Fire Risk Dashboard for Bosque Pehuén: Interactive Visualization of Wildfire Danger Using Open Meteorological Data

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January 2026

Abstract

Wildfire risk assessment is critical for ecosystem and community protection in southern Chile's Araucanía region. This project develops an interactive web-based dashboard that visualizes wildfire risk in the vicinity of Bosque Pehuén, a privately protected area managed by Fundación Mar Adentro, to bolster community preparedness. The system integrates two complementary approaches: a rule-based fire-danger index using the Rodríguez-Moretti index (temperature, humidity, wind speed, days without rain) and a machine learning model trained on 30 years of regional fire history. Risk is visualized through multiple interactive representations that translates complex fire science into intuitive visualizations that enable informed decision-making for fire mitigation and preparedness.

Keywords: wildfire risk, wildfire prevention, data visualization, interactive dashboard, machine learning, open data

1. Introduction

Wildfire poses a critical threat to Chile's forest ecosystems and communities, with recent fire seasons causing extensive damage across Araucanía and Los Ríos regions (Miranda et al., 2022). Climate change projections indicate increasing fire frequency and intensity (IPCC, 2021), making proactive risk communication essential for effective fire management.

Bosque Pehuén —an 890 hectare privately protected area in southern Chile managed by Fundación Mar Adentro (FMA) —encompasses native forests including the endangered Monkey Puzzle Tree (Araucaria Araucana). While Chile's national fire-danger system provides regional-scale forecasts, site-level stakeholders need locally-specific, accessible risk information. This project addresses this gap by developing an open-source dashboard delivering real-time, site-specific fire-risk estimates through accessible interactive visualization.

2. Background

Wildfire rating systems assess several key meteorological factors to predict occurrence (Zacharakis & Tsihrintzis, 2023). They are employed both at a national and regional scale. Outstanding fire risk platforms include Canada's CFFDRS[1], and the U.S. NFDRS[2]. Chile's national model follows a similar architecture[3], incorporating temperature, humidity, wind, drought indices, and others. For ease of use and replicability using open

[1] For more information, visit : https://cwfis.cfs.nrcan.gc.ca/background/summary/fdr
[2] For more information, visit: https://research.fs.usda.gov/firelab/projects/firedangerrating#the-nfdrs-model
[3] For more information, visit: https://www.conaf.cl/incendios/situacion-actual-y-pronostico-de-incendios/

software, here Argentina's Rodríguez-Moretti Index (IRM) was employed as a simple and effective alternative (Dentoni & Muñoz, 2012; Cavalcante et al., 2021)).

This project adopts a dual approach: (1) a rule-based index using the IRM with four variables (temperature, humidity, wind speed, days without rain); and for robustness, (2) a machine learning model trained on regional fire history. These methods use open meteorological data from the Open-Meteo API, and the Landscape Fire Scars Database (Miranda, A., et al., 2022).

Effective risk visualization requires clarity, multiple perspectives, and interactivity (Inglis & Vukomanovic, 2020). The dashboard employs color-coded risk scales (green to red), complementary chart types (polar plots, time-series, compasses, maps), and interactive controls enabling users to explore patterns and forecast trajectories.

3. System Design and Implementation

3.1 Data Source

The Open-Meteo API provides free global weather forecasts from ECMWF, GFS, and ICON models under CC BY 4.0 license. For Bosque Pehuén (39.61°S, 71.71°W), the system retrieves hourly temperature, humidity, wind speed/direction, and precipitation with a 14-day forecast horizon. Data are cached at startup to reduce latency.

The Landscape Fire Scars Database is an open database that maps the historical burned areas and fire severity of wildfires that occurred in Chile at a high-resolution (~30 m). The database registries span from 1984 to 2018.

3.2 Fire Risk Index and Machine Learning Model

Rule-Based Index: The system computes a composite risk score (0–100) from four variables based on the IRM. Scores are calculated for afternoon hours (14:00–16:00) when fire danger peaks, then averaged daily.

Variable	Range	Relationship	Weight
Temperature (C°)	0–25 pts	Direct	25%
Relative Humidity (%)	0–25 pts	Inverse	25%
Wind Speed (km/hr)	0–15 pts	Direct	15%
Days Without Rain (≥2mm)	0–35 pts	Direct	35%

Table 1 Fire risk index composition showing variable contributions and total score calculation

Machine Learning Model: A Random Forest classifier (100 trees) trained on 616 historical fires from Araucanía (1984-2018, Datos para Resiliencia dataset) predicts fire probability using the same four weather variables.

3.3 System Architecture

The codebase employs a modular architecture separating concerns across six Python modules: config.py, data_fetcher.py, risk_calculator.py, visualizations.py, map_utils.py, fire_model.pkl, and app.py. This design ensures testability (independent module testing), maintainability (isolated changes), and reproducibility (version-controlled dependencies via environment.yml).

3.4 Visualization Design: Multiple Complementary Views

The dashboard integrates six visualization types to communicate fire risk from complementary perspectives:

1. Daily Polar Plot: A polar coordinate plot displays the four risk variables as normalized axes (0–1 scale) rendered as a filled radial polygon. The polygon's color reflects total risk category (from green to red), instantly communicating variable contributions and overall risk level. Interactive date selection buttons ("Today," "Tomorrow," "Next 3 days," "Next 7 days") enable exploration of forecast patterns and identification of high-risk windows.

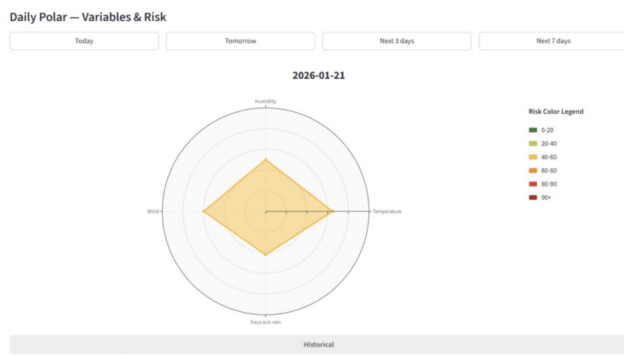

Figure 1 Polar plot visualization showing relative contributions of meteorological variables.

2. Dual Risk Gauge Display: Two semi-circular gauges present the rule-based risk index and ML fire probability side-by-side, enabling direct comparison. Color zones indicate risk levels, and an agreement indicator shows when methods align . This dual approach is made to increase user confidence by combining established protocols with data-driven predictions.

Figure 2 Risk gauge comparison for rule based and ML models

3. Wind Compass with Risk-Coded Wedge: A polar compass displays wind direction and speed using a wedge visualization. The wedge extends from the center in the direction wind is coming from, with length scaled to wind speed and color matching the day's risk level. This integration helps stakeholders simultaneously assess wind-driven spread potential and overall danger.

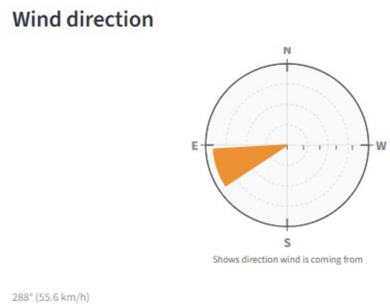

Figure 3 Wind compass displaying wind direction and speed

4. Risk Forecast Time-Series: A 14-day bar chart shows projected risk scores color-coded by category, which can be further extended to 21 days. It allows stakeholders a more comprehensive understanding on high-risk periods, and safe periods at a glance.

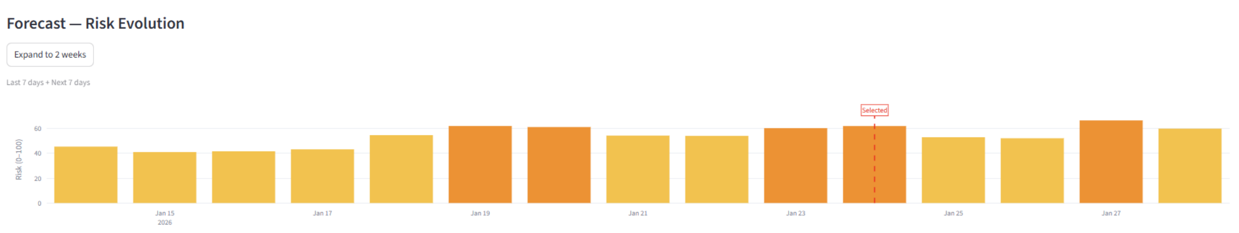

Figure 4 14-day risk forecast showing projected fire danger levels

5. Regional Wind-Flow Map: A map provides geographic context. Wind streamlines overlay the Araucanía region, with Bosque Pehuén highlighted. This visualization communicates regional wind patterns and situates local conditions within the broader landscape.

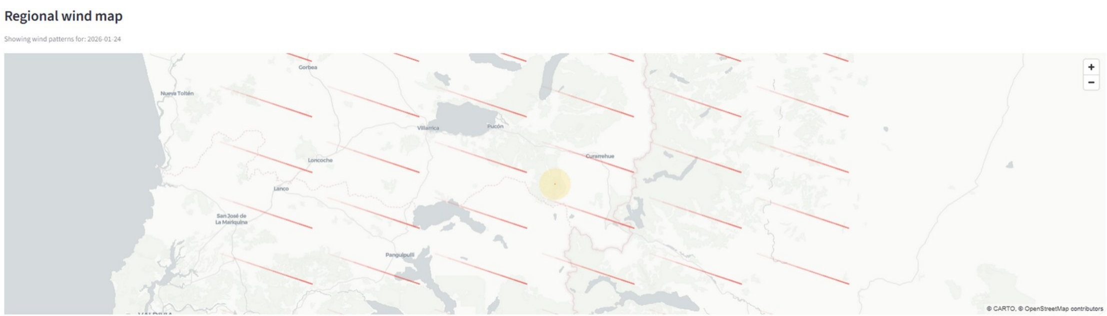

Figure 5 Regional wind flow map displaying directional patterns across Araucanía

6. Risk Score Summary Table: A tabular display provides exact numerical scores for each variable and its total risk score, accommodating users who prefer precise numbers over visual representations.

3.5 User Interface and Interactivity

The dashboard layout emphasizes clarity: main display with polar plot and dual gauges (left column) for immediate fire risk levels for the day, and wind compass (right column) for wind direction; the 14-day forecast, wind map, and summary table are further below, for deeper analysis. Interactive elements (date buttons, 14-day to 21-day forecast, and hover tooltips) provide basic exploration and information. The system is deployable via Streamlit Cloud or local execution using a reproducible Conda environment (environment.yml with Python 3.11).

4. Results

The dashboard achieves real-time risk assessment with 14-day forecasts, presenting fire science through accessible, interactive visualizations. Testing across seasonal conditions demonstrates accurate risk computation, and the forecast view successfully identifies multi-day high-risk periods corresponding to regional fire-danger patterns.

Model Validation: The model achieved 87.8% accuracy and excellent discrimination between fire and non-fire conditions (ROC AUC = 0.94). Statistical validation revealed limited agreement between methods (concordance correlation coefficient = 0.57). McNemar's test showed the methods make significantly different prediction errors ($p < 0.001$). This divergence, however, should not be interpreted as a deficiency in either method, but rather as evidence of their complementary nature. The rule-based system provides stakeholder-accessible risk categories grounded in established fire science, while the ML model offers data-driven validation and identifies conditions where expert rules may over- or underestimate actual fire probability.

Limitations: The system uses modelled meteorological data (not in-situ sensors), potentially missing microclimate variations. Risk assessment also only focuses on meteorological hazards, not fuel load or vegetation type. The "days without rain" proxy is simpler than comprehensive fuel moisture models, but balances accuracy with data availability.

5. Conclusion

This project demonstrates how interactive data visualization bridges fire science and local communities, translating complex meteorological data and machine learning predictions into actionable communication. By integrating rule-based fire-danger indices with data-driven ML models, the dashboard offers both established protocols and adaptive learning from regional fire patterns.

The system's key contributions include: (1) a dual-method risk assessment combining Argentinian standars with ML trained on 30 years of regional fires; (2) a comprehensive visualization design using polar plots, dual gauges, wind compasses, forecasts, and regional maps; and (3) a modular, open-source architecture enabling adaptation to other protected areas and communities.

As climate change intensifies fire frequency across Chile, tools that democratize access to fire-danger information become essential. Effective visualization transforms raw forecasts into intuitive displays that empower communities, rangers, and emergency managers to make informed, timely decisions. Future enhancements include integration of local weather station data, automated alerting for high-risk thresholds, and regional expansion across the Araucanía and Los Ríos regions. This dashboard represents a foundation for more resilient management in Chile's fire-prone landscapes.

References

1. Cavalcante, R. B. L., Souza, B. M., Ramos, S. J., Gastauer, M., Nascimento, W. R., Caldeira, C. F., & Souza-Filho, P. W. M. (2021). Assessment of fire hazard weather indices in the eastern Amazon: a case study for different land uses. *Acta Amazonica*, 51, 1–13. https://doi.org/10.1590/1809-4392202101172

2. Dentoni, M. C., & Muñoz, M. M. (2012). Fire Danger Assessment Systems. Technical Report No. 1. National Fire Management Plan. *National Program for Fire Danger and Early Warning*. Esquel, Chubut, Argentina. ISSN 2313-9420.
3. Inglis, N. C., & Vukomanovic, J. (2020). *Visualizing when, where, and how fires happen in U.S. parks and protected areas*. *ISPRS International Journal of Geo-Information*, 9(5), 333. https://doi.org/10.3390/ijgi9050333
4. Intergovernmental Panel on Climate Change (IPCC). (2021). Climate change 2021: The physical science basis. *Contribution of Working Group I to the Sixth Assessment Report*. Cambridge University Press.
5. Miranda, A., Mentler, R., Moletto Lobos, Í., Alfaro, G., Aliaga, L., Balbontín Montecinos, D., Barraza, M., Baumbach Cubillos, S., Calderón, P., Cárdenas, F., Castillo, I., Contreras, G., Barra, F., Galleguillos, M., González, M., Hormazábal, C., Lara, A., Mancilla, I., Muñoz, F., Oyarce, C., Pantoja, F., Ramírez, R. y Urrutia, V. (2022). The landscape fire scars database: mapping historical burned area and fire severity in Chile. *Earth Systems Science Data, 14, 3599–3613*. Available at: https://repositorio.uchile.cl/handle/2250/196521
6. Open-Meteo. (2022–2025). Weather Forecast API. Retrieved from https://open-meteo.com/en/docs
7. Zacharakis, I., & Tsihrintzis, V. A. (2023). Environmental forest fire danger rating systems and indices around the globe: A review. *Land*, 12(1), 194. https://doi.org/10.3390/land12010194

Appendix: Fire Risk Index Scoring Summary

Variable	Range (risk score value)									
Temperature (°C)	< 0 (2.7)	0-5 (5.4)	6-10 (8.1)	11-15 (10.8)	16-20 (13.5)	21-25 (16.2)	26-30 (18.9)	31-35 (21.6)	35 < (25)	
Humidity (%) ***inverse***	91-100 (2.5)	81-90 (5)	71-80 (7.5)	61-70 (10)	51-60 (12.5)	41-50 (15)	31-40 (17.5)	21-30 (20)	11-20 (22.5)	0-10 (25)
Wind Speed (km/h)	<3 (1.5)	3.0-5.9 (3)	6.0-8.9 (4.5)	9.0-11.9 (6)	12.0-14.9 (7.5)	15.0-17.9 (9)	18.0-20.9 (10.5)	21.0-23.9 (12)	24.0-26.9 (13.5)	>26.9 (15)
Days Without Rain	0-1 (3.5)	2-4 (7)	5-7 (10.5)	8-10 (14)	11-13 (17.5)	14-16 (21)	17-19 (24.5	20-22 (28)	23-25 (31.5)	≥26 (35)

Risk computation: Scores calculated for afternoon hours (14:00-16:00) when fire danger peaks, averaged daily. Total index = sum of four variable scores.