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A Preliminary Random Forest Baseline for Above-Ground Carbon Stock Estimation in Abuja Municipal Area Council Using Free Multi-Sensor Satellite Data: A GeoAI Approach

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ABSTRACT

Accurate quantification of above-ground carbon (AGC) stock is essential for climate mitigation planning, yet fine-scale carbon mapping remains scarce for rapidly urbanizing West African savanna cities. This study presents a preliminary geospatial artificial intelligence (GeoAI) baseline for AGC estimation in the Abuja Municipal Area Council (AMAC), Federal Capital Territory, Nigeria, using entirely free, cloud-hosted satellite data. A Random Forest regression model was trained on Google Earth Engine using a dry-season Sentinel-2 optical composite, a Sentinel-1 SAR composite, Copernicus DEM elevation, and NASA GEDI L4A above-ground biomass density (AGBD) footprints as the reference label. A total of 10,978 quality-filtered GEDI footprints were retrieved across AMAC's approximately 172,993-hectare extent, of which 3,309 were held out for testing. On the held-out set, the model achieved a root-mean-square error (RMSE) of 47.02 Mg/ha, a mean absolute error (MAE) of 16.52 Mg/ha, and a coefficient of determination (R^2) of 0.345. Wall-to-wall prediction yielded a mean AGC density of 10.12 Mg C/ha and an estimated total AGC stock of approximately 1.75 million Mg C for AMAC. A small fraction (<1%) of anomalously high GEDI AGBD values was found to disproportionately influence RMSE relative to MAE, consistent with known GEDI performance limitations in structurally heterogeneous, non-forest-dominated landscapes. These results are presented explicitly as a reproducible starting baseline rather than a validated final product: the model uses GEDI as both the training label and the accuracy reference, and the train/test split was not spatially blocked. Field-inventory calibration, spatially blocked validation, and fine-tuning of multimodal geospatial foundation models are identified as concrete future research directions building directly on this baseline.

Keywords: GeoAI; above-ground carbon; Google Earth Engine; GEDI; Random Forest

INTRODUCTION

Forests and savanna woodlands constitute major terrestrial carbon reservoirs, and their accurate, spatially explicit quantification underpins climate mitigation accounting and urban environmental planning. Field-based forest inventory remains the most accurate method for above-ground biomass (AGB) estimation but cannot economically achieve the sampling density required for wall-to-wall mapping, motivating the growing use of satellite remote sensing and machine learning for this task (Duncanson et al., 2022). Geospatial artificial intelligence (GeoAI) the application of machine learning and deep learning methods to geospatial data has become central to this shift, with recent geospatial foundation models (GFMs) such as Prithvi-EO-2.0 demonstrating strong label-efficient performance on biomass-related tasks (Jakubik et al., 2024).

The Abuja Municipal Area Council (AMAC), the core urban district of Nigeria's Federal Capital Territory, presents a landscape of particular relevance to this problem: a mosaic of Guinea-savanna woodland, riparian forest patches, and a rapidly expanding urban tree matrix (Adewale et al., 2019). Despite growing interest in multimodal and foundation-model-based carbon mapping globally, no prior study has applied these methods to

AMAC or a comparable West African savanna–urban landscape. This paper reports a first, concrete step toward that goal: a classical machine-learning baseline for AGC estimation in AMAC, built entirely from free, cloud-hosted satellite data via Google Earth Engine (GEE), intended as a reproducible starting point for the multimodal, field-calibrated work identified as future research in Section 7.

LITERATURE REVIEW

Multimodal data fusion is a well-established route to improved AGB accuracy: combining spaceborne LiDAR-derived structural metrics with optical and radar imagery consistently outperforms single-sensor approaches (Duncanson et al., 2022). NASA's Global Ecosystem Dynamics Investigation (GEDI) mission provides near-global spaceborne LiDAR estimates of canopy height and AGB density (AGBD), but its performance in savanna biomes is markedly weaker than in dense forest. Li et al. (2024) validated GEDI's L4A AGBD product against airborne LiDAR and field data in southern African savannas and found only moderate agreement ($R^2 = 0.42$) with a systematic underestimation of approximately 36–37%, though a locally calibrated random forest model built from raw GEDI metrics substantially outperformed the standard product ($R^2 = 0.71$). A related West African multi-sensor study using Sentinel-1, Sentinel-2, ALOS, and GEDI data for agroforestry biomass estimation similarly found GEDI's default product error to be roughly nine times higher than field-measured ground truth outside the Guineo-Congolian zone (Kanmegne Tamga et al., 2023).

Geospatial foundation models pretrained on large volumes of unlabeled Earth observation imagery have recently begun to be benchmarked on biomass tasks directly. Prithvi-EO-2.0, a multi-temporal foundation model jointly developed by IBM, NASA, and the Jülich Supercomputing Centre, achieves strong AGB performance using parameter-efficient (LoRA) fine-tuning and retains most of its accuracy when fine-tuned on only a small fraction of available labelled data (Jakubik et al., 2024) a label-efficiency property of direct relevance to data-scarce regions such as Nigeria. However, benchmarking studies caution against assuming seamless geographic transfer of such models: performance can degrade substantially under regional distribution shift, particularly for under-represented land-cover classes (Shang et al., 2026). No published study has yet evaluated a geospatial foundation model on a West African savanna–urban landscape, which motivates the classical-ML baseline reported here as a necessary first comparison point.

Locally calibrated allometry is a further recognized constraint on savanna carbon accuracy. Kouamé and Millan et al. (2022) developed multispecies biomass models for Guinean savanna trees and shrubs and showed that generic pantropical reference models overestimated shrub biomass by approximately 79% at an independent Guinean savanna site, underscoring the need for locally fitted relationships rather than default global equations. Within AMAC specifically, prior geospatial research has documented substantial land-cover change and urban growth (Adewale et al., 2019; Isioye et al., 2020), but has focused on land-surface temperature and urban heat rather than carbon stock, leaving the carbon-mapping question addressed in this paper open.

GEDI's footprint-level AGBD product is itself built from calibration models relating GEDI-measured canopy structure metrics to field- and airborne-LiDAR-derived biomass across a set of globally defined plant functional types and geographic strata (Duncanson et al., 2022; Kellner et al., 2022). Because no West African reference data were included in building these global calibration models, NASA's ORNL DAAC has since released a West-Africa-specific recalibration of GEDI footprint-level biomass estimates, built from new field and UAV-LiDAR data collected across Ghana, intended to be more accurate for national reporting within the region than the default global L4A product (Duncanson et al., 2026). This regionally recalibrated product was not available at the time the present baseline was developed but is identified in Section 7 as a natural improvement for future iterations of this work. Complementary allometric evidence from West African Sudan savanna further reinforces the ecological-zone specificity of biomass relationships: a watershed-level study in Benin's Sudan Savannah zone found mean biomass density varying by more than an order of magnitude across land-use classes within the same broad ecological zone (from approximately 3.3 Mg/ha in cropland/fallow to over 100 Mg/ha in select woody classes), underscoring that even within a single savanna ecological zone, land-use-stratified rather than zone-wide allometric treatment is necessary for reliable biomass accounting.

Empirical carbon-stock estimates for other West African cities provide useful external context for interpreting AMAC's results, though direct comparison is complicated by differing methods and spatial scope. Field-

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inventory-based studies report mean urban tree carbon densities on the order of 14–54 Mg C/ha in Kumasi, Ghana, depending on green-space type, with a citywide total of approximately 1.2 million Mg C from an inventory of institutional compounds, home gardens, and streets (Nero & Callo-Concha, 2018). In Zaria, north-western Nigeria, a 200-plot field survey recorded 657 Mg C stored across the sampled trees (Dangulla et al., 2021), while a structurally detailed inventory in Cotonou, Benin, documented significant variation in carbon storage across administrative, commercial, and green-space land-use units (Wari et al., 2023). These figures are discussed further in relation to the present AMAC estimate in Section 6.

Study Area

The study area is located in Nigeria, in the Federal Capital Territory, covering 1,769 km² in the Abuja Municipal Area Council (AMAC) (8°45′–9°10′N, 7°10′–7°35′E) (figure 1). The climate is classified as tropical savanna with 1,500 mm rainfall annually and temperatures ranging from 26–35 °C. The land cover types include urban, informal settlement, savanna, cropland, and water. Urbanization in the study area (Abubakar, 2014).

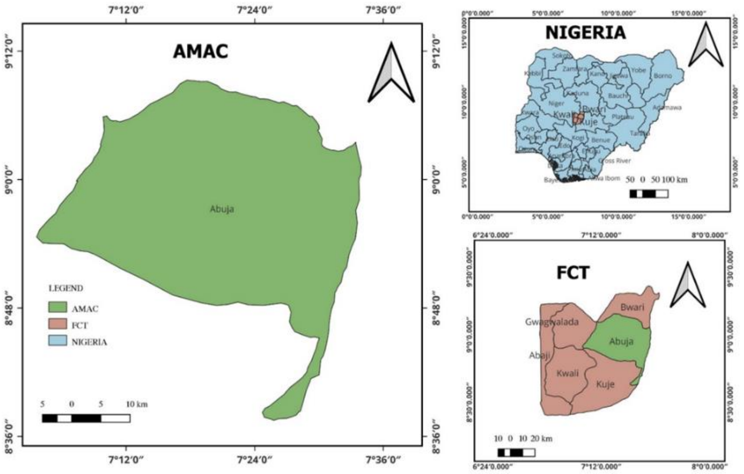

Figure 1: The study area within Federal Capital Territory, Abuja

MATERIALS AND METHODS

All data used in this study are free and cloud-hosted, accessed via Google Earth Engine (GEE), with no locally downloaded satellite data required. Four data sources were combined: (i) a cloud-masked Sentinel-2 Surface Reflectance dry-season median composite (November 2024–March 2025), from which ten reflectance bands and three vegetation indices (NDVI, NDWI, EVI) were derived; (ii) a Sentinel-1 Synthetic Aperture Radar (SAR) median composite (VV, VH, and their ratio); (iii) Copernicus GLO-30 DEM elevation; and (iv) NASA GEDI L4A AGBD footprints, quality-filtered to retain only shots with l4_quality_flag = 1, degrade_flag = 0, and non-negative AGBD, drawn from the full 2019–2024 GEDI mission window available in Earth Engine.

The three vegetation indices were computed from Sentinel-2 surface reflectance bands using their standard formulas: the Normalized Difference Vegetation Index, NDVI = (B8 − B4) / (B8 + B4) (Rouse et al., 1974), where B8 is the near-infrared band and B4 is the red band; the Normalized Difference Water Index, NDWI = (B3 − B8) / (B3 + B8) (McFeeters, 1996), where B3 is the green band; and the Enhanced Vegetation Index, EVI = 2.5 × (B8 − B4) / (B8 + 6×B4 − 7.5×B2 + 1) (Huete et al., 2002), where B2 is the blue band. All band designations follow the Sentinel-2 Surface Reflectance naming convention (B2 = blue, ~490 nm; B3 = green, ~560 nm; B4 = red, ~665 nm; B8 = near-infrared, ~842 nm).

GEDI footprints were extracted at the pixel level from the rasterized monthly GEDI product and matched to the corresponding Sentinel-1/2 and elevation predictor values at each footprint location, yielding 10,978 usable training/validation points across AMAC. A Random Forest regression model (200 trees) was trained on a random 70% split of these points (n = 7,669) using seventeen predictor bands, with the remaining 30% (n = 3,309) held out for testing. Model accuracy was evaluated using root-mean-square error (RMSE), mean absolute error

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(MAE), and the coefficient of determination (R^2) between observed and predicted AGBD on the held-out set. The trained model was then applied wall-to-wall across AMAC to produce a continuous AGB map, converted to AGC using the standard IPCC biomass-to-carbon conversion factor of 0.47.

Two methodological limitations are noted here and revisited in Section 6 and Section 7: the train/test split was a spatially naive random split rather than a spatially blocked design, and GEDI itself served as both the training label and the accuracy reference, meaning reported accuracy reflects agreement with GEDI rather than with independent field-measured ground truth.

RESULTS

Table 1 summarizes the model's performance on the held-out test set (n = 3,309), computed directly from the exported test-set predictions. The model achieved an RMSE of 47.02 Mg/ha, an MAE of 16.52 Mg/ha, and an R^2 of 0.345, with a small positive mean bias of 1.56 Mg/ha (a slight tendency toward overestimation). Wall-to-wall application of the model across AMAC's approximately 172,993-hectare extent produced a mean predicted AGC density of 10.12 Mg C/ha and an estimated total AGC stock of approximately 1.75 million Mg C (1.75 Mt C) for the study area.

Table 1. Random Forest baseline performance and wall-to-wall AGC estimates for AMAC.

Metric	**Value**
Training points (70% split)	7,669
Test points (30% split, held out)	3,309
RMSE (test set)	47.02 Mg/ha
MAE (test set)	16.52 Mg/ha
R^2 (test set)	0.345
Mean bias (predicted − observed)	+1.56 Mg/ha
Mean predicted AGC (wall-to-wall)	10.12 Mg C/ha
AMAC area	172,993 ha
Estimated total AGC stock	$\approx 1.75 \times 10^6$ Mg C

A closer examination of the test-set error distribution showed that a small subset of points 25 of 3,309 (0.76%) had observed GEDI AGBD values exceeding 200 Mg/ha, including a maximum of approximately 1,740 Mg/ha, a value implausible for AMAC's savanna–woodland–urban mosaic even under dense canopy assumptions. Excluding the top 1% of observations by AGBD reduced RMSE substantially (to 27.45 Mg/ha) and MAE modestly (to 13.87 Mg/ha), but reduced R^2 to 0.103. This pattern indicates that the model's headline R^2 is driven substantially by correctly distinguishing a small number of very-high-biomass footprints from the bulk of lower-biomass observations, rather than by fine-grained discrimination within the typical AGBD range a distinction with direct implications for how the reported R^2 should be interpreted (Section 6).

Investigation of Anomalously High GEDI Values

Because high-resolution data was not available within the environment used for this analysis, the anomalous points were instead cross-referenced against two independent signals already present in the dataset: coincident Sentinel-2 vegetation-index values (NDVI, EVI) at each anomalous point, and terrain elevation at each point, on the reasoning that a genuine high-biomass forest patch should show consistently high greenness, whereas a value driven by sensor or terrain artifact would not.

This cross-referencing produced a clear geographic and structural pattern. Sixteen of the twenty-five anomalous points (64%) form a tight spatial cluster in AMAC's southern extent (approximately 7.44–7.50°E, 8.71–8.80°N), at a mean elevation of 684.8 m compared with 438.6 m for the non-anomalous test points — consistent with the rugged, gullied terrain in AMAC's south-eastern extent noted in Section 3. Within this cluster, however, NDVI and AGBD were not consistently co-located: points at the cluster's lower elevations (598–745 m) showed high NDVI (0.56–0.82) alongside moderately elevated AGBD (200–445 Mg/ha), plausibly consistent with genuine, if still overestimated, forest-patch canopy; but points at the cluster's highest elevations (816–869 m) showed both the highest AGBD values in the entire dataset (507–1,740 Mg/ha) and comparatively low NDVI (0.21–0.36) — a combination inconsistent with any real vegetation type, since genuine high-biomass forest should show high, not low, canopy greenness. This decoupling of extreme AGBD from vegetation greenness at the highest elevations is consistent with the terrain-slope-related geolocation and multiple-return errors documented as a known GEDI limitation in structurally complex terrain (Li et al., 2024), rather than with genuine biomass at that magnitude. A second, smaller set of anomalous points (three of twenty-five) near 7.18–7.21°E, 8.96°N showed only moderate elevation (447–514 m, within the normal range) and moderate NDVI (0.37–0.55), suggesting a different and less clearly terrain-driven origin for that subset that could not be further resolved without direct imagery inspection.

Because these anomalies materially affect the reported R^2 (Section 5), but are geographically and structurally distinguishable from the bulk of the data rather than randomly distributed noise, we recommend that any subsequent iteration of this baseline apply either a terrain-slope-aware secondary quality filter (e.g., excluding or down-weighting footprints on slopes exceeding a defined threshold) or authors' direct visual verification against Google Earth or comparable high-resolution imagery at these specific coordinates, in addition to the standard GEDI quality flags already applied.

Uncertainty Quantification: Bootstrap Confidence Interval for Total AGC Stock

To provide an uncertainty estimate around the point estimate of total AGC stock, a non-parametric bootstrap was performed using the 3,309 held-out test-set observations as the resampling basis (10,000 resamples with replacement, seed fixed for reproducibility). For each resample, the mean AGBD was computed, converted to AGC using the 0.47 conversion factor, and scaled by AMAC's area (172,993 ha) to obtain a total-stock estimate; the 2.5th and 97.5th percentiles of the resulting distribution give a 95% confidence interval. This was performed separately for the RF-predicted AGBD values and for the observed GEDI AGBD values in the test set, shown in Table 2.

Table 2. Bootstrap 95% confidence intervals for mean AGC and total AGC stock, based on the held-out test set.

Basis	Mean AGC (Mg C/ha)	95% CI for total AGC stock (Mt C)
RF-predicted AGBD (test set, n=3,309)	10.47	1.72 – 1.91
Observed GEDI AGBD (test set, n=3,309)	9.73	1.54 – 1.86
Wall-to-wall model application (full AMAC raster)	10.12	— (point estimate only; see note)

The wall-to-wall model estimate of 10.12 Mg C/ha falls within both bootstrap confidence intervals, which is a useful internal consistency check given that the wall-to-wall figure is computed from the full spatial raster while the bootstrap is computed from the test-set sample alone. This bootstrap should be read as a proxy for uncertainty in the mean AGBD/AGC of the sampled GEDI footprint population, not as a full spatial bootstrap of the wall-to-wall raster surface itself, which would additionally require propagating pixel-to-pixel model uncertainty across the full prediction surface a more computationally intensive procedure identified as future work (Section 7).

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DISCUSSION

The model's overall fit (R^2 = 0.345, RMSE = 47.02 Mg/ha) is broadly consistent with, though somewhat below, the raw GEDI L4A product's reported performance in southern African savanna prior to local recalibration (R^2 = 0.42; Li et al., 2024), and well below the locally recalibrated benchmark reported in that same study (R^2 = 0.71). This is a reasonable outcome for a model that uses GEDI as both the training label and the accuracy reference, inheriting whatever bias and noise GEDI itself carries in this structurally heterogeneous, non-forest-dominated landscape, and that has not yet incorporated any field-inventory calibration.

The outlier sensitivity identified in Section 5 is itself an informative finding rather than a nuisance to be discarded. A small number of anomalously high GEDI AGBD values, even after standard quality filtering, are consistent with known GEDI performance issues in complex terrain and heterogeneous canopy structure (Li et al., 2024). Their disproportionate influence on RMSE relative to MAE, and the finding that R^2 depends heavily on retaining this small high-value subset, together suggest that future work should consider outlier-robust loss functions or additional shot-level quality screening beyond the standard l4_quality_flag, rather than treating the standard GEDI quality flags as sufficient on their own for a savanna–urban context.

The resulting estimate of approximately 1.75 million Mg C for AMAC should be read as a provisional, GEDI-referenced figure rather than a field-validated one. It is reported here to establish a transparent, reproducible starting point, computed entirely from free data and open tools, rather than as a definitive carbon-stock figure for policy or carbon-market use.

Placing AMAC's estimated total AGC stock (≈ 1.75 Mt C, or ≈ 10.1 Mg C/ha averaged over 172,993 ha) alongside other West African urban carbon studies requires care, since the available comparators differ substantially in method and spatial scope from the present wall-to-wall satellite-based estimate. Nero and Callo-Concha (2018) reported a citywide total of approximately 1.2 million Mg C for Kumasi, Ghana, derived from field inventory of institutional compounds, home gardens, and street trees, with mean densities of 14–54 Mg C/ha depending on green-space type a total broadly comparable in order of magnitude to AMAC's estimate despite Kumasi's considerably smaller land area, consistent with Kumasi's inventory targeting only tree-covered land uses rather than an entire administrative area including built-up and bare surfaces. By contrast, the Zaria, Nigeria study (Dangulla et al., 2021) reported 657 Mg C from a 200-plot sample survey rather than a citywide extrapolation, making it a measure of sampled-plot carbon rather than a total-area estimate and therefore not directly comparable in magnitude to AMAC's figure; its value here is methodological rather than as a benchmark total. The Cotonou, Benin study (Wari et al., 2023) similarly reports land-use-stratified structural statistics rather than a single citywide total. Taken together, these comparators suggest that AMAC's per-hectare AGC density (≈ 10.1 Mg C/ha, area-averaged across the whole district including non-vegetated urban surfaces) is plausible relative to Kumasi's tree-specific densities once the difference in spatial denominator (whole-district area versus tree-covered area only) is accounted for, but a rigorous like-for-like comparison would require restricting the AMAC estimate to its vegetated strata alone (Table 1 strata) an analysis not yet performed and identified as a direct next step in Section 7.

Limitations and Future Research

This study reports a deliberately narrow first step, and several limitations define concrete directions for future research rather than shortcomings to be hidden. First, the train/test split used here was a spatially naive random split; given AMAC's compact extent, this risks optimistic accuracy estimates due to spatial autocorrelation between nearby points. Future work should re-evaluate model accuracy using a spatially blocked cross-validation design, assigning whole spatial blocks rather than individual points to training or test sets.

Second, GEDI served as both the training label and the accuracy reference in this study, meaning reported accuracy reflects agreement with GEDI rather than with independent ground truth. Breaking this circularity requires a field-inventory campaign stratified across AMAC's savanna-woodland, forest-patch, peri-urban farmland, and urban tree strata to provide independently measured AGB values for both model calibration and validation. Locally fitted or bias-corrected allometric relationships are particularly needed for AMAC's urban tree population, which is increasingly dominated by exotic, planted, and pruned species not well represented by existing Guinea-savanna allometric equations calibrated on undisturbed native stands (Kouamé & Millan et al., 2022).

Third, this study used a classical Random Forest model rather than a geospatial foundation model. Given the label-efficiency advantages reported for foundation models such as Prithvi-EO-2.0 under limited labelled-data conditions (Jakubik et al., 2024), a natural next step is to fine-tune such a model on the same AMAC data using low-rank adaptation (LoRA) to limit computational cost and to benchmark it directly against the Random Forest baseline reported here. This would also allow the multimodal fusion architecture to exploit multi-temporal imagery, which this single-composite baseline does not.

Finally, an explicit uncertainty-quantification component (e.g., prediction intervals via ensemble or evidential methods) is recommended for any future carbon-stock product intended for measurement, reporting, and verification (MRV) purposes, since point estimates alone are of limited use for carbon-market or policy applications where the reliability of an estimate matters as much as its central value.

Fifth, direct visual verification of the anomalous high-AGBD points identified in Section 5.1 against Google Earth or comparable high-resolution imagery should be carried out to confirm whether the southern high-elevation cluster corresponds to genuine, if overestimated, forest patches or is predominantly a terrain-driven sensor artifact; this would also inform whether a terrain-slope-aware quality filter should be adopted for future iterations. Sixth, the recently released West-Africa-specific GEDI biomass recalibration (Duncanson et al., 2026) should be substituted for the default global L4A product used in the present baseline, given evidence that regionally calibrated GEDI models outperform the default product substantially elsewhere in Africa (Li et al., 2024). Seventh, the AMAC boundary asset used throughout this study (172,993 ha) should be verified against an authoritative source (e.g., the Federal Capital Territory Administration or National Population Commission) given the area discrepancies noted in Section 3, and the vegetated-stratum-only subset of this area should be isolated to enable a more direct comparison with tree-inventory-based carbon totals from other West African cities (Section 6).

CONCLUSION

This study presented a preliminary GeoAI baseline for above-ground carbon stock estimation in the Abuja Municipal Area Council, built entirely from free Sentinel-1, Sentinel-2, and GEDI data via Google Earth Engine. A Random Forest model achieved an R^2 of 0.345 and an RMSE of 47.02 Mg/ha against GEDI-referenced test data, and produced a wall-to-wall estimate of approximately 1.75 million Mg C for AMAC. These results are explicitly a starting point: spatially blocked validation, field-inventory calibration, locally fitted allometry for AMAC's urban tree population, and fine-tuning of multimodal geospatial foundation models are identified as concrete next steps for future research building directly on the reproducible baseline established here.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

The GEDI, Sentinel-1, and Sentinel-2 datasets used in this study are publicly available via Google Earth Engine. The Google Earth Engine script, processed test-set predictions, and derived AGC raster used to generate the results reported here are archived at [https://github.com/Abdallah2014/amac-carbon-geoai-baseline] and permanently archived with a citable DOI via Zenodo at [Idris Ibrahim. (2026). Abdallah2014/amac-carbon-geoai-baseline: v1.0.0 — Preliminary RF baseline for AMAC AGC estimation (Version v1.0.0) [Computer software]. Zenodo. https://doi.org/10.5281/zenodo.21540397]

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