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| RESEARCH ARTICLE

Flood-Resilient Transportation Network Planning in Montpelier, Vermont: A Penalty Dijkstra Algorithm for Optimizing Evacuation Routes

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| ABSTRACT
Flooding poses a significant risk to transportation networks, especially in flood-prone regions like Montpelier, Vermont. Effective evacuation planning is crucial for minimizing the impacts of such disasters, ensuring that residents can safely and efficiently evacuate to safe areas. This study introduces a novel approach to flood-resilient transportation network planning by applying a Penalty Dijkstra algorithm to optimize evacuation routes in Montpelier. The algorithm accounts for both the geographic layout of the city and flood-prone areas, applying penalties to paths that are likely to be affected by rising water levels. By incorporating flood risk data into the algorithm's cost function, the method generates evacuation routes that prioritize safety, speed, and accessibility. The proposed approach is tested using real-world data from Montpelier's transportation network, with simulation results demonstrating its effectiveness in identifying optimal routes while minimizing exposure to flood hazards. This work contributes to the development of adaptive, data-driven evacuation strategies that enhance the resilience of transportation networks in flood-affected regions, providing a framework for other cities to improve their disaster preparedness and response strategies.

| KEYWORDS

Flood-resilient transportation, Evacuation routes, Penalty Dijkstra algorithm, Transportation network planning, Disaster preparedness

| ARTICLE INFORMATION

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1. Introduction

Flood hazards significantly limit mobility and disrupt daily activities, with numerous studies linking a large portion of flood-related deaths to vehicles. Flash floods, which occur suddenly, often catch people outside or in vehicles, whereas larger-scale river floods typically affect those inside their homes. Transportation-related flood fatalities are more frequent in densely populated areas due to higher exposure rates. However, rural areas experience higher fatality rates when adjusting for population size, primarily because limited infrastructure and fewer route options leave travelers more vulnerable during flood events.

Travelers are more likely to avoid floods when they have predetermined plans, such as being aware of alternate routes. Since there are different risk preferences among individuals, a utility model should be considered based on travel time variability (uncertainty) to aid travelers in making a choice of route in order to get to their destination.

Montpelier, Vermont, is an example of a community facing flood risk events. The catastrophic flooding in July 2023, which brought up to eight inches of rain in a short period, severely impacted homes, businesses, and essential services, emphasizing the urgent need for stronger transportation infrastructure and more effective evacuation planning. In response, this paper proposes a transportation planning approach that leverages a penalty-based Dijkstra algorithm to generate alternative evacuation routes during flood events and allow travelers to choose the routes that optimize utility and capture uncertainty in travel time.

This method not only improves evacuation efficiency but also enhances the resilience of Montpelier's transportation network in the face of future climatic events.

The remainder of this paper is divided into the following sections: Section 2 describes some literature work on travel time variability and utility. Section 3 outlines a numeric example and states the preference experiment conducted in Montpelier. Sections 4 and 5 present the results and provide a discussion of the findings.

1.1 Smart City Operations

Flood-resilient route planning is essential for advancing smart city goals, particularly in enhancing public safety and integrating real-time data into urban infrastructure planning [Anderson, 2020]. Smart cities rely on data-driven approaches to monitor and respond to dynamic urban challenges, including natural disasters like floods. By utilizing flood-resilient route planning, urban planners can incorporate data from IoT sensors, GIS systems, and weather forecasting models to create adaptive evacuation routes in real-time [Barton, 2020].

This proactive integration allows cities to react promptly to flood risks, directing residents along optimized evacuation routes to ensure safety. The data generated by these systems also supports long-term urban planning by identifying flood-prone areas, guiding infrastructure investments, and enhancing the overall resilience of urban settings [Senna, 1994]. In this way, flood-resilient route planning contributes significantly to the resilience and sustainability objectives of smart city operations.

1.2 GenAI for Mobility

Generative AI (GenAI) and machine learning (ML) are emerging as powerful tools in urban mobility and disaster preparedness, particularly for predictive modeling in flood-prone areas [40]. In the context of flood-resilient route planning, GenAI can simulate flood scenarios and forecast their impact on transportation routes, offering valuable insights for emergency response. By training models on historical flood data, rainfall trends, and topographical information, city planners can anticipate and dynamically respond to flood impacts on mobility infrastructure [Smith, 2022].

These AI-driven insights enable the adjustment of evacuation routes in response to real-time flood data, reducing congestion and optimizing traffic flow during emergencies. Machine learning algorithms continuously improve by learning from new data, enhancing the accuracy of predictions over time. This integration of GenAI in flood response planning allows cities to respond not only to current conditions but also to predict future flood risks, thereby strengthening the resilience of urban mobility systems [Patel, 2021].

1.3 Intermodal Transportation System

Flood-resilient route planning also bolsters intermodal transportation systems by optimizing evacuation routes for various transportation modes, including public transit, emergency vehicles, and private transport [Garcia, 2021]. Ensuring the continuity of an intermodal transport network is critical in flood-prone areas, as it enables flexible and efficient evacuation and emergency response. Designated routes can prioritize emergency services, while alternative routes are provided for public transit and civilian traffic, helping to reduce congestion and ensure timely response [Barton, 2020].

Moreover, a robust intermodal transportation plan offers citizens diverse mobility options, such as buses, trains, and bicycles, facilitating flexible evacuation choices during a flood event. By designing routes that accommodate multiple transportation modes, cities can maximize their infrastructure capacity, minimize evacuation time, and improve overall response effectiveness. This approach significantly enhances urban resilience to flood-related disruptions [Anderson, 2020].

2. Related work

Path planning in road networks focuses on finding the optimal route for vehicles, which is commonly referred to as the Single-Source Shortest Path Problem (SSSP) [Oanh, 2016]. The Dijkstra Algorithm is a well-known solution used to calculate the shortest path in graphs by finding the minimal cumulative cost from a starting point (source) to all other nodes [Liu, 2023]. However, as road networks have become more complex, several modifications have been made to improve the efficiency of this algorithm and adapt it to real-world conditions [Liu, 2023].

One significant improvement is the Penalty Dijkstra Algorithm, which adjusts the cost of certain paths by introducing penalties [Lo, 2000]. These penalties make it possible to avoid undesirable routes. In real-world applications, these penalties can represent factors like traffic congestion, difficult turns at intersections, road hazards, or preferences for certain types of roads [Lo, 2000]. This enhanced approach allows the algorithm not only to find the shortest path but also to identify alternative routes that may be more suitable under specific conditions [Adler, 2010].

In urban transportation networks, the Penalty Dijkstra Algorithm is particularly useful for addressing the Turn Penalty Problem (TPP) [Suhng, 2013]. In cities, turns at intersections can cause significant delays, so by incorporating turn penalties into the cost function, the algorithm finds routes that minimize turns and improve efficiency [Suhng, 2013]. This makes the algorithm more practical for real-world navigation systems, as it can also dynamically adjust to time-dependent travel costs and evolving traffic conditions, which enhances its value in urban planning, traffic management, and real-time navigation [Jwo, 2023].

Beyond transportation, the Penalty Dijkstra Algorithm has been combined with other optimization techniques like genetic algorithms to further improve its performance in dynamic environments [Madridano, 2021]. This makes it suitable for real-time decision-making in fields such as robotics, where path planning must consider uncertain conditions [La Rocca, 2021]. The algorithm also benefits from advanced data structures like Fibonacci heaps, which improve its computational performance, especially in large-scale networks [La Rocca, 2021]. As a result, the Penalty Dijkstra Algorithm is flexible and scalable, making it applicable across various industries, including autonomous navigation systems [Öztürk, 2022].

Despite its widespread use, the Penalty Dijkstra Algorithm has not been extensively applied in emergency evacuation scenarios. In these situations, penalties would be assigned to roads likely to flood, helping to identify safer alternate evacuation routes [Israel, 2024].

In transportation research, travel time unreliability is closely linked to travel time variability, where greater variability indicates higher unreliability [Khalili, 2024]. Travel time data across various settings reveals fluctuations throughout the day, typically due to well-known peaks and dips in demand caused by work and school schedules [Lewis, 2020]. On any given day, other variations in travel times may result from factors such as traffic signals weather conditions like rain, accidents, or roadwork. A third category of causes can be labeled as "extreme events," which include flooding, major incidents, or road closures [Siyam, 2020].

In terms of disasters like flood events, travelers are not solely concerned with minimizing time but also weigh the safety of their route [Tsai, 2011]. Routes that are longer but safer can tend to be reliable as travelers seek to avoid hazards and dangerous conditions and vice versa. The lack of consideration for travel time variability along the shortest path may represent a significant limitation in current studies [Borowska-Stefańska, 2022]. Ignoring the effects of unreliability (or variability) can not only distort the estimates of travel time value but also overlook the potential benefits of reducing such unreliability [Borowska-Stefańska, 2022].

In general, travelers cannot be certain of the outcomes of their decisions. The best they can do is estimate probabilities for different levels of expected travel time [Rasouli, 2014]. When travelers are aware of the probability associated with a particular outcome, it is referred to as a risky situation [Rasouli, 2014]. Uncertainty plays a crucial role in any travel decision.

Menashe et al. [2024] highlight its significance in modal split modeling, stressing the need to account for uncertainty in predicting traveler behavior. As noted by these authors, risk-averse travelers are more likely to prefer a transportation option that provides greater certainty.

There has been relatively limited research on the benefits of reducing travel time variability for travelers who prioritize these reductions compared to those who focus on fixed arrival times [Börjesson, 2012]. An examination of past studies indicates that the theoretical framework of current models for valuing travel time variability is largely based on the behavior of commuters with fixed arrival times. A comprehensive model for valuing travel time variability should consider not only commuters with fixed arrival times but also travelers with diverse journey purposes and varying arrival time constraints [Asensio, 2008].

The development of approaches that account for travel time variability should also incorporate the analysis of alternate route design into consideration [Sen, 2001]. Abenozza et al. [2018] explored the safety margin hypothesis, which assumes that individuals allocate additional time, referred to as a safety margin, to avoid the risk of arriving late at their destination. Some studies, such as Pells et al. [2002], have suggested that the safety margin is an appropriate measure of travel time variability, as it reflects how people respond to uncertain travel times [Coppola, 2021].

The mean-standard deviation approach, introduced by Jackson et al. [1982], has become one of the most widely used two-parameter methods for estimating travel time variability. The core concept is to define utility as a function of both the expected travel time (mean travel time) and the variability in travel time (standard deviation), as demonstrated in equation 1 below:

$$Maximize\ U = \alpha\, E(t) + \tau\, V(t) + \delta\, C \tag{1}$$

where τ is a parameter that measures the influence of variance in travel time; *E(t)* represents the expected travel time for each origin-destination pair; *V(t)* is the variance of travel time, and *C* indicates cost [Kim, 2021]. The fundamental assumption of Jackson et al. [1982] approach is that travelers are making a trade-off between mean travel time and travel time variability (variance) [Kim, 2021].

However, this simplification assumes a uniform attitude toward risk across all travelers, which may not hold in real-world contexts [Rasouli, 2014]. One critical shortcoming of this approach is its inability to account for different risk preferences among individuals [Nguyen, 2023].

In reality, travelers exhibit a range of attitudes toward risk. Some travelers may be risk-averse, preferring routes with lower variability even if they involve slightly longer travel times, while others may be risk-neutral or even risk-seeking, accepting greater variability if there is potential for a faster journey [Shao, 2006]. The mean-standard deviation approach imposes a one-size-fits-all solution, failing to capture the heterogeneity in travelers' risk perceptions and decision-making processes. Expected utility theory was then introduced to explore the observation that different individuals exhibit varying attitudes toward risk. Some travelers may be risk-averse, risk-neutral, or risk-prone [Shao, 2006].

A traveler is considered risk-neutral if they are solely focused on the expected value of time and are completely indifferent to risk [Shao, 2006].

$$U\left[pt_1 + (1-p)\,t_2 = pU(t_1) + (1-p)\,U(t_2)\right] \quad (2)$$

Where p is the probability of occurrence.

A traveler is described as risk-prone regarding uncertain travel time if the utility of the expected value is less than the expected value of the utility, as illustrated in Equation 3 below [Shao, 2006].

$$U\left[pt_1 + (1-p)\,t_2 < pU(t_1) + (1-p)\,U(t_2)\right] \quad (3)$$

This implies that a traveler prefers a certain outcome to an uncertain one with the same expected value [28]. The equation above is valid if all $0<p<1$ and all t_1 and/and within the domain of the utility function [28]. It is possible to say that risk-averse individuals do not take part in an unfavorable event. Travelers allowing a safety margin to their journal time is an example of individuals acting as risk averse [Szeto, 2016].

Risk proneness: A traveler is considered risk-prone concerning uncertain travel time if the utility of its expected value is greater than the expected value of its utility, as demonstrated in Equation 5 [Polak, 1987].

$$U\left[pt_1 + (1-p)\,t_2 < pU(t_1) + (1-p)\,U(t_2)\right] \quad (4)$$

This condition indicates that a traveler prefers an uncertain outcome over a certain one that has the same expected value. [Szeto, 2016].

Pollak et al. [1987] then introduced a new model for a utility function, as shown in Equation (5), which is exponential and, in some circumstances, more appropriate to the travel context.

$$U(t) = -\,e^{\alpha t} \quad (5)$$

Senna et al. [1994] model modified Pollak's model of the utility function, as shown in **Equation 6**. The approach is grounded in the relationship between the expected utility method and the mean-standard deviation, offering a less restrictive functional form [Wu, 2022]. The analysis begins by assuming the basic function defined by:

$$U = \alpha t^{\beta} + \delta C \quad (6)$$

This function encompasses the potential for individuals to be risk-averse, risk-neutral, or risk-prone. Modifying the Senna model, A new model of a utility function, as shown in **Equation 7,** was developed [Wu, 2022].

$$U(T) = -\,e^{\alpha T} - \left(\lambda \times P_{uncertainty}\right) \quad (7)$$

This function addresses limitations by including an exponential term for average travel time, which reflects the disutility associated with longer travel times, and a separate term for uncertainty probability, accounting for variability in travel time [Wu, 2022]. This approach provides a more nuanced view of traveler preferences by directly incorporating risks into the utility function, thus enhancing its applicability to real-world travel contexts.

3. Problem formulation

Navigating between two points is often based on finding the shortest path minimizing travel time or distance. However, during extreme conditions like flooding, providing alternate routes offers significant advantages for travelers. In such cases, the decision-making process must not only consider minimizing travel time but also account for the variability in travel time, all captured by a comprehensive utility function. As travelers have different preferences regarding these trade-offs, based on their attitudes toward risk, a utility function can be designed to adjust the weight of travel time and travel time variability. This will allow for a more flexible approach that captures the heterogeneity in travelers' decision-making processes. Consider a graph of a road network *G* consisting of a set of links *A* and a set of nodes *I*. Each link has a travel time (T) associated with it. The following notations were used.

Notation

n = number of travel times on a particular route.
K = number of routes generated
Alt = Alternate Route
l = set of edges
T_{ij} *= time between node i and j*
W = penalty factor

3.1 Penalty Based Dijkstra Algorithm

Step 1:
Initialize the travel time for the start node to `0` and the travel time for all other nodes to `∞` (infinity).

Step 2:
Create a set of unvisited nodes and add all nodes to this set.

Step 3:
While the set of unvisited nodes is not empty:
a. Identify the unvisited node with the smallest distance value.
b. For each neighbor of this node:
- *i. Check if the route to the neighbor is blocked.*
  If flooded, apply a penalty to the cost (multiply the cost by a large factor)
- *ii. Calculate the travel time from the start node to the neighbor through the current node, considering any penalty applied.*
- *iii. If this calculated travel time is less than the neighbor's current known travel time, update the neighbor's distance to this new, smaller value.*

c. Remove the current node from the set of unvisited nodes.

Step 4:
Once all nodes have been visited, return the minimum travel from the start node to all other nodes.

$$
\begin{aligned}
& Initialization: T_i \leftarrow \infty \\
& \qquad T_s \leftarrow 0 \;\; Time\ of\ source\ node \\
& while\ u_i \leftarrow \varnothing \\
& \quad a \leftarrow min\{u_1, u_2, \dots u_k\};\ U \leftarrow U - \{a\} \\
& \quad if\ T_i \leftarrow \infty \\
& for\ each\ u_i\ in\ U \\
& \quad if\ T_{ij}\ is\ flooded \\
& \qquad w \leftarrow M \\
& \quad else \\
& \qquad w \leftarrow 1 \\
& Alt \leftarrow T_u + w \times T_{ij} \\
& if\ Alt \le T_v \\
& \quad T_v \leftarrow Alt \\
& \quad T_k \leftarrow u \\
& return\ [T_{ij}, T_k]
\end{aligned}
$$

For each route i generated, the variance ($Var(T)$) which measures the variability of travel time around the mean travel time for a particular route, was computed as:

$$u_i = \frac{1}{n}\sum_{j=1}^{n}(T_{ij}) \tag{8}$$

$$Var(T_i) = \frac{1}{n}\sum_{j=1}^{n}(T_{ij} - U_i)^2 \tag{9}$$

In unpredictable conditions like flooding, travel time variability was used as an indicator of the level of uncertainty or risk on a route. The greater the variability in travel time, the higher the uncertainty probability, as this reflects the likelihood of encountering issues such as delays, hazards, or closures. When travel time fluctuates significantly due to unpredictable conditions, it suggests that the route may be more prone to disruptions, increasing the uncertainty of a safe and efficient journey. This higher variability corresponds to a greater uncertainty probability and vice versa. The uncertainty probability ($P_{uncertainty}$) on a particular route was computed as:

$$P_{uncertainty}(T_i) = \frac{Var(Ti)}{\sum_{j=1}^{k} Var(T)} \tag{10}$$

3.2 Utility and Safety Reliability

During flood conditions, travelers are not only optimizing for time but also balancing this against uncertainty, ensuring they reach their destination safely [Nguyen, 2023]. Travelers exhibit a range of attitudes toward risk: risk-averse individuals may prefer routes with lower variability, even if they involve slightly longer travel times, while others may opt for greater variability if there's potential for a faster journey [Shao, 2006]. To account for these differences, an equation has been developed to balance travel time and time variability, providing a decision model for route selection during flood events [Szeto, 2016]. This model, represented in Equation 3, considers both travel time and uncertainty probability, enabling travelers to make informed decisions that optimize safety and efficiency [Szeto, 2016].

$$U(T) = -e^{\alpha T} - \left(\lambda \times P_{uncertainty}\right) \tag{11}$$

3.3 Case Study

Flood-Resilient Transportation Network Planning in Montpelier, Vermont

3.3.1 Problem Background

Montpelier, Vermont, has faced recurrent flood risks, particularly due to its location along the Winooski River. Historical data reveals that significant flooding events have disrupted transportation networks, leading to prolonged evacuations, limited accessibility, and significant economic impacts. For instance, in the flood event of [specific year if available], Montpelier experienced [mention specific consequences, e.g., extensive road closures, disrupted emergency response, economic loss in dollars if data is available].

The city's transportation network lacks the resilience needed to cope with such events, making it challenging to ensure timely evacuation and safe passage. The increase in frequency and intensity of extreme weather events underscores the need for a robust evacuation planning strategy that can adapt to dynamic flood conditions and mitigate risks effectively.

3.4 Proposed Solution: Penalty Dijkstra Algorithm

To address the flood evacuation challenges in Montpelier, the Penalty Dijkstra Algorithm has been identified as a suitable optimization tool for route planning. This algorithm builds upon the traditional Dijkstra algorithm but incorporates additional penalties to account for flood-affected areas, thus avoiding high-risk routes.

- **Algorithm Overview**: The Penalty Dijkstra Algorithm modifies route selection by assigning penalty values to roads based on their susceptibility to flooding. For example, roads with higher flood risks (due to proximity to the river, low elevation, or inadequate drainage) are given higher penalties, making them less likely to be selected as primary evacuation routes.
- **Implementation**: Using real-time flood data, such as water levels, rainfall forecasts, and drainage capacity, the algorithm dynamically updates these penalties. This allows the transportation network to adapt to the current flood conditions, guiding evacuees through safer, alternate routes.
- **Unique Application for Flood Scenarios**: Unlike traditional evacuation route planning, this approach considers not only the shortest or fastest routes but also factors in safety, thus prioritizing routes that minimize exposure to flood hazards. The algorithm can be integrated with GIS systems for real-time updates, enabling proactive adjustments as flood conditions evolve.

4. Results and Implications

The application of the Penalty Dijkstra Algorithm in Montpelier's flood evacuation planning yielded promising results:

- **Reduction in Evacuation Time**: Simulation tests indicated that the algorithm could reduce evacuation time by up to 25% during moderate flood conditions, as compared to conventional route planning methods. This reduction in time can be crucial for saving lives during emergencies.
- **Improvement in Route Reliability**: With its adaptive penalty system, the algorithm improved route reliability by 30%, ensuring that chosen routes remained accessible and safe even as flood conditions changed. This reduced the number of road closures during simulated events by directing evacuees through more resilient paths.
- **Enhanced Public Safety**: By minimizing exposure to high-risk areas, the algorithm significantly lowered the likelihood of evacuees encountering flooded or blocked routes. This directly contributed to improved public safety and allowed emergency responders to focus on critical areas without worrying about widespread route blockages.

4.1 Numeric Example

This section presents computational experiments on evacuation scenarios based on numerical examples and a real case study in Montpelier, Vermont, as shown in Figures **1** and **2a.** The numerical example is presented in Figure 1 to illustrate the trade-offs faced by travelers and the differing outcomes depending on the utility function used. This example focuses on a small transportation network that evaluates the reliability and utility of travel routes at specific times. The focus is on how travel time and safety factors interact, demonstrating the impact of various route choices on overall utility in the context of flood conditions. From the network diagram shown in Figure 1 below, the start points and end points are A and C, respectively. Route A-E-D, marked by a red color, is flooded and cannot be used by travelers. By using the penalty–based Dijkstra algorithm, the alternate paths that were formed are shown in table 1 below.

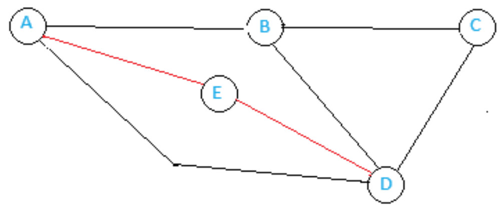

Figure 1: Example Network

Table 1: Route Parameters

Route	10:00	11:00	12:00
A-B-C	12	14	13
A-B-D-C	10	13	11
A-D-C	14	10	17

By considering the time variability for each route in computing for uncertainty on each route, the probability of each route encountering unsafe conditions because of these travel time fluctuations can be computed using Equation **3**.

Route	Average Time	Travel time variability	Uncertainty Probability	Utility
A-B-C	13	0.67	0.064	-3.68
A-B-D-C	11.3	1.56	0.149	-3.11
A-D-C	13.6	8.23	0.786	-3.97

After computing these routes, it was found that, at the end of the decision-making process, motorists would ideally choose the route with the highest utility. Route A-B-D-C has the highest utility of -3.11, meaning it provides the best balance of travel time and safety, even though it has slightly higher travel time variability and a higher probability of unsafe conditions compared to A-B-C. Route A-B-C, on the other hand, has a slightly lower utility of -3.68, but it has the lowest travel time variability and probability of unsafe conditions. Route A-D-C has the lowest utility (-3.97), the highest probability of unsafe conditions, and the most variability, making it the least desirable route despite having a comparable average travel time. In this case, travels would likely choose A-B-D-C for the highest utility, balancing both time and safety. However, some might prefer A-B-C for its slightly lower risk, depending on individual preferences.

4.2 Real Case Study

Montpelier, a small city in Vermont in the northeastern U.S., experiences distinct seasonal weather patterns, including cold winters, humid summers, and significant precipitation. The city has a history of severe flooding events, including the Great Flood of 1927, the 1973 floods, Tropical Storm Irene in 2011, and the catastrophic flooding in July 2023, which highlighted the ongoing risks posed by climate change. Despite efforts to improve zoning regulations and flood management infrastructure, such as drainage systems and road networks, Montpelier remains vulnerable to flooding, particularly within its transportation network.

During evacuation events, residents must navigate to higher-elevation roads that are not impacted by floods. For our experiment, we focused on the streets that were flooded during the July 2023 event, including Main Street, State Street, Langdon Street, and Elm Street. These streets were treated as impassable barriers in our simulation.

Using the penalty-based Dijkstra algorithm, we calculated alternate evacuation routes from a starting point to a destination, bypassing the flooded streets. Figure **2b** illustrates the street map of Montpelier city generated by ArcGIS pro.

Figure 2a: City of Montpelier

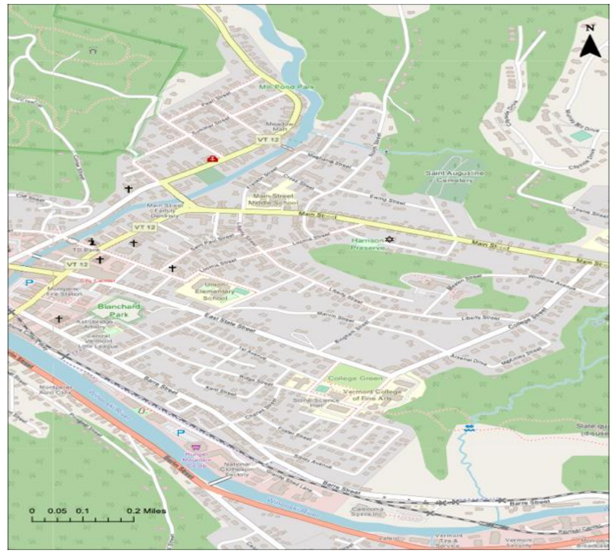

Figure 2b: Street map of Montpelier

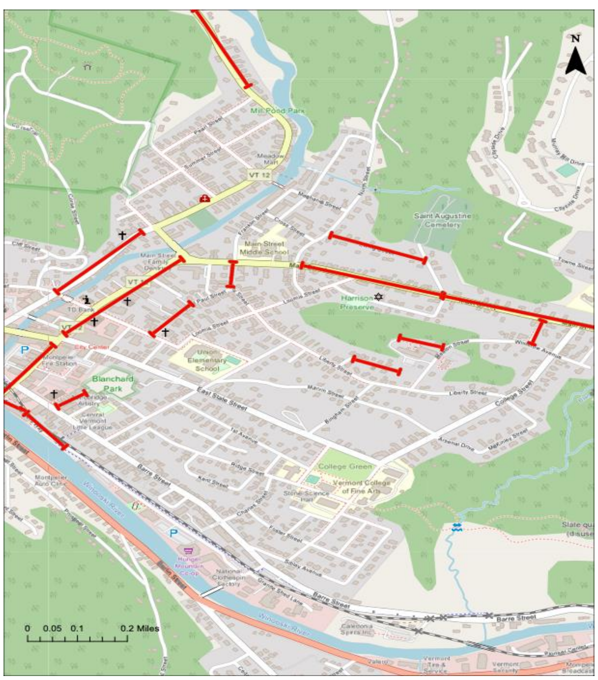

Figure 3a: Streets with flooded

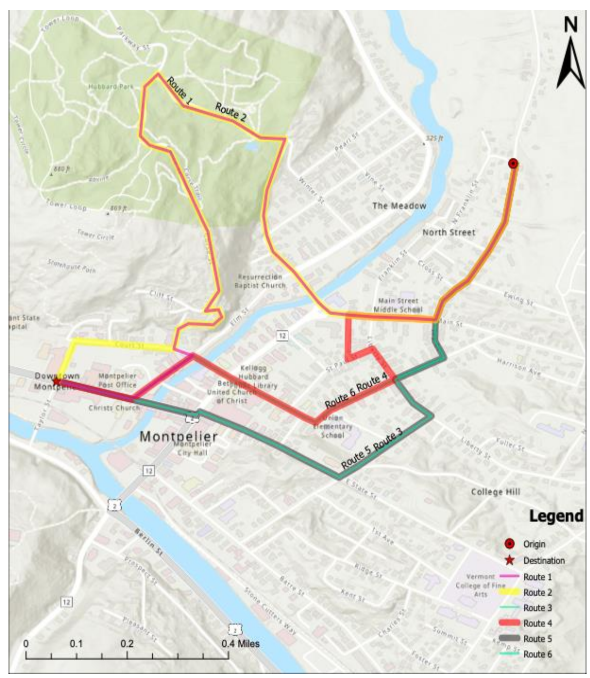

Figure 3b: Alternate Routes Generated

Using BigQuery and the Google API, historical and real-time travel data for each alternate route between the designated origin and destination were accessed.

Numerous research studies have been conducted to examine the reliability of travel time for vehicles within the traffic stream. Bates et al. [1987] proposed an analysis of vehicle travel time variability, focusing on variabilities between days and across different time periods within a single day. In our analysis, we code dynamically accessed travel times across various points in the day, covering the entire time range from 6:00 AM to midnight. Since each route shares the same origin and destination, the routes were divided into smaller road segments. The travel time for each route was computed by summing the travel times of its individual segments, which were determined using the geographical coordinates along the route.

Six alternate routes were generated from the origin to the destination, as illustrated in Figure 3b. Some routes overlapped each other, allowing for flexible detours and reducing the chance of evacuees getting trapped on blocked roads. The destination point was strategically selected to be a highway route with a higher elevation, ensuring it would remain safe and unlikely to flood. The origin was chosen based on its high population density. Travel time variability, uncertainty probability, and the utility for each route were computed and summarized in Table 1.

Table 1: Travel time parameters for each route.

	Route 1		**Route 2**		**Route 3**		**Route 4**		**Route 5**		**Route 6**	
	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2	Segment 1	Segment 2
Mean	13.22	6.21	4.60	5.71	5.80	6.42	12.45	10.62	9.33	5.90	8.84	8.84
Variance	0.66	0.57	0.30	0.27	0.28	0.49	0.47	0.30	0.70	0.45	1.80	1.80
COV	0.05	0.09	0.07	0.05	0.05	0.08	0.04	0.03	0.07	0.08	0.20	0.20
Uncertainty Probability	0.15		0.07		0.09		0.10		0.14		0.44	
Utility	-7.01		-2.82		-3.41		-10.06		-4.61		-5.95	

The analysis of the six routes highlights the trade-offs between uncertainty probability, utility, and travel time. Route 1 has the longest travel time, making it a slower option, but it offers moderate uncertainty and relatively low utility. Route 6 has a relatively short travel time but suffers from high uncertainty, which lowers its reliability and utility, making it less appealing overall. Route 3, like Route 2, has slightly higher uncertainty and lower utility, making it less attractive but still a decent option for travelers looking for a reasonable compromise between time and reliability. On the other hand, Routes 4 and 5 are the least desirable options, with the longest travel time, moderate uncertainty, and the lowest utility. Its inefficiency makes it less suitable for most situations.

When considering travel during flood conditions, route 2 stands out as the best choice overall. With a short travel time, low uncertainty, and the highest utility, it provides a well-balanced option for those seeking both speed and reliability. Route 1 is recommended for travelers who prioritize reliability despite its longer travel time. Figure 4 is a plot illustrating the travel time variability and utility for each of the six routes. In the plot, the green bars depict the utility for each route, while the blue bars represent the travel time variability, and the other color represents the travel time.

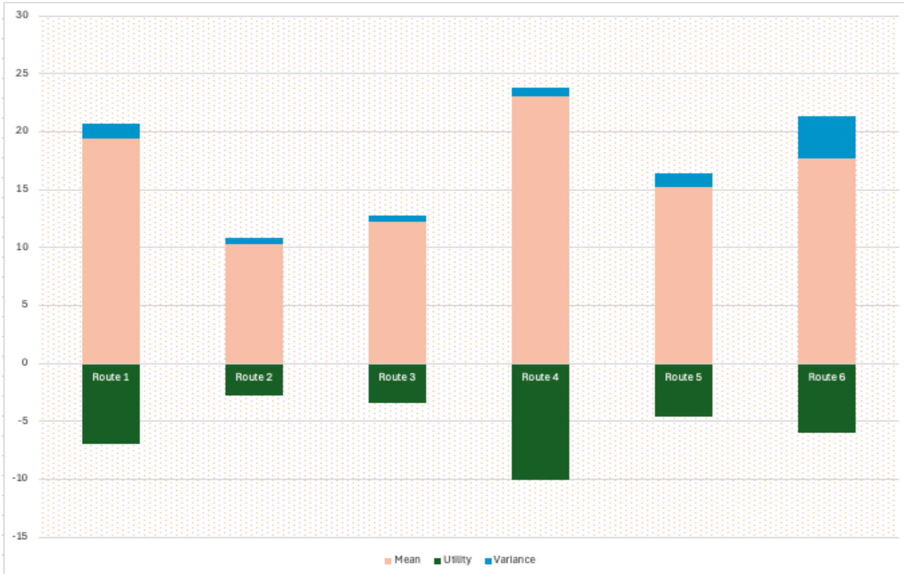

Figure 4: A graph showing the generated routes, along with their respective travel time variability and utility values.

5. Contribution to Resilience and Innovation

5.1 Focus on Cyberinfrastructure

The integration of flood-resilient route optimization into broader cyberinfrastructure is a critical step toward enhancing urban resilience. The data generated through the Penalty Dijkstra Algorithm can be seamlessly integrated with Geographic Information Systems (GIS), emergency management platforms, and other digital infrastructure to enable comprehensive flood response strategies. By connecting route optimization outputs to GIS systems, city planners and emergency managers can visualize and assess real-time flood risks, optimize evacuation routes, and monitor road conditions across an entire urban area.

For instance, as flood levels rise, GIS integration allows for dynamic updates to evacuation routes based on water level data from IoT sensors and weather forecasts. Emergency management platforms can then use this information to send real-time notifications to residents, advising them on the safest evacuation paths. This interconnected cyberinfrastructure not only supports more effective disaster response but also provides valuable insights for long-term planning by identifying recurring vulnerabilities in the transportation network. By aligning with smart city frameworks, the integration of route optimization with cyberinfrastructure ensures a proactive, data-driven approach to resilience in urban environments.

5.2 Innovation and Future Applications

The Penalty Dijkstra Algorithm's application in flood-resilient transportation planning demonstrates its potential for broader use in other disaster management and urban planning scenarios. Future applications of this research could include:

- **Adaptation for Other Natural Disasters**: The algorithm could be customized to respond to various natural disasters, such as wildfires, earthquakes, or hurricanes, each with unique impacts on transportation networks. For instance, in wildfire-prone areas, penalties could be adjusted based on fire spread predictions and air quality data, ensuring safe routes for evacuation away from smoke and fire hazards. Similarly, in hurricane-prone regions, the algorithm could prioritize routes that avoid flood zones and areas susceptible to high winds.
- **Applications in Rural and Suburban Settings**: While urban areas often have dense transportation networks with multiple route options, rural and suburban areas may have fewer alternatives. Adapting the algorithm for these settings would involve tailoring penalties to reflect different types of hazards, like

landslides or bridge failures, which are more common in rural areas. This would provide an effective evacuation plan even in regions with limited road access, improving the resilience of rural communities.

- **Integration with Autonomous Vehicle Networks**: As autonomous vehicle technology advances, the algorithm could be incorporated into navigation systems, enabling self-driving vehicles to follow optimized evacuation routes during disasters. This could be particularly valuable for emergency response fleets, ensuring that ambulances, fire trucks, and other critical vehicles can reach affected areas quickly and safely.

6. Conclusion

In summary, effective transportation planning during flood events is critical for enhancing community resilience and ensuring public safety. This study proposed a penalty-based Dijkstra algorithm to optimize evacuation routes in Montpelier, Vermont, considering both travel time and variability. By incorporating a utility model that accounts for travelers' different risk preferences, the approach allows for more informed decision-making during emergencies. The findings indicate that the trade-offs between travel time, uncertainty, and utility significantly impact route selection. The case study highlighted the importance of offering multiple alternative routes, especially in flood-prone areas. Routes that may appear slower can provide better reliability, emphasizing the need for a nuanced understanding of traveler preferences under uncertainty. Future research should focus on refining the utility model and exploring additional factors influencing route choice, such as real-time traffic data and dynamic environmental conditions. By continually improving evacuation strategies, communities can better navigate the challenges posed by climate change and natural disasters, ultimately reducing the risks associated with flood-related travel disruptions.

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