Climate-Informed, Risk Assessment and Optimal Vegetation Management for Enhancing Power Grid Resilience

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***Abstract*—Vegetation-related outages remain a major threat to the reliability of the distribution grid, even as utilities gain access to higher-resolution LiDAR and weather data. However, current vegetation management practices still rely on fixed trimming cycles and clearance rules that do not reflect physics-based failure mechanisms or span-level risk variations. To address this challenge, this article proposes a climate-informed scenario-based optimization framework that integrates LiDAR-derived tree–span geometry, wind-driven failure probabilities, and budget-constrained selection of mitigation actions that include targeted tree removal, pole elevation, and undergrounding. A real-world case study on a distribution circuit demonstrates that the proposed framework can efficiently identify high-value mitigation actions, significantly reduce expected outage impacts, and outperform traditional encroachment-based trimming in both cost-effectiveness and resilience improvement.**

***Index Terms*—Grid resilience, vegetation management, tree-induced outages, LiDAR point clouds, mitigation optimization**

I. Introduction

VEGETATION-RELATED power outages remain one of the most persistent threats to the reliability of electric distribution systems worldwide. Severe storms and high winds frequently cause trees or branches to strike overhead conductors, leading to widespread service disruptions, high restoration costs, and significant societal impacts [1], [2]. In the United States alone, utilities spend billions annually on vegetation management, yet tree-induced interruptions continue to be a leading contributor to customer outages [3]. This challenge is amplified by increasing storm intensity and evolving vegetation patterns [4].

Despite the critical importance of vegetation management, existing utility practices largely rely on fixed maintenance cycles, visual inspections, and clearance-based regulations that enforce minimum vegetation distances from conductors [5]. These approaches treat all trees within a buffer zone similarly, overlooking key physical drivers of failure, such as species characteristics, tree height, structural health, and wind-induced loading. Consequently, fixed-cycle trimming can lead to inefficient resource allocation, resulting in over-treatment of low-risk spans while leaving high-risk spans vulnerable.

A substantial body of literature has sought to improve vegetation and reliability planning by introducing cost–benefit models, reliability-centered maintenance, and risk-based prioritization. Early work focused on scheduling vegetation maintenance under budget limits [5], and later studies incorporated stochastic outage models driven by weather variability [6], [7]. Economic analyses have emphasized the long-term cost impacts of tree mortality and maintenance practices [8]. More recent advances integrate probabilistic modeling and scenario analysis to guide investments in hardening and infrastructure upgrades [9], [10]. Combinatorial optimization models have also been used to select mitigation actions, such as tree cutting, pole elevation, and undergrounding, based on risk-reduction efficiency [11]. Submodular frameworks provide approximation guarantees for large-scale applications [12].

However, despite these advances, existing studies still exhibit several major limitations. First, many models rely on coarse spatial representations of vegetation and do not explicitly incorporate tree-level geometry or physics-based wind–tree interaction mechanisms. Second, most prior work evaluates individual mitigation options in isolation rather than jointly selecting among targeted tree removal, conductor elevation, and undergrounding. Third, few approaches integrate real-world cost structures, customer criticality, and scenario-driven span-level outage probabilities into one coherent planning framework. Finally, the scalability and practical utility of many existing models are limited when applied to large, real utility circuits with thousands of trees and spans.

To address these gaps, this paper proposes a climate-informed, scenario-based optimization framework that unifies physics-based tree failure modeling, LiDAR-derived span–tree geometry, and budget-constrained selection of heterogeneous mitigation strategies. The model quantifies span-level outage probabilities under wind scenarios, evaluates mitigation impacts using annualized life-cycle costs, and leverages the submodularity of the outage-cost function to enable efficient, near-optimal decision-making.

The key contributions of this paper are as follows:

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- A unified, scenario-driven vegetation management optimization model that integrates tree-level wind-failure probabilities, span-level outage impacts, and life-cycle mitigation costs;
- Joint optimization of multiple mitigation strategies, including targeted tree removal, conductor elevation, and undergrounding, with adjusted cost formulations that prevent double-counting and capture engineering trade-offs;
- A proof of submodularity that ensures computational tractability and supports the use of a greedy approximation algorithm with near-optimal performance guarantees;
- A real-world demonstration using LiDAR point clouds and multi-year meteorological records, validating the framework on a rural distribution circuit in Massachusetts and demonstrating utility-scale applicability;
- A comprehensive performance evaluation showing significant gains in avoided outage impact and economic performance, where the proposed targeted strategy achieves approximately 35%–115% positive return on investment (ROI) across budget levels, while traditional encroachment-based trimming results in –20% to –60% ROI even over a 40-year horizon.

II. Problem Formulations

The optimization model establishes a structured methodology for deciding which mitigation actions to take and where, to maximize resilience benefits subject to budgetary and operational constraints, as shown in Fig. 1. The optimization model will be equipped with multi-source real-world data and solved using a submodularity-based greedy algorithm to ensure computational efficiency in practical applications. The economic and resilience benefits will be evaluated through a life-cycle analysis.

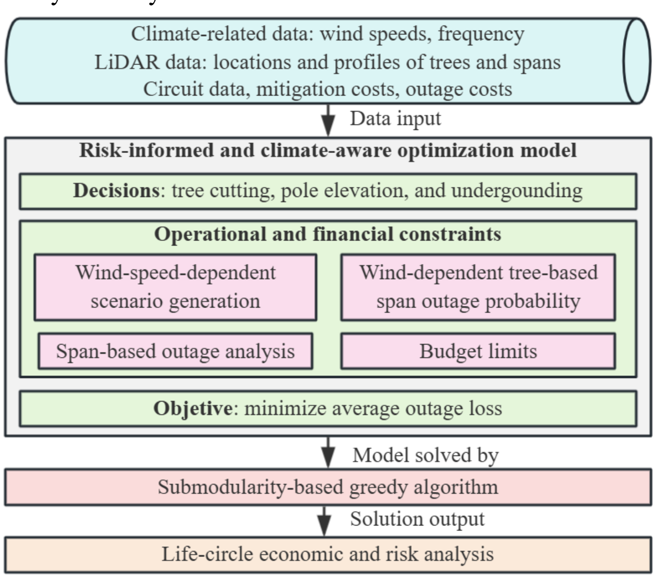

Fig. 1: Flowchart of the vegetation management framework.

A. Foundations of the Optimization Model

The baseline formulation introduced models the power distribution network as a graph $G = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is the set of nodes (poles or substations) and $\mathcal{E}$ the set of spans (edges). Each span $s \in \mathcal{E}$ is associated with a set of hazardous trees $\mathcal{T}_s$ that could fall and cause an outage on that span. Each tree $t \in \mathcal{T} = \cup_{s\in E}\mathcal{T}_s$ may be cut at cost C_t, and a binary decision variable $x_t \in \{0, 1\}$ records whether tree t is removed ($x_t = 1$) or left standing ($x_t = 0$).

The probability of span failure depends on the weather. A wind random variable W is quantized into discrete scenarios $w_1, \dots, w_K$ with empirical probabilities $\pi_1, \dots, \pi_K$, derived from historical and projected meteorological data. For a given scenario w_k, let $q_{st}(w_k)$ denote the conditional probability that tree t causes span s to fail. Assuming conditional independence of tree-induced failures given the scenario, the span-level probability of failure is:

$$p_s(x \mid w_k) = 1 - \prod_{t\in\mathcal{T}_s} \big(1 - q_{st}(w_k)(1 - x_t)\big). \tag{1}$$

Taking expectations across scenarios yields the expected failure probability:

$$\mathbb{E}_W[p_s(x \mid W)] = \sum_{k=1}^{K} \pi_k \left(1 - \prod_{t\in\mathcal{T}_s} (1 - q_{st}(w_k)(1 - x_t))\right). \tag{2}$$

This probability is then weighted by the social cost of failure, as shown in (3).

$$\kappa_s = H(C_m \cdot m_s + C_n \cdot n_s + C_f \cdot f_s), \tag{3}$$

where m_s, n_s, and f_s represent the number of residential customers, small Commercial and Industrial (C&I) customers, and critical facilities (large C&I customers) affected by span s in the event of that span's failure. C_m, C_n, and C_f are the corresponding costs of failures per customer-interruption. Once a span is broken, all downstream loads (customers) will lose power supply (services). H represents the expected annual frequency of interruptions per customer.

The expected outage cost is therefore:

$$f(x) = \sum_{s\in E} \mathbb{E}_W[p_s(x \mid W)] \cdot \kappa_s. \tag{4}$$

The optimization is to minimize $f(x)$ under a budget B_v:

$$\min_{x\in\{0,1\}^{|\mathcal{T}|}} f(x), \quad \text{s.t.} \quad \sum_{t\in\mathcal{T}} C_t x_t \le B_v. \tag{5}$$

B. Submodularity and Greedy Approximation

A central theoretical property of this formulation is *submodularity*. Intuitively, submodularity captures the law of diminishing returns: once many high-risk trees are removed, cutting additional trees yields smaller incremental benefits. Mathematically, the outage cost function $f(x)$ is submodular in x, meaning that marginal reductions in risk from cutting a tree are greater when fewer other trees have already been cut. This property is important because it guarantees that greedy algorithms, which iteratively select the action with the largest benefit-to-cost ratio, can achieve provably near-optimal performance. Specifically, the greedy algorithm achieves a $(1 - 1/e) \approx 63\%$ approximation to the optimal solution [13], a strong guarantee for a problem that is otherwise NP-hard.

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In practice, this means utilities can prioritize trees with the greatest expected risk-reduction-per-dollar and still achieve a solution that is close to optimal, even without solving the full combinatorial problem exactly.

C. Extension to Multiple Mitigation Options

While tree cutting is the most common vegetation management strategy, utilities also deploy engineering interventions such as raising poles or undergrounding spans. The optimal management framework extends the basic tree-cutting model to include these additional actions. Explicit modeling of branch trimming as a lower-cost, partial-risk-reduction action is left for future extensions of the framework.

- **Pole Raising:** A variable z_{hs} raises span s to height h, at amortized cost C_s^h, eliminating risk from a subset $\mathcal{T}_s^h \subseteq \mathcal{T}_s$ of trees. $\mathcal{H}$ is set of height options.
- **Undergrounding:** A variable y_s puts span s underground at cost C_s^u, eliminating all tree-related risk for that span.

Because pole raising or undergrounding may eliminate the need to cut certain trees, *adjusted costs* are introduced to avoid double-counting:

$$\widehat{C}_s^u = C_s^u - \sum_{t \in T_s} C_t, \tag{6}$$

$$\widehat{C}_s^h = C_s^h - \sum_{t \in T_s^h} C_t. \tag{7}$$

These adjusted costs reflect the net incremental expense of the engineering option, once avoided tree removals are accounted for. Negative adjusted costs indicate that raising or undergrounding may be strictly preferable if within budget.

D. Optimization Constraints

The optimization problem is governed by four key sets of constraints: integrality, budget, disjointness, and risk elimination. Each plays a distinct role in ensuring that the mitigation strategy remains feasible, implementable, and aligned with real-world operational limitations.

a) Integrality Constraints:

$$x_t, y_s, z_s^h \in \{0,1\}, \forall s \in \mathcal{S}, \forall t \in \mathcal{T}, \forall h \in \mathcal{H}, \tag{8}$$

where y_s indicates whether span s is undergrounded. z_s^h indicates whether span s is raised by increment h. Such binary restrictions reflect the indivisible nature of interventions; trees are either cut or left standing, lines are either raised or not, etc. This also ensures the problem remains combinatorial in nature, fitting the submodular optimization structure.

b) Budget Constraint:

$$\sum_{t \in \mathcal{T}} C_t x_t + \sum_{s \in \mathcal{S}} \left(\widehat{C}_s^u y_s + \sum_{h \in \mathcal{H}} \widehat{C}_s^h z_s^h \right) + C_l \cdot L \leq B. \tag{9}$$

where C_l represents the cost of LiDAR campaign (acquisition + processing) per mile. L and B represent the length of the whole circuit and the annual investment budget, respectively. Note that all one-time mitigation costs are converted into annualized values using the capital recovery factors (CRF), as shown in (10). It allows consistent comparison of options with different lifetimes.

$$C_{ann} = C_0 \times \frac{r(1+r)^n}{(1+r)^n - 1}, \tag{10}$$

where $C_{ann} = \{C_t, C_s^h, C_s^u, C_l\}$, $C_0 = \{\check{C}_t, \check{C}_s^h, \check{C}_s^u, \check{C}_l\}$, and $n = \{n_t, n_h, n_u, n_l\}$.

c) Disjointness Constraint:

$$y_s + \sum_{h \in \mathcal{H}} z_s^h \leq 1, \quad \forall s \in \mathcal{S}. \tag{11}$$

This enforces that at most one type of span-level action is applied to a given span. A span cannot be both undergrounded and raised, nor raised to multiple clearance levels simultaneously. This reflects practical field implementation rules, where mutually exclusive interventions are necessary.

d) Risk Elimination Constraints:

$$y_s \leq x_t, \quad \forall t \in T_s, \; \forall s \in \mathcal{S}, \tag{12}$$

$$z_s^h \leq x_t, \quad \forall t \in T_s^h, \; \forall h \in \mathcal{H}, \; \forall s \in \mathcal{S}. \tag{13}$$

These constraints guarantee logical consistency between span-level and tree-level decisions. In (12), iff a span s is undergrounded ($y_s = 1$), then all trees $t \in \mathcal{T}_s$ that previously posed a hazard to s must be marked as neutralized ($x_t = 1$). In (13), if a span s is raised by option h ($z_s^h = 1$), then all trees $t \in \mathcal{T}_s^h$ that no longer threaten the line at the new clearance must also be marked as neutralized. This avoids situations where interventions are implemented but associated risks remain flagged in the model. In essence, these constraints enforce consistency between mitigation choices and the resulting hazard profile.

Together, these constraints balance **practical feasibility** (binary choices), **financial realism** (budget limit), **operational exclusivity** (disjointness), and **risk logic** (elimination consistency). By coupling these with the submodular risk-reduction objective, the optimization model (14) and (15) produce strategies that are cost-effective, logically sound, and directly actionable for utility operators.

$$\min_{x,y,z} f(x) \tag{14}$$

$$\text{s.t.} \quad (1) - (4), (6) - (13). \tag{15}$$

E. Algorithmic Implementation

The inclusion of pole raising and undergrounding retains submodularity of the objective, ensuring that greedy algorithms remain effective. In practice, the algorithm evaluates the marginal risk reduction per dollar of each action, tree cut, pole raise, or undergrounding, and selects the best available until the budget is exhausted. This iterative process yields a solution that balances immediate cost-effectiveness with long-term resilience.

III. Simulation Case Studies

A circuit in the U.S. is selected for this study, with its topology shown in Fig. 2. To capture meteorological conditions (wind speeds and frequency) in different scenarios, we sourced hourly weather data from the nearest weather station,

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covering the period from 2019/01/01 to 2024/07/16. These meteorological data, together with 3D point cloud data of trees and spans generated by LiDAR sensors, can be used to calculate $q_{st}(w_k)$ based on the tree-induced outage risk model in [11]. Different tree-induced outage mechanisms, such as stem breakage and uprooting, are captured using sigmoid formulations and integrated into the overall risk model. The parameter settings in this study are summarized in Tab. I.

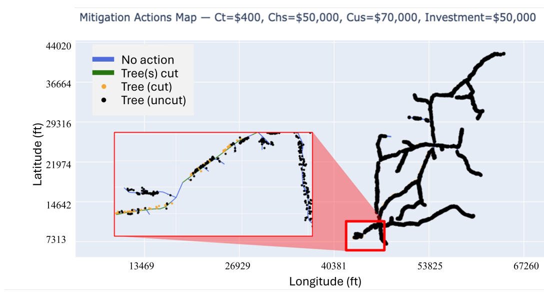

Fig. 2: Mitigation via targeted trees. The longitude and latitude have been modified to protect privacy.

TABLE I: Parameter Settings in the Case Study.

Parameter	Value	Parameter	Value
H	0.655	$C_m/C_n/C_f$	$ 5/627/8222
$\check{C}_t$	400 $/tree	$\check{C}_s^h/\check{C}_s^u$	50000/70000 $/span
$\check{C}_l$	645 $/mile	L	30.05 miles
r	0.05	$n_t/n_h/n_s/n_l$	6/40/50/5 years

Note: the parameters are based on industry reports, utility data, and recent academic literature [14].

A. Mitigation results

Fig. 3 illustrates the spatial distribution of optimal mitigation actions across the circuit as the available budget increases from $5,000 to $1,000,000. The results show how the optimization framework progressively selects spans for tree cutting (in red) while leaving others unmitigated (in gray).

At very low budgets (e.g., $5,000–$10,000), only a handful of spans are treated, capturing approximately 1–5% of the circuit. These early actions are concentrated on high-impact spans with disproportionate risk contributions, confirming that the algorithm prioritizes cost-effective interventions first.

As budgets increase to the intermediate range ($50,000–$200,000), cutting expands to additional spans, with circuit coverage rising from 17% to nearly 50%. This stage represents the "knee" of the benefit curve, where most of the outage risk reduction is achieved through modest investments.

Beyond $500,000, more than 60% of spans are mitigated, but returns diminish: each additional dollar yields smaller improvements in resilience. At the maximum tested budget ($1,000,000), the system approaches saturation, treating 86% of spans, leaving only low-risk or cost-inefficient spans unaddressed. We also found that, once the budget increases to five million USD, 8% of the spans are mitigated through undergrounding and 92% through tree cutting.

Fig. 2 illustrates the precision of the optimization framework by zooming into a critical zone of the circuit. Trees marked in orange represent those cut under the optimized plan, while

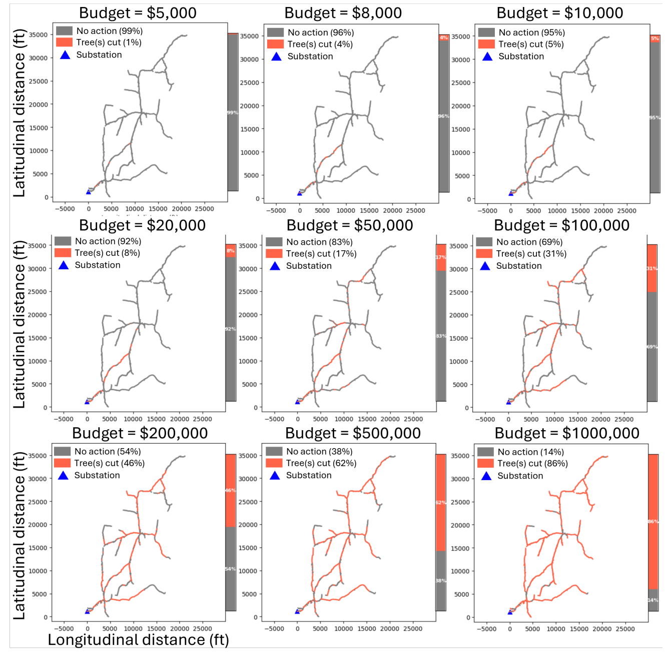

Fig. 3: Mitigation choices at different investment levels.

black dots represent trees left uncut. As we can see, only a subset of trees within a corridor are trimmed, while the majority remain untouched. This not only reduces costs but also minimizes environmental disturbance, addressing both *economic* and *sustainability* objectives. By moving from uniform clearance to targeted, risk-based cutting, utilities can achieve superior reliability outcomes with fewer resources.

B. Expense Breakdown by Mitigation Strategy

Fig. 4 presents the allocation of mitigation expenses across different strategies with different investment budgets. Tree cutting dominates the expense profile across all budget levels, reflecting its relatively low unit cost ($400 per tree) and high benefit-to-cost ratio. Elevation and undergrounding are absent from the expense structure in the tested range. This is consistent with their higher unit costs, which make them less competitive under constrained budgets. LiDAR analytic expenses (AE) remain minimal across all budgets to reflect their fixed overhead nature. These costs are negligible compared to direct mitigation actions, but essential for targeting.

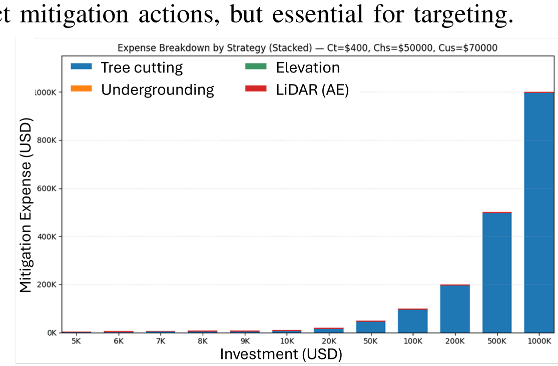

Fig. 4: Expense breakdown by mitigation strategy under increasing investment levels.

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C. Effectiveness of Targeted vs. Traditional Approaches

Fig. 5 compares the avoided outage impact costs achieved by the risk-based optimization framework (blue bars) against a benchmark traditional encroachment-based trimming approach (orange bars), across a range of investment levels. The encroachment-based method trims rights-of-way every four to five years to maintain regulatory clearance. The red dashed line indicates the theoretical maximum (100%) avoidable impact.

The results in Fig. 5 show that the targeted strategy not only delivers higher total avoided costs, but also achieves near-saturation at significantly lower budget levels. While traditional practices continue trimming even low-risk trees, the optimization framework concentrates resources on spans where vegetation encroachment is most strongly correlated with outage probability.

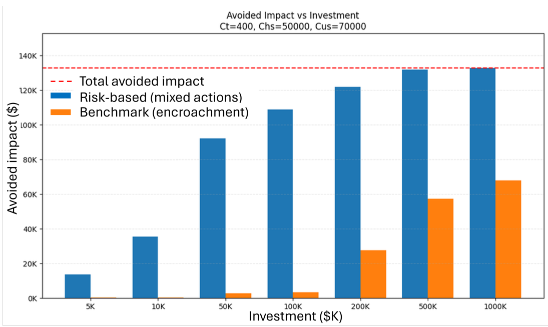

Fig. 5: Avoided impact cost versus investment for risk-based and encroachment-based vegetation management strategies.

D. ROI Comparison (40-Year Horizon)

Fig. 6 contrasts the ROI profiles of the risk-based optimization strategy (left) against the benchmark encroachment-based trimming program (right). Both analyses are conducted over a 40-year lifecycle horizon. The Targeted strategy removal delivers positive ROI and rapid payback, especially at low-to-moderate budgets where the marginal resilience gain is highest. However, the traditional encroachment-based trimming produces negative ROI even over 40 years, underscoring the inefficiency of indiscriminate clearance cycles.

From a resilience perspective, the proposed framework enhances distribution system performance by reducing expected outage impacts under extreme weather scenarios, improving adaptive capacity through climate-informed risk projections, and enabling efficient allocation of limited mitigation budgets. By prioritizing interventions with the highest avoided outage cost per dollar, the model strengthens both short-term reliability and long-term resilience, outperforming traditional encroachment-based vegetation management strategies.

IV. Conclusions

This paper proposes a span-based mitigation model for power grids to minimize outage costs resulting from vegetation and climate change. By integrating span-level outage probabilities, life-cycle cost modeling, and budget-constrained optimization, the proposed model illustrates how predictive analytics can inform both operational and financial planning in vegetation management. Results indicate that risk-informed, mixed-action strategies, combining targeted tree cutting, pole elevation, and selective undergrounding, have the potential to outperform traditional fixed-cycle vegetation programs under modeled conditions. The future work will focus on enhancing real-time responsiveness, integrating event-duration-dependent nonlinear cost functions, broadening geographic and asset applicability, incorporating new utility practices, and refining economic perspectives.

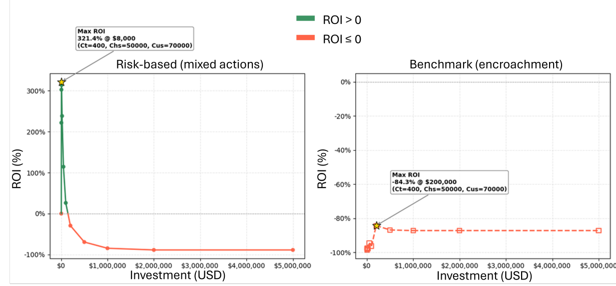

Fig. 6: Comparison of ROI (%) versus investment between risk-based optimization (left) and traditional encroachment-based trimming (right) over a 40-year horizon.

References

[1] U.S. FERC, "Transmission Line Vegetation Management," https://www.ferc.gov/transmission-line-vegetation-management, 2025, accessed: 2025-11-10.

[2] U. T. Salman, Z. Wang, and T. M. Hansen, "Power system resilience metrics based on tree failure model," in *2024 56th North American Power Symposium (NAPS)*. IEEE, 2024, pp. 1–6.

[3] Electric Power Research Institute (EPRI), "Vegetation management in the electric utility industry," EPRI, Tech. Rep., 2014.

[4] S. Pryor, R. Barthelmie, D. Young, E. Takle, R. Arritt, D. Flory, W. Gutowski Jr, A. Nunes, and J. Roads, "Wind speed trends over the contiguous united states," *Journal of Geophysical Research: Atmospheres*, vol. 114, no. D14, 2009.

[5] P. A. Kuntz, R. D. Christie, and S. S. Venkata, "Optimal vegetation maintenance scheduling of overhead electric power distribution systems," *IEEE Transactions on Power Delivery*, vol. 17, no. 4, pp. 1164–1169, 2002.

[6] L. Radmer and Others, "Predicting vegetation-related failure rates for overhead distribution feeders," *IEEE Trans. Power Del.*, vol. 17, no. 4, pp. 1170–1175, 2002.

[7] R. Nateghi and Others, "Power outage estimation for tropical cyclones: Improved accuracy with simpler models," *Risk Analysis*, vol. 34, no. 6, pp. 1069–1078, 2014.

[8] S. Guggenmoos, "Effects of tree mortality on power line security," *Journal of Arboriculture*, vol. 29, no. 4, pp. 181–196, 2003.

[9] D. W. Wanik, J. Parent, E. Anagnostou, and B. Hartman, "Using vegetation management and lidar-derived tree height data to improve outage predictions for electric utilities," *Electric Power Systems Research*, vol. 146, pp. 236–245, 2017.

[10] D. Cerrai and Others, "Predicting storm outages through new representations of weather and vegetation," *IEEE Access*, vol. 7, pp. 29 639–29 654, 2019.

[11] Y.-Y. Chen, B. Gardiner, F. Pasztor, K. Blennow, J. Ryder, A. Valade, K. Naudts, J. Otto, M. J. McGrath, C. Planque *et al.*, "Simulating damage for wind storms in the land surface model orchidee-can (revision 4262)," *Geoscientific Model Development*, vol. 11, no. 2, pp. 771–791, 2018.

[12] S. J. Mitchell, "Wind as a natural disturbance agent in forests: a synthesis," *Forestry*, vol. 86, no. 2, pp. 147–157, 2013.

[13] G. L. Nemhauser, L. A. Wolsey, and M. L. Fisher, "An analysis of approximations for maximizing submodular set functions—i," *Mathematical Programming*, vol. 14, no. 1, pp. 265–294, 1978.

[14] M. J. Sullivan, J. Schellenberg, and M. Blundell, "Updated value of service reliability estimates for electric utility customers in the united states," 2015.

979-8-3315-8138-1