# A Gaussian Process Regression-Based Geospatial Framework for Emergency Shelter Suitability Assessment

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### Abstract

Disaster resilience often overlooks the suitability of schools and community shelters, leading to uneven safety outcomes during emergencies. This research addresses that gap by developing a data-driven shelter suitability prediction model using Gaussian Process Regression (GPR). The model integrates key urban parameters such as environmental risk factors, infrastructure stability, and population density to predict shelter safety scores across the city. These scores are then visualized spatially to identify safer zones, schools with better access to open spaces, emergency resources, and lower hazard exposure. Conversely, low-scoring areas highlight regions at elevated risk, guiding authorities toward targeted reinforcement and resource allocation. Outlier detection techniques further refine the analysis, pinpointing schools with unusually high or low suitability for deeper investigation. The model's performance, evaluated through five-fold cross-validation, reveals variability in Mean Squared Error (MSE) across folds, suggesting the potential for ensemble-based optimization. By coupling predictive modeling with geospatial visualization, this study provides a powerful decision-support framework for urban planners and disaster management authorities to prioritize structural improvements and evacuation planning, enhancing community resilience before a crisis strikes.

## 1. Introduction

Urban disaster preparedness depends not only on emergency response capacity but also on how effectively potential shelters are assessed before a crisis takes place. In large and densely populated cities, schools and colleges are frequently viewed as practical options for temporary shelter because they are widely distributed, publicly accessible, and often equipped with basic infrastructure. However, the suitability of these institutions cannot be determined solely by the physical condition of their buildings. Their surrounding environment also plays a major role. Exposure to hazards, proximity to fault lines or waterbodies, access to transportation networks, availability of nearby open spaces, and the density of the surrounding population all influence whether a location can safely support evacuees during an emergency. For this reason, shelter evaluation requires a broader framework that considers spatial, infrastructural, and environmental conditions together rather than treating them as separate factors.

Recent developments in geospatial technologies and data-driven modeling have created new opportunities for this kind of integrated assessment. Tools such as Geographic Information Systems (GIS), remote sensing, and machine learning allow researchers and planners to combine information from multiple urban datasets and examine how different risk factors interact across space. Data related to land use, transport connectivity, terrain characteristics, hazard-prone zones, and population distribution can be analyzed jointly to reveal patterns that are difficult to identify through conventional manual assessment. This makes it possible to move beyond reactive disaster management and toward a planning approach that identifies vulnerable areas in advance. At the same time, one of the central challenges remains the design of models that can evaluate shelter suitability across several criteria while still producing results that are interpretable and useful for decision-makers in real planning contexts.

Against this background, the present study introduces an Emergency Shelter Assessment framework for evaluating schools and colleges in Delhi as potential emergency shelters. The framework uses Gaussian Process Regression (GPR) to estimate shelter suitability scores from variables associated with environmental risk, infrastructure condition, and population density. By learning the relationships among these factors, the model generates location-specific suitability values that reflect the relative safety and practicality of each institution under emergency conditions. The predicted scores are then represented through an interactive geospatial map, enabling planners to distinguish safer institutions from more vulnerable ones and to recognize broader spatial patterns across the city. This integration of predictive modeling and spatial visualization provides a practical basis for identifying priority locations for reinforcement, preparedness planning, and resource distribution. In doing so, the study contributes to stronger urban resilience by supporting more informed and location-sensitive shelter planning before disasters occur.

## 2. Related Works

Research on emergency shelter evaluation has increasingly shifted toward integrated methods that account for the spatial and functional complexity of urban disaster response. In rapidly growing cities, shelter suitability is influenced by more than a single physical attribute; it depends on the interaction of hazard exposure, infrastructure condition, accessibility, and surrounding population characteristics. For this reason, recent studies have moved toward combining geospatial datasets with analytical and predictive models to assess shelters in a more comprehensive way. The integration of GIS with statistical and machine learning methods has been especially useful in identify-


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ing vulnerable areas, supporting prioritization, and improving planning decisions before disasters occur.

Bakhshi Lomer et al. (1) focused on improving the accuracy and realism of shelter vulnerability assessments by integrating hazard proximity with infrastructure robustness. Their research demonstrated that spatial proximity to hazards such as fault lines, flood zones, and industrial areas plays a critical role in determining shelter safety. By combining these environmental variables with structural and infrastructural attributes such as building materials, accessibility, and available facilities the study introduced a multi-criteria evaluation framework that provides actionable insights for policymakers. This integration of physical and environmental data enabled a more comprehensive risk evaluation model, supporting local authorities in identifying shelters that require reinforcement or relocation to ensure greater public safety.

A. Karatas et al. (2) expanded upon this approach by proposing the development of composite indices that incorporate socio-spatial variables such as accessibility, land use, and population density to guide decision-making in disaster management. Their framework highlighted how combining social and geographic factors produces a more equitable and inclusive understanding of shelter suitability, ensuring that vulnerable populations are not overlooked. The study also demonstrated the potential of statistical weighting methods in quantifying the relative importance of each criterion, making the evaluation process both transparent and adaptable to different urban contexts. These findings underscore the importance of integrating environmental, infrastructural, and demographic dimensions in shelter suitability assessments, laying the groundwork for advanced, data-driven models such as the one developed in the present study.

An intelligent end-to-end disaster response pipeline was introduced by Gorthi et al. (3) capable of automating post-disaster analysis and optimizing resource allocation. Their framework employs a custom lightweight convolutional neural network (CNN) to identify disaster events such as floods, wildfires, and earthquakes from aerial imagery, followed by a fine-tuned MobileNetV2 model to estimate severity levels. These outputs are integrated with live inventory data and processed using a LightGBM gradient boosting engine to generate optimized, real-time resource distribution plans. The study emphasizes how deep learning models can evolve continuously with new data, thereby reducing manual intervention, accelerating response time, and strengthening overall disaster management strategies. This approach highlights the growing trend of coupling visual analytics with predictive modeling to support data-driven, adaptive disaster response systems.

Yakovenko et al. (4) proposed a model for evaluating and selecting urban civilian shelters capable of withstanding missile and unmanned aerial vehicle (UAV) attacks. Their framework introduces a generalized optimality criterion that combines multiple local evaluation factors into a linear weighted model, allowing for the systematic ranking of shelter facilities. Using multivariate regression analysis, the study identifies relationships between physical and technical attributes of shelters such as structural resistance, reliability, and accessibility and their overall protective efficiency. This regression-based approach enables data-driven selection of optimal shelter sites and provides a quantifiable method for assessing civilian protection measures in non-combat urban regions. The model contributes to urban safety planning by integrating engineering characteristics with decision-support analytics, enhancing civilian protection during high-risk aerial attack scenarios.

Another emerging direction in disaster management research involves the use of knowledge graphs (KGs) for multi-hazard risk assessment and data integration. Senarathne et al. (5) proposed a novel framework titled *"A Knowledge Graph for Multi-Hazard Risk Assessment and Management in Rainfall-Prone Regions,"* which leverages KGs to unify heterogeneous data sources related to landslides, floods, and other rainfall-induced disasters. The system integrates environmental, infrastructural, and humanitarian datasets to support dynamic risk evaluation and forecasting. Through a combination of knowledge graph reasoning and machine learning algorithms, the framework identifies interdependencies among disaster-related factors, enabling contextualized and precise assessment of multi-hazard scenarios. The researchers further developed an interactive dashboard that visualizes these insights, aiding decision-makers in evaluating shelter routes, predicting cascading effects, and improving preparedness. This study demonstrates the potential of semantic data representation in enhancing the interpretability, usability, and consistency of disaster risk management systems.

Taken together, these studies show a clear movement toward multi-parameter and data-driven shelter assessment. The present study contributes to this direction by examining schools and colleges as potential community shelters and by combining environmental, infrastructural, and demographic indicators into a normalized suitability score. Through predictive modeling and geospatial visualization, the framework is intended to support locally relevant planning decisions and improve urban disaster preparedness.

## 3. Methodology

The *Emergency Shelter Assessment* framework is designed to evaluate the vulnerability and shelter potential of schools and colleges within the study area through a structured geospatial and predictive modeling workflow. At the core of the framework is a Gaussian Process Regression (GPR) model, which is used to estimate shelter suitability scores for individual institutions based on a combination of environmental, infrastructural, and demographic conditions. Rather than relying on a single indicator, the framework brings together multiple spatial factors to produce a more balanced assessment of how effectively a location can function as an emergency shelter during a disaster.

The workflow begins with the collection of diverse geospatial datasets that describe both the physical environment and the surrounding urban context. These datasets include information related to population density, earthquake occurrence, fault line distribution, metro connectivity, waterbody locations, land-use patterns, and educational infrastructure. Since these sources differ in format, scale, and coordinate structure, they undergo a preprocessing stage before analysis. During this stage, the datasets are geocoded where necessary, standardized into a consistent structure, and spatially aligned so that all layers can be integrated accurately within a common geographic framework. This step is essential to ensure that spatial comparisons and feature extraction are performed reliably across all institutions.

Once the datasets are prepared, the framework derives a set of features that reflect both shelter accessibility and disaster-related exposure. Variables such as surrounding population density, availability of nearby open spaces, and proximity to transport networks help capture the accessibility and operational usefulness of each institution. At the same time, distances to hazard-related features such as fault lines and waterbodies are calculated to represent environmental risk. This proximity-based analysis provides location-specific insight into the balance between safety, accessibility, and vulnerability. By converting these geospatial relationships into measurable variables, the framework transforms raw urban data into a structured input suitable for predictive modeling.

These extracted features are then supplied to the GPR model, which learns the underlying relationships among the different variables and generates a normalized shelter suitability score for every school or college in the dataset. The use of GPR is particularly valuable because it can capture non-linear interactions among factors that may not be adequately represented through simpler linear methods. The resulting scores provide a relative indication of shelter suitability across the study area. Higher scores correspond to institutions located in comparatively safer and more resilient settings, often with better access to infrastructure and lower levels of surrounding hazard exposure. Lower scores, in contrast, point to institutions that may be less suitable for emergency shelter use and may therefore require structural improvement, additional emergency support, or closer planning attention.

Through this step-by-step integration of geospatial preprocessing, feature extraction, proximity analysis, and predictive modeling, the framework offers a practical method for identifying educational institutions that can support disaster response more effectively. The overall workflow of the proposed system is illustrated in Figure 1.

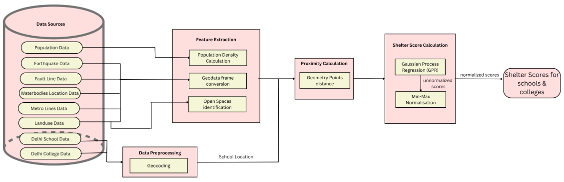


Figure 1. Overall architecture of the proposed *Emergency Shelter Assessment* framework

The proposed system architecture, illustrated in Figure 1, consists of four main stages: data acquisition, preprocessing, model training, and visualization. These stages work together to transform raw geospatial data into shelter suitability predictions for schools and colleges in the study area.

In the data acquisition stage, geospatial datasets related to environmental hazards, infrastructure conditions, and population density are collected from public sources. Since these datasets differ in format and scale, they are prepared in the preprocessing stage through cleaning, normalization, feature extraction, and spatial alignment. This ensures that the data are consistent and suitable for integrated analysis.

The processed features are then used to train the Gaussian Process Regression (GPR) model, which predicts normalized shelter suitability scores based on identified risk and resilience factors. Finally, the predicted results are displayed on an interactive map interface, enabling decision-makers to identify vulnerable educational institutions and prioritize areas that may require structural reinforcement or improved emergency resource allocation.

### 3.1 Data Collection and Preprocessing

The first stage of the framework focuses on collecting and preparing geospatial datasets required for shelter suitability analysis. These datasets include population census data, earthquake intensity records, mapped fault lines, waterbody locations, metro rail routes, land use maps, and educational institution data for the study area. Since these sources differ in format and spatial structure, they are processed to ensure consistency before analysis. For schools, address-based records are geocoded into latitude and longitude coordinates using GIS tools and online geocoding APIs, allowing them to be integrated with other spatial layers. All datasets are then cleaned, checked for missing or inconsistent values, and reprojected into a common coordinate reference system (CRS). This preprocessing stage establishes spatial compatibility and improves the reliability of the subsequent analysis.

### 3.2 Geocoding School Locations Using Nominatim

The next step involves converting school location records into geographic coordinates using the Nominatim geocoding service. Each school entry contains village names and pincodes, which are used to construct geocoding queries. If a village name is available, it is used as the primary search input; otherwise, the pincode is used as a fallback. For every successful query, the returned latitude and longitude values are added to the dataset, while unsuccessful cases are recorded as *None*. To comply with the service's usage limitations, a delay of three seconds is maintained between consecutive requests. The geocoded school dataset is then exported in CSV format for further spatial analysis.

After geocoding, the school data are converted into a GeoDataFrame to support GIS-based operations. These coordinates are used to measure distances to important spatial features such as geological risk zones, population density regions, and nearby open spaces. The resulting spatial attributes are then merged with facility-related school data, and categorical variables are encoded to create a structured dataset suitable for predictive modeling.

### 3.3 Feature Engineering and Risk Scoring

In the feature engineering stage, multiple variables are derived to represent both risk exposure and accessibility. Factors such as proximity to fault lines, earthquake intensity zones, metro connectivity, and surrounding population density are extracted and normalized so that they contribute on a comparable scale. A weighted combination of these normalized values is then used to compute a composite risk index for each educational institution.

This index acts as an important intermediate input for model training because it summarizes key aspects of environmental exposure and infrastructural resilience. In the case of schools, internal characteristics such as electricity availability, playground space, and structural quality are also included. For colleges, the emphasis is placed mainly on external spatial factors. These combined features are first used to derive an initial shelter score, which is later refined through the Gaussian Process Regression model.

### 3.4 Emergency Shelter Assessment for Colleges

The emergency shelter assessment for colleges follows a similar geospatial workflow, beginning with the extraction of location information from a GeoJSON file. The GeoJSON contains college geometries represented either as points or polygons. For each feature, the properties and coordinates are read, and where polygon geometries are present, a representative centroid is calculated. Invalid or incomplete entries are removed from the dataset. The processed output, containing college names and coordinates, is then saved in CSV format for integration with the remaining analysis steps.

Next, spatial joins are used to link each college to its corresponding district boundary. If a college falls outside a district polygon, the nearest district centroid is assigned. Additional spatial variables are then calculated, including distance to fault lines, proximity to earthquake-prone areas, nearness to metro routes and waterbodies, and surrounding land use patterns. Population density is also included to reflect the possible impact of crowding during emergencies. These variables are weighted according to their relevance and combined to form a cumulative spatial risk score. The resulting feature set is passed to the GPR model, which predicts normalized shelter suitability scores on a scale from 1 to 10, where higher values indicate safer and more accessible shelter locations.

### 3.5 Gaussian Process Regression for Shelter Scoring

Gaussian Process Regression (GPR) serves as the core predictive model for computing the final shelter suitability scores. GPR is a non-parametric, Bayesian approach capable of modeling complex, non-linear relationships without assuming a fixed functional form. It is particularly effective for spatial datasets where uncertainty estimation and smooth interpolation are crucial.

The model utilizes a composite kernel structure combining a Constant Kernel and a Radial Basis Function (RBF) Kernel. The Constant Kernel adjusts the overall magnitude of the covariance, allowing the model to adapt to variations in signal strength, while the RBF Kernel captures smooth, non-linear dependencies between the spatial features. The kernel function is expressed as:

$$k(x, x') = C \cdot \exp\left(-\frac{\|x - x'\|^2}{2l^2}\right)$$

where $C$ is the scaling constant, $l$ is the characteristic length scale, and $x, x'$ represent feature vectors.

The modeling process begins by normalizing the input feature matrix $X$ using standard scaling to remove the influence of differing feature magnitudes. The GPR model is then trained on the scaled feature set and corresponding target values. After training, the model predicts unnormalized shelter scores, which are subsequently transformed to a 1–10 scale using min–max normalization:

$$S_i = 1 + 9 \cdot \frac{\hat{y}_i - \min(\hat{y})}{\max(\hat{y}) - \min(\hat{y})}$$

where $S_i$ is the normalized shelter score for the $i^{th}$ institution, and $\hat{y}$ represents the set of predicted scores. These normalized scores are appended to the GeoDataFrame and exported for visualization and interpretation.

The resulting shelter scores provide a clear spatial representation of safety and accessibility, allowing decision-makers to identify high-risk zones and prioritize infrastructure reinforcement or evacuation resource planning accordingly.

## 4. Results

The results of the *Emergency Shelter Assessment* framework reveal a distinct spatial pattern in the shelter suitability of educational institutions across the study area. The predicted scores for schools and colleges, shown in Figures 2 and 3, provide a clear view of how shelter suitability varies from one region to another. These differences reflect the combined influence of several factors considered in the Gaussian Process Regression (GPR) model, including environmental hazard exposure, infrastructural condition, accessibility, and surrounding population density. By translating these variables into suitability scores, the framework makes it easier to understand how urban conditions affect the potential of schools and colleges to function as emergency shelters.

The interactive spatial maps show that institutions located in the central and southern parts of the study area generally achieve higher shelter suitability scores. This pattern suggests that these regions benefit from comparatively favorable conditions, such as stronger infrastructure, greater availability of open spaces, and better access to emergency support facilities and transport networks. In contrast, many schools and colleges in the northern and eastern parts of the city record lower suitability values. These areas are more often associated with dense population clusters, closer proximity to fault lines, and limited access to safe evacuation spaces, all of which reduce the overall effectiveness of these institutions as potential shelters during emergencies.

This spatial variation is important because it helps reveal not only which institutions appear safer, but also how vulnerability is distributed across the urban landscape. Institutions with higher scores can be viewed as relatively better candidates for emergency shelter use, while those with lower scores may require structural improvement, additional emergency resources, or more detailed on-site evaluation. By presenting these results through an interactive map, the framework offers a practical and visually interpretable tool for planners and local authorities, helping them identify priority areas and design more targeted disaster mitigation and preparedness strategies.

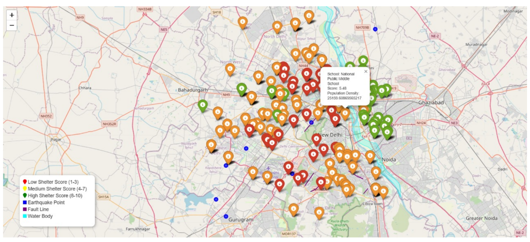


Figure 2. Visualization of predicted shelter suitability scores for schools in our study area using the GPR model.

Higher shelter suitability scores generally correspond to schools and colleges located in comparatively safer areas. These institutions are typically associated with stronger infrastructure, improved access to emergency resources, larger nearby open spaces, and lower levels of environmental hazard exposure. Such conditions increase their potential to function effectively as temporary shelters during disaster situations. In contrast, lower scores indicate institutions situated in more vulnerable settings, often characterized by close proximity to geological fault lines, dense surrounding populations, limited evacuation space, or weaker infrastructure support.

This distinction between high- and low-scoring institutions is useful for practical disaster planning because it helps translate model predictions into actionable priorities. Institutions with lower suitability values can be identified as locations that may require structural reinforcement, improved emergency facilities, or more detailed preparedness planning. At the same time, higher-scoring institutions may serve as stronger candidates for emergency shelter deployment. By making these differences visible, the analysis supports decision-makers in directing resources and interventions more effectively to improve overall disaster readiness.

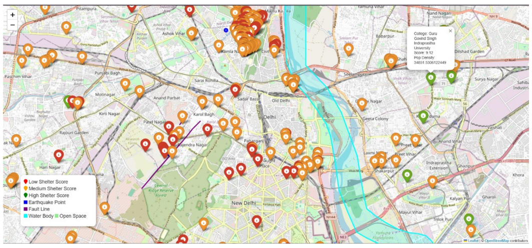

Figure 3. Visualization of predicted shelter suitability scores for colleges in our study area.

In addition to the overall suitability maps, outlier analysis was carried out to identify educational institutions whose predicted shelter scores differed noticeably from the broader spatial pattern observed across the study area. As shown in Figure 4, the red points represent schools and colleges with unusually high or low suitability values when compared with nearby institutions or regional trends. These cases are important because they may indicate locations where the model has captured a distinctive local condition that is not widely shared by surrounding areas.

Such anomalies can arise for several reasons. In some instances, they may reflect localized environmental characteristics, such as unusual proximity to hazards, availability of open space, or access to transport infrastructure. In other cases, they may result from incomplete or uneven infrastructure-related data, or from unique geospatial settings that set a particular institution apart from others in the same region. For this reason, outlier detection adds an important layer of interpretation to the broader shelter suitability assessment.

Identifying these institutions is useful not only for improving the reliability of the model, but also for strengthening practical decision-making. Schools and colleges flagged as outliers may require closer examination to confirm whether their predicted suitability accurately reflects on-ground conditions. This can support policymakers and planners in conducting focused field inspections, validating unusual cases, and refining shelter recommendations before the framework is used in real operational settings.

To evaluate the reliability and generalization performance of the Gaussian Process Regression (GPR) model, a five-fold cross-validation procedure was carried out using Mean Squared Error (MSE) as the primary evaluation metric. This validation approach helps assess how consistently the model performs when the dataset is divided into different training and testing subsets. The MSE values obtained across the five folds, presented in

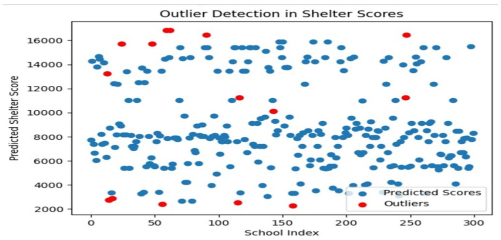


Figure 4. Outlier detection in predicted school shelter scores.

Figure 5, show moderate variation in prediction error from one fold to another.

This variation indicates that the model's performance is somewhat influenced by the way the data are partitioned. Such sensitivity is not unexpected in this study, since the input data combine diverse geospatial, infrastructural, and demographic variables that may vary considerably across locations. In other words, some subsets of the data may contain more complex spatial patterns or stronger local irregularities than others, which can affect the model's ability to generalize uniformly across all folds.

Even with this variability, the cross-validation results suggest that the GPR model is able to capture meaningful relationships among the selected features and produce useful shelter suitability predictions. At the same time, the differences observed across folds point to opportunities for further refinement. Improvements such as kernel parameter tuning, feature selection adjustments, or the use of ensemble-based GPR approaches could help increase prediction stability and reduce fold-wise variation. This makes the cross-validation analysis an important step in understanding both the current strengths of the model and the directions for improving its robustness in future work.

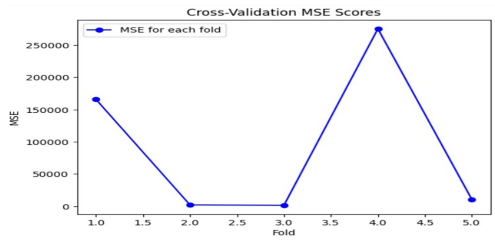


Figure 5. Five-fold cross-validation Mean Squared Error (MSE) scores showing variability across folds

In addition to predictive modeling, an interactive user interface (UI) was developed to enhance accessibility and practical usability of the system. The interface integrates dynamic geospatial maps displaying all identified emergency shelters across the study area. Users can interact with the map to visualize shelter locations, their respective suitability scores, and surrounding infrastructure such as roads, open spaces, and metro connectivity. A key feature of this interface is the route-finding functionality, which allows users to input their current location manually or through GPS-based detection. Once the location is entered, the system automatically computes and displays the shortest and safest path to the nearest available shelter using optimized routing algorithms that account for real-time spatial constraints such as road connectivity and accessibility. Figure 6 displays the Nearest emergency shelter with path to reach the selected shelter.

This feature ensures that individuals can quickly identify and


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navigate to the most suitable shelter during emergencies, significantly improving response efficiency and public safety. The interface is designed to be intuitive and user-friendly, enabling both disaster management authorities and citizens to utilize it effectively. Furthermore, the integration of predictive shelter data with an interactive visualization tool bridges the gap between analytical modeling and real-world application, demonstrating how geospatial intelligence can directly support informed decision-making during disaster response operations.

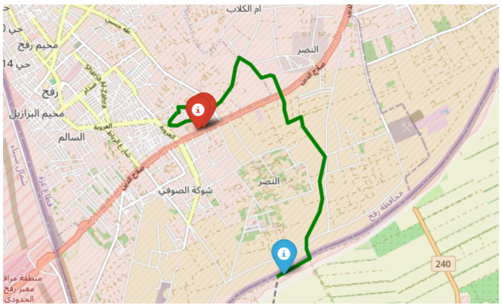


Figure 6. Nearest emergency shelter with path

The combination of spatial visualization, outlier detection, and cross-validation evaluation demonstrates the effectiveness of the proposed framework in identifying safe and vulnerable zones across our study area. The results emphasize the utility of machine learning and geospatial integration for data-driven disaster preparedness, supporting proactive decision-making to minimize risk and improve the resilience of educational infrastructure.

## 5. Conclusion and Discussion

This study presented an *Emergency Shelter Assessment* framework for evaluating schools and colleges as potential emergency shelters in disaster-prone urban areas. Using Gaussian Process Regression (GPR) together with geospatial variables such as hazard exposure, infrastructure condition, and population density, the framework generated normalized suitability scores for educational institutions across the study area. These scores made it possible to distinguish relatively safer locations from sites that may require structural improvement, additional emergency support, or closer planning attention.

A key contribution of the work lies in linking predictive modeling with spatial interpretation. The mapped shelter scores, outlier identification, and route-based visualization together show how geospatial data can be translated into planning support for disaster preparedness. Rather than relying only on isolated infrastructure indicators, the framework evaluates shelter potential through a combination of environmental, demographic, and accessibility-related factors. This makes the approach more relevant for practical urban emergency planning.

The framework can also be extended beyond schools and colleges to other facilities such as community halls, government buildings, residential complexes, and NGO-managed spaces. With further development, the system could be connected to widely used mapping platforms and updated with dynamic inputs such as traffic conditions, weather information, or active hazard data. Such additions would improve its usefulness during real emergency situations by helping users identify nearby safe shelters and more feasible evacuation routes.

Overall, the study shows that the integration of machine learning and geospatial analysis can support more informed shelter assessment in complex urban settings. By identifying both high-suitability and vulnerable locations, the proposed approach offers a practical basis for improving preparedness, guiding infrastructure upgrades, and strengthening disaster resilience at the community level.

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