International Cartographic Association
Association Cartographique Internationale

Understanding the role of geographical environments in emergency dispatches with GPS trajectories

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Keywords: emergency dispatch, geographical features**,** emergency incident, space syntax, unsuccessful dispatch

Abstract:

Emergency management attends to expedite the emergency response and mitigate the impact on human lives and the economy caused by emergency incidents. One of the primary tasks of emergency management is ensuring that emergency response teams arrive at the incident location within a specified time frame. Previous studies have focused on reducing response times by identifying optimal locations for emergency vehicles (EVs) and emergency departments, assigning EV to a call, designating the optimal dispatch routes, and giving priority to emergency vehicles at traffic lights (Chen et al., 2014; Panahi & Delavar, 2008). However, despite these efforts, many emergency vehicles still miss their target response time. A comprehensive analysis is lacking to evaluate geographical environmental variables contributing to unsuccessful and successful emergency dispatches. Exploring the relationship between the geographical environment and emergency dispatch to improve emergency response services in neighbourhoods, this study aimed to identify geographic environmental determinants that differentiate successful and unsuccessful dispatches: (1) road characteristics, (2) topology of street segments, (3) weather conditions, (4) land use, (5) time and (6) dispatch operations (e.g., number of dispatched vehicles).

We obtained 554,891 Dallas emergency incidents records for October 2015 to November 2017 and dispatch routes with a total of 26,185,419 GPS points from the Dallas Fire and Rescue Department. These incidents included all emergency (911) calls with incident time and location as well as dispatch times and routes for dispatched emergency vehicles. s. We downloaded Dallas' Road data from the Texas Department of Transportation to extract significant road features as previous studies have suggested. For example, Brady & Park (2016) found that an EV would travel better on roads with more lanes, softer medians, or no medians. Traffic congestion and poor traffic clearance at intersections cause prolonged waiting times for EVs (Agrawal & Paulus, 2021). Time (temporal component) is another critical parameter in dispatch strategies. Chen et al., (2014) has pointed out the bigger delay in a certain hour due to traffic flow, especially in peak hour. Therefore, we use the hour of the day and day of the week to measure the influence from the temporal component. Based on previous research, we consider more relevant factors that influence emergency dispatch. First, a remote location with fewer connected roads is more likely to have a longer emergency response time than other places. Integration in space syntax analysis can be used to quantify the centrality of a street segment by measuring the normalized distance between all other locations to a given street segment (Acker & Yuan, 2019). A location with higher network centrality has less travel distance from other places and hence higher accessibility. Second, choice in space syntax measures how likely a street segment is to be a part of all shortest routes from all origins and destinations on a network and street segments with higher choice are likely with a higher traffic flow. Third, the number of emergency vehicles that are dispatched to the emergency incident and the distance to the nearest Fire Department are likely to play a role in determining successful and unsuccessful dispatches.

As such, our workflow includes the following three analyses to build a predictive model for dispatch success: (1) identify successful and unsuccessful emergency incidents and use them as the binary dependent variable, (2) determine geographical environmental determinants for the aforementioned dimensions as independent variables, (3) develop a model to identify the environmental variables that could predict the success of an emergency dispatch.

The expectation of emergency response length is 8 minutes which can be used to identify whether an EV gets to the incident location in time. A Call Center commonly dispatched multiple EVs to an incident. As long as one EV arrived at the incident site in 8 minutes, the dispatch was considered successful for this incident. On the contrary, an unsuccessful incident means that all EVs failed to arrive in time. The results show that across the years 2015 to 2017, the incidents of 14.92% in 2015, 15.16% in 2016, and 16.51% in 2017 were unsuccessful (Figure 1). Random forest models are known for capturing complex non-linear relationships between responses and predictors. It can avoid overfitting issues by using prespecified bootstrap samples or subsamples and limiting the variables to split in the trees. The hierarchical nature of a

https://doi.org/10.5194/ica-abs-6-276-2023 |

random forest model can capture the scalar differences among the effects of environmental determinants on dispatch success. Support vector machine (SVM) can maximize the decision boundary and capture a non-linear boundary between the classes. To minimize the scale effect, we need to scale data with each dimension. Due to the large data size (887,825 emergency runs in total), we use data from 2015 to show the preliminary result and we will contain more data in the next step. Specifically, SVM results in an overall accuracy of 70%, ~60% accuracy for sensitivity, and ~71% for specificity. The random forest model based on 2015 dispatch data suggested the relative contribution of environmental determinants to emergency dispatch success, in descending order from dispatch operations, topology, road characteristics, time, and weather. In 2015, there were $n = 45{,}721$ emergency incidents, separated into 80% as a training set and 20% as a testing set. The random forest model resulted in 3,000 decision trees with randomly selected independent variables ($\sqrt{12} \approx 4$) at each split when building the decision trees. The performance of the model is measured by accuracy of 77.08%, Root mean square error (RMSE) of 0.4803, sensitivity of 92.46%, and specificity of 30.05%. For the explanatory power of the variable in the model, we used the mean decrease in accuracy (Figure 2(a)) and mean decrease in Gini (Figure 2(b)) to show the importance of variables in the model. It indicates that the variable of the distance to the nearest Fire Rescue Department and space syntax are more important than others. On the contrary, hour, number of dispatched vehicles and precipitation is the three least important. The comparison between these two models indicates that the SVM can learn the complex decision boundaries that can separate the minority class (unsuccessful incident) from the majority class (successful incident). In the future study, we need to consider the route complexity (e.g., the deviation between the actual path and shortest path) of each path to measure the influence of the route taken by emergency vehicles on emergency dispatch.

Figure 1. The proportion of unsuccessful dispatches in different years

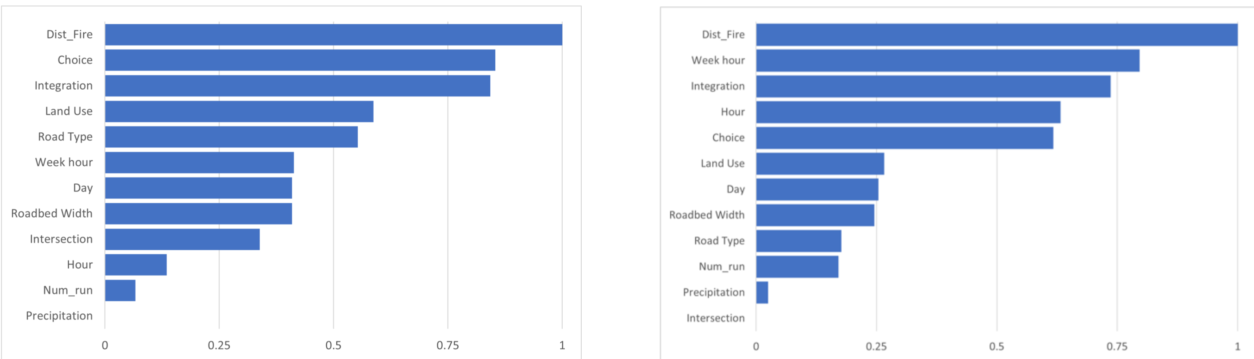

Figure 2. Evaluation of variable performance in the random forest model. Left (a); Right (b)

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Abstracts of the International Cartographic Association, 6, 276, 2023.
31st International Cartographic Conference (ICC 2023), 13–18 August 2023, Cape Town, South Africa.
https://doi.org/10.5194/ica-abs-6-276-2023 |