Weathering the Rails: Impact of Extreme Temperature and Fluctuations on Railroad Safety

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***Abstract*— Extreme weather events, driven by climate change, present significant challenges to railroad safety, particularly in the context of track-related accidents. This study explores the relationship between extreme temperatures and temperature fluctuations and their role in derailments caused by track failures. Using ten years of historical derailment and weather data, this analysis was developed to predict high-risk, track-related conditions and derailment locations, enabling proactive maintenance strategies.**

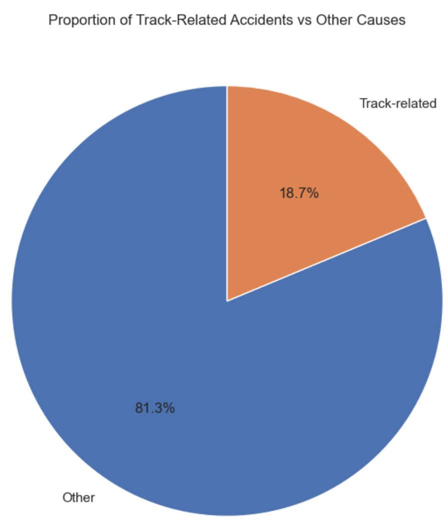
Findings indicate that track-related accidents account for 19 percent of all reportable rail incidents, with an average cost of over two hundred thousand dollars per event and a maximum exceeding twenty-two million dollars. High-risk conditions include temperature changes greater than twelve degrees Fahrenheit, train speeds over forty miles per hour, specific geographic locations, and seasonal transitions such as Summer and Winter. High-risk routes, including the Cleveland to Washington D.C. corridor and urban centers like Chicago and Houston, were identified as critical areas for intervention.

Recommendations focus on enhanced inspections and maintenance in areas with forecasted temperature fluctuations, high-speed tracks, and seasonal transitions. This data-driven approach aims to reduce derailment risks, protect human and environmental health, and optimize operational costs by prioritizing maintenance in vulnerable areas. This study highlights the importance of leveraging predictive analytics to adapt railroad safety practices to evolving climate patterns.

Keywords*— *railroad safety; extreme temperature impact; climate change and railroads; seasonal temperature effects; climate adaptation in transportation;

I. Introduction

The U.S. rail network has faced significant challenges over the past decade, with 4,595 incidents attributed to track failures (19% of all incidents' root causes), of which 4,301 resulted in derailments. These accidents, driven by infrastructure vulnerabilities, incur substantial costs, averaging $208,356 per incident and in some cases exceeding $22 million. As climate change drives more extreme and unpredictable weather patterns, the risks associated with track failures due to temperature extremes and fluctuations are likely to grow. Addressing these risks is critical to ensuring rail safety, protecting human and environmental health, preserving infrastructure, and reducing operational costs linked to emergency response, cleanup, and repairs.



This study focuses on predicting high-risk derailment locations caused by track failures linked to extreme temperatures and rapid temperature changes. Using ten years of historical derailment data from the Federal Railroad Administration and weather data from Visual Crossing Weather, this analysis integrates machine learning techniques with national weather forecasts to identify vulnerable areas. Findings will provide rail companies with actionable insights, enabling targeted inspections and enhanced maintenance strategies.

II. Data Sources and Descriptions

A. *Federal Railroad Administration: Accident Data*

The Federal Railroad Administration (FRA) safety data serves as a comprehensive resource for understanding hazards and risks across the U.S. rail network. Collected under Title 49 Code of Federal Regulations (CFR) Part 225, these reports classify and investigate railroad accidents and incidents. The primary purpose of this data is to provide the FRA with accurate, actionable information to fulfill its regulatory and enforcement duties under federal railroad safety statutes [2].

The FRA safety data includes detailed records of railroad accidents and incidents, enabling comparative trend analysis and the development of programs aimed at hazard elimination and risk reduction. This information is systematically analyzed and presented in statistical tables, charts, and reports available on the FRA Safety Data site. By leveraging this dataset, researchers and industry stakeholders can identify critical safety trends and develop targeted interventions to prevent injuries and accidents on the Nation's railroads [2].

Fetching the data. To retrieve and process data from the Federal Railroad Administration (FRA) API, start by fetching data in manageable batches using parameters like *limit* and *offset* to handle large datasets efficiently. The API only allows for 1,000 rows to be pulled at a time and there are over 250,000 records. Use a loop to make successive API calls, appending each batch of data into a comprehensive list. Convert the collected data into a pandas data frame for analysis. To focus on specific areas of interest, filter the data by excluding rows based on predefined criteria, such as accident cause codes, and retain only relevant columns. Ensure that date columns are in a consistent date-time format and apply a time filter to narrow the dataset to a specific range, such as the past 10 years. Finally, export the cleaned and filtered dataset to a CSV file for further analysis. This approach streamlines the data retrieval and preprocessing steps, ensuring a clean and targeted dataset for analysis.

B. *Visual Crossing Weather API*

Visual Crossing Weather is a leading provider of accessible, cost-effective weather data and analysis tools. Established in 2003, the company offers a robust Weather API designed to seamlessly integrate into applications, supporting a wide range of users, including business analysts, data scientists, insurance professionals, energy producers, and academics. Visual Crossing's mission is to empower data consumers with high-quality weather data to make informed decisions [3].

The Visual Crossing Weather API delivers comprehensive historical and forecast weather data at competitive prices, making it an industry leader in affordability and usability. The platform provides access to various weather metrics, including climate summaries, historical forecasts, solar radiation, degree days, and weather alerts. This diverse dataset is crucial for applications in transportation, energy, construction, and risk management [3].

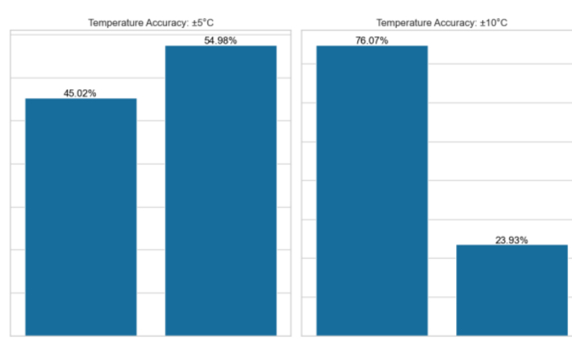
In this study, Visual Crossing's data is utilized to analyze the impact of extreme temperatures and fluctuations on railroad safety. Its detailed and scalable weather data supports the identification of high-risk conditions, enabling actionable insights for targeted interventions and enhanced rail infrastructure resilience.

Fetching the data. To collect weather data for rail incidents using the Visual Crossing API, first ensure you have an API key and are aware that the free account limits you to 1,000 data points per day. Therefore, this process will need to be split across multiple days to gather data for the day before, the day of, and the day after each incident.

For each incident, extract the relevant location and date, then use the API to request weather data for the desired date range. The function will retrieve daily summaries, including temperatures, which are then added to the incident data. After processing a subset of incidents, save the results in a CSV file. This method ensures you stay within the daily API limits while gathering the necessary weather data.

The FRA data uses features *station* and *stateabbr* to identify city and state respectively. There were approximately 80 stations (cities) that were misspelled or not identifiable by Visual Crossings Weather. To address this issue, each record location was identified by the included latitude and longitude coordinates and either updated with correct, full city spelling or altered to the nearest large city (most likely to be included in the Weather data provider).

We chose to use the Visual Crossing Weather data for local temperatures on the day of each incident, as it provides a more accurate and reliable source compared to the manually recorded temperatures in the FRA reports. The FRA data often lacks precision due to reporting delays as incidents can be filed as late as the month following the event. To illustrate this discrepancy, the plot below compares the FRA-reported temperatures to the actual temperatures retrieved from Visual Crossing. The comparison reveals that most reported temperatures deviate from the actual values by 5 to 10 degrees Celsius, highlighting the need for using an independent weather data source for accurate analysis.



III. Data cleaning and preprocessing

As of November 15, 2024, the past 10 years of railroad incident data, augmented with the weather temperature data, produced a dataset with 24,572 observations. We selected to include only 24 features that would be most relevant to this analysis. Twelve features are numeric and twelve are categorical.

A. Imputation

Nine features contain missing values, with eight of them missing fewer than six values. We will drop the rows with missing values in these features, as their removal will not significantly impact the analysis. However, the *equipmenttype* feature has over 1,000 missing values. While this feature is unlikely to correlate with temperature, it may still hold business value for future analysis. To address the missing data, we imputed the missing values using the Random Forest algorithm. The imputation model achieved an accuracy of 56%, so while the feature's values have been imputed, it will not be used further in this analysis.

Features. Relevant features considered in this analysis include:

- *reportingrailroadcode*: Identifies each railroad by a unique term, e.g., UP, BNSF, NS, CSXT, etc.
- *accidentnumber*: An incident ID number that is unique only to each railroad, while unlikely, there may be duplicates.
- *date*: Date of the incident.
- *time*: Time of the incident.
- *hazmatrealsedcars*: Quantity of rail cars containing and releasing hazardous commodities.
- *station*: The city or nearest city to the incident location.
- *stateabbr*: The state abbreviation, e.g., AL, MS, NC, etc.
- *temperature*: This is a manually entered temperature at the time of the incident. Note this is subject to data entry error.
- *visibility_code*: Ordinal values to represent weather visibility conditions.
- *visibility*: Descriptive terms to represent weather visibility conditions, e.g., Clear, Cloudy, Rain, etc.
- *tracktype*: Descriptive term to represent the type of track or operating location, e.g., Mainline, Yard, Siding, etc.
- *equipmenttype*: Descriptive term identifying the type of rail equipment involved in the accident, e.g., Yard/Switching, Freight Train, Cut of Cars, Work Train, Spec. MoW Equip., Single Car, etc.
- *trainspeed*: The speed train was traveling at the time of the incident in miles per hour (mph).
- *equipmentdamagecost*: Cost to repair or replace in-kind the equipment damaged in the incident.
- *trackdamagecost*: Cost to repair or replace in-kind the track and grading damaged in the incident.
- *totaldamagecost*: Select, comprehensive costs incurred due to the incident, including equipment and track and some others. Does not include environmental, litigation, and other non-railroad operations expenses.
- *primaryaccidentcausecode*: An alpha-numeric code to represent the root cause of the accident, e.g., T110-Wide gage, T207-Broken rail, etc.
- *latitude*: A geospatial coordinate.
- *longitude*: A geospatial coordinate.
- *prior_temp*: The local temperature the day before the incident (daily average).
- *actual_temp*: the local temperature on the day of the incident (daily average).
- *following_temp*: the local temperature the day following the incident (daily average) [2].

B. Feature Engineering

To evaluate the temperature change, we must create the necessary features and calculate the appropriate values.

We have created three features based on daily averages:

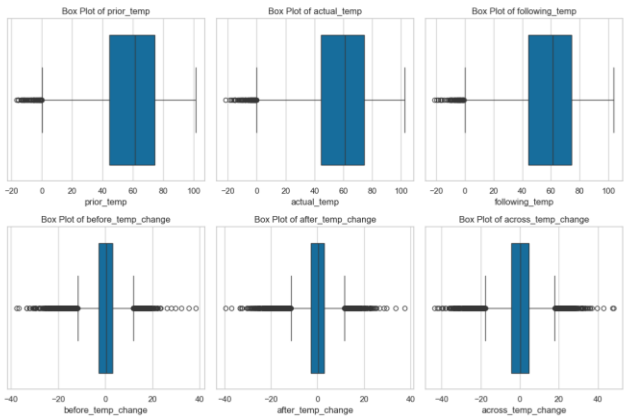
- *before_temp_change*: Represents the temperature change leading up to the incident.
- *after_temp_change:* Represents the temperature shift immediately after the incident.
- *across_temp_change:* Captures the overall temperature variability around the incident.

We did not explore the daily max and min temperatures. Further analysis into such variance might yield actionable insights.

C. Basic Statistics

Here are the basic statistics for all numerical features in the dataset.

	count	mean	std	min	25%	50%	75%	max
hazmatreleasedcars	24564.0	0.013679	0.315397	0.00000	0.000000	0.000000	0.000000	2.800000e+01
temperature	24564.0	59.484001	21.524710	-36.00000	44.000000	62.000000	75.000000	1.150000e+02
visibility_code	24564.0	2.686289	1.061220	1.00000	2.000000	2.000000	4.000000	4.000000e+00
trainspeed	24564.0	11.454364	16.772020	0.00000	3.000000	5.000000	10.000000	1.350000e+02
equipmentdamagecost	24564.0	83707.133814	422041.551285	0.00000	5000.000000	17000.000000	45000.000000	2.714000e+07
trackdamagecost	24564.0	42830.834473	206166.186341	0.00000	0.000000	1750.000000	19201.750000	1.040000e+07
totaldamagecost	24564.0	159077.917196	654785.585706	0.00000	19095.000000	36847.500000	97333.250000	3.153875e+07
latitude	24564.0	37.666360	5.089550	0.00000	33.649549	38.682012	41.294779	6.484530e+01
longitude	24564.0	-92.659629	13.737429	-683.19219	-97.670749	-90.384649	-83.554021	0.000000e+00
prior_temp	24564.0	58.547851	18.887286	-16.80000	44.600000	61.300000	74.300000	1.015000e+02
actual_temp	24564.0	58.456945	19.039748	-21.70000	44.500000	61.200000	74.300000	1.024000e+02
following_temp	24564.0	58.359990	19.026871	-21.20000	44.400000	61.150000	74.200000	1.037000e+02
before_temp_change	24564.0	-0.090905	5.846359	-37.60000	-2.800000	0.300000	3.100000	3.830000e+01
after_temp_change	24564.0	-0.096955	5.801030	-39.60000	-2.800000	0.300000	3.000000	3.750000e+01
across_temp_change	24564.0	-0.187860	8.405219	-43.70000	-4.400000	0.200000	4.500000	4.800000e+01

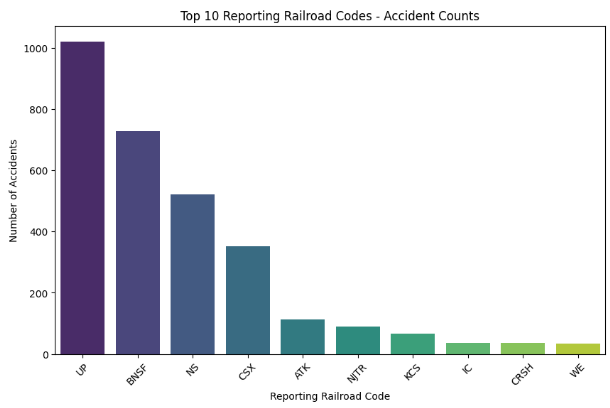


It is worth noting that most incidents occur when temperatures are between 40 and 80 degrees Fahrenheit, a "moderate" temperature range as seen in the 1st row of the Box Plots above.

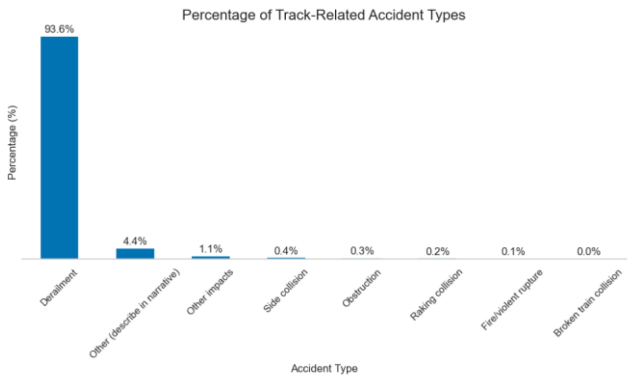
Because we are specifically looking at extreme temperatures and temperature changes, we do not exclude any outliers in the temperature analysis.

IV. Exploratory Data Analysis

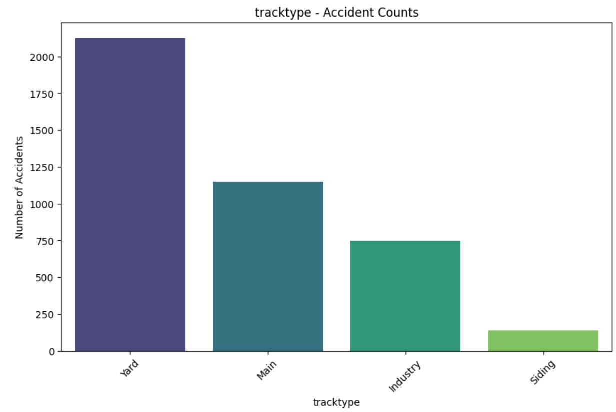
The four largest railroads in the U.S. account for the majority of track-related incidents. The UP and BNSF are similar in geographic operating areas and total track miles, while NS and CSX are similar with each other as well.

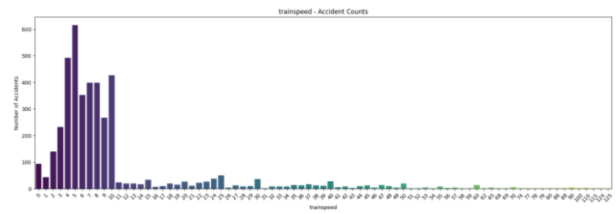


94% of track-related incidents result in a derailment. The definition of a derailment is any time a train car's wheels leave the track. So, the term derailment does not always equate to a catastrophic event resulting in damage to the environment or property.

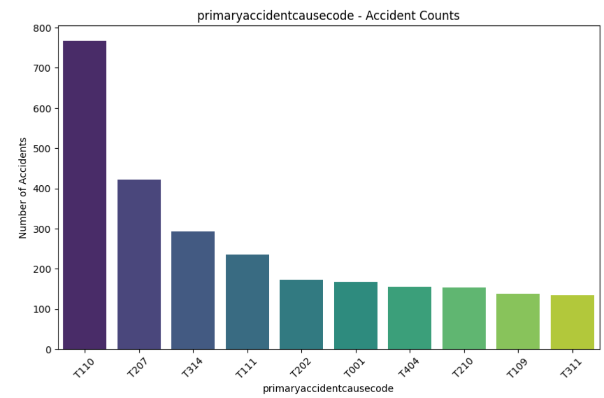


Most accidents occur in rail yards, which accounts for the fact that most accidents also occur at very low speeds.





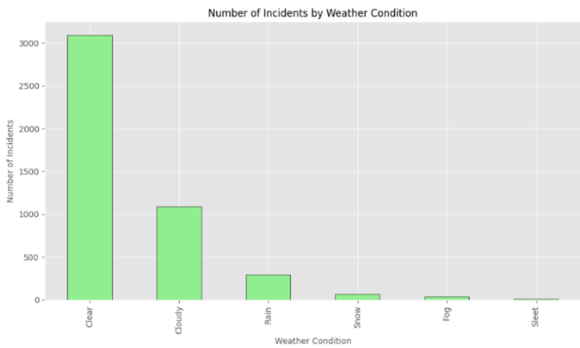
Here is a list of the top 10 root causes of track-related accidents, as identified by the primary accident cause code.



- T110: Wide gage (defect/missing crossties)
- T207: Broken Rail (detail fracture from shelling or head check)
- T314: Switch point worn or broken
- T111: Wide gage (defective/missing spikes or fasteners)
- T202: Broken Rail (base)
- T001: Roadbed settled or soft
- T404: Catenary system defect
- T210: Broken Rail (head and web separation)
- T109: Track alignment irregular (buckled/sunk-in)
- T311: Switch damaged or out of adjustment

The highlighted cause codes can be impacted by extreme temperatures and temperature changes [3].

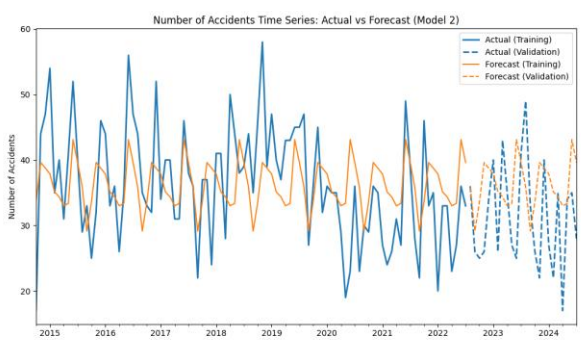
Not only do most accidents occur during moderate weather, most also occur on clear days between the hours of 9am and 5pm, considered as 1st shift on the railroad.



V. Time Series Analysis

Model 2 performed the best of the 5 models in an attempt to predict quantities of track-related accidents per year. Such predictions could be used by the business as performance metrics and to set goals. It is worth noting that in all attempted models, track-related incidents were forecasting a continued reduction year-over-year.

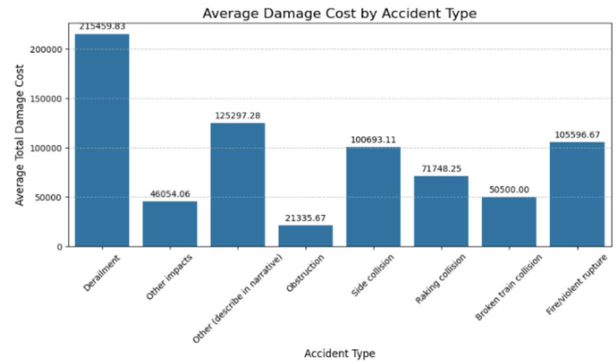
To evaluate the performance of a time series model, first generate predictions for both the training (in-sample) and validation (out-of-sample) datasets by using the predict() method on the model for each respective dataset. Afterward, calculate the model's performance metrics, such as RMSE, R-squared, MAE, and MAPE, by comparing the actual vs. predicted values for both datasets. Next, visualize the results by plotting the actual and forecasted values for both the training and validation sets, using distinct line styles for clarity. Add labels and a title to the plot to ensure the data is easily understood. Finally, display the performance metrics in a data frame to summarize the model's accuracy.



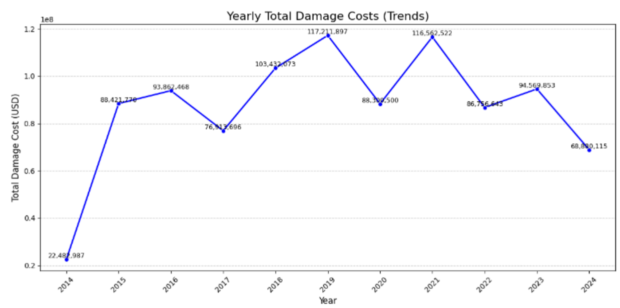
In terms of model performance, the training set results show a moderate fit, with an RMSE of 7.90, R-squared of 0.17, and MAE of 6.38. However, the validation set performs less well, with an R-squared of -0.53, indicating poor generalization, and a higher RMSE of 9.43. The MAE on the validation set is 7.61, and the MAPE is 28.85%, suggesting the model has considerable forecasting errors on unseen data.

VI. Financial Impact Analysis

Track-related accidents can be costly for the company, averaging $208 thousand per incident, with derailments resulting from the track failure being the most costly.



These costs have increased over time considering that such incident occurrences have decreased year-to-year.



Train speed is directly correlated with incident cost and is worth exploring in future analysis.

VII. Temperature Analysis

This analysis examines the relationship between extreme temperatures and track-related incidents to assess potential risks to rail infrastructure. The study involves testing two null hypotheses: the first evaluating whether extreme temperatures (below 32°F or above 85°F) impact track incidents and the second exploring whether changes in temperature correlate with track-related incidents. Chi-square tests were used to analyze the data, with varying results for temperature thresholds and temperature changes. Additionally, the analysis identifies critical temperature thresholds for track incidents and visualizes high-risk geographic locations, highlighting areas where temperature fluctuations are most prevalent. The findings provide insight into the potential impact of extreme temperatures on rail safety and maintenance planning.

A. Test Null Hypothesis – Extreme Temperatures

To test the relationship between extreme temperatures and track incidents, a hypothesis test was conducted. The null hypothesis (H_0) states that extreme temperatures, defined as below 32°F or above 85°F, have no impact on-track incidents. The alternative hypothesis (H_1) posits that extreme temperatures do have an impact.

Feature	**Chi^2**	**P-Value**	**Null Hypothesis**
< 32˚F	0.057	0.812	Fail to Reject
> 85˚F	1.235	0.266	Fail to Reject

Using the Chi-square test, the analysis of extreme temperatures revealed the following: for temperatures below 32°F, the Chi-square statistic was 0.057 with a p-value of 0.812, indicating no significant relationship between these temperatures and track incidents as the null hypothesis could not be rejected. Similarly, for temperatures above 85°F, the Chi-square statistic was 1.235 with a p-value of 0.266, again failing to reject the null hypothesis and showing no significant relationship between these higher temperatures and track incidents.

B. Test Null Hypothesis – Extreme Temperature Changes

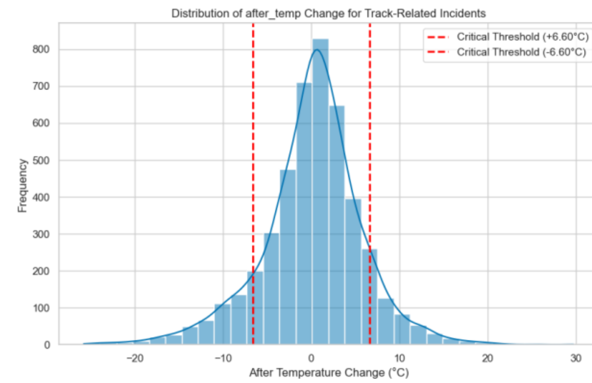
To evaluate the impact of temperature changes on-track incidents, the null hypothesis (H_0) states that temperature change does not affect track incidents, while the alternative hypothesis (H_1) posits that it does.

Feature	**Chi^2**	**P-Value**	**Null Hypothesis**
before_temp_change	2.754	0.097	Fail to Reject
after_temp_change	6.149	0.013	Reject
across_temp_change	0.310	0.578	Fail to Reject

Using the Chi-square test, three features were assessed: *before_temp_change*, *after_temp_change*, and *across_temp_change*. For *before_temp_change*, the Chi-square statistic was 2.754 with a p-value of 0.097, indicating no significant relationship as the null hypothesis could not be rejected. For *after_temp_change*, the Chi-square statistic was 6.149 with a p-value of 0.013, leading to the rejection of the null hypothesis, suggesting a significant relationship between temperature change after an incident and track incidents. Finally, for *across_temp_change*, the Chi-square statistic was 0.310 with a p-value of 0.578, indicating no significant relationship, as the null hypothesis was not rejected.

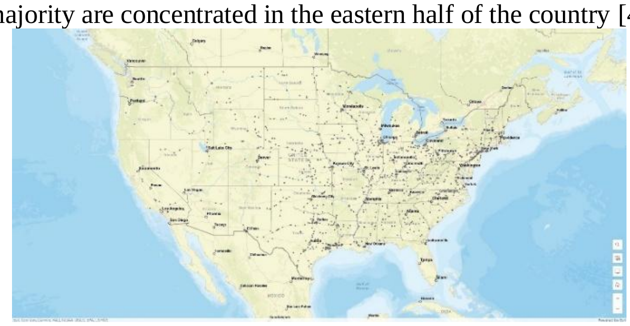
C. Critical Temperature Change Threshold

A temperature change of 6.6°C represents the 90th percentile threshold for track-related incidents, meaning that 90% of incidents involve temperature changes below this value, while only 10% occur at or above it. Over the past decade, 21% (973 out of 4,595) of track-related incidents occurred during such extreme temperature changes.

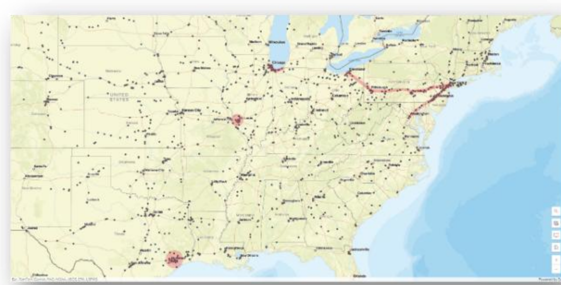


D. High-Risk Geographic Locations

ESRI ArcGIS Online can be utilized to visualize high-risk, temperature-impacted track-related incidents. While track-related incidents involving a 12°F temperature change have occurred across the United States over the past decade, the majority are concentrated in the eastern half of the country [4].



The map highlights high-risk cities, including Houston, St. Louis, Chicago, New York City, Philadelphia, and Washington, D.C. Additionally, high-risk rail routes are prominently clustered along the corridor from Cleveland to New York City and Washington, D.C.



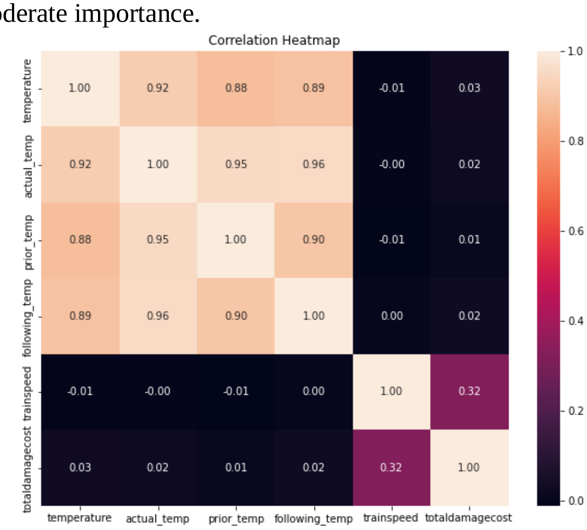
VIII. PROBABILITY ANALYSIS

This analysis focuses on identifying high-risk conditions for track-related incidents by engineering features such as temperature changes, volatility, and train speed. By training machine learning models like Random Forest and XGBoost, we classify incidents based on whether the total damage cost exceeds a defined threshold. Key findings include the high importance of temperature volatility and actual temperature, with train speed also playing a significant role. Critical factors such as sudden temperature shifts, extreme temperatures, and seasonal variations (particularly in Summer and Winter) are linked to increased accident risks. Temperature changes greater than 10°F and train speeds over 40mph further elevate accident probabilities.

A. *High-Risk Conditions*

We begin by preparing the dataset with relevant features and a target variable. Create a copy of the dataset for processing, then engineer additional features such as temperature change metrics (e.g., the difference between actual and prior temperatures, and volatility as the sum of absolute temperature changes). Define the target variable as a binary classification, such as whether the total damage cost exceeds a specific threshold (e.g., the median damage cost). Select relevant features for modeling and handle missing data by filling them with appropriate values. Split the dataset into training and testing sets, typically with an 80-20 ratio, and standardize the feature values using a scaling technique such as StandardScaler to ensure uniformity. Train multiple machine learning models, such as a Random Forest Classifier and an XGBoost Classifier, using the scaled training data. Evaluate the models on the test set using metrics like precision, recall, F1-score, and accuracy, and generate predictions for comparison. Finally, assess the feature importance from the Random Forest model to interpret the key drivers of the predictions. This process provides a robust framework for building and analyzing predictive models.

Important Features. Important features include temperature volatility (of the highest importance), actual temperature (2nd highest importance), then train speed (of moderate importance).



Critical Factors. Sudden temperature changes correlate with increased accidents. Extreme temperatures show higher risk patterns. And volatility is more significant than absolute values.

```
Top Features by Importance:
                feature  importance
4            trainspeed    0.145137
...
1           temp_change    0.121203
2  following_temp_change   0.121159
3        temp_volatility   0.121058
0           temperature    0.112731
```

High-Risk Conditions. Temperature changes > 10˚F have a 2x accident probability. Train speeds > 40mph with temperature variations increase accident probability. And Seasonal changes around Summer and Winter are risk peaks.

IX. Conclusion

In conclusion, railroads should continue their current track maintenance best practices while enhancing efforts to address high-risk conditions identified through this analysis [5]. Key actions to consider include:

- **Perform more frequent and enhanced track inspections** for areas with predicted temperature changes of **±12°F**.
- **Focus on high-risk cities** such as Houston, St. Louis, Chicago, New York City, and Philadelphia.
- **Monitor key high-risk rail routes**, particularly the corridor from Cleveland to New York City to Washington, DC.
- **Perform more frequent and enhanced inspections for tracks designated for speeds > 40 mph** to mitigate the risk of temperature-related incidents.
- **Perform more frequent and enhanced inspections for tracks during seasonal transitions**, particularly at the start of Summer and Winter, when temperature fluctuations are most significant.

By focusing on these high-risk conditions, railroads can enhance safety and more effectively manage track maintenance practices.

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