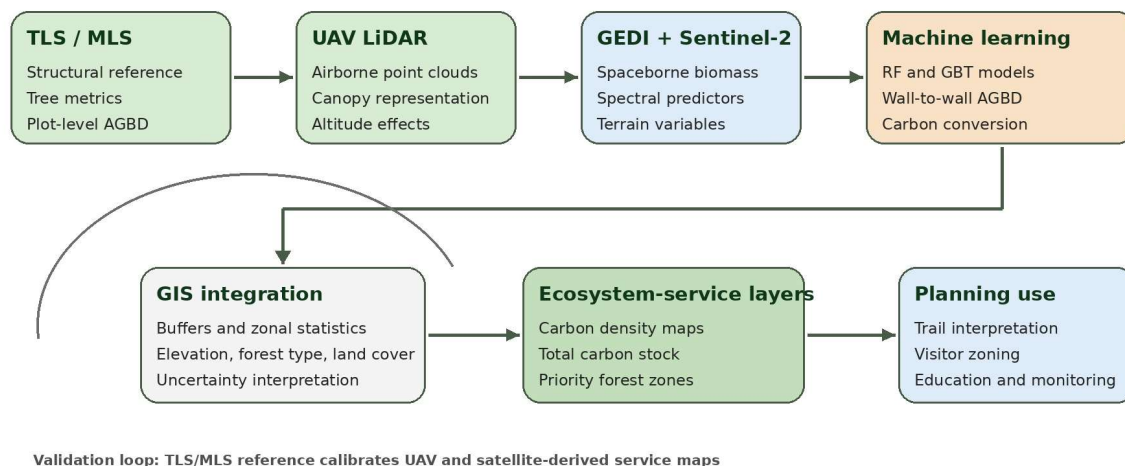
treated as ecological-capacity layers that may later be combined with trail networks, visitor observations, participatory mapping, or perception surveys.

2.2. Conceptual Framework: Measured Carbon Storage and Future Cultural-Service Integration

The framework separates three analytical levels. First, measured ecological capacity is represented by AGBD and aboveground carbon storage. Second, the validation layer compares terrestrial/mobile, airborne, and spaceborne estimates and identifies platform-specific bias. Third, a prospective regulating–cultural interface treats the carbon map as an ecological baseline that may later be overlaid with trail, visitation, or perception data. This third level is not a cultural ecosystem-service assessment. The workflow followed four connected digital stages: MLS point clouds provided structural reference; UAV LiDAR tested airborne canopy representation and acquisition-height effects; GEDI, Sentinel-2 and terrain predictors supported wall-to-wall biomass modelling; and GIS transformed raster outputs into planning-relevant service layers by elevation, forest type and land cover (Figure 2).

Cross-platform GIS tools for forest ecosystem services

Measured service: aboveground carbon storage | Planning bridge: interpretation, zoning, trails and education



Outputs are GIS-ready layers for forest ecosystem-service monitoring; cultural services require future visitor and perception data.

Figure 2. Cross-platform workflow for aboveground carbon mapping. MLS provides independent plot-level structural reference; UAV LiDAR tests canopy representation and flight-height effects; GEDI, Sentinel-2, and terrain variables support wall-to-wall modelling; and GIS converts the outputs into screening-level carbon-service layers. The curved arrow denotes the validation loop linking the TLS/MLS reference to the evaluation of UAV- and satellite-derived service maps.

2.3. Multi-Platform Data and Technology Stack

The workflow combined complementary platforms rather than treating remote-sensing layers as interchangeable. Each platform contributed a distinct spatial support, viewing geometry, and source of uncertainty (Table 1). The design therefore emphasizes cross-platform comparability and the intended decision scale of the mapped carbon output.

Table 1. Cross-platform datasets and analytical tools used to map and evaluate aboveground carbon storage.

Dataset or Tool	Period or Acquisition	Role in Workflow	Spatial Scale
MLS point clouds	Field campaign, 16 plots	Independent plot-level AGBD reference and structural comparison	Plot and tree level

UAV LiDAR	70, 120 and 150 m flights	Airborne comparison of canopy representation and flight-height effects	Plot to local landscape
GEDI L4A AGBD	January 2019–December 2023	Spaceborne biomass samples used for training and scaling	Nominal ~25 m diameter footprint
Sentinel-2 surface reflectance	June–August 2023	Wall-to-wall spectral predictors and summer median composite	10–20 m
SRTM DEM and derived terrain	Static topographic layer	Elevation, slope and aspect predictors	30 m
Google Earth Engine and GIS	Processing environment	Filtering, modelling, extraction, zonal summaries and map production	Study-area scale

2.4. GEDI Filtering and Predictor Preparation

GEDI L4A Version 2.1 data were accessed in Google Earth Engine (cloud platform; Google LLC, Mountain View, CA, USA) from ‘LARSE/GEDI/GEDI04_A_002’ for April 2019 to December 2023. Observations were retained when ‘l4_quality_flag = 1’, ‘algorithm_run_flag = 1’, ‘degrade_flag = 0’, and ‘sensitivity ≥ 0.90 ’. Footprints with invalid or non-positive ‘agbd’ values were removed. Urban, water, agricultural, wetland, bare-land, and other non-forest footprints were excluded using ‘ESA/WorldCover/v200’, retaining only tree-cover class 10. No additional statistical outlier removal was applied. After filtering, 11,833 footprints remained.

Sentinel-2 surface reflectance data were obtained from ‘COPERNICUS/S2_SR_HARMONIZED’ for 1 June to 31 August 2023. Scenes with more than 20% cloud cover were excluded. Bands B2, B3, B4, B5, B6, B7, B8, B8A, B11, and B12 were retained. SCL classes 1, 2, 3, and 6–11 were masked. A pixel-wise median composite was then produced to calculate spectral predictors, including NDVI, EVI, NDII, SAVI, shadow index, brightness index and narrow-band near-infrared information.

Elevation, slope, and aspect were derived from ‘USGS/SRTMGL1_003’. Forest type was added from the Copernicus High-Resolution Layer Forest-Type product [32,33]. Bilinear resampling was used for continuous variables and nearest-neighbour resampling for categorical layers. Native 10 m, 20 m, and 30 m predictors were independently aligned to the same grid. Predictor values were sampled at GEDI footprint centres rather than averaged within the footprints.

2.5. Model Selection, Training, Evaluation, and Carbon Conversion

Two ensemble-tree regression algorithms were implemented in Google Earth Engine: Random Forest (RF) and Gradient Boosted Trees (GBT). The 11,833 filtered GEDI footprints were randomly divided into 70% training and 30% hold-out samples. RF used 500 trees and GBT used 1000 trees, both in regression mode, and predictions were produced at 25 m resolution. Performance was evaluated with R^2 , RMSE, and MAE. RF and GBT were selected because they accommodate nonlinear relationships and mixed spectral-terrain predictors [34]; comparing bagging and boosting also tested whether the mapped pattern depended strongly on algorithm family. The reported metrics are based on a random rather than spatially blocked split. The tree counts were fixed a priori; no formal hyperparameter optimization is reported in the current analysis. The tree counts were selected a priori (500 for RF, 1000 for GBT) as sufficiently large ensembles to reduce run-to-run instability while keeping processing practical in Google Earth Engine; no formal hyperparameter optimization was conducted, and the selected values are not claimed to be optimal. Aboveground carbon density was calculated as predicted AGBD multiplied by a carbon fraction of 0.47, consistent with IPCC Tier 1 practice [35,36]. The fixed factor does not represent species-specific or regional variation in carbon content. Although species-specific carbon fractions are available for certain Romanian forest types, a universal factor

was utilized to simplify landscape-scale accounting; however, it should be noted that this introduces a degree of uncertainty as it does not represent regional variation in carbon content. Its effect was therefore evaluated in a deterministic sensitivity range of 0.45–0.50.

$$\text{Carbon density (Mg C ha}^{-1}\text{)} = \text{AGBD (Mg ha}^{-1}\text{)} \times \text{carbon fraction}$$

2.6. Uncertainty and Sensitivity Analysis

Uncertainty was characterized at three levels. Hold-out and plot-level RMSE, MAE, and signed bias described model and cross-platform disagreement; RF-GBT differences represented algorithmic sensitivity at aggregated scales; and the carbon fraction varied from 0.45 to 0.50. No prediction intervals or pixel-level uncertainty map were generated. Consequently, interpretation emphasizes agreement in broad spatial strata and model direction of bias rather than the apparent precision of individual 25 m cells. These analyses do not constitute full uncertainty propagation because plot sampling, GEDI product error, spatial autocorrelation, geolocation, predictor uncertainty, and allometric uncertainty were not jointly modelled.

2.7. MLS and UAV LiDAR Validation Chain

Field data were acquired using an FJD Trion S1 mobile laser scanner (FJDynamics, Shenzhen, China), a SLAM-based terrestrial/mobile LiDAR system integrating a 16-channel LiDAR sensor, inertial measurement unit (IMU), and dual-battery data logger for continuous point-cloud acquisition in GNSS-challenging forest environments. The scanner records up to 320,000 points s⁻¹, has a 360° × 270° field of view, has an effective measurement range of 120 m (high-reflectivity targets), and operates with a 905 nm Class 1 eye-safe laser. According to the manufacturer, the system provides 0.8–2.0 cm relative accuracy under optimal post-processing conditions, while practical field accuracy depends on scan trajectory, vegetation density, and SLAM loop closure [37].

The MLS data were collected in 16 circular forest plots (20 m radius; 0.126 ha per plot) distributed across the study area using a systematic grid-based strategy intended to include the main gradients of forest type, elevation, slope, and stand structure. The plots were not selected through a probability-based landscape inventory, no fixed quotas were imposed for each forest or elevation class, and no formal representativeness test was possible with the available sample. The external comparison therefore diagnoses the direction and magnitude of cross-platform disagreement within the sampled conditions; it should not be interpreted as an unbiased estimate of landscape-wide validation accuracy. Point clouds were processed within the VirtSilv digital forest-twinning web platform (continuously updated; Forest Design SRL, Braşov, Romania), including point-cloud registration, ground normalization, individual-tree detection and segmentation, and extraction of tree-level structural attributes. Registration quality was verified during post-processing before biomass estimation.

Stem volume was estimated for each segmented tree and converted to aboveground biomass using species-specific wood-density values, biomass-expansion factors, and volume-to-biomass conversion parameters derived from Romanian and Central European forest carbon literature [38,39]. Plot-level aboveground biomass density (AGBD) was obtained by aggregating tree-level biomass within each sample plot. Boundary trees were included when more than 50% of the stem base was located inside the circular plot; otherwise, they were excluded. The VirtSilv digital-twinning workflow has previously been applied to derive tree-level forest structure and biomass metrics from mobile LiDAR point clouds [40]. Importantly, the MLS-derived AGBD was used exclusively as an independent field reference for external validation and cross-platform comparison. It was not used to calibrate or train the Random Forest or Gradient Boosted Tree models, which were

developed solely from filtered GEDI L4A biomass samples together with Sentinel-2 spectral and terrain predictors. MLS-derived AGBD was used exclusively as an independent plot-level reference for external comparison. It was not used to train, calibrate, tune or select the RF and GBT models. Crucially, the MLS-derived AGBD was used exclusively as an independent plot-level field reference for external cross-platform validation. It was not used to calibrate, train, or select the RF and GBT models, which were developed solely from filtered GEDI L4A samples and geospatial predictors.

Data were acquired using a DJI Matrice 350 RTK equipped with the Zenmuse L1 LiDAR sensor (DJI Technology Co., Ltd., Shenzhen, China), integrating a Livox laser scanner, RGB camera, GNSS/RTK positioning, and inertial measurement unit (IMU) [41]. Flights were conducted at 70, 120, and 150 m above ground level using terrain-following mode to maintain a constant flying height over the mountainous terrain. RTK positioning and IMU calibration were enabled before each mission to improve trajectory accuracy and georeferencing consistency [41]. The three flight altitudes were intentionally selected to represent typical operational UAV LiDAR acquisition scenarios. The 70 m survey maximized structural detail, producing an average point density of approximately 328 points m⁻² with a ground sampling distance (GSD) of approximately 1.91 cm, whereas the 120 m survey increased area coverage (approximately 111.5 ha per mission) while reducing point density to approximately 123 points m⁻² and increasing the GSD to approximately 3.27 cm. The 150 m survey further emphasized operational efficiency and landscape coverage at the expense of point density. This experimental design allowed evaluation of the trade-off between structural detail and acquisition efficiency across typical operational flight heights [42,43]. Raw point clouds were processed in DJI Terra (DJI Technology Co., Ltd., Shenzhen, China; version information was not retained), including trajectory optimization, point-cloud classification, ground filtering, and normalization before extracting canopy structural metrics [41]. Plot-level point clouds were clipped using the same circular plot boundaries employed for the MLS analysis to ensure spatial consistency among datasets. For each sample plot, RF- and GBT-predicted AGBD values were extracted using the same 25 m radius neighbourhood employed in the original GIS workflow. Because the nominal GEDI footprint is approximately 25 m in diameter, this extraction neighbourhood is larger than an exact GEDI footprint and therefore represents a local landscape comparison rather than a strict footprint-to-footprint validation [17]. Representative MLS and UAV LiDAR point clouds are shown in Figure 3.

2.8. GIS-Based Spatial Summaries

RF and GBT carbon maps were summarized with GIS zonal statistics. Elevation was reclassified into 200 m bands from 400 to 2000 m. Forest type was summarized as broad-leaved, coniferous, and non-forest using the Copernicus High-Resolution Layer Forest-Type dataset; selected ESA WorldCover classes were used for land-cover summaries. Because the source products have different masks and valid-pixel extents, area totals from elevation, forest-type, and land-cover summaries are not directly interchangeable unless a common mask is enforced.

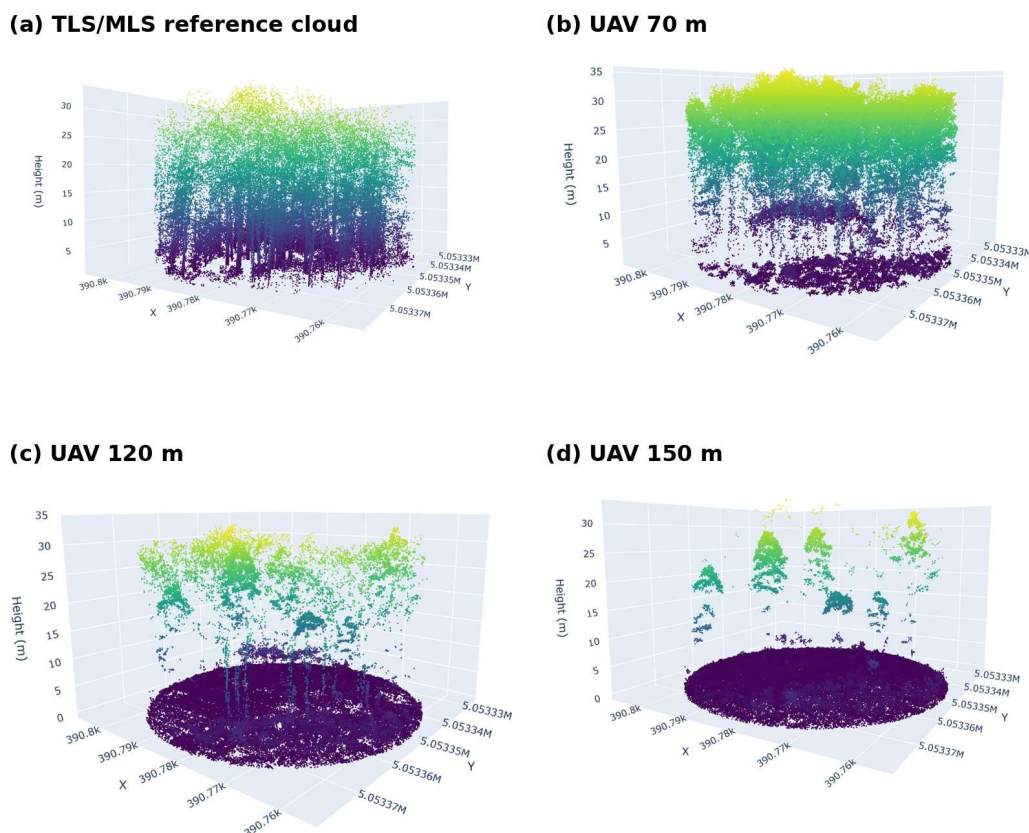


Figure 3. Example MLS and UAV LiDAR point clouds used in cross-platform comparison: (a) MLS; (b) UAV at 70 m; (c) UAV at 120 m; and (d) UAV at 150 m. Colours encode normalized point height. The panels illustrate how sensor viewing geometry and decreasing point density with flight height alter the representation of canopy, understory, and ground returns.

3. Results

3.1. GEDI-Based Modelling of Aboveground Biomass

A total of 11,833 filtered GEDI L4A footprints were used to train and evaluate RF and GBT models. Predictive performance was modest: GBT achieved $R^2 = 0.34$ and $RMSE = 106.42 \text{ Mg ha}^{-1}$, while RF achieved $R^2 = 0.33$ and $RMSE = 107.45 \text{ Mg ha}^{-1}$ (Table 2). The similar errors show that changing from bagging to boosting did not overcome the principal limitations of the available spectral-terrain predictors and GEDI training response. These metrics do not support operational stand inventory; subsequent maps are evaluated only as screening layers and through aggregated patterns. The corresponding hold-out and external-validation relationships are shown in Figure 4.

Table 2. GEDI-based validation metrics for AGBD prediction.

Model	R^2	RMSE (Mg ha^{-1})	MAE (Mg ha^{-1})
Random Forest	0.33	107.45	83.49
Gradient Boosted Trees	0.34	106.42	80.49

Predictor importance differed between algorithms and should be interpreted as model-specific rather than causal. RF distributed importance across elevation, B8A, NDII, slope, and other spectral predictors. In a mountain landscape, elevation can act as a proxy for temperature, moisture regime, species composition, and productivity, while B8A and NDII contain information related to canopy structure and moisture. GBT relied strongly

on NDVI, suggesting that sequential boosting captured canopy greenness and cover as a dominant first-order gradient. However, NDVI commonly loses sensitivity in closed, high-biomass canopies; this saturation is consistent with the compressed prediction range and underestimation of the highest MLS AGBD values. The contrast implies that topographic context remains important for mountain-forest biomass mapping and that strong NDVI importance should not be interpreted as evidence that NDVI resolves high-biomass variation.

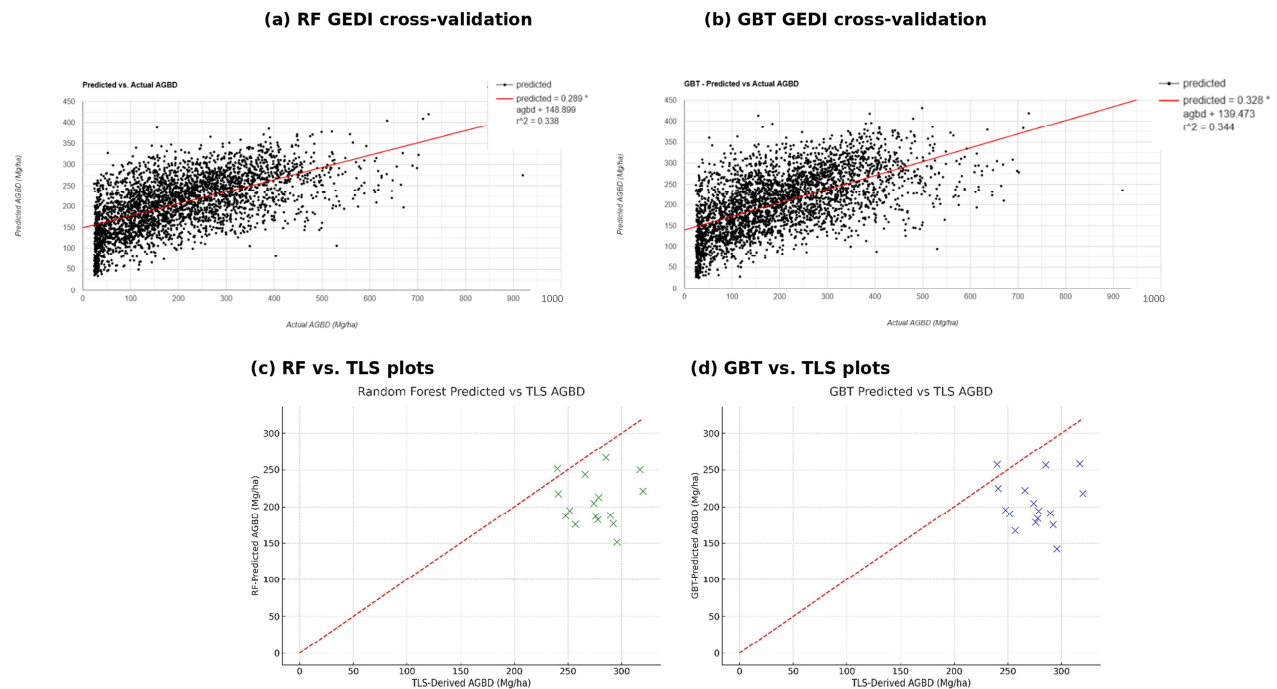


Figure 4. Model and external-validation scatterplots: (a) RF predictions against hold-out GEDI AGBD; (b) GBT predictions against hold-out GEDI AGBD; (c) RF predictions against MLS-derived plot AGBD; and (d) GBT predictions against MLS-derived plot AGBD. The dashed 1:1 line in panels (c,d) shows the systematic underestimation of higher-biomass MLS plots. In panels (a,b), the asterisk (*) denotes multiplication in the fitted regression equation. Green and purple crosses in panels (c,d) denote individual plot observations for RF and GBT, respectively.

3.2. Cross-Platform Validation Against MLS and UAV LiDAR

To evaluate how spatial scale and sensor viewing geometry influence biomass mapping, the GEDI-derived estimates and airborne UAV surveys were compared against the high-resolution terrestrial MLS baseline. Cross-platform validation confirmed that the mapped ecosystem-service layer is strongly dependent on sensor perspective (Table 3). Using MLS-derived AGBD as a structural reference, RF produced the lowest plot-scale error, with RMSE = 79.05 Mg ha⁻¹, MAE = 70.13 Mg ha⁻¹ and bias = −68.71 Mg ha⁻¹. GBT had slightly higher error, with RMSE = 82.58 Mg ha⁻¹, MAE = 74.11 Mg ha⁻¹ and bias = −71.98 Mg ha⁻¹. Both GEDI-Sentinel models underestimated the MLS reference, especially in high-biomass plots. Because the 16 plots were not a probability sample of the entire landscape, these values characterize the sampled validation conditions rather than unbiased landscape-wide accuracy.

Table 3. Cross-platform validation metrics using MLS-derived AGBD as the structural reference for carbon-service quantification.

Estimate Source	RMSE (Mg ha ⁻¹)	MAE (Mg ha ⁻¹)	Bias (Mg ha ⁻¹)
Tree volume-based	110.92	87.78	−15.34
UAV 70 m	96.36	92.43	88.15
UAV 120 m	117.34	113.23	109.42
UAV 150 m	102.03	92.10	88.81
Random Forest	79.05	70.13	−68.71
Gradient Boosted Trees	82.58	74.11	−71.98

UAV LiDAR showed the opposite pattern, overestimating MLS biomass across all tested flight altitudes. The 70 m UAV dataset had the lowest UAV error among tested heights, while the 120 m dataset produced the highest positive bias. UAV estimates showed positive bias at all three flight heights.

3.3. Algorithmic and Carbon-Factor Sensitivity

Summing Table 4 across elevation bands yielded 1,679,722.91 Mg C for RF and 1,641,254.03 Mg C for GBT, a difference of 38,468.88 Mg C (2.3% of their mean). Varying the carbon fraction from 0.45 to 0.50 changed the RF total to 1.608–1.787 million Mg C and the GBT total to 1.571–1.746 million Mg C. Relative to the adopted factor of 0.47, this range changes all carbon estimates linearly by approximately −4.3% to +6.4%. Romanian forestry literature provides species-specific biomass and wood-density parameters [36], but species- and tissue-specific carbon fractions were not spatially available for every mapped cell. The sensitivity range therefore quantifies the effect of this simplification, but it does not include sampling, sensor, allometric, or model uncertainty.

Table 4. Mean and total carbon storage by elevation band.

Elevation (m)	Area (ha)	RF Mg C ha ⁻¹	GBT Mg C ha ⁻¹	RF Total Mg C	GBT Total Mg C
400–600	244.23	49.06	45.61	11,980.72	11,139.13
600–800	4562.19	78.80	78.35	359,490.23	357,425.56
800–1000	5934.89	95.56	92.87	567,164.05	551,173.36
1000–1200	3226.05	109.11	106.18	351,992.96	342,533.65
1200–1400	2161.38	113.84	111.71	246,041.12	241,453.65
1400–1600	1031.11	107.75	104.07	111,101.03	107,304.36
1600–1800	373.69	83.20	78.46	31,090.19	29,318.22
1800–2000	24.40	35.36	37.14	862.61	906.10

3.4. Spatial Distribution of Carbon Storage

The integration of machine learning predictions with continuous geospatial layers allowed for the seamless mapping of regional carbon capacity. The predicted AGBD and carbon maps showed coherent spatial patterns (Figure 5). Higher biomass and carbon densities were concentrated in densely forested mountain zones, while lower values occurred near fragmented lower-elevation areas and transitional land covers. The maps should be interpreted as GIS-based ecosystem-service monitoring layers rather than simple thematic maps: the MLS and UAV validation chain helps identify where satellite models may underestimate dense forests and where UAV canopy representation may overestimate biomass relative to plot-scale structure.

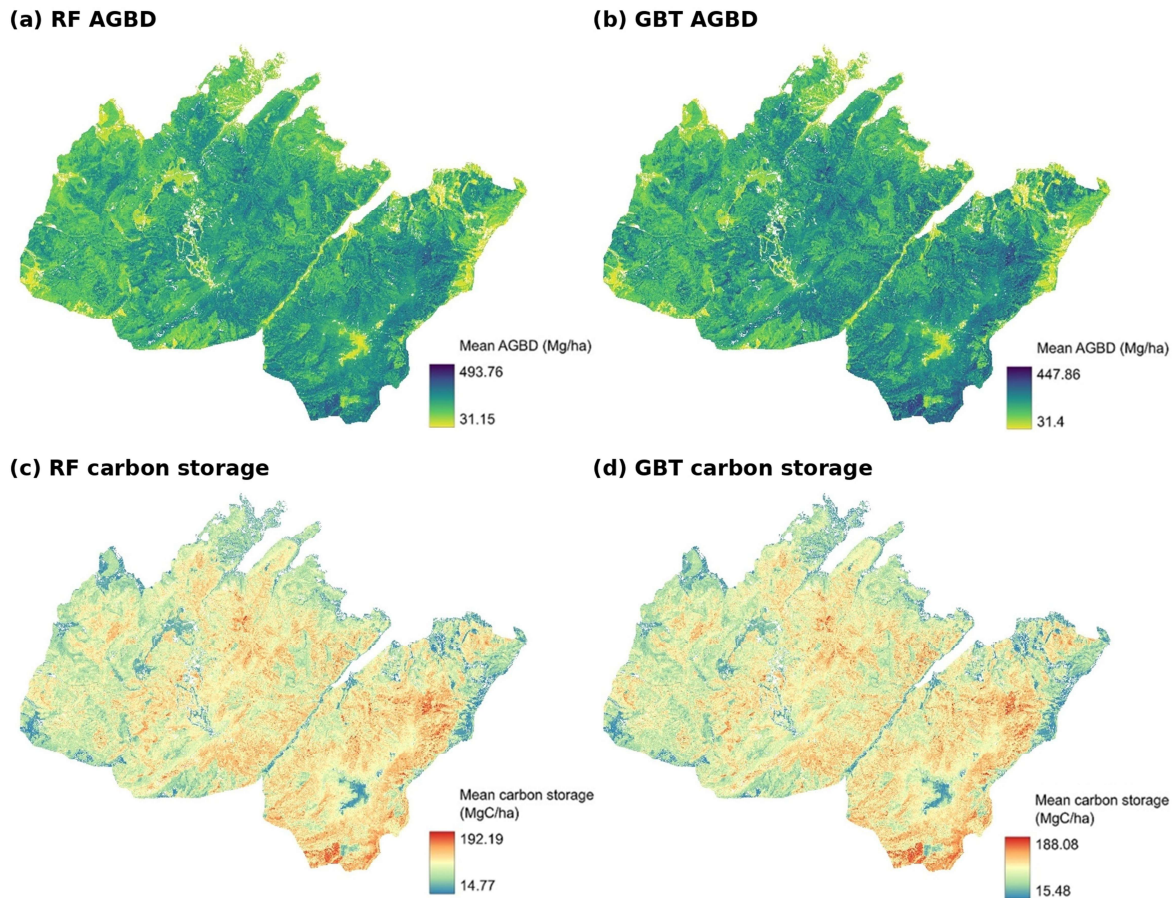


Figure 5. Predicted AGBD and carbon storage maps generated from RF and GBT models.

3.5. Elevation Effects on Carbon Storage

Topography represents a primary driver of vegetation dynamics; thus, analysing carbon patterns across elevation gradients reveals the core ecological capacity of the landscape. Carbon density varied clearly along with the elevation gradient (Table 4). Mean carbon density peaked in the 1200–1400 m elevation band, reaching 113.84 Mg C ha⁻¹ for RF and 111.71 Mg C ha⁻¹ for GBT. However, the largest total carbon stock occurred in the 800–1000 m band because this band covered the largest area. Above 1600 m, carbon density declined sharply, reflecting the transition toward sparse subalpine vegetation and reduced tree biomass.

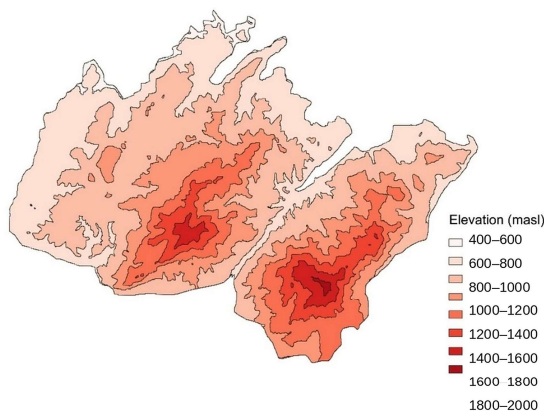
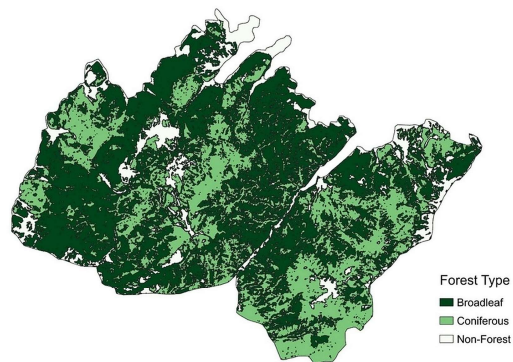
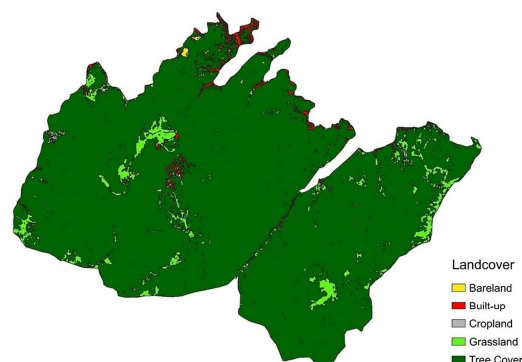
3.6. Forest Type, Land Cover and Planning-Relevant Patterns

Coniferous forests showed the highest mean carbon density, reaching 114.50 Mg C ha⁻¹ for RF and 111.18 Mg C ha⁻¹ for GBT (Table 5). Broadleaved forests stored more total carbon because they covered a larger area. Tree-covered land represented the dominant carbon reservoir, storing approximately 1.60 million Mg C under RF and 1.57 million Mg C under GBT. Grassland and cropland had much lower carbon density and total carbon stock. The elevation, forest-type, and land-cover zones used for these summaries are shown in Figure 6.

Table 5. Carbon storage by forest type and selected land-cover classes.

Grouping	Class	Area (ha)	RF Mg C ha ⁻¹	GBT Mg C ha ⁻¹	RF Total Mg C	GBT Total Mg C
Forest type	Non-forest	1954.36	47.98	47.95	93,765.72	93,718.35
Forest type	Broadleaved	9317.84	90.35	88.61	841,849.55	825,659.92
Forest type	Coniferous	6543.53	114.50	111.18	749,241.79	727,508.32
Land cover	Grassland	1054.24	42.88	44.23	45,200.40	46,628.50
Land cover	Tree cover	16,111.74	99.58	97.18	1,604,329.60	1,565,816.00
Land cover	Cropland	45.44	29.81	32.22	1354.56	1464.12

For GIS-based planning, the maps should be used to flag broad candidate zones for additional field verification rather than to prescribe infrastructure or visitor access directly. Mid-elevation and conifer-dominated zones consistently showed high mapped carbon density and may therefore warrant closer assessment before intensive recreational development. The same zones may also support interpretation trails, educational routes, and nature-based tourism narratives that communicate the climate-regulating function of forests, provided that trail suitability, biodiversity, disturbance sensitivity, and visitor evidence are evaluated separately.

(a) Elevation bands**(b) Forest type****(c) Land cover****Figure 6.** Elevation, forest type and land-cover zones used for carbon-service summaries. (a) Elevation bands; (b) forest type; and (c) land cover.

4. Discussion

4.1. Cross-Platform Carbon Mapping and the Regulating–Cultural Interface

The main contribution of this study is not the independent use of MLS, UAV LiDAR, GEDI, Sentinel-2, or machine learning, but their integration within a common framework for evaluating aboveground biomass density and carbon storage in a steep peri-urban mountain forest. Previous studies have combined GEDI with optical, radar, and terrain information for biomass mapping [19–24], while others have compared terrestrial and airborne LiDAR for forest structural attributes [29,30]. Here, these observational levels are connected within the same landscape to examine prediction performance and the direction of disagreement among terrestrial/mobile, airborne, and spaceborne estimates.

The platforms represent complementary scales rather than interchangeable measurements: MLS resolves stems and internal stand structure, UAV LiDAR captures canopy structure from above, GEDI provides footprint-scale AGBD observations, and Sentinel-2 and terrain data support wall-to-wall extrapolation. In mountain forests, terrain, canopy heterogeneity, viewing geometry, and differences in spatial support complicate direct comparison [20–22,28].

Both GEDI–Sentinel models underestimated AGBD relative to MLS, particularly at high biomass, whereas UAV LiDAR showed positive bias at all flight heights. This demonstrates that sensor perspective and scale influence biomass estimates, so the GIS outputs should be interpreted as screening products rather than stand-level inventories.

The ecosystem service quantified here is aboveground carbon storage as a regulating service. Cultural ecosystem services were not measured. Recreation, aesthetic appreciation, environmental education, and sense of place require independent social evidence such as visitor surveys, participatory mapping, mobility data, or perception studies [4,5,7–10]. Carbon-rich locations cannot therefore be assumed to have high cultural value. Instead, the carbon maps provide ecological-capacity layers that could later be combined with visitor information, biodiversity, and disturbance sensitivity in a broader ecosystem-service assessment.

4.2. Cross-Platform Validation and Uncertainty

The modest predictive performance of the GEDI-based models is the principal limitation of the carbon maps. GBT achieved $R^2 = 0.34$ and $RMSE = 106.42 \text{ Mg ha}^{-1}$, while RF achieved $R^2 = 0.33$ and $RMSE = 107.45 \text{ Mg ha}^{-1}$. A large proportion of AGBD variability therefore remained unexplained, and individual 25 m predictions should not be interpreted as precise local biomass estimates or used for stand-level carbon accounting.

The near-identical RF and GBT performance indicates that changing the ensemble approach did not materially improve the information extracted from the predictors. Their aggregated carbon totals differed by only 2.3%, showing consistency at the landscape scale, but not independent evidence of accuracy because both models rely on the same GEDI response.

Several mechanisms may explain the limited performance. GEDI L4A AGBD is itself model-derived and affected by calibration, footprint quality, geolocation, and forest structure [13,28,44,45]. Sentinel-2 predictors lose sensitivity in dense, high-biomass canopies, contributing to compressed predictions [46]. In mountain terrain, slope-related waveform effects [47], residual geolocation uncertainty [48], centre-point rather than footprint-averaged predictor extraction, and differences in spatial support introduce further mismatch. The random 70/30 GEDI split is another limitation because spatial autocorrelation can make transferability appear better than it is; the reported R^2 values should therefore be treated as internal hold-out statistics [49].

The MLS comparison provides an independent assessment because MLS data were not used for model training or selection. RF produced RMSE = 79.05 Mg ha⁻¹ and bias = -68.71 Mg ha⁻¹ relative to MLS, while GBT produced RMSE = 82.58 Mg ha⁻¹ and bias = -71.98 Mg ha⁻¹. However, the 16 plots do not constitute a probability-based landscape inventory and cannot represent the full variation in forest type, biomass, elevation, slope, canopy density, and disturbance history. These metrics therefore characterize disagreement within the sampled conditions, not unbiased landscape-wide accuracy. MLS is also a structural reference rather than error-free ground truth because its estimates contain measurement and biomass-conversion uncertainty.

UAV LiDAR showed the opposite bias direction. RMSE was 96.36 Mg ha⁻¹ at 70 m, 117.34 Mg ha⁻¹ at 120 m, and 102.03 Mg ha⁻¹ at 150 m; bias was +88.15, +109.42, and +88.81 Mg ha⁻¹, respectively. The 70 m survey performed best, consistent with its higher point density and finer canopy representation. However, the response was not monotonic because 150 m performed better than 120 m. Flight altitude should therefore be interpreted as part of a broader acquisition configuration affecting point density, scan geometry, canopy penetration, and representation of canopy gaps, rather than as an isolated experimental factor. The consistently positive UAV bias may also reflect the top-down viewing geometry of airborne LiDAR compared with the stem- and understory-oriented information captured by MLS [29,30].

4.3. Spatial Carbon Patterns, Limitations, and Planning Implications

Despite uncertainty in absolute magnitude, both models produced similar broad spatial tendencies. Mean carbon density peaked at 1200–1400 m, while the largest total stock occurred at 800–1000 m because this band covered the greatest area. Coniferous forests had the highest mean carbon density, whereas broadleaved forests and the tree-cover class contributed the greatest total stock because of their larger extent. These patterns are ecologically plausible because elevation integrates temperature, moisture, soils, species composition, disturbance exposure, and productivity [50].

Nevertheless, agreement between RF and GBT does not remove uncertainty inherited from GEDI, Sentinel-2, terrain, sampling, and model structure. The most defensible use of the maps is comparative screening: identifying broad candidate zones for field verification, detailed inventory, or integration with independent biodiversity and disturbance information. They should not be used independently for stand-level accounting, infrastructure siting, or regulatory decisions.

The same caution applies to recreation planning. Carbon maps do not contain visitor preferences, accessibility, perceived landscape value, or recreational demand, so their role is limited to one ecological layer in a future multi-criteria assessment. Such an analysis could combine carbon storage with trails, visitor counts, biodiversity, habitat sensitivity, disturbance, and participatory-mapping data to identify areas where ecological and social priorities coincide or conflict.

Future work should expand the MLS validation network using stratified or probability-based sampling, implement spatial cross-validation, test local GEDI calibration and additional predictors, and develop spatial uncertainty layers. A controlled UAV experiment separating altitude from other acquisition parameters would improve interpretation of flight-height effects. With these improvements, the workflow could progress from exploratory landscape screening toward more rigorous carbon monitoring while retaining the central lesson of this study: cross-platform differences must be made explicit before remotely sensed carbon maps are used as planning evidence.

5. Conclusions

This study integrated MLS, UAV LiDAR, GEDI, Sentinel-2, terrain data, machine learning, Google Earth Engine, and GIS to map and evaluate aboveground biomass density and carbon storage in the Postavaru-Piatra Mare mountain landscape. Its contribution lies in the cross-platform comparison of terrestrial/mobile, airborne, and spaceborne estimates and in translating these outputs into landscape-scale carbon screening layers.

Both GEDI–Sentinel models showed modest predictive performance ($R^2 = 0.33\text{--}0.34$) and systematically underestimated higher-biomass MLS plots. UAV LiDAR showed the opposite tendency, with positive bias at all three acquisition heights. The 70 m survey produced the lowest UAV RMSE, but the non-monotonic response across 70, 120, and 150 m indicates that flight altitude should be interpreted together with point density and acquisition geometry rather than as an isolated factor.

At landscape scale, both models identified similar broad patterns: mean carbon density was highest at mid elevations and in coniferous forests, whereas broadleaved forests and the tree-cover class contributed the largest total carbon stocks because of their greater area. These patterns are suitable for comparative screening, but the 25 m maps should not be used for stand-level carbon accounting or direct management prescriptions.

Aboveground carbon storage was the only ecosystem service quantified and remains an important proxy layer for cultural ecosystem services measurement; future integration with visitor, trail, perception, biodiversity, and disturbance data should therefore be treated as a separate analytical step in future analysis.

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Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Meaning
AGB	Aboveground biomass
AGBD	Aboveground biomass density
CES	Cultural ecosystem services
GBT	Gradient Boosted Trees
GEDI	Global Ecosystem Dynamics Investigation
GEE	Google Earth Engine

GIS	Geographic Information System
MAE	Mean absolute error
ML	Machine learning
MLS	Mobile laser scanning
RF	Random Forest
RMSE	Root mean squared error
TLS	Terrestrial laser scanning
UAV	Unmanned aerial vehicle

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