International Cartographic Association
Association Cartographique Internationale

# Exploring the Spatio-temporal Patterns of Urban Fire Incidents

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**Keywords:** Urban Fires, Spatial-temporal Data Mining, Time Series, Machine Learning

**Abstract:**
Due to rapid urbanization in the United States, urban fires impose increasing threats to public safety and the liveability of modern cities (Ma et al., 2021). Developing a data-driven approach to predict fire incidents is not only of paramount importance for protecting public safety, but it is also essential for understanding how human-environment interactions may impact the occurrence of urban fires. Previous studies applied machine learning (ML) approaches to fire prediction, detection, and spread rate analysis, such as burn area classification and identifying the environmental factors of fire. Commonly used ML techniques include Bayes Network, Naïve Bayes, Decision Trees, Random Forest, Multivariate Logistic regression, etc. (Perez-Porras et al., 2021) In addition, researchers also compared the performance of ML models to traditional time series models, such as the autoregressive integrated moving average (ARIMA) model, in predicting fire incidents (Sayad et al., 2019, Kouassi et al., 2020). However, most of these studies were limited to predicting wildfires instead of urban fires.

In this research, we test the effectiveness of the random forest model and the ARIMA model in predicting urban fires and explore whether and how the occurrence of fire incidents depends on a collection of variables, such as urban districts with different socioeconomic factors and the type of fires. The dataset used in this study is a collection of fire incidents within Austin, Texas that is collected and maintained by the City of Austin Fire department. This dataset collection ranges from January 2009 to December 2019 and contains information such as the time and date of the fire incident, the fire type (e.g., trash fire, construction fire, electric fire), and a latitude and longitude record for each individual incident (Table 1). The study area in Austin is divided into ten city council districts (Figure 1).

Table 1. Example record from Fire Incident Dataset

| DATE | Fire Type | Priority Level | Longitude | Latitude |
|---|---|---|---|---|
| 01/01/2009 00:04:09 | TRASH - Trash Fire | 4 | 97.713095 | 30.256751 |
| 01/01/2009 00:19:58 | GRASS - Small Grass Fire | 2 | 97.782500 | 30.441064 |

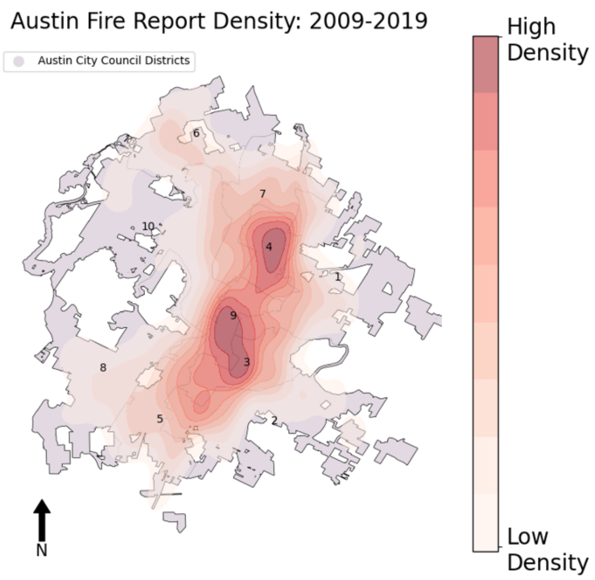


Figure 1. Fire incidents in the ten Austin City Council Districts


https://doi.org/10.5194/ica-abs-6-289-2023 

We first constructed a random forest regression model for the monthly fire incident data by district and by fire type. The features used for the random forest model were 1) the type of fire, 2) the city council district, and 3) the prior five years of fire incident data. We used the last 12 months of data from Jan 2019 to Dec 2019 as the testing data, and the rest of the dataset as training data. There were ten city council districts and five main types of fire incidents, so a total of 600 (12*5*10) scenarios were in the testing set. The result showed a mean absolute error (MAE) of 2.635 for all fire types. We used MAE instead of the mean absolute percentage error (MAPE) because there are zero values in the time series. Figure 2 showed that the predicted values were effective in reflecting the overall pattern of urban fire occurrences, but they failed to capture some of the extreme values. After evaluating the importance of the three features, the results also indicated that the type of fire is the most important feature in model fitting.

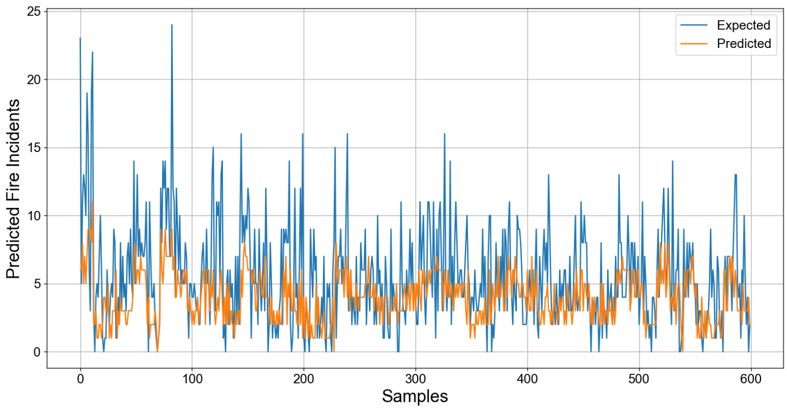


Figure 2. Predicted values based on a random forest model.

To compare the performance between random forests and ARIMA, we constructed models for each type of fire and compared their MAE. As can be seen from Table 2, overall, ARIMA outperformed random forests in predicting the occurrence of fire incidents; however, the performance varied for different fire types. In particular, a random forest model demonstrated better results with a lower MAE for auto fires.

Table 2. Comparing random forest and ARIMA

| **Fire Type** | **MAE (Random Forest)** | **MAE (ARIMA)** | **Difference in MAE** |
|---|---|---|---|
| TRASH - Trash Fire | 24.41 | 19.06 | -21.92% |
| GRASS - Small Grass Fire | 22.34 | 18.37 | -17.77% |
| BOX -Structure Fire | 9.32 | 7.03 | -24.57% |
| AUTO - Auto Fire | 6.68 | 13.05 | 95.36% |
| ELEC - Electrical Fire | 11.55 | 9.47 | -18.01% |

The results confirmed that random forest models are effective in predicting the occurrence of urban fires; however, the type of fire plays an important role in the prediction. When comparing random forest models with ARIMA models, the performance of models also depends on the fire types, suggesting that future studies should take fire types into consideration when predicting urban fires. In the next step of this analysis, we will extend the analysis to other cities and include more datasets to test the robustness of the results. We will also investigate the outliers in data points to reduce the MAE values.

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Abstracts of the International Cartographic Association, 6, 289, 2023.
31st International Cartographic Conference (ICC 2023), 13–18 August 2023, Cape Town, South Africa.
https://doi.org/10.5194/ica-abs-6-289-2023 | 