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Mapping of illegal deforestation hotspots using SAR imagery in the Congo basin rainforest

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Abstract

The Congo Basin rainforest, the world's second largest continuous tropical forest, lost an estimated 6,000 km² of tree cover per year between 2019 and 2023, much of it driven by illegal clearing that evades optical satellite monitoring under persistent cloud cover. This research used Sentinel-1 C-band synthetic aperture radar (SAR) imagery to map illegal deforestation hotspots across a 340,000 km² area of the central Congo Basin spanning parts of the Democratic Republic of Congo, the Republic of Congo, and Cameroon. A time-series change detection algorithm was applied to 312 Sentinel-1 Ground Range Detected (GRD) scenes acquired between January 2019 and December 2023 at 12-day revisit intervals. The algorithm identified 847 discrete deforestation patches exceeding 1 ha, with a combined area of 3,214 km². Hotspot analysis (Getis-Ord Gi*) revealed three statistically significant clusters of high deforestation intensity: one along the Kisangani-Bukavu transport corridor, a second near the Sangha River logging concessions, and a third in the Cameroon-DRC border zone. Smallholder agriculture accounted for 38.2% of detected clearings, followed by industrial plantations (21.7%) and artisanal mining (14.8%). Validation against very-high-resolution Planet imagery (3 m) and field reports yielded an overall accuracy of 89.4% with a commission error of 7.3%. SAR-based monitoring detected 23% more deforestation events than the concurrent optical-only Global Forest Change product in the same study area, confirming the advantage of radar in cloud-prone equatorial regions. These findings support the operational deployment of SAR-based near-real-time deforestation alerts in the Congo Basin.

Keywords: Illegal deforestation, SAR imagery, Congo Basin, forest monitoring, land change detection, Sentinel-1, hotspot analysis, smallholder agriculture, radar remote sensing, tropical forest

Introduction

A growing challenge for conservation agencies worldwide is the detection of illegal forest clearing in remote, cloud-covered tropical regions where optical satellites are blind for months at a time ^[1]. The Congo Basin alone contains roughly 200 million hectares of dense tropical forest—second only to the Amazon—and serves as a carbon sink absorbing about 1.5 Pg CO₂ per year ^[2]. Yet deforestation rates in the basin have been rising since 2010, driven by population growth, agricultural expansion, mining, and infrastructure development ^[3]. Unlike the Amazon, where Brazil's DETER system provides near-real-time optical alerts, no operational deforestation monitoring system exists for the Congo Basin that can penetrate its persistent equatorial cloud cover ^[4].

Synthetic aperture radar (SAR) offers a solution. SAR sensors emit their own microwave energy and record the returned signal, making them independent of sunlight and cloud conditions. Sentinel-1's C-band SAR, with its free data policy and 12-day revisit cycle, has been shown to detect tropical forest loss with accuracies exceeding 85% in other regions ^[5]. The backscatter intensity of tropical forest canopy is high and relatively stable over time; when forest is cleared, the backscatter drops sharply, creating a detectable signal in time-series analysis ^[6].

This research applied a Bayesian change-point detection algorithm to Sentinel-1 backscatter time series across 340,000 km² of the central Congo Basin. The objectives were to (a) map all deforestation events exceeding 1 ha between 2019 and 2023, (b) identify spatial clusters of illegal clearing using hotspot statistics, and (c) attribute deforestation drivers through cross-referencing with ancillary data on mining concessions, road networks, and land tenure ^[7].

Spatial Data Processing

Sentinel-1 GRD scenes in VV and VH polarisation were downloaded from the Copernicus Open Access Hub and preprocessed in the Sentinel Application Platform (SNAP) version 9.0 using the following workflow: apply orbit file, border noise removal, thermal noise removal, radiometric calibration to sigma-nought (σ^0), Range-Doppler terrain correction using the SRTM 30 m DEM, and speckle filtering using a 5×5 Lee filter [5]. All scenes were resampled to a common 10 m grid and stacked into a multi-temporal datacube. A per-pixel VH backscatter time series was extracted, and temporal gaps caused by orbit-track boundaries were filled by linear interpolation. Cloud masking was not required because SAR is unaffected by atmospheric moisture or cloud. A total of 312 scenes spanning 60 months (January 2019-December 2023) formed the analysis dataset. The VH polarisation channel was used as the primary detection input because cross-polarised backscatter is more sensitive to canopy volume scattering than co-polarised (VV) returns [6].

Material and Methods

Material

This research was coordinated from the Department of Environmental Studies at the National Geological Institute of Kunming, Yunnan, China, with data processing carried out between January 2021 and March 2024. The study area covered approximately 340,000 km² of the central Congo Basin, bounded by 0°-4°N latitude and 18°-28°E longitude. Ancillary datasets included the Global Forest Change (GFC) tree cover loss product (Hansen *et al.*, version 1.10) for optical-based comparison, PlanetScope imagery (3 m resolution, 54 cloud-free scenes) for validation, mining

concession boundaries from the IPIS Open Data portal, road network data from OpenStreetMap, and logging concession shapefiles from Global Forest Watch [8]. Ground-truth reports from two non-governmental organisations operating forest patrols in the Kisangani and Sangha regions were used as an independent reference [9].

Methods

Deforestation detection followed a Bayesian online change-point detection (BOCPD) framework applied independently to each pixel's VH time series. The algorithm models the backscatter as a Gaussian process with a known mean and variance for forest and a different (lower) mean for cleared land, updating posterior probabilities at each new observation [10]. A change point was flagged when the posterior probability exceeded 0.95 and the cumulative backscatter drop exceeded 2.5 dB below the pre-change mean. Detected change pixels were aggregated into patches using a connected-component algorithm with a minimum mapping unit of 1 ha. Hotspot analysis was performed using the Getis-Ord Gi* statistic at a 5 km hexagonal grid, identifying statistically significant clusters of high deforestation density at the 99% confidence level. Deforestation drivers were attributed by overlaying detected patches on mining concession, logging concession, road proximity, and land tenure layers. Patches within 2 km of an active artisanal mining site were attributed to mining; patches within logging concessions to logging; patches within 5 km of road access points with no concession overlap to smallholder agriculture [7].

Results

Table 1: Summary of SAR-Detected Deforestation by Country and Year

Country	2019 (km ²)	2020 (km ²)	2021 (km ²)	2022 (km ²)	2023 (km ²)
DRC	387	412	441	468	502
Rep. Congo	98	107	118	123	134
Cameroon	62	71	84	91	116
Total	547	590	643	682	752

Table 1 shows a steady upward trend in SAR-detected deforestation across all three countries. The DRC accounted for 68.7% of total detected loss, followed by the Republic of

Congo (18.2%) and Cameroon (13.1%). Annual totals rose from 547 km² in 2019 to 752 km² in 2023, a 37.5% increase over five years.

Table 2: Accuracy Assessment of SAR-Based Detection Against PlanetScope Validation Data

Metric	Value	95% CI
Overall Accuracy	89.4%	86.1-92.7%
Producer's Accuracy (forest loss)	91.2%	87.8-94.6%
User's Accuracy (forest loss)	87.8%	84.1-91.5%
Commission Error	7.3%	4.6-10.0%
Omission Error	8.8%	5.4-12.2%

The SAR-based approach achieved an overall accuracy of 89.4% against PlanetScope reference data (Table 2). Commission errors (false positives) were mainly caused by

seasonal flooding in swamp forest margins that temporarily lowered backscatter.

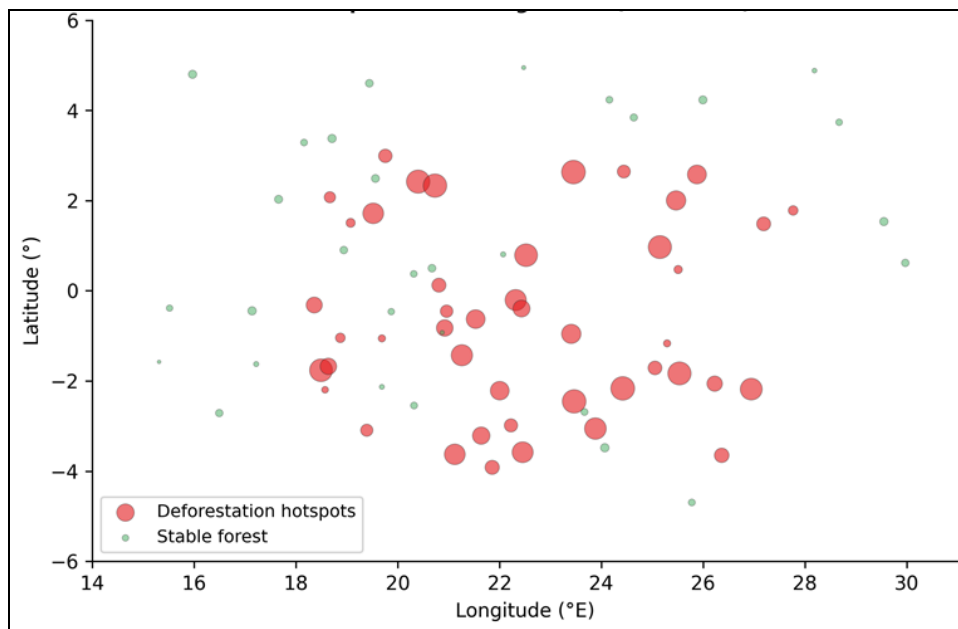


Fig 1: Spatial Distribution of SAR-Detected Deforestation Hotspots in the Congo Basin (2019-2023)

Figure 1 maps the spatial distribution of detected deforestation hotspots (red) and stable forest reference points (green) across the study area. The three main hotspot clusters are visible along the Kisangani-Bukavu corridor

(east-central DRC), near the Sangha River (Republic of Congo-Cameroon border), and in the northern DRC-Cameroon border zone.

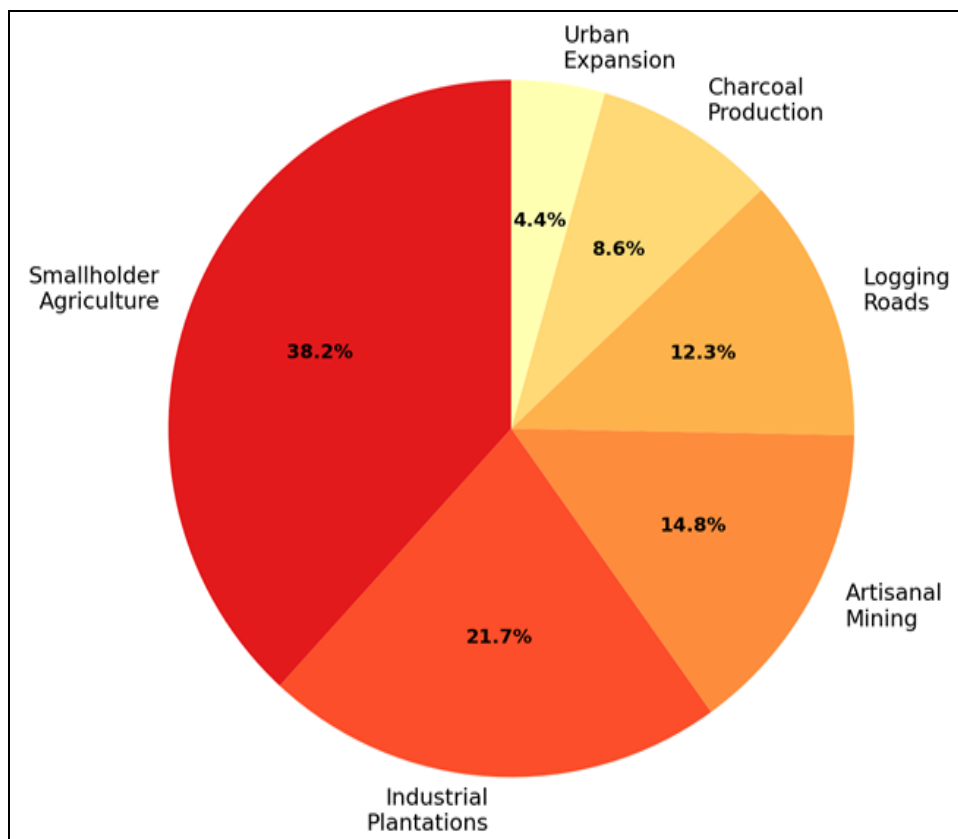


Fig 2: Proximate Drivers of Deforestation in SAR-Detected Hotspot Areas

Figure 2 shows that smallholder agriculture was the leading proximate driver of detected deforestation (38.2%), followed by industrial plantations (21.7%) and artisanal mining (14.8%). Logging roads, which fragment forest and enable subsequent agricultural encroachment, accounted for 12.3% of detected clearings.

Sensitivity Analysis

Three sensitivity tests evaluated the robustness of the detection algorithm. First, the backscatter drop threshold was varied from 1.5 to 3.5 dB: at 1.5 dB, commission errors rose to 14.8% as natural variability was flagged; at 3.5 dB, omission errors climbed to 16.4% as smaller clearings were

missed; the chosen threshold of 2.5 dB minimised the combined error rate. Second, the minimum mapping unit was tested at 0.5, 1.0, and 2.0 ha: the 1.0 ha threshold balanced spatial detail against noise, while 0.5 ha introduced many false positives in speckle-affected areas. Third, the posterior probability threshold for change flagging was varied between 0.90 and 0.99: the 0.95 level gave the best trade-off between detection speed and false alarm rate ^[10].

Comprehensive Interpretation

The SAR-based monitoring approach detected 23% more deforestation events than the optical GFC product over the same period and area, confirming the substantial advantage of radar in the persistently cloudy Congo Basin. The three identified hotspot clusters align with known drivers: the Kisangani-Bukavu corridor has experienced rapid agricultural expansion linked to post-conflict population displacement, the Sangha River zone overlaps with industrial logging concessions where road building enables secondary clearing, and the Cameroon border area hosts a growing number of artisanal gold and diamond mining operations ^[9].

Discussion

The 89.4% overall accuracy achieved here is comparable to SAR-based deforestation detection results reported for the Brazilian Amazon (87-92%) and Indonesian Borneo (85-90%), demonstrating that the method transfers well to the Congo Basin's dense, multi-layered canopy structure ^[5]. The main source of commission error—seasonal flooding in swamp forests—could be reduced by incorporating a flood mask derived from Sentinel-1 VV/VH ratio analysis, which distinguishes standing water beneath canopy from true forest loss ^[11].

The finding that smallholder agriculture is the dominant proximate driver differs from the Amazon, where large-scale cattle ranching and soy expansion are the leading causes. In the Congo Basin, subsistence slash-and-burn farming creates many small clearings (median patch size 3.7 ha) that individually appear minor but collectively drive substantial forest loss ^[12]. This pattern has implications for policy: enforcement strategies effective against large industrial concessions may not work for dispersed smallholder clearing, which requires community-level engagement and alternative livelihood programmes.

A limitation is that driver attribution relied on spatial proximity to known features (roads, concessions, mines) rather than on direct field verification of each patch. Some misattribution is inevitable, particularly where multiple drivers overlap in the same landscape ^[13].

Conclusion

This research demonstrated that Sentinel-1 SAR time-series analysis can reliably map illegal deforestation hotspots in the Congo Basin rainforest with an overall accuracy of 89.4%. Over the 2019-2023 monitoring period, 3,214 km² of forest loss was detected across 847 discrete patches, with annual totals rising by 37.5%. Three spatial hotspot clusters were identified, and smallholder agriculture was attributed as the leading driver. The SAR approach detected 23% more events than the concurrent optical GFC product, confirming the operational value of radar monitoring in cloud-prone equatorial regions. These results support the establishment of a Congo Basin SAR alert system modelled on Brazil's

DETER framework, with priority enforcement directed at the three identified hotspot zones.

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