ECS 171 Winter 2025 Group 1 Final Project:

Predictive Modeling of Spatiotemporal Natural Disasters Across the US

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II. Introduction

Given recent disasters in the United States within the last year, it has become increasingly apparent that they can become extremely destructive in a short period of time. In light of these unpredictable events, it is crucial for residents, emergency agencies, and local governments to have the tools to help them prepare for instances like these and respond effectively. The ability to predict the most probable time and location of these events can save lives, minimize destruction, and allow the government to allocate resources and funds in advance. This project aims to aid disaster preparedness by predicting the likelihood of future disasters based on historical data.

Our primary objective with this project is to develop a predictive model that can forecast the location and time of upcoming disasters. By analyzing data taken directly from the OpenFEMA Dataset, the Federal Emergency Management Agency, we analyzed historical data from 1953 till now to build models that can forecast when disasters are most likely to occur. This predictive capability can be impactful for residents across the U.S. by helping them take proactive measures to safeguard their homes and livelihoods.

Understanding the distribution of disaster risks throughout the U.S. is critical especially for institutional entities. This can help response agencies such as FEMA plan effectively for weather events, focusing on where to establish evacuation routes and allocating resources. It can also help governments manage civil infrastructure investment decisions and determine where to enhance evacuation services.

To achieve these goals, we utilized machine learning algorithms such as Random Forest classifiers, a Long Short-Term Memory (LSTM) network, and a Gaussian Process Regression model to represent various facets of disaster occurrence and risk. Our data consisted of records of water based disaster types, their locations, and dates. We first performed some exploratory data analysis to analyze the historical distribution of these disasters, discovering that some types were much more likely than others. We were able to find patterns in the frequency of specific disasters and determine which regions were the most impacted at a certain period of time. We approached the problem from different perspectives by investigating where and when any water based disaster was most likely to occur, the specific type it would most likely be, and potential scale of the disaster.

This project focused on recognizing the trends and relationships in disasters, particularly water based events. When looking at the correlation between the different factors like the location, disaster type, and time of year, our models can be used as a tool to spread awareness across the country and to assist agencies, local governments, and emergency responders in allocating federal disaster relief spending and resources efficiently. Overall, our models can aid the decision making process for disaster response and recovery, preparing residents and communities ahead of time for these events.

III. Literature Review

Applying Machine Learning techniques to model and forecast susceptible regions and/or timings of natural disasters has been a widely studied challenge for several years. Engineers have viewed the prediction task through a variety of lenses, including as a risk level classification problem, spatial risk likelihood prediction task, time-series risk likelihood prediction task, and more. We will be discussing several recent research papers which shed light on three prominent perspectives which have recently been taken by data analysts and AI engineers, with regards to solving this problem. These perspectives are the spatiotemporal point process view, the satellite imagery view, and the weather data modeling view.

The first perspective–the spatiotemporal point processes view–approaches the problem of modeling and forecasting risk distribution as if it is based primarily on prior disaster occurrences. Algorithms of this nature are suited to find spatiotemporal trends in past event occurrence data which may inform us of the future.

This approach is adopted by Zhou et al., in their project AutoSTPP. In their paper, "Neural Point Process for Learning Spatiotemporal Event Dynamics," they discuss how their algorithm – a Graph Transformer model – trains on prior point process data to predict sequences of upcoming disastrous events. Their model achieves superior predictive modeling performance compared to any other contemporary model for several famous datasets, including Earthquakes Japan, a catalog of earthquakes in Japan from 1990 to 2020, and COVID-19, a catalog of the daily county level COVID-19 cases in the state of New Jersey published by The New York Times.

The second approach to predictive risk distribution modeling is the geographic satellite imagery view. Analysts try to predict upcoming disasters by correlating many features extracted from satellite images with regional disaster risk likelihoods. A survey by Akhyar et al., titled "Deep artificial intelligence applications for natural disaster management systems: A methodological review," overviews several state-of-the-art approaches to predicting risk regions based off of satellite imagery. They discuss how special deep CNN architectures are needed to segment the images, such as SegNet, U-Net, FCNs, FCDenseNet, PSPNet, HRNet, and DeepLab. These models are able to extract both low-level features in the images, such as edges and corners, and high-level ones, such as broad shapes. This robust segmentation has enabled scientists to predict the risks of forest fires, floods, and earthquakes at various locations with a reasonably high degree of accuracy.

The third approach to predictive risk distribution modeling is the weather station sensors data modeling view. Analysts build time-series-based machine learning models of past seismic activity and/or weather conditions to predict the risk levels of new space-time locations. For example, a public article titled "Predictive Analytics in Disaster Prevention: Machine Learning Models for Early Warning Systems" by the IEEE shares several common methods analysts have taken to model these risks. Neural networks have shown promising results for effectively modeling high-dimensional and complex data. For example, Convolutional Neural Networks have been applied to predict storms and hurricane trajectories, based on atmospheric weather data. Recurrent Neural Networks have been applied to model seismic activity data and predict earthquake timings. Support Vector Machines have proven to be well-suited for classification tasks, such as classifying the risk levels of regions for experiencing floods, based on information about their past river levels, soil moisture, and rainfall.

All three of these perspectives have been taken to model the spatiotemporal distribution of natural disaster risks for real geographic regions, and have yielded strong results. However, there still remains room for improvement in disaster-modeling, as more unpredictable events occur and more data on disaster occurrences continuously becomes available. As a result, we decided to implement our own spatio-temporal models, following Zhou et al.'s perspective, to see if we could create an accurate prediction algorithm that is not based on a graph transformer model. Advancements in predictive modeling approaches enable disaster preparedness agencies to prepare better, plan ahead, and proactively work to mitigate effects.

IV. Dataset Description

As mentioned previously, we used the OpenFEMA Dataset on Disaster Declarations Summaries from the Federal Emergency Management Agency. This dataset contains all federally declared disasters from 1953 to 2025 in the United States. It has three disaster declaration types: major disaster, emergency, and fire management assistance. The dataset offers crucial information to the duration and region of the disaster as well as its scale by indicating the type of funding or assistance program that was required. In our project proposal, we planned to predict and model the risk of wildfires in the United States. However, our initial visualization of the distribution of disasters across the United States revealed that water-based disasters accounted for a majority of the dataset. Since water-based disasters were a more predominant threat across the country, we decided to redefine the scope of our project to predict water-based disasters such as storm, flood, rain, ice, snow, blizzard, and hurricane. To ensure that we were working with relevant data, we preprocessed the dataset to filter out all data related to fire or non-water-based disasters. This allowed us to create a new CSV file with our disasters of interest. We conducted further exploratory data analysis on the CSV file and found that we needed to remove occurrences that contained declarationTitles ending in EVACUATION or EVACUEES since these entries were listed as disaster locations, when they really described places where people escaping the disaster had evacuated to.

V. Proposed Solution & Experimental Results

For our project, our proposed solution was to implement various prediction algorithms such as Random Forest, LSTM, and Gaussian Regression on the dataset. These models predict the probability of a water based disaster occurring given a timestamp and coordinates, the probability of a specific type of disaster occurring based on time of year and region, and the funding class for these specific disasters.

A. ***LSTM***

We developed a Long Short-Term Memory (LSTM) model for predicting disaster probabilities based on latitude, longitude, and time. The purpose of this model is to analyze spatial-temporal patterns in disaster occurrences and estimate the likelihood of any water based event occurring at a given location and time. This RNN was chosen because it allows the model to retain important information over long sequences which helps with determining spatio-temporal patterns that may not be linearly correlated.

LSTMs are particularly well fit for disaster prediction because they can capture long-term dependencies in temporal data while mitigating the vanishing gradient problem in traditional RNNs. By using a gated memory cell, LSTMs can selectively store relevant past information and forget irrelevant data, allowing them to learn non-linear relationships between past and future events. Additionally, natural disasters such as hurricanes and floods exhibit time-dependent behaviors. An LSTM can process sequences of disasters and capture how specific locations are more vulnerable than others based on historical data.

Due to the dataset only including positive data points where disasters occurred, synthetic negative data points had to be generated in order to properly train the model. This was done by constructing a cKDTree using the real disaster data which allows for fast nearest-neighbor lookups to check if a generated negative point is too close to a real disaster point.

After generating negative data, the model was trained with different sets of components to improve performance. First, the model started out with a single LSTM layer along with a fully connected layer and a sigmoid activation function. This didn't seem to capture much complexity in the data and tried to find linear relationships between the prediction variables. The final model consists of two fully connected layers, three LSTM layers as well as a ReLU and sigmoid activation function to enhance non-linearity and ensure predictions are mapped to probabilities. The training strategy included using Binary Cross-Entropy Loss function, which is effective for binary classification tasks like disaster occurrence prediction. The Adam optimizer was used for adaptive learning rate adjustments. The performance metrics are show in the table below: Below is a graphical demo of the LSTM model. The graph on the left (Figure 2) displays all disaster and non-disaster points in a 1 year time frame. The graph on the right (Figure 3) takes all the points from the left graph, (including both disaster and non-disaster points), and uses the LSTM model to predict whether each point is a disaster or not.

Fig. 1. Deep LSTM (5 layers) Performance Metrics

Metric	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC-ROC**
Deep LSTM (5 layers)	0.838	0.8404	0.8382	0.8377	0.9109

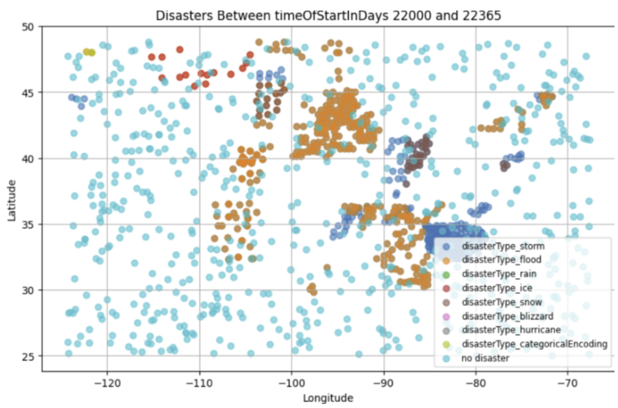


Fig. 2. Ground Truth Disaster Events

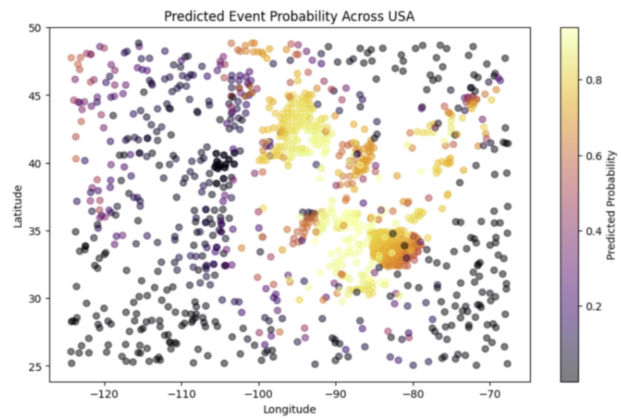


Fig. 3. Predicted Disaster Events

B. Gaussian Process Regression

We implemented a Gaussian Process Regression (GPR) model to investigate whether a probabilistic machine learning approach for predicting disaster occurrence likelihoods based on geospatial coordinates and temporal patterns would be a good fit for our data. Unlike classification-based approaches that have binary outputs, GPR provides continuous probability estimates with quantified uncertainty which is valuable for risk assessment and emergency planning. Disasters highlight complex relationships with location, seasonality, and historical patterns, making them well-suited for GPR's non-parametric approach. At its core, GPR defines a prior distribution over possible functions and updates this prior with observed data to create a posterior distribution, allowing the model to adapt to varying patterns across different regions and seasons without requiring a predefined functional form. Our model was initially developed with a simple RBF kernel, but this provided insufficient data for capturing multi-scale disaster patterns. We subsequently enhanced the model with a composite kernel structure that better captured the complex dynamics of disaster occurrences.

The GPR model employed a kernel structure utilizing specific prior beliefs about disaster occurrence patterns that combined four components: a ConstantKernel (prior mean=1.0, bounds=(0.1, 10.0)) to control overall amplitude, a RationalQuadratic kernel (length-scale prior=5.0, alpha=0.5, bounds=(1.0, 10.0)) to capture long-term trends, an RBF kernel (length-scale prior=3.0, bounds=(0.5, 10.0)) to model local spatial correlations, and a WhiteKernel (noise level prior=0.2, bounds=(0.05, 0.5)) to account for any observational noise. Alpha controls the relative weights of the different length-scales, allowing the model to capture patterns at multiple scales. Length-scale parameters define the characteristic distance in feature space where points become uncorrelated. Prior means represent the expected initial values before optimization. This structure represented our initial belief that disaster patterns would exhibit both smooth global trends and localized effects with moderate noise levels. After optimization, the final kernel parameters became a signal amplitude of 2.32^2, a RationalQuadratic kernel having alpha=0.167 and length-scale=8.35, an RBF kernel with length-scale=10, and a WhiteKernel with noise level=0.05. These optimized values suggested that the data exhibited stronger signal amplitude than initially assumed, considerably smoother long-range patterns, and lower noise which provided great insight into the spatial and temporal dynamics of disasters for predictive modeling.

In the implementation, we first loaded the preprocessed disaster data focusing on water-based disasters. To transform temporal features, sine and cosine encodings of month values to properly capture cyclical patterns were utilized to ensure January and December were considered adjacent in the annual cycle rather than distant within a linear representation. We also incorporated explicit seasonal indicators and historical disasters frequencies from multiple time windows (1, 3, 6, and 12 months prior). The algorithm implemented a two-stage feature optimization process. Feature selection using the f_regression metric identified the most informative predictors, followed by PCA to reduce the dimensionality whilst preserving 97% of the variance. This dimensionality reduction greatly improved computational efficiency and helped prevent overfitting by eliminating any redundant or noisy features. We also used 5-fold cross-validation to validate the model's performance across different data subsets.

A significant advantage that is unique to GPR is that it has the capability to quantify prediction uncertainty through confidence intervals. Our implementation leveraged this by applying a comprehensive filtering approach that used probability thresholds (>0.5), confidence requirements (confidence factor > 0.6), and historical precedent. Consequently, only locations meeting these criteria were retained in the final result, ensuring that predictions focused on areas with more legitimate disaster risk while accounting for model uncertainty. The performance metrics and visualizations can be seen below:

Fig. 4. Gaussian Process Regression Performance Metrics

Metric	Gaussian Process Regression
Accuracy	0.795
Precision	0.7684
Recall	0.7944
F1-Score	0.7763
ROC-AUC	0.8726

Fig. 5. Gaussian Process Regression Model Training Metrics

Metric	Gaussian Process Regression
Train RMSE	0.5509
Test RMSE	0.6452
Test R2 Score	0.4933
Average Uncertainty	0.3156

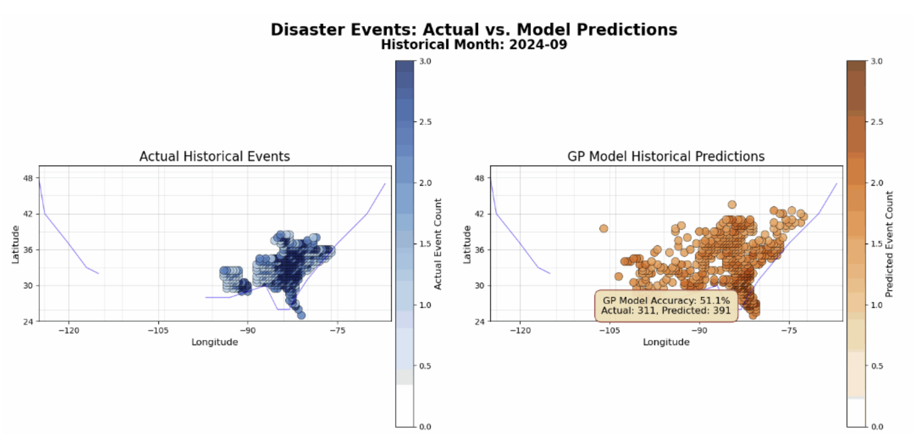


Fig. 6. Snapshot of GPR model results for a single month

C. *Random Forest Classifier*

Next, we decided to use two Random Forest Classification models to predict the type of disaster likely to occur at a given location and time, and to predict what funding category a predicted disaster would be placed in. Random

Forest Classification is a form of supervised learning that we implemented since the preprocessed dataset can have labeled binary values to indicate if a disaster has occurred or not. It uses many decision trees to make reliable predictions by considering all the factors and choosing the prediction with the majority vote. This method trains each decision tree on a random sample of the dataset with a random variety of features taken into consideration, which helps prevent overfitting and is especially helpful for our dataset and disasters in general as they have many features such as location, season, and region.

We use Random Forest Classification since it handles unbalanced data well, which is a good fit for our dataset since some water based disasters occur at a much lower frequency than others. Although these disasters are underrepresented in our dataset, they are still catastrophic events we would like to accurately predict. Random forest takes this class balance into account, and we also added balanced weights for the different disaster types for these scenarios. Also since disasters have many complex factors and are not linear, Random Forest was the best choice because of how it handles feature importance.

To implement this model we first loaded the dataset which was preprocessed to focus on specific water-based disasters. Then, based on the month, we added a column for the season that correlates to that month, and a column for the region based on its longitude/latitude location with one hot encoding. The month is implemented with the sine/cosine functionality since months are cyclical (ex: Jan is similar to Dec and Feb since they are all considered winter months). We did this because if we used the numerical values of the months the model will interpret the months as linear and not cyclical (month 1 is close to month 12 but if linear it will be seen as further apart). Therefore by converting these into sine and cosine we can get the position of the month in a sine/cosine wave format (ex: June will be opposite end of cycle because it is peak but January and December will be the same level as they are winter months).

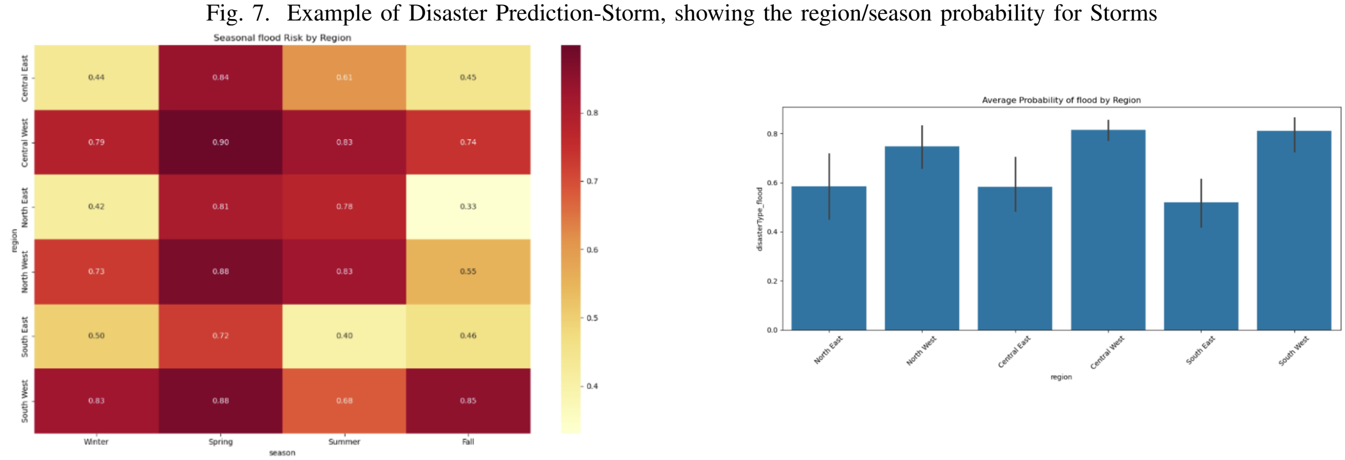
We then trained a Random Forest model for each disaster type and also implemented Stratified K-fold Cross Validation to ensure there is an even distribution present of various classes within training and testing. We chose to train the classifier with class_weight = balanced to handle class imbalances as discussed above. The class weight parameter encourages the model to pay closer attention to rare classes. We then evaluated the trained model using accuracy, F1 score, recall and precision which was important for us to understand how well the model fit to the data. A bit of hyperparameter tuning was also included to help ensure that the model is trained on various different features including: how deep the trees can grow, how many trees are built, and how features are selected during training. These are built in features into RandomForest that greatly assist with this classification process and are important to product robustness.

Then, we created a regional dataframe called regional predictions to collect the probabilities based on the different factors we are taking into account and adding to the data. We create bar charts to compare disaster risks across various regions (showing average probability) while the heatmaps also implement the seasons and the avg disaster probability for each region during a specific season. In an effort to not skew the predictions towards certain disasters with more occurrences, hyperparameters and balanced weights were added to Random Forest classification. As seen in the table below, the model had high accuracy in predicting the type of disaster based on the region and season. Our precision, which quantifies how often the model's positive predictions were correct, was high for the storm, flood, and hurricane data but was low for the rest of the classes, likely because these three classes made up the majority of our data. Likewise our recall, which is the true positive rate, was high for the storm, flood, and hurricane classes, but was low for the underrepresented classes. A high recall means fewer false negatives so therefore the model rarely misses real occurrences because it identifies most of the relevant occurrences of a class. This pattern is seen through F1 scores as well which implements both precision and recall in its equation. As we can see, the hurricane and ice classes had the best accuracy prediction while overall the storm class had the best predictions across all metrics. The Random Forest model was able to provide overall prediction trends in a helpful way depending on regions. However, the variability in our results despite our data preprocessing and choice of this algorithm also indicates that we need a way to balance the data in the model further, either by collecting more data or through hyperparameter tuning or further grid search for the future.

TABLE I
TABLE 3.1: RANDOM FOREST CLASSIFICATION METRICS

Metric	**Storm**	**Flood**	**Rain**	**Ice**	**Blizazrd**	**Hurricane.**
Accuracy	0.85	0.87	0.92	0.94	0.96	0.94
Precision	0.92	0.89	0.19	0.24	0.23	0.76
Recall	0.86	0.84	0.32	0.44	0.34	0.99
F1-Score	0.89	0.87	0.24	0.31	0.27	0.86

Fig. 7. Example of Disaster Prediction-Storm, showing the region/season probability for Storms



D. Random Forest Classifier for Funding Prediction

The FEMA dataset utilized in this project also includes information regarding the type of federal funding provided in response to a disaster call. This federal funding arrived through four distinct channels—the Individuals and Households program, Individual Assistance program, Public Assistance program, and Hazard Mitigation program. Predicting this information is valuable as it allows for efficient resource allocation and more informed decision making during disaster response and recovery situations. Loosely, the types of federal funding provided is also useful as a proxy for the severity of a particular disaster. For example, an event necessitating only individual level funding is likely to be less severe/damaging than an event requiring more widespread public funding through a Public Assistance program or through the combination of multiple programs.

Predicting the types of federal funding allocated in response to a given disaster entails the development of an algorithm able to predict a binary classification for multiple classes. When provided features available prior to the occurrence of a water based natural disaster, the algorithm should predict a label of ‘0’ or ‘1’ for each of the four federal funding initiatives, indicating whether this channel of funding was or was not provided to the populations/areas affected by a particular disaster.

The first approach we considered was the creation of a neural network. We created a Multi-Layer perceptron with two hidden layers both utilizing ReLu as the activation function. The output layer consisted of four nodes, corresponding to the four federal funding initiatives. Each output node applied a sigmoid activation function, which was thresholded in order to determine the final classification. Ultimately, this approach proved to be unsuccessful, since the first two categories of federal funding (Individuals and Households and Individual Assistance programs) were never predicted. This likely arose due to class imbalances in the dataset, as these represent less frequent funding initiatives. The model became biased towards predicting the more frequent categories, and ignored these less frequent classifications. The model also suffered from overfitting, and didn’t generalize well to unseen data.

Our finalized algorithm implemented a Random Forest Classifier, which was chosen for a variety of reasons. Firstly, the features in the FEMA dataset consisted of both categorical and continuous data, which Random Forest Classifiers inherently deal well with. Secondly, Random Forest Classifiers are often more effective in dealing with imbalanced data. Both of these advantages addressed challenges that were present in our previous approaches. We used a grid search to optimize the hyperparameters of the Random Forest Classifier and used bootstrap resampling, ultimately developing a robust model that could, with reasonable accuracy, predict the types of funding given in response to a disaster event. The performance metrics of the resulting model are shown below. The model performed the worst on predicting whether the 'Individuals and Household' program would be provided, which is likely because qualification for this program can depend on factors outside of the scope of this dataset (like insurance coverage). Overall, the model performed well, being able to predict the exact federal funding provided correctly about 77% of the time.

Overall Accuracy (Predicting ALL funding programs correctly): 0.76907

Fig. 8. Table 4.1: Random Forest Classifier for Funding Prediction Metrics

Program	Precision	Recall	F1-Score	Support
Public Assistance	0.97	0.95	0.96	8709
Individual Assistance	0.90	0.96	0.93	2929
Hazard Mitigation	0.90	0.92	0.91	4659
Individuals & Household	0.65	0.75	0.69	1356

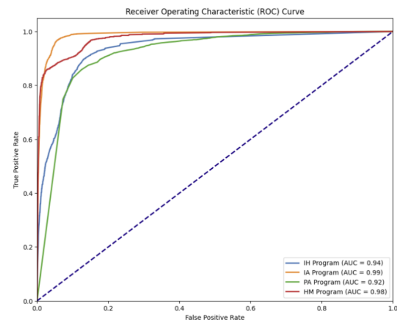


Fig. 9. ROC-AUC Curve for Program Classifications

VI. Comparative Analysis of Models

In terms of our disaster prediction models, our LSTM model performed better across all of our classification metrics, in particular it had higher recall than the GPR model, which is important since we want to prevent false negatives. Through our visualization comparing the historical events with the predicted events we found that the GPR model predicted a higher quantity of disasters compared to the ground truth data. This is an indicator that this model is prone to false positives, which could also be problematic since the public might be less likely to trust the model if it is routinely predicting false disasters. We also found that our RF model for funding prediction had more consistent recall and F1-score compared to our model to predict disaster type, which may be due to differences in hyperparameter tuning or a better balance of funding types being represented in the data as opposed to disaster types.

VII. Conclusion

Our models aim to provide crucial semantics regarding disaster occurrence and risk assessment within a specific region of the United States. Within any region, agencies looking to prepare for water-based hazards can predict the probabilities of any potential disasters affecting the area. To prepare for these disasters, agencies can also predict the risk levels of these disasters through funding classes, and better prepare residents of their communities. With our tool, necessary evacuations and risk-based assessments can be carried out even before disaster strikes, saving countless lives and resources.

In order to achieve our goal in providing disaster-based statistics, we developed four models that provided different information like the disaster type, the probability of the type of disaster, and the potential funding class the disaster could fall in. From the variety of models developed (Random Forest Classifiers, LSTM models, and Gaussian models), we found that the LSTM model (84% accuracy) outperformed the Gaussian model (80% accuracy) when it came to disaster probability prediction and that Random Forest Classifiers worked best for disaster type (91% accuracy over all disasters) and funding level predictions.

Currently, our models have been compiled together in our Web UI application (currently in its demo stage). The application currently runs off of a Streamlit architecture, a useful framework for machine-learning-based application development due to its compatibility with Python and other Python-friendly ML libraries. Our application currently takes in user information about their location (region, latitude, and longitude) and temporal information (date and time of year) to predict and describe the semantics presented above (forecasting heatmaps, seasonal probabilities, funding information, etc.). This application could become a stepping stone to a more comprehensive disaster forecasting architecture for government agencies and communities.

All of the models deployed have their own set of limitations, all of which can affect their performance, structure, and reliability. When processing spatial-temporal data, it's key to have models that can account for the time-series structure of the data. LSTM's use memory blocks and concurrent processing to account for the temporal nature of the data, while Gaussian models and random forest classifiers can sometimes struggle with high-dimensional and evolving data. Moreover, the structure of the training data can make or break the models specified above. Considering the fragility of the models, having imbalanced data can lead to potential overfitting within certain regions, reducing the credibility of these models. With enhanced data preprocessing and hyperparameter tuning to avoid overfitting, these models could be improved to better predict and classify data. An additional improvement to these prediction factors could be the employment of hybrid models, using reactive and proactive models in combination to highlight the benefits of both. Although computationally expensive, using reactive models for short-term forecasting and proactive models for long-term historical feature prediction could result in better-performing models.

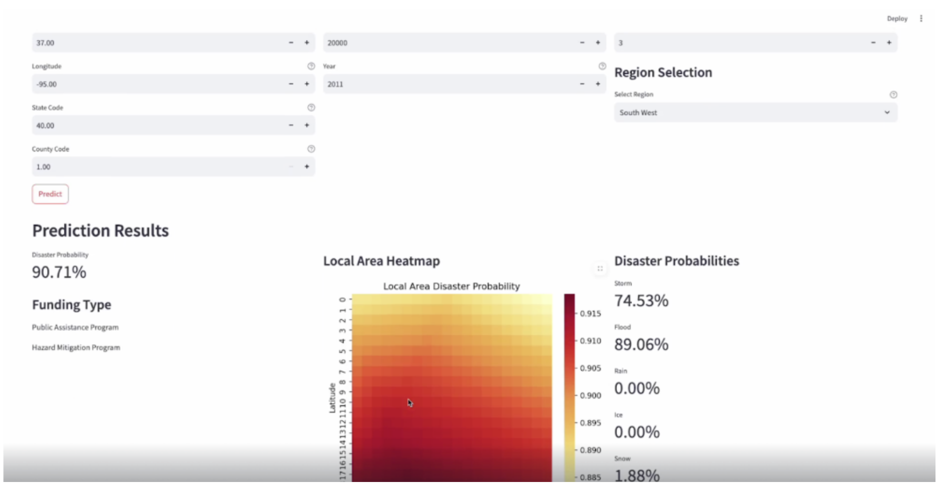


Fig. 10. Visual Representation of our UI Demo

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