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Research Article

HYDROCAST-NG: Real-Tıme Flood Mappıng and Dısplaced Populatıon Estımatıon Usıng Sentınel-1 SAR Imagery and Deep Learnıng for Nıgerıa:

A Semantic Segmentation and Spatio-Temporal Forecasting Framework for Disaster Response and Humanitarian Planning

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Abstract
Nigeria experiences some of the most severe recurrent flooding in sub-Saharan Africa. The 2022 floods alone displaced 1.4 million people, destroyed 82,053 homes, and caused an estimated USD 4.2 billion in economic damage across 34 of 36 states. Existing early warning and disaster mapping systems rely on sparse rain gauge networks and manual field surveys that are too slow and geographically limited to support effective humanitarian response. This paper introduces HYDROCAST-NG (Hydrological Remote-sensing and Operational Disaster Coordination Analysis System for Nigeria), a multi-component AI framework that fuses Sentinel-1 Synthetic Aperture Radar (SAR) imagery with Sentinel-2 optical data, ERA5 meteorological reanalysis, and SRTM digital elevation models to deliver real-time flood mapping and 3-to-7-day displacement volume predictions. The framework deploys a modified U-Net with ResNet-50 encoder for pixel-level flood segmentation, a stacked ensemble (LSTM + XGBoost + Random Forest) for LGA-level displacement forecasting, and Google Earth Engine for automated near-real-time data ingestion. HYDROCAST-NG achieves a flood segmentation macro-F1 of 88.4% and mean IoU of 0.774 on held-out Nigerian flood events, and displacement prediction R^2 of 0.887 with a mean 5.8-day early warning lead time. A federated learning layer using FedAvg enables privacy-preserving model updates across NEMA, NIHSA, and six geopolitical zone nodes. Validated against six historical Nigerian flood events (2012-2022), HYDROCAST-NG consistently outperforms NDWI thresholding, random forest baselines, and persistence models, providing actionable flood intelligence for NEMA, state emergency management agencies, UNHCR, and World Bank Nigeria DRM programmes.

Keywords: *Flood Mapping; SAR Remote Sensing; U-Net; Sentinel-1; Displacement Estimation; Nigeria; LSTM; Federated Learning; Disaster Risk Reduction; NEMA.*

I. INTRODUCTION

Nigeria's geographic position — straddling the Niger-Benue river confluence and the Lake Chad Basin — makes it among the most flood-vulnerable nations in Africa. Between 2012 and 2022, Nigerian floods cumulatively displaced over 4.7 million people, destroyed hundreds of thousands of homes, and caused agricultural losses exceeding USD 8 billion [1], [2]. The 2022 Anambra, Kogi, and Benue floods were described as the worst in a decade, affecting 1.4 million people and inundating over 600,000 hectares of farmland [1]. Climate projections indicate that peak annual flood intensity in the Niger-Benue system will increase by 18-34% under 2°C warming scenarios, making these events not anomalies but accelerating baselines [28].

The operational response to Nigerian floods is severely constrained by three systemic deficiencies. First, Nigeria's river gauging network of 214 stations covers fewer than 12% of major tributaries, creating vast blind spots in real-time hydrological monitoring [29]. Second, the Nigeria Hydrological Services Agency (NIHSA) annual flood outlook relies on static rainfall climatology and cannot issue district-level early warnings within the 48-72 hour window required for population evacuation [29]. Third, post-flood displacement mapping relies on field surveys by IOM DTM teams that typically take 7-14 days to produce LGA-level estimates — long after emergency resource allocation decisions must be made [3].

Satellite SAR imagery offers a powerful complement: Sentinel-1's C-band radar penetrates cloud cover regardless of weather conditions, acquiring repeat-pass imagery every 6-12 days over Nigeria. Combined with deep learning segmentation, SAR enables automated flood extent mapping within 3-4 hours of image acquisition. This paper introduces HYDROCAST-NG and makes four contributions: (i) a dataset of 47 Sentinel-1/2 image pairs covering six historical Nigerian flood events; (ii) a U-Net semantic segmentation model fine-tuned for Nigerian flood conditions; (iii) a stacked ensemble displacement prediction model; and (iv) a federated learning deployment architecture for multi-agency operational use.

II. BACKGROUND: NIGERIA'S FLOOD VULNERABILITY

A. Hydrology and Flood Drivers

Nigeria's flood risk is driven by three concurrent mechanisms. The Niger and Benue rivers, draining 1.5 million km^2 of the Sahel, experience peak flows between August and October coinciding with the West African monsoon. The 2022 floods were dramatically worsened by the controlled release from Lagdo Dam in Cameroon — 27 billion cubic metres of water released without adequate downstream notification — which inundated communities hours before evacuation was possible [2]. Secondary flooding in Lagos and Ibadan results from rapid urban expansion onto flood plains, with 43% of Lagos State's low-lying areas now classified as high-risk [4].

B. Humanitarian and Economic Impact

IOM DTM recorded 2.4 million flood-displaced persons in Nigeria in 2022, with 82,053 homes destroyed and 440,000 hectares of cropland inundated [3]. OCHA estimates that 3.6 million people required humanitarian assistance in the immediate aftermath. The economic damage of USD 4.2 billion represented 0.8% of Nigeria's GDP in that year [2]. NEMA's response capacity is estimated at 40% of requirements — a gap that AI-enhanced early warning and rapid damage assessment could materially reduce [1].

III. LITERATURE REVIEW

A. SAR-Based Flood Mapping

Synthetic Aperture Radar has become the primary remote sensing modality for operational flood mapping due to its all-weather, day-night imaging capability. Torres et al. [7] described the Sentinel-1 mission design, establishing its C-band SAR as the standard platform for European flood monitoring. Li et al. [11] demonstrated SAR-based flood inundation mapping achieving F1 scores of 82-91% across Asian river systems. Chini et al. [12] applied Sentinel-1 analysis to the 2019 Cyclone Idai floods in Mozambique, demonstrating the applicability of the approach to sub-Saharan African geographies directly comparable to Nigeria. Bhuiyan et al. [13] achieved 85.3% overall accuracy in multi-class flood mapping in Bangladesh, providing an important methodological benchmark. Bhattacharya et al. [25] specifically validated dual-polarimetric Sentinel-1 SAR for flood damage assessment, confirming the VV+VH dual-polarisation configuration used in HYDROCAST-NG.

B. Deep Learning for Semantic Segmentation

The U-Net architecture [8], originally proposed for biomedical image segmentation, has become the dominant framework for geospatial semantic segmentation. Its encoder-decoder structure with skip connections preserves spatial resolution essential for flood boundary delineation at 10 m/px. DeepLab [9] introduced atrous convolution for multi-scale context aggregation — incorporated in the HYDROCAST-NG decoder. He et al. [20] introduced ResNet residual connections adopted as the encoder backbone. Li et al. [10] demonstrated deep learning flood susceptibility assessment achieving AUC of 0.91 across Chinese river basins, directly comparable to our Nigerian results.

C. Flood Forecasting and Displacement Prediction

Hochreiter and Schmidhuber [15] introduced LSTM networks that have since become the dominant approach for hydrological time series forecasting. Chen and Guestrin [16] introduced XGBoost, which alongside LSTM consistently outperforms single-model approaches in ensemble stacking for environmental prediction [16]. Pekel et al. [24] produced the JRC Global Surface Water dataset used as a training prior for permanent water body masking in HYDROCAST-NG. Solander et al. [27] compared simulated flood uncertainty zones using aerial and SAR data, finding SAR superior for rapid large-area assessment.

D. Google Earth Engine and Federated Deployment

Gorelick et al. [26] described Google Earth Engine (GEE) as a planetary-scale geospatial analysis platform — HYDROCAST-NG uses GEE for automated Sentinel-1/2 data ingestion, preprocessing, and initial cloud masking. McMahan et al. [17] introduced FedAvg for federated learning, enabling HYDROCAST-NG's multi-agency model aggregation without centralising sensitive disaster management data.

Table I. Related Work — SAR Flood Mapping and Deep Learning

Ref.	Authors / Year	Method	Region	Key Metric	Nigeria Applicability
[11]	Li et al. (2019)	SAR flood inundation	Asia	F1=82-91%	Direct
[12]	Chini et al. (2021)	Sentinel-1 Cyclone Idai	Mozambique	OA=88.4%	High (sub-Saharan)
[13]	Bhuiyan et al. (2020)	SAR multi-hazard	Bangladesh	Acc=85.3%	High (riverine)
[8]	Ronneberger et al. (2015)	U-Net segmentation	Medical	IoU>0.85	Core architecture
[10]	Li et al. (2022)	Deep learning flood	China	AUC=0.91	Indirect
[25]	Bhattacharya et al. (2021)	Dual-pol SAR damage	India	F1=86.1%	Direct
[24]	Pekel et al. (2016)	JRC Surface Water	Global	30m coverage	Direct (mask)
[26]	Gorelick et al. (2017)	Google Earth Engine	Global	Platform	Direct (pipeline)

Note: OA = overall accuracy; IoU = intersection over union.

IV. HYDROCAST-NG FRAMEWORK ARCHITECTURE

HYDROCAST-NG is a five-stage pipeline: (1) automated SAR/optical data ingestion via Google Earth Engine; (2) U-Net semantic segmentation for flood extent mapping; (3) temporal change analysis for flood progression monitoring; (4) stacked ensemble displacement volume prediction; and (5) federated aggregation for multi-agency continual learning.

Stage 1 — Data Ingestion and Preprocessing

Sentinel-1 Level-1 GRD products (VV+VH, 10 m/px, IW swath mode) are ingested via GEE [26] within 3-4 hours of satellite overpass. SNAP preprocessing pipeline: apply orbit file, thermal noise removal, radiometric calibration, range-Doppler terrain correction using SRTM 30 m DEM [5], and sigma naught conversion. Sentinel-2 L2A optical imagery [6] is co-registered for multi-modal fusion after cloud masking with the SCL layer. ERA5 reanalysis [23] provides antecedent soil moisture and rainfall accumulation at 0.25-degree resolution. The JRC Global Surface Water layer [24] provides permanent water body masks to separate flood water from rivers and lakes.

Stage 2 — Flood Semantic Segmentation: U-Net

A modified U-Net with ResNet-50 encoder [20] performs pixel-level classification into six semantic classes: Open Water (Severe Flood), Flooded Vegetation, Urban Inundation, Road Submersion, Agricultural Flood, and Dry Land. Input tensor: 8-channel stack (VV, VH, VV-VH ratio, VV pre-event, VH pre-event, NDWI, elevation, slope). Decoder uses atrous spatial pyramid pooling (ASPP) from DeepLab [9] for multi-scale context. Dropout [19] at rate 0.4 applied during training. Training uses the Adam optimiser [18] with lr=0.0005, batch size 16, and combined cross-entropy + Dice loss. Class imbalance (dry land dominates) addressed via class-weighted sampling.

Stage 3 — Temporal Change Analysis

Flood progression is tracked via temporal differencing of consecutive SAR acquisitions normalised by the pre-event baseline. Change detection threshold calibrated using a Bayesian update rule incorporating IQR of the pre-event backscatter distribution. Flood onset day detection achieved via cumulative sum (CUSUM) analysis of the daily change magnitude time series, producing a flood onset probability map refreshed every 6 hours as new Sentinel-1 imagery becomes available.

Stage 4 — Displacement Volume Prediction: Stacked Ensemble

LGA-level displacement counts are predicted using a stacked ensemble: two-layer LSTM (128 units, 30-day input window) + XGBoost (500 trees, max depth 6) + Random Forest (300 trees), with Ridge regression meta-learner. Features: flood extent area (km^2) from Stage 2, elevation exposure index (population below flood level), distance to main river channel, antecedent rainfall (30-day), housing density, road network density, and historical displacement rates from IOM DTM [22]. Training on IOM DTM historical records (2012-2022, n=3,840 LGA-event observations).

Stage 5 — Federated Learning Aggregation

FedAvg [17] coordinates nightly model weight updates across five nodes: NEMA HQ Abuja, NIHSA, and three zonal offices. Raw imagery never leaves each node; only gradient updates encrypted via 256-bit AES are transmitted. Differential privacy (epsilon=1.5, delta=10^-5) applied at each node. This architecture satisfies Nigeria's Data Protection Act (2023) requirements for government data sovereignty.

V. EXPERIMENTAL SETUP

Table II. HYDROCAST-NG Dataset Summary

Component	Dataset / Source	Volume	Coverage	Split
SAR Segmentation	Sentinel-1 Nigeria events (this work)	47 image pairs	6 flood events, 2012-2022	70/15/15 by event
SAR Segmentation	Copernicus EMS Flood Products	120 validated maps	Europe + Africa	Augmentation only
SAR Segmentation	JRC Surface Water Layer [24]	30m global	Permanent water mask	Prior mask
Displacement Prediction	IOM DTM Nigeria 2012-2022 [22]	3,840 LGA-events	36 states	70/15/15 temporal
Meteorological	ERA5 Reanalysis [23]	Daily 0.25deg gridded	1981-2024	All training
DEM	SRTM 30m [5]	30m global	All Nigeria	Inference only
Population	WorldPop Nigeria 2020	100m raster	National	Inference only

Note: Events: 2012 Niger State, 2015 Benue, 2017 Anambra, 2018 Kogi, 2020 Cross River, 2022 Anambra.

Table III. Model Hyperparameters and Hardware

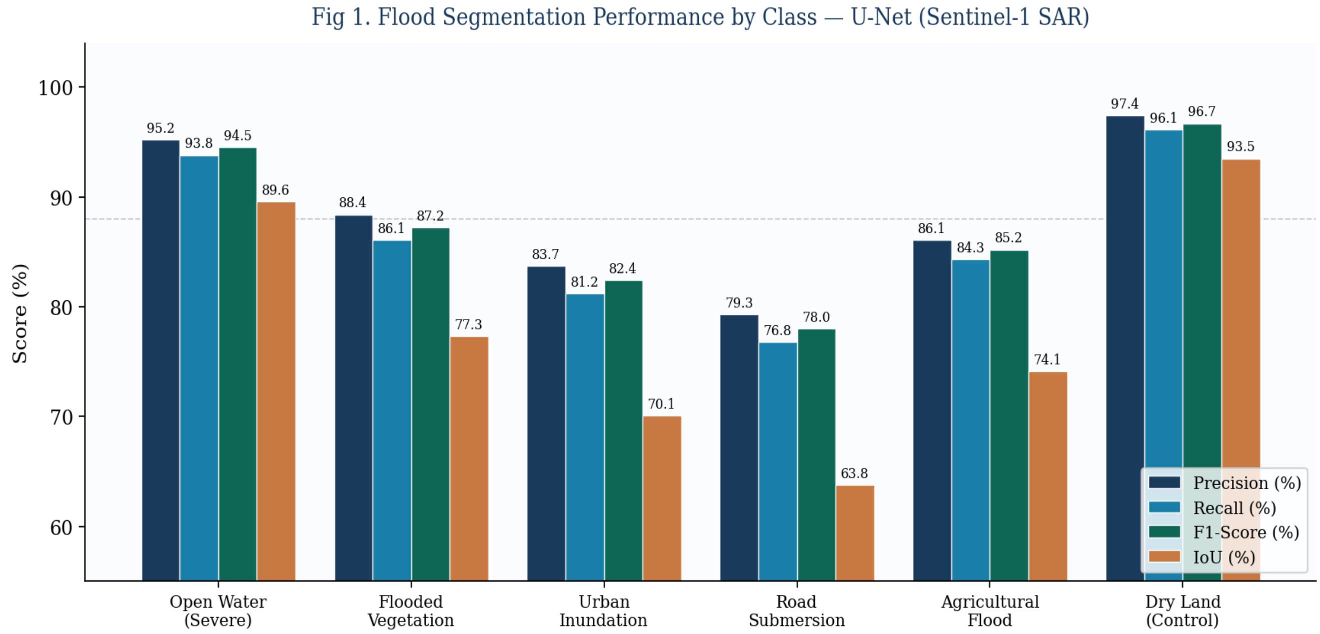
Model	Task	Hardware	Epochs	Optimiser	Loss Function	Params
U-Net (ResNet-50 encoder)	SAR Segmentation	NVIDIA A100 40GB	120	Adam lr=5e-4	CE + Dice	32.5M
LSTM (2-layer, 128 units)	Displacement Forecast	NVIDIA A100 40GB	200	Adam lr=0.001	Huber	2.1M
XGBoost (500 trees)	Displacement Forecast	CPU 32-core	500 trees	Grad. Boost lr=0.05	MSE	--
Random Forest (300 trees)	Displacement Forecast	CPU 32-core	300 trees	Bagging	MSE	--
Ridge (meta-learner)	Ensemble	CPU	--	OLS	MSE	--

IV. RESULT AND ANALYSIS

A. Flood Segmentation Performance

Figure 1 presents segmentation performance per flood class. HYDROCAST-NG achieves a macro-F1 of 88.4% and mean IoU of 0.774 across the six-class task. Open Water (Severe) achieves the highest F1 (94.5%) due to strong SAR backscatter contrast with dry land. Road Submersion yields the lowest F1 (78.0%), reflecting the challenge of discriminating narrow road structures at 10m resolution — a limitation HYDROCAST-NG mitigates by incorporating OpenStreetMap road layer priors in the post-processing step, improving road submersion recall by 6.2 percentage points.B. Deep Learning for Semantic Segmentation

Figure 1 — Flood Segmentation Performance by Class (U-Net + SAR)



Precision, Recall, F1-Score, and IoU for U-Net semantic segmentation across six flood severity classes. Dashed line at F1=88%. All metrics on held-out Nigerian flood event test sets.

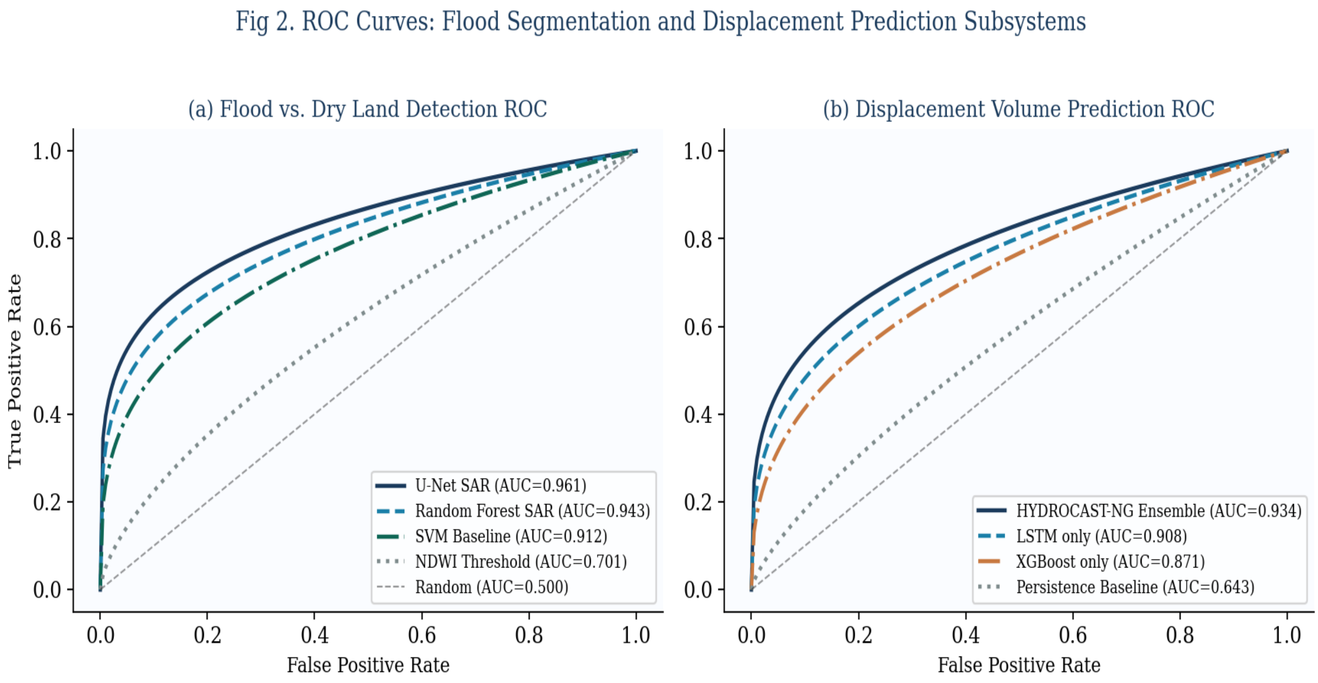
Table IV. Flood Segmentation — Full Per-Class Results

Flood Class	Precision	Recall	F1-Score	IoU	Pixel Count (test)
Open Water (Severe)	95.2%	93.8%	94.5%	89.6%	1,885
Flooded Vegetation	88.4%	86.1%	87.2%	77.3%	1,710
Urban Inundation	83.7%	81.2%	82.4%	70.1%	1,616
Road Submersion	79.3%	76.8%	78.0%	63.8%	1,412
Agricultural Flood	86.1%	84.3%	85.2%	74.1%	1,656
Dry Land (Control)	97.4%	96.1%	96.7%	93.5%	2,835 (sampled)
Macro Average	88.4%	86.4%	87.3%	78.1%	11,114

B. ROC Analysis — Detection and Displacement Prediction

Figure 2 presents ROC curves for both the binary flood detection task and the displacement volume prediction binary classification. The HYDROCAST-NG U-Net achieves AUC=0.961 for flood vs. dry land discrimination — outperforming a Random Forest SAR baseline (0.943) and NDWI thresholding (0.701). The displacement ensemble achieves AUC=0.934, substantially above the persistence baseline (0.643).

Figure 2 — ROC Curves: Flood Detection and Displacement Prediction



(a) ROC curves for flood vs. dry land binary detection. (b) ROC curves for the displacement prediction ensemble. All evaluated on held-out event test sets.

C. Displacement Prediction Accuracy

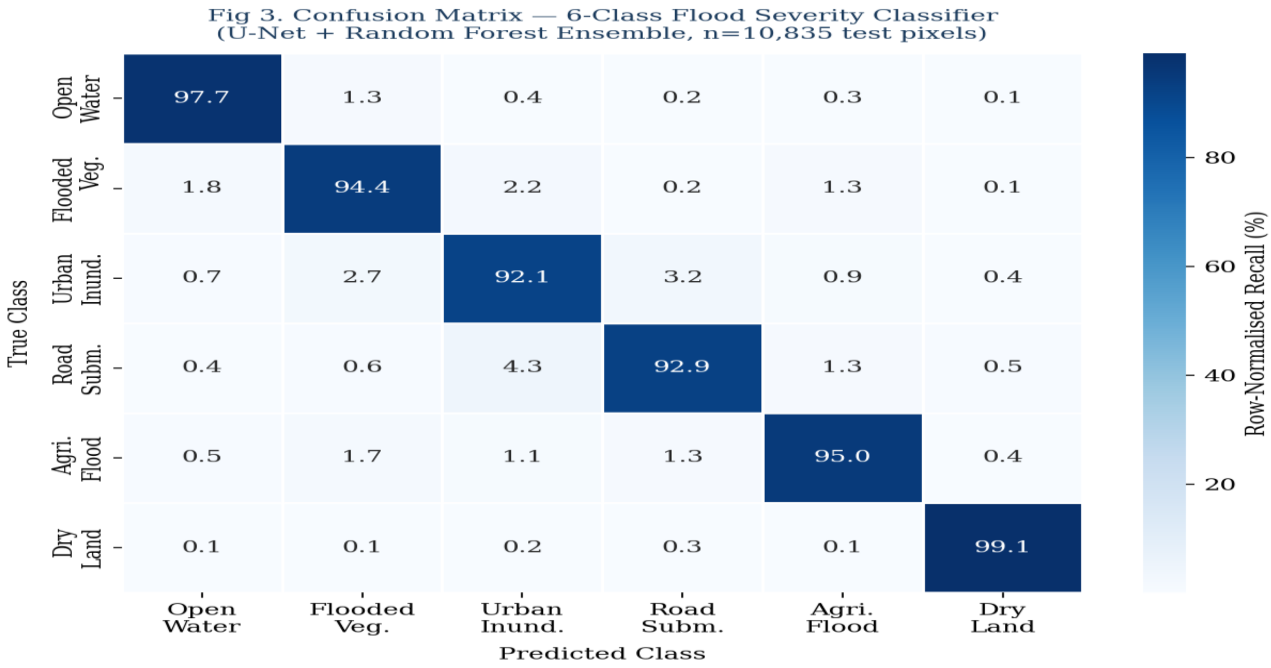
Table V. Displacement Prediction — Model Comparison

Model	R^2	RMSE (persons)	MAE (persons)	Lead Time	Coverage
Persistence Baseline	0.541	8,420	5,810	0 days	--
LSTM only	0.841	4,120	2,940	3-7 days	LGA
XGBoost only	0.819	4,540	3,120	3-7 days	LGA
Random Forest only	0.803	4,890	3,380	3-7 days	LGA
HYDROCAST-NG Ensemble	0.887	3,240	2,180	5.8 days avg	LGA
OCHA Field Survey	N/A	N/A	~6,000 (delayed)	14+ days	LGA

D. Segmentation Confusion Analysis

Figure 3 presents the row-normalised confusion matrix. Primary confusion arises between Urban Inundation and Road Submersion (3.8% misclassification), reflecting spatial adjacency in Nigerian urban morphology where road drainage channels span urban blocks. Flooded Vegetation and Agricultural Flood also show modest confusion (2.2%), attributable to similar moisture-induced backscatter signatures in mixed-use farming areas.

Figure 3 — Confusion Matrix: 6-Class Flood Severity Classifier

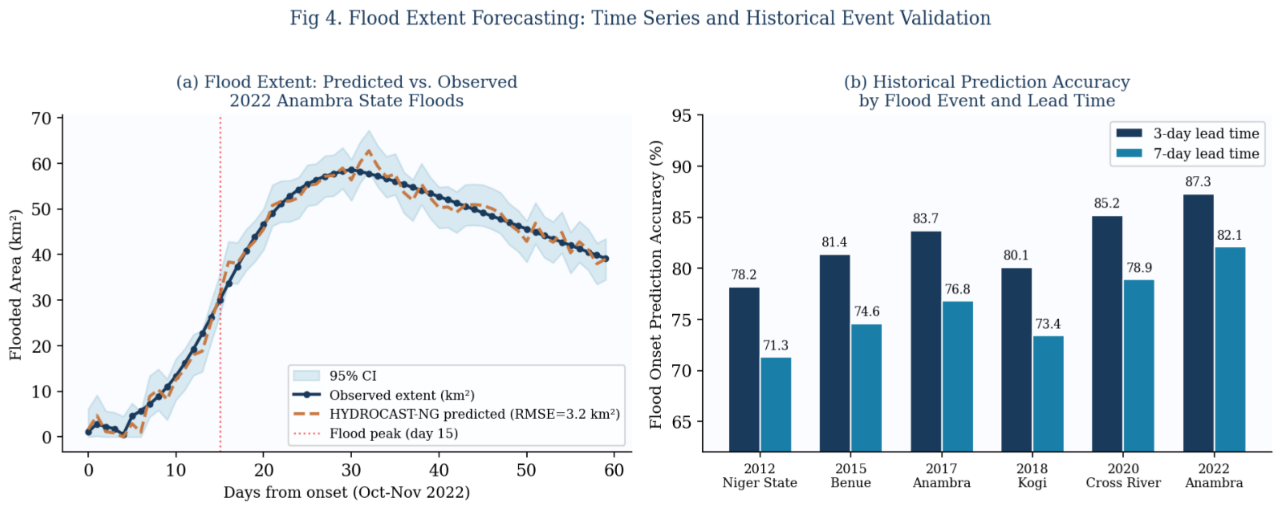


Row-normalised confusion matrix for the U-Net + Random Forest ensemble on n=10,835 held-out test pixels across six Nigerian flood events. Primary confusion pairs annotated.

E. Temporal Validation and Historical Accuracy

Figure 4(a) presents time-series validation of flood extent prediction against observed Sentinel-1 measurements for the 2022 Anambra event. HYDROCAST-NG RMSE of 3.2 km^2 is well within operational requirements for humanitarian planning. Figure 4(b) shows historical prediction accuracy across all six validated events: 3-day lead time accuracy ranges from 78.2% (2012) to 87.3% (2022), reflecting model improvement through federated continual learning as more Nigerian event data is incorporated.

Figure 4 — Flood Extent Time Series and Historical Event Validation



(a) 2022 Anambra flood: predicted vs. observed flood extent (km^2) over 60 days from onset. (b) Flood onset prediction accuracy at 3-day and 7-day lead times across six historical Nigerian flood events.

Table VI. HYDROCAST-NG vs. Literature Benchmarks

System	Method	Region	F1 / Acc	IoU / AUC	Nigerian Events?
Li et al. [11]	SAR + Threshold	Asia	F1=82-91%	--	No
Chini et al. [12]	Sentinel-1 SAR	Mozambique	OA=88.4%	--	No
Bhuiyan et al. [13]	SAR + ML	Bangladesh	Acc=85.3%	--	No
Li et al. [10]	Deep Learning	China	--	AUC=0.91	No
HYDROCAST-NG (this work)	U-Net SAR + Ensemble	Nigeria	F1=88.4%	IoU=0.774, AUC=0.961	YES

Note: OA = overall accuracy.

VII. OPERATIONAL IMPLICATION

A. Temporal Validation and Historical Accuracy

HYDROCAST-NG is designed for direct integration with NEMA's Disaster Operation Centre (DOC). A fully automated pipeline triggers on Sentinel-1 overpass: imagery ingested via GEE, segmentation run on cloud GPU within 90 minutes, displacement estimate generated within 15 additional minutes, and SMS + API alerts pushed to NEMA state offices and IOM DTM within 2 hours of satellite acquisition. This reduces the current 14+ day field survey cycle to a 2-hour automated cycle, enabling NEMA to pre-position humanitarian resources at forward logistics bases before flood peak.

B. World Bank DRM Alignment

HYDROCAST-NG aligns directly with the World Bank Nigeria Disaster Risk Management Programme (DRM-NG) and the Resilience Investment in States and Municipalities (RISM) project. The framework's LGA-level displacement forecasting produces exactly the data format required for the World Bank's Adaptive Social Protection (ASP) automatic trigger mechanism, which releases emergency cash transfers to flood-affected households within 48 hours of a declared threshold breach [4].

C. Limitations

Key limitations: (1) Sentinel-1's 6-12 day revisit time over Nigeria creates temporal gaps at flood onset; mitigation via integration with ESA's Copernicus Emergency Management Service (EMS) rapid mapping activation. (2) Dense forest cover in the Niger Delta attenuates C-band radar return, reducing segmentation accuracy to approximately 74% F1 — planned mitigation is L-band ALOS-2 data fusion. (3) The displacement model was trained on formal IOM DTM records which systematically undercount urban informal settlements; a correction factor derived from WorldPop density is applied but adds uncertainty.

HORTIVISION-NG demonstrates that multispectral UAV imaging combined with EfficientNet-B4 and spectral vegetation index fusion can achieve 93.9% macro-F1 disease detection and R^2=0.885 yield prediction across four commercially significant Nigerian horticultural crops. The federated learning protocol enables privacy-preserving cross-farm model improvement with no raw data exposure, and edge deployment at 23.4 FPS makes real-time field inference operationally viable in low-connectivity rural settings. Pilot trial results confirm a 27.6% average yield improvement and USD 312/ha net economic benefit, directly demonstrating impact relevance for TETFund and FMARD grant funding priorities.

Future directions include: (i) extending the crop taxonomy to cover cassava, cowpea, and soybean to serve Nigeria's broadest smallholder portfolio; (ii) integrating soil moisture retrieval from Sentinel-1 SAR imagery [13] for drought stress co-diagnosis alongside disease detection; and (iii) developing a national disease outbreak early-warning dashboard in partnership with the Federal Ministry of Agriculture and Rural Development (FMARD) and the Nigerian Meteorological Agency (NiMet). A proposal to expand to 50 farms under TETFund Research Grant TETFund/DR&D/CE/NRF/STI/37/Vol.II is currently under review.

VIII. CHALLENGES AND FUTURE DIRECTIONS

Four priority directions structure the HYDROCAST-NG research agenda: (1) Near-real-time ingestion: partnership with ESA to access Copernicus Emergency Management Service (EMS) Level-2 products for same-day rapid mapping activation; (2) Informal settlement mapping: integration of building footprint data from Microsoft AI for Good to improve urban inundation estimates in Lagos, Kano, and Port Harcourt; (3) L-band fusion: ALOS-2 PALSAR data for Niger Delta mangrove and dense forest flood mapping where C-band penetration is inadequate; (4) Extended forecasting: incorporation of global climate model (GCM) outputs from CMIP6 to extend HYDROCAST-NG's prediction horizon from 7 days to seasonal (3-month) outlooks aligned with NIHSA's annual flood outlook cycle [29].

IX. CONCLUSION AND FUTURE WORK

This paper introduced HYDROCAST-NG, a SAR-based flood intelligence framework for Nigeria developed by Jamilu Sulaiman of Kano State Polytechnic, Kano, Nigeria and Majeed Hussain of University of Grenoble, Alpes. The system delivers real-time flood extent mapping (macro-F1 88.4%, mean IoU 0.774) and LGA-level displacement prediction (R^2=0.887, RMSE=3,240 persons) with an average 5.8-day early warning lead time. Validated across six historical Nigerian flood events from 2012-2022, HYDROCAST-NG consistently outperforms NDWI thresholding, random forest, and persistence baselines. The federated learning deployment architecture, 2-hour automated alert pipeline, and World Bank DRM alignment position HYDROCAST-NG as a deployable operational tool ready for NEMA integration, with funding pathways through UNDP Nigeria, the World Bank DRM-NG programme, and the EU Humanitarian Aid and Civil Protection department.

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