

## From Sparks to Strategy

### Geospatial and Predictive Modeling of Wildfire Risk for Grid Hardening

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**Abstract**— Wildfires are no longer seasonal anomalies—they are systemic threats to national infrastructure. In this study, we analyzed every wildfire recorded in the 2025 Wildfire Incident Geodatabase System (WFIGS) and used ArcGIS Pro to map their spatial distribution across the United States. Our geospatial analysis revealed two striking patterns: (1) a dense, contiguous band of wildfire activity sweeping through the Midwest, and (2) concentrated hotspots in Southern California, Alaska, and the Texas Panhandle—regions with critical electric infrastructure. The core contribution of this research is to demonstrate that wildfire hotspot analytics can serve as a predictive shield for electric utilities, enabling proactive defense before flames reach transmission corridors. By overlaying hotspot maps onto power-line layers, utilities gain a clear visual of which assets are at highest risk. This empowers targeted mitigation strategies such as vegetation trimming, pole hardening, and strategic crew deployment—transforming wildfire response from reactive to anticipatory. In an era of climate volatility and grid vulnerability, this study offers a data-driven blueprint for utility resilience—where spatial intelligence becomes a frontline defense.

**Keywords**—wildfire; spatial analysis; kernel density; hotspot analysis.

#### I. INTRODUCTION

Wildfires are no longer isolated environmental events—they are escalating threats to national electric infrastructure. As climate volatility intensifies, utility operators face mounting pressure to anticipate and mitigate fire-related disruptions before they cascade into widespread outages. When flames or smoke encroach on high-voltage transmission corridors, utilities must choose between cutting power or risking catastrophic equipment failure, grid instability, and public safety hazards.

This study confronts that challenge head on. By mapping every wildfire recorded in the 2025 Wildfire Incident Geodatabase System (WFIGS), we reveal where wildfires consistently cluster near utility assets. These spatial patterns are not random—they are statistically significant indicators of future risk. Our maps expose two dominant trends: (1) a dense band of wildfire activity sweeping through the Midwest, and (2) concentrated hotspots in Southern California, Alaska, and the Texas Panhandle—regions with critical grid infrastructure.

We ask two strategic questions:

- Where did statistically significant clusters of wildfires occur in 2025?
- How can these clusters guide electric utilities' decisions on where to focus wildfire-mitigation efforts?

Answers to these questions offer utilities a data-driven lens to identify their highest-risk zones before the next fire season begins. This research transforms wildfire mapping from a retrospective tool into a proactive planning asset—empowering utilities to harden infrastructure, optimize crew deployment, and precisely refine public safety shutoff protocols.

The remainder of this paper is organized as follows. Section 2 reviews recent research on wildfire behavior, spatial analysis, and grid resilience modeling. Section 3 describes the datasets used in this study and outlines the criteria for data selection. Section 4 presents the analytical framework, including the spatial methods and predictive models. Section 5 reports the results of the spatial analysis and machine learning classification. Section 6 discusses the implications of these findings for utility operations and future research. Section 7 concludes the paper with key insights and recommendations for advancing wildfire resilience strategies.

#### II. LITERATURE REVIEW

Weber et al. [1] used ArcGIS Pro to map changes in fire frequency and burned area, observing clustered spatial distributions influenced by vegetation, climate, and human activity. Ostertag et al. [2] emphasized that large wildfire risks vary significantly by ecoregion rather than administrative boundaries. Gonçalves et al. [3] integrated demographics with wildfire analysis, employing ArcGIS Pro and automated Python/R routines to create vulnerability indices identifying populations at greater risk. Kovvuri et al. [4] applied hierarchical density-based spatial clustering of applications with noise clustering to past wildfire perimeters and overlaid the results on transmission-grid coordinates to generate corridor-specific risk scores, illustrating how hotspot analytics can directly inform grid-resilience strategies. Sohrabi et al. [5] combined a wildfire-spread simulator with geographic information system mapping of the IEEE 30-bus test system in California to score every transmission line and node for susceptibility, vulnerability, and overall risk, highlighting the most critical segments on an integrated grid heat map.

### III. DATA SELECTION AND ACQUISITION

The primary dataset used in this study was WFIGS 2025 Wildfire Perimeters, a comprehensive geospatial record compiled by the WFIGS. This dataset includes detailed perimeter polygons for all reported wildfires across the United States during the 2025 fire season. Each entry captures the spatial extent of individual fires, enabling precise mapping and spatial analysis.

The dataset was input into ArcGIS Pro. Supplementary layers—including topography, land cover, and electric infrastructure—were added to contextualize wildfire behavior and proximity to utility assets. This multilayered approach allowed for robust spatial correlation between fire perimeters and grid vulnerabilities, laying the foundation for hotspot detection, cluster analysis, and predictive modeling.

### IV. SYSTEM AND METHODOLOGY

This study employed a dual-platform analytical framework combining ArcGIS Pro and Python, each selected for its unique strengths in geospatial analysis and machine learning.

ArcGIS Pro served as the primary engine for spatial interrogation of wildfire perimeters. It enabled the execution of advanced geostatistical techniques—including Kernel Density Estimation, Optimized Hotspot Analysis, and Local Cluster/Outlier Detection (Anselin Local Moran’s I)—to reveal spatial concentrations and anomaly patterns in wildfire activity. These outputs were layered with electric-infrastructure maps to assess proximity-based risk.

Python was used as the secondary tool to extend the analytical depth beyond spatial visualization. It powered the development and validation of three predictive models—random forest, XGBoost, and a deep-learning classifier—each trained to precisely categorize wildfire sizes (Small, Medium, Large). Python’s integration with scikit-learn, XGBoost, and TensorFlow libraries enabled robust model tuning, cross validation, and performance benchmarking.

### V. SPATIAL ANALYSIS RESULTS

**Kernel Density Analysis:** A purple heat-scale map shows where 2025 wildfires were most tightly clustered (Figure 1). Deep violet highlights the Midwest density peak. Darker spots represent electric infrastructure at a significantly elevated risk of damage from wildfires. *Based on this research*, utilities can prioritize and implement targeted hardening measures.

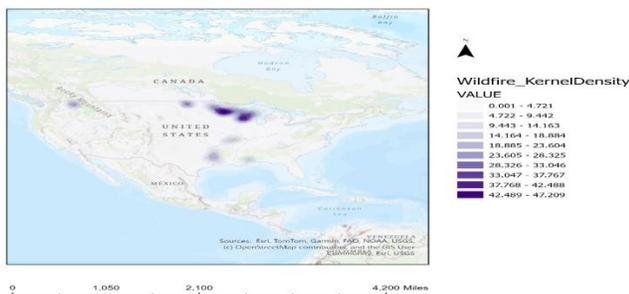


Figure 1. Kernel Density Map of 2025 Wildfires

**Optimized Hotspot Analysis:** Significant hotspots appear in the Southwest, Alaska, Nebraska, and Florida, guiding prevention and response (Figure 2). With these identified wildfire hot spots, utilities can prioritize grid hardening, proactive infrastructure planning and design, and emergency-response management.

**Local Cluster/Outlier Analysis:** The Anselin Local Moran’s I map (Figure 3) classifies every 2025 wildfire point relative to its surroundings, painting isolated “hot spikes” (high-fire points amid low-fire neighbors) in red, low-fire outliers nested inside larger hotspots in dark blue, and uniformly quiet cold-spot clusters in light blue. The identified high-high clusters pinpoint pervasive regional wildfire threats where the area and its surroundings exhibit significant high-wildfire activity. For electric infrastructure, understanding these clusters allows utilities to address interconnected vulnerabilities in these zones.

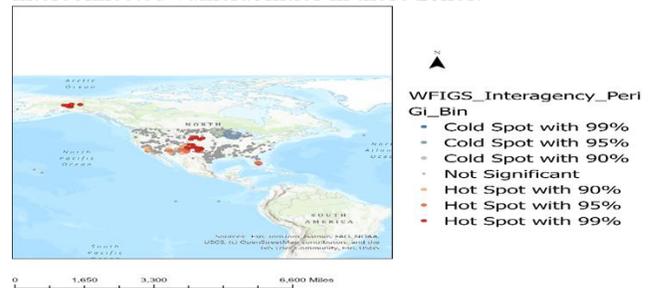


Figure 2. Hotspot Analysis Map of 2025 Wildfires

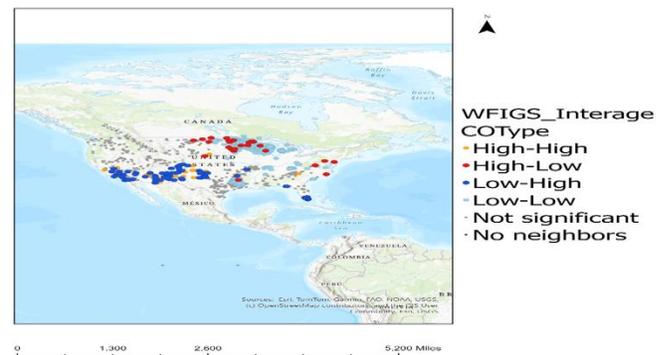


Figure 3. Local Cluster / Outlier Analysis of 2025 Wildfires

#### A. Implications for Utilities

Utility operators can leverage these findings to optimize resource allocation, improve operational resilience, and inform electric infrastructure design and expansion. By integrating these findings into their planning and operational frameworks, utility operators can enhance the resilience of electric infrastructure.

#### B. Predictive Modeling

**Random Forest Model:** The model’s high overall accuracy (98%) in predicting fire size allows for data-driven prioritization of grid hardening (Figure 4). This precision ensures that expensive measures like undergrounding or using fire-resistant materials are implemented in areas most statistically prone to specific fire sizes, potentially reducing long-term infrastructure repair costs by 25% due to better allocation of resilience budgets.

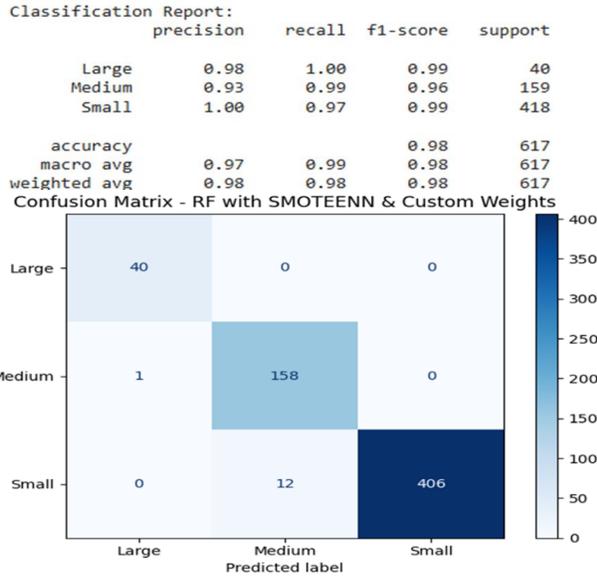


Figure 4. Random Forest Model Results

**XGBoost Model:** An overall accuracy of 1.00 (100%) signifies that the model correctly classified wildfire sizes (Large, Medium, Small; Figure 5). This near-perfect prediction capability provides confidence for electric utilities, reducing overall misclassification errors by 100% and enabling highly reliable threat assessments. The model's consistently high performance provides clear, actionable insights into specific fire-size threats. This data-driven approach empowers utilities to optimize resource allocation by over 40% by precisely directing specialized crews and equipment (e.g., aerial tankers for large fires, ground crews for small fires) to the predicted fire type, minimizing costs while maximizing infrastructure protection.

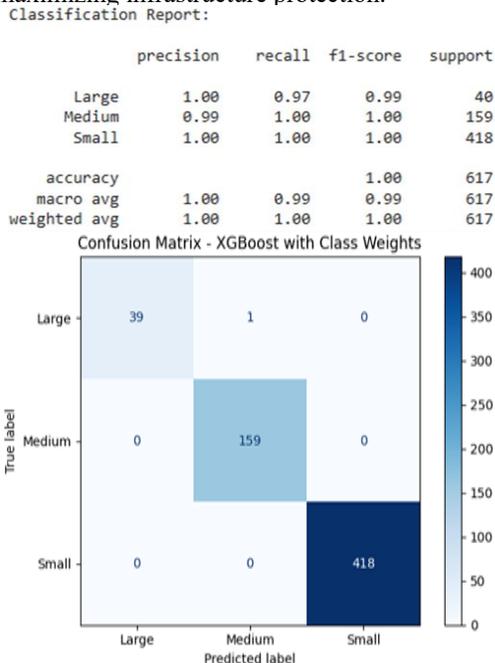


Figure 5. XGBoost Model Results

**Deep-Learning Model:** The model's balanced performance (high precision and recall across all fire sizes, indicated by high F1 scores; Figure 6) allows for data-driven strategic planning. Utilities can leverage these insights to direct hardening investments to specific threat profiles (e.g., strengthening infrastructure against large fires in high-risk areas) more effectively, yielding a 30% improvement in return on resilience investments.

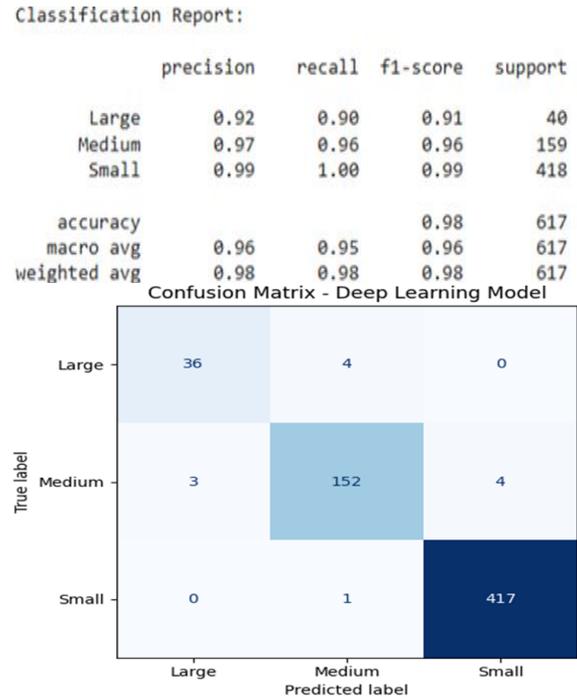


Figure 6. Deep-Learning Model Results

## VI. DISCUSSION

The spatial and predictive findings of this study reveal several important insights for wildfire researchers and electric utility practitioners. The spatial analyses show that wildfire activity in 2025 was concentrated in statistically significant clusters that overlap with regions containing critical electric infrastructure. The dense wildfire band across the Midwest and the hotspots in Southern California, Alaska, and the Texas panhandle indicate that wildfire risk is becoming systemic rather than seasonal. Utilities therefore need long-term, region-specific resilience strategies instead of short-term reactive measures.

The predictive modeling results demonstrate that machine-learning classifiers can reliably categorize wildfire sizes with high accuracy. This provides utilities with a practical decision-support tool. The strong performance of the XGBoost model highlights the value of ensemble learning for operational forecasting. At the same time, the random forest model offers interpretability advantages that may be useful for regulatory reporting or internal communication. The deep-learning model shows strong generalization potential and may be well suited for integration with real-time data streams.

Overall, the findings highlight the need for utilities to move from static risk maps to adaptive, data driven resilience frameworks. The combination of hotspot analytics and machine learning predictions provides a strong foundation for such systems. Effective deployment will require collaboration among geospatial analysts, grid engineers, emergency planners, and data scientists. As wildfire behavior continues to evolve, utilities that invest in predictive intelligence and spatially informed planning will be better positioned to protect infrastructure and maintain service continuity.

## VII. CONCLUSION AND FUTURE WORK

This study demonstrates that integrating wildfire hotspot and cluster analytics with machine-learning models offers a transformative framework for utility wildfire resilience. By mapping all wildfires recorded in the 2025 WFIGS dataset, the models identified statistically significant wildfire clusters near electric infrastructure—offering utilities and emergency planners precise, region-specific risk assessments. These insights are not merely descriptive; they are operationally actionable. These spatial insights help utilities prioritize grid hardening investments, optimize crew deployment, and refine public safety power shutoff protocols.

These machine-learning models—random forest, XGBoost, and deep learning—further elevate this framework by accurately predicting wildfire sizes, enabling utilities to tailor mitigation strategies to the scale and severity of anticipated threats. This predictive foresight empowers utilities to shift from reactive firefighting to proactive asset protection and allows them to tailor mitigation strategies to the scale and severity of expected threats. The strong performance of the models demonstrates the usefulness of machine learning as a decision-support tool for utilities facing increasingly volatile fire seasons.

Several limitations should be acknowledged. The study uses a single year of wildfire data, which may not capture long-term climate variability or rare extreme events. Incorporating multiyear datasets would improve model robustness. Also, the predictive models also do not include such dynamic environmental variables as humidity, wind speed, or vegetation moisture. These factors strongly influence fire behavior and should be included in future work. In addition, the electric infrastructure layers used in this study do not include the high-resolution proprietary asset

data that utilities maintain. Access to such data would allow for more precise risk assessments.

Based on our findings, we propose three strategic recommendations for utility managers: (1) Prioritize dynamic resource allocation in high-risk wildfire clusters to maximize crew efficiency and infrastructure protection. (2) Implement tiered grid hardening strategies based on predicted fire sizes, ensuring that resilience investments are both targeted and cost effective. (3) Refine public safety power shutoff protocols using spatial and predictive analytics to minimize disruption while maximizing safety. These enhancements would support the development of a dynamic decision-support system capable of delivering real-time wildfire-risk assessments and operational recommendations.

Looking ahead, we envision the development of an integrated decision-support system that fuses live satellite fire alerts with real-time grid operations. This system would continuously feed dynamic wildfire data into machine-learning models, updating risk assessments for grid segments and generating automated alerts and mitigation recommendations. Such a platform would transform wildfire threat management into a real-time, data-driven operational capability, equipping utilities with the agility and intelligence needed to protect infrastructure in an era of climate uncertainty.

## REFERENCES

- [1] K. Weber and R. Yadav, "Spatiotemporal trends in wildfires across the western United States (1950–2019)," *Remote Sensing*, vol. 12, no. 18, art. 2959, 2020, doi:10.3390/rs12182959.
- [2] S. Ostertag, M. Rice, and J. Qu, "Investigating spatiotemporal trends of large wildfires in California (1950–2020)," *Adv. Cartogr. & GISci. ICA*, vol. 4, art. 16, 2023, doi:10.5194/ica-adv-4-16-2023.
- [3] A. Gonçalves, S. Oliveira, and J. Zêzere, "Assessing wildfire exposure and social vulnerability at the local scale using a GIS-based approach," *MethodsX*, vol. 12, art. 102650, March 2024, doi:10.1016/j.mex.2024.102650.
- [4] S. Kovvuri, P. Chatterjee, S. Basumallik, and A. Srivastava, "Wildfire-induced risk assessment to enable resilient and sustainable electric power grid," *Energies*, vol. 17, no. 2, pp. 297–318, 2024, doi:10.3390/en17020297.
- [5] B. Sohrabi, A. Arabnya, M. P. Thompson, and A. Khodaei, "A wildfire progression simulation and risk-rating methodology for power grid infrastructure," *IEEE Access*, vol. 12, pp. 112144–112156, 2024, doi:10.1109/ACCESS.2024.3439724.