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Wildfire Early Warning Systems: A Multisensor and Predictive Modelling Comparison Across Countries with a Canadian Perspective

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Abstract

This study evaluates wildfire early warning systems (EWS) across fifteen countries spanning four World Bank income tiers (high, upper-middle, lower-middle, and low) using a two-parameter framework: P1 (multi-sensor satellite integration) and P2 (hotspot detection and predictive modelling). The assessment examines how geostationary (GEO) and low Earth orbit (LEO) satellites are integrated with temporal resolution, spectral capability, forecast horizon, and operational deployment.
The United States and Australia score 5/5 through continuous GEO/LEO fusion and validated multi-day predictive models. Canada, Spain, and Greece score 4/5 with operational multi-sensor systems still improving high-frequency integration. Chile scores about 3.5/5, lower than expected for a high-income country due to incomplete sensor integration. Upper-middle-income countries (Brazil, Mexico, South Africa) score around 3/5, while lower-middle-income countries (India, Nepal) score 2 to 2.5/5, both groups showing only partial predictive model integration. Uganda, Mozambique, Madagascar, and Niger (1 to 1.5/5) depend on global satellite products with minimal predictive capability.
The results show a clear maturity gradient tied to income level, driven by GEO/LEO fusion, predictive modelling development, and operational readiness. These findings highlight the need for international support to help lower-capacity countries reduce wildfire risk.

1. Introduction

Wildfire early warning systems (EWS) are growing in importance as fires become more frequent and intense due to climate variability and changes in land use. Satellite monitoring and predictive modelling have improved how these systems operate, but the level of maturity differs greatly from one country to the next. Most existing reviews focus on single aspects of the problem, for example multisensor burned-area mapping or standalone prediction models, and few studies have tried to evaluate satellite data fusion together with real-time forecasting at a global level (Picotte and Robertson, 2011).

It is important to understand how geostationary Earth orbit (GEO) and low Earth orbit (LEO) satellite integration, temporal resolution, spectral capability, and predictive modelling work together to affect early warning performance. GEO satellites with 10 to 15 minute revisit intervals, when combined with polar-orbiting LEO satellites, can provide continuous monitoring. Systems that rely on LEO satellites alone face revisit gaps of several hours to one full day (Chatzopoulos-Vouzoglanis et al., 2023).

This work evaluates fifteen countries at different income levels (World Bank classification) and provides a comparative assessment linking sensor infrastructure with forecasting capability. The goal is to identify where temporal monitoring, predictive modelling, and operational deployment differ, and to highlight where improvements would have the greatest effect.

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The study pairs multi-sensor geospatial data (P1) with hotspot detection and predictive modelling (P2) across the fifteen countries. The literature base consists of about 120 papers from 2021 to 2025, drawn from Scopus and Web of Science, along with selected national fire department websites. Key sources include Solano-Correa et al. (Solano-Correa et al., 2018), Rodrigues et al. (Rodrigues et al., 2020), Radočaj et al. (Radočaj et al., 2022), Bastarrika et al. (Bastarrika et al., 2024), De Luca et al. (De Luca et al., 2022), Angelino et al. (Angelino et al., 2020), Negri et al. (Negri et al., 2022), and Palk et al. (Palk et al., 2025). The aim is to compare sensor integration, temporal resolution, spectral capability, predictive modelling, and operational deployment across regions with different technological and institutional capacities.

The multisensor geospatial component (P1) covers a wide range of Earth observation systems at different spatial, spectral, and temporal scales. LEO satellites include MODIS, VIIRS, Sentinel-2, and Landsat. Geostationary platforms include GOES, Himawari-8, and INSAT. Very high-resolution data come from unmanned aerial vehicles (UAVs) and Light Detection and Ranging (LiDAR). Ground-based measurements come from Remote Automated Weather Stations (RAWS) and Internet of Things (IoT) sensors.

This mix of sensors captures fire activity at both broad and fine scales. Geostationary satellites observe every 10 to 15 minutes, which supports near real-time monitoring. LEO satellites have longer revisit intervals, from several hours to multiple days. UAV data are typically collected during specific events and are used for detailed local analysis. Multitemporal fusion of very high-resolution imagery from different sensors requires careful registration and radiometric handling (Molch, 2010), while ground-based LiDAR and optical composites can further improve canopy and fuel characterisation (Su et al., 2019). Together, these sources cover both rapid fire detection and longer-term monitoring (Radočaj et al., 2022, Angelino et al., 2020).

The hotspot detection and predictive modelling component (P2) uses near real-time fire detection platforms: the Fire Information for Resource Management System (FIRMS), the Global Wildfire Information System (GWIS), the European Forest Fire Information System (EFFIS), and the Advanced Fire Information System (AFIS). These platforms offer API access to active fire data, which allows them to feed into predictive workflows and operational EWS.

The predictive modelling side includes machine learning methods such as Random Forests, deep learning architectures like Convolutional Long Short-Term Memory (ConvLSTM) networks for spatio-temporal modelling, statistical methods including Generalised Additive Models and Bayesian approaches, and unsupervised probabilistic models for burned-area classification and multitemporal change detection (Negri et al., 2022). Model inputs also include fuel characteristics from spectral indices, meteorological variables (temperature, humidity, wind speed), topographic parameters (slope, aspect, elevation), and socioeconomic factors related to human-caused ignitions (Rodrigues et al., 2020). Validation of these models requires careful statistical testing (Hamada and Abes, 2014), and forecast skill can be measured through predictability horizon indices (Du et al., 2019).

2. Study Area

Countries were grouped by World Bank income classification and wildfire exposure. The six high-income countries (United States, Canada, Australia, Spain, Greece, and Chile) cover Mediterranean, temperate, boreal, and Andean fire regimes. The three upper-middle-income countries (Brazil, South Africa, and Mexico) span Cerrado, Amazon, and fynbos zones with moderate EWS maturity. The two lower-middle-income countries (India and Nepal) cover semi-arid and montane environments where EWS capacity is growing but incomplete. The four low-income countries (Uganda, Mozambique, Madagascar, and Niger) include savanna, miombo, and tropical dry forest zones where EWS capacity is limited. Figure 1 shows the World Bank income classification used to group the fifteen study countries.

3. Methodology

System performance was evaluated on a country-by-country basis across all fifteen countries. Table 1 summarises the agencies and operational capabilities for each country.

In the United States, EWS combine MODIS, VIIRS, Landsat, Sentinel-2, GOES, UAV, and LiDAR data with RAWS networks. Monitoring intervals range from 10 minutes (GEO) to weekly (LEO composites). Predictive models including Random Forest and ConvLSTM reach accuracies of 83 to 97% (Radočaj et al., 2022, Angelino et al., 2020). Differenced Normalised Burn Ratio (dNBR) thresholds above 0.27 show strong predictive power for ecological transitions and reburn probability (Holden et al., 2010).

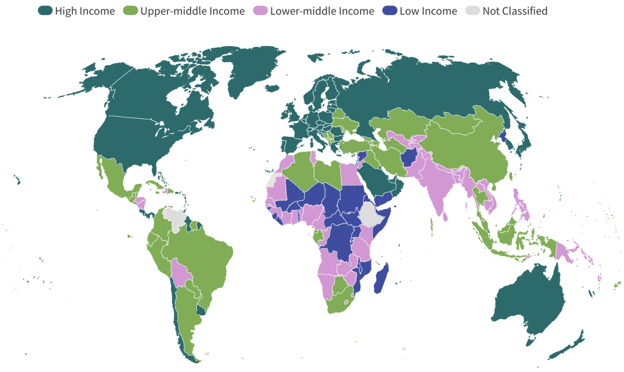

Figure 1. World Bank classification of countries by income level (source: World Bank, 2024).

Canada uses MODIS, VIIRS, and Sentinel-2 but has limited geostationary coverage. Phased Random Forest models reach F1-scores of 0.987 and precision of 0.958. Burned-area classification F1-scores are 0.942, though UAV and in-situ coverage is limited (Radočaj et al., 2022).

Australia has advanced GEO/LEO integration through Himawari-8 combined with LEO and UAV systems, reaching predictive accuracies of 92 to 97% (Palk et al., 2025). Multi-sensor fusion of MODIS and Sentinel-2 evapotranspiration models yields a relative RMSE of 0.26, and VIIRS calibration improves temporal consistency.

Spain and Greece both use the EFFIS framework, combining Sentinel-2, Landsat, and VIIRS with statistical and machine learning models. Spain reaches F-scores of 0.91 to 0.96 and AUC values of 0.88 for containment probability (Rodrigues et al., 2020, De Luca et al., 2022). Greece shows about 94% agreement with Copernicus burned-area products.

Chile uses routine MODIS and VIIRS data together with ground reports and has begun integrating GOES-16 geostationary observations. Its sensor diversity is still expanding, and predictive model automation lags behind the other high-income countries in this study (De Luca et al., 2022).

Brazil combines MODIS, VIIRS, and Sentinel-2 with probabilistic unsupervised learning, reaching overall accuracies of about 90% and F1-scores of 0.71. However, the lack of GEO and very high-resolution coverage limits real-time capability (Negri et al., 2022).

Mexico uses MODIS and VIIRS with limited UAV support. Convex hull-based perimeter modelling improves early fire boundary estimation, and sensor fusion reduces omission errors for large fires (Bastarrika et al., 2024).

South Africa runs AFIS systems that combine MODIS and Sentinel-2, with moderate sensor coverage and geospatial modelling capability (Bastarrika et al., 2024, Kganyago et al., 2025). India combines INSAT GEO data with MODIS, VIIRS, and Sentinel-2, which improves temporal resolution for hotspot detection. However, its predictive modelling is still mainly index-based, with limited UAV use and validation (Bastarrika et al., 2024).

Nepal is classified as lower-middle-income by the World Bank but has limited EWS infrastructure. Localised geospatial modelling has identified high-risk zones with strong statistical links

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Country	Agencies	Justification	References
USA (High)	USFS, NOAA, NASA; CAL FIRE, ODF	GEO satellites (GOES) at 5 to 15 min combined with LEO (VIIRS, MODIS); continuous detection integrated with HRRR-Smoke models.	NOAA/NASA docs
Australia (High)	BoM, NHRA; NSW RFS, VIC CFA, QFES	High temporal resolution via Himawari GEO combined with ground obs and met-models for near real-time spread prediction.	(Palk et al., 2025)
Canada (High)	NRCan, CFS, CWFIS; BC Wildfire, Ontario MNRF	CWFIS integrates MODIS and VIIRS with met-data for daily danger assessment; frequency limited by LEO overpass intervals.	CWFIS docs; (Radočaj et al., 2022)
Spain (High)	MITECO; EFFIS; Regional agencies	EFFIS integrates multisensor data, fire weather indices, and burned-area mapping; supports WUI risk modelling.	(Rodrigues et al., 2020, De Luca et al., 2022)
Greece (High)	Hellenic Fire Service, NOA; Local forest services	Uses EFFIS for hotspots and burned-area mapping with statistical risk models; limited UAS integration.	(De Luca et al., 2022)
Chile (High)	CONAF; Regional offices	Routine MODIS and VIIRS data with ground reports; heavy LEO reliance though sensor diversity is expanding.	(De Luca et al., 2022)
Brazil (Upper-Mid)	INPE (Queimadas), IBAMA; State brigades	Queimadas integrates MODIS and VIIRS for NRT hotspots; predictive outputs not fully automated.	(Negri et al., 2022, Bastarrika et al., 2024)
Mexico (Upper-Mid)	CONAFOR, CONABIO; Regional units	Uses MODIS and AVHRR for seasonal monitoring; predictive modelling integration remains limited.	(Bastarrika et al., 2024)
South Africa (Upper-Mid)	CSIR (AFIS); Fire Protection Assoc.	AFIS provides NRT hotspot detection; predictive modelling is regional; national integration is limited.	AFIS docs; (Kganyago et al., 2025)
India (Lower-Mid)	ISRO, FSI; State forest depts.	Combines INSAT GEO with MODIS/VIIRS; improved frequency via GEO but predictive modelling lacks automation.	(Bastarrika et al., 2024)
Nepal (Lower-Mid)	DoFSC, ICIMOD; Provincial offices	Satellite data used for hotspot detection; predictive frameworks are research-based, not fully operational.	(Negri et al., 2022)
Uganda (Low)	NFA; District forestry offices	Relies on global MODIS/VIIRS products; lack of local validation limits operational use.	Global lit.
Mozambique (Low)	ANAC; Local conservation offices	Detection based on global products with limited temporal resolution; no automated alert systems.	Global lit.
Madagascar (Low)	Min. of Environment; Local authorities	Depends on thermal anomalies from global satellites without predictive model integration.	Global lit.
Niger (Low)	DG Eaux et Forêts, CNEDD; Local services	Depends on LEO satellites with 12 to 24 h revisits; limited dissemination infrastructure.	Global lit.

Table 1. Wildfire jurisdictions and operational capabilities across the fifteen study countries.

between fire occurrence and climatic variables (Cramér's $V = 0.67$) (Bastarrika et al., 2024), though predictive frameworks are still at the research stage rather than in operational use.

Uganda, Mozambique, Madagascar, and Niger rely on FIRMS-based thermal anomaly detection using MODIS and VIIRS. These systems have little multispectral diversity, no UAV integration, and limited validation. Madagascar has seen better detection with VIIRS, but still has no advanced predictive modelling.

Common limitations across all systems include interference from cloud and smoke, limited UAV and IoT use in lower-resource regions, and calibration differences between sensors. The methodology accounts for these through cross-sensor fusion, standardised evaluation metrics, globally applicable algorithms such as Sentinel2BAM, and emerging multisensor geospatial foundation models (Han et al., 2024).

In summary, the methodology combines multisensor data fusion, predictive modelling, and comparative analysis at the country level to evaluate wildfire EWS. By linking sensor capabilities to modelling performance and operational status, it shows where the gaps are and where improvements would matter most.

P1. Multisensor Geospatial Data: This parameter covers GEO (10 to 15 min) and LEO (hours to days) satellites across thermal, near-infrared (NIR), and shortwave infrared (SWIR) bands at coarse (250 to 1000 m), moderate (10 to 60 m), and very high resolution ($\leq$5 m, UAV), with 12 to 16-bit radiometry. Sensors include MODIS, VIIRS, Sentinel, Landsat, GEO platforms, commercial systems, UAV/LiDAR, and in-situ/IoT networks. Table 2 presents the P1 evaluation for each country.

P2. Hotspot Display & Predictive Modelling: Hotspot data are accessible through FIRMS/GWIS, national portals, and APIs. Models range from index-based and statistical/ML approaches to coupled spread and ensemble methods with 0 to 15-day forecast horizons. Validation uses burned-area back-testing, and operations follow standard procedures, reporting cadence, and inter-agency coordination. Table 3 presents the P2 evaluation for each country.

4. Results

The results show clear differences in wildfire EWS maturity across the fifteen countries.

The United States and Australia score highest in both parameters. Both countries combine GOES or Himawari GEO satellites

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Country	Multitemporal	Multispectral	Multiresolution	Multiradiometric	Sensor Diversity
USA	Daily (MODIS/VIIRS, GOES, Sentinel-2)	Thermal + NIR + SWIR	VHR + UAV	GEO + LEO	RAWS + IoT
Australia	Daily (Himawari-8, Sentinel-2, VIIRS)	Thermal + NIR + SWIR	VHR + UAV	GEO + LEO	RAWS + IoT
Canada	Daily (MODIS, VIIRS, Sentinel-2)	Thermal + NIR + SWIR	UAV	GEO + LEO	RAWS
Spain	Sentinel-2, Landsat, VIIRS	Thermal + NIR + SWIR	Limited UAV	GEO + LEO (EFFIS)	Limited RAWS
Greece	Sentinel-2, VIIRS (EFFIS)	Thermal + NIR + SWIR	Limited UAV	GEO + LEO (EFFIS)	Minimal RAWS
Chile	MODIS, Sentinel-2, Landsat, GOES-16	Thermal + NIR + SWIR	UAV (limited)	GEO + LEO	Sparse RAWS
Brazil	MODIS, VIIRS, Sentinel-2	NIR + SWIR	Limited UAV	LEO only	Sparse RAWS
Mexico	MODIS, VIIRS, Sentinel-2	NIR + SWIR	Moderate res. only	LEO only	Sparse RAWS
South Africa	MODIS, Sentinel-2 (AFIS)	NIR + SWIR	UAV pilots	LEO only	Sparse RAWS
India	Sentinel-2, INSAT-3D/3DR, VIIRS, MODIS	Thermal + NIR + SWIR	Limited UAV	GEO + LEO	RAWS (pilot)
Nepal	MODIS, VIIRS (ICIMOD)	Thermal + Topo/LC	None	LEO only	Localised (ICIMOD)
Uganda	MODIS, VIIRS (FIRMS)	Thermal only	None	LEO only	None
Mozambique	MODIS, VIIRS (FIRMS/AFIS)	Thermal only	None	LEO only	None
Madagascar	MODIS, VIIRS (FIRMS)	Thermal only	None	LEO only	None
Niger	MODIS, VIIRS (FIRMS)	Thermal only	None	LEO only	None

Table 2. Evaluation of multisensor geospatial data integration (Parameter P1) across the fifteen study countries.

Country	Display/Access	Model Class	Forecast Horizon	Validation
USA	FIRMS, NFDRS portals, APIs	NFDRS, spread tools, operational ML, ensemble met	1–7 d + seasonal	Routine/per-season
Australia	AFDRS portals; FIRMS; APIs	AFDRS + operational spread (Spark/Phoenix)	1–5 d	Routine
Canada	CWFIS/FWI portals; FIRMS; APIs	FWI-family; smoke spread (FBP)	1–5 d	Routine
Spain	EFFIS + national dashboards	Index-based + met ensembles	1–7 d + seasonal	Regular
Greece	EFFIS + risk notices	Index-based + met	1–7 d + seasonal	Regular
Chile	CONAF Geoportal, EFFIS	Index-based, operational ML (RF), PYROCAST	1–3 d	Regular
Brazil	INPE Queimadas; CEMADEN	Danger maps; emerging ML	1–3 d	Partial
Mexico	National dashboards + FIRMS	Index-based (fuel) + ignition modelling	1–3 d	Limited
South Africa	AFIS (alerts, mobile, API)	Index-based; ML pilots	1–3 d	Partial
India	FSI Fire Alerts + FIRMS	Index-based; pilots	1–2 d	Limited
Nepal	FIRMS + ICIMOD Portal	Operational FWI (2-day outlook)	0–2 d	Regular (ICIMOD)
Uganda	FIRMS email/web	None (operational)	0 d	None
Mozambique	FIRMS/AFIS exposure	Index-based (regional)	0–1 d	Limited
Madagascar	FIRMS	None	0 d	None
Niger	FIRMS	None	0 d	None

Table 3. Evaluation of hotspot detection and predictive modelling (Parameter P2) across the fifteen study countries.

with MODIS and VIIRS, giving them revisit intervals of about 10 to 15 minutes. This allows hotspot detection within the hour and fire behaviour forecasting out to 5 to 10 days, using validated machine learning and ensemble models.

Canada, Spain, and Greece perform well but score slightly lower. They use MODIS, VIIRS, Sentinel-2, and Landsat for operational monitoring and fire danger assessment, often through the EFFIS framework. Because they do not yet have fully continuous geostationary coverage, detection updates are tied to satellite overpass times rather than running continuously (Hall et al., 2020). Chile is a high-income country but scores lower than the rest of that group because it still relies heavily on LEO data and has limited automation of its predictive models.

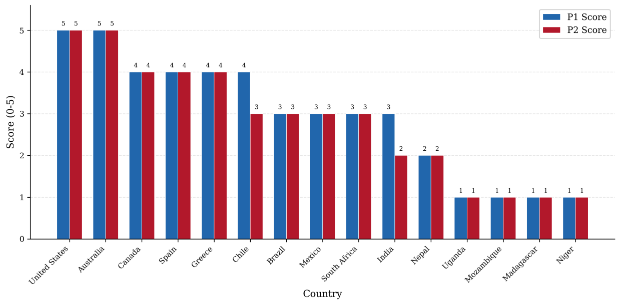

Figure 2. Composite scores for all fifteen study countries across the P1 and P2 parameters.

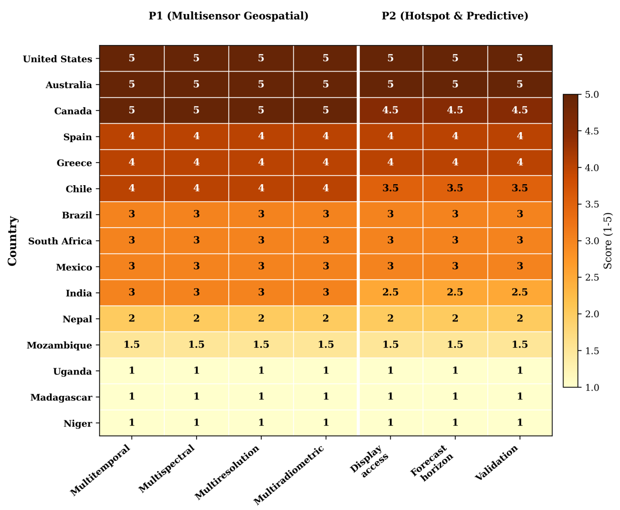

Figure 3. Heat map of sub-dimension scores across all study countries.

The upper-middle-income countries (Brazil, Mexico, and South Africa) score around 3/5. Their systems use MODIS and VIIRS thermal anomaly detection, and predictive modelling exists but is generally limited to short-term forecasts of 1 to 3 days. The lower-middle-income countries (India and Nepal) score between 2 and 2.5/5. India incorporates geostationary satellites such as INSAT, which improves detection frequency, but predictive modelling in both countries is not yet built into automated operational tools.

Uganda, Mozambique, Madagascar, and Niger score lowest. They rely on global fire detection products from MODIS and VIIRS, with detection intervals of roughly 12 to 24 hours. Predictive modelling is minimal or absent, and there are few automated operational workflows.

The overall pattern follows income level: high-income countries score 3.5 to 5, upper-middle-income countries around 3, lower-middle-income countries 2 to 2.5, and low-income countries 1 to 1.5 (Figures 2 and 3).

5. Discussion

Temporal resolution and multisensor integration turn out to be the main factors affecting EWS performance. Countries that combine GEO and LEO satellites can detect fires sooner because they get both frequent updates and fine spatial detail, which helps catch ignitions early and track fire spread more reliably.

When a system depends on LEO satellites alone, revisit gaps of up to 24 hours delay hotspot detection. This is a particular problem for fast-moving fires, where a few hours of missed data can make the difference between an effective response and a missed window.

The second major factor is whether predictive models are actually wired into operational systems. In high-income countries, machine learning and ensemble models feed into real-time workflows that produce continuous updates and multi-day forecasts. In upper-middle-income countries, predictive models tend to operate in a more limited or regional capacity, without being fully connected to national forecasting systems. In lower-middle-income countries like India and Nepal, predictive capability exists but is still largely index-based and lacks automation.

In low-income countries, satellite data itself is not the bottleneck. Global products from MODIS and VIIRS are freely available everywhere. The gap is in what happens next: there are not enough ground stations for calibration, no automated alert pipelines, and limited institutional capacity to turn satellite detections into actionable warnings.

6. Conclusion

This study compared wildfire early warning systems across fifteen countries using a framework built on multisensor satellite integration and predictive modelling capability. The results show large differences in system maturity, and those differences come down to GEO/LEO data integration, temporal resolution, predictive modelling, and how well operations are automated.

The best-performing systems have continuous monitoring, validated forecasts running several days ahead, and decision-support workflows that are fully operational. Systems in the middle tier show partial integration with shorter forecast windows. The lowest-performing systems use global satellite data but have no operational predictive framework behind it.

Closing these gaps requires better fusion of GEO and LEO satellite data, validated predictive modelling frameworks that go beyond index-based approaches, and automated operational workflows backed by ground-based observations. The framework presented here offers a way to assess and compare wildfire EWS across different countries and institutional settings, with the goal of making disaster preparedness more effective where it is needed most.

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