Risk Assessment of Power Outages as Rare Events with Learning Models and LLMs

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Abstract

As large language models (LLMs) are increasingly considered for high-stakes decision support, their ability to conduct risk analysis in practical settings remains underexplored. This work investigates the capability of LLMs to perform risk reasoning for rare events, using power outage prediction as a representative case. We introduce a context-aware framework that compares traditional machine learning models and LLMs under varying levels of prior contextual information. Our findings reveal that LLMs are not as effective when operating solely on raw data, but their performance improves when provided with contextual cues and reasoning guidance. These results underscore both the current limitations and emerging opportunities of LLMs in infrastructure risk forecasting and offer a foundation for more context-sensitive and trustworthy AI systems.

1 Introduction

In recent years, rare but high-impact events have become increasingly frequent. Extreme phenomena such as major earthquakes, severe weather, and large-scale social disruptions are no longer isolated anomalies; they are reshaping how we understand and manage risk. Traditional risk measures, defined as the ratio of positive events to the total number of events, break down in this context. Since negative cases vastly outnumber positive ones, this ratio approaches zero, making the assessment of rare-event risk challenging. Power outages offer a meaningful case study in this regard: although individual outages are spatially and temporally sparse, they can be consequential events whose frequency and impact are growing under climate change and infrastructure stress, and they benefit from reliable documentation. Studying outage risks thus provides both practical insights into infrastructure resilience and a broader methodological example of how rare-event risk should be studied and remedied.

While accurate prediction of individual outage events is not feasible, an analysis of historical and real-time data helps us to understand the patterns and risks of power outages. By leveraging data from weather patterns, grid performance metrics, equipment health, and energy consumption trends, machine learning models can identify patterns and correlations that signal potential failures. Predictive analytics can help utilities anticipate outages before they occur, allowing for proactive maintenance and resource allocation. Advanced models, such as deep learning and ensemble methods, can improve forecasting accuracy by integrating diverse data sources, including satellite imagery and IoT sensor readings from power infrastructure. Additionally, reinforcement learning can optimize grid operations, reducing the likelihood of cascading failures. As the energy sector continues to modernize, machine learning will play a crucial role in enhancing grid resilience, minimizing downtime, and ensuring reliable power delivery.

Recently, large language models (LLMs) have emerged as powerful tools for risk reasoning and interpretation, capable of combining statistical cues with contextual knowledge. Unlike conventional models that rely solely on structured data, LLMs can process descriptive and semi-structured information — such as weather reports, equipment logs, or local narratives — to infer relative risk. Their ability to synthesize quantitative features and textual context opens new possibilities for interpretable and adaptable risk prediction frameworks.

2 Related Work

Research on rare-event prediction emphasizes the need for specialized data handling and model designs to overcome data imbalance and complex dependencies (Shyalika et al., 2024; Chen et al., 2024).

In the context of power outage prediction, ma-

chine learning has been widely applied to assess failure risks and restoration processes (Toubeau et al., 2022; Arora and Ceferino, 2023; Castillo, 2014). Prior studies combine meteorological, environmental, and infrastructure data to predict outages under extreme weather or equipment stress. Models range from logistic regression and ensemble learning (Eskandarpour and Khodaei, 2016; He and Cheng, 2021) to deep learning and probabilistic frameworks (Yang et al., 2020; Ghasemkhani et al., 2024; Gu et al., 2023; Zhai et al., 2021; Wang et al., 2024). Recent works have also used non-parametric and Bayesian methods for localized and non-weather-related outage prediction (Wedagedara et al., 2024; Owolabi and Sunter, 2022).

More recently, LLMs have shown promise in supporting risk analysis across diverse domains, including hazard assessment and product safety (Collier et al., 2025; Kattamreddy and Chinnam, 2025; Cruz et al., 2024; Diemert and Weber, 2023). Their ability to integrate quantitative and contextual reasoning suggests potential for enhancing interpretability and decision support in infrastructure risk evaluation.

3 Methods

3.1 Risk Assessment Modeling for Rare Events

An event is represented by a tuple $(\text{location}, \text{time})$, capturing its spatio-temporal dimensions. Traditionally, the risk of positive events under a given condition is defined as

$$R|_{\text{cond}} = \frac{N_{\text{pos}}|_{\text{cond}}}{N_{\text{tot}}|_{\text{cond}}} = \frac{N_{\text{pos}}|_{\text{cond}}}{N_{\text{pos}}|_{\text{cond}} + N_{\text{neg}}|_{\text{cond}}}.$$

Since space and time are continuous, the default negative set is conceptually infinitely large, $N_{\text{neg}}|_{\text{cond}} \to \infty$, yielding $R|_{\text{cond}} \to 0$ and making traditional risk evaluation unreliable.

To address this, we consider constructing a finite negative sample set satisfying the following properties: (i) The relative distribution of negative events under each condition remains proportional to that of the infinitely large default set. (ii) Under each condition, the number of negative events in the sample is much greater than the positive events, $N_{\text{neg}}|_{\text{cond}} \gg N_{\text{pos}}|_{\text{cond}}$, so that $N_{\text{tot}}|_{\text{cond}} \simeq N_{\text{neg}}|_{\text{cond}}$.

We then define the ratio of positive to negative events under a condition as $r_{\text{cond}} = \frac{N_{\text{pos}}|_{\text{cond}}}{N_{\text{neg}}|_{\text{cond}}}$, and under the baseline condition (covering all conditions) as $r_{\text{baseline}} = \frac{N_{\text{pos}}|_{\text{all}}}{N_{\text{neg}}|_{\text{all}}}$. Finally, the **relative risk increment** under the condition is defined as

$$\Delta R|_{\text{cond}} = \frac{r_{\text{cond}} - r_{\text{baseline}}}{r_{\text{baseline}}}. \quad (1)$$

Notably, the relative risk increment ΔR is robust to changes in the size of the negative sample, provided that the two properties of the negative set are preserved.

This formulation allows us to quantify risk under different conditions while avoiding the vanishing-risk problem inherent in rare-event analysis.

3.2 Data Preparation

3.2.1 Data Collection and Feature Selection

In this study, we integrated power outage records, high-resolution weather forecasts, and spatial features to construct a unified dataset suitable for modeling the probability of rare outages under varying environmental and infrastructural conditions.

Specifically, outage data (positive events) were obtained from the Massachusetts state portal (mass.gov) (see Appendix A.0.1). Weather forecasts were retrieved from the NOAA High-Resolution Rapid Refresh (HRRR) model. We extracted meteorological variables most relevant to outage occurrence, including wind, precipitation, temperature, etc. (see Appendix A.0.2).

To account for spatial heterogeneity, we further incorporated census-based population density, utility service territories, and land cover characteristics. These spatial attributes served as background covariates describing exposure, infrastructure distribution, and land development intensity (see Appendix A.0.3).

3.2.2 Negative Events Generation

To ensure the validity of the risk assessment method described in Section 3.1, we adopted the following principles for sampling negative events: (i) negative events were uniformly distributed across the same temporal range as the outage dataset to ensure temporal comparability, (ii) event locations were sampled in proportion to housing density so that the non-outage set reflects the spatial distribution of power facility exposure, and (iii) negative events within 2 km of an outage were discarded to avoid overlap in feature space between outage and non-outage cases. To maintain balance while preserving rarity, the number of negative samples was set to 10 times the number of recorded outage events.

3.2.3 Combining Data and Derived Features

The positive and negative event samples were merged into a unified dataset covering the period from August 2018 through the end of 2023, where each entry represents either an outage (Section A.0.1) or a non-outage event (Section 3.2.2). Spatial features were aggregated according to each event's location, while weather attributes were extracted from HRRR forecasts corresponding to the respective time and location of occurrence.

Temporal factors play a crucial role in outage prediction, reflecting both meteorological and human activity patterns. Our analysis (Section 3.3) indicates that outages occur more frequently during winter months and weekdays, and may also vary with natural cycles such as the lunar phase. To capture these effects, the `datetime` attribute was decomposed into `month_of_year`, `day_of_lunar_cycle`, `day_of_week`, and `time_of_day`, each encoded using sine–cosine transformations to preserve periodicity for machine learning methods.

3.3 Data Analysis

For each feature in the dataset, we partitioned its range into several intervals (bins), each representing a distinct condition. Within each condition, we aggregated counts of positive and negative events within each interval, and the relative risk increment was computed according to Equation (1). This approach enables the estimation of how outage risk changes across varying feature levels.

Gust Interval (m/s)	Relative Risk Increase
0 – 9.5	≈ -0.5
9.5 – 11.3	-0.18
11.3 – 15.1	+0.16 – +1.01
15.1 – 18.9	+2.50 – +5.46
18.9 – 22.6	+12.6 – +25.1
22.6 – 28.3	+52 – +133
28.3+	+226 – ∞

Table 1: Condensed relative risk increase across gust speed intervals. Risk begins to rise noticeably above **11 m/s** and escalates rapidly beyond **18 m/s**.

4 Experiments

We investigate risk assessment through both traditional machine learning (ML) methods and large language models (LLMs). Although the main focus of this study is on the latter, the former remains essential for two reasons. First, it provides a quantitative benchmark for evaluating the performance of LLM-based risk assessment when computational resources are fully utilized. Second, it allows us to extract interpretable rules and statistical patterns that can be incorporated into contextual prompts for LLMs.

4.1 LLM Experiment Design

Each event (positive or negative) is converted into a concise paragraph describing all relevant features, simulating a natural language report from a user about local conditions. Using a carefully designed prompt, the LLM is asked to assess the risk of a power outage for the described scenario and return its response in a structured JSON format with two fields: (i) a risk level (7 levels ranging from "very low" to "very high"), and (ii) a brief reasoning statement explaining the factors contributing to the assessment.

For quantitative evaluation, each categorical risk level is mapped to a continuous scale (0–1) and compared with the ground-truth outage label, treating the task as a binary classification problem. We report the area under the ROC curve (AUC) and the F1 score for outage class as evaluation metrics.

All records from 2023 are held out as the test set, from which 450 events are randomly sampled to generate LLM queries. This setup enables direct comparison between the LLM-predicted risks and actual outage occurrences.

4.2 Knowledge Context

Each LLM can be regarded as having a fixed base of general knowledge about power outages. For example, recognizing that extreme weather such as strong winds or heavy rainfall increases outage risk. Thus, even without additional input, the model should perform better than random guessing.

However, such embedded knowledge is generic and may lack regional or quantitative specificity. We therefore investigate how LLM performance changes when supplemented with contextual information about outage risk.

First, while LLMs encode broad global patterns, real-world outage behavior often varies regionally. For instance, our Massachusetts data reveal a correlation between outage risk and the lunar cycle, possibly reflecting coastal influences. Introducing localized information into the context may enhance model accuracy.

Second, LLM knowledge is primarily linguistic rather than statistical. By embedding structured context derived from domain-specific statistical

Feature Category	Example Features	Natural-Language Description Snippet
Temporal	Date = 2023-03-07, Day = Tuesday, Time = 14:28, Holiday = No, Lunar Cycle = 1.94 (Waxing Crescent)	"Today is March 7, Tuesday, and it is not a holiday. The time is 2 PM. The moon phase is waxing crescent."
Meteorological	Temperature = 275.25 K, Dew Point = 269 K, Gust = 10.68 m/s, Wind = 6.90 m/s,	"It's cold. The air is very dry. There are moderate wind gusts up to 23.9 mph."
Spatial / Geographic	Town = Billerica, Latitude = 42.60, Longitude = -71.28, Utility = NationalGrid	"The location is in Billerica, Massachusetts. The utility group is NationalGrid."
Socio-environmental	Population Density = 4.57 ($\approx$ 457 people/km²), Land Cover = Suburban mix, Tree Canopy = 48%	"The area has a low population density. The location is suburban, with houses, small shops, and moderate tree coverage."

Table 2: Example of converting structured event features into a natural-language paragraph.

knowledge, we aim to strengthen the model's quantitative reasoning about risk.

We experiment with four context settings: (i) **No Context**, a zero-shot baseline where the model receives only the event description; (ii) **Quantitative Risk Context**, summarizing relative outage risk across feature intervals using pre-2023 data (Section 3.3); (iii) **Risk Summary**, a highly condensed version of (ii); and (iv) **The Gradient Boosting Decision Tree (GBDT)-derived Rules Context** incorporates knowledge extracted from the traditional GBDT model, where a subset of the most influential rules from the top few trees are converted into textual prompts. We provide the detailed contexts in the Appendix B.

5 Results

In this section, we present the results from our analysis with machine learning methods and LLMs. We evaluate three large language models, **Llama3-8b-Instruct** (Dubey et al., 2024), **Qwen-2.5-7B** (Hui et al., 2024), and **GPT-4o** (Hurst et al., 2024), under four different contextual setting.We also tested using the GBDT, a traditional ML model, which serves as a non-LLM baseline. The results are shown in Table. 3. We also provide one qualitative example in Appendix C.

Across all three models, incorporating contextual information generally improves performance compared to the No-Context setting. GPT-4o demonstrates the most consistent gains, particularly under the Risk Summary Context, reflecting its superior ability to interpret semantically meaningful cues and integrate them into probabilistic reasoning.

Interestingly, Llama-3's performance declines when given the full "Quantitative Risk" table but improves when provided with the condensed "Risk Summary." This suggests that Llama-3 struggles with dense numerical listings but benefits from simplified, linguistically structured representations such as "GUST > 28.3 $\rightarrow$ risk $\times$ 280." In other words, LLMs appear more capable of leveraging compact, human-readable expressions of statistical patterns than exhaustive numeric data, indicating that interpretability and format simplicity can be as important as content richness when designing prompts for model reasoning.

Table 3: Comparison between LLMs under Different Context Settings

Context	Model	AUROC	F1
- No Context	Llama3-8b-Instruct	**0.679**	0.536
	Qwen-2.5-7B	0.642	**0.544**
	GPT-4o	0.647	0.515
+ Quantitative Risk	Llama3-8b-Instruct	0.586	0.514
	Qwen-2.5-7B	0.661	0.542
	GPT-4o	**0.731**	**0.590**
+ Risk Summary	Llama3-8b-Instruct	0.717	**0.611**
	Qwen-2.5-7B	0.657	0.535
	GPT-4o	**0.736**	0.581
+ GBDT-derived Rule	Llama3-8b-Instruct	0.618	0.502
	Qwen-2.5-7B	0.539	**0.598**
	GPT-4o	**0.652**	0.532
GBDT (Traditional ML Model)		0.757	0.678

6 Conclusion and Future Work

This study represents an initial exploration into applying large language models to rare-event risk assessment through contextual prompting. Our findings indicate that well-designed contexts incorporating expert-derived statistical knowledge can meaningfully improve model reasoning about outage risk, though the degree of improvement varies across architectures.

Future work will focus on systematically exploring different forms of statistical and causal knowledge, as well as more adaptive prompt-engineering strategies tailored to model behavior. With deeper integration of domain expertise and structured reasoning, LLMs hold promise as complementary tools for data-driven risk analysis in complex systems.

Limitations

Our study is limited in several ways. First, we only evaluate a subset of LLMs and may not generalize to all models. Second, our experiments focus on English-language power outage data, which may not reflect other languages or domains. Third, while we provide contextual guidance, real-world deployment would involve additional practical considerations such as safety, interpretability, and human-in-the-loop validation. Additionally, all measurements and reported quantities in our experiments use the SI unit system, which may require conversion for applications in regions using other unit conventions.

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A Data preparation

A.0.1 Power Outage Data: Positive Data

We collected outage records from the Massachusetts state portal (mass.gov), covering 2013–2023. Each record includes attributes such as outage duration, start and end times, and reported causes. In this study, we use only the event location (longitude, latitude) and the report time, which we use to define an outage (positive) event.

A.0.2 Weather Data

We obtained weather data from the High-Resolution Rapid Refresh (HRRR) model operated by the National Oceanic and Atmospheric Administration (NOAA). The HRRR model provides both real-time analysis and forecast data. However, we use only the forecast data in this work, as our goal is to predict potential outages before they occur—when only forecast information is available. The HRRR model issues forecasts every 6 hours, with predictions extending up to 48 hours ahead. For each specific outage event, we extract the forecast issued at 6:00 PM (UTC) on the previous day. We consider the following weather features, which are likely to be most relevant to power outages:

Variable Name	Level	Description
`WEASD_1hr_acc_fcst`	Surface	Water equivalent of accumulated snow depth (1-hr accumulated forecast)
`WIND_1hr_max_fcst`	10 m above ground	Maximum wind speed over the past hour
`SHTFL`	Surface	Sensible heat flux from the surface
`PRATE`	Surface	Precipitation rate (instantaneous)
`DPT`	2 m above ground	Dewpoint temperature
`GUST`	Surface	Wind gust at the surface
`TMP`	2 m above ground	Air temperature

Table 4: Weather features extracted from HRRR forecasts

A.0.3 Spatial Features: Geospatial and Census Data

Three datasets from the Massachusetts government were used for geospatial analysis.

Population density. Census information was obtained from MassGIS 2020 U.S. Census data. Although the dataset does not directly provide population density, it includes population counts for each census block (a tract of land) together with the block's square footage. From these values, we computed population density at the block level, providing an estimate of population density across Massachusetts (`pop20_density`).

Utility service areas. Utility company service territories were obtained from MassGIS Public Utility Service Providers data. This dataset was used to assign the serving utility for each municipality (`utility_group`).

Land cover. Land cover data was retrieved from MassGIS 2016 Land Cover/Land Use data. This dataset contains 19 land cover categories, from which we derived two types of features: (i) level of land development, and (ii) type of land cover. The derived variables include: `lc_dev_0`, `lc_dev_1`, `lc_dev_2`, `lc_dev_3`, `lc_is_water/wetland`, `lc_is_forest/shrub`, `lc_is_grass/crop`, and `tcc`.

Data sources:

- MassGIS Data: 2020 U.S. Census
- MassGIS Data: Public Utility Service Providers
- MassGIS Data: 2016 Land Cover/Land Use

B Contexts

B.1 Quantitative Risk Context

The table below shows the relative risk (compared to the average) across different intervals for each analyzed feature.:

```
--- Relative risk and risk increase for Gust ---
                     relative_risk  relative_risk_increase
feature_bin
(-0.00509, 1.92]m/s          0.405                  -0.595
(1.92, 3.8]m/s               0.425                  -0.575
(3.8, 5.69]m/s               0.453                  -0.547
(5.69, 7.57]m/s              0.523                  -0.477
(7.57, 9.46]m/s              0.623                  -0.377
(9.46, 11.3]m/s              0.819                  -0.181
(11.3, 13.2]m/s              1.156                   0.156
(13.2, 15.1]m/s              2.013                   1.013
(15.1, 17]m/s                3.497                   2.497
(17, 18.9]m/s                6.460                   5.460
(18.9, 20.8]m/s             13.569                  12.569
(20.8, 22.6]m/s             26.134                  25.134
(22.6, 24.5]m/s             53.337                  52.337
(24.5, 26.4]m/s             81.513                  80.513
(26.4, 28.3]m/s            133.875                 132.875
(28.3, 30.2]m/s            280.400                 279.400
(30.2, 32.1]m/s            227.667                 226.667
(32.1, 34]m/s              248.000                 247.000
(34, 35.8]m/s               73.000                  72.000
(35.8, 37.7]m/s                inf                     inf

--- Relative risk and risk increase for Dew point Temperature ---
             relative_risk  relative_risk_increase
feature_bin
(241, 244]K          0.091                  -0.909
(244, 247]K          0.154                  -0.846
(247, 250]K          2.655                   1.655
(250, 253]K          1.042                   0.042
(253, 255]K          0.624                  -0.376
(255, 258]K          0.514                  -0.486
(258, 261]K          0.613                  -0.387
(261, 264]K          0.772                  -0.228
(264, 267]K          0.717                  -0.283
(267, 270]K          0.540                  -0.460
(270, 273]K          0.642                  -0.358
(273, 276]K          0.873                  -0.127
(276, 279]K          0.772                  -0.228
(279, 281]K          1.227                   0.227
(281, 284]K          1.283                   0.283
(284, 287]K          1.437                   0.437
(287, 290]K          0.946                  -0.054
(290, 293]K          1.171                   0.171
(293, 296]K          1.657                   0.657
(296, 299]K          1.409                   0.409

--- Relative risk and risk increase for Percipitation rate ---
                            relative_risk  relative_risk_increase
feature_bin
(-0.001, 0.00049]kg/m^2/s           0.875                  -0.125
(0.00049, 0.00098]kg/m^2/s          5.307                   4.307
(0.00098, 0.00147]kg/m^2/s          8.675                   7.675
(0.00147, 0.00196]kg/m^2/s          8.669                   7.669
(0.00196, 0.00245]kg/m^2/s          9.022                   8.022
(0.00245, 0.00294]kg/m^2/s         10.620                   9.620
(0.00294, 0.00343]kg/m^2/s         15.156                  14.156
(0.00343, 0.00392]kg/m^2/s         12.043                  11.043
(0.00392, 0.00441]kg/m^2/s          9.714                   8.714
(0.00441, 0.0049]kg/m^2/s          20.308                  19.308

--- Relative risk and risk increase for Temperature ---
             relative_risk  relative_risk_increase
```

```
feature_bin
(246, 249]K          0.000                  -1.000
(249, 252]K          0.273                  -0.727
(252, 256]K          0.936                  -0.064
(256, 259]K          0.877                  -0.123
(259, 262]K          0.831                  -0.169
(262, 266]K          0.674                  -0.326
(266, 269]K          0.670                  -0.330
(269, 272]K          0.809                  -0.191
(272, 276]K          0.691                  -0.309
(276, 279]K          0.659                  -0.341
(279, 282]K          0.987                  -0.013
(282, 286]K          1.540                   0.540
(286, 289]K          1.545                   0.545
(289, 292]K          0.871                  -0.129
(292, 296]K          0.992                  -0.008
(296, 299]K          1.066                   0.066
(299, 302]K          1.134                   0.134
(302, 306]K          1.413                   0.413
(306, 309]K          1.659                   0.659
(309, 312]K          1.036                   0.036

--- Relative risk and risk increase for popluation density ---
                                  relative_risk  relative_risk_increase
feature_bin
(-12.4, 619]persons/km^2                  1.934                   0.934
(619, 1.24e+03]persons/km^2               0.706                  -0.294
(1.24e+03, 1.86e+03]persons/km^2          0.510                  -0.490
(1.86e+03, 2.47e+03]persons/km^2          0.428                  -0.572
(2.47e+03, 3.09e+03]persons/km^2          0.327                  -0.673
(3.09e+03, 3.71e+03]persons/km^2          0.276                  -0.724
(3.71e+03, 4.33e+03]persons/km^2          0.308                  -0.692
(4.33e+03, 4.95e+03]persons/km^2          0.321                  -0.679
(4.95e+03, 5.57e+03]persons/km^2          0.261                  -0.739
(5.57e+03, 6.19e+03]persons/km^2          0.388                  -0.612
(6.19e+03, 6.8e+03]persons/km^2           0.257                  -0.743
(6.8e+03, 7.42e+03]persons/km^2           0.587                  -0.413
(7.42e+03, 8.04e+03]persons/km^2          0.389                  -0.611
(8.04e+03, 8.66e+03]persons/km^2          0.346                  -0.654
(8.66e+03, 9.28e+03]persons/km^2          0.275                  -0.725
(9.28e+03, 9.9e+03]persons/km^2           0.695                  -0.305
(9.9e+03, 1.05e+04]persons/km^2           0.847                  -0.153
(1.05e+04, 1.11e+04]persons/km^2          0.268                  -0.732
(1.11e+04, 1.18e+04]persons/km^2          0.127                  -0.873
(1.18e+04, 1.24e+04]persons/km^2          0.300                  -0.700

--- Relative risk and risk increase for day of month ---
      relative_risk  relative_risk_increase
Jan           0.532                  -0.468
Feb           1.130                   0.130
Mar           0.535                  -0.465
Apr           0.932                  -0.068
May           0.469                  -0.531
Jun           0.672                  -0.328
 Jul          1.072                   0.072
Aug           1.164                   0.164
Sep           0.607                  -0.393
Oct           2.914                   1.914
Nov           0.785                  -0.215
Dec           0.896                  -0.104

--- Relative risk and risk increase for hour of day ---
         relative_risk  relative_risk_increase
Hour 0           0.625                  -0.375
Hour 1           0.620                  -0.380
Hour 2           0.665                  -0.335
Hour 3           0.577                  -0.423
Hour 4           0.649                  -0.351
Hour 5           0.762                  -0.238
Hour 6           0.926                  -0.074
```

```
Hour 7           1.030                   0.030
Hour 8           1.064                   0.064
Hour 9           1.084                   0.084
Hour 10          1.055                   0.055
Hour 11          1.120                   0.120
Hour 12          1.212                   0.212
Hour 13          1.204                   0.204
Hour 14          1.261                   0.261
Hour 15          1.442                   0.442
Hour 16          1.582                   0.582
Hour 17          1.671                   0.671
Hour 18          1.275                   0.275
Hour 19          0.959                  -0.041
Hour 20          0.829                  -0.171
Hour 21          0.826                  -0.174
Hour 22          0.771                  -0.229
Hour 23          0.801                  -0.199

--- Relative risk and risk increase for day of week ---
           relative_risk  relative_risk_increase
Sunday             0.568                  -0.432
Monday             1.036                   0.036
Tuesday            1.036                   0.036
Wednesday          1.272                   0.272
Thursday           1.087                   0.087
Friday             1.158                   0.158
Saturday           0.848                  -0.152

--- Relative risk and risk increase for day of lunar cycle ---
        relative_risk  relative_risk_increase
Day 1           1.118                   0.118
Day 2           1.737                   0.737
Day 3           0.936                  -0.064
Day 4           0.830                  -0.170
Day 5           1.309                   0.309
Day 6           2.196                   1.196
Day 7           2.981                   1.981
Day 8           3.381                   2.381
Day 9           1.323                   0.323
Day 10          1.068                   0.068
Day 11          0.579                  -0.421
Day 12          0.784                  -0.216
Day 13          0.498                  -0.502
Day 14          0.625                  -0.375
Day 15          0.590                  -0.410
Day 16          0.648                  -0.352
Day 17          0.858                  -0.142
Day 18          0.459                  -0.541
Day 19          0.622                  -0.378
Day 20          1.082                   0.082
Day 21          0.802                  -0.198
Day 22          0.481                  -0.519
Day 23          0.670                  -0.330
Day 24          0.693                  -0.307
Day 25          0.578                  -0.422
Day 26          0.511                  -0.489
Day 27          0.650                  -0.350
Day 28          0.444                  -0.556
Day 29          0.892                  -0.108

--- Relative risk and risk increase for tree canopy converage ---
               relative_risk  relative_risk_increase
feature_bin
(-0.1, 4.95]%          0.742                  -0.258
(4.95, 9.9]%           0.608                  -0.392
(9.9, 14.8]%           0.620                  -0.380
(14.8, 19.8]%          0.649                  -0.351
(19.8, 24.8]%          0.926                  -0.074
(24.8, 29.7]%          1.196                   0.196
(29.7, 34.6]%          1.134                   0.134
```

```
(34.6, 39.6]%          1.267                  0.267
(39.6, 44.5]%          1.255                  0.255
(44.5, 49.5]%          1.276                  0.276
(49.5, 54.5]%          1.538                  0.538
(54.5, 59.4]%          0.917                 -0.083
(59.4, 64.3]%          5.794                  4.794
(64.3, 69.3]%          1.248                  0.248
(69.3, 74.2]%          1.300                  0.300
(74.2, 79.2]%          0.908                 -0.092
(79.2, 84.2]%          0.965                 -0.035
(84.2, 89.1]%          0.512                 -0.488
(89.1, 94]%            0.289                 -0.711
(94, 99]%              0.017                 -0.983

--- Relative risk and risk increase for land coverage ---
                     relative_risk  relative_risk_increase
Feature
All lc_ are 0                0.024                  -0.976
lc_dev_0                     2.802                   1.802
lc_dev_1                     1.570                   0.570
lc_dev_2                     1.077                   0.077
lc_dev_3                     0.543                  -0.457
lc_is_water/wetland          0.122                  -0.878
lc_is_forest/shrub           0.923                  -0.077
lc_is_grass/crop             0.270                  -0.730

lc_dev_0 – Developed land, intensity level 0 (lowest, e.g. open space, very sparse development).
lc_dev_1 – Developed land, low intensity (small buildings, light residential areas).
lc_dev_2 – Developed land, medium intensity (denser housing, small commercial areas).
lc_dev_3 – Developed land, high intensity (urban cores, industrial areas, downtown).
lc_is_water/wetland – Areas covered by water (lakes, rivers) or wetlands.
lc_is_forest/shrub – Areas covered by forests or shrubland.
lc_is_grass/crop – Areas dominated by grassland or cropland (agriculture, pasture).
```

B.2 Risk Summary

```
Here, the relative risk of a power outage is based on the distribution of the history feature.
The following patterns were observed:
 • Wind Gust (GUST):
Risk increases drastically with speed.
 • GUST > 28.3 → risk ×280
 • GUST 17.5–20.3 → risk ×3.7
 • GUST < 6.1 → risk ×0.07
 • Dew Point (DPT):
 • DPT 247–250 K → highest risk (×2.2)
 • DPT < 240 or > 260 K → lower risk
 • Precipitation Rate (PRATE):
 • PRATE > 0.004 → risk ×20
 • PRATE near 0 → low risk
 • Population Density:
 • Low density (< 600/km²) → higher outage risk (×1.9)
 • High density (> 4,500/km²) → low risk (×0.3)
 • Time of Day:
 • Hours 15–17 (afternoon/evening) → highest risk
 • Early morning hours → low risk
```

B.3 The Gradient Boosting Decision Tree (GBDT)-derived Rules Context

```
Tree #0
IF Gust <= 17.54m/s AND Population Density <= 1.02persons/km^2 THEN Probability of power outage is 0.117
IF Gust <= 17.54m/s AND Population Density > 1.02persons/km^2 THEN Probability of power outage is 0.109
IF Gust > 17.54m/s AND Gust <= 20.30m/s THEN Probability of power outage is 0.123
IF Gust > 17.54m/s AND Gust > 20.30m/s THEN Probability of power outage is 0.134
-------------------------------------------------------------
Tree #1
IF Gust <= 16.52m/s AND Town in {"ASHFIELD", "BECKET", "CHARLEMONT", "COLRAIN", "EGREMONT", "GRANVILLE",
"NEW MARLBOROUGH", "OTIS", "PAXTON", "PLYMPTON", "SANDISFIELD", "SAVOY", "SUDBURY", "WEST BROOKFIELD",
"WEST STOCKBRIDGE", "WINDSOR"} THEN Probability of power outage is 0.542
IF Gust <= 16.52m/s AND Town not in {"ASHFIELD", "BECKET", "CHARLEMONT", "COLRAIN", "EGREMONT", "GRANVILLE",
"NEW MARLBOROUGH", "OTIS", "PAXTON", "PLYMPTON", "SANDISFIELD", "SAVOY", "SUDBURY", "WEST BROOKFIELD",
"WEST STOCKBRIDGE", "WINDSOR"} THEN Probability of power outage is 0.497
```

```
IF Gust > 16.52m/s AND Gust <= 19.68m/s THEN Probability of power outage is 0.524
IF Gust > 16.52m/s AND Gust > 19.68m/s THEN Probability of power outage is 0.545
------------------------------------------------------------
Tree #2
IF Gust <= 15.53m/s AND Town in {"ASHFIELD", "BECKET", "CHARLEMONT", "CHESTERFIELD", "COLRAIN", "CONWAY",
"EGREMONT", "GRANVILLE", "HUNTINGTON", "NEW MARLBOROUGH", "OTIS", "PAXTON", "RICHMOND", "ROYALSTON",
"SANDISFIELD", "SAVOY", "SUDBURY", "WEST BROOKFIELD", "WEST STOCKBRIDGE", "WESTON", "WINDSOR"}
THEN Probability of power outage is 0.533
IF Gust <= 15.53m/s AND Town not in {"ASHFIELD", "BECKET", "CHARLEMONT", "CHESTERFIELD", "COLRAIN", "CONWAY",
"EGREMONT", "GRANVILLE", "HUNTINGTON", "NEW MARLBOROUGH", "OTIS", "PAXTON", "RICHMOND", "ROYALSTON",
"SANDISFIELD", "SAVOY", "SUDBURY", "WEST BROOKFIELD", "WEST STOCKBRIDGE", "WESTON", "WINDSOR"}
THEN Probability of power outage is 0.496
IF Gust > 15.53m/s AND month_progres_sin <= -0.68 THEN Probability of power outage is 0.542
IF Gust > 15.53m/s AND month_progres_sin > -0.68 THEN Probability of power outage is 0.521
------------------------------------------------------------
Tree #3
IF Gust <= 15.11m/s AND Town in {"ASHFIELD", "BECKET", "BLANDFORD", "CHARLEMONT", "CHESTERFIELD", "COLRAIN",
"CONWAY", "EGREMONT", "GRANVILLE", "HUNTINGTON", "LEVERETT", "LUNENBURG", "MONSON", "NEW MARLBOROUGH",
"NORTHFIELD", "OTIS", "PAXTON", "PLYMPTON", "RICHMOND", "ROCHESTER", "ROYALSTON", "SANDISFIELD", "SAVOY",
"SHEFFIELD", "STOCKBRIDGE", "SUDBURY", "WEST BROOKFIELD", "WEST STOCKBRIDGE", "WESTON", "WINDSOR"}
THEN Probability of power outage is 0.525
IF Gust <= 15.11m/s AND Town not in {"ASHFIELD", "BECKET", "BLANDFORD", "CHARLEMONT", "CHESTERFIELD",
"COLRAIN", "CONWAY", "EGREMONT", "GRANVILLE", "HUNTINGTON", "LEVERETT", "LUNENBURG", "MONSON",
"NEW MARLBOROUGH", "NORTHFIELD", "OTIS", "PAXTON", "PLYMPTON", "RICHMOND", "ROCHESTER", "ROYALSTON",
"SANDISFIELD", "SAVOY", "SHEFFIELD", "STOCKBRIDGE", "SUDBURY", "WEST BROOKFIELD", "WEST STOCKBRIDGE",
"WESTON", "WINDSOR"} THEN Probability of power outage is 0.496
IF Gust > 15.11m/s AND Gust <= 19.16m/s THEN Probability of power outage is 0.516
IF Gust > 15.11m/s AND Gust > 19.16m/s THEN Probability of power outage is 0.533
------------------------------------------------------------
Tree #4
IF Gust <= 14.41m/s AND Town in {"ASHFIELD", "CHARLEMONT", "COLRAIN", "EGREMONT", "GRANVILLE", "LEVERETT",
"NEW MARLBOROUGH", "OTIS", "PAXTON", "PLYMPTON", "SANDISFIELD", "SAVOY", "SUDBURY", "WINDSOR"}
THEN Probability of power outage is 0.529
IF Gust <= 14.41m/s AND Town not in {"ASHFIELD", "CHARLEMONT", "COLRAIN", "EGREMONT", "GRANVILLE", "LEVERETT",
"NEW MARLBOROUGH", "OTIS", "PAXTON", "PLYMPTON", "SANDISFIELD", "SAVOY", "SUDBURY", "WINDSOR"}
THEN Probability of power outage is 0.496
IF Gust > 14.41m/s AND month_progres_sin <= -0.68 THEN Probability of power outage is 0.533
IF Gust > 14.41m/s AND month_progres_sin > -0.68 THEN Probability of power outage is 0.515
------------------------------------------------------------
Tree #5
IF Gust <= 13.96m/s AND Town in {"ASHFIELD", "BECKET", "BLANDFORD", "BUCKLAND", "CHARLEMONT", "COLRAIN",
"CONWAY", "EGREMONT", "GRANVILLE", "HARDWICK", "HUNTINGTON", "LENOX", "LEVERETT", "MONTEREY",
"NEW MARLBOROUGH", "OTIS", "PAXTON", "PLYMPTON", "RICHMOND", "ROCHESTER", "SANDISFIELD", "SAVOY",
"SHEFFIELD", "SUDBURY", "WEST BROOKFIELD", "WEST STOCKBRIDGE", "WESTON", "WINDSOR"}
THEN Probability of power outage is 0.521
IF Gust <= 13.96m/s AND Town not in {"ASHFIELD", "BECKET", "BLANDFORD", "BUCKLAND", "CHARLEMONT", "COLRAIN",
"CONWAY", "EGREMONT", "GRANVILLE", "HARDWICK", "HUNTINGTON", "LENOX", "LEVERETT", "MONTEREY",
"NEW MARLBOROUGH", "OTIS", "PAXTON", "PLYMPTON", "RICHMOND", "ROCHESTER", "SANDISFIELD", "SAVOY",
"SHEFFIELD", "SUDBURY", "WEST BROOKFIELD", "WEST STOCKBRIDGE", "WESTON", "WINDSOR"}
THEN Probability of power outage is 0.496
IF Gust > 13.96m/s AND Population Density <= 1.77persons/km^2 THEN Probability of power outage is 0.529
IF Gust > 13.96m/s AND Population Density > 1.77persons/km^2 THEN Probability of power outage is 0.512
------------------------------------------------------------
Tree #6
IF 1-hour Max Wind Forecast <= 7.57m/s AND Population Density <= 1.02persons/km^2
THEN Probability of power outage is 0.512
IF 1-hour Max Wind Forecast <= 7.57m/s AND Population Density > 1.02persons/km^2
THEN Probability of power outage is 0.496
IF 1-hour Max Wind Forecast > 7.57m/s AND lunary_progress_sin <= 0.89
THEN Probability of power outage is 0.514
IF 1-hour Max Wind Forecast > 7.57m/s AND lunary_progress_sin > 0.89
THEN Probability of power outage is 0.528
------------------------------------------------------------
Tree #7
IF 1-hour Max Wind Forecast <= 8.00m/s AND 1-hour Max Wind Forecast <= 5.74m/s
THEN Probability of power outage is 0.497
IF 1-hour Max Wind Forecast <= 8.00m/s AND 1-hour Max Wind Forecast > 5.74m/s
THEN Probability of power outage is 0.504
IF 1-hour Max Wind Forecast > 8.00m/s AND lunary_progress_sin <= 0.87
THEN Probability of power outage is 0.515
```

```
IF 1-hour Max Wind Forecast > 8.00m/s AND lunary_progress_sin > 0.87
THEN Probability of power outage is 0.526
------------------------------------------------------------
Tree #8
IF Gust <= 13.82m/s AND Population Density <= 1.02persons/km^2 THEN Probability of power outage is 0.510
IF Gust <= 13.82m/s AND Population Density > 1.02persons/km^2 THEN Probability of power outage is 0.496
IF Gust > 13.82m/s AND Population Density <= 5.08persons/km^2 THEN Probability of power outage is 0.521
IF Gust > 13.82m/s AND Population Density > 5.08persons/km^2 THEN Probability of power outage is 0.507
------------------------------------------------------------
Tree #9
IF Gust <= 13.82m/s AND Town in {"ASHFIELD", "BECKET", "BLANDFORD", "CHARLEMONT", "CHESTERFIELD", "COLRAIN",
"CONWAY", "DOVER", "EGREMONT", "GRANVILLE", "GREAT BARRINGTON", "HANCOCK", "HARDWICK", "HARVARD",
"LEVERETT", "LINCOLN", "LUNENBURG", "NEW MARLBOROUGH", "OTIS", "PAXTON", "RICHMOND", "ROCHESTER",
"SANDISFIELD", "SAVOY", "SHEFFIELD", "STOCKBRIDGE", "SUDBURY", "WEST BROOKFIELD", "WEST STOCKBRIDGE",
"WESTON", "WINDSOR"}
THEN Probability of power outage is 0.517
IF Gust <= 13.82m/s AND Town not in {"ASHFIELD", "BECKET", "BLANDFORD", "CHARLEMONT", "CHESTERFIELD",
"COLRAIN", "CONWAY", "DOVER", "EGREMONT", "GRANVILLE", "GREAT BARRINGTON", "HANCOCK", "HARDWICK", "HARVARD",
"LEVERETT", "LINCOLN", "LUNENBURG", "NEW MARLBOROUGH", "OTIS", "PAXTON", "RICHMOND", "ROCHESTER",
"SANDISFIELD", "SAVOY", "SHEFFIELD", "STOCKBRIDGE", "SUDBURY", "WEST BROOKFIELD",
"WEST STOCKBRIDGE", "WESTON", "WINDSOR"}
THEN Probability of power outage is 0.496
IF Gust > 13.82m/s AND month_progres_sin <= -0.68 THEN Probability of power outage is 0.523
IF Gust > 13.82m/s AND month_progres_sin > -0.68 THEN Probability of power outage is 0.509
------------------------------------------------------------
Tree #10
IF 1-hour Max Wind Forecast <= 6.94m/s AND Town in {"ASHFIELD", "BECKET", "BLANDFORD", "CHARLEMONT",
"CHESTERFIELD", "COLRAIN", "CONWAY", "DEERFIELD", "EGREMONT", "GRANVILLE", "GREAT BARRINGTON", "HARDWICK",
"HUNTINGTON", "LEVERETT", "LUNENBURG", "MILLVILLE", "NEW MARLBOROUGH", "NORTHFIELD", "OTIS", "PAXTON",
"PLYMPTON", "ROCHESTER", "ROYALSTON", "SANDISFIELD", "SAVOY", "SHUTESBURY", "SUDBURY", "WAYLAND",
"WEST BROOKFIELD", "WEST STOCKBRIDGE", "WESTON", "WINDSOR"} THEN Probability of power outage is 0.517
IF 1-hour Max Wind Forecast <= 6.94m/s AND Town not in {"ASHFIELD", "BECKET", "BLANDFORD", "CHARLEMONT",
"CHESTERFIELD", "COLRAIN", "CONWAY", "DEERFIELD", "EGREMONT", "GRANVILLE", "GREAT BARRINGTON", "HARDWICK",
"HUNTINGTON", "LEVERETT", "LUNENBURG", "MILLVILLE", "NEW MARLBOROUGH", "NORTHFIELD", "OTIS", "PAXTON",
"PLYMPTON", "ROCHESTER", "ROYALSTON", "SANDISFIELD", "SAVOY", "SHUTESBURY", "SUDBURY", "WAYLAND",
"WEST BROOKFIELD", "WEST STOCKBRIDGE", "WESTON", "WINDSOR"} THEN Probability of power outage is 0.496
IF 1-hour Max Wind Forecast > 6.94m/s AND Gust <= 18.27m/s THEN Probability of power outage is 0.508
IF 1-hour Max Wind Forecast > 6.94m/s AND Gust > 18.27m/s THEN Probability of power outage is 0.520
------------------------------------------------------------
Tree #11
IF Gust <= 13.82m/s AND Town in {"ASHFIELD", "BECKET", "BLANDFORD", "CHARLEMONT", "CHARLTON", "CHESTERFIELD",
"COLRAIN", "CONWAY", "EGREMONT", "GRANVILLE", "HANCOCK", "HARDWICK", "HARVARD", "HUNTINGTON", "LENOX",
"LEVERETT", "LUNENBURG", "MONSON", "MONTEREY", "NEW MARLBOROUGH", "OTIS", "PAXTON", "PLYMPTON", "RICHMOND",
"SANDISFIELD", "SAVOY", "STOCKBRIDGE", "SUDBURY", "WAYLAND", "WEST BROOKFIELD", "WESTON", "WINDSOR"}
THEN Probability of power outage is 0.515
IF Gust <= 13.82m/s AND Town not in {"ASHFIELD", "BECKET", "BLANDFORD", "CHARLEMONT", "CHARLTON",
"CHESTERFIELD", "COLRAIN", "CONWAY", "EGREMONT", "GRANVILLE", "HANCOCK", "HARDWICK", "HARVARD",
"HUNTINGTON", "LENOX", "LEVERETT", "LUNENBURG", "MONSON", "MONTEREY", "NEW MARLBOROUGH", "OTIS", "PAXTON",
"PLYMPTON", "RICHMOND", "SANDISFIELD", "SAVOY", "STOCKBRIDGE", "SUDBURY", "WAYLAND", "WEST BROOKFIELD",
"WESTON", "WINDSOR"}
THEN Probability of power outage is 0.496
IF Gust > 13.82m/s AND Population Density <= 5.08persons/km^2 THEN Probability of power outage is 0.517
IF Gust > 13.82m/s AND Population Density > 5.08persons/km^2 THEN Probability of power outage is 0.506
------------------------------------------------------------
Tree #12
IF 1-hour Max Wind Forecast <= 6.63m/s AND Town in {"ASHFIELD", "BECKET", "BLANDFORD", "BUCKLAND",
"CHARLEMONT", "CHESTERFIELD", "COLRAIN", "CONWAY", "EGREMONT", "GRANVILLE", "GREAT BARRINGTON",
"HANCOCK", "HUNTINGTON", "LEVERETT", "MILLVILLE", "OTIS", "PAXTON", "RICHMOND", "ROCHESTER",
"ROYALSTON", "SANDISFIELD", "SAVOY", "SHEFFIELD", "SHUTESBURY", "STOCKBRIDGE", "SUDBURY", "WEST BROOKFIELD",
"WEST STOCKBRIDGE", "WESTON", "WILBRAHAM", "WINDSOR"} THEN Probability of power outage is 0.515
IF 1-hour Max Wind Forecast <= 6.63m/s AND Town not in {"ASHFIELD", "BECKET", "BLANDFORD", "BUCKLAND",
"CHARLEMONT", "CHESTERFIELD", "COLRAIN", "CONWAY", "EGREMONT", "GRANVILLE", "GREAT BARRINGTON", "HANCOCK",
"HUNTINGTON", "LEVERETT", "MILLVILLE", "OTIS", "PAXTON", "RICHMOND", "ROCHESTER", "ROYALSTON", "SANDISFIELD",
"SAVOY", "SHEFFIELD", "SHUTESBURY", "STOCKBRIDGE", "SUDBURY", "WEST BROOKFIELD", "WEST STOCKBRIDGE",
"WESTON", "WILBRAHAM", "WINDSOR"}
THEN Probability of power outage is 0.496
IF 1-hour Max Wind Forecast > 6.63m/s AND Population Density <= 10.60persons/km^2
THEN Probability of power outage is 0.515
IF 1-hour Max Wind Forecast > 6.63m/s AND Population Density > 10.60persons/km^2
THEN Probability of power outage is 0.503
```

```
-----------------------------------------------------------
Tree #13
IF Gust <= 13.82m/s AND Population Density <= 1.77persons/km^2 THEN Probability of power outage is 0.506
IF Gust <= 13.82m/s AND Population Density > 1.77persons/km^2 THEN Probability of power outage is 0.496
IF Gust > 13.82m/s AND month_progres_sin <= -0.68 THEN Probability of power outage is 0.519
IF Gust > 13.82m/s AND month_progres_sin > -0.68 THEN Probability of power outage is 0.508
-----------------------------------------------------------
Tree #14
IF 1-hour Max Wind Forecast <= 6.94m/s AND Town in {"ASHFIELD", "BECKET", "BLANDFORD", "BROOKFIELD",
"BUCKLAND", "CHARLEMONT", "CHESTERFIELD", "COLRAIN", "CONWAY", "DEERFIELD", "EGREMONT", "GRANVILLE",
"HANCOCK", "HUBBARDSTON", "LANESBOROUGH", "LENOX", "LEVERETT", "LUNENBURG", "MONSON", "NEW MARLBOROUGH",
"NORTHFIELD", "PAXTON", "RICHMOND", "ROYALSTON", "SANDISFIELD", "SAVOY", "SHEFFIELD", "SHUTESBURY",
"SUDBURY", "WEST BROOKFIELD", "WESTON", "WINDSOR"}
THEN Probability of power outage is 0.514
IF 1-hour Max Wind Forecast <= 6.94m/s AND Town not in {"ASHFIELD", "BECKET", "BLANDFORD", "BROOKFIELD",
"BUCKLAND", "CHARLEMONT", "CHESTERFIELD", "COLRAIN", "CONWAY", "DEERFIELD", "EGREMONT", "GRANVILLE",
"HANCOCK", "HUBBARDSTON", "LANESBOROUGH", "LENOX", "LEVERETT", "LUNENBURG", "MONSON", "NEW MARLBOROUGH",
"NORTHFIELD", "PAXTON", "RICHMOND", "ROYALSTON", "SANDISFIELD", "SAVOY", "SHEFFIELD", "SHUTESBURY",
"SUDBURY", "WEST BROOKFIELD", "WESTON", "WINDSOR"}
THEN Probability of power outage is 0.497
IF 1-hour Max Wind Forecast > 6.94m/s AND Gust <= 19.68m/s THEN Probability of power outage is 0.507
IF 1-hour Max Wind Forecast > 6.94m/s AND Gust > 19.68m/s THEN Probability of power outage is 0.518
-----------------------------------------------------------
```

C Qualitative Analysis

Table5 illustrates how different context influence the model's risk assessments. **No context** provides only a basic interpretation using the models' internal parametric knowledge, leading to a moderate risk estimate based on the weather conditions. **Quantitative Risk Context** uses structured numerical features, resulting in a high-risk prediction driven by extreme wind speed and precipitation. **Risk Summary Context** also integrate textual information, also producing a high-risk assessment. **GBDT-derived Rule** concludes a low risk because it only uses part of decision trees, which can not fully capture the complexity of the complete model.

Query: Today is January 23, Monday, and it is not a holiday. It's cold. The air is dry. There are strong wind gusts. It is raining. There has been recent snowfall. There is some wind. The location is in QUINCY, Massachusetts. The area has a moderate population density. The utility group is NationalGrid. The location is in the middle of a city, with tall buildings everywhere, mostly concrete, and roads with little open land. There is very little tree canopy coverage.	
Context	RESPONSE
NO CONTEXT	`{"risk_level": "medium", "Explanation": "Strong wind gusts and rain could cause tree branches to fall, potentially damaging power lines in an area with little tree canopy coverage."}`
+ QUANTITATIVE RISK CONTEXT	`{"risk_level": "high", "Explanation": "Strong wind gusts, cold temperatures, dry air, and heavy precipitation create a high risk of power outages."}` **Reasoning:** • **Wind Gusts:** Likely above 28.3 m/s — may damage power lines. • **Cold Temperatures:** Risk of ice on lines; system stress. • **Dry Air:** Exacerbates wind/cold effects. • **Heavy Precipitation:** May cause short circuits. • **Urban Environment:** Dense infrastructure increases impact. • **Low Tree Canopy:** Less insulation from wind/weather. These combined factors contribute to a high risk.
+ RISK SUMMARY CONTEXT	`{"risk_level": "high", "Explanation": "Strong wind gusts and precipitation increase the risk significantly."}` **Reasoning:** • **Wind Gusts (GUST):** The description mentions "strong wind gusts," which puts the GUST value in the range where the risk increases drastically (GUST > 28.3 → risk ×280). • **Precipitation Rate (PRATE):** It is raining (PRATE > 0.004 → risk ×20), further increasing the risk. • **Population Density:** The area has a "moderate" population density, which does not significantly alter the risk level. • **Time of Day:** Not specified, but being in the middle of a city means moderate to high risk at any time due to the urban environment. • **Environmental Conditions:** Cold and dry air do not significantly impact the risk based on given patterns. • **Recent Snowfall:** While recent snowfall may affect road conditions, it is not directly included as a factor in the risk calculation. Given the significant contributions from strong wind gusts and precipitation, the overall risk level is classified as "high."
+ GBDT-DERIVED RULE CONTEXT	`{"risk_level": "low", "reason": "The location in Quincy, Massachusetts, with its moderate population density and urban environment, reduces the likelihood of power outages despite strong winds."}` **Reasoning:** • **Location:** Quincy is an urban area with tall buildings and little open land, which generally means fewer trees that could fall and cause power outages. • **Population Density:** Moderate population density suggests a more developed area where infrastructure is likely better maintained. • **Wind Conditions:** While there are strong wind gusts, the urban environment provides natural protection against significant damage. • **Other Factors:** The presence of tall buildings and concrete structures can help shield power lines from direct impact, reducing the risk of outages. Given these factors, the overall risk level is considered "low."

Table 5: Qualitative Analysis of Qwen2.5-7B Across Different Contexts.