Wildfire-Power Grid Interactions: Feedback, Impacts, Monitoring, Modeling, and Mitigation Strategies

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Abstract

Wildfires are increasingly interacting with electric power systems through a two-way hazard chain: fires damage grid assets and trigger cascading outages, while grid faults can ignite new fires under hot, dry, and windy conditions. This review synthesizes the state of knowledge across five domains: (i) physical impacts of flames, heat, and smoke on lines, towers, insulators, and substations; (ii) power-infrastructure-initiated ignitions via conductor clash, high-impedance faults, and corona discharge; (iii) widespread blackouts and disproportionate societal impacts; (iv) multi-scale monitoring spanning laboratory tests, in-situ and grid-integrated sensors, and Earth observation; (v) coupled modeling that links fire behavior with grid operations; and (vi) technological and strategic mitigation pathways spanning prevention, response, and recovery. We integrate these domains into a novel 'feedback-aware' socio-technical framework. Through a longitudinal analysis (2005–2025) of global incidents, we identify that while vegetation contact remains the most frequent ignition source, aging infrastructure failure has emerged as a critical driver of catastrophic 'mega-fires'. We further identify persistent gaps, including limited interoperability of high-frequency grid and environmental data, scarce real-time data assimilation, and under-developed equity metrics for outage management. We conclude by outlining a research agenda to (1) deploy interoperable sensing architectures, (2) advance feedback-coupled fire–grid simulations, and (3) evaluate mitigation portfolios through techno-economic and fairness lenses. Recognizing wildfire–grid interactions as coupled socio-technical systems is essential for protecting infrastructure and communities and for ensuring reliable, sustainable electricity in a changing world.

Keywords: Wildfires; Power grids; Ignition mechanisms; Remote sensing; Coupled modeling; Public Safety Power Shutoffs (PSPS)

1. Introduction

Wildfires have become increasingly frequent, severe, and widespread over the past several decades [1–4]. This escalation reflects the combined influence of intensified extreme fire weather, including higher temperatures, lower humidity, and the occurrence of extreme wind events [5,6], enhanced vegetation growth and fuel accumulation in certain regions [7–10], and a rising likelihood of both natural and human-caused ignitions [11,12]. As urban development encroaches further into the wildland–urban interface (WUI), electrical power systems simultaneously face unprecedented exposure to wildfires [16,17]. This proximity creates a dangerous bidirectional hazard: power grids are increasingly vulnerable to fire-induced damage [18,19], while concurrently acting as a primary ignition source for some of the most destructive fires in modern history [20]. The complex, bidirectional relationship between wildfires and electric power systems underscores the urgent need for comprehensive resilience strategies [21,22].

The complexity of this interaction lies in its coupled feedback mechanisms. Wildfires pose immediate and severe threats to electric power infrastructure, rapidly degrading or destroying critical components such as utility poles, transmission and distribution lines, substations, transformers, and insulators [23,24]. The resulting physical damage triggers cascading effects, including widespread outages, hazards for emergency responders and the public, and substantial economic losses associated with system downtime, emergency repairs, and long-term restoration [25,26]. In addition, intense fire-induced heat and smoke compromise high-voltage system performance by reducing breakdown voltage by 70–80% through flame bridging and by an additional 20–50% due to smoke particle insulation degradation [24]. These interactions establish a reinforcing cycle in which wildfires damage power infrastructure, intensifying energy insecurity and hindering emergency response operations [27,28]. Electrical faults during high wind conditions can become potent ignition sources, as conductor clashing or vegetation contact may release high-temperature particles capable of igniting dry fuels [32]. Such fires often originate from failure mechanisms including conductor clashing, vegetation intrusion, or equipment breakdown [33–35]. Under strong winds, even relatively minor electrical faults can generate high-temperature arcs or molten metal particles that readily ignite nearby dry vegetation [36,37]. High-profile investigations, particularly in California, Colorado, and Australia, have repeatedly traced the origins of devastating wildfires to grid failures under extreme fire-weather conditions [38]. As wildfire seasons grow longer and more intense, the role of power infrastructure in ignition dynamics demands greater scientific, regulatory, and policy attention. However, critical knowledge gaps exist regarding how ignition risks vary across environmental and operational contexts, limiting predictive capabilities and effective mitigation strategies [25,39].

Effective management is currently hindered by fragmented monitoring and modeling capabilities. While satellite systems [40–48] and ground sensors [49–52] provide vast environmental data, integration with high-frequency grid diagnostics [53,54] remains limited by inconsistent formats and coverage gaps [55–57]. Similarly, coupled modeling frameworks often treat the grid as a static element, failing to capture dynamic ignition probabilities or the feedback effects of preventive de-energization [58–61]. Furthermore, mitigation strategies like Public Safety Power Shutoffs (PSPS) often lack integrated frameworks to evaluate their disproportionate socio-economic impacts on vulnerable communities [66,67].

This article bridges these gaps by presenting a holistic, 'feedback-aware' synthesis of wildfire–grid interactions. While existing reviews typically focus on isolated components such as specific ignition mechanisms or static risk planning, we integrate a longitudinal failure analysis (2005–2025) to quantify evolving risks, link the physics of ignition directly to cascading societal consequences, and center equity in the evaluation of mitigation strategies. Specifically, our contributions are threefold: (1) we formalize the bidirectional hazard chain connecting ignition, fire behavior, and grid stress; (2) we integrate monitoring and modeling advances into an interoperable data-to-decision pipeline; and (3) we evaluate mitigation portfolios by combining technical performance, costs, and equity considerations.

2. Wildfire's Assault on Power Infrastructure

Wildfires can severely compromise the structural and operational integrity of electric power systems (**Figure 1**). Analysis of major wildfire events between 2005 and 2025 indicates that distribution-level infrastructure—specifically poles, conductors, and insulators—accounts for approximately 91% of grid-wildfire interactions, significantly outweighing transmission-level structural failures (**Figure 1**). Exposure to flame, heat, smoke, and debris can degrade or destroy poles, insulators, conductors, substations, and transformers, resulting in prolonged outages and grid instability [73]. Damaged lines may even spark secondary fires if they contact smoldering vegetation [37]. These disruptions also hinder firefighting by disabling water pumps and emergency communications, as seen during the 2023 Lahaina Fire [74]. Power loss to critical facilities amplifies wildfire impacts, reinforcing a dangerous feedback loop between infrastructure failure and fire spread [75]. Understanding these mechanisms and identifying research gaps is essential for enhancing grid resilience under extreme fire conditions.

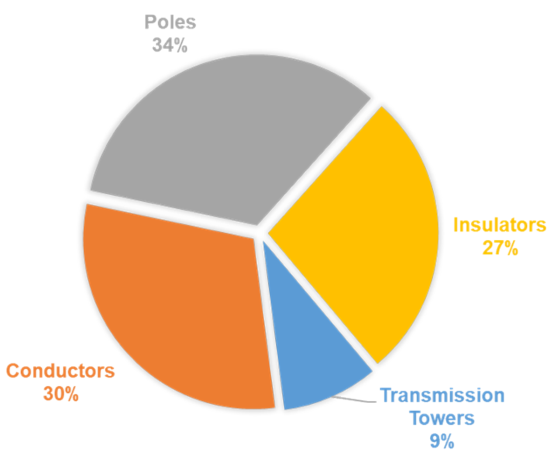

Figure.1 Proportional Impact of Wildfires on Key Power Network Components. *The chart illustrates the proportional frequency of involvement for distribution poles (34%), conductors (30%), insulators (27%), and transmission towers (9%). The statistical analysis is derived from the historical event data and failure mechanisms compiled in* ***Table S1****.*

Wildfires expose electric grid components to severe thermal and environmental stress, degrading materials, disabling assets, and increasing the risk of cascading failures. Radiant heat from intense flame fronts can elevate ambient temperatures to between 800 °C and 1200 °C, weakening or deforming metallic structures, annealing conductors, and in the most severe cases leading to partial or complete tower collapse [76]. While transmission towers represent only 9% of recorded impacts (Figure 1), failures when they do occur are often catastrophic; for instance, extreme wind-fire coupling led to the collapse of steel towers during the 2009 Black Saturday bushfires and caused structural damage in the 2016 Fort McMurray wildfire (**Table S1**). Simultaneously, fire-driven winds place additional mechanical stress on already heat-compromised systems [77,78]. Insulators, accounting for 27% of asset involvement (**Figure 1**), are particularly susceptible to these operational failures. Historical data confirms that smoke-induced flashovers triggered the massive 500kV line trips during the 2007 Witch Creek Fire and forced shutdowns during the 2013 Rim Fire (**Table S1**). Furthermore, dense smoke and ash clouds laden with ionized particles reduce the dielectric strength of air, thus raising the likelihood of electrical flashovers, insulator tracking, and phase-to-ground faults [79,80]. These failures are particularly detrimental when they disrupt critical facilities such as substations, water pumping stations, or emergency coordination hubs, as they can cause automatic shutdowns that hamper firefighting efforts and public safety communications [39,75]. The 2020 “Labor Day” wildfires in Oregon offer a stark example: entire communities lost power because of fire-damaged lines and substations, while essential emergency services struggled with reduced pumping capacity and limited communication capabilities [81]. Studies of grid resilience confirm that once a major transmission corridor or key substation is disabled, the surrounding network experiences heightened susceptibility to cascading outages and load imbalances [68,82]. Despite growing awareness of these compounding hazards, significant research gaps remain. These include the development of high-fidelity models capable of capturing both intense thermal exposures and secondary mechanical or electrical stresses, a clearer understanding of how ionized smoke evolves under varying fuel types [79], and more robust design standards for conductor and tower materials that can sustain or recover from short-term exposure to extreme temperatures [83]. Efforts to address these knowledge deficits, possibly through large-scale experiments or cross-disciplinary collaborations, would help utilities and policymakers define best practices for designing, operating, and upgrading infrastructure to withstand wildfire-relevant compound hazards [25].

Physical damage to grid components during wildfires involves intense heat, strong winds, and corrosive particulates, creating a scenario in which the destruction of critical elements not only hinders containment but also amplifies the disaster’s overall impact [84]. Wooden poles, widely used in distribution lines, are particularly vulnerable to combustion, representing the single most vulnerable asset category at 34% of recorded impacts (**Figure 1**). They can be completely consumed under severe flame exposure, disconnecting entire circuits and sometimes causing additional spot fires if energized lines drop onto unburned vegetation [85]. Recent incidents corroborate this vulnerability: the 2023 Maui Wildfires saw the destruction of aging wood infrastructure, while the 2024 Smokehouse Creek Fire was initiated when a decayed wood pole snapped under wind load (**Table S1**). Overhead conductors and associated hardware also face high-temperature risks, constituting 30% of documented failures (**Figure 1**). In aluminum-steel designs, or separation; in extreme cases, a sagging line in contact with ground fuels can propagate the existing wildfire perimeter or ignite secondary fires [78]. Notable examples include the 2007 Witch Creek Fire, where conductor slap and arcing ejected molten metal, and the 2021 Dixie Fire, which began after a Douglas Fir fell onto a conductor (Table S1). Furthermore, emerging threats such as "Zombie Lines"—abandoned infrastructure contacting live wires—have been implicated in recent events like the 2025 Eaton Fire (**Table S1**). Substations are similarly at risk, as heat, smoke, and ash can reduce insulation margins on transformers or switchgear, prompting flashovers and localized equipment failures that ripple through the broader grid. During the 2023 Lahaina Fire, multiple pole-mounted transformers and sectionalizing switches were visibly damaged or melted, offering a stark demonstration of the sensitivity of these key nodes to high-temperature events [86]. The resulting power outages curtailed the local water supply and hindered real-time updates on evacuation orders [75]. Empirical studies corroborate that when poles, substations, or other grid nodes fail, the network becomes highly susceptible to cascading disturbances, allowing wildfires to escalate more rapidly and complicating emergency response [82]. For example, the mechanical failure of a single C-hook on a transmission tower during the 2018 Camp Fire led to the catastrophic incineration of the town's entire distribution grid (**Table S1**). However, research on strengthening these components under realistic fire conditions remains relatively limited. Questions about the long-term durability of alternative materials, such as composite or steel-reinforced poles, and the performance of advanced fire-resistant coatings or enclosure systems are not fully resolved [87]. Large-scale testing that simulates extended flame exposure, combined with improved monitoring for early signs of mechanical stress or thermal damage, could markedly enhance infrastructure reliability in fire-prone regions [88,89].

3 Triggering Wildfires by Power Infrastructure

Electrical power systems have increasingly been recognized as significant ignition sources for wildfires, particularly under hot, dry, and windy conditions [33,90,91]. In regions like California, utility-related failures historically account for a relatively small fraction of total ignition events but result in disproportionately large burned areas and substantial financial losses [38]. This imbalance highlights that even isolated failures, such as conductor clashes, high-impedance faults, or corona discharges, can generate enough thermal energy to ignite nearby fuels, particularly during severe drought conditions. The following subsections describe the primary mechanisms through which electrical infrastructure can initiate wildfires.

As illustrated in **Figure 2**, we provide a longitudinal analysis (2005–2025) of these ignition mechanisms, synthesizing forensic data from major global wildfire incidents (detailed in Supplementary **Tables S2–S4**). The figure integrates physical illustrations of the three primary failure modes—vegetation contact, equipment failure, and conductor clash—with a temporal frequency analysis of major events.

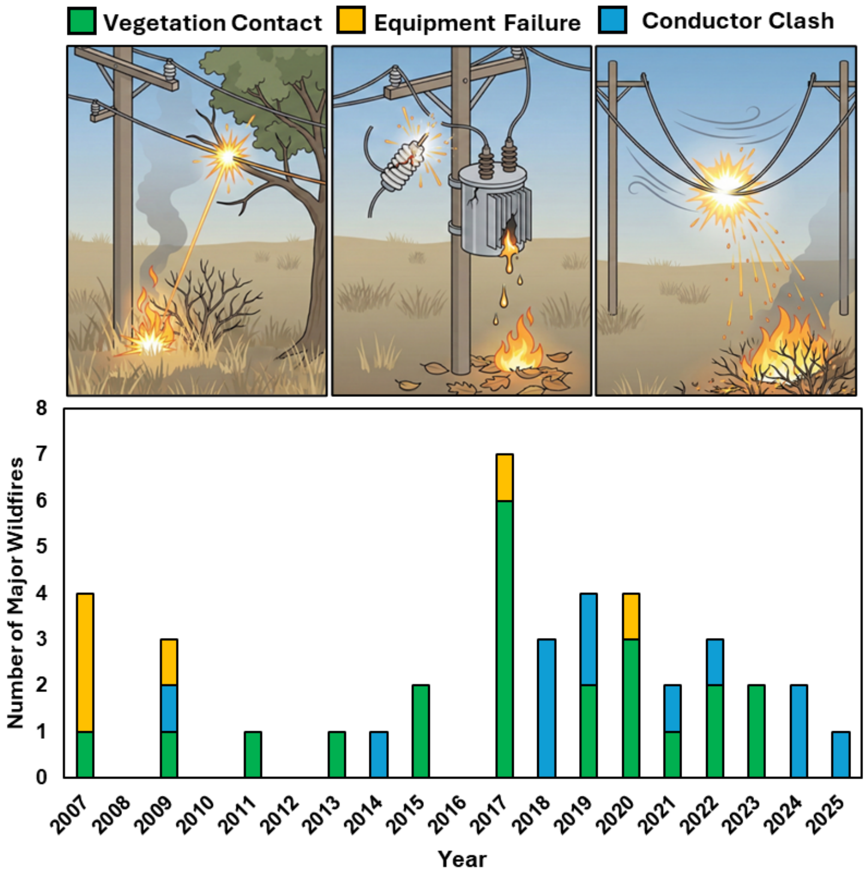

Figure.2 Temporal Distribution and Classification of Electrical Ignition Sources in Major Wildfires. *Figure 2 illustrates the three primary physical mechanisms by which power grid infrastructure initiates wildfires, alongside a temporal analysis of their occurrence in major events from 2005 to 2025. The statistical data and categorization of events presented in this figure are derived from the comprehensive incident records detailed in* ***Tables S2, S3, and S4****.*

This comparative analysis reveals distinct temporal characteristics: vegetation contact (green bars) remains the predominant ignition source, showing a marked surge during the 2017–2020 period driven by drought-induced timber fall. Equipment failure (yellow bars), while less frequent in absolute numbers, has been a critical driver of catastrophic 'mega-fires' during specific high-stress years. Meanwhile, conductor clash (blue bars) exhibits a volatile, event-driven pattern, spiking during years with extreme wind events. These trends underscore how environmental change is actively reshaping the risk profile of grid infrastructure.

Crucially, these failure mechanisms do not occur in a vacuum; they are amplified by compound weather extremes that simultaneously degrade grid physical limits and maximize fuel flammability. Heatwaves, in particular, create a dangerous 'Heatwave-Load-Sag' feedback loop that exacerbates grid vulnerability. Physically, high ambient temperatures reduce the convective cooling capacity of overhead conductors, lowering their dynamic line rating (ampacity). Coincidentally, extreme heat drives peak electrical demand (due to air conditioning loads), increasing the current density (I) and resistive heating (I^2R) within the lines. This combination of internal and external thermal stress causes excessive thermal expansion, forcing conductors to sag below safe clearance heights and increasing the probability of contact with underlying vegetation. This vulnerability is further compounded by hydrometeorological extremes. Prolonged droughts increase soil resistivity, which can impede the operation of grounding protection systems, allowing high-impedance faults to persist undetected for longer durations. Similarly, extreme wind events—often associated with 'Red Flag' warnings—impose mechanical shear stresses on aging poles and cross-arms that may have already been weakened by thermal cycling. Therefore, the ignition mechanisms detailed below (line clash, vegetation contact, equipment failure) must be understood as the terminal failure points of a grid pushed beyond its design envelope by synergistic weather stressors.

3.1 High-Impedance Faults from Vegetation Contact

As shown by the green bars in, vegetation contact remains the most frequent ignition source, accounting for ~40–50% of utility-related ignitions. This mechanism occurs when a live conductor contacts tree limbs or the ground in such a way that the resulting fault current remains too small to trigger protective devices [100,101]. Because this low-level current barely exceeds normal load currents, standard overcurrent relays or circuit breakers may not detect the anomaly, allowing the conductor to heat nearby fuels gradually until ignition ensues [32,37]. Supplementary Table S1 documents the persistence of this risk, ranging from the 2007 Rice Fire to the 2023 Maui (Lahaina) Fire. Documented cases have shown that downed lines can arc intermittently on grass or branches for hours without causing a fuse to blow [102]. Recent trends indicate a shift from preventable "grow-in" contacts to unpredictable "fall-in" events driven by megadroughts. Similarly, partial faults, though not purely classified as High-Impedance Faults (HIFs), have contributed to catastrophic blazes like the 2018 Camp Fire in California, where worn line components produced sustained arcing that remained undetected long enough to ignite surrounding fuels [103].

Detecting HIFs remains particularly challenging because the fault current rarely presents an unambiguous waveform signature [104]. Advanced machine learning algorithms [105], wavelet-based signal analysis [106], and specialized sensors capable of identifying subtle harmonic distortions [101] have been proposed as detection solutions, although these methods often require high-resolution data and extensive training datasets. Cost-effectiveness is a concern, since upgrading protective infrastructure across sprawling territories imposes substantial financial burdens on utilities, especially in rural and socioeconomically disadvantaged areas [70]. The development of economically viable, modular detection systems represents a key research gap. More robust field validation of algorithmic detection strategies could accelerate their adoption [107].

3.2 Electrical Equipment Failure

Electrical Equipment Failure and Insulation Degradation Equipment failure, represented by the yellow bars in **Figure 2**, encompasses mechanical and electrical breakdowns—such as transformer explosions, broken C-hooks, or insulator flashovers—often exacerbated by aging infrastructure. As detailed in Supplementary Table S2, this mechanism drives catastrophic "mega-fires" (e.g., the 2018 Camp Fire and 2024 Smokehouse Creek Fire) where asset failure coincides with extreme weather. A critical, albeit subtle, precursor to these failures is Corona Discharge. Corona discharges, which arise from ionized air around high-voltage lines and insulators under strong electric fields, also have the potential to ignite vegetation even in the absence of visible sparks or direct contact [37]. Factors that amplify corona phenomena include aging infrastructure, accumulations of dust or salt, and vegetation that sags close to conductors, all of which reduce the effective insulation distance and intensify localized discharge [108]. Sustained corona activity can lead to "flashover" events or pole fires—classified ultimately as equipment failure. Laboratory research indicates that the voltage required to ignite fine fuels such as eucalyptus leaves or pine needles can decline by as much as 11% when the conductor is within a few centimeters of the plant material [37]. Real-world incidents provide further insight into this hazard. Although the 2018 Woolsey Fire in California was primarily attributed to a broken guy wire, investigators raised the possibility that corona activity near compromised insulators preheated local fuels, increasing their susceptibility to ignition under fierce Santa Ana winds [109]. During the 2020 Labor Day wildfires in Oregon, extreme wind gusts not only downed several power lines but also brought some lines and vegetation dangerously close, creating conditions in which corona discharge might have contributed to sporadic ignitions [81]. Sustained corona events can smolder undetected, making them particularly insidious in dry environments.

A key research gap lies in developing cost-effective monitoring systems, such as radiofrequency sensors or reflectometry-based detectors, capable of scanning extensive transmission corridors for early corona activity [108]. Additionally, a better understanding of partial drying or repeated discharge episodes would help quantify the time windows during which vegetation transitions from damp to readily ignitable [110]. While insulator cleaning and stricter vegetation clearance standards can diminish corona-related risks, more detailed field experiments and remote-sensing integration are needed to pinpoint early ignition hotspots [49].

3.3 Molten Aluminum Droplets from Line Clash

Under high wind conditions, overhead power lines can be forced into contact, resulting in a phenomenon known as conductor slap or line clash. When energized conductors collide, intense electrical arcing occurs at the point of impact, producing sufficient heat to melt the aluminum in the wires and eject droplets of molten metal [92,93]. These aluminum droplets can remain at temperatures between 300–400 °C during descent, with arc-generated flame temperatures approaching 3,800 K—well above the ignition threshold of most wildland fuels [94]. If the falling droplets land on dry vegetation or accumulated biomass debris, ignition is highly likely. This ignition mechanism has been linked to several major wildfire events. For example, during the 2017 Thomas Fire in California, strong winds caused Southern California Edison's lines to clash, ejecting molten particles that ignited surrounding vegetation. The resulting wildfire burned over 440 square miles and destroyed more than 1,100 structures [95]. Similarly, in the 2007 Grass Valley Fire, a downed tree caused conductor contact and equipment overheating, leading to melted aluminum dripping onto dry biomass and triggering an 850-acre fire [96]. Field observations indicate that line clash events can account for 17–18% of utility-related wildfire ignitions in wind-prone areas [97,98], yet research gaps remain regarding how wind turbulence, local humidity, and vegetation density influence ignition thresholds. Existing detection methods typically rely on post-incident relay data or mechanical damage reports [98], but high-speed sensor arrays and conductor improvements, such as arc-resistant coatings or real-time tension control, may offer earlier interventions [38,99]. Further studies that integrate large-scale experiments with advanced sensing technology could refine our understanding of how molten droplets ignite fuels in diverse environmental regions. Separately, on a practical level, a critical engineering challenge remains in the development of low-cost, fire-resistant grid components, such as interphase spacers, to prevent conductor arcing in the first place.

4. Widespread Wildfire-related Blackouts and Societal Impacts

While the preceding sections detailed the physical mechanisms of grid failure and ignition, these engineering challenges cannot be decoupled from their cascading societal consequences. In a feedback-aware framework, societal impacts—ranging from economic paralysis to healthcare disruptions—serve as the critical 'error signal' that recalibrates grid operations and planning.

Wildfire-induced power outages, illustrated in **Table 1**, are increasingly common and posing wide-ranging risks to health, safety, and economic stability [25,111]. Currently, utilities face an optimization dilemma: minimizing wildfire ignition risk (via de-energization) often maximizes societal disruption. While preemptive shutoff strategies like the PSPS help reduce ignition risk, they often exacerbate social imbalances and disrupt essential services [38,112,113]. Such blackouts affect beyond energy access; they impact healthcare delivery, communication networks, water systems, and economic continuity [75,114–116].

The severity of these impacts directly dictates engineering constraints, such as the wind-speed thresholds for triggering PSPS or the prioritization of microgrid deployments in vulnerable communities [38,112,113]. Therefore, understanding these specific societal vulnerabilities is not merely a sociological exercise but a prerequisite for designing protection schemes that are both technically effective and socially licensed. To elucidate these multifaceted dynamics, the following subsections expand upon specific dimensions of the societal impacts of wildfire-driven outages, existing mitigation strategies, and the research gaps that persist.

Table.1 Taxonomy of wildfire-induced power outages and cascading societal impacts.

Impact Domain	Mechanism of Disruption	Societal Impact Trend
Economic Continuity	Business Closure: Loss of power forces closure of retail and industrial operations; spoilage of refrigerated goods [119,123].	Rising Cost: Small businesses in rural areas face disproportionately long recovery times compared to urban centers with redundant power [112,121]
Vulnerable Populations	Life-Support Failure: Loss of power for home medical devices (e.g., oxygen concentrators) and HVAC during smoke events [75,114–116].	Critical Vulnerability: Reliance on home-based care has increased, making PSPS events life-threatening for the medically vulnerable [125].
Critical Infrastructure	Service Interruption: Loss of power to water pumps (firefighting) and cellular towers (emergency alerts) [75,114–116].	Systemic Risk: Communication blackouts have been a contributing factor in fatalities during recent rapid-onset fires (e.g., Lahaina, Paradise) [126–128].
Mitigation Displacement	Backup Reliance: Shift to diesel generators increases local pollution and fuel dependency [119,123].	Inequitable Adaptation: Wealthier households adopt solar storage, while lower-income residents suffer prolonged outages [124].

4.1 Economic Disparities and Community Vulnerability

Wildfire-induced blackouts can impose far-reaching economic costs, including business interruptions, production losses, and diminished consumer spending [112,121]. Small businesses operating on tight margins may be forced to close during repeated outages, compromising local livelihoods and driving community-level disinvestment [122]. In agricultural regions, extended power losses can disrupt irrigation systems or cold-storage facilities, leading to crop spoilage or reduced yields [119,123]. In particularly vulnerable rural economies, even short-term interruptions can trigger disproportionate losses in local supply chains, as farms or food processors depend on constant refrigeration and precise watering schedules [123,124]. This economic fragility often forces grid planners to re-evaluate de-energization protocols in agricultural corridors during harvest seasons. Although some utility-driven compensation programs exist, they rarely cover the full costs incurred by small enterprises or low-income households, underscoring critical gaps in existing policies

[70,112].

Evidence also indicates that historically marginalized and low-income communities bear a disproportionate share of these impacts [124]. Residents who rely on public assistance or have fewer social networks often lack the funds to purchase backup generators or solar-plus-storage systems [122]. This disparity highlights a failure in current resilience planning: technical reliability metrics (like SAIDI) often mask the concentrated suffering of specific demographics. While PSPS decisions may be justified by high wildfire risks, these shutoffs often fail to account for the compounding vulnerabilities that certain populations face [112]. Collaborative partnerships between utilities, governmental agencies, and community organizations can help identify targeted subsidies or resource-sharing initiatives to mitigate these imbalances [125].

4.2 Impacts on Critical Infrastructure and Essential Services

Beyond residential consumers, critical infrastructure such as hospitals, water treatment plants, and communication networks can be severely compromised during wildfire-induced blackouts [126–128]. Water utilities often depend on electricity for pumping and filtration, meaning that a loss of power can reduce water pressure for firefighting efforts or limit potable water availability to [127]. In the 2020 "Labor Day" wildfires in Oregon, for instance, extensive outages impaired emergency response, leaving entire communities offline for extended periods [128]. This loss of firefighting capacity creates a dangerous positive feedback loop: the de-energization intended to prevent fires can hamper the ability to fight them. Furthermore, prolonged service disruptions to water plants and wastewater facilities may increase health risks by degrading sanitation and hygiene standards [129,130].

Wildfires that severely damage power lines can also knock out telecommunication relay stations, making it more difficult for residents to receive evacuation alerts or locate safe shelters [129,130]. In rural areas, local radio transmitters and internet hubs may have minimal backup systems, further undermining timely dissemination of critical warnings [131]. These interdependencies highlight the urgent need for coordinated infrastructure planning that prioritizes distributed power generation for these critical nodes [126,131]. Hospitals and healthcare facilities may resort to emergency generators, yet these systems can fail if maintenance has been neglected or if fuel supplies run low [132]. Rapid identification of at-risk sites, along with cross-sector contingency planning (involving fire agencies, utilities, and medical providers), is essential to minimize disruptions and fatalities [126,131].

4.3 Strategies for Minimizing Blackout Consequences

A growing body of research and practical experience suggests that both engineering solutions and policy reforms can help limit the societal fallout from wildfire-induced outages [39]. Alongside technical interventions, effective public communication regarding wildfire risks and planned de-energizations, such as the PSPS, is a critical strategy for managing consequences. Drawing on insights from social and behavioral sciences, robust communication aims to enhance public risk perception, build trust, and provide clear, actionable guidance for protective measures. However, challenges remain in reaching vulnerable populations and ensuring consistent messaging across agencies, highlighting this as a key area for further research and policy development. Engineers have tested real-time adjustment of power flows and line ratings to prevent conductor overheating, combined with advanced fault-detection methods to isolate faults quickly and reduce the spatial scope of de-energization [134]. However, these technical measures must be calibrated against socioeconomic data. For instance, advanced line ratings can be particularly effective in high-wind or extreme-heat scenarios, but rapid redeployment of maintenance crews also matters for timely repairs [134,136]. Some utilities have piloted automated reclosers with built-in fire detection sensors, enabling partial or conditional restoration of non-faulted segments [137,138]. However, the success of these measures hinges on reliable telemetry and communication links—infrastructure that is often most fragile in the very areas targeting for protection [130]. To bridge these technology and workforce gaps, coordinated investment in grid modernization and skill-building programs is needed, especially in historically under-resourced regions [139,140]. Microgrids and distributed generation remain vital for sustaining critical loads when segments of the main grid are intentionally shut down [141,142]. Public facilities, such as schools or community centers, can be upgraded with battery storage and renewable energy sources, creating hubs of electricity supply for evacuees and first responders [143,144]. Additionally, demand response programs can shift non-essential loads or reduce system stress during peak fire risk periods [145]. Yet these approaches often face regulatory, financial, and operational barriers, leading to uneven deployment across different utilities and regions [146,147].

5. Monitoring and Observational Techniques for Wildfire–Grid Interactions

Robust, multi-scale observations are indispensable for elucidating the bidirectional interactions between wildfires and electric power systems and for quantifying their cascading socio-economic impacts. Contemporary efforts draw upon a suite of laboratory tests, field trials, remote-sensing platforms, and sensor-based grid analytics that together provide time-synchronized data on ignition processes, fire behavior, infrastructure stress, service interruptions, and community disruption (**Table 2**). This section reviews the principal classes of monitoring techniques, highlights their respective capabilities and limitations, and outlines future research priorities. Furthermore, we address the fundamental technical barrier of integrating these diverse data streams, specifically examining the inherent spatiotemporal mismatches between high-frequency electrical analytics and broad-scale environmental observations.

Table 2. Integrated inventory of wildfire–grid monitoring and experimental approaches.

Major category	Subsystem / Method	Key variables measured or tested	Scale / Cadence or Test Conditions	Typical wildfire-grid applications	Ref
Controlled laboratory & field experiments	Full-scale pole burn tests	Residual bending strength, char depth after 1 000–1 150 °C exposure	Full-length wood/steel /composite poles; minutes of direct flame	Ranks pole materials & fire-retardant coatings for hardening programmes	[85]
	Energized-conductor flame-plume tests	Flash-over voltage, leakage current in flames + smoke	69–230 kV lab span; kHz sampling	Defines clearance-to-fuel & emergency de-rating thresholds	[24]
	Medium-voltage arc-fault signature library	High-freq. V/I waveforms, arc duration, impedance trajectory	4–25 kV loop; staged gap-clash & down-conductor events	ML training set for early HIF/arc detection & pre-emptive trip	[148]
	Composite-insulator / cross-arm furnace ageing	Mass loss, dielectric strength after repeated 200–600 °C cycles	Coupons & half-strings; 200–600 °C thermal cycling	Life-cycle models for asset-hardening cost–benefit analysis	[32,149]
	Tree-related HIF ignition tests	Arc energy, fault resistance, ignition probability	12 kV feeder mock-ups contacting dry/wet vegetation	Calibrates trip settings that avoid re-energizing ignitable HIFs	[32]
Remote-sensing platforms	Polar-orbiting satellites (MODIS, VIIRS, Sentinel-3)	Thermal anomalies, FRP, burn scar, night-lights	375–1 000 m; 2–4 revisits day^{-1}	Detect remote ignitions; regional blackout mapping	[43,46,150–152]
	Airborne IR & LiDAR surveys (crewed aircraft and UAVs)	Sub-meter flame-front temperature, vegetation clearance, conductor sag	On-demand sorties; ≤30 min revisit with rotary-wing or tethered VTOL; multi-hour loiter for fixed-wing UAS	Verify satellite/ground-camera detections; map hottest spans and asset thermal margins while lines remain energized; guide patrol crews after PSPS or once the fire front has passed	[42]
	Geostationary imagers (GOES-R, Himawari-8)	2 km sub-pixel hotspots, plume height	5–15 min	Minute-scale alerts as fire flanks approach conductors	[48]
	Daily CubeSats (PlanetScope)	3 m RGB/near-IR; vegetation height & vigor	1 day; 3 m	Monitors fuel accumulation & sag-to-fuel clearance	[153]

	SAR (Sentinel-1, ALOS-2)	Back-scatter & coherence loss for heat-damaged towers	10 m; 6–12 day	Rapid post-fire line-asset damage assessment	[154]
	Hyperspectral smallsats (PRISMA, EnMAP)	Fuel moisture indices, canopy chemistry	30 m; 11–16 day	Fine-scale fuel-moisture mapping for ignition risk	[155]
	Internet of Things camera networks + AI	RGB/IR video, smoke pixel ratios	Continuous; ≤30 km Line of Sight	<60 s smoke confirmation & ±100 m triangulation	[156]
In-situ environmental & grid-integrated sensors	Weather radar (e.g., NEXRAD)	Precipitation intensity, storm cell structure, wind velocity	~1 km; 2–5 min updates	Tracks convective cells that produce lightning; identifies gust fronts and wind shifts that influence fire spread.	
	Ground-based lightning detection networks	Lightning strike location, polarity, peak current	Real-time; <500 m accuracy	Pinpoints lightning-caused ignitions near power lines; informs patrol dispatch after storms; provides forensic data.	
	Mesonet station	Wind gust, T, RH, fuel-moisture deficit	1–10 min; ≤5 km spacing	Drives DLR & PSPS thresholds; refines fire-spread models	[157]
	Crowdsourced smartphone sensors	Calibrated T & RH → VPD index	10 min; quasi-dense users	Supplements sparse wx network in WUI zones	[50]
	Clamp-on IoT sag/tilt nodes	Current, conductor T, sag, vibration	0.1–1 s; per span	Real-time clearance alarms; galloping/clash detection	[51]
	Travelling wave / PMU analytics	kHz V/I, impedance trajectory	1–5 kHz (TW); 30–240 Hz (PMU)	Localises HIFs within ±200 m; pre-arc shut-off	[158]
	DAS on OPGW fibre	Vibration spectrum every 10–20 m	100 Hz; 10 km–50 km reach	Detects branch strike, pole fall, conductor slap in real time	[159]
	DTS (Raman/Brillouin)	Continuous conductor temperature profile	1 m spatial; 1–5 min	Validates weather-based DLR; flags wildfire heating	[52]
Socio-economic consequence monitoring	AMI + SCADA outage analytics	Time-stamped loss-of-supply, breaker status	1 s–15 min	Customer-minute tracking; critical-load restoration triage	[160]

	Satellite night-lights radiance	Spatially explicit outage footprint	Nightly; 500 m	Independent verification of restoration progress	[43]
	GPS / CDR-based mobility flows	Evacuation rate, travel times	5–30 min; ≈100 m	Real-time routing & shelter allocation during PSPS	[161]
	Point-of-sale & smart-meter load curves	Sales volume, load rebound lag	15 min–hourly	Quantifies economic shock & recovery trajectory	[162]
	Health-impact surveillance	ED visits, respiratory admissions	Hourly (ED); daily aggregates	Links outage + smoke exposure to public-health burden	[163]

Abbreviations: AMI (Automated Metering Infrastructure), CDR (Call Detail Record), DAS (Distributed Acoustic Sensing), DLR (Dynamic Line Rating), DTS (Distributed Temperature Sensing), ED (Emergency Department), EnMAP (Environmental Mapping and Analysis Program), FRP (Fire-Radiative Power), GOES-R (Geostationary Operational Environmental Satellite - R Series), GPS (Global Positioning System), HIF (High-Impedance Fault), IoT (Internet of Things), IR (Infrared), LiDAR (Light Detection and Ranging), ML (Machine Learning), MODIS (Moderate Resolution Imaging Spectroradiometer), OPGW (Optical Ground Wire), PMU (Phasor Measurement Unit), PRISMA (PRecursore IperSpettrale della Missione Applicativa), PSPS (Public-Safety Power Shut-off), RH (Relative Humidity), SAR (Synthetic Aperture Radar), SCADA (Supervisory Control and Data Acquisition), SLSTR (Sea and Land Surface Temperature Radiometer), TW (Travelling Wave), UAS (Uncrewed Aircraft System), UAV (Unmanned Aerial Vehicle), VIIRS (Visible Infrared Imaging Radiometer Suite), VTOL (Vertical Take-Off and Landing), and WUI (Wildland-Urban Interface).

5.1 Controlled Laboratory and Field Experiments

Field experiments and laboratory studies provide fundamental insights by directly observing fire behavior and its effects on grid components under controlled conditions. Utilities and research institutions have conducted full-scale burn tests on power system hardware to quantify fire resistance and failure modes. For example, Southern California Edison developed a wildfire fire-testing protocol in which full-size utility poles are exposed to intense flames (≈1000–1150 °C for several minutes) before measuring residual bending strength and char depth [85]. Such tests have compared materials and protective coatings to determine which designs best survive wildfire exposure, aiding in ranking pole materials and fire-retardant coatings for hardening programs [85]. Likewise, high-voltage laboratories have simulated wildfires under energized lines by igniting fuels beneath test conductors (e.g., in 69–230 kV lab spans) to study how flames and dense smoke reduce air insulation strength by measuring variables like flash-over voltage and leakage current [24]. In addition to destructive testing, controlled experiments are used to capture the signatures of electrical faults that can ignite fires. A notable effort is the creation of fault signature libraries through staged ignition tests. For example, a recent project is conducting medium-voltage (e.g., 4–25 kV) arc experiments, including staged gap-clash and down-conductor events, to build a database of high-frequency V/I waveforms, arc duration, and impedance trajectory that characterize conditions leading to line-induced ignitions, intended as an ML training set for early HIF/arc detection [148]. Field demonstrations have also been carried out in real fire environments to test new sensors. During a 2021 wildfire in Tennessee caused by downed lines, researchers deployed drones around live transmission infrastructure to monitor how close the equipment was to thermal failure. Using infrared cameras, they identified overheated transformers and lines in the active fire zone so that damaged components could be replaced proactively.

Although these experiments are pivotal for model calibration, they often lack the complexity of real-world fire scenarios, where variables such as wind-driven ember storms, shifting fuel conditions, and dynamic load profiles may complicate outcomes. Additionally, scaling results from laboratory conditions to large, geographically dispersed networks can be challenging. Further research should strive for multi-parameter test conditions, including repeated thermal cycling (e.g., 200-600 °C) on various composite materials to assess mass loss and dielectric strength for life-cycle models and realistic ignition events involving vegetation contact (e.g., on 12 kV feeder mock-ups) to calibrate trip settings based on arc energy, fault resistance, and ignition probability [32,149]. Collaborations between utilities, fire labs, and academic institutions can help develop standardized testing protocols that better reflect field complexities and support comprehensive asset-hardening strategies.

5.2 Remote-Sensing Platforms

Polar-orbiting instruments such as MODIS, VIIRS, and Sentinel-3 SLSTR resolve thermal anomalies at 375–1000 m resolution and revisit sub-daily [43,46,150–152], whereas geostationary imagers (e.g., GOES, Himawari-8) update every 5–15 min [48]. Meanwhile, high-spatial-resolution CubeSats like PlanetScope deliver daily 3 m imagery to monitor vegetation vigor and conductor clearance-to-fuel, informing proactive vegetation management [153]. Synthetic Aperture Radar (SAR) from satellites like Sentinel-1 and ALOS-2 contributes to rapid post-fire line-asset damage assessment by detecting backscatter and coherence loss for heat-damaged towers, typically at 10 m resolution with a 6–12-day revisit cycle [154]. Furthermore, hyperspectral smallsats such as PRISMA and EnMAP can provide fine-scale (e.g., 30 m resolution) fuel-moisture mapping for ignition risk by assessing fuel moisture indices and canopy chemistry [155]. These complementary data streams delineate active fire perimeters, fire-radiative power, and smoke advection, thereby supporting early warnings for transmission corridors situated kilometers to tens of kilometers from the flame front [45]. Crewed aircraft and fixed-wing or rotary-wing UAS equipped with long-wave infrared, ultraviolet, or LiDAR payloads deliver meter-scale maps of flame intensity, vegetation clearance, and conductor sag [42]. Rapid mobilization enables post-fire line inspections and hotspot confirmation during public-safety power-shutoff windows. Persistent fixed-wing UAS have demonstrated multi-hour loiter times, permitting continuous thermal surveillance of inaccessible corridors and verification of satellite/ground-camera detections [42]. Pan-tilt-zoom camera arrays, as part of Internet of Things networks, mounted on towers and ridgelines now offer 360° optical and IR surveillance (capturing RGB/IR video and smoke pixel ratios) with AI-assisted smoke recognition for rapid confirmation and triangulation [164].

Despite improvements in revisit times and spatial resolution, certain limitations in remote sensing persist. Thermal sensors may be obscured by dense smoke plumes or cloud cover, while geostationary coverage can be too coarse for localized infrastructure planning and deployment of mitigation strategies. Additionally, multi-sensor data fusion approaches—such as combining MODIS with VIIRS, Sentinel-1 SAR, and CubeSat imagery—still face challenges in cross-calibration and data latency [165]. Future developments should focus on enhancing data interoperability, improving on-board processing for rapid data downlink, and refining algorithms for near-real-time detection of power grid threats and fire risks. Advanced machine learning approaches, trained on multi-resolution satellite data, may further improve fire behavior forecasting and damage assessment.

5.3 In-Situ Environmental and Grid-Integrated Sensors

In-situ sensor networks deliver high-frequency, localized data critical for wildfire risk assessment and grid protection. Ground-based weather radars track storm cell structure and gust fronts, while lightning detection networks provide real-time mapping of strikes that could cause natural ignitions near grid infrastructure. In parallel, utility-operated mesonets, comprising dense weather stations, measure wind gusts, temperature, relative humidity, and fuel-moisture deficits, which feed into dynamic line rating (DLR) and PSPS decisions [157]. Simultaneously, clamp-on IoT nodes track conductor temperature, sag, and vibration at sub-second intervals, alerting operators to potential mechanical stress or flashover risks [51]. Distributed Temperature Sensing (DTS) using Raman or Brillouin techniques in OPGW fiber offers continuous conductor temperature profiles, valuable for validating weather-based DLR and flagging wildfire heating [52]. More advanced systems include traveling-wave analytics and distributed acoustic sensing (DAS) to localize high-impedance faults and detect real-time events such as pole collapse or conductor slap over tens of kilometers [158]. DAS on OPGW fiber can detect real-time physical events such as branch strikes, pole collapse, or conductor slap over tens of kilometers [159].

While these sensors greatly enhance situational awareness, wide-scale deployment faces cost and integration barriers, particularly in remote or rugged terrain. Balancing data volume with practical bandwidth and power constraints also remains a concern, as does the calibration of crowdsourced smartphone sensor data for supplementing weather monitoring in wildland–urban interface zones [50]. Future research should examine how to seamlessly integrate these diverse sensor feeds—ranging from low-frequency SCADA data to high-frequency acoustic signatures—into advanced classification, forecasting, and decision-support tools. Developing robust data communication infrastructures and standardizing sensor protocols can further elevate the utility and reliability of in-situ monitoring.

5.4 Monitoring Socio-Economic Consequences of Fire-Induced Outages

Socio-economic indicators offer another layer of critical information on the broader impacts of wildfires on electrical infrastructure. Automated metering infrastructure (AMI) and SCADA analytics provide near-real-time outage data, breaker statuses, and time-stamped restorations — metrics crucial for quantifying customer-minute interruptions and prioritizing critical loads [160]. In tandem, satellite-based nighttime lights data (e.g., VIIRS Black Marble) can independently verify the extent and duration of power loss over large areas [43]. Further downstream, mobility flow analysis from GPS or call detail records sheds light on evacuation patterns and the effectiveness of emergency response in PSPS scenarios [161], while point-of-sale and smart-meter load curves track economic disruptions and recovery trends [162]

Despite their utility, these socio-economic datasets often lack integration with technical grid parameters, leaving operators with partial views of wildfire impacts. For instance, health-impact surveillance data on respiratory admissions may be available only at daily intervals, limiting immediate health response coordination [162] Additionally, sensitive user mobility or spending data presents privacy and regulatory hurdles, complicating real-time data sharing. Future work should focus on developing frameworks that securely combine socio-economic metrics with infrastructure status, enabling refined, equitable restoration strategies. Clear guidelines for data privacy, along with standardized metrics for outage and health impact reporting, will be essential for comprehensive, community-focused wildfire management.

5.5 The Challenge of Spatiotemporal Mismatch in Data Fusion

A fundamental technical barrier to realizing the 'smart monitoring' vision is the inherent spatiotemporal mismatch between electrical and environmental data streams. As depicted in the data taxonomy, these datasets occupy opposite ends of the resolution spectrum, creating significant hurdles for real-time fusion algorithms [55].

Temporally, the discrepancy is orders of magnitude. Grid sensors, particularly Phasor Measurement Units (PMUs), stream voltage and current data at 30–60 samples per second (milliseconds resolution), capturing transient fault dynamics. In contrast, environmental data is often latency-bound: satellite-based vegetation indices (e.g., NDVI from Sentinel-2) are updated every 5–10 days, while standard weather stations report hourly. This mismatch implies that a transient wind gust causing a conductor clash may occur entirely between two weather sampling points, leading to a 'missing predictor' problem in risk models [195]. Current research addresses this via temporal upsampling techniques (e.g., cubic spline interpolation) or by deploying localized IoT anemometers that match the reporting frequency of SCADA systems.

Spatially, the challenge lies in topological alignment. Grid data is discrete and nodal (specific to a tower or substation), whereas environmental data is continuous and raster-based (pixels covering km²). Aligning these requires mapping gridded meteorological data onto the linear topology of transmission corridors. Recent approaches utilize 'virtual sensor' techniques, where weather variables are spatially interpolated (kriging) to the exact coordinates of transmission towers [56]. Failure to rigorously address this alignment results in significant monitoring errors, where a model may correctly detect an electrical fault but fail to correlate it with the localized microenvironment that caused it, thereby reducing the predictive accuracy of ignition warning systems.

6. Coupled Modeling Approaches

Over the past two decades, researchers have developed a spectrum of models to link wildland fire behavior with the resilience of electric power systems. These range from fire-centric simulators that overlay fire spread on grid maps, to grid-centric resilience tools that incorporate wildfire as an external stress, to more fully coupled frameworks that attempt to intertwine the two domains. **Table 3** outlines these approaches, highlighting their focus, strengths, and limitations. A clear evolution emerges: early studies tended to treat wildfire and power systems separately, while recent efforts strive for integration—combining fire spread dynamics, infrastructure vulnerability, predictive analytics, and even multi-hazard considerations into unified frameworks.

Table 3. Key Modeling Approaches for Wildfire Risk and Electric Power System Resilience.

Model	Key Focus	Strengths	Key Gaps	Example
Wildfire Spread + Grid Overlay	Overlay empirical fire spread onto electrical networks to assess exposure	Well-validated fire spread methods; straightforward infrastructure impact assessment	One-way coupling; requires high-resolution input data; manual scenario design	SPARK [166] FARSITE [167] + Grid Overlay [168] Technosylva Wildfire Analyst (used by SCE)
Coupled Fire–Vegetation–Atmosphere Simulation	Two-way modeling of wildfire and atmospheric feedbacks	Captures dynamic wind-fire interactions; open-source implementations	Computationally expensive; limited representation of power infrastructure	WRF-Fire [169]
Probabilistic Wildfire Risk	Monte Carlo-based burn probability estimates over large landscapes	Quantifies uncertain ignitions and weather; identifies high-risk	Snapshot of current fuel/weather conditions; no real-time capability;	Burn Probability (BP) models [170] Pyrologix, used by PGE)

		corridors	separate infrastructure step	
Data-Driven Predictive Analytics	ML-based methods to predict or detect power line ignitions and fire risks[171]	Real-time or near-term warnings; leverages operational data	Less transparent; does not simulate fire spread; strongly data-dependent	FireCast [172]
Power System Resilience Models (Wildfire Scenarios)	Grid performance under wildfire-induced outages; optimization of emergency measures	Evaluates cascading failures and load loss; informs resilience planning	Typically uses static fire scenarios; lacks feedback to fire spread	Impacts forecasting models [173]

6.1 Physics-Based and Probabilistic Wildfire Simulations

Traditional wildland fire models, such as SPARK[166] and FARSITE[167], have been instrumental in bringing wildfire science into utility risk analysis. These models incorporate terrain, fuel types, and wind to produce credible estimates of fire behavior (e.g., spread rates, flame lengths, intensities) under specified conditions. Analysts then intersect these outputs with power substation and line data to identify threatened components, estimate time to respond, or plan emergency actions. However, this integration is typically one-way: the simulation assumes the grid is static, and there is no feedback from grid failures (e.g., a downed line) into the fire model. Moreover, such models depend heavily on accurate, high-resolution input data (fuels, weather) and often rely on carefully chosen ignition points and weather scenarios, which may overlook unexpected but significant risk combinations[168,174]. Advanced models like WRF-Fire capture fire-induced winds, plume dynamics, and heat transfer via computational fluid dynamics, offering high-resolution simulations that can evolve on timescales of seconds [169]. Although these models can theoretically provide very accurate wildfire predictions, they have seen limited use in utility planning due to their high computational cost and the complexity of integrating them into real-time or multi-scenario analyses. They do not inherently include power system elements, so any coupling with electrical infrastructure typically mirrors the one-way approach of empirical models—but with a far greater computational burden. Burn Probability (BP) models [170] take a Monte Carlo approach to simulate thousands of fires with randomized ignition locations, weather sequences, and fuel conditions. This produces a burn probability map over a defined region, indicating where fires are most likely to occur and how intense they might be [170]. Utilities can use these outputs for long-term planning, identifying transmission corridors at higher risk or regions where vegetation management should be prioritized. Nonetheless, these probabilistic approaches often treat fires as isolated events and stop at the hazard quantification stage, leaving it to separate models or manual overlays to assess the consequences for the power grid [170].

To bridge this gap, utilities are increasingly using forward-looking simulations for risk analysis, though their approaches and tools vary. As highlighted in recent surveys of utility practices, some, like Portland General Electric (PGE), employ Monte Carlo simulations for their risk modeling. Others, such as Southern California Edison (SCE), use machine learning models. These efforts are often supported by specialized commercial platforms; for instance, PGE uses a tool from Pyrologix, while SCE uses tools from Technosylva and SimTable. A primary application of these advanced models is to inform critical operational decisions, such as the activation of PSPS events. However, a key limitation identified in current practice is that these tools focus heavily on anticipating utility-caused ignitions, with less emphasis on modeling the grid's ability to withstand or recover from wildfires of any origin.

6.2 Data-Driven Ignition Prediction and Grid Resilience Modeling

Alongside these physics-based studies, machine-learning techniques—such as XGBoost, deep neural networks, or hybrid algorithms—have surged in popularity, fueled by the increasing availability of high-frequency grid sensor data (e.g., line sag, fault detection, vegetation encroachment) [172,175,176]. These models can rapidly predict the likelihood that a power line fault will lead to ignition, enabling proactive interventions like targeted de-energization. Their primary advantage is speed and adaptability, as they learn from new data in each fire season [172]. However, they often act as "black boxes," complicating regulatory acceptance and stakeholder trust. Most such models do not simulate fire spread; instead, they focus on ignition potential, requiring separate fire behavior tools for full risk assessment. On the power system side, specialized tools and open-source solvers now simulate how a wildfire footprint (either real or simulated) causes sequential failure of multiple lines [66,97]. These studies track the knock-on effects—how load is shed, how the network reroutes power, and how restoration might proceed once the fire recedes [66,97]. Optimization methods (e.g., Markov decision processes) help plan operational responses and guide infrastructure investments to mitigate risk from spatially correlated hazards such as wildfires [177]. The limitation is that these power-focused models must rely on external fire scenario inputs; if actual fire behavior differs markedly from the scenario, the proposed mitigation may falter [178]. Additionally, damage modeling of electric assets is often simplified, and truly co-simulating fire dynamics and grid operations remains a research frontier [29].

6.3 Challenges in Bidirectional Fire–Grid Coupling

Despite growing recognition of power lines as a major ignition source, most current fire-vegetation-atmosphere modeling frameworks only address electrical infrastructure in a rudimentary way—typically by inserting ignition points along transmission corridors based on historical patterns or expert judgment [179]. The mechanical and electrical processes that lead to sparks or arcing (e.g., line slap under high winds, vegetation contact, or equipment fatigue in extreme heat) are rarely embedded within the core fire spread algorithms, leaving little room for real-time feedback or dynamic updates (for instance, new ignition spots appearing mid-simulation) [20]. Recent research has introduced probabilistic parameterizations of line swing and clearance breaches, but these remain largely standalone modules rather than fully coupled submodels [34,35]. Consequently, infrastructure failures are not treated as evolving phenomena that might themselves alter the trajectory of a fire, nor are potential mitigation measures (e.g., de-energizing lines or re-routing power) factored into the fire's propagation [21]. This gap underscores the need for truly integrative modeling approaches that incorporate the mechanical, electrical, and operational characteristics of power systems into wildfire simulations, thereby capturing both the ignition potential and vulnerability of electrical assets in an era of intensifying wildfire risk [20].

6.4 Engineering and Data Governance Barriers to AI Integration

While the integration of AI and machine learning into these coupled frameworks offers transformative potential, its practical deployment in safety-critical power systems faces distinct engineering and data governance hurdles. From an engineering perspective, the primary barrier is the 'Black Box' nature of deep neural networks; grid operators are often reluctant to authorize automated de-energization based on opaque model outputs without explainable causal logic (e.g., using SHAP values) [105]. Furthermore, standard data-driven models often fail to generalize to 'out-of-distribution' tail events—such as unprecedented wind gusts—necessitating the integration of physics-based constraints (Physics-Informed Neural Networks) to ensure stability in unseen scenarios [61, 64]. Beyond these algorithmic challenges, the fragmentation of data between utilities and researchers remains a critical bottleneck. To transition from theoretical data sharing to practical integration, the industry must adopt privacy-preserving architectures like Federated Learning (FL), which allows models to be trained locally on utility servers without exposing sensitive Critical Infrastructure Information (CII) [56], alongside Differential Privacy (DP) standards and the Common Information Model (CIM) to automate the secure ingestion of disparate sensor streams [55, 57].

7. Technological and Strategic Pathways for Risk Mitigations

Drawing on insights from feedback mechanisms, system impacts, and integrated data modeling, we frame our discussion of mitigation strategies within the three critical phases of the resilience cycle: Pre-event (Prevention/Hardening), During-event (Response/Survival), and Post-event (Restoration/Recovery). Each phase presents distinct engineering challenges and necessitates targeted technological solutions.

- Phase 1: Pre-event (Prevention & Hardening). The primary objective is to reduce ignition probability and enhance physical survivability. Strategies include Infrastructure Hardening (Section 7.1), such as deploying covered conductors and steel poles, and Remote Sensing for proactive vegetation management.
- Phase 2: During-event (Response & Survival). When a fire occurs, the focus shifts to minimizing system impact. Key solutions involve Intelligent Fault Detection (Section 7.2) to isolate faults in milliseconds, and Microgrids (Section 7.3) that island critical loads to ensure continuity during the PSPS.
- Phase 3: Post-event (Restoration & Recovery). After the fire, goals turn to rapid restoration and adaptation. This includes deploying mobile generation units and

implementing Adaptive Governance frameworks (Section 7.4) for cost recovery and updated safety codes.

To provide a clear overview of these diverse interventions, we summarize the taxonomy of technological and strategic mitigation pathways in **Table 4**, detailing their primary functions, technological maturity, and implementation challenges.

Table.4 Taxonomy of technological and strategic pathways for wildfire risk mitigation in power systems

Resilience Phase	Mitigation Category	Key Technologies / Strategies	Function & Mechanism	Implementation Challenge
Pre-event (Prevention)	Infrastructure Hardening	• Covered Conductors • Steel/Composite Poles • Undergrounding	Physically prevents ignition by insulating lines or removing fuel contact; increases structural survival during active fires.	High Capital Cost: Undergrounding is 5–10x more expensive than overhead; supply chain constraints for composite materials.
	Remote Sensing & Warning	• Satellite Hotspot Detection • AI Camera Networks • Dynamic Line Rating	Provides situational awareness; monitors real-time conductor sag and vegetation proximity relative to fire weather.	Latency & Integration: Satellite revisit times can be too slow; fusing disparate sensor streams remains computationally intensive.
During-event (Response)	Intelligent Fault Detection	• High-Impedance Sensors • Synchrophasors (PMUs) • Machine Learning Algs	Detects non-standard fault signatures (e.g., arcing, falling conductors) and trips power in milliseconds before ignition occurs.	Data Quality: Requires high-bandwidth comms; risk of false positives in rural networks with legacy SCADA.
	Microgrids & DERs	• Islandable Storage • Mobile Generation • Community Hubs	Decouples critical loads (hospitals, shelters) from the main grid during PSPS or outages, ensuring continuity.	Equity & Financing: Deployments currently skew toward wealthy areas; regulatory hurdles for islanding operations.
Post-event (Recovery)	Adaptive Governance	• PSPS Protocols • Firescaping Codes • Cost-Recovery Models	Aligns operational risk tolerance with public safety; creates financial incentives for hardening investments.	Socio-Economic Impact: Preemptive shutoffs disproportionately affect medically vulnerable populations.

7.1 Infrastructure Hardening

Infrastructure hardening typically involves retrofitting or replacing the grid's most vulnerable components to withstand high temperatures, flames, and mechanical stresses. Wooden poles and crossarms, for instance, are easily consumed by intense flames, prompting many utilities to replace them with composite or steel structures [85,181]. These materials generally exhibit lower combustibility and can also maintain structural integrity when exposed to prolonged heat. In fire-prone areas such as northern California [130] or parts of Australia [182], pilot programs have demonstrated measurable reductions in ignitions after replacing sections of overhead wood poles with steel or fiberglass alternatives. Some utilities also apply fire-retardant coatings to poles, conductor attachments, and switchgear, reducing the likelihood of ignition from airborne embers or direct flame impingement [91,183].

Conductor upgrades can involve shifting from standard aluminum conductor steel-reinforced (ACSR) lines to advanced high-temperature, low-sag (HTLS) designs [184,185]. These modern conductors withstand higher operational temperatures and exhibit lower thermal expansion, thereby reducing sag-related risks if exposed to fire fronts [184,185]. Where feasible, underground circuits remain a robust complementary strategy. Although large-scale undergrounding is often cost-prohibitive—especially in steep or densely forested terrain—line-specific risk-optimization studies show that selectively burying segments situated in corridors with recurrent ignitions or extreme wind improves overall wildfire-risk profiles at acceptable lifecycle cost [186]. In Sonoma County, California, local authorities documented a considerable drop in utility-caused ignitions along a pilot undergrounded circuit that had previously experienced frequent clash events [187]. Although exact cost–benefit ratios vary, strategic undergrounding remains an important option in high-risk areas [186].

Despite these advantages, infrastructure hardening poses logistical and economic challenges, particularly in remote or low-density service areas. Transporting and installing heavy steel or composite materials can strain utility budgets and complicate maintenance. Additional research is needed to refine installation methods and develop lower-cost composite technologies that retain strength under both high heat and mechanical loads. Further work on performance testing under realistic wildfire conditions would also help utilities prioritize limited capital more effectively.

7.2 Intelligent Fault Detection

Early fault detection stands at the core of wildfire risk reduction, as undetected arcs or slow smoldering events can transition into large ignitions [34,130]. Utilities increasingly rely on advanced protective relays, current sensors, and machine learning algorithms to recognize subtle patterns indicative of high-impedance faults, conductor clashing, or corona discharges [188,189]. In remote forest corridors, utilities have begun to deploy specialized sensors that monitor high-frequency waveforms and electromagnetic emissions, quickly distinguishing high-impedance arcs from normal load fluctuations [190,191]. This capability enables operators to isolate or de-energize faulty lines within seconds, drastically limiting thermal energy release at the incident site.

Some utilities also integrate high-speed communication channels that link substation relays with synchro phasor data streams from phasor measurement units (PMUs); the combined stream of voltage and current waveforms reveals incipient faults or broken conductors almost in real time [192,193]. For instance, in parts of the western United States, pilot programs have demonstrated how synchro phasor-based detection systems can locate the site of a broken conductor to within a few hundred meters, drastically improving response times compared with conventional circuit-breaker logs [194].

Although promising, these methods face multiple hurdles. Sensor data quality and reliability remain uneven in rural areas with limited communication infrastructure. Many algorithms trained on well-instrumented pilot sites must be adapted to different feeder configurations and weather regimes [195,196]. Machine learning approaches can suffer from false positives if local conditions diverge significantly from training data, leading to unnecessary service interruptions [188,197]. Hence, continued research on transfer learning, sensor fusion, and cost-effective hardware design is imperative to ensure that intelligent fault detection can scale to entire service territories.

7.3 Microgrids and Distributed Energy

Distributed energy resources (DERs), including solar, battery storage, and locally sited microgrids, have gained traction as resilient solutions that decouple essential loads from large-scale grid failures [119]. In high-risk zones, microgrids already keep critical loads such as water pumps, emergency shelters, and medical clinics online through PSPS and post-fire outages [141]. Fast-acting battery inverters, together with micro phasor measurement unit-based controls, let a microgrid island from the main network in seconds and seamlessly resynchronize when conditions stabilize [195].

However, both technical and regulatory barriers remain substantial. The up-front capital for solar-plus-storage installations can be prohibitive, particularly in rural or lower-income regions. Several jurisdictions are testing “mobile microgrids,” containerized solar-plus-battery units or diesel-hybrid pods that can be trucked into fire-damaged communities to restore minimal service for hospitals or command centers within hours [198]. As microgrid deployments expand, additional research is needed to refine control algorithms that coordinate multi-source generation, anticipate changing load profiles, and handle prolonged isolation without compromising power quality [199]. Continuing research and development is needed on adaptive control algorithms, load forecasting under prolonged islanding, and low-cost hardware to broaden deployment beyond affluent districts [200]. There is also a growing call for balanced financing mechanisms, ensuring that vulnerable communities can access these technologies and are not left dependent on unreliable or expensive diesel backup during PSPS events.

7.4 Fairness-Focused Policy and Resilience Governance

Technological and engineering innovations alone cannot fully address the risks caused by the intertwined wildfires and power systems unless supported by balanced policies, community engagement, and streamlined governance. Cost-allocation mechanisms and insurance frameworks are pivotal in motivating utilities to invest in hazard-mitigation projects in fire-prone regions, particularly where the expenses of undergrounding, advanced detection systems, or conductor replacements can be substantial [70,201]. For instance, revised regulations in California now require utilities to develop detailed wildfire mitigation plans, prompting widespread adoption of enhanced vegetation management, high-impedance fault detection, and increased line inspection frequencies [201]. However, these measures can elevate consumer electricity rates, posing affordability challenges for rural or lower-income communities.

Land-use regulations also play a critical role. WUI-specific building codes and zoning ordinances that mandate “firescaping” or defensible space near distribution lines can reduce both ignition likelihood and property losses, though they require careful balancing of environmental conservation, property rights, and safety [202,203]. Additionally, preemptive de-energization effectively lowers ignition risk but may disproportionately harm individuals lacking backup power solutions, including medically vulnerable or economically disadvantaged residents [204,205]. Recognizing these impacts has led to calls for transparent decision-making, improved shutoff notifications, and investment in localized backup systems such as microgrids and battery incentives [119,206].

Moving forward, collaborative planning among utilities, emergency services, fire management agencies, and local community representatives is crucial. Nonetheless, knowledge gaps remain regarding the long-term social and economic effects of repeated PSPS events on mobility, public safety, and productivity, as well as the cascading impacts of shifting insurance markets. In California, for example, insurers have declined to renew millions of homeowner policies in high-risk areas, forcing residents onto more expensive, last-resort state plans and creating significant financial strain on communities. Further empirical research is warranted to ensure that strategies for mitigating wildfire risks in electric power systems are both balanced and sustainable.

8. Cross-cutting Gaps and Future Directions

Building on the discussions in the preceding sections, **Figure 3** illustrates why wildfire and electric grid risks must be analyzed as interconnected challenges rather than in isolation. The framework reveals how continuous observational data streams—ranging from satellite thermal anomalies to tower-mounted weather sensors—drive predictive models of fire behavior and grid vulnerability. These models inform real-time grid control strategies, emergency responses, and post-fire recovery efforts. Central to this system is the active feedback mechanism that links the three core pillars: performance metrics and outcomes from decision-support actions loop back to identify observational gaps, recalibrate model assumptions, and reprioritize monitoring targets. This closed-loop design fosters a self-correcting, adaptive system, in which new data and real-world outcomes iteratively refine each component. The integration of feedback not only strengthens the coupling between empirical data and analytical predictions but also enhances our capacity to understand ignition dynamics, fire–infrastructure interactions, and cascading societal impacts. Ultimately, embedding feedback at the heart of this framework enables more precise, responsive, and equitable wildfire–grid risk management.

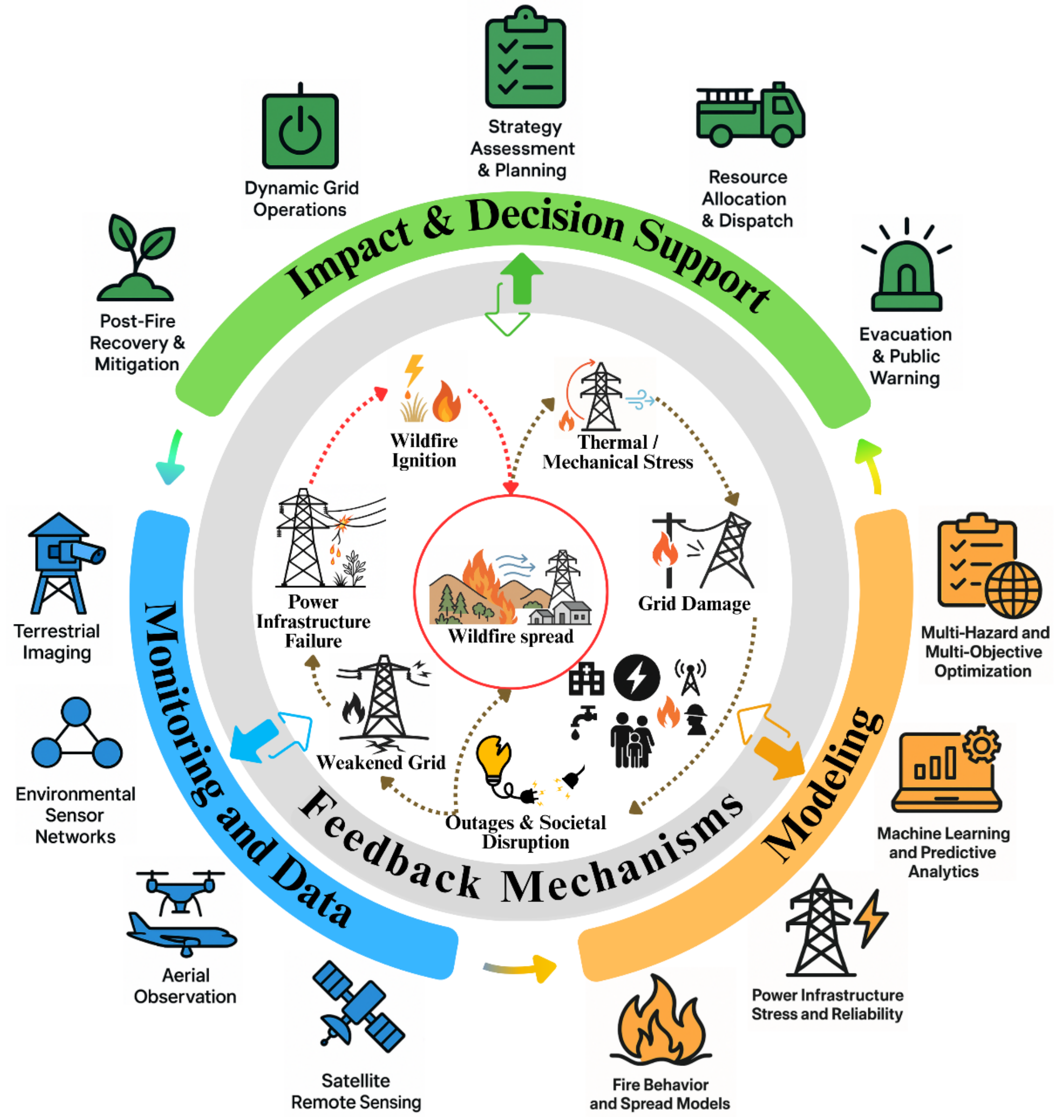

Figure.3 Data-Driven Decision Support Framework for Managing Wildfire-Induced Grid Risks. *Figure 3 presents a holistic framework for enhancing power grid resilience against wildfires, illustrating the interplay between physical feedback mechanisms and*

strategic intervention layers (Monitoring and Data, Modeling, and Impact and Decision Support).

8.1 Wildfire–Powerline Feedback Mechanisms and Data Gaps

Existing research recognizes that fire behavior and power line faults can exacerbate one another, with smoldering ignition or arcing events accelerating wildfire growth and further compromising electrical infrastructure [35,70,186]. However, laboratory-scale experiments seldom capture the entire chain of events—from initial conductor ignition and subsequent fire spread to cascading damage across other grid elements [37,206]. Field observations tend to be siloed, focusing on either fire suppression activities or grid reliability, rather than the rapid transitions between minor line faults and emerging flame fronts [35,175].

To address these limitations, researchers could conduct targeted, full-scale mock-up experiments with controlled arcs and partial discharges in vegetation-laden corridors, enabling real-time tracking of molten droplets, fuel pyrolysis, and fire expansion under near-realistic conditions [37,207]. Combining these observations with airborne and satellite remote sensing can further clarify how local electrical arcs evolve into sustained flaming combustion, improving parameters for integrated fire–power system simulations [208]. Finally, cross-sector data-sharing frameworks—linking utility SCADA logs, ignition forensics and meteorological measurements—are essential for standardized post-event archives and for refining predictive tools that keep minor electrical faults from blossoming into catastrophic wildfires [29].

8.2 Standardized Data Infrastructures for Interdisciplinary Collaboration

Numerous studies propose sophisticated models of wildfire–powerline interactions, but they often rely on fragmented or proprietary datasets that just cover wildfire behavior, meteorology, or grid operations. This fragmentation hampers direct comparisons of risk assessments across utilities or regions. For example, while some researchers leverage remote sensing and meteorological data to assess wildfire risk near transmission corridors [209], but they also note the difficulty of reconciling inputs that originate from multiple agencies and sensor platforms. Likewise, data-driven decision frameworks that couple spatio-temporal wildfire models with power-system optimization [210].

Addressing these gaps requires common data protocols and genuinely open repositories, allowing researchers and utilities to share operational, meteorological, and ignition datasets more effectively. By adopting harmonized metadata standards (e.g., spatiotemporal resolution, sensor calibration) and cloud-based infrastructures, modelers can validate findings and build upon others' work more easily. In turn, such efforts should boost reproducibility and enable meta-analyses across diverse geographies, ultimately improving the accuracy and robustness of wildfire–power-line risk assessments [211]. However, achieving this outcome requires more than technical solutions; it necessitates a culture of deep collaboration and co-creation between researchers and utility decision-makers. Such partnerships are essential to ensure that new models and analyses are not only scientifically sound but also operationally relevant, directly addressing the practical challenges faced by grid operators.

8.3 Scalable Modeling with Real-Time Capabilities

Although advanced simulation frameworks (e.g., coupled fire–vegetation–atmosphere models, ML-based ignition forecasting) have high predictive power, their computational costs often restrict them to offline analyses rather than real-time applications. Deep learning approaches, for instance, can process massive satellite datasets to predict fire-radiative power, but the required GPU resources can be prohibitive for continuous monitoring. Likewise, integrated early warning systems that assimilate real-time weather data and grid security metrics often report high CPU loads when fire scenarios escalate rapidly [212]. To move beyond these limitations, researchers could employ reduced-order or surrogate models that approximate full simulations with far lower computational overhead or parallelize key algorithms on high-performance clusters [213]. Implementing modular architectures where updates do not require rerunning the entire code base can further reduce latency. These improvements would help push advanced wildfire–powerline simulations closer to real-time decision support, guiding emergency responders and utility operators when every minute counts.

8.4 Integrated Socio-economic and Fairness Considerations

Numerous technical measures—from predictive arc-fault detection to selective undergrounding—reduce ignition risk, yet the resulting outages or pre-emptive PSPS can disproportionately burden lower-income and medically vulnerable residents who lack backup power [214]. Recent distributional analyses show that community microgrids, rooftop-solar, and other resilience upgrades cluster in wealthier census tracts, while disadvantaged areas remain dependent on diesel generators or have no backup at all [124]. Extended shut-offs further exacerbate inequality when hospitals and other critical services are sited primarily in high-income districts, heightening health risks for surrounding populations. To close these gaps, future risk models should embed social-vulnerability indices and equity metrics, and data on fire insurance availability and cost, blending quantitative outage data with qualitative evidence from household surveys and community focus groups; such mixed-methods approaches can better capture the full spectrum of socio-economic impacts—from tangible financial burdens like insurance premiums to intangible costs like stress, lost wages, and health impacts—guiding utilities toward fairer resilience investments.

8.5 Evolving Environment Context and Adaptive Policy Frameworks

Environmental change is lengthening fire seasons, intensifying heat waves, and altering wind regimes, rendering historic design baselines obsolete. During Australia's 2019-2020 "Black Summer," prescribed-burn strategies and conventional suppression tactics proved inadequate under record-breaking extremes [215], and Canada's 2023 season likewise overwhelmed firefighting resources across an unprecedented 18 million ha burn scar [216] . Traditional overhead-line specifications—often drafted decades ago—do not account for today's higher wind and temperature envelopes, raising failure probabilities unless lines adopt dynamic ratings that adjust ampacity in real time [217].

Accordingly, next-generation modelling must test grid resilience against ensembles of future-environment scenarios, while regulators update standards to allow dynamic line ratings, weather-informed vegetation buffers, and coordinated fuel-management aligned with shifting precipitation patterns; Alongside these technical and regulatory shifts, developing robust public communication strategies is essential for managing public expectations and building support for adaptive measures. These steps demand tight collaboration among utilities, fire agencies, and environmental regulators.

8.6 Scaling Innovations from Pilot Studies to System-Wide Implementation

Pilot reconductoring projects using HTLS composites and fire-resistant poles show major sag-reduction and survivability gains, yet capital costs and supply-chain hurdles impede broad rollout [185]. Likewise, "resilience microgrids" proven in community pilots still face financing and regulatory barriers that slow expansion beyond well-funded locales [218]. Behind-the-meter solar-plus-storage markedly improves outage resilience but remains concentrated in higher-income households, reflecting persistent adoption disparities [219]. Early-warning concepts such as multi-Doppler radar arrays for fire detection near transmission corridors demonstrate technical promise but carry high installation and processing costs that must be weighed against alternative sensor networks [220]. Comprehensive cost–benefit frameworks—factoring avoided fire damages and health costs against up-front expenditures—along with standardized performance metrics and public-private financing mechanisms are essential for translating these successful pilots into equitable, system-wide wildfire-resilience programs.

9. Conclusion

Wildfire–power grid interactions constitute a growing and multifaceted hazard, intensified by the global expansion of electrical infrastructure into fire-prone landscapes and the increasing frequency and severity of wildfires. Recent progress in multi-scale observational systems, fire behavior modeling, grid vulnerability assessment, and predictive analytics has improved our understanding of how power systems both contribute to and suffer from wildfire events. However, persistent gaps remain in standardized data infrastructures, real-time and scalable modeling integration, socio-economic impact evaluation, adaptive governance frameworks, and the system-wide deployment of mitigation technologies. Addressing this dual-threat system demands a coordinated, interdisciplinary approach. Effective mitigation will require enhanced sensor networks, interoperable and computationally efficient modeling platforms, and operational protocols capable of supporting rapid response and riskinformed planning. Our longitudinal analysis (2005–2025) reveals that the narrative of wildfire-grid interactions has evolved from a maintenance issue to a systemic environment adaptation challenge. Technical insights into ignition mechanisms—such as molten aluminum droplets from line clash, high-impedance faults, and corona discharges—reinforce the urgency of developing early-warning systems and intelligent fault detection. Simultaneously, studies of fire-induced grid failures reveal the systemic vulnerabilities that hinder emergency operations and amplify community-level impacts. Interdisciplinary collaboration across electrical engineering, fire science, remote sensing, economics, and social sciences is critical. Shared data platforms, unified modeling standards, and inclusive stakeholder engagement must underpin future research and policy development. Utilities and regulators should prioritize diverse, adaptive strategies—including microgrids, targeted undergrounding, machine-learning–based diagnostics, and fairness-focused resilience governance. By formalizing the bidirectional feedback loops between physical infrastructure and social vulnerability, this review provides a roadmap for the next generation of resilient, equitable power systems

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