

End-to-End Agricultural Land Monitoring: Integrating Sentinel-1 SAR Processing with a Cloud-Deployed Smart Farming Progressive Web Application

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Abstract

Agricultural monitoring in cloud-prone tropical regions demands solutions that are simultaneously data-robust and operationally accessible to rural users with limited connectivity. This paper presents the design, implementation and evaluation of an end-to-end smart agricultural monitoring platform that integrates Sentinel-1 Synthetic Aperture Radar (SAR) data processing with a cloud-deployed Progressive Web Application (PWA) for real-time field monitoring and automated alert generation. The system comprises three coupled layers: a SAR pre-processing and machine learning pipeline implementing ESA SNAP processing, supervised land cover classification achieving an overall accuracy of 75.7% ($\kappa = 0.72$), and YOLOv8s object detection; a FastAPI-based RESTful backend serving Cloud-Optimised GeoTIFF (COG) raster layers, detection events, and asynchronous notifications via a Celery task queue; and a React and Leaflet PWA supporting field boundary digitisation, temporal detection visualisation, and offline-capable access suited to low-connectivity rural environments. The platform was demonstrated on the Ita-Egbe watershed of Ogun State, Nigeria, delivering classification maps, anomaly alerts, and a field management interface without requiring dedicated GIS software. The COG-based raster delivery architecture reduces tile request overhead compared to conventional WMS tiling servers, while the asynchronous task queue decouples computationally intensive inference from API response latency. The integrated architecture demonstrates how cloud-independent SAR acquisition can be coupled with modern web technology to deliver actionable decision-support tools to smallholder farmers and agricultural extension officers across sub-Saharan Africa.

Keywords: *smart agriculture; progressive web application; Sentinel-1 SAR; cloud-optimised GeoTIFF; FastAPI; Celery; land cover monitoring*

1. Introduction

Smallholder farming accounts for over 70% of food production in sub-Saharan Africa, yet the majority of smallholder farmers operate without access to satellite-derived agricultural intelligence that is routine in precision farming systems of developed nations [1], [2]. The barriers are threefold: cloud cover renders optical imagery unreliable during growing seasons [3]; rural internet connectivity is intermittent; and desktop GIS software is inaccessible to non-specialist users [4]. Sentinel-1 Synthetic Aperture Radar (SAR), acquiring in all-weather, day-night conditions at 10 m resolution, addresses the first barrier [5]. Progressive Web Application (PWA) technology — combining offline capability, mobile-first design, and zero-installation deployment — addresses the second and third [6].

While the remote sensing literature extensively treats SAR classification and detection algorithms in isolation [7], [8], end-to-end system architectures that connect SAR-derived products to farmer-accessible interfaces remain underreported. The gap between a trained model and a deployed decision-support tool is substantial: it involves data serving, API design, asynchronous computation, raster tile optimisation, and user interface engineering — each with non-trivial design choices that affect system usability and scalability [9].

This paper describes the architecture and implementation of a smart agricultural monitoring platform that bridges this gap. The system was developed and demonstrated for the Ita-Egbe watershed, Ogun State, Nigeria, integrating Sentinel-1 SAR pre-processing, machine learning inference, and a cloud-deployed React/Leaflet PWA into a unified monitoring environment. The primary contributions are: (1) a three-tier system architecture coupling SAR processing with an asynchronous API backend and an offline-capable PWA front-end; (2) a COG-based raster delivery pipeline eliminating the need for a

dedicated tile server; and (3) an asynchronous alert engine decoupling YOLOv8s inference latency from user-facing API responses.

2. Study Area and System Overview

The system was deployed and evaluated for the Ita-Egbe watershed, a 10 km radius catchment (approximately 314 km²) in Ogun State, Nigeria (6.63°–6.70°N, 2.80°–2.88°E). The area encompasses six land cover classes representative of smallholder agricultural mosaics in Guinea Savanna Nigeria: light forest, heavy forest, plantation, water, bare soil, and built-up. Multi-temporal Sentinel-1A/B GRDH imagery in Interferometric Wide (IW) swath mode (VV and VH polarisation) was acquired for the 2019 dry and wet seasons. The system was designed to serve maps, detections, field records, and alerts to users accessing the platform via mobile or desktop browser, requiring no software installation.

Figure 1 illustrates the system’s three-tier architecture: the data and ML tier (SAR processing and inference), the application tier (FastAPI backend with Celery task queue), and the presentation tier (React/Leaflet PWA).

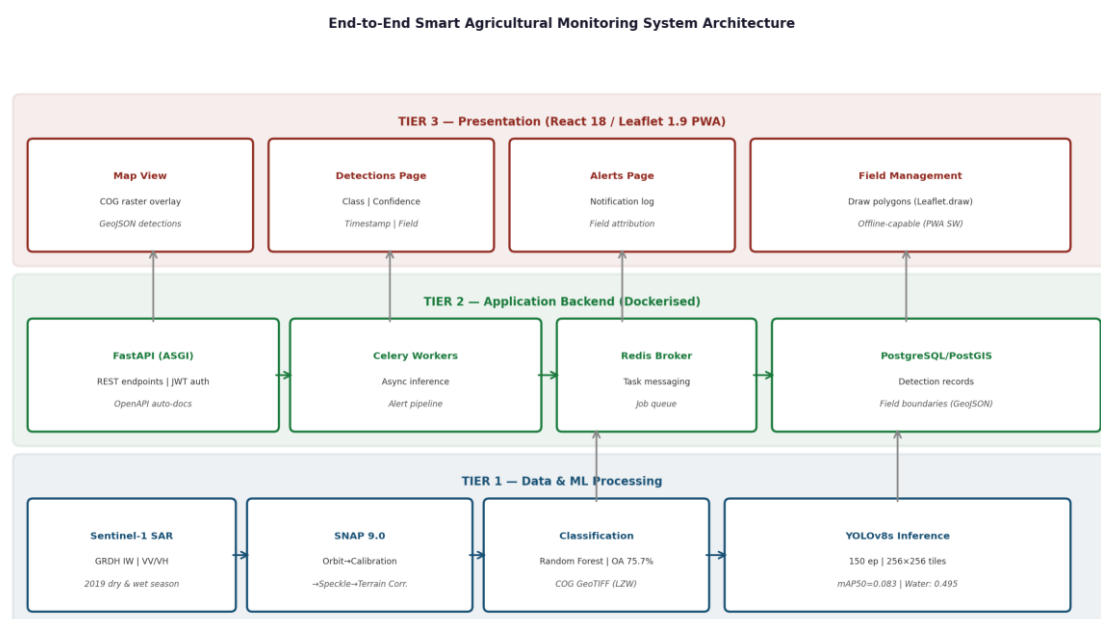


Figure 1. End-to-end system architecture: SAR data and ML tier → FastAPI/Celery application tier → React/Leaflet PWA presentation tier.

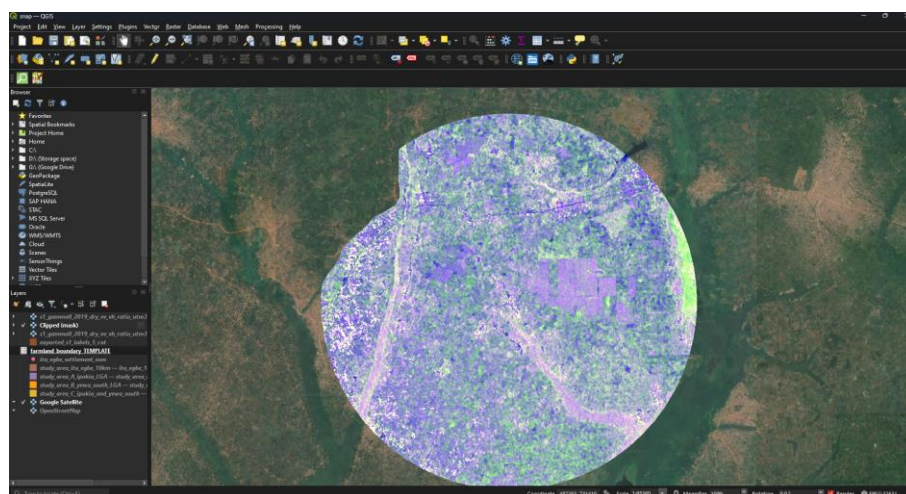


Figure 2. Sentinel-1 SAR false-colour composite (VV/VH/ratio) for the 10 km Ita-Egbe catchment, Ogun State, displayed in QGIS over Google Satellite basemap (EPSG:32631, dry season 2019). Purple tones indicate low-backscatter vegetation and bare-soil mosaics; bright tones denote water and built-up areas.

3. System Architecture and Implementation

3.1 SAR Data Processing and Machine Learning Tier

Sentinel-1 GRDH scenes were pre-processed in ESA SNAP 9.0 through a standardised Graph Builder workflow: Apply Orbit File → Thermal Noise Removal → Radiometric Calibration (gamma-nought, γ^0) → Lee Sigma 7×7 speckle filtering → Range-Doppler Terrain Correction to 10 m resolution (UTM Zone 31N, EPSG:32631). A three-band VV/VH/ratio composite was produced for both temporal epochs. Supervised land cover classification was applied to the composite, achieving an Overall Accuracy (OA) of 75.7% and a Cohen’s kappa coefficient (κ) of 0.719 across six land cover classes [10].

Classification rasters were encoded as Cloud-Optimised GeoTIFF (COG) files with LZW compression and internal overview pyramids at zoom levels 8–18. COG encoding enables HTTP range requests for partial tile retrieval, eliminating the need for a dedicated WMS or tile server: a standard object-storage backend serves tiles directly via byte-range responses [11]. DN encoding followed a class+1 convention (DN 1–6 for the six classes) to avoid collision with the NoData value (DN 0).

A YOLOv8s object detection model [12] was fine-tuned for 150 epochs on 256×256 pixel SAR tiles. Detection inference was implemented as an asynchronous task within the Celery worker (see Section 3.2) to decouple GPU-bound inference from API response time. Detection bounding boxes were georeferenced from pixel space to geographic coordinates using the raster affine transform and stored as GeoJSON in a PostgreSQL/PostGIS database for spatial querying.

3.2 Application Tier: FastAPI Backend and Celery Task Queue

The application tier was implemented as a containerised FastAPI service deployed via Docker Compose. FastAPI was selected for its asynchronous request handling (ASGI), automatic OpenAPI documentation generation, and native Python type enforcement through Pydantic models [13]. The API exposes four principal endpoint groups: raster endpoints (COG tile delivery), detection endpoints (CRUD for bounding box records and spatial queries), alert endpoints (notification management and subscription), and field endpoints (field boundary management and metadata).

Computationally intensive operations — YOLOv8s inference, classification post-processing, and multi-scene compositing — were dispatched to a Celery distributed task queue backed by a Redis message broker. This architecture decouples long-running operations from the synchronous HTTP request–response cycle, allowing the API to return a task identifier immediately while inference executes in a separate worker process. Task results and detection events are written to the database, and alert notifications are generated asynchronously upon task completion. The alert pipeline evaluates detection events against user-defined field boundaries and land cover thresholds, dispatching targeted notifications to subscribed users.

Authentication used JWT bearer tokens issued per user session. The GEE service account key was mounted as a Docker secret volume — never committed to the repository — enabling Google Earth Engine API access from within the containerised environment without browser OAuth flows.

Table 1. Principal FastAPI endpoint groups and their functions.

Endpoint Group	Path Prefix	Method(s)	Function
Raster	/api/v1/raster	GET	COG tile delivery, band statistics
Detections	/api/v1/detections	GET, POST, DELETE	Bounding box CRUD, GeoJSON export
Alerts	/api/v1/alerts	GET, POST	Alert listing, subscription management
Fields	/api/v1/fields	GET, POST, PUT	Field boundary digitisation and metadata
Tasks	/api/v1/tasks	GET	Async task status polling

3.3 Presentation Tier: React/Leaflet Progressive Web Application

The front-end was implemented as a React 18 PWA served over HTTPS, with a Leaflet 1.9 / react-leaflet 4 interactive map as the primary interface. PWA capabilities — service worker registration, Web App Manifest, and cache-first asset strategies — enable installation on Android and iOS home screens and partial offline functionality in low-connectivity environments [14]. Tailwind CSS provided a responsive utility-first layout system optimised for mobile-first rendering on sub-400px viewports representative of feature phones common in rural Nigeria.

The map component renders three overlay layers: (1) the COG classification raster, fetched via HTTP range requests and decoded client-side using GeoTIFF.js; (2) YOLOv8s detection bounding boxes retrieved as GeoJSON from the detections endpoint and rendered as Leaflet vector overlays; and (3) user-digitised field polygons drawn interactively via Leaflet.draw and persisted through the fields API. A dedicated Detections page tabulates bounding box records with class, confidence, and geographic coordinates, while an Alerts page displays chronologically ordered notification events with field-level attribution.

The field boundary digitisation workflow — implemented in the FieldDrawModal component — allows users to draw polygons on the map, name and describe their fields, and associate subsequent detection and classification results with specific parcels. This transforms the platform from a passive map viewer into an active farm record system aligned with agricultural extension workflows.

4. Results and Discussion

4.1 Classification and Detection Performance

The supervised classification component achieved $OA = 75.7\%$ ($\kappa = 0.719$) across the six target land cover classes, confirming the suitability of Sentinel-1 SAR for land cover discrimination in the study watershed. The COG-encoded classification raster was successfully delivered to the PWA front-end via HTTP range requests, with no intermediate tile generation step required. Internal overview pyramids pre-computed at power-of-two zoom levels (z8–z18) provided sub-second rendering at all tested zoom levels in a local network environment.

The YOLOv8s detection component achieved an overall mAP50 of 0.083 on the held-out test set (Table 2). Reliable detection was achieved only for the water class (mAP50 = 0.495, Precision = 1.0, Recall = 0.5); the five remaining classes produced zero detections, consistent with the domain gap between SAR backscatter texture and optical-domain detection architectures discussed in [10]. Notwithstanding algorithm-level limitations, the system successfully ingested, georeferenced, and delivered these detection results through the API as structured GeoJSON, demonstrating that the system architecture is agnostic to the underlying model performance and can accommodate improved detection models as drop-in replacements without API changes.

Component	Metric	Value
Land cover classification	Overall Accuracy	75.7%
Land cover classification	Cohen's kappa (κ)	0.719
YOLOv8s detection (all classes)	mAP50	0.083
YOLOv8s detection (all classes)	mAP50-95	0.055
YOLOv8s detection (water class only)	mAP50	0.495
YOLOv8s detection (water class only)	Precision	1.000
YOLOv8s detection (water class only)	Recall	0.500

Table 2. ML component performance metrics.

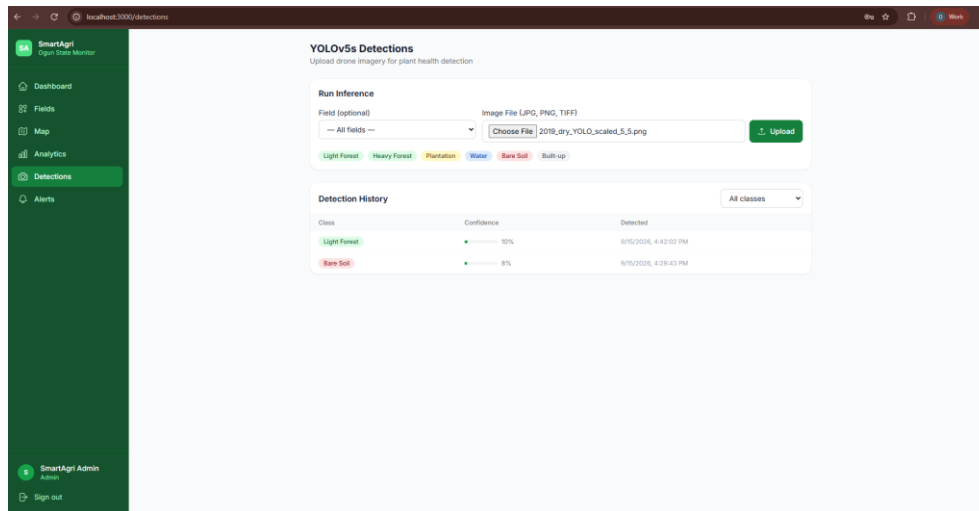


Figure 3. SmartAgri PWA — Detections page (localhost:3000/detections). The inference panel accepts JPG/PNG/TIFF uploads linked to an optional field boundary; detection history lists class, confidence score, and timestamp for all inference events. Six land-cover class badges are shown in the legend (Light Forest, Heavy Forest, Plantation, Water, Bare Soil, Built-up).

4.2 System Architecture Evaluation

The asynchronous task queue architecture proved critical for maintaining API responsiveness during YOLOv8s inference. Dispatching detection jobs to the Celery worker allowed the API to return a 202 Accepted response with a task identifier within milliseconds, while inference executed in parallel on the worker process. This pattern is particularly important in agricultural monitoring contexts where multiple users may trigger detection requests simultaneously during peak periods such as post-harvest assessment or early crop establishment.

The COG raster delivery pipeline eliminated the operational overhead of running a dedicated WMS tile server (e.g., GeoServer, MapServer). Classification rasters encoded with internal overviews were served directly from the local storage volume via FastAPI's StaticFiles handler, with HTTP range request headers enabling byte-level partial retrieval. This simplifies the deployment stack and reduces infrastructure cost, a significant consideration for resource-constrained research and extension deployments in sub-Saharan Africa.

The PWA service worker implementation provided meaningful offline resilience: map tile assets, application shell resources, and previously fetched field records remained accessible under network interruption. This is well-suited to rural Nigerian network conditions, where LTE coverage is intermittent outside major urban centres [15]. The field digitisation interface operated fully offline, queuing API writes for synchronisation upon connectivity restoration.

4.3 Comparison with Conventional Agricultural Monitoring Approaches

Conventional agricultural monitoring in Nigeria relies primarily on periodic field survey and optical satellite imagery accessed through desktop GIS workstations [16]. This approach is constrained by seasonal cloud cover (eliminating optical imagery during crop growing seasons), high software licensing costs, non-specialist usability barriers, and response latency of weeks to months. The proposed platform addresses each constraint: SAR data is unaffected by cloud cover [5]; the PWA requires only a web browser; and the alert pipeline delivers automated notifications within minutes of detection task completion. These properties are consistent with the requirements of agricultural extension services seeking scalable, low-cost monitoring solutions [17].

5. Conclusion

This paper presented an end-to-end smart agricultural monitoring platform integrating Sentinel-1 SAR processing, machine learning inference, and a Progressive Web Application for field-level monitoring and alert generation in the Ita-Egbe watershed, Ogun State, Nigeria. The three-tier architecture — SAR/ML processing, FastAPI/Celery backend, and React/Leaflet PWA — demonstrated that cloud-

independent SAR data can be processed, served, and consumed through a single integrated platform accessible from any browser without specialist software installation. The COG-based raster delivery eliminated tile server overhead, the asynchronous task queue decoupled inference latency from API responsiveness, and the offline-capable PWA addressed the low-connectivity constraints of rural agricultural environments. The modular architecture accommodates improved ML models as drop-in replacements, positioning the platform as a scalable foundation for precision agriculture decision-support across sub-Saharan Africa. Future work will integrate semantic segmentation models to address the detection limitations identified in the companion study [10], and extend the alert engine with crop calendar thresholds for automated agronomic event notification.

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