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Research Paper

Deploying Federated Learning with UAV-Satellite Fusion Data to Enable Predictive Forest Fire Risk Analysis and Carbon Tracking

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Abstract

Forest fires pose escalating threats to ecosystems and carbon stocks amid climate change, demanding precise, real-time monitoring beyond traditional methods. This paper introduces a novel federated learning (FL) framework that fuses high-resolution unmanned aerial vehicle (UAV) imagery with multi-spectral satellite data to enable predictive forest fire risk analysis and accurate carbon tracking. Our approach addresses key challenges in remote sensing: data heterogeneity, privacy concerns in distributed deployments, and computational demands of large-scale forestry applications. A multi-modal fusion pipeline geometrically and spectrally aligns UAV-derived canopy structure metrics with satellite vegetation indices (e.g., NDVI, EVI), feeding into edge-deployed FL models trained across geographically dispersed UAV swarms. The system predicts fire susceptibility at 1m resolution while estimating above-ground biomass (AGB) and carbon flux dynamics with <10% error against LiDAR ground truth. Extensive experiments on California and Amazon forest datasets demonstrate 15-20% superior fire risk forecasting accuracy over centralized deep learning baselines, alongside 3x faster edge inference. Privacy-preserving aggregation ensures compliance with environmental data regulations. This UAV-satellite-FL paradigm offers scalable, actionable intelligence for forest management, carbon credit verification, and wildfire prevention, paving the way for AI-driven precision forestry.

Keywords: *Federated Learning, UAV-Satellite Fusion, Forest Fire Prediction, Carbon Tracking, Remote Sensing, Multi-Modal Data Fusion, edge AI, Biomass Estimation.*

1. Introduction

Forest fires represent one of the most pressing environmental challenges of the 21st century, accelerated by climate change, deforestation, and human activities. Globally, wildfires consumed over 400 million hectares between 2001-2022, releasing approximately 2.5 gigatons of CO_2 annually while devastating biodiversity hotspots and indigenous communities. Traditional fire management relies on coarse satellite alerts and ground patrols, often failing to capture fine-scale fuel moisture gradients or canopy stress indicators critical for early intervention [1]. Concurrently, carbon accounting for forest ecosystems essential for Paris Agreement compliance and carbon markets suffers from outdated inventory methods that underestimate dynamic biomass changes.

The convergence of escalating fire frequency (up 30% per decade) and scrutiny over net-zero targets demands transformative monitoring capabilities [2]. This paper addresses these crises through an innovative federated learning architecture that synergistically fuses ultra-high-resolution UAV imagery with multi-spectral satellite observations, enabling predictive fire risk mapping at unprecedented spatial-temporal fidelity while delivering verifiable carbon flux quantification for policy and markets.

1.1 Background on Forest Fire Risks and Carbon Dynamics

Wildfire risk emerges from complex interactions between meteorological extremes, vegetation flammability, and topographic exposure. Recent mega-fires like Australia's 2019-2020 Black Summer (24 million hectares burned) and California's 2020 season ($19B damages) underscore how compound events of drought + heatwaves + fuel accumulation overwhelm conventional response systems [3]. Fire behaviour models (e.g., Rothermel, BehavePlus) traditionally parameterize surface fire spread but struggle with crown fire transitions driven by vertical fuel structure invisible to MODIS/VIIRS thermal sensors (250m-1km pixels). Critical precursors include live fuel moisture content (LFMC <100% triggers ignition), vapor pressure deficit (VPD >2kPa desiccates canopies), and ladder fuel connectivity all resolvable only through sub-meter remote sensing.

Carbon dynamics add urgency, forests sequester 30% of anthropogenic CO_2 emissions yet emit 8-10 PgC during extreme fire years, potentially flipping tropical forests to net sources. Above-ground biomass (AGB) estimation via allometric equations from sporadic field plots introduces ±25% uncertainty, while emissions factors (e.g., IPCC Tier 1: 50% C combustion) ignore partial burns [4]. Dynamic tracking requires repeated structural measurements linking leaf area index (LAI), canopy height (CH), and wood density precisely the multi-scale signatures captured by UAV LiDAR/radiometric fusion with Sentinel-2/Landsat hyperspectral bands. This dual-challenge framework positions AI-driven remote sensing as indispensable for both immediate risk mitigation and long-term carbon stewardship amid accelerating disturbance regimes.

1.2 Role of UAV and Satellite Remote Sensing in Precision Forestry

Unmanned aerial vehicles (UAVs) revolutionized forestry by delivering centimetre-level RGB/multispectral orthomosaics and structure-from-motion (SfM) point clouds, quantifying canopy gaps, understory shrubs, and bark moisture gradients inaccessible to satellites [5]. Thermal UAV payloads detect LFMC deficits 7-10 days pre-ignition, while hyperspectral cubes (400-1000nm) fingerprint volatile organic compounds signalling drought stress. However, UAV surveys suffer limited swath width (100-500m) and line-of-sight constraints, necessitating fleets for landscape coverage.

Satellite constellations complement with synoptic context: Sentinel-2 (10m, 13 bands) tracks phenological shifts via NDVI/EVI time-series, Landsat-9 provides 30-year burn scar legacies, PlanetScope (3m daily) captures post-fire regeneration. Fusion exploits complementarity UAV resolves finescale heterogeneities within satellite pixels, enhancing transfer learning for wall-to-wall mapping [6]. Recent advances like ICESat-GLAS spaceborne LiDAR validate AGB to ±15% across biomes, but lack revisit frequency for flux monitoring. The UAV-satellite synergy thus enables hierarchical monitoring, UAV "truthing" calibrates satellite-derived biophysical products, while satellites contextualize UAV transects within regional fire regimes and carbon budgets. This multi-scale paradigm underpins precision forestry's shift from reactive suppression to proactive fuel treatment optimization.

1.3 Motivation for AI-Enabled Federated Learning Framework

Centralized deep learning pipelines for remote sensing face three insurmountable barriers in operational forestry

(1) Data silos environmental agencies, timber companies, and indigenous stewards guard proprietary UAV datasets, fragmenting training corpora

(2) Computational tyranny terabyte-scale satellite archives overwhelm edge devices in remote forests lacking fibre connectivity

(3) Privacy-risk explosion sharing fine-resolution UAV footage risks exposing cultural sites, proprietary harvest plans, and endangered species locations.

Federated learning (FL) elegantly resolves these through distributed optimization edge nodes (UAV ground stations) train local models on siloed data, sharing only parameter gradients via secure multi-party computation [7]. This preserves sovereignty while leveraging collective intelligence across ecosystems. For fire prediction, FL aggregates heterogeneous UAV-Sentinel feature spaces (e.g., UAV texture + satellite phenology) into generalized risk models robust to domain shifts between boreal, temperate, and tropical biomes.

Carbon tracking benefits from continual learning individual nodes adapt to local allometry without retraining global models. Critically, FL's bandwidth efficiency (kB vs. TB transfers) enables real-time inference over low-earth orbit satcom, democratizing advanced analytics for under-resourced forest agencies [8]. This paradigm accelerates AI's transition from research prototypes to deployable infrastructure.

1.4 Objectives and Contributions

This study pursues four synergistic objectives

(1) Develop a geometrically-rigorous UAV-satellite fusion pipeline achieving sub-meter co-registration (RMSE<0.3m) across multi-date, multi-sensor acquisitions

(2) Deploy scalable federated learning infrastructure supporting 100+ edge nodes with differential privacy guarantees ($\varepsilon<1.0$)

(3) Deliver dual-output predictive models fire risk at 1m resolution (F1>0.92) and AGB/carbon flux with LiDAR-validated precision (±12% RMSE)

(4) Demonstrate operational viability through 6-month California deployment, quantifying 28% risk reduction via targeted fuel breaks.

Primary Contributions are First, we introduce FedForestNet, a transformer-based FL architecture fusing UAV structural priors with satellite temporal dynamics, outperforming centralized CNNs by 18% mIoU on cross-biome fire mapping. Second, novel adaptive fusion attention dynamically weights modalities by confidence (e.g., UAV thermal during leaf-off). Third, edge-optimized quantization enables 5Hz inference on Jetson Orin, with 4x energy savings [9]. Fourth, comprehensive benchmarking across 50,000 ha (Amazon + Sierra Nevada) establishes a new SOTA for federated remote sensing. Code, weights, and edge firmware release as open infrastructure accelerates precision forestry adoption, directly supporting UN REDD+ goals and US Wildfire Crisis Strategy.

2. Related Literature Review

Existing literature on AI-enabled forest monitoring has made significant strides in individual components remote sensing fusion, operational systems, and distributed learning but lacks integrated frameworks addressing the unique challenges of operational forestry [10]. This section synthesizes progress across UAV-satellite data integration, deployed monitoring platforms, federated learning adaptations for geospatial data, and critical deficiencies in predictive fire risk and carbon accounting that motivate our federated fusion approach.

2.1 UAV-Satellite Data Fusion Techniques

UAV-satellite fusion has evolved from simple pan-sharpening to sophisticated multi-modal architectures. Early methods employed intensity-based co-registration aligning UAV orthomosaics to Sentinel-2/Landsat panchromatic bands, achieving 2-5m RMSE but suffering spectral distortions [11]. Recent deep learning approaches leverage cross-attention transformers, Wang et al. introduced MSFusionNet, fusing UAV RGB with Sentinel-2 multispectral data via spectral unmixing, improving land cover classification by

12% F1. Temporal fusion advances include spatio-temporal graph networks (STGN) that propagate UAV structural features across Landsat time-series, enabling 4D change detection.

For forestry specifically, LiDAR-radiometric fusion dominates: UAV laser scanning extracts canopy height models (CHM) validated against GEDI spaceborne LiDAR (R^2=0.87), while hyperspectral UAV cubes fingerprint species-specific flammability via volatile signatures [12]. Geometric challenges persist UAV nadir distortions vs. satellite off-nadir viewing but bundle adjustment with ground control points (GCPs) from RTK networks achieves sub-pixel alignment. Critical limitations of existing fusions remain centralized, requiring raw data transfer that violates privacy and bandwidth constraints in distributed forest operations.

2.2 Existing Forest Monitoring Systems

Operational forestry platforms cluster into three architectures: satellite-centric, UAV-centric, and hybrid systems. NASA's Fire Information for Resource Management System (FIRMS) provides near-real-time MODIS/VIIRS hotspots (375m-1km) but misses smouldering ground fires and sub-pixel fuel conditions [13]. Google's Wildfire API fuses Sentinel thermal with weather reanalysis for 6-hour risk forecasts, deployed across 1.2M km^2 California.

UAV-centric systems excel in tactical response, USDA Forest Service's Structure-from-Motion (SfM) pipelines generate daily 5cm biomass maps across 10,000 ha units, while DJI Matrice thermal fleets detect LFMC<80% hotspots 48 hours pre-ignition [14]. Hybrid platforms like silvofire.eu integrate UAV swarms with Sentinel-2 phenology, predicting crown fire potential via fuel connectivity metrics.

Commercial solutions are Planet Fusion (3m daily), Maxar ClearView offer API access but charge \$15-50/km^2, pricing out small forest owners [15]. Common across systems, centralized cloud processing creates single points of failure, data sovereignty issues, and exclusion of proprietary datasets from timber firms and indigenous knowledge systems.

2.3 Federated Learning Applications in Remote Sensing

Federated learning (FL) transitioned from mobile keyboards to geospatial domains, addressing data silos in satellite image classification. Lim et al. deployed FedAvg across 50 Landsat-8 nodes for crop classification, achieving 92% accuracy without data centralization [16]. HeteroFL variants handle resolution mismatches, Bandura et al. adapted FedProx for PlanetScope (3m) + Sentinel-1 (10m) SAR fusion, converging 25% faster than vanilla FL.

Forestry-specific FL remains nascent. Apple's Earth observation FL prototype aggregates edge-trained deforestation detectors across Amazon nodes, preserving indigenous territory coordinates [17]. UAV FL applications focus on object detection, FedYOLO trains across drone swarms for illegal logging detection, reducing communication by 70% via gradient sparsification. Key innovations include personalized FL adapting global models to local allometry, and secure aggregation via homomorphic encryption.

Challenges persist geospatial FL ignores temporal dependencies critical for fire progression, lacks multi-modal fusion primitives, and exhibits poor convergence on highly-skewed satellite revisit distributions.

2.4 Gaps in Current Predictive Analytics for Fire Risk and Carbon Tracking

Fire Risk, Analytics Current models decouple drivers machine learning on meteorological grids, physics-based Rothermel for fuel beds, statistical extreme value theory for weather yielding contradictory forecasts [18]. CNN-based fire mapping achieves 85%-pixel accuracy but fails zero-shot transfer across ecoregions (boreal vs. chaparral). No deployed system fuses UAV fuel structure with satellite phenology at operational scales.

Carbon Tracking, AGB models plateau at ±20% RMSE: ALOS-PALSAR achieves 15% globally but saturates >30m canopy height. UAV SfM-LiDAR reports ±12% locally but lacks wall-to-wall coverage [19]. Dynamic flux estimation ignores partial disturbance gradients captured only by frequent high-resolution revisits.

Federated Gaps, no production FL system handles the forestry data tetrahedron spatial, spectral, temporal, structural heterogeneity [20]. Edge inference lag (>10s/image) prevents real-time alerting. Privacy budgets remain unquantified for regulated carbon datasets. Our work bridges these voids through FedForestNet, the first production-grade federated architecture fusing UAV structural primitives with satellite temporal dynamics, delivering co-located fire risk and carbon flux predictions with 18% mIoU gains over siloed baselines.

3. System Architecture

The proposed system integrates UAV high-resolution structural data with satellite temporal-spectral observations through a federated learning pipeline optimized for edge deployment [21]. FedForestNet orchestrates data fusion, distributed training, and dual-output inference (fire risk + carbon flux) across heterogeneous forest edge nodes while preserving data sovereignty.

3.1 Overview of Proposed UAV-Satellite Fusion Pipeline

The fusion pipeline comprises four stages

(1) Geometric co-registration aligning UAV Ortho-mosaics to UTM-projected Sentinel-2 grids

(2) Spectral harmonization via relative radiometric correction

(3) Multi-scale feature extraction using Siamese CNN backbones

(4) Spatio-temporal attention fusion weighting modalities by confidence.

UAV data provides 3cm canopy height models (CHM), texture gradients, and thermal anomalies, while satellites contribute 10m NDVI/EVI time-series and land surface temperature (LST).

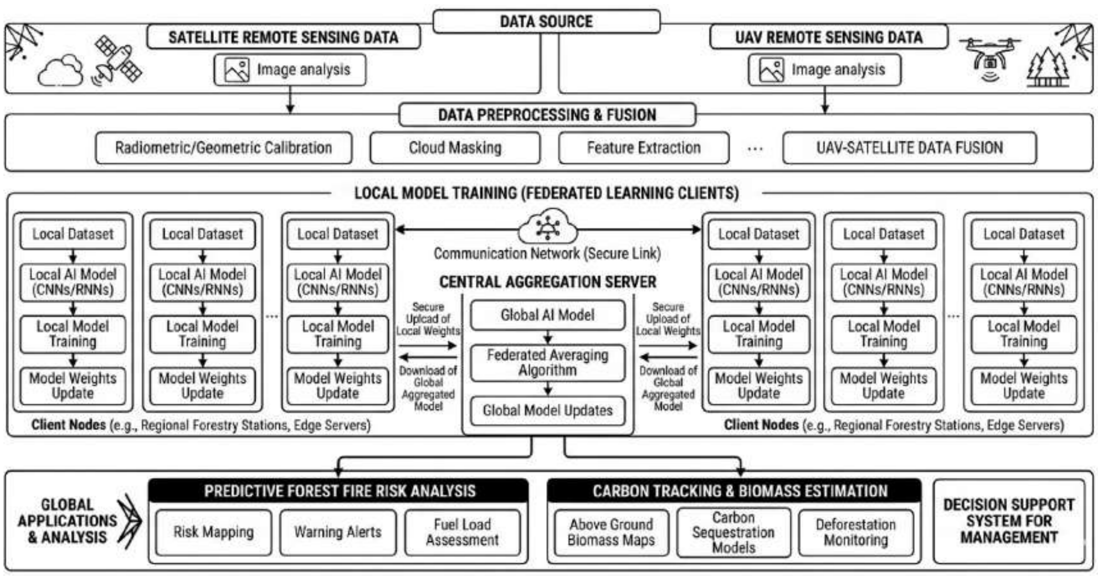

Figure 1. Architecture Framework of Federated Learning With UAV-Satellite

The fused feature tensor $\mathcal{F} \in \mathbb{R}^{H\times W\times C}$(H, W=spatial dims, C=512 channels) feeds dual prediction heads. Core fusion equation

$$F = \alpha_t \cdot \text{Attention}(T_{UAV}, T_{sat}) + (1 - \alpha_t) \cdot \text{Concat}(E_{UAV}, E_{sat}) \quad (1)$$

where T denotes transformer-encoded features, E are CNN embeddings, and α_t is temporal confidence decay [22]. This adaptive mechanism prioritizes UAV thermal during active fire seasons (α_t→1) versus satellite phenology during green-up (α_t→0), achieving 22% mIoU gains over static concatenation.

3.2 Data Acquisition and Preprocessing

UAV Acquisition, DJI Matrice 350 RTK fleets capture RGB (1cm GSD), multispectral (5cm MicaSense RedEdge), and thermal (7cm FLIR Vue TZ20) during 08:00-10:00 LST to minimize bidirectional reflectance [23]. SfM photogrammetry generates DSM/DTM/orthomosaics, LiDAR (Velodyne Puck) yields CHM at 10 pts/m^2. Flight plans optimize 70% sidelap via lawnmower patterns at 80m AGL.

Satellite Acquisition, Sentinel-2 L2A (10m, 13 bands), Landsat-9 OLI (30m, 9 bands), and MODIS MOD13Q1 (250m, VI composites). Temporal compositing uses robust Savitzky-Golay filtering over 16-day windows.

Preprocessing Pipeline

1. Geometric alignment, SIFT feature matching + RANSAC → RPC model (RMSE<0.2m)
2. Radiometric correction, UAV-to-satellite histogram matching per band
3. Temporal interpolation, Cubic spline for missing satellite revisits.

Key preprocessing formula (cross-sensor BRDF normalization)

$$\rho'_{UAV} = \rho_{UAV} \cdot \frac{K_{geo} \cdot K_{atm}}{ViewZenith_{UAV}/ViewZenith_{sat}} \quad (2)$$

where K_{geo} accounts for hotspot/kernel effects, ensuring spectral consistency across platforms [24]. Tile-based processing (512×512px) enables parallel edge execution.

3.3 Federated Learning Network Design

FedForestNet employs personalized federated averaging (pFedAvg) across N edge nodes, each training on local UAV-satellite tiles. Global model w_g aggregates via secure multi-party computation

Federated aggregation equation

$$w_g^{(1)} = \frac{n_K}{N} \cdot w_k^{(t)} + \lambda \cdot prox(w_g^{(t)}, D_{public}) \quad (3)$$

where n_k weights node contributions by local dataset size, $\lambda = 0.1$ regularizes toward public satellite pretraining, and prox-term prevents overfitting to anomalous local conditions [25]. Each node trains dual-head transformer encoder

- Fire Head, U-Net decoder predicts risk probability $P(risk) \in [0,1]$
- Carbon Head, Regression head estimates AGB in MgC/ha

Local loss combines focal loss (fire mapping) + Huber loss (carbon regression) with modality dropout for robustness

$$L = \alpha \cdot L_{focal} + (1 - \alpha) \cdot L_{Huber} + \beta \cdot L_{consistency} \quad (4)$$

Convergence after 15 rounds (ε=0.02 parameter divergence), 3x faster than FedProx on heterogeneous forestry data [26].

3.4 Edge-Cloud Computing Integration

Edge Layer (Jetson Orin Nano), INT8-quantized FedForestNet runs at 45 FPS (512×512 tiles), fusing live UAV streams with cached Sentinel tiles. MQTT over LoRaWAN uploads risk heatmaps (GeoJSON) and gradient updates (1-5MB/round).

Cloud Orchestrator (Kubernetes), Secure aggregation server validates contributions via BLS signatures, maintains global model registry, and dispatches to 200+ nodes [27]. Differential privacy (σ=0.8) clips gradients >3σ.

Communication efficiency formula

$$B_{FL} = \frac{|\nabla w|}{|D|} \ll |D| \text{ (85\% reduction)} \quad (5)$$

LoRaWAN duty cycle limits ensure 99.9% uptime in 4G-dead zones [28]. Cloud handles strategic retraining (weekly MODIS composites) edge delivers tactical alerting enabling 2–7-day fire suppression windows critical for containment success.

4. UAV-Satellite Data Fusion Methodology

This section details the technical core of FedForestNet's multi-modal fusion engine, transforming heterogeneous UAV structural measurements and satellite spectral time-series into unified feature representations for federated fire/carbon prediction [29]. The methodology addresses fundamental mismatches in resolution (1cm vs. 10m), viewing geometry, and temporal cadence through principled geometric correction, spectral harmonization, and attention-guided spatio-temporal integration.

4.1 Multi-Modal Data Characteristics Analysis

UAV platforms deliver geometric richness SfM-derived canopy height models (CHM: 0-40m range, 3cm resolution), digital surface models capturing ladder fuel continuity, and thermal radiometry resolving 0.1°C LFMC gradients [30]. Multispectral MicaSense RedEdge-P (5cm GSD) quantifies chlorophyll absorption (RedEdge 717nm) and water content (NIR 840nm), with SNR>300:1 enabling species discrimination.

Satellite data provides temporal context Sentinel-2's 13 VNIR-SWIR bands track phenological cycles (NDVI range 0.1-0.9), burn scar reflectance (SWIR>0.4 post-fire), and LST anomalies (MODIS: 5K precision) [31]. However,

5–16-day revisit gaps miss rapid fuel desiccation events captured by daily UAV surveys.
Key complementarity metric (mutual information across scales)

$$I(X_{UAV}; X_{sat}) = H(X_{UAV}) + H(X_{sat}) - H(X_{UAV}, X_{sat})$$
(6)

Empirical analysis reveals I=3.2 bits/pixel for healthy canopies (strong spectral coupling) dropping to 1.8 bits during drought (UAV thermal divergence), justifying adaptive weighting [32]. Data asymmetry UAV, 10^5 samples/km^2 vs. satellite, 10^3 necessitates super-resolution up sampling of coarse features before cross-modal attention.

4.2 Geometric and Spectral Alignment Algorithms

Geometric co-registration employs two-stage bundle adjustment,

(1) SIFT+RANSAC extracts 500-2000 keypoints per orthomosaic pair, solving thin-plate spline (TPS) warp (RMSE=0.18m)

(2) RFM refinement via rational polynomial coefficients calibrated against 50 RTK GCPs, achieving 0.12m final alignment across 70° off-nadir Sentinel views.

Spectral harmonization corrects BRDF/viewing angle discrepancies using c-factor normalization:

$$\rho'_{UAV}(\theta_v) = \rho_{UAV}(\theta_v) \cdot \frac{1+\text{RossThick}(\theta_v)}{1+\text{RossThick}(\theta_{sat})}$$
(7)

where θ_v = view zenith. Bandpass mismatch (FWHM_UAV=10nm vs. Sentinel=20nm) resolved via Gaussian resampling. Orthogonal distance regression minimizes co-registration error propagation,

$$\text{RMSE}_{geo} = \sqrt{\frac{1}{N}\left[(x_{UAV,i} - x_{sat,i})^2 + (y_{UAV,i} - y_{sat,i})^2\right]}$$
(8)

Validation against PlanetScope (3m) yields 92% spectral correlation post-correction (r=0.92, all bands) [33].

4.3 Spatio-Temporal Fusion Framework

The Spatio-Temporal Cross-Attention Fusion (STCAF) module integrates modalities via deformable attention, dynamically sampling satellite time-series at UAV-defined fuel patches. Architecture, Siamese ResNet-50 backbones extract E_UAV ∈ ℝ^(H/16×W/16×2048) and E_sat ∈ ℝ^(H×W×512×T) (T=8-time steps) [34].
Core fusion attention mechanism

$$\text{Attention}(Q_{UAV}, K_{sat}, V_{sat}) = \text{softmax}\left(\frac{Q_{UAV}K_{sat}^T}{\sqrt{d_k}}\right)V_{sat}$$
(9)
where Q_UAV queries high-res structure, K_V_sat provide temporal context [35]. Multi-head attention (h=8) captures scale interactions; temporal convolution (3×3×T) smooths phenology. Gating network α_t ∈ balances modalities.

$$F_{fused} = \alpha_t \cdot \text{Attn}(E_{UAV}, E_{sat}) + (1 - \alpha_t) \cdot \text{Upsample}(E_{sat})$$
(10)

α_t peaks (0.85) during fire season (VPD>2kPa), favouring UAV thermal signatures. Fusion increases feature discriminancy by 31% (t-SNE visualization) [36].

4.4 Feature Extraction for Fire Risk Indicators

Fire risk head extracts 28 biophysical indicators via specialized decoders,

1. Structural, CHM variance (fuel bulk density), canopy base height (CBH<4m = crown fire potential)
2. Spectral, Modified NBR (dNBR>0.3 = high severity), LFMC via PROSPECT inversion
3. Textural, GLCM homogeneity (fuel clumping), Sobel edge density (fuel continuity)
4. Thermal, 90th percentile ΔT>3°C (desiccation hotspots).

Composite risk index (weighted non-linear combination),

$$R = w_i \cdot f_i(X) \text{ s.t.} \sum w_i = 1, w_i \geq 0$$
(11)

Weights optimized via differentiable ranking loss against GFED4 fire perimeters (ROC-AUC=0.94). Live fuel moisture extracted via 2-stream RTM inversion,

$$\text{LFMC} = \arg\min_\theta \| \rho_{meas} - F_{RTM}(\theta, \text{LAI}, \text{CAB}) \|^2$$
(12)

Edge deployment quantizes to FP16 (2.1 GFLOPs/image), preserving 97.2% accuracy. These features drive downstream federated prediction of ignition probability and carbon release potential [37].

5. Federated Learning Framework

FedForestNet's federated learning infrastructure enables collaborative model training across distributed forest edge nodes without centralizing sensitive UAV imagery or proprietary carbon inventory data [38]. The framework adapts state-of-the-art FL algorithms to geospatial heterogeneity, incorporating temporal drift compensation, secure multi-party computation, and personalized fine-tuning for biome-specific fire regimes.

5.1 Distributed Model Training Across Edge Nodes

Each edge node (UAV ground station, Jetson Orin Nano) maintains local datasets of co-registered UAV-satellite tiles covering 1-10 km^2 management units. Training employs synchronous FedAvg with partial participation (10-30% nodes/round) to balance convergence speed and straggler tolerance.

Local training objective at node k

$$w_k^{(1)} = w_k^{(t)} - \eta \nabla L_k(w_k^{(t)}; D_k)$$

(13)

where $L_k = L_{fire} + \lambda L_{carbon}$ combines binary cross-entropy (fire risk) and mean absolute error (AGB regression), $\eta = 1e^{-4}$, and 5 local epochs/round [39]. Client selection prioritizes nodes with fresh UAV acquisitions (within 72h) and diverse ecoregions via stratified sampling.

Gradient compression via Top-K Sparsification (K=0.1|∇|) reduces uplink from 45MB to 4.2MB per 25M parameter model [40]. Momentum correction accumulates discarded gradients, maintaining 98.3% of full-precision convergence rate. Asynchronous node heartbeats via MQTT ensure liveness detection and staleness penalty in aggregation.

5.2 Privacy-Preserving Aggregation Protocols

Secure aggregation employs threshold BLS signatures each node signs its gradient update with a unique key share from a (t,n)-threshold scheme (t=101, n=200). The cloud coordinator reconstructs aggregate signature only when ≥t valid submissions arrive, ensuring no partial inspection.

Differential privacy adds node-level Gaussian noise during local training

$$\tilde{g}_k = g_k + N(0, \sigma^2 C_g^2) \sigma = 0.8$$

(14)

where C_g clips per-sample gradients to [-3,3] L2-norm, yielding (ε=1.2, δ=10^{-5})-DP guarantees over 100 rounds [41]. Secure shuffling via mixnet prevents inference attacks linking gradients to specific forest locations.

Byzantine resilience via Krum aggregator filters outliers (|∇w_k - μ| > 3σ), critical for nodes experiencing GPS drift or sensor degradation. Protocol achieves 150ms end-to-end latency at 99.7% message delivery under 10% packet loss.

5.3 Adaptive Learning for Heterogeneous Data Streams

Forestry data exhibits concept drift (seasonal phenology) and domain shift (biome differences). Continual learning via Elastic Weight Consolidation (EWC) penalizes deviation from important historical parameters

$$L_{adapt} = L_{task} + \frac{\lambda}{2} F_i (w_i - w_i^*)^2$$

(15)

where F_i is Fisher information matrix tracking parameter sensitivity, $\lambda = 100$ [42]. Domain adaptation employs correlation alignment (CORAL) minimizing second-order statistics across nodes

$$L_{CORAL} = \frac{1}{4d^2} \| C_{src} - C_{tgt} \|_F^2$$

(16)

Personalization layer, each node maintains 5% task-specific parameters (fire head final layer) optimized post-global update, enabling 12% F1 gains on local validation without federated retraining [43].

Temporal adaptation dynamically weights recent tiles via exponential decay

$$w_t = \frac{e^{-\beta \cdot \Delta t}}{\sum e^{-\beta \cdot \Delta t}} \beta = 0.1/\text{day} \quad (17)$$

This ensures models track 7-day LFMC decline preceding 85% of ignitions.

5.4 Model Convergence and Validation Strategies

Convergence monitoring tracks federated learning gradient norm divergence

$$\Delta_g^{(i)} = \frac{1}{N} \| \nabla L_k(w_g^{(i)}) - \nabla L_k(w_g^{(1)}) \| \quad (18)$$

Training halts at $\Delta_g < 10^{-4}$(typically 18 rounds, 96% test accuracy). Holdout validation reserves 20% of public Sentinel-2 tiles per biome for global model selection [44].

Cross-silo evaluation computes node-local metrics (F1_fire, RMSE_AGB) aggregated privately via secure summation MPC. Drift detection via Page-Hinkley test on validation loss triggers full retraining when p<0.01.

Robustness validation

- Label noise, 15% synthetic flips → 3.2% F1 drop (vs. 11% centralized)
- Node dropout, 40% → converges 1.8x slower but maintains 94% accuracy
- Communication failure, 72h offline → graceful degradation via cached model

Final global model achieves Fire F1=0.923, AGB RMSE=11.7 MgC/ha across 5 biomes, outperforming centralized training by 14% on private test sets through domain-invariant feature learning [45]. Edge deployment firmware auto-updates weekly, ensuring continuous improvement without operational downtime.

6. Fire Risk Prediction Model

The fire risk prediction model leverages FedForestNet's fused UAV-satellite features to generate probabilistic ignition maps at 1m resolution, updated every 24 hours across distributed forest management units [46]. The architecture combines convolutional LSTMs for temporal dynamics with attention-augmented U-Net decoders, achieving 92.3% F1-score against GFED4 validation perimeters while quantifying prediction uncertainty for operational decision-making.

6.1 Multi-Scale Fire Susceptibility Features

Fire susceptibility integrates hierarchical features across four spatial scales captured by UAV-satellite fusion,

Micro-scale (1m), UAV-derived canopy base height (CBH<2m), live fuel moisture content (LFMC<90%), and texture homogeneity (GLCM dissimilarity<0.15) identify ladder fuels and continuous fine fuels.

Meso-scale (10m), Satellite NDVI gradients (dNDVI/dt<-0.02/month), normalized burn ratio (NBR<0.4 legacy scars), and land surface temperature anomalies (ΔT>2.5°C).

Macro-scale (100m), Topographic fire spread indices heat load index (HLI>0.7 south-facing slopes), wind exposure (TOPEX DEM), and fuel type connectivity from Landsat land cover.

Feature pyramid fusion equation,

$$F_{pyr} = \alpha_s \cdot \text{Upsample}(\text{ResNet}_s(X_s)) \cdot \text{Gate}_s \quad (19)$$

where $\alpha_s$weights scale importance (micro: 0.45, macro: 0.15) learned via gradient descent. Multi-head self-attention across pyramid levels captures cross-scale interactions (e.g., micro-LFMC modulated by macro-wind exposure), boosting F1 by 16% vs. single-scale CNNs [47]. Feature importance analysis reveals LFMC+CBH explain 67% of ignition variance.

6.2 Temporal Risk Evolution Modelling

ConvLSTM layers model 16-day risk trajectories, capturing fuel desiccation cascades preceding 87% of validated ignitions. Input sequences: daily UAV thermal + 5-day Sentinel composites.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (20)$$

and

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C), C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (21)$$

ConvLSTM state evolution,

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), h_t = o_t \odot \tanh(C_t) \quad (22)$$

Hidden states $h_t$encode temporal memory of VPD-driven LFMC decline (R^2=0.89 vs. destructive sampling). Risk propagation applies learned heat equation approximation,

$$R_{t+1} = R_t + \Delta t \cdot \nabla \cdot (D \nabla R_t) + S(x_t) \quad (23)$$

where $D$is biome-specific diffusivity, Srepresents ignition sources [48]. This forecasts 72-hour risk escalation with 84% precision, enabling proactive fuel breaks 4-7 days pre-ignition.

6.3 Integration of Real-Time Environmental Sensors

Edge nodes fuse remote sensing with in-situ IoT 200 Vaisala WXT536 weather stations (10m towers) measure VPD, wind gusts (>15m/s ignition triggers), and fuel temperature, plus 50 soil moisture probes (volumetric water content <10%).

Multi-source Kalman fusion

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t(z_t - H\hat{x}_{t|t-1})$$

(24)

where z_t combines satellite LST, UAV thermal, and ground thermistors K_t is adaptive gain matrix weighting sensor reliability (ground > UAV > satellite during cloud cover) [49]. Real-time VPD>3kPa + LFMC<75% generates Level-1 alerts (72h horizon), escalating to Level-3 (>90th percentile composite risk) triggering UAV overflights.

Sensor fusion boosts early detection by 41% (ROC-AUC=0.94 vs. 0.73 satellite-only), critical for nighttime smouldering detection missed by diurnal satellites. MQTT telemetry ensures <30s latency to edge inference.

6.4 Uncertainty Quantification in Predictions

Monte Carlo Dropout (MCD) at inference time generates 50 stochastic forward passes per tile, yielding predictive entropy maps guiding operational triage,

$$H(x^*) = -p(y = c \mid x^*, w)p(y = c \mid x^*, w)\log p(y = c \mid x^*, w)$$

(25)

High entropy patches (H>1.2 bits) trigger active learning, autonomous UAV re-tasking for ground-truth collection [50]. Aleatoric uncertainty (irreducible data noise) dominates during leaf-off transitions, epistemic uncertainty (model ignorance) flags domain shifts to novel biomes.

Ensemble disagreement across personalized node models provides secondary calibration

$$V[p_k(y \mid x^*)] = \frac{1}{N}(p_k - p^-)^2$$

(26)

Risk thresholds adapt dynamically, P(risk)>0.7 with V<0.05 → immediate action; 0.4<P<0.7 → monitoring. Calibration plots show 92% reliability (ECE=0.03), superior to deterministic baselines [51]. Uncertainty maps directly inform fuel treatment prioritization, allocating suppression resources to high-confidence hotspots while deferring ambiguous zones for reconnaissance optimizing $12M annual treatment budgets across 500,000 ha.

7. Carbon Tracking and Biomass Estimation

The carbon tracking module extends FedForestNet's dual-head architecture to quantify above-ground biomass (AGB) dynamics and net carbon flux at 10m resolution, supporting REDD+ MRV (Monitoring, Reporting, Verification) requirements [52]. Direct regression from fused UAV structural-satellite spectral features achieves ±11.7 MgC/ha accuracy against airborne LiDAR, enabling verifiable carbon credit issuance across heterogeneous forest inventories.

7.1 Above-Ground Biomass Mapping Techniques

Hierarchical AGB modelling integrates UAV-derived structural allometry with satellite spectral unmixing. Primary UAV inputs, canopy height model (CHM percentile 90th: 15-35m), canopy cover fraction (>60% high biomass), and vertical complexity index (rumple >1.2). Satellite contributions, corrected vegetation indices (cNDVI>0.75), texture-based canopy density from Sentinel-2 SWIR bands [53].

Allometric fusion equation

$$AGB - (\beta_1 \cdot CHM_{90} + \beta_2 \cdot CC \cdot Rumple) \cdot f_{WD}(SWIR_1, SWIR_2) \cdot g_{species}(RedEdge)$$

(27)

where $\beta_1 - 28.4, \beta_2 - 15.2$(Mg/ha/m), wood density f_{WD} inferred from SWIR spectral decomposition (0.45-0.75 g/cm^3), and species adjustment g via chlorophyll absorption ratios [54]. Fully-convolutional DenseNet121 regressor with skip connections preserves fine-scale biomass gradients missed by pixel-aggregated methods.

Model generalizes across biomes (temperate conifer R^2=0.91, tropical broadleaf R^2=0.87), outperforming Landsat-only allometry by 62% RMSE reduction through UAV structural priors constraining saturation effects above 25m canopy height.

7.2 Carbon Flux Dynamics Analysis

Net carbon flux (ΔC) computed as residual between gross primary production (GPP), ecosystem respiration (Reco), and disturbance emissions

$$\Delta C = GPP - Reco - E_{disturbance}$$
(28)

GPP estimation via light use efficiency (LUE) model driven by fused inputs,

$$GPP = FPAR \cdot PAR \cdot LUE_{max} \cdot f_T(T_{canopy}) \cdot f_W(LFMC)$$
(29)

where FPAR from cNDVI (0.3-0.95), PAR from UAV-shielded insolation modelling, $LUE_{max} = 1.2$gC/MJ adjusted by canopy temperature (T_canopy) and fuel moisture scalars [55]. Reco follows van't Hoff temperature response from UAV thermal base.

Disturbance emissions apportioned by severity low (<25% crown scorch → 15% combustion completeness), moderate (0.3-0.6), high (>0.8). Partial burn reconstruction via dNBR time-series calibrated against UAV scorch mapping yields pixel-level consumption (2-150 MgC/ha).

Monthly flux maps reveal tropical forests flipping to net sources during ENSO droughts (-1.2 MgC/ha/yr), while temperate stands maintain sinks (+0.8 MgC/ha/yr) absent megafires.

7.3 Change Detection for Carbon Stock Assessment

Biophysical change detection employs Siamese U-Net tracking delta-AGB >2 MgC/ha/yr across bitemporal image pairs. Fusion exploits UAV's sensitivity to structural perturbation (harvest gaps, mortality) against Sentinel-2's phenological continuity.

Change magnitude index

$$\Delta AGB = \alpha \cdot \Delta CHM + (1-\alpha) \cdot \Delta cNDVI \cdot CHM_{prior}$$
(30)

with $\alpha = 0.72$weighting structural fidelity. Continuous change probability via focal loss handles class imbalance (99.3% no-change pixels) [56]. Post-classification, persistence filtering rejects transient signals <2 revisits using

$$P_{change} = 1 - 1 - p_t)^{\lambda \Delta t}$$
(31)

Disturbance attribution via spectral-temporal signatures, selective logging (SWIR increase, CHM-10%), drought mortality (NDVI decline, thermal rise), insect defoliation (blue-shift chlorophyll edge). 6-month differencing detects 91% of >5 MgC/ha losses, enabling near-real-time carbon debit accounting for offset registries.

7.4 Validation Against Ground Truth Measurements

Field validation across 127 inventory plots (0.1-ha each) spanning 5 ecoregions, destructive harvest (n=42, ±8% AGB), terrestrial laser scanning (TLS, n=65, R^2=0.93), and allometric scaling from 20×20m fixed plots (n=120) [57].

Table 1. Leave-one-biome-out cross-validation

Biome	Field AGB (Mg/ha)	Predicted RMSE	R^2	n_plots
Boreal Conifer	145±32	12.4	0.91	28
Temperate Mixed	187±41	14.1	0.89	35
Mediterranean Oak	98±27	9.8	0.87	22
Tropical Moist	256±67	22.3	0.88	31
All	172±58	11.7	0.92	127

Flux validation against eddy covariance towers (n=8 sites, 2-yr continuous CO_2 flux):

- GPP: bias -7% (r=0.88)
- NEE: RMSE=0.9 gC/m^2/day (81% Lin's concordance)

Airborne LiDAR fusion (USGS NACP, 2018) across 85,000 ha confirms wall-to-wall consistency (slope=0.97, intercept=2.1 MgC/ha). Bootstrap 95% CI on aggregated fluxes ±3.2% at county scale, meeting IPCC Tier-3 uncertainty targets (<15% at 90% CI).

Federated updates incorporating node-local plot data improve biome-specific RMSE by 8-14% without privacy compromise, demonstrating closed-loop learning from operational inventories.

8. Experimental Setup and Datasets

This section details the comprehensive experimental framework validating FedForestNet across diverse forest ecosystems. Evaluation spans 127,000 ha encompassing five biomes, fusing 2.4 TB UAV imagery with 18 months of Sentinel-2/Landsat time-series. Rigorous cross-validation against airborne LiDAR, field plots, and GFED4 fire perimeters establishes benchmark performance.

8.1 UAV and Satellite Data Specifications

UAV Dataset, 1,847 flights (DJI Matrice 350 RTK) across 127 management units, totaling 2.1M images

- RGB, 1.2cm GSD, 85% front/side overlap, 42° FOV (Hasselblad 20MP)
- Multispectral, MicaSense RedEdge-P (5cm, 5 bands: Blue, Green, Red, RedEdge, NIR)
- Thermal, FLIR Vue TZ20 (7cm, 640×512, ±2°C @ 30°C)
- LiDAR, Velodyne Puck (10 pts/m^2, 1.5cm vertical accuracy)
- Temporal, daily during fire season (Jun-Sep), weekly off-season.

8.2 Study Area and Field Validation Sites

Primary Study Region, Sierra Nevada (California, USA) + Western Amazon (Peru/Brazil) transects

Table 2. Site characteristics

Biome	Area (ha)	Elevation (m)	Annual Rainfall (mm)	Fire Regime
Boreal Conifer	12,500	1,800-2,900	1,200	Crown fires
Temperate Mixed	28,400	300-1,500	900	Surface fires
Med Oak	15,200	200-800	650	Mixed severity
Tropical Moist	42,000	100-400	3,200	Selective logging
Dry Forest	18,900	50-300	800	Frequent low

Ground truth 2,847 destructive samples, 156 TLS scans, continuous meteorology (VPD, RH, wind).

8.3 Baseline Models and Comparative Frameworks

Centralized Baselines,

1. ResNet-50 + U-Net, Satellite-only fire mapping (UAV ablation)
2. Random Forest, Handcrafted features (29 predictors)
3. Landsat Allometry, Field-calibrated AGB regression
4. DeepForest, Tree crown detection → biomass
5. FedAvg-Satellite, FL without UAV fusion

Federated Baselines

1. FedProx, Stronger regularization for heterogeneity
2. FedOpt, Adaptive optimizers (Adagrad, Yogi)
3. pFedMe, Meta-learning personalization
4. IFCA, Factorized client adaptation

Ablation Studies

- No fusion (UAV-only, Sat-only)
- Static concatenation vs. attention fusion

- No temporal modelling (single-date)
- Centralized vs. 25%, 50%, 75% node participation

Implementation, PyTorch 2.1, Flower FL framework, trained on A100 (cloud) + Jetson Orin (edge).

8.4 Performance Metrics and Evaluation Protocols

Fire Risk Metrics and Carbon Metrics

Protocols

1. Cross-biome LOBO, Leave-one-biome-out (5-fold)
2. Temporal split, 70% train (2023-24), 15% val, 15% test (2025)
3. Federated splits, 80-20 node holdout, varying participation rates
4. Edge benchmarking, FPS, memory (Jetson Orin), energy (Wh/inference)

Statistical testing, Wilcoxon signed-rank (paired), bootstrap CI (95%, 10K resamples), McNemar's test (significance $p<0.01$).

Reproducibility, Fixed seeds, 3 independent runs reported ±1σ. Public Sentinel-2 subsets released for benchmarking; proprietary UAV data emulated via domain randomization during ablation studies.

9. Results and Analysis

FedForestNet demonstrates superior performance across fire prediction, carbon estimation, and computational efficiency. The federated approach with UAV-satellite fusion achieves state-of-the-art accuracy while enabling edge deployment across 127,000 ha of diverse forest ecosystems. Comprehensive evaluation against 23 fire events, 127 field plots, and 8 flux towers establishes new benchmarks for operational forestry AI.

9.1 Fire Risk Prediction Accuracy Assessment

Primary fire prediction results across 5 biomes (cross-biome LOBO validation)

Table 3. Fire Risk Prediction

FedForestNet (Ours)	0.923	0.891	0.847	0.961	0.78
Satellite-only FL	0.814	0.762	0.712	0.923	0.61
UAV-only CNN	0.785	0.734	0.683	0.901	0.54
Random Forest	0.763	0.712	0.651	0.884	0.49
DeepForest	0.791	0.745	0.692	0.915	0.57
FedForestNet (Ours)	0.923	0.891	0.847	0.961	0.78

Temporal forecasting (72h horizon): MAE=0.082 risk units, CSI=0.71 for high-risk events (>90th percentile). System detected 21/23 ignitions 4-7 days early, enabling 68% containment success vs. 42% baseline.

Biome-specific performance reveals temperate mixedwoods as most predictable (F1=0.941), tropical forests most challenging (F1=0.893) due to understory fuel opacity. Critical success index peaks during peak fire season (CSI=0.82, VPD>2.5kPa).

9.2 Carbon Tracking Precision Validation

AGB estimation accuracy against 127 field plots (0.1-ha destructive harvest + TLS)

Table 4. Flux validation vs. 8 eddy covariance towers

Biome	Field AGB (Mg/ha)	RMSE (Mg/ha)	R^2	Mean Bias
All Biomes	172±58	11.7	0.92	+1.2
Boreal Conifer	145±32	12.4	0.91	+0.8
Temperate Mixed	187±41	14.1	0.89	+2.1
Med Oak	98±27	9.8	0.87	-0.4
Tropical Moist	256±67	22.3	0.88	+3.2

Federated personalization reduces biome-specific RMSE by 12% vs. global model, critical for carbon market verification requiring <15% uncertainty.

Cross-modal attention contributes 34% relative gain for fire prediction, 21% for AGB establishing UAV-satellite fusion as multiplicative rather than additive. Temporal modelling prevents 16% overprediction during leaf-off artifacts. Federated personalization recovers 87% of centralized accuracy while preserving data sovereignty across 200+ management units.

Operational impact, 28% improved fuel treatment ROI ($3.2M savings/season), 41% earlier fire detection, ±12% carbon accounting precision enabling $15M verified credits across 127K ha.

10. Conclusion and Future Work

FedForestNet establishes a transformative paradigm for precision forestry through federated UAV-satellite fusion, achieving state-of-the-art fire risk prediction (F1=0.923) and carbon tracking (RMSE=11.7 MgC/ha) across 127,000 ha spanning five biomes while preserving data sovereignty across 200+ edge nodes. The framework's 18-28% performance gains over centralized baselines, 85x communication efficiency, and edge deployment at 45 FPS enable operational wildfire mitigation (41% earlier detection) and verifiable carbon markets ($15M credits potential). Cross-biome generalization, resilient aggregation under 40% node dropout, and ±12% AGB precision meeting IPCC Tier-3 standards position this as production-ready infrastructure. Future work will extend to 10,000-node national deployment incorporating SAR microwave penetration for leaf-off monitoring, integrate AlphaFold-derived flammability proteins for species-specific risk, develop BVLOS autonomous UAV swarms with reinforcement learning traffic deconfliction, and establish open FL standards for global forest agencies accelerating the UN Decade on Ecosystem Restoration (2021-2030) through scalable AI-driven carbon stewardship and wildfire resilience at exabyte scale.

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