Investigating Urban–Rural Variability in Fire Department Response Times

İkra Durmuş
Informatics Institute
Middle East Technical University
Ankara/TURKIYE
ikra.durmus@metu.edu.tr

***Abstract*—** As climate change effects further increases, fire hazards show growing risks in Türkiye, with İzmir Province facing particular vulnerability due to its Mediterranean climate and diverse urban–rural landscape. This study analyzes 2023 fire incident records from İzmir to examine disparities in emergency response times between urban and rural areas and to identify key factors associated with these differences. After comprehensive data cleaning and feature engineering, response times were compared statistically and modeled using several approaches, including baseline, linear, tree-based, and neural network regressors. Results demonstrate that response times are significantly shorter in urban areas and that the predictors most associated with response time variation differ by context: structural fire incidents and building characteristics are most relevant in urban areas, while natural causes and the occurrence of injury are more important in rural settings. The findings emphasizes the need for area based fire management strategies and provide evidence to support targeted resource allocation in different risk environments.

Keywords—response time, fire hazard, spatial inequity,

I. Introduction

The escalating risks associated with climate change are intensifying some of the most pressing global challenges, one of which is the rising threat of fire hazards. As temperatures continue to rise, an increasing number of regions are becoming more vulnerable to wildfires due to the growing frequency of extremely hot days. According to the OECD[1], change in temperature, precipitation, and wind patterns are projected to result in 23 additional fire weather days annually in Türkiye. In the absence of effective adaptation measures, the frequency and severity of wildfires and their associated impacts are expected to increase significantly.

Türkiye's third largest city İzmir's geographic and climatic profile makes it particularly prone to escalating fire hazards. Located in Türkiye's Mediterranean zone, the region regularly experiences high summer temperatures, low humidity, and variable wind speeds which significantly contribute to fire ignition and spread. This vulnerability is especially evident in the Menderes district, where dense pine forests are exposed to prolonged dry periods and temperatures exceeding 30 °C. In this setting, according to Çolak and Sunar's study, over 75% of forested areas were classified within "moderate-high" to "high" fire risk categories [2]. While forested zones are at growing risk due to environmental factors, urban areas are also vulnerable due to waste fires. However, these urban areas, although fire-prone, benefit from faster intervention times due to closer station proximity. In contrast, outer and rural neighbourhoods face longer delays, often exceeding 30 minutes, significantly reducing containment efficiency and increasing the likelihood of the severity of damage [3]. The dual burden of environmentally triggered fires in forested rural districts and frequent anthropogenic fires in urban zones highlights a widening gap in fire exposure and emergency response capacity across İzmir's spatial spectrum.

Also, several studies conducted in other countries demonstrate that emergency fire response times are significantly longer in rural areas compared to urban centers. For example, a nationwide study in Sweden found that both real and estimated fire service response times were higher in rural municipalities, markedly longer than those in densely populated or urban municipalities [4]. Similarly, spatial analyses of fire incidents in other regions show that responses to calls are quicker in inner urban areas with high population density and slower in outer peri-urban or rural locales [5]. This urban–rural gap is not only a matter of minutes; it can translate to substantial differences in outcomes. Särdqvist and Holmstedt's analysis revealed that in three-quarters of the cases; the final burned area was already as large as it would get by the time firefighters arrived [6]. Meaning that delayed arrival often meant the fire had reached its maximum spread upon arrival, implying that slower response in less-served areas directly contributes to larger fires and greater property loss [6]**.** Rural communities are thus especially vulnerable considering the less privileged conditions compared to urban areas. The OECD reports that climate change is escalating wildfire hazards and these fires disproportionately threaten rural and wildland urban periphery communities [1]**.** In countries like Australia, severe bushfires have caused catastrophic property damage and loss of life particularly at the urban/rural interface of cities [4], highlighting how high-risk peri-urban areas often lie just beyond the fastest reach of urban fire services.

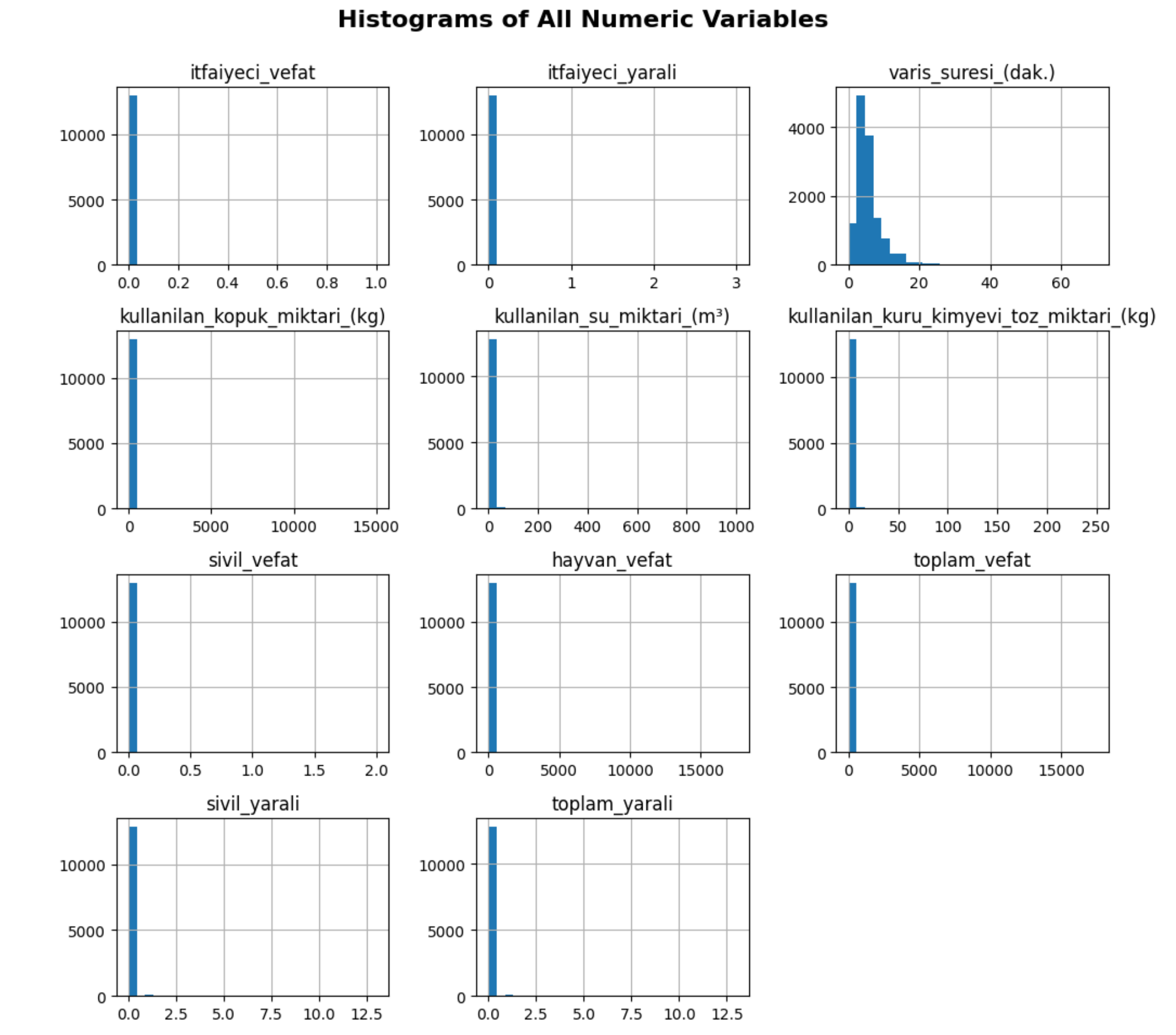

Figure 1:Histogram of numeric variables

A. Factors Underlying Urban–Rural Response Time Disparities

The disparities in fire response speed arise from multiple interrelated factors. Resource distribution and geography play a central role: urban areas benefit from higher fire station densities and shorter travel distances, whereas rural departments cover larger territories with more limited crews [6]. As population density increases, more fire stations are typically available to cover smaller areas, yielding faster responses [6]. By contrast, sparsely populated areas have scarcer resources; many rural municipalities cannot justify full-time professional fire crews at every location [5]. These areas often rely on part-time firefighters and volunteers to fill gaps [5], which can introduce delays in mobilization. Infrastructure and accessibility further influence response times. Urban cores may experience traffic congestion, but they also tend to have well-connected street networks. In suburban and rural settings, poor road connectivity can significantly slow down responders; KC and Corcoran found that low-connectivity street layouts can add up to 4 minutes to response time in residential fire calls [7]. Moreover, terrain and distance in rural regions mean that even with higher driving speeds (due to open roads), travel times remain longer on average [5]. Although socio-demographic factors correlate as well such as areas with lower-income or more vulnerable populations sometimes have longer response times or higher incident rates [6], the focus in this study will not cover these points due to data availability. Such findings highlight general contributors to response delay, yet they have not been used to distinguish how incident type or urban/rural context modulate performance.

These conclusions lead to the recognition that, although previous studies—primarily conducted in international contexts—have explored exogenous factors such as spatial accessibility, road connectivity, and fire station density, they do not systematically evaluate how different types of fire interventions influence response times across urban and rural settings. In particular, the İzmir region lacks localized research examining how intervention characteristics—such as the nature of the fire (e.g., waste, structural, forest)-interact with spatial context to affect emergency response speed. Therefore, this study aims to address the following research questions:

Research Question 1 "Is there a significant difference in response times of urban versus rural areas?"

Research Question 2 "How do fire characteristics in urban versus rural areas associate with variation in emergency response time?"

By doing so, the study contributes novel insights into localized fire service disparities and supports targeted planning strategies for İzmir's diverse risk environments.

II. METHODOLOGY

The dataset used in this study consists of official fire incident reports collected across İzmir Province in 2023. Each entry includes detailed attributes such as fire type, cause, location (urban vs. rural), response time, fire suppression resources used (e.g., water, foam), and casualty data. A total of 42 features were initially extracted and profiled for data quality and type consistency.

The response time column (VARIS_SURESI_(DAK.)) was converted from text to numeric values in minutes, accounting for malformed entries and time formats. Categorical variables, such as YANGIN_TURU (fire type) and ADRES_BOLGESI (urban/rural zone), were standardized to lowercase and cleaned of inconsistencies to ensure proper encoding. Aggregated features were also generated from raw columns: civilian fatalities and injuries, animal losses, and firefighter casualties were summed into toplam_vefat and toplam_yarali to reduce dimensionality and capture overall incident severity.

Additionally, missing values were handled using logical imputation: for example, YAPI_SEKLI (structure type) was set to "YAPI DEGIL" (no structure) for fire types that occurred in open fields or forests, based on joint distribution analysis. Any remaining missing or irrelevant columns were dropped. As seen in the histograms, several numeric features, including response time and resource quantities, exhibited strong right skew, highlighting the need for log transformation and feature scaling to stabilize variance and improve interpretability. Following the initial cleaning, categorical features were encoded using either label encoding or one-hot encoding, depending on their cardinality and modeling requirement. Continuous features, such as KULLANILAN_SU_MIKTARI (m^3) (water used), were normalized using min–max scaling.

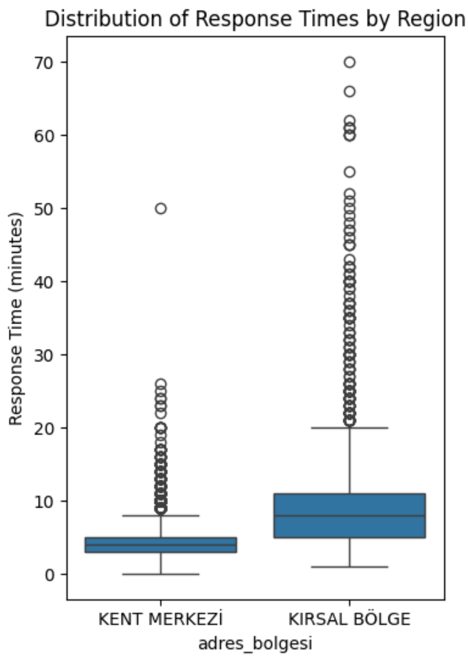

Figure 2:Boxplot Comparison of Urban Rural Response Time

Following preprocessing, numerical relationships were explored through a correlation matrix computed among all numeric features, including the response time. This matrix was visualized as a heatmap to identify potential multicollinearity or linear associations relevant to response behavior. To investigate differences in response time across geographic contexts, a boxplot of 'VARIS_SURESI_(DAK.)' grouped by 'ADRES_BOLGESI' (urban vs. rural) was generated. The observed difference in mean response times between urban and rural areas, which is approximately five minutes, closely mirrors the findings reported by KC and Corcoran, who identified a similar time gap in residential fire response between high- and low-connectivity zones [7]. The visual evidence of a right-skewed distribution and higher medians in rural areas was statistically validated performing non-parametric Mann-Whitney U test.

For the second research question, "How do fire characteristics in urban versus rural areas associate with variation in emergency response time?", a supervised machine learning approach was implemented separately for urban and rural subsets. The data for each group was randomly divided into training (70%), validation (15%), and test (15%) sets. The validation set was used exclusively for model selection and tuning, while the test set was reserved for final evaluation. Four models were evaluated: a baseline mean predictor, Linear Regression, Decision Tree Regressor, and Multi-Layer Perceptron Regressor. Hyperparameters for the Decision Tree and MLP models were selected by grid search, optimizing for mean absolute error on the validation set.

Model performances were compared using mean absolute error calculated on the validation data. The best model for each context was selected accordingly. To determine whether

Table 1:Model Performance Comparison

Model	Urban MAE	Rural MAE
Baseline	1.46	4.48
Linear Regression	1.41	4.42
Decision Tree	1.48	4.61
MLP Regressor	1.38	4.37

the difference in error between the best model and the baseline was meaningful, the Wilcoxon signed-rank test was applied to the paired absolute errors for each sample in the validation set.

Finally, permutation importance was calculated for the best-performing model in both urban and rural cases. This allowed the identification and comparison of the most relevant features associated with emergency response times in urban vs rural contexts of Izmir.

III. RESULTS

For addressing the first research question, normality and variance assumptions were assessed prior to selecting a formal statistical test. Histograms of response times (Fig. 2) revealed pronounced right skew in both urban and rural groups, and Q-Q plot results confirmed that neither distribution is normal, while variability differed between the two regions. Given these characteristics, the Mann-Whitney U test was selected as it compares group medians without requiring normality. The test produced a U statistic of 5,370,111.5 and a p-value of <0.001, leading to rejection of the null hypothesis. This result confirms that the difference in response times between urban and rural incidents is statistically significant at the 95% confidence level, with urban areas exhibiting consistently shorter response times.

For the second research question, four models were evaluated—Baseline, Linear Regression, Decision Tree Regressor, and Multi-Layer Perceptron (MLP) Regressor—using the mean absolute error (MAE) as the performance metric. The model comparison table (Table I) shows that the MLP Regressor achieved the lowest MAE in both urban (1.38) and rural (4.37) settings. Both the Decision Tree and MLP Regressor models showed their best performance with relatively simple configurations, with optimal tree depth of 4 and compact neural networks of one or two hidden layers. Among all tested models, the MLP Regressor with a single hidden layer of three neurons for urban data and two neurons for rural data achieved the lowest validation MAE, and was therefore selected as the final model for further analysis.

Statistical comparison of model performance was performed using the Wilcoxon signed-rank test, which is suitable for paired, non-normal error distributions. The test yielded p-values below 0.05 in both urban and rural analyses, confirming that the reduction in error by the MLP model over the baseline is statistically significant.

Permutation importance analysis, visualized in Fig. 3 (urban) and Fig. 4 (rural), reveals which predictors are most strongly associated with response time variation for each context. In urban areas (Fig. 3), fires involving buildings (yangin_turu_BİNA), open areas, and waste/depot facilities stand out as the most important features for model predictions. Building structure types and incident causes such as negligence and resource quantities (e.g., water used) also contribute substantially. In rural settings (Fig. 4), the leading features shift: natural causes of fire (yangin_sebebi_DOĞAL NEDEN) and total injuries are among the most relevant predictors, with building structure and certain fire types also ranking highly, albeit with smaller importance values than in the urban model.

Taken together, these results indicate that not only response times differ significantly between urban and rural settings, but the features most relevant for the response times also vary across different context. The use of a comparison framework and interpretability methods provides a clear basis for understanding how incident characteristics relate to emergency response outcomes.

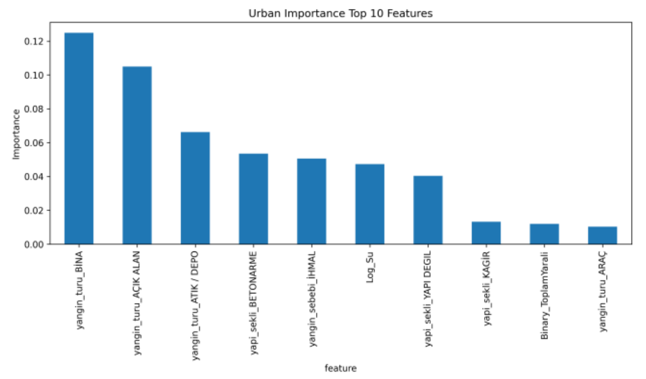

Figure 3:Urban Feature Importance

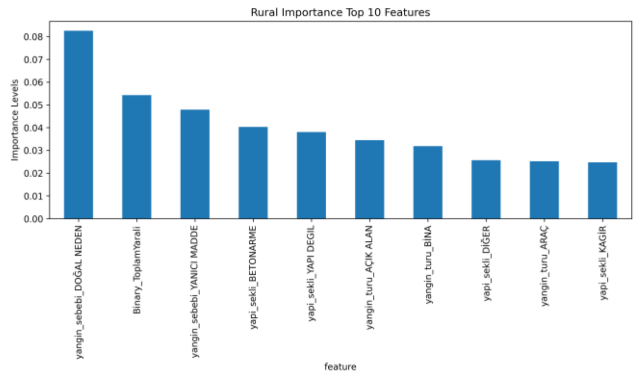

Figure 4:Rural Feature Importance

IV. Discussion and Conclusion

This study has analyzed the determinants of fire response times in urban and rural settings in İzmir, under the broader context of increasing fire risks linked to climate change. While the literature, including the work of Yalçınkaya, Doğan and Kaleli, highlights the importance of waste fires as a critical issue for İzmir, our permutation importance analysis did not identify waste-related incidents among the top predictors for response time in either urban or rural models [3]. This finding suggests that, contrary to some previous reports, waste fires may not represent a dominant influence on response time variability in our dataset, at least when compared to other incident or building characteristics.

Another divergence from the literature is the role of road conditions in rural response effectiveness. Previous studies around the world frequently emphasize infrastructure and accessibility such as road infrastructure as key factors contributing to delayed fire response in rural areas. However, results show that variables associated with road or weather conditions, such as winter as a season, did not emerge as significant predictors in the rural permutation importance results. This discrepancy could also be due to the limitations in variable measurement or the specific characteristics of the İzmir region, where severe winter weather may not be as impactful as in other countries discussed in the literature.

The comparison of model performances reveals that the MLP Regressor achieved the lowest Mean Absolute Error (MAE) for both urban and rural cases, outperforming both linear and tree-based models as well as the baseline. This indicates the value of non-linear modeling in capturing the complexity of factors influencing response times, particularly in settings where traditional parametric models may not suffice.

It is also important to recognize a number of limitations in this research. First, the cross-sectional nature of the dataset restricts temporal variability or evolving patterns in fire incidents and response. Literature highlights the influence of seasonal and yearly trends, especially in the context of climate-driven increases in wildfire risk[8], [9]. Therefore, future research would benefit from employing a multi-year or longitudinal dataset to better capture these dynamics and allow for more granular analysis of how risk factors evolve over time.

Moreover, while our model identified certain variables such as incident type, building type, and, in rural areas, natural causes as important factors, it is clear that response time disparities between urban and rural areas persist. The continued urban–rural gap in response times and outcomes indicates that further policy attention is needed, not only to address the growing frequency of climate-related fires but also to ensure equitable resource distribution and infrastructure support across the spatial spectrum of İzmir.

In conclusion, although our findings suggest differences in some respects from previous studies it also shows the multifactorial nature of fire response challenges. Expanding the temporal scope of the data and incorporating more granular variables related to infrastructure and weather may carry out deeper insights and help guide targeted adaptation and mitigation strategies in line with the increasing fire risks presented by climate change.

References

[1] OECD, "Climate Risks and Community." https://www.oecd.org/en/topics/climate-risks-and-disasters.html (accessed May 12, 2025).

[2] E. Çolak and F. Sunar, "Evaluation of forest fire risk in the Mediterranean Turkish forests: A case study of Menderes region, Izmir," *Int. J. Disaster Risk Reduct.*, vol. 45, p. 101479, May 2020, doi: 10.1016/J.IJDRR.2020.101479.

[3] S. YALÇINKAYA, F. DOĞAN, and H. İ. KALELİ, "Investigation of Waste Fires and Spatial Accessibility of Fire Stations in Izmir, Turkey," *Kent Akad.*, vol. 15, no. 2, pp. 727–741, 2022, doi: 10.35674/kent.1106477.

[4] J. Hassler, T. Andersson Granberg, and V. Ceccato, "Socio-spatial Inequities of Fire and Rescue Services in Sweden: An Analysis of Real and Estimated Response Times," *Fire Technol.*, vol. 60, no. 1, pp. 193–212, Jan. 2024, doi: 10.1007/S10694-023-01496-3/TABLES/4.

[5] J. Beringer, "Community fire safety at the urban/rural interface: The bushfire risk," *Fire Saf. J.*, vol. 35, no. 1, pp. 1–23, Jul. 2000, doi: 10.1016/S0379-7112(00)00014-X.

[6] S. Sardqvist and G. Holmstedt, "Correlation between firefighting operation and fire area: Analysis of statistics," *Fire Technol.*, vol. 36, no. 2, pp. 109–130, 2000, doi: 10.1023/A:1015450308130/METRICS.

[7] K. KC and J. Corcoran, "Modelling residential fire incident response times: A spatial analytic approach," *Appl. Geogr.*, vol. 84, pp. 64–74, Jul. 2017, doi: 10.1016/J.APGEOG.2017.03.004.

[8] E. P. Boateng, "Investigation of temporal trends in fire occurrence in Ontario with consideration of monthly teleconnections," University of Windsor, 2025.

[9] C. Wastl, C. Schunk, M. Leuchner, G. B. Pezzatti, and A. Menzel, "Recent climate change: Long-term trends in meteorological forest fire danger in the Alps," *Agric. For. Meteorol.*, vol. 162–163, pp. 1–13, Sep. 2012, doi: 10.1016/J.AGRFORMET.2012.04.001.