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Spatially Granular Fragility Modeling of Transmission Lines for Enhanced Loss of Offsite Power Risk Assessment: A Cell-Based Approach Using Multimodal Earth Observations

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ABSTRACT

Accurate transmission line fragility modeling is crucial for Loss of Offsite Power (LOOP) risk assessment at nuclear power plants, where weather-induced outages represent a significant safety concern. Determining the probability of transmission line interruption during extreme weather conditions is essential for comprehensive LOOP risk assessment. Recent data-driven machine learning approaches have emerged that learn interruption patterns from historical data, but these models typically focus on the most extreme weather condition along a line as the representative data point for prediction. This paper introduces a novel approach that considers the spatial heterogeneity of transmission lines by dividing them into cells based on weather data grids, with each cell characterized by its own weather and environmental features. Unlike traditional single-cell models that select only the cell with the most intense conditions, we propose a Reliability-Informed Multiple Instance Learning (RI-MIL) framework that effectively handles variable-length spatial representations while incorporating reliability engineering principles. Our approach addresses two key challenges: modeling lines with varying numbers of overlapping weather cells and ensuring physically meaningful cell-level predictions. The framework includes a reliability-informed pooling function that aggregates cell-level predictions and a novel loss function that enforces consistency with physical understanding of system failure mechanics. Comparative analysis demonstrates that the RI-MIL model outperforms traditional single-cell approaches, achieving 76.1% accuracy compared to 71.8% for the single-cell model. A case study reveals how the model captures complex interactions between moderate winds and challenging terrain features that would be missed by single-cell representations. Importantly, the model is explicitly parameterized with respect to environmental, hazard, and infrastructure characteristics, making it inherently transferable to modeling transmission line interruptions from similar weather hazards in other regions. This spatially granular modeling approach provides transmission system operators and nuclear safety analysts with detailed vulnerability assessments that could support reliability-informed decision-making for both preventive and responsive measures.

INTRODUCTION

Electric power transmission systems are critical infrastructure that underpin modern society, with particular importance to nuclear power plants where they provide essential offsite power. For nuclear facilities, a

Loss of Offsite Power (LOOP) event represents a significant safety concern, potentially requiring emergency systems to maintain safe shutdown conditions (Johnson and Ma, 2022). These transmission systems are increasingly vulnerable to extreme weather events, which have been growing in frequency and severity due to climate change. In the United States, severe weather has been identified as the primary driver of power outages, accounting for 58% of all outages observed since 2002 and 87% of outages affecting 50,000 or more customers (Executive Office of the President, 2013). This vulnerability extends globally, with studies indicating that weather-related power disruptions affecting nuclear facilities have been increasing worldwide, with the average frequency of climate-induced disruptions rising from 0.2 outages per reactor-year in the 1990s to 1.5 in the past decade (Ahmad, 2021). For nuclear safety assessment, the ability to accurately predict transmission line interruptions during extreme weather is essential, enabling both preventive measures to reduce LOOP probability and more effective emergency response planning.

Recent research has made significant progress in developing predictive models for weather-related transmission line interruptions. Traditional approaches have focused primarily on statistical methods and more recently on machine learning techniques (Guikema et al., 2014; Han et al., 2009). These models typically aggregate weather data across the entire transmission line or select a single representative point (often the point of maximum weather intensity) as input features for prediction. While effective to some degree, these approaches face limitations in capturing the spatial heterogeneity of environmental conditions along transmission lines. More recent studies have attempted to integrate more complex environmental data into prediction models (Dokic and Pavlovski, 2019), but most continue to rely on simplified spatial representations of transmission lines.

This spatial simplification presents a significant challenge: transmission line interruptions can occur at any point along a line's length, with vulnerability varying considerably due to local terrain, vegetation, and weather conditions. Typical machine learning approaches require fixed-size inputs, forcing researchers to aggregate spatially variable data into simplified representations that lose critical information, particularly for longer lines spanning diverse geographical areas where a single data point cannot capture complex environmental interactions.

In this paper, we propose a novel Reliability-Informed Multiple Instance Learning (RI-MIL) framework that transitions from line-level to cell-level interruption prediction. By dividing transmission lines into cells based on overlapping weather data grids, we develop models that estimate interruption probabilities at a finer spatial resolution. Our approach addresses two key challenges: modeling lines with varying numbers of overlapping weather cells and ensuring physically meaningful cell-level predictions. The framework includes a reliability-informed pooling function that aggregates cell-level predictions and a novel loss function that enforces consistency with physical understanding of system failure mechanics. Through comparative analysis with traditional single-cell approaches, we demonstrate that our RI-MIL model achieves superior predictive performance while providing valuable spatial insights into transmission line vulnerability. These insights enable more targeted hardening strategies and efficient resource allocation during restoration efforts, ultimately enhancing the resilience of power transmission systems against extreme weather events.

DATASET

This study utilizes datasets covering transmission line characteristics, historical interruption records, weather conditions, and environmental factors across the Bonneville Power Administration (BPA) service area.

Transmission Line and Interruption Data

The interruption data was sourced from the BPA, which manages power infrastructure spanning approximately 300,000 square miles across the Northwestern United States. This region encompasses diverse topographical features, including mountains, valleys, forests, and open plains, with 696 transmission lines totaling 15,169 miles (*BPA Facts*, 2014). The historical records, spanning from 1999 to 2022, yield 22 years

of interruption records that include seasonal and annual patterns in outages across this varied terrain.

Each interruption record includes attributes such as out datetime, in datetime, line name, line length, line voltage, interruption duration, and interruption cause. For geographical reference, we obtained coordinates for each transmission line from the BPA ArcGIS website ("Bonneville Power Administration Data", 2023). This spatial data is critical for our cell-based analysis, as it allows us to map transmission lines to weather and environmental data cells.

For this study, we focused specifically on wind-induced interruptions, identified through appropriate cause codes in the dataset. To ensure the relevance of our analysis, we excluded momentary interruptions (duration = 0) that do not significantly impact grid operations or LOOP.

Weather Data

Weather data was obtained from two complementary reanalysis datasets: ERA5 and ERA5-Land, both developed by the European Centre for Medium-Range Weather Forecasts (ECMWF).

ERA5 provides hourly weather variables at a spatial resolution of approximately 30×30 km cells globally, while ERA5-Land offers an enhanced resolution of approximately 9×9 km cells over land areas (Copernicus Climate Change Service, 2019). From these datasets, we extracted several variables relevant to transmission line interruptions, including wind gust (m/s), wind speed (m/s), surface pressure (Pa), surface temperature (K), mean sea level pressure (Pa), and total precipitation (m).

Environmental Data

Environmental factors can significantly influence transmission line vulnerability to wind and other weather conditions. To capture these effects, we incorporated several environmental datasets. For vegetation, we obtained Leaf Area Index (LAI) data from ERA5-Land, representing the total leaf surface area relative to ground area for high vegetation commonly associated with line interruptions. Elevation data came from Digital Elevation Models with 1/3 arc-second resolution from the U.S. Geological Survey's 3D Elevation Program "USGS", n.d., while land cover classification was sourced from the National Land Cover Database Wickham et al., 2021, categorizing land into classes such as water, developed areas, forest, and wetlands. Figure 1 illustrates this spatial heterogeneity, showing how wind speed, wind gust, slope, and elevation vary across cells intersecting transmission lines.

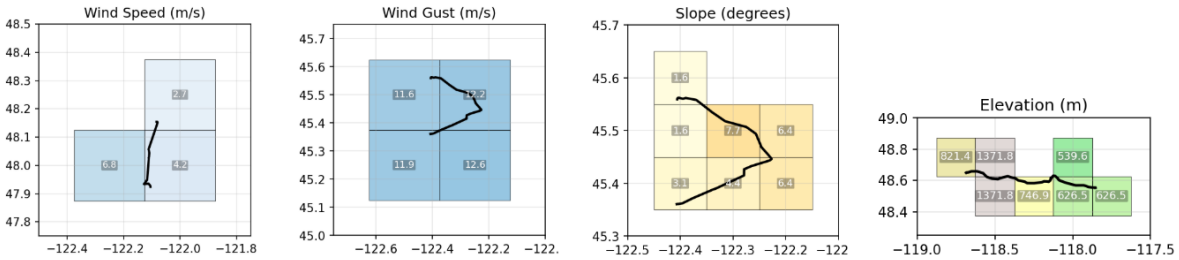

Figure 1: Sample visualization of cell-level data for various transmission lines. The maps show the spatial distribution of different features across the cells intersecting the transmission line. This heterogeneity in environmental and weather conditions along a single line motivates our cell-based modeling approach.

Data Processing for Cell-Level Analysis

For our cell-level analysis approach, we developed a methodology to map each transmission line to multiple overlapping weather and environmental data cells. This process involved several steps:

First, we identified all ERA5 and ERA5-Land cells that intersect with each transmission line using spatial overlay techniques. For each cell, we calculated the length of line segment falling within the cell boundaries, allowing us to determine the percentage of the total line length contained in each cell.

Second, we extracted weather and environmental data for each cell-line intersection, creating a multi-cell representation of each transmission line. This resulted in a variable-length set of features per line, with the number of cells depending on line length and orientation relative to the cell grid.

Table 1 summarizes the input features used in our model. These features represent a comprehensive set of weather, environmental, and line characteristics that influence vulnerability to interruptions.

Table 1: Input features for cell-level transmission line interruption prediction

Category	**Feature**	**Description**
Line Characteristics	Voltage	Transmission line voltage (kV)
	Length	Total length of the transmission line (miles)
	Cell Length Percentage	Percentage of line length in the cell (%)
Weather Variables	Wind Gust	Maximum wind gust at 10m height (m/s)
	Wind Speed	10m wind speed (m/s)
	Surface Pressure	Atmospheric pressure at surface level (Pa)
	Surface Temperature	Temperature at surface level (K)
	Mean Sea Level Pressure	Atmospheric pressure at mean sea level (Pa)
	Total Precipitation	Total precipitation (m)
Environmental Factors	Leaf Area Index	Vegetation density indicator (unitless)
	Slope	Terrain slope (degrees)
	Elevation	Height above sea level (m)
	Land Cover	Categorical classification of land surface

While our ground truth data provides interruption information at the line level without specifying the exact location along the line where the interruption occurred, this cell-level mapping allows us to develop models that can estimate the relative probability of interruption for different segments of the line. This represents a significant advancement over treating each line as a homogeneous entity, particularly for longer lines that traverse diverse geographical and environmental conditions.

METHODOLOGY

In this section, we present our approach for spatially granular transmission line interruption prediction. First, we establish a connection between our problem domain and Multiple Instance Learning (MIL). Then, we introduce our novel Reliability-Informed Multiple Instance Learning (RI-MIL) framework, which enhances traditional MIL by incorporating system reliability principles.

Multiple Instance Learning Framework

Traditional supervised learning assigns each data point a label. However, in many real-world scenarios, obtaining labels for individual instances is challenging or impossible, while labels for groups of instances might be readily available. Multiple Instance Learning (MIL) addresses this limitation by learning from labeled bags (groups) of instances, where only the bag-level labels are known (Carbonneau et al., 2018).

In MIL, a bag is positive if at least one instance within it is positive, and negative if all instances are negative. Formally, given a bag $X = \{x_1, x_2, ..., x_m\}$ containing m instances, the bag label Y is:

$$Y = \begin{cases} 1, & \text{if } \exists i \text{ such that } y_i = 1 \\ 0, & \text{if } \forall i, y_i = 0 \end{cases} \tag{1}$$

where y_i is the unknown label of instance x_i.

This paradigm naturally maps to our transmission line interruption prediction problem. Each transmission line represents a bag, while each cell overlapping the line represents an instance. The line-level interruption status represents the bag label, while the unknown cell-level status represents the instance label. The MIL assumption aligns with our physical understanding of transmission line interruptions: a line is interrupted if at least one cell along its length experiences conditions severe enough to cause interruption.

Reliability-Informed Multiple Instance Learning (RI-MIL)

While MIL provides a suitable foundation for our problem, it faces significant limitations in transmission line interruption prediction. First, standard MIL approaches typically assume a fixed number of instances per bag, whereas transmission lines intersect with varying numbers of weather data cells depending on their length and geographical orientation. Second, conventional MIL focuses primarily on bag-level predictions without ensuring that instance-level scores are physically meaningful—a critical shortcoming when the goal is not only to predict interruptions but also to identify vulnerable segments for targeted hardening.

To address these limitations, we incorporate reliability engineering principles to develop our Reliability-Informed Multiple Instance Learning (RI-MIL) framework, illustrated in Figure 2. Our approach addresses two key challenges in transmission line interruption prediction that traditional machine learning models struggle with.

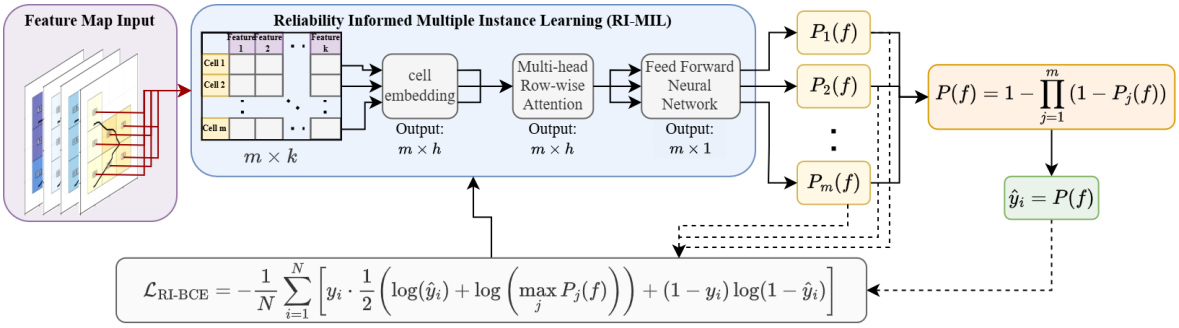

Figure 2: Reliability-Informed Multiple Instance Learning (RI-MIL) framework for transmission line interruption prediction.

The first challenge concerns the variable-length input representation of transmission lines. Different transmission lines intersect with varying numbers of weather data cells, resulting in inconsistent input dimensions for traditional models that expect fixed-size inputs. To address this, we implement an attention-based neural network architecture that can process any number of input cells. For each cell i overlapping a transmission line, we construct a feature vector x_i containing weather variables (wind gust, precipitation), environmental factors (vegetation, elevation), and transmission line characteristics (voltage, length). These heterogeneous features are processed through fully connected layers to obtain a cell embedding $e_i = \phi(x_i; \theta_\phi)$ where ϕ represents the embedding network with parameters θ_ϕ.

To handle the variable number of cells across transmission lines, we employ a multi-head attention mechanism that aggregates information across all cells. This mechanism assigns different importance to different cells and captures complex interactions between cells. For a line with m cells and their corre-

sponding embeddings $\{e_1, e_2, ..., e_m\}$, the attention mechanism produces cell-level interruption probabilities $\{P_1(f), P_2(f), ..., P_m(f)\}$, where $P_i(f)$ represents the probability of cell i experiencing an interruption.

Based on the reliability principle that a transmission line fails if any of its components fails, we define a reliability-informed pooling function that aggregates cell-level predictions into a line-level interruption probability $P(f)$:

$$P(f) = 1 - \prod_{j=1}^{m}(1 - P_j(f)) \tag{2}$$

This formulation represents the probability of at least one cell failing, assuming cell failures are independent events. Both our attention-based architecture and pooling function naturally accommodate variable-length inputs, enabling processing across transmission lines of different lengths and configurations.

The second challenge relates to potentially uninformative cell-level predictions despite accurate line-level predictions. Consider a case where a transmission line with 100 overlapping weather cells has been interrupted. If a model assigns a 1% probability of interruption to each cell, the line-level interruption probability computed would be approximately 63.3%, correctly classifying it as an interruption (assuming a 50% threshold). However, from a reliability standpoint, this prediction is physically implausible, as it suggests no single cell has a significant probability of failure despite the line being interrupted.

To address this issue, we introduce a reliability-informed loss function that enforces a critical constraint: if a line is interrupted, at least one cell must have a high interruption probability. Our reliability-informed loss function is defined as:

$$\mathcal{L}_{RI-BCE} = \frac{1}{N}\sum_{i=1}^{N}\left[y_i \cdot \frac{1}{2}\left(\log(y_i) + \log\left(\max_j P_j(f)\right)\right) + (1 - y_i)\log(1 - \hat{y}_i)\right] \tag{3}$$

where N is the number of training samples, y_i is the true label for line i (0 or 1), $\hat{y}_i = P(f)$ is the predicted line-level interruption probability, and $\max_j P_j(f)$ is the maximum cell-level interruption probability.

When a line is not interrupted ($y_i = 0$), the loss function behaves like standard binary cross-entropy, encouraging the model to predict low interruption probabilities. However, when a line is interrupted ($y_i = 1$), the loss function considers both the line-level prediction and the maximum cell-level prediction. This forces the model to identify at least one cell with a high interruption probability, aligning with the physical reality that line interruptions occur at specific vulnerable points rather than being uniformly distributed along the line. This approach bridges the gap between data-driven prediction and physical reliability principles, creating a model that respects the underlying failure mechanisms of transmission systems.

Model Evaluation and Comparison

To evaluate the effectiveness of our proposed RI-MIL framework, we establish a baseline model that follows the conventional approach of representing each transmission line by a single weather cell. Since our focus is on wind-induced interruptions, this single-cell model selects the cell with the maximum wind gust value as representative of the entire line. This baseline approach mirrors the traditional practice in transmission line reliability assessment where analysis focuses on the point of maximum environmental stress.

Both the single-cell model and our proposed multi-cell RI-MIL model are trained using identical feature sets and training procedures to ensure a fair comparison. The models are evaluated on a standard holdout test set comprising 20% of the available interruption data and a matching number of no-interruption cases, randomly selected and not used during training or validation.

This evaluation framework allows us to assess the performance improvements of the RI-MIL approach and its specific advantages in scenarios where simplified single-cell representations may fail to capture the complex spatial heterogeneity of environmental conditions along transmission lines.

RESULTS AND DISCUSSION

In this section, we present a comprehensive evaluation of our proposed RI-MIL model against the single-cell baseline approach. We analyze performance metrics, examine the distribution of predicted probabilities, and showcase a case study demonstrating the effectiveness of our cell-based approach.

Performance and Classification Capabilities

Table 2 presents the performance metrics of both the single-cell and multi-cell (RI-MIL) models. The RI-MIL model outperforms the single-cell approach across all metrics, demonstrating consistent improvement rather than trading off between different aspects of performance. This balanced enhancement suggests that the spatial granularity of our approach captures patterns in the data that a single-cell representation cannot.

Table 2: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score
Single-cell model	0.718	0.701	0.777	0.737
Multi-cell model	**0.761**	**0.729**	**0.843**	**0.782**

The confusion matrices in Figure 3 further illustrate this comprehensive improvement. The RI-MIL model correctly identifies 140 out of 166 interruption cases and 109 out of 161 non-interruption cases, compared to the single-cell model's 129 and 106, respectively. Notably, our approach reduces false negatives by 29.7% (from 37 to 26) while maintaining a similar level of false positives (52 vs. 55). This characteristic is particularly valuable for reliability applications where missing an interruption event can have severe consequences, yet false alarms must also be minimized to avoid unnecessary resource deployment.

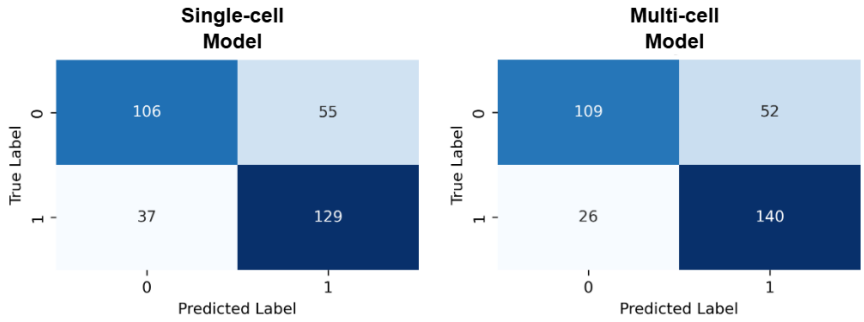

Figure 3: Confusion matrices comparing the performance of single-cell and multi-cell (RI-MIL) models.

The improved detection capabilities across both interruption and non-interruption scenarios confirm that the RI-MIL framework's advantage stems from its ability to integrate multiple perspectives of the transmission line's environmental context rather than simply applying a more aggressive classification threshold. By considering the entire spatial profile of weather and environmental conditions along a transmission line, the model builds a more comprehensive understanding of the complex failure mechanisms involved.

Model Confidence and Decision Boundary

Figure 4 reveals a striking difference in prediction probability distributions between the two models. The RI-MIL model produces a sharper separation with a distinct bimodal pattern—non-interruption cases concentrated near 0 probability and interruption cases above 0.8—whereas the single-cell model frequently assigns probabilities closer to 0.5. This difference highlights the inherent uncertainty in the single-cell

approach, which, by focusing solely on the maximum wind gust location, cannot account for how environmental factors might combine across different locations to create vulnerable conditions.

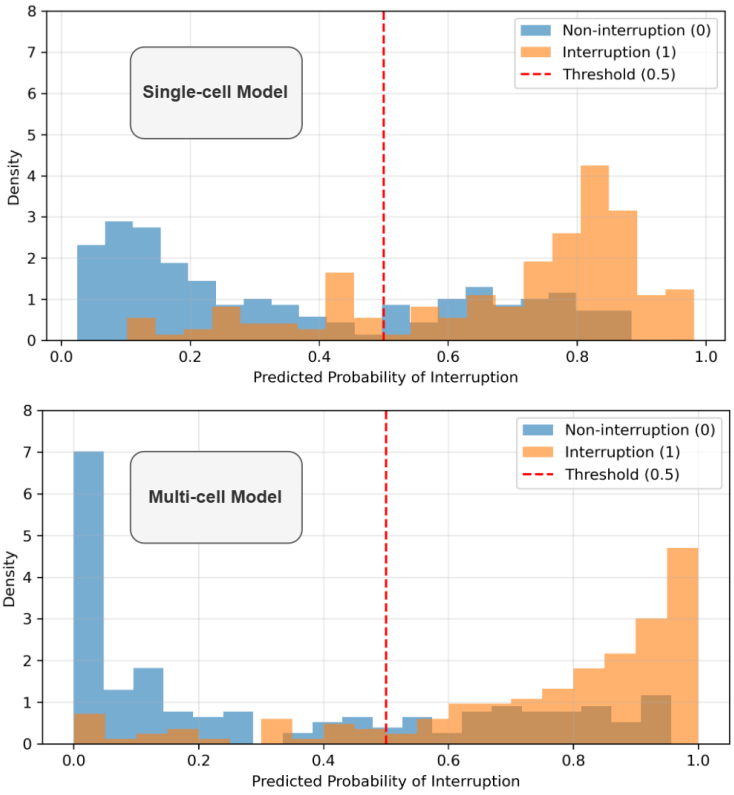

Figure 4: Distribution of predicted interruption probabilities for single-cell and multi-cell RI-MIL models.

The RI-MIL model's more deterministic pattern stems from its ability to identify specific vulnerable segments by analyzing combinations of weather, environmental, and line characteristics at each cell. This enhanced discrimination capability has practical significance for grid operators and emergency response planners, as more decisive predictions allow for clearer operational decision thresholds and reduce ambiguous cases that might require additional human judgment or information gathering.

Integrating Multiple Environmental Factors

The case study in Figure 5 showcases how our Multi-cell approach leverages spatial heterogeneity to improve prediction accuracy. For this particular interruption event, the single-cell model predicted only a 5.3% probability of interruption, incorrectly classifying it as a non-interruption. In contrast, the RI-MIL model correctly predicted an 88.7% probability of interruption.

Examining the cell-level predictions reveals an intriguing pattern: both models effectively "agree" on the low interruption probability for the maximum wind gust cell. However, the RI-MIL model identifies two other cells with high interruption probabilities despite their slightly lower wind gust values. These cells are characterized by significantly higher elevation and steeper slopes—terrain features that can amplify wind effects and increase transmission line vulnerability.

This observation highlights how the RI-MIL model integrates multiple vulnerability factors rather than focusing exclusively on wind gust magnitude. The model has effectively learned that the interaction between moderate winds and challenging terrain can create more hazardous conditions than stronger winds

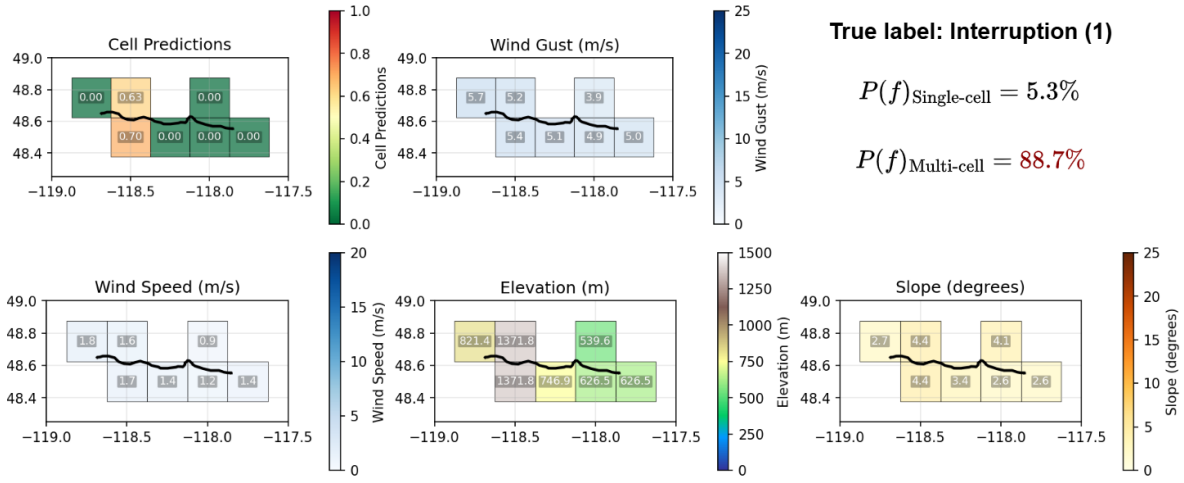

Figure 5: Case study visualization of cell-level predictions and environmental factors for a transmission line. Despite moderate wind gust values (top-right), the RI-MIL model correctly predicted interruption (88.7% probability) by capturing complex interactions between multiple environmental factors across cells, while the single-cell model incorrectly predicted non-interruption (5.3% probability).

in more favorable terrain. Such nuanced understanding would be impossible with a single-cell approach that reduces each transmission line to its point of maximum wind stress.

The case study demonstrates that the RI-MIL model's improved performance stems from its ability to analyze the spatial context of each transmission line. By considering all weather cells across a line, it captures complex interactions between weather variables and environmental features that may occur at locations other than the maximum wind gust point. This capability is particularly valuable for long transmission lines that traverse diverse geographical regions, where vulnerability can vary along the line's length.

CONCLUSION

This paper introduces a novel cell-based approach for spatially granular transmission line interruption prediction, transitioning from traditional line-level modeling to a more refined spatial resolution that captures the heterogeneous vulnerability of transmission lines to extreme weather events. Our proposed Reliability-Informed Multiple Instance Learning (RI-MIL) framework effectively addresses the challenges inherent in this transition while producing physically meaningful predictions.

The key contributions of this work include: (1) formulation of the transmission line interruption prediction problem within the Multiple Instance Learning paradigm, where each line represents a bag and its overlapping weather cells represent instances; (2) development of a reliability-informed pooling function that aggregates cell-level predictions while respecting the system's failure mechanics; and (3) introduction of a novel loss function that ensures cell-level predictions align with physical understanding of transmission line vulnerabilities.

The RI-MIL model consistently outperforms the single-cell approach across all performance metrics, with particularly significant improvements in recall. The case study demonstrated how our approach captures complex interactions between moderate wind conditions and challenging terrain features that would be missed by single-cell representations. This cell-based approach provides transmission system operators with spatially explicit vulnerability assessments, offering more actionable information for both short-term operational response to extreme weather events and long-term infrastructure hardening decisions. Such granular insights enable more targeted resource allocation during restoration efforts and more efficient invest-

ment in system resilience, ultimately enhancing the reliability of power supply to critical facilities including nuclear power plants. Finally, the model is structured to explicitly account for variations in environmental conditions, hazard characteristics, and infrastructure features, enabling its application to transmission line interruption modeling in other regions facing similar extreme weather hazards.

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