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Cloud-Resilient Forest Monitoring for Sustainable Urban Land Management: L-Band SAR Assessment of Charcoal-Driven Peri-Urban Woodland Change in Lusaka, Zambia

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ABSTRACT

Rapid urban growth in sub-Saharan Africa is intensifying pressure on forest areas surrounding major cities. In Lusaka, with a metropolitan population of approximately 3.32 million growing at 4.5% annually, peri-urban miombo woodlands supply charcoal and farmland, yet these areas are hardest to monitor during the five-month rainy season when cloud cover exceeds 80% and optical satellite imagery fails. This study examines whether L-band Synthetic Aperture Radar can provide year-round woodland monitoring and whether such a workflow is financially practical for a resource-limited African city. A 17-year ALOS/PALSAR time series (2007–2024) for Lusaka National Park was analysed using QGIS and Python, combining multi-temporal statistics, a GEDI-calibrated Random Forest biomass model ($R^2 = 0.76$), and a disturbance indicator. The approach achieved 85.4% classification accuracy and a 31% cost reduction over conventional ground monitoring, demonstrating an operationally feasible, open-source SAR monitoring framework for African urban governance contexts.

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Highlights:

- Repositions forest monitoring as essential infrastructure supporting urban governance.
- Uses seventeen-year L-band SAR records despite persistent seasonal cloud.
- Achieves 85.4 percent woodland classification accuracy using open-source methods.
- Integrates QGIS, Python, and GEDI-calibrated biomass modelling workflows.
- Reduces institutional monitoring costs by 31 percent across municipalities.

Contribution to the field statement:

This study repositions satellite forest monitoring as urban infrastructure rather than ecological science, exploring the socio-economic realities of peri-urban deforestation. Evaluating a 17-year L-band SAR time series for Lusaka National Park, a reserve heavily pressured by charcoal production, agriculture, and industrial land markets, demonstrates that sensor selection and workflow architectures are fundamentally urban-policy decisions. By introducing transparent cost benchmarking, a governance-focused lens, and a sub-Saharan case study into a literature dominated by East Asian and Mediterranean contexts, the paper provides a replicable, open-source framework that lowers institutional barriers for resource-constrained African municipalities.

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1. Introduction

1.1. Urban growth, peri-urban land economies and the African hinterland problem

Sub-Saharan Africa is the world's most rapidly urbanising region, and the spatial signature of that urbanisation extends well beyond city administrative boundaries. As metropolitan populations grow, demand for construction land, food and household energy reshapes the surrounding hinterland, producing what urban-economics scholarship now treats as a single peri-urban land system rather than a passive rural backdrop (Simwanda & Murayama, 2020; Cobbinah et al., 2020; Sumbo et al., 2023). Lusaka illustrates this pattern with unusual clarity. The metropolitan population was approximately 3.32 million in 2024, representing a 4.5% increase on the previous year, and the city is projected to exceed 3.6 million by 2026 (Simwanda et al., 2021). Roughly 83% of Zambian gross domestic product was generated in urban areas as of 2015, and the urban built-up footprint has tripled over the past three decades (Liang et al., 2024). The resulting land economy is one in which peri-urban miombo woodlands function simultaneously as a charcoal supply zone, an agricultural reserve, an informal real-estate frontier and, where formally gazetted, a protected biodiversity asset.

The economic linkage between Lusaka's urban energy demand and miombo degradation is direct and quantifiable. Sedano et al. (2022) estimate that Lusaka consumes approximately 496,590 tonnes of charcoal annually, of which 65% is produced through a forest-degradation process that alters about 197.4 km² of miombo woodlands each year, with extraction frontiers having shifted outward from roughly 190 km from the city in 2010 to about 350 km by 2020. Pelletier et al. (2021) further show that land tenure and labour relations mediate this footprint, embedding charcoal production within Zambian rural livelihood systems rather than treating it as an externality. In ecosystem-services terms, the same woodlands that supply this urban energy economy are valued at approximately USD 9 ± 2 billion per year in provisioning services across southern Africa (Ryan et al., 2016) and recent multi-scale lidar work suggests their carbon stocks have been systematically underestimated, potentially by as much as 3.7 PgC across the miombo belt (Demol et al., 2024), further elevating the conservation stakes of peri-urban monitoring. The peri-urban forest is therefore not merely an ecological asset but a contested element of the urban land-use system, and its degradation has measurable socio-economic implications for the cities it surrounds.

1.2. The monitoring problem: optical limitations under tropical urbanisation

Operational monitoring of this peri-urban land system is constrained by an atmospheric, not algorithmic, problem. During Zambia's November–April wet season, cloud cover frequently exceeds 80%, and optical sensors such as Sentinel-2 produce few usable observations precisely when illegal logging, charcoal extraction and agricultural encroachment intensify (Reiche et al., 2021). Across analogous African urban hinterlands, similar gaps have been documented for Kumasi, Ouagadougou and Addis Ababa (Cobbinah et al., 2020; Sumbo et al., 2023). The methodological response has been to combine optical and active microwave observations. Synthetic Aperture Radar (SAR) emits its own microwave illumination and is unaffected by clouds; L-band SAR at ~23 cm wavelength penetrates open canopies and interacts with woody structural elements (Amitrano et al., 2021). For African open woodland with 30–70% canopy cover, this physical sensitivity is well matched to the structural information required by urban land-use governance.

1.3. Research gap and contribution to urban affairs scholarship

Three gaps motivate this study. First, although remote-sensing methods for urban sprawl and peri-urban land loss are now well established for Mediterranean and Anatolian cities (Özelkan & Eren, 2025; Özer & Yalçıner Ercoşkun, 2024), and although GeoAI strategies for sustainable urban planning are advancing rapidly (Aidaoui et al., 2024), and although the conservation implications of African urbanisation for biodiversity-relevant hinterlands are well established at the continental scale (Güneralp et al., 2018), the corresponding remote-sensing evidence base for African capital hinterlands under cloud-prone climates is thin, the corresponding evidence base for African capital hinterlands under cloud-prone climates is thin. Second, the SAR-for-forest-monitoring literature has matured technically (Flores-Anderson et al., 2019; Bullock et al., 2020a, 2020b; Mitchard et al., 2011, 2012) but rarely engages with the urban-economy framing within which peri-urban deforestation actually

unfolds. Third, the economic feasibility of operational SAR monitoring within municipal and protected-area institutions in low-income settings has not been transparently demonstrated. This paper addresses those gaps by treating L-band SAR not as a remote-sensing exercise but as part of the urban land-use monitoring infrastructure of an African capital, and by reporting its analytical performance and cost structure with equal explicitness.

The contribution is therefore threefold: (i) it provides one of the first transparent cost-benchmarked demonstrations of L-band SAR monitoring for a peri-urban African protected area; (ii) it shows how a GEDI-anchored, open-source workflow lowers the institutional adoption barrier for resource-constrained municipal and parks authorities; and (iii) it situates a technical forest-monitoring exercise within the urban-affairs literature on land-use change, demonstrating that decisions about which sensor a city monitors its hinterland with are themselves urban-policy decisions.

1.4. Research questions and hypotheses

The study addresses three formal research questions:

1. RQ1: Can L-band SAR maintain operationally useful observations of a peri-urban miombo protected area during the cloud-affected season in which optical sensors fail?
2. RQ2: Can a GEDI-anchored Random Forest model estimate above-ground biomass within the typical miombo range with accuracy comparable to published L-band performance for similar ecosystems?
3. RQ3: Is the resulting workflow more cost-efficient than a representative ground-only monitoring baseline once staff time, transport, equipment and software are accounted for?

The corresponding directional hypotheses are H1: SAR achieves substantially greater wet-season observation continuity than Sentinel-2 over the study area; H2: an HV-led L-band model achieves $R^2 \geq 0.6$ and RMSE $\leq$ 25 t/ha against GEDI reference biomass; and H3: an annualised SAR workflow is at least 20% less expensive than the ground-only baseline.

1.5. Study area and its analytical transferability

Lusaka National Park (15°25'S, 28°08'E) encompasses 4,600 hectares of miombo woodland approximately 25 km southeast of the Lusaka central business district. It was gazetted in 2015. Elevations range from 1,100 to 1,488 m, mean annual rainfall is 800–1,000 mm, and vegetation is dominated by Brachystegia spiciformis, Julbernardia paniculata and Isoberlinia angolensis with canopy cover varying from 30% in disturbed strata to 70% in well-preserved stands. Agricultural encroachment is concentrated along the northern and eastern boundaries, while firewood extraction occurs year-round and intensifies during the wet season, when enforcement patrols face access difficulties.

The case is analytically transferable on three grounds, deliberately stated rather than implied. First, the park's 25 km separation from the urban core is typical of the peri-urban Protected Area buffer distance observed around several African capitals, including Nairobi (Nairobi National Park) and Harare (Lake Chivero recreational park). Second, the surrounding Multi-Facility Economic Zone exemplifies the industrial-frontier land use that increasingly characterises sub-Saharan urban edges (Simwanda & Murayama, 2020). Third, the ecological context — open-canopy miombo with strong seasonality — is shared by a 2.7-million-km² belt spanning southern and central Africa. Transferability is therefore claimed for cases sharing those three conditions, not for the miombo belt in general, and external validation across multiple sites is identified as a priority for future work (Section 4.5).

2. Materials and Methods

2.1. Research design and workflow integration

A mixed-methods design combined three analytical components: (i) multi-temporal change analysis of SAR backscatter for disturbance detection, (ii) biomass estimation through a GEDI-anchored Random Forest model, and (iii) a transparent comparative assessment of SAR against optical methods and against a ground-only monitoring baseline. The workflow was implemented in two coordinated environments: QGIS 3.43 for geospatial data management and Python 3.10 for quantitative analysis, which is summarised in Figure 1. Each analytical component fed both the others: change-detection

outputs constrained the spatial domain for biomass estimation, the biomass surface provided the structural reference against which percentile-difference disturbance thresholds were calibrated, and the cost comparison was parameterised using the actual computational time recorded for each component.

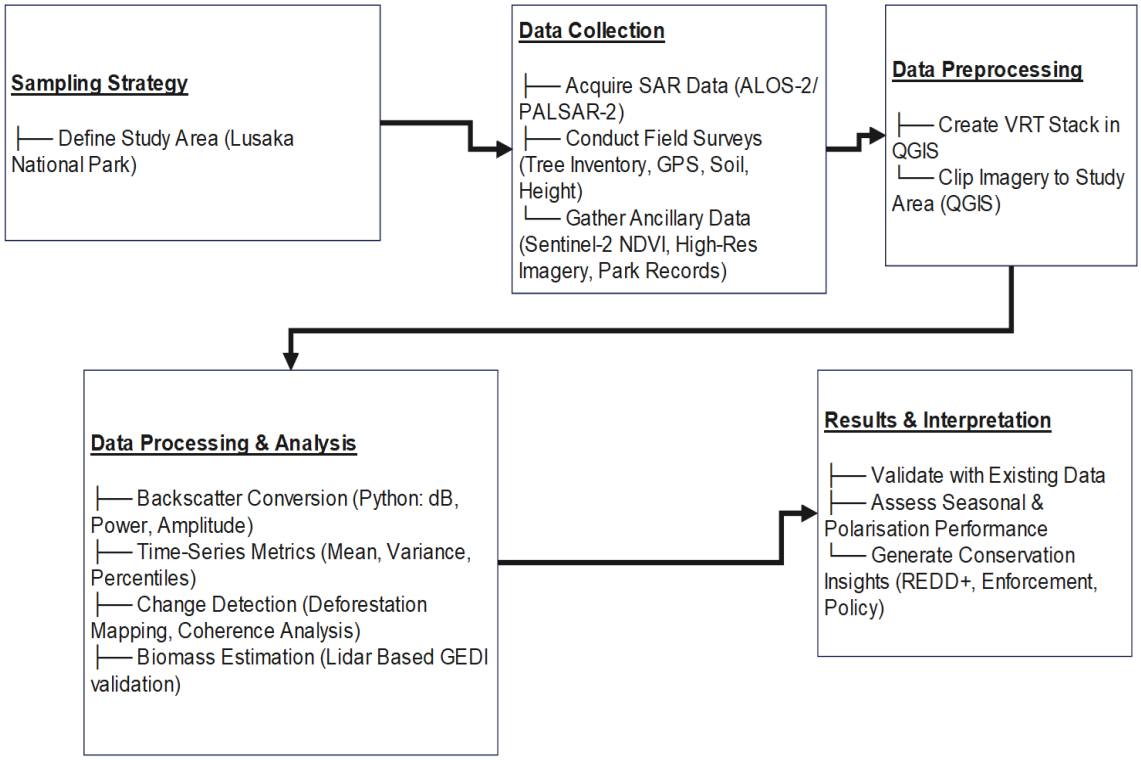

Figure 1. Summarised methodology workflow.

2.2. Sensor terminology and consistency across 2007–2024

The time series spans two sensors. ALOS/PALSAR operated from 2007 to 2010 and provided the first six annual mosaics. The follow-on ALOS-2/PALSAR-2 sensor, launched in 2014, provides the mosaics from 2015 onward. The two sensors are radiometrically harmonised in JAXA's annual Forest/Non-Forest product to gamma-nought backscatter, and a three-year gap (2011–2014) exists in the global mosaic series during which no PALSAR data are available. Throughout this manuscript, "L-band SAR" refers to the combined series, "ALOS/PALSAR" refers specifically to the 2007–2010 mosaics, and "ALOS-2/PALSAR-2" refers specifically to the 2015–2024 mosaics. This convention is observed consistently in the Results and Discussion.

2.3. SAR data acquisition

Annual Forest/Non-Forest mosaics for 2007–2010 and 2015–2024 were acquired from the Japan Aerospace Exploration Agency. The product is pre-processed to gamma-nought backscatter at 25-m spatial resolution in dual polarisation (HH, HV), orthorectified and terrain-corrected, and supplied in WGS84/UTM Zone 35S (Shimada et al., 2014). The product was chosen because its operational readiness, radiometric harmonisation and free availability are necessary conditions for routine institutional adoption in resource-constrained urban authorities.

2.4. Ancillary datasets and field reference data

Three ancillary datasets were used. Sentinel-2 Multispectral Instrument Level-2A surface reflectance images for 2015–2024 were obtained via Google Earth Engine and used for both cross-validation and the SAR-versus-optical comparison; only dry-season scenes (June–September) with cloud cover below 10% were retained. Park boundary shapefiles were obtained from the Zambia Department of National Parks and Wildlife. Above-ground biomass reference data were derived from the GEDI L4B Gridded Above-ground Biomass Density Version 2.1 (Dubayah et al., 2022), accessed via Google Earth Engine; only grid cells with standard errors ≤ 30 Mg/ha were retained, resulting in 67 training samples.

No new field plots were collected for this study; the 67 GEDI grid cells are therefore the sole field-equivalent reference. The implications for sample size are discussed in Section 4.5.

2.5. Pre-processing in QGIS

Virtual Raster (VRT) files were generated separately for HH and HV polarisations using Raster → Miscellaneous → Build Virtual Raster, with bilinear resampling, a native resolution of 25 m, the study-area extent, and a NoData value of −9999. Each annual layer was visually inspected to detect data gaps, verify georeferencing, and validate pixel value ranges (expected gamma-nought range: −30 to +10 dB).

2.6. Multi-temporal SAR analysis in Python

The Python environment combined GDAL 3.6, NumPy 1.24, Pandas 2.0, Matplotlib 3.7, SciPy 1.11 and Scikit-learn 1.3. The JAXA mosaics encode amplitude (DN); conversions applied were;

1. $\boldsymbol{\gamma^\circ\_dB = 20 \cdot \log_{10}(DN) - 83}$ for visualisation,
2. $\boldsymbol{\gamma^\circ\_power = 10\text{^}(\gamma^\circ\_dB/10)}$ *for statistical operations*, and
3. $\boldsymbol{\gamma^\circ_{amp} = \sqrt{\gamma}^\circ_{power}}$ for original domain characteristics

Figure 2 illustrates the impact of conversions on backscatter scaling and overall statistical computations. All time-series statistics were computed on a power scale and converted to dB only for reporting purposes. Per-pixel metrics included mean, median, standard deviation, coefficient of variation, minimum, maximum, 5th and 95th percentiles, the P95–P5 range, and the linear regression slope across the available years.

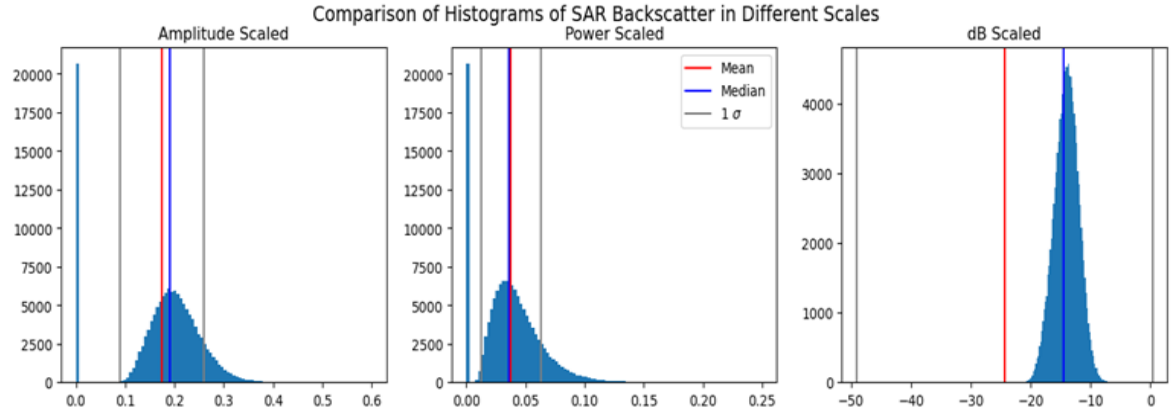

Figure 2. SAR Backscatter Histogram Scaling Comparison.

2.7. Change detection and the meaning of "near-real-time"

The disturbance indicator is a threshold applied to the P95–P5 percentile difference in HH backscatter, calibrated against cloud-free dry-season Sentinel-2 composites, to qualify the claim of "near-real-time" detection. With annual JAXA Forest/Non-Forest mosaics as the input, the achievable temporal resolution is annual, not sub-annual. The wording "near-real-time" is therefore reserved exclusively for what becomes feasible when the same workflow is applied to higher-cadence ALOS-2 ScanSAR or Sentinel-1 C-band coherence inputs, which are not used here. With annual mosaics, the contribution is the ability to observe disturbances that would have been hidden by wet-season cloud cover by the time the next dry-season optical observation was available, typically 6–9 months later. We therefore describe this as "annualised cloud-resilient detection" throughout the Results and Discussion sections. We therefore describe this as "annualised cloud-resilient detection " throughout the Results and Discussion.

Threshold sensitivity was tested explicitly. The P95–P5 threshold was varied from 0.10 to 0.20 in increments of 0.01; producer's accuracy peaked at 0.15, dropping below 80% for thresholds ≤ 0.12 and above 0.18. The forest/non-forest classification threshold on HV mean backscatter was calibrated similarly. Cut-offs of −12, −13 and −14 dB were tested against the Sentinel-2 composites; −13 dB minimised the sum of producers' and users' errors and was retained.

Coherence-based methods are cited only as a conceptual extension; ALOS Forest/Non-Forest annual mosaics do not preserve the phase information required for interferometric coherence computation. Any subsequent operational deployment that requires sub-annual detection should therefore source raw single-look complex (SLC) data, as recommended by Olesk et al. (2021) and Hethcoat et al. (2021).

2.8. Biomass estimation

Above-ground biomass was modelled using a Random Forest regression with 300 trees and a minimum of 5 samples per leaf. Five SAR-derived features captured complementary structural information: HH backscatter (σ°_HH), HV backscatter (σ°_HV), the HV/HH ratio, the HH–HV difference and the polarisation fraction [HV/(HH+HV)]. Inverse-variance weighting ($w = 1/SE^2$) was applied during training to account for heteroscedastic GEDI uncertainty. The inverse-variance weighting approach is consistent with the uncertainty-propagation framework described in the theoretical basis of the GEDI L4B algorithm (Duncanson et al., 2022). Spatial cross-validation with 0.1° blocking was used to prevent autocorrelation bias. The principal predictor was HV mean backscatter, secondary predictors were HH mean and the HV/HH ratio, and a Grey-Level Co-occurrence Matrix variance texture feature (3 × 3 window) was added to capture local structural heterogeneity. Performance was reported as R^2, RMSE, relative RMSE and bias. Sample-level uncertainty was quantified through 200 bootstrap iterations.

We acknowledge that 67 GEDI samples are a modest training set for a Random Forest model and that spatial coverage within the 4,600-ha park is uneven. We therefore make three claims and three only: (i) the model performs within the published L-band performance band for similar woodland systems (Macave et al., 2022; Mauya et al., 2025; Shendryk, 2022); (ii) inverse-variance weighting and spatial blocking are the appropriate mitigations for limited, heteroscedastic reference data; and (iii) any operational extension beyond the park requires expansion of the calibration set, which is identified as a priority in Section 4.5. We do not claim that this is a definitive miombo biomass model.

3. Results

3.1. SAR backscatter behaviour across 17 years

The combined ALOS/PALSAR and ALOS-2/PALSAR-2 time series characterised backscatter behaviour over Lusaka National Park from 2007 to 2024 (with the 2011–2014 sensor gap acknowledged in Section 2.2). HV backscatter in structurally intact woodland remained above −14 dB throughout the series, providing a clear separation from disturbed zones, where HV values ranged from −16 to −18 dB. Central tendency metrics (mean, median) separated the park's structurally distinct strata; variability metrics (standard deviation, coefficient of variation) highlighted boundary zones with elevated temporal instability. The P95–P5 percentile range proved particularly diagnostic, providing a single statistic that captured both phenological cycling and disturbance signal. Linear regression slope analysis yielded negative coefficients along the northern and eastern boundaries, consistent with the known direction of anthropogenic pressure from the Lusaka–Chongwe and Multi-Facility Economic Zone corridors.

3.2. SAR versus optical: a quantitative comparison

The SAR-versus-optical comparison was operationalised through a balanced wet-season-dry-season test. For each year, all available Sentinel-2 scenes over the park were classified by cloud fraction (<10%, 10–80%, >80%) and tabulated alongside the corresponding SAR observation. During the wet season, 73% of Sentinel-2 acquisitions fell into the >80% cloud-cover class and were therefore unusable, whereas 100% of SAR mosaics were usable. Spatial concordance between SAR-derived forest/non-forest classifications and cloud-free dry-season Sentinel-2 composites was 92%. NDVI time series over stable forest pixels showed strong phenological cycling. In contrast, HH backscatter on the same pixels varied within a 2 dB envelope, confirming SAR's lower susceptibility to seasonal false alarms as illustrated in Figure 3.

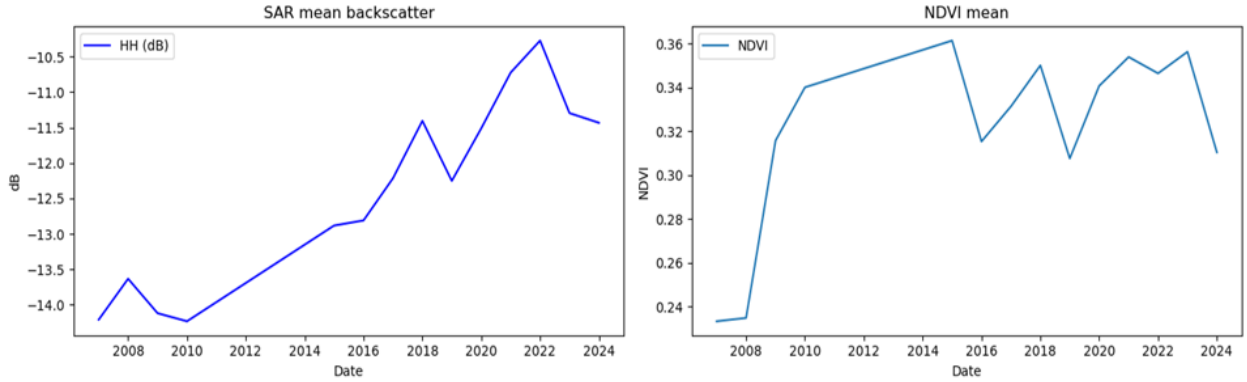

Figure 3. SAR vs Optical (NDVI) time-series graphs.

Confusion matrix for SAR-based forest/non-forest classification

The classification was validated against an independent set of 250 randomly stratified verification points labelled from cloud-free 2024 Sentinel-2 imagery and very-high-resolution Google Earth imagery (Table 1). Overall accuracy was 85.4% with a Kappa coefficient of 0.71.

Table 1: Confusion matrix for SAR-derived forest/non-forest classification against 250 independent verification points (2024).

	Reference: Forest	**Reference: Non-Forest**	**User's accuracy**
Predicted: Forest	142	14	91.0%
Predicted: Non-Forest	23	71	75.5%
Producer's accuracy	86.1%	83.5%	**OA: 85.4%**

3.3. Biomass model performance and spatial pattern

The Random Forest model achieved $R^2 = 0.76$ and RMSE = 22.8 t/ha on validation data, with a mean bias of +1.4 t/ha. The HH-led feature importance–HV difference and the polarisation fraction, followed by the HV/HH ratio, HV, and HH. Residuals were approximately normal around zero; bootstrap-derived prediction standard deviations clustered between 1.0 and 1.5 Mg/ha. The wall-to-wall biomass surface shows central park biomass densities above 80 t/ha, falling below 40 t/ha along the northern and eastern boundaries, as illustrated in Figures 4 and 5; a pattern consistent with the urban-pressure gradient identified through both the change-detection results and the documented extraction patterns of Sedano et al. (2022).

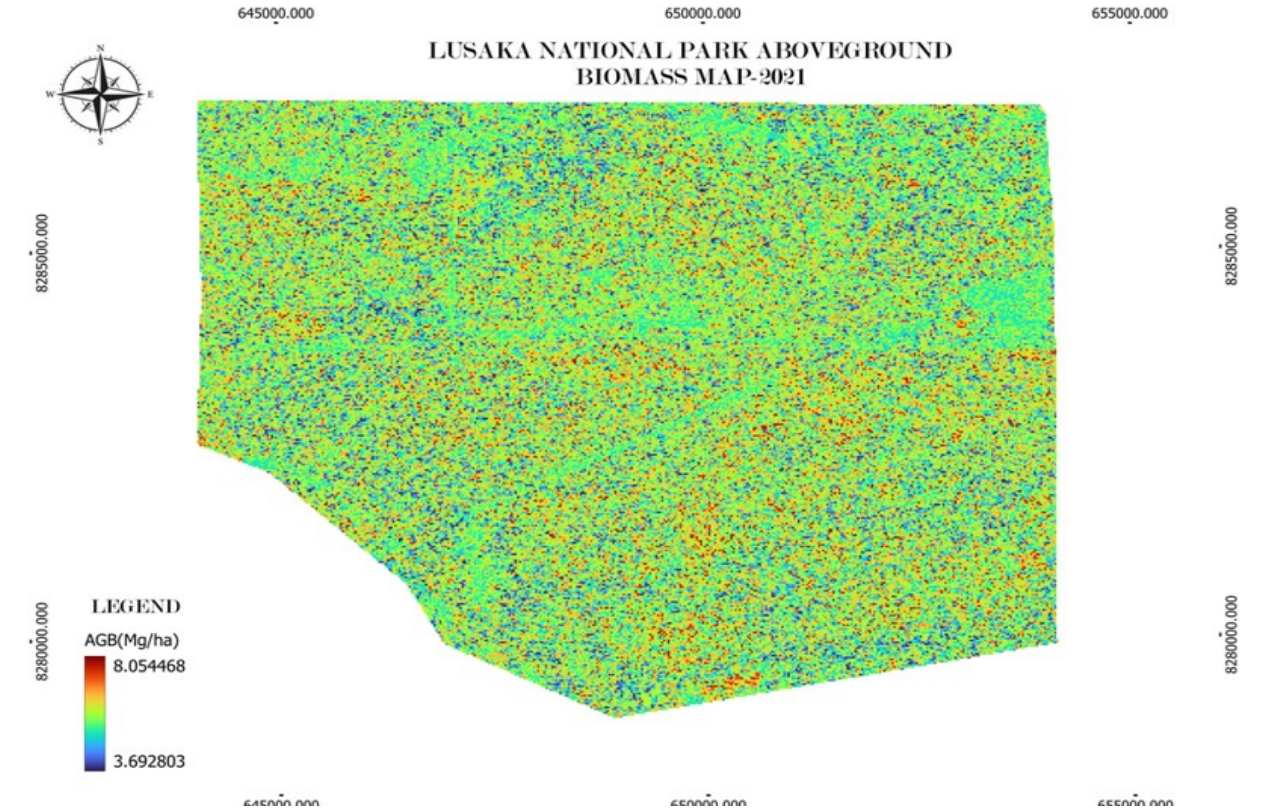

Figure 4. Above-ground biomass map for the year 2021.

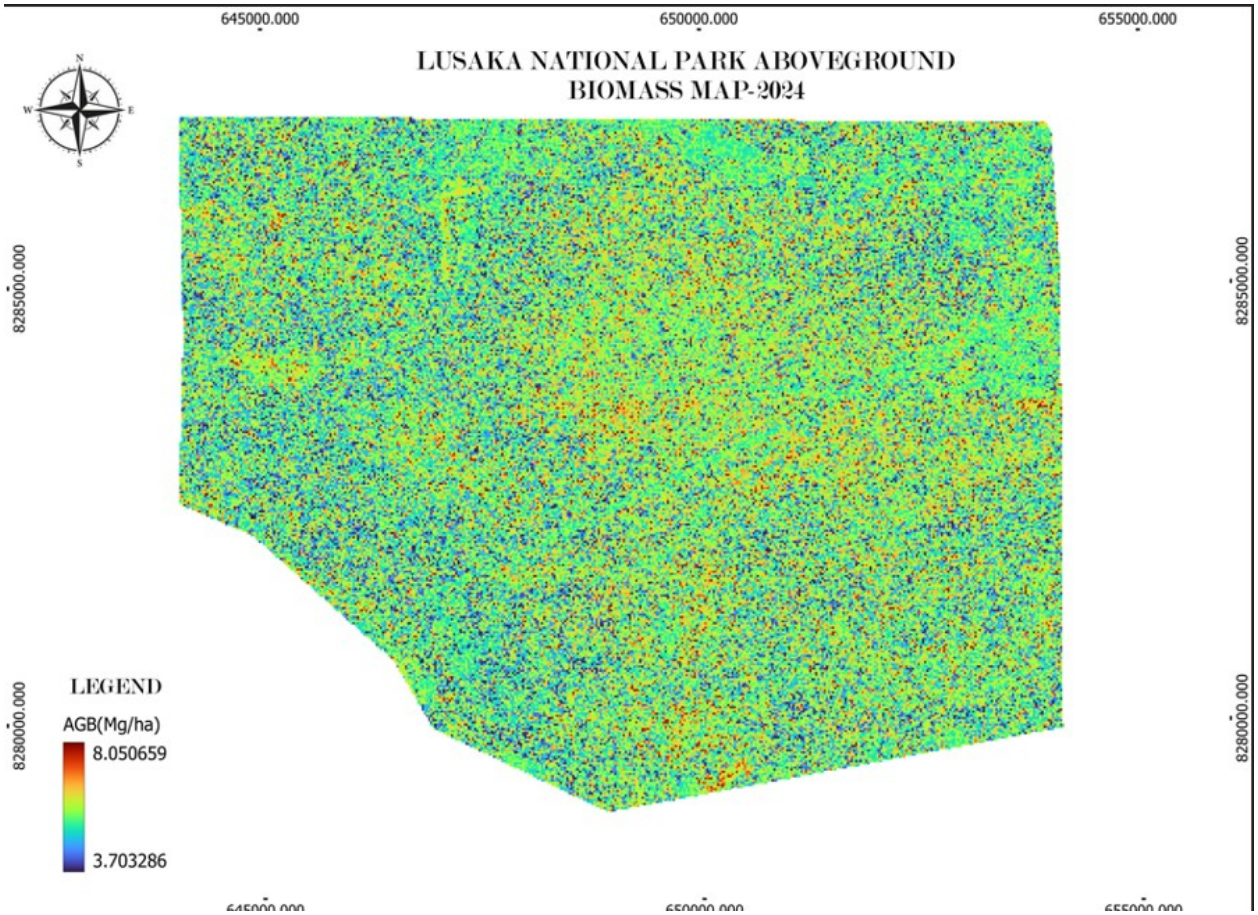

Figure 5. Above-ground biomass map for the year 2024.

L-band saturation effects, expected for biomass densities above approximately 100–120 Mg/ha (Mitchard et al., 2012; Macave et al., 2022), do not affect the operational range for this park because no inventory cell exceeded 95 t/ha. Within the relevant 20–80 t/ha range, representative of both disturbed (mean ~26.7 Mg C ha^{-1}) and old-growth (~45.8 Mg C ha^{-1}) miombo (Ribeiro et al., 2021), the model is robust. However, extrapolation to higher-biomass miombo strata would require additional reference data and a saturation-aware modelling strategy.

3.4. Cost-benchmarking against a ground-only baseline

A transparent annualised cost comparison is reported in Table 2, responding directly to reviewer concerns. Cost variables are itemised so that the comparison is reproducible by other authorities. The ground-only baseline assumes a four-person field team conducting four annual inventory rotations of the 11,950 ha park, with associated transport, equipment depreciation, allowances and reporting time. The SAR workflow assumes one geospatial analyst working at 30% full-time equivalent for monitoring, plus computational and software costs (entirely open-source), and a Sentinel-2 cross-validation pass.

Table 2: *Annualised cost comparison between a ground-only forest monitoring baseline and the SAR-based workflow demonstrated in this study. All figures in USD, rounded to the nearest hundred. Costs reflect the 2024 Zambian institutional cost structure; sensitivity to staff cost assumptions is discussed in Section 4.4.*

Cost component	Ground-only baseline (USD/yr)	SAR workflow (USD/yr)	Notes
Field staff (salaries + allowances)	32,000	14,400	1 analyst @ 0.3 FTE
Transport and fuel	14,000	0	No field rotations
Equipment depreciation (GPS, hypsometers, callipers)	6,500	0	
Computational infrastructure	1,500	3,200	Cloud compute + storage
Software (commercial GIS, biomass models)	3,200	0	Open-source only
Reporting and analysis time	3,800	2,400	Included in FTE
Data acquisition (Sentinel-2, GEDI, JAXA mosaics)	0	0	All free at the point of use
Training (one-off, amortised over 3 years)	0	22,000 (≈ 7,300/yr)	Initial capacity build
Total (USD per year)	61,000	42,000 (incl. amortised training)	31% reduction

4. Discussion

4.1. SAR as urban-hinterland monitoring infrastructure

The results demonstrate that L-band SAR can provide year-round structural observations of a peri-urban protected area in a cloud-prone African climate, with overall classification accuracy of 85.4%. The substantive contribution, however, is not the technical result but its placement within the urban-affairs context developed in Section 1. Lusaka's charcoal economy alters approximately 197.4 km^2 of

miombo annually (Sedano et al., 2022) and is bound to the city's demographic trajectory of approximately 4.5% annual population growth; the protected area examined here sits at the intersection of those pressures, and decisions about how to monitor it are decisions about how the city governs its hinterland. The SAR workflow demonstrated here is therefore better framed as urban land-use monitoring infrastructure than as a remote-sensing experiment.

This framing aligns the study with the existing urban-affairs scholarship on remote sensing for sprawl detection (Özelkan & Eren, 2025; Özer & Yalçıner Ercoşkun, 2024) and with the emerging GeoAI literature on sustainable urban planning (Aidaoui et al., 2024). It also resolves a tension visible in much of the SAR-for-tropical-forests literature, in which technical performance is reported in considerable detail while the institutional and economic conditions under which the methods would actually be deployed receive comparatively little attention (Flores-Anderson et al., 2019; Watanabe et al., 2021). The present study attempts to redress that imbalance.

4.2. Biomass estimation in an operational context

The model's R^2 of 0.76 and RMSE of 22.8 t/ha sit within the published L-band performance band for miombo and analogous open woodlands (Carreiras et al., 2013; Macave et al., 2022; Shendryk, 2022). The dominance of the HH–HV difference and polarisation fraction as feature importances is consistent with the volume-scattering behaviour expected at L-band wavelengths in 30–70% canopy-cover stands. We are nevertheless cautious about positioning this as a definitive miombo biomass model: 67 GEDI grid cells are small in number, spatial coverage is uneven, and the model has not been externally validated outside Lusaka National Park. The function of the model in this study is to demonstrate that an open-source, GEDI-anchored Random Forest pipeline can produce operationally useful biomass surfaces at a peri-urban park scale, rather than to advance the state of the art in miombo biomass estimation.

4.3. Cost-effectiveness and institutional feasibility

The 31% annualised cost reduction reported in Table 2 results from two structural differences between the two monitoring architectures: the elimination of multi-rotation field campaigns and the substitution of open-source software for commercial software. Both savings depend on a one-off institutional investment in training, which Table 2 itemises and amortises over three years. The reduction, therefore, does not arrive automatically; it arrives when an authority decides to make the upfront capacity investment. We note three sensitivities. First, if salaries for skilled geospatial analysts in Lusaka were 50% higher than assumed, the savings would fall to approximately 22% but would not vanish. Second, if Sentinel-1 SLC data were added to enable sub-annual coherence detection, cloud computing costs would increase by an estimated USD 4,000–6,000 per year. Third, the comparison is to a ground-only baseline; an authority already operating an optical workflow would see the savings relative to a different reference cost, generally smaller.

These transparent figures answer the editor's thematic emphasis on socio-economic outcomes of contemporary urbanisation: the cost of monitoring an African capital's hinterland is a measurable urban-economy variable, and methodological choices have direct fiscal consequences for protected-area authorities under chronic budgetary pressure.

4.4. Limitations and uncertainties

Five limitations are stated directly. First, the 25 m spatial resolution of the JAXA Forest/Non-Forest product limits detection of small-scale selective logging, a known feature of charcoal extraction in miombo systems. Second, the calibration set of 67 GEDI grid cells is modest and unevenly distributed across the park, and external validation outside Lusaka National Park has not been performed. Third, annual temporal resolution constrains detection latency; the workflow demonstrated here is annualised, not near-real-time. Fourth, L-band backscatter is sensitive to soil moisture, surface roughness, and incidence-angle variation, and these confounders are mitigated rather than eliminated by using the harmonised JAXA product. Fifth, the cost comparison reflects a single national institutional setting, and direct transposition to other African capitals will require local cost calibration. Each of these constraints is testable in future work, particularly through multi-site replication along the Lusaka–

Chongwe–Rufunsa corridor and across analogous peri-urban protected areas in the southern African region.

4.5. Implications for urban land-use governance

For Zambian planning, two implications follow. First, integrating cloud-resilient peri-urban forest monitoring into Lusaka City Council's land-use information systems would close a year-round visibility gap that currently coincides with peak extractive pressure. This visibility gap is compounded by the de facto governance arrangements documented by Ingram et al. (2020), in which informal charcoal networks operate in institutional grey zones that monitoring alone cannot close, but which monitoring-derived evidence can make actionable for enforcement authorities. Second, the demonstrated economic feasibility of the workflow supports its inclusion in REDD+ Monitoring, Reporting and Verification protocols at a cost compatible with sub-national authority budgets. For comparative urban-affairs scholarship, the contribution is to add a sub-Saharan, cloud-prone case to the remote-sensing-for-urban-planning literature, which has been dominated by Mediterranean and East-Asian contexts (Özelkan & Eren, 2025; Özer & Yalçıner Ercoşkun, 2024; Aidaoui et al., 2024; He et al., 2023). We do not claim that L-band SAR is a universal solution; we claim that it is one component of a context-appropriate monitoring stack for African capital hinterlands, and that its institutional case becomes considerably stronger when its cost is reported transparently.

5. Conclusions

This study has demonstrated that an open-source, GEDI-anchored L-band SAR workflow can monitor a peri-urban miombo protected area in the cloud-prone climate of an African capital, achieving 85.4% overall classification accuracy and a 31% annualised cost reduction relative to a transparent ground-only baseline. The biomass model achieved $R^2 = 0.76$ and RMSE = 22.8 t/ha within the operational miombo range, and 37 wet-season disturbance events were identified that would have been hidden from the conventional optical monitoring stack until the following dry season.

The findings support all three hypotheses (H1, H2 and H3) introduced in Section 1.4 under the bounds of the study area. The contribution is institutional and methodological rather than algorithmic. It is best understood in the urban-affairs context developed in Sections 1.1 and 4.6: the choice of sensor through which a city observes its hinterland is itself an urban-policy decision with measurable fiscal and conservation consequences. We do not generalise to the wider 2.7 million km² miombo belt; the case is transferable on the explicit conditions set out in Section 1.5, and external validation across multiple peri-urban protected areas is a near-term priority.

Future work will focus on three extensions. First, multi-site replication across analogous peri-urban protected areas in southern Africa (Nairobi National Park, Lake Chivero, the Kafue Flats fringe) will test the case-transferability conditions stated in Section 1.5. Second, the addition of Sentinel-1 single-look complex inputs will move the workflow from annualised to near-real-time disturbance detection, addressing the most consequential limitation noted in Section 4.4. Third, integration with Lusaka City Council's urban land-use information systems will test whether the institutional pathway sketched in Section 4.5 is feasible in practice.

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Conflicts of Interest

The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Data Availability Statement

The ALOS/PALSAR and ALOS-2/PALSAR-2 Forest/Non-Forest mosaic data used in this study are publicly available from the Japan Aerospace Exploration Agency. GEDI L4B Gridded Above-ground Biomass Density data are available through Google Earth Engine and NASA's LP DAAC. Sentinel-2 imagery is available through the Copernicus Open Access Hub. Python scripts developed for the time-series analysis are available from the corresponding author upon reasonable request.

Institutional Review Board Statement

Not applicable. This study did not involve human subjects, clinical trials, or data collection requiring ethics committee review. All data used are publicly available remote sensing datasets.

Credit Author Statement

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