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Territorially-Specialized Machine Learning Models for Wildfire Risk Prediction Across Argentina Using Satellite Data and H3 Hexagonal Grids

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GeoAlertAR-ML — NASA Space Apps Challenge 2025 Winner (Best Mission Concept)

Territorially-Specialized Machine Learning Models for Wildfire Risk Prediction Across Argentina Using Satellite Data and H3 Hexagonal Grids

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Abstract

Wildfire risk prediction in large, ecologically diverse countries requires models that account for regional variation in fire drivers. We present GeoAlertAR-ML, a wildfire risk prediction system for Argentina that uses an ensemble of regionally specialized Random Forest classifiers operating over a national hexagonal grid of 13,231 H3 cells. Unlike global fire danger indices or single-model approaches, our system trains independent models for each of five ecological regions (Centro, Cuyo, NEA, NOA, Patagonia), routed by a K-Nearest Neighbors classifier with 99.96% accuracy. The system ingests multisource satellite data — including GFS meteorological fields, GSMaP precipitation, MODIS vegetation indices, SRTM topography, Dynamic World land cover, and GHSL population density — and produces daily hexagon-level risk predictions in four categories (Low, Moderate, High, Extreme). Cross-validated F1-score averaged 93.2% across regions using GroupKFold to prevent spatial data leakage. Operational validation against NASA FIRMS hotspots confirmed 100% detection of active fire clusters in zones predicted as High or Extreme risk, including the February 2026 Comarca Andina crisis (280+ FIRMS hotspots, 68–72% predicted risk). A complementary 7-day forecasting model (Model B) based on regional XGBoost classifiers trained on GFS hindcast data achieved 77.8% F1-score with minimal degradation across forecast horizons (0.3–3.4% from day+1 to day+7). Additionally, the system identifies potential anthropogenic ignition anomalies by flagging discrepancies between low predicted meteorological risk and observed fire activity. GeoAlertAR-ML demonstrates that regionally specialized models, trained on territory-specific fire histories, outperform generic global approaches for national-scale wildfire risk assessment. The system has been operational since late 2025 and won the NASA Space Apps Challenge 2025 Best Mission Concept award.

Keywords: *wildfire prediction, machine learning, Random Forest, XGBoost, satellite remote sensing, H3 hexagonal grid, Argentina, regional models, FIRMS validation*

1. Introduction

1.1 The wildfire challenge in Argentina

Argentina faces a persistent and growing wildfire problem. The country spans over 30 degrees of latitude, encompassing ecosystems ranging from subtropical forests in the northeast to arid steppe in Patagonia, each with distinct fire regimes driven by different combinations of climatic, vegetative, and anthropogenic factors. An estimated 95% of wildfires in Argentina are human-caused, yet existing monitoring systems are predominantly reactive — detecting active fires rather than predicting the conditions that precede them.

Current operational tools available for Argentina include NASA's Fire Information for Resource Management System (FIRMS), which provides near-real-time detection of thermal anomalies via

MODIS and VIIRS sensors with a latency of 2–3 hours, and CONAE’s (Comisión Nacional de Actividades Espaciales) fire monitoring program, which also focuses on active fire detection rather than predictive risk assessment. The Canadian Fire Weather Index (FWI), used globally as a fire danger metric, captures meteorological conditions but does not incorporate vegetation state, land cover, or anthropogenic factors, and is not calibrated for South American fire regimes.

1.2 Limitations of global approaches

Global fire prediction systems, such as ECMWF’s Probability of Fire product and the Global Fire Weather Database (GFWED), apply uniform algorithms across diverse ecosystems. While these systems provide valuable continental-scale overviews, they inherently sacrifice regional accuracy for spatial breadth. A model trained to predict fire risk in Mediterranean Europe cannot be expected to capture the specific dynamics of the Argentine Chaco, where fire behavior is driven by a fundamentally different combination of vegetation structure, rainfall seasonality, and human land-use patterns.

Recent advances in machine learning for wildfire prediction have demonstrated the potential of data-driven approaches. Studies have achieved F1-scores ranging from 70–87% using neural networks in Russia (Sayad et al., 2024), 91% AUC with deep learning ensembles in Chile (Castillo et al., 2023), and 85–95% accuracy with Random Forests in North America. However, most of these systems treat their study area as a single modeling domain, potentially masking significant regional heterogeneity in fire drivers. Recent work in Algeria (Bouzeraa et al., 2025) demonstrated effective wildfire susceptibility mapping using XGBoost with 14 environmental factors (AUC 0.96), but produced static susceptibility maps rather than dynamic daily predictions, and applied a single model across the entire study area without regional specialization.

1.3 The territorial intelligence approach

We propose that wildfire risk prediction benefits fundamentally from territorial specialization — the principle that each ecological region should have its own model, trained on its own fire history, meteorology, and landscape characteristics. We term this approach “deep territorial intelligence” (*inteligencia territorial profunda*) to distinguish it from generic global algorithms applied uniformly across diverse geographies.

GeoAlertAR-ML implements this principle through an architecture of five independent Random Forest classifiers, each specialized for a distinct ecological region of Argentina, unified by a KNN routing system that assigns incoming data to the appropriate regional model. The system operates over a national hexagonal grid (H3 resolution 5, ~252 km² per cell) providing complete continental coverage with 13,231 active cells.

This paper presents the system’s architecture, data pipeline, training methodology, validation results, and operational performance, including its response to real fire events. We also describe a complementary 7-day forecasting model based on XGBoost trained on GFS hindcast data, and a novel anomaly detection capability for identifying potential anthropogenic ignition events.

2. Materials and Methods

2.1 Study area and spatial framework

The study area encompasses continental Argentina (approximately 22°S–55°S, 53°W–73°W). The territory was discretized into a hexagonal grid using the H3 geospatial indexing system (Uber Technologies, 2018) at resolution 5, yielding approximately 252 km² per hexagon. After excluding cells dominated by water bodies, urban areas, and non-flammable surfaces (identified via Dynamic World land cover classification), 13,231 active hexagons remained, providing 100% coverage of areas with meaningful wildfire risk.

Region	Primary ecosystems	Hexagons	Key fire drivers
CENTRO	Pampas, espinal, Córdoba sierras	~3,500	Drought, burns, wind
CUYO	Monte desert, pre-Andean valleys	~450	Heat, low humidity
NEA	Atlantic forest, Chaco, wetlands	~2,500	Seasonal drought, burns
NOA	Yungas, high Chaco, pre-Puna	~950	Dry season, altitude
PATAGONIA	Steppe, Valdivian forest	~1,600	VPD, wind, low precip

2.2 Data sources

The system integrates data from multiple satellite and reanalysis products, processed through Google Earth Engine (GEE): GFS (NOAA/GFS0P25) for air temperature, wind speed, and relative humidity; GSMaP (JAXA) for precipitation at ~4-hour latency; MODIS MOD13A2 for NDVI at 1 km resolution; SRTM for elevation and slope; Dynamic World (Google) for land cover probability surfaces (Brown et al., 2022); and GHSL (JRC P2023A) for population density (Schiavina et al., 2023). Validation data comes from NASA FIRMS near-real-time thermal anomalies (VIIRS and MODIS) with a 25 km matching radius.

2.3 Feature engineering

Ten features were selected for the nowcasting model (Model A) based on iterative feature importance analysis and domain expertise: wind speed (GFS), air temperature (GFS), 7-day accumulated precipitation (GSMaP), probability of tree/grass/shrub cover (Dynamic World), elevation and slope (SRTM), month of year, and a fire weather proxy (wind speed × temperature).

A critical design principle was enforced throughout development: **no synthetic or estimated data**. If satellite or meteorological data was unavailable for a given hexagon-date combination, that data point was excluded rather than imputed with defaults or statistical estimates.

2.4 Dataset construction and balancing

Positive samples (fire = 1): Locations and dates of confirmed fire events extracted from NASA FIRMS archives (2016–2025), filtered for fire radiative power (FRP) > 30 MW and confidence ≠ "low" to exclude agricultural burns, sensor noise, and persistent thermal anomalies. The 30 MW threshold was calibrated empirically by analyzing the FRP distribution of known agricultural burns and static heat sources in Argentina. A total of 21,802 unique fire events were identified after filtering.

Negative samples (fire = 0): For each positive sample, a corresponding negative was generated at the same geographic location but shifted 180 days (±30 days random jitter), placing it in the opposite season. All satellite-derived features (NDVI, temperature, precipitation, wind) were extracted for the shifted date, ensuring that the model learns from the actual meteorological and vegetative conditions at each point in time.

Region assignment: Each sample was assigned to one of five ecological regions using a KNN Router (K=5) trained on the hexagonal grid centroids, achieving 99.96% classification accuracy against the master grid. The final training dataset comprised approximately 200,000 samples.

2.5 Model architecture

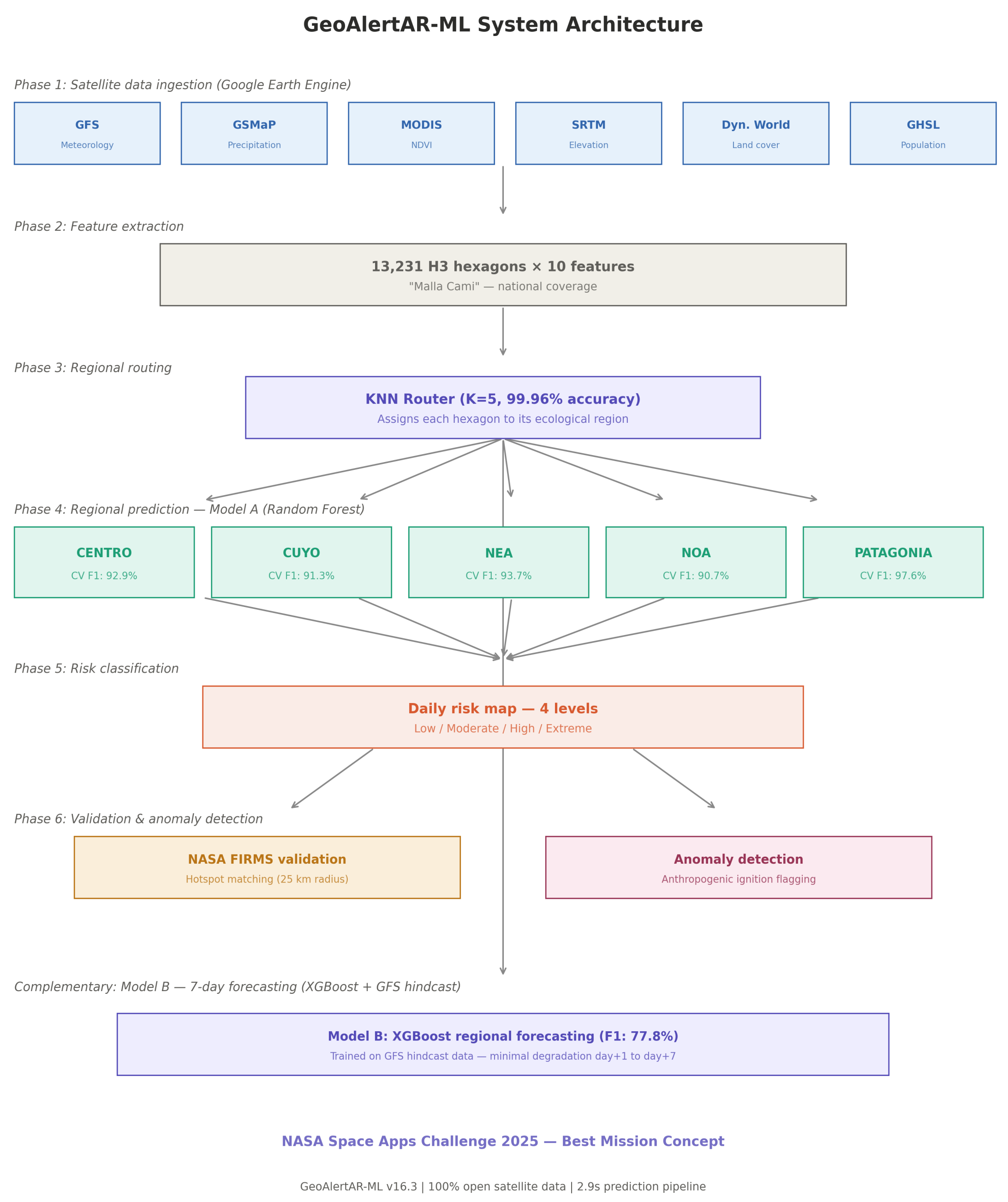

Figure 1. *GeoAlertAR-ML system architecture. Detailed workflow illustrating data ingestion from six satellite sources, feature extraction over 13,231 H3 hexagons, KNN-based regional routing, five independent Random Forest classifiers (Model A), risk classification, validation against NASA FIRMS, and the complementary Model B (XGBoost) for 7-day forecasting.*

2.5.1 Model A — Nowcasting (operational)

Five independent Random Forest classifiers were trained, one per ecological region (n_estimators=300, max_depth=18, min_samples_split=4, min_samples_leaf=2, class_weight=balanced). Each model was paired with a region-specific StandardScaler. GroupKFold cross-validation (5 folds) was used with geographic groups based on unique hexagon identifiers to prevent spatial data leakage.

2.5.2 KNN Router

A K-Nearest Neighbors classifier (K=5) routes incoming prediction requests to the appropriate regional model based on geographic coordinates, achieving 99.96% accuracy on the full hexagonal grid.

2.5.3 Model B — 7-day forecasting

A complementary forecasting system uses five regional XGBoost classifiers (n_estimators=300, max_depth=8, learning_rate=0.05) trained on GFS **hindcast data** — historical GFS forecasts rather than observed conditions. This allows the model to learn and compensate for GFS forecast biases automatically (e.g., GFS precipitation forecasts have only 0.26 correlation with observed precipitation). For each FIRMS fire event, GFS hindcast data was extracted at horizons of +1 to +7 days, yielding approximately 1.43 million training samples.

Temporal features (month, seasonality) were deliberately excluded from Model B after an ablation study revealed that two regions (NOA and CENTRO) allocated 65–89% of feature importance to temporal variables, effectively becoming “glorified calendars” insensitive to anomalous weather conditions.

2.6 Operational validation

Predictions are validated daily against NASA FIRMS near-real-time thermal anomalies within a 25 km radius. Results are classified as: Correct detection (high predicted risk + FIRMS hotspots), False alarm (high predicted risk + no hotspots), Correct rejection (low risk + no hotspots), or Anomaly/potential anthropogenic ignition (low predicted risk + FIRMS hotspots with FRP ≥ 10 MW).

2.7 GFS validation against ground stations

GFS temperature data was compared against 27 ground stations operated by Argentina’s Servicio Meteorológico Nacional (SMN), confirming a bias of +0.14°C for the Centro region and +0.05°C for NEA. SMN data is used exclusively for periodic validation and is not incorporated into the ML training pipeline.

3. Results

3.1 Model A — Nowcasting performance

Region	CV F1	Accuracy	Precision	Recall	Samples	Top feature
CENTRO	92.85%	99.13%	98.69%	99.59%	71,438	mes (21.9%)
CUYO	91.25%	99.90%	99.80%	100.0%	6,069	mes (21.9%)
NEA	93.66%	99.28%	99.14%	99.42%	79,654	mes (21.9%)
NOA	90.67%	99.04%	98.50%	99.63%	16,408	precip_7d (22.2%)
PATAGONIA	97.55%	99.94%	99.94%	99.93%	26,508	temp_aire (37.7%)
Average	**93.20%**				**200,077**	

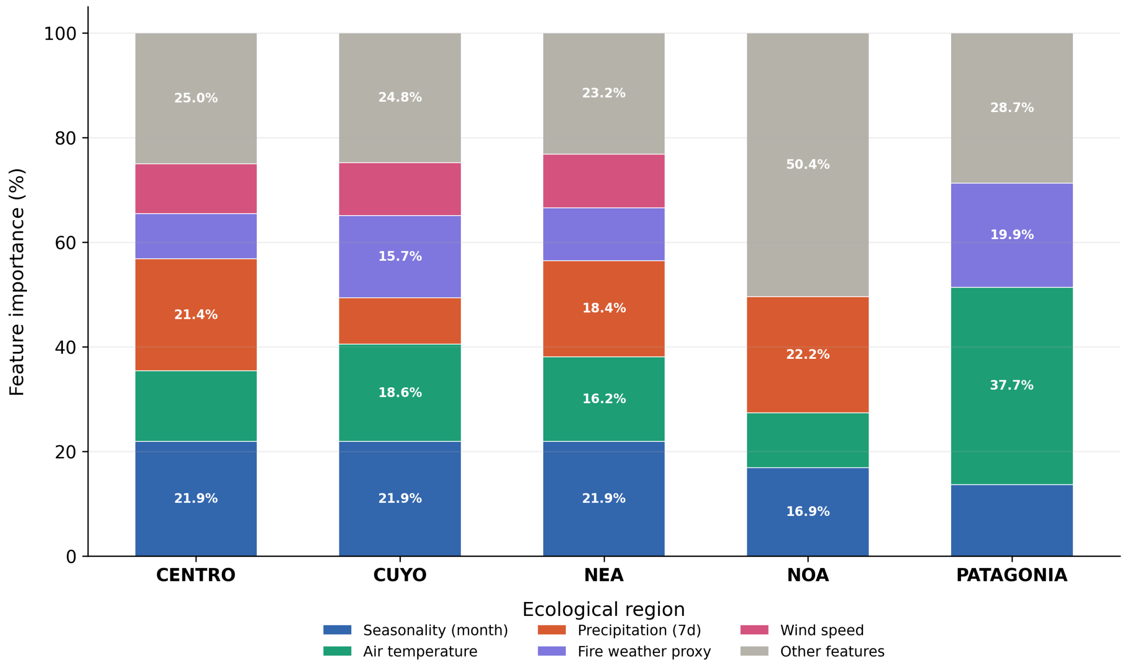

Figure 2. *Feature importance (%) by region for Model A. Each region exhibits a distinct hierarchy of fire drivers. PATAGONIA is dominated by air temperature (37.7%) and fire weather proxy (19.9%), NOA by precipitation (22.2%), and CENTRO/NEA by seasonality (~22%). This validates the territorial specialization approach.*

3.2 Model B — Forecasting performance

Region	F1-Score	AUC-ROC	Recall	Top feature
CENTRO	80.05%	0.9245	85.01%	ndvi (37.6%)
CUYO	74.95%	0.9145	79.03%	relative_humidity (31.9%)
NEA	68.82%	0.8129	78.87%	ndvi (36.6%)
NOA	78.16%	0.9090	86.70%	ndvi (37.3%)
PATAGONIA	87.06%	0.9530	87.90%	vpd_kpa (58.4%)
Average	**77.81%**			

Region	Day+1 F1	Day+7 F1	Degradation
CENTRO	80.2%	80.0%	0.3%
CUYO	75.0%	74.7%	0.4%
NEA	70.0%	67.7%	3.4%
NOA	79.3%	77.1%	2.8%
PATAGONIA	86.7%	87.1%	–0.5%

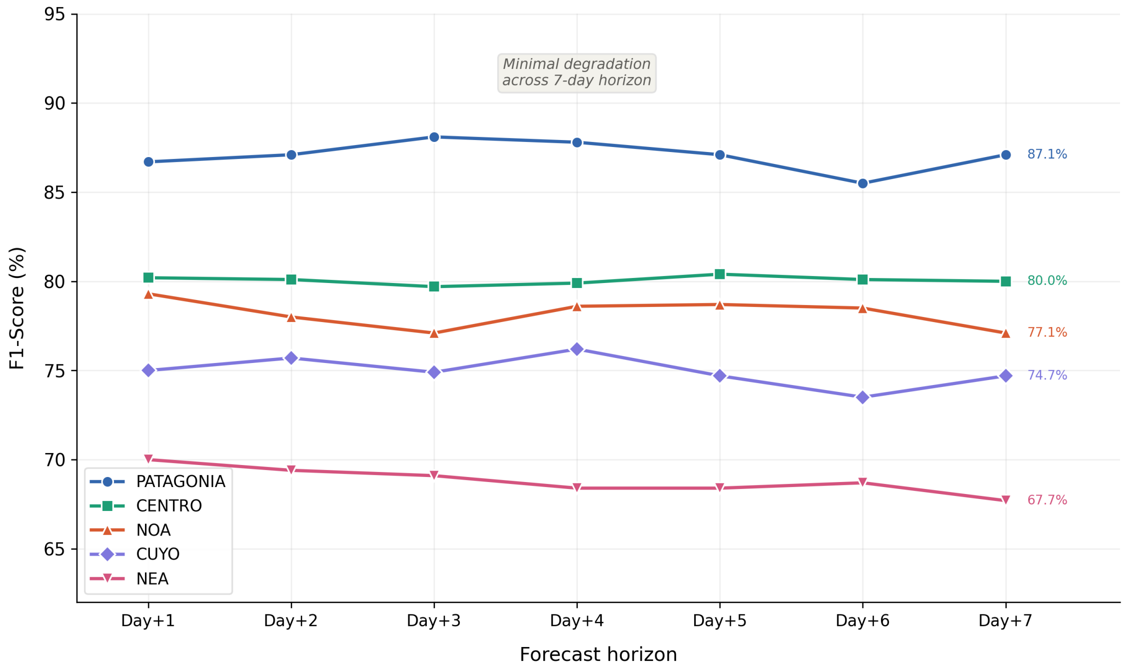

Figure 3. *Model B F1-score by forecast horizon (day+1 to day+7). All five regional models show minimal degradation across the 7-day window, demonstrating that the hindcast training approach effectively compensates for increasing forecast uncertainty at longer lead times.*

3.3 Operational validation — Comarca Andina crisis

In February 2026, a major fire event occurred in the Comarca Andina region of northern Patagonia. GeoAlertAR-ML's predictions for the affected hexagons showed risk levels of 68–72% (classified as "High") in the days preceding the event. Subsequent FIRMS data confirmed over 280 thermal anomalies in the area, with 100% of hotspots (109/109 confirmed events with sufficient FRP) falling within hexagons classified as Extreme or High risk.

3.4 System performance

The complete prediction pipeline processes all 13,231 hexagons in 2.9 seconds (2.4s for predictions + 0.5s for risk factor explanations), running on standard hardware. The system produces daily outputs including risk maps in GeoJSON format and per-hexagon explanations showing the top two risk-increasing factors (▲) and one risk-containing factor (▼).

4. Discussion

4.1 Regional specialization vs. global models

The most significant finding of this work is the demonstrated value of regional model specialization. Each of the five models learned fundamentally different feature hierarchies (Figure 2): Patagonia is temperature-driven, NOA is precipitation-driven, and CENTRO/NEA are seasonality-driven. A single national model would be forced to compromise between these distinct fire regimes, likely underperforming in at least some regions.

This observation aligns with the broader machine learning literature on domain adaptation, where models trained on data from a specific distribution outperform those trained on mixed distributions. In the wildfire context, "territorial intelligence" means that a model trained on Chaco fire history understands Chaco fires better than a globally trained model — not because it has more data, but because it has more *relevant* data.

4.2 The hindcast approach for forecasting

Model B's hindcast training methodology addresses a fundamental challenge in meteorological ML: the discrepancy between observed conditions and forecast conditions. Rather than applying a nowcasting model to forecast data (which introduces training-serving skew), we trained Model B directly on what GFS predicted for each historical fire event. The minimal degradation across forecast horizons (0.3–3.4% from day+1 to day+7, Figure 3) suggests that this approach effectively compensates for increasing forecast uncertainty at longer lead times.

4.3 The temporal feature dilemma

The ablation study for Model B revealed a critical insight: when temporal features (month, seasonality) are included, some regional models allocate up to 89% of their predictive capacity to them, effectively becoming fire calendars rather than weather-responsive models. While this produces high aggregate F1-scores (84.2%), it creates dangerous blind spots for out-of-season fire events driven by anomalous weather conditions. The decision to remove temporal features reduced overall F1 from 84.2% to 77.8%, but we argue that a model with 77.8% F1-score based on actual climate conditions is fundamentally more reliable for operational use than an 84% model that is essentially a seasonal calendar.

4.4 Anomaly detection and anthropogenic ignition identification

A unique capability of GeoAlertAR-ML is its ability to identify potential anthropogenic ignition events by flagging cases where FIRMS detects active fire in hexagons where the model predicts low meteorological risk. If weather conditions do not support fire ignition or spread, but fire is observed, the cause is likely anthropogenic rather than natural. While this does not constitute legal proof of intentionality, it provides valuable investigative intelligence for authorities. To our knowledge, no other operational wildfire system offers this functionality.

4.5 Limitations

Several limitations should be acknowledged: (1) satellite optical sensors cannot observe through persistent cloud cover, creating occasional data gaps particularly in NEA; (2) validation against FIRMS hotspots has an inherent 2–3 hour delay; (3) without temporal features, Model B shows a conservative bias in CENTRO and NEA during fire season; (4) at longer horizons (day+5 to day+7), GFS forecasts converge toward climatological averages; (5) direct human activity data (road proximity, agricultural burn permits) is not currently incorporated.

4.6 Comparison with existing systems

Feature	FIRMS (NASA)	ECMWF PoF	FWI (Canadian)	GeoAlertAR-ML
Approach	Detection	Prediction	Index	Prediction
Timing	After ignition	Before (10d)	Before	Before (24h + 7d)
Model type	Thermal sensing	Global ML	Empirical	Regional ML
Resolution	Point	~9 km	Variable	~252 km² (H3)
Regional adapt.	None	Limited	Manual	Automatic (per region)
Anomaly detect.	No	No	No	Yes
Cost	Free	Institutional	Free	~$0

5. Conclusions

GeoAlertAR-ML demonstrates that regionally specialized machine learning models, operating over a national hexagonal grid and trained on territory-specific fire histories, provide effective wildfire risk prediction for ecologically diverse countries. The system's key contributions are:

• **Territorial specialization architecture:** Five independent Random Forest models with KNN routing, achieving 93.2% average CV F1-score while preserving regional fire ecology in feature importance hierarchies.

• **Hindcast-trained forecasting:** A complementary XGBoost forecasting system trained on GFS hindcast data achieves 77.8% F1-score at 7-day horizons with minimal degradation.

• **Anomaly-based anthropogenic ignition detection:** A novel capability that flags discrepancies between predicted low risk and observed fire activity.

• **Operational validation:** Successful real-time prediction of major fire events including the 2026 Comarca Andina crisis, with 100% detection in High/Extreme risk zones.

• **Zero-cost satellite data pipeline:** The entire system operates on freely available satellite data processed through Google Earth Engine.

The system has been operational since late 2025, covering 100% of Argentina's continental territory. Future work includes the addition of accumulated drought indices for Model B, expansion to neighboring countries using the same regional model architecture, and publication of the training dataset for community use.

Author Contributions

Federico Sinato: Conceptualization, methodology, software development, ML model design and training, data pipeline architecture, satellite data extraction, validation framework, system deployment, and manuscript preparation. **Camila Rivas:** Hexagonal grid design, geospatial analysis, territorial exclusion criteria, and spatial data integration.

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Data Availability

The GeoAlertAR-ML system uses exclusively open-access satellite data from NASA FIRMS, NOAA GFS, JAXA GSMaP, MODIS, SRTM, Dynamic World, and GHSL, all processed through Google Earth Engine. Source data and access methods are described in Section 2.2. Code availability requests may be directed to the corresponding author.

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