CSE6730 Project Checkpoint 1

Group 9: Atticus Rex,
Garyoung Lee, Li-Yen Yang,
Flavia Kung'u, Yifan Zhao

Traffic Network Simulation in Pluvial Flash Flood: Rerouting and Impact Assessment

Project Description

1. Abstract

In contemporary transportation systems, the management of traffic flow under unpredictable events such as flash floods is a critical challenge. The conventional static traffic assignment, where routes are fixed at the onset, is insufficient in addressing real-time variations in trip volumes, accidents, work zones, and weather conditions. Dynamic Traffic Assignment (DTA) emerges as a pragmatic solution, adapting routing strategies continuously to evolving circumstances. Existing navigation services, while adept at adapting to incidents like accidents and road closures, often neglect unreported events like flash floods, posing a significant threat to both drivers and network integrity.

Unlike accidents or work zones, flash floods exhibit distinct characteristics: they spread spatially and temporally, impede rerouting options when vehicles are submerged, cause physical damage, confound drivers with safe detours, and significantly reduce network capacity. Despite the gravity of this issue, an efficient and safe rerouting strategy tailored for flash floods remains elusive in existing research.

Addressing this gap, our research endeavors to develop a bespoke Dynamic Traffic Assignment model. This model is engineered to swiftly respond to flash floods, ensuring the shortest and safest travel time for commuters. Our approach involves crafting a dynamic traffic assignment algorithm that integrates real-time data on flash floods, accidents, and road closures. The objective is to reroute vehicles dynamically, optimizing paths to circumvent flooded areas while prioritizing safety and efficiency.

To assess the efficacy of our methodology, we will subject it to rigorous testing across a spectrum of flash flood scenarios, ranging from minor incidents affecting peripheral lanes to major events submerging entire thoroughfares. Utilizing advanced traffic simulation models, we will replicate diverse flooding intensities, enabling comprehensive evaluation of our dynamic traffic assignment strategy. By systematically analyzing these simulations, our research aims to establish a robust and adaptive framework for rerouting under flash flood conditions, thereby enhancing the resilience and safety of modern transportation networks.

2. Descriptions of the system:

The focus of the research is to develop a Dynamic Traffic Assignment (DTA) model to conduct **Traffic Assignment** based on a flash flood situation with a transportation network that is determined by **Trip Generation, Trip Distribution and Mode Choice.** Explanations of these terms utilized in our research are given as follows.

Trip Generation: the transportation network is divided into N zones, each serving as both origin (O) and destination (D). This process, denoted as OD, quantifies the number of trips generated from each origin zone (O_i) and the number of trips arriving at each destination zone (D_i), where i ranges from 1 to N.

Group 9: Atticus Rex,
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Trip Distribution: In this step, we distribute trips between origin zones and destination zones. The precise number of trips between each pair of zones, represented as T_{ij}, is determined.

Mode Choice: the total number of trips between zones (T_{ij}) is distributed among M transportation modes, such as buses, automobiles, and taxis. This allocation ensures that the total number of trips assigned to each mode corresponds to the actual trips between the zones, optimizing the utilization of different transportation options within the network.

Traffic Assignment determines the routes (routing) for trips (T_{ij}^{m}) associated with each mode (m). The assignment of routes is a critical step and can be based on various criteria, including shortest travel time, minimum distance, or overall network efficiency. Common modeling approaches utilized for this purpose include All-or-Nothing (AoN), User Equilibrium (UE), and System Optimal (SO) methods. We are planning on using a **dynamic traffic assignment** method described in the next section.

The transportation network studied with signal settings would be either an arbitrary network or a real network from open street map (OSM) to be determined from further research. Once determined, the network, signal settings and original travel time among all links are set to be constant in the model.

The OD matrix (trips and modes) and time series information of flash flood would be variables of the model. Incorporating the flood conditions will either reroute traffic away from affected areas by deleting the link from the network or adjust travel times based on slower traffic speed due to floods. This impact will differ under different severities of the floods or road inundations.

3. Conceptual Model

Given a normal traffic flow and a flash flood situation, we model how flood dynamics disrupt traffic flow (e.g., road closures, reduced speed) and develop dynamic traffic assignment model that responds to flash flood (from flood dynamics) by optimizing the safety and efficiency of the route.

Input of the model:

- **Urban topology and drainage system layout network:** can be either generated using an open street map (OSM) or be defined by the user.
- **Flash flood scenarios** (e.g., water accumulation, spread based on terrain, drainage efficiency): can either be modeled by a basic hydrological model such as CA-ffé or be predefined using historical weather and flood records of the specific region.
- **Normal traffic flow**: can either be modeled using algorithms like cellular automata or agent-based models or be provided using historical traffic data.

Dynamic traffic assignment: The Dynamic Traffic Assignment (DTA) model will incorporate developed routing algorithms (such as Dijkstra's Algorithm or A*) and modify them to account for the flood conditions. The model would be multi-objective optimization at the end, taking both safety and shortest travel time into account.

Modeling of the traffic flow: Based on the suggested route generated by our dynamic traffic assignment, we will then model the traffic flow affected by the fast flood and the traffic assignment. How the original traffic flow is modified will be determined by a weight in our model. Several factors including driver adaptation rate, rain severity, and level of emergency can affect the weight.

Group 9: Atticus Rex,
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Output of the model:

- **Rerouting paths:** Paths suggested by the dynamic traffic assignment after the flood based on safety and efficiency.
- **Modified traffic flow:** The modeling result of the traffic flow affected by the flood.
- **Visualization of the traffic flow:** Visualization of the traffic flow on the open street map or a map defined by the user

4. Platform of development

- Collaborating through GitHub
- Modeling based on Python and potentially python-based models (e.g. SUMO)

5. Core features

- Dynamic rerouting model in response to varying flood scenarios.
- Simple visualization (Simulation) of flood impact on traffic and effectiveness of reroutes.

6. Literature review

Blöschl, G., Reszler, C., & Komma, J. (2008). A spatially distributed flash flood forecasting model. *Environmental Modelling & Software, 23*(4), 464-478. **https://doi.org/10.1016/j.envsoft.2007.06.010**

The study develops a spatially distributed hydrological model aimed at forecasting flash floods. This model operates on a grid basis to represent runoff generation within the studied area by employing a pixel-based model that uses Kalman filtering to forecast the incidence of flash flooding in Northern Austria. This paper provides a particularly useful approach to parameter calibration and state estimation.

- Model inputs: Temperature, soil moisture, precipitation, elevation, slope steepness.
- Assumption for forecast inputs: The model makes use of forecasts of precipitation and air temperature over a lead time of 48 hours for actual flash flood forecasting
- Data
  - Runoff Data: Data collected from 12 stream gauges from 1990 to 2005 was used to develop the distributed model. The catchment sizes of these gauges ranged from 77 to 1493 km2.
  - Operational Use: The model has been put into operational use for forecasting flash floods in northern Austria, indicating that it utilizes real-world data for its functionality

Choo, K. S., Kang, D. H., & Kim, B. S. (2020). Impact assessment of urban flood on traffic disruption using rainfall–depth–vehicle speed relationship. *Water*, 12(4), 926. **https://doi.org/10.3390/w12040926**

This study assesses the impact of urban flooding on traffic disruptions utilizing a relationship among rainfall, flood depth, and vehicle speed. The model is applied to 3 districts in Seoul under previous flood events (More focused on the rainfall-depth part in which drainage played a vital role).

- Model:

- Spatial Runoff Assessment Tool (S-RAT) and Flood Inundation Model (FLO-2D): calculate the flooding levels in urban areas caused by rainfall and to use the flooding rate for analysis.
- Rainfall–Flood Depth Curve and Flood–Vehicle Speed Curve: These curves were presented during the analysis to aid in understanding the relationship between rainfall, flood depth, and vehicle speed, which in turn helps in assessing the traffic disruption caused by urban flooding.

- Data:
  - Geographic Data and 3-hour Rainfall Profiles is used to establish the Rainfall-Vehicle speed curve and Rainfall-Depth curve.
  - Road network and traffic flow data, Verification with 2011 rainfall events
- Additional Insights: A traffic disruption map was prepared using the analyzed data, which could potentially assist drivers in route selection by understanding the urban flood damage and vehicle driving speed analysis.

Jamali, B., Bach, P. M., Cunningham, L., & Deletic, A. (2019). A Cellular Automata fast flood evaluation (CA-ffé) model. *Water Resources Research, 55*(6), 4936-4953. https://doi.org/10.1029/2018WR023679

This study developed a rapid flood inundation model (CA-ffé) using a novel cellular automata approach. The model does not require preprocessing or postprocessing, and thus it has the advantage of efficiency. The author compared the prediction results between their model and existing hydrodynamic models (TUFLOW and HEC-RAS), and the CA-ffé model agrees with the results from TUFLOW and HEC-RAS in general but with some discrepancies.

- Model inputs: four grid maps (DEM, cell height, boundary type, and cell Excess water volume) and transition rules.
- Case studies (data used): four urban subcatchments located in the Mordialloc Creek and Elster Creek Catchments, Melbourne (Australia), and one small urban area in the UK

Kouroshnejad, K., Sushama, L., Sandanayake, H., Cooke, R., & Ziya, O. (2023). Pluvial flash flood-traffic interactions in current and future climates for the City of Ottawa. *Safety in Extreme Environments*, 5(3), 161-176. https://doi.org/10.1007/s42797-023-00077-5

The article explores the interactions between pluvial flash floods and traffic in both current and projected future climatic conditions for the City of Ottawa.

- Model:
  - Regional Climate Model (RCM) Simulations: The study integrates ultra-high-resolution (4 km) RCM simulations to investigate the climate conditions related to flash flood occurrences.
  - Inundation Modeling using PCSWMM: PCSWMM, a software for modeling stormwater, wastewater, watershed, and water quality systems, is utilized to model the inundation caused by flash floods.
  - Transport Network Modeling: The transport network is modeled to understand and assess the impact of flash floods on traffic within the city.
- Urban flood simulation from City Catchment Analysis Tool (CityCAT)
- GIS-based transport network model (Ford et al. 2015)
- Depth-disrutpion function (basically depth-speed relationship) (Kouroshnejad et al 2016)

CSE6730 Project Checkpoint 1

Group 9: Atticus Rex,
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Li, M., Huang, Q., Wang, L., Yin, J., & Wang, J. (2018). Modeling the traffic disruption caused by pluvial flash flood on intra-urban road network. ***Transactions in GIS*****, 22(1), 311-322. https://doi.org/10.1111/tgis.12311**

This study modeled traffic delays by PFF-related road closure ("combine hydrodynamic model outputs with static transportation network," being criticized by Kouroshnejad for not accounting for precipitation variability, but their study focused on an area about 2km radius and 4-hr window). The modeling outputs from a case study in the city center of Shanghai demonstrated that the delay of vehicles, either diverted to dry links or trapped in flooded links, could range from 0.5 to 8 times the travel time compared to no-flood scenarios. The article mentions a lack of precision and detail in existing approaches to account for realistic flood-induced disruptions to the traffic network, thus underlining the need for a more robust model to assess the impact of pluvial flash floods on traffic

Pregnolato, M., Ford, A., Glenis, V., Wilkinson, S., & Dawson, R. (2017). Impact of climate change on disruption to urban transport networks from pluvial flooding. ***Journal of Infrastructure Systems*****,** ***23*****(4), 04017015. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000372**

PFF-related traffic delays model for a UK city based on a depth-disruption (especially speed change) function

- ultra-high resolution regional climate model GEM (Côté et al. 1998)
- hydrodynamic model PCSWMM (by Computational Hydraulics International (CHI)
- GIS-based transport network model

CSE6730 Project Checkpoint 1

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Update and Initial Results

1. Update of the state of the project

We have determined the structure of the project as described above and made an initial attempt at traffic flow modeling (please refer to the attached pages). There are still topics to be discussed and determined in the following research work:

- Whether the transportation network and DO matrix are arbitrary or generated from the real world.
- Whether to build our own traffic network simulation model or apply the new model as a rerouting strategy in microscopic traffic simulation software SUMO. If time allows, the ideal situation is to develop both and make comparisons.

2. Assignment of work

Till now the team has been working together for literature review of the problem (including on how people have approached the problem and possible modeling tools for solving it) and research plan and conceptual model discussion, because we have diverse backgrounds and there's a learning curve for most of us. During this learning stage, the member with more experience in transportation modeling has shared her experiences and guided the direction.

We have set up a weekly meeting time for progress check and discussion. Starting from the next meeting, the work will be split up and assigned among team members. The next stage of work includes algorithm selection, data searching and cleaning and preliminary modeling.

GitHub Repository

https://github.gatech.edu/glee388/2023Fall-CSE6730-Group9

Appendix: Preliminary Traffic Flow Model

The first step in modeling flood prevention is first to model how traffic propagates through a graph or network. We are interested in how traffic tends to accumulate on the edges (or streets) of a graph over time. First, let's outline some assumptions:

- **Homogeneous Demand**: We are assuming that the demand for the different roads does not change over time. Of course, we know this is case as many Atlanta natives have come to hate rush hour traffic. Later, we will introduce boundary conditions to demonstrate how an influx/outflux of vehicles would affect the model.

- **Steady Flow**: We will neglect the nonlinear stop-and-go nature of intersections and instead average traffic flows from one street to another per unit time. This makes the model much more generalizable and is a common practice within large-scale transportation modeling.

- **Constant Intersection Split**: In this model, we will assume that the proportion of cars that move from one street to another remains constant over time. In other words, consider a four-way stop; we are assuming that the proportion of cars that go left, the proportion of cars that go right, and the proportion of cars that go straight are not necessarily equal, but do remain constant over time.

Smaller quantitative assumptions will be described in further detail later on. Now let's get into the specifics of the model. Let us consider a graph, G, with m edges and n nodes. We will denote a state vector $X \in \mathbb{R}^m$ as the number of vehicles present in each edge. Further, we define V as the flow of vehicles across a certain boundary measured in (vehicles / 10 minutes). If we consider each edge to only have one entry and one exit, then we can form the following simple differential equation:

$$\frac{dX_i}{dt}(t) = V_{in}^i(t) - V_{out}^i(t)$$

From this equation, we would theoretically be able to use some numerical integration scheme such as Euler's method or Runge-Kutte for more accuracy. Let us consider Euler's method for simplicity to illustrate some constraints of the problem. Two of them become immediately obvious:

- **A street cannot have negative vehicles**: This realization should be obvious, but we will have to adjust our numerical integration method to account for this.

- **The number of vehicles cannot exceed some maximum capacity**: We can approximate the maximum number of vehicles on a given street by dividing the length of the street by the length that an average vehicle takes up.

Hence, if we're using Euler's method to integrate, we can see that the number of vehicles evolves over time according to the following formula:

$$X_i^{(t+1)} = \min(X_i^{max}, \max(0, X_i^{(t)} + \frac{dX_i}{dt}(t) \cdot \Delta t))$$

$$X^{max} = \vec{L} \cdot \frac{1}{l_{avg}}$$

Where $\vec{L}$ is a vector of the lengths of each street and l_{avg} is the average length a car takes up. This equation effectively clips the possible values for the number of vehicles on a street to only fall on the interval $[0, X_i^{max}]$. We should notice, however, that this function is both nonlinear and nonconvex, which may complicate optimization later.

Now that we have a general framework in place, we need to be more specific about V_{in} and V_{out}. To begin, some more assumptions need to be made. First, there is some maximum flow rate that cars can move from one street to another. This will likely change depending on the type of turn, capacity of the next street, etc. For example, it is typically much easier to take a right on a two-lane road than it is to turn left and hence the maximum flow rate for right turns may be higher than that of left turns. We will denote all the maximum flow rates in the matrix, $\mathbf{V_{max}}$. Each entry, $[\mathbf{V_{max}}]_{ij}$ denotes the maximum flow rate from street i to street j. If there is no connection from street i, to street j, the maximum flow rate is 0. Hence, $\mathbf{V_{max}}$ will be highly sparse, as for a given street there will only be a handful of connecting streets.

Further, for a given number of cars at street X_i there will be an expected proportion of the cars to move to the next street. In practice, this distribution is likely to be highly dependent on the time of day and other parameters, but they can be assumed to be uniformly distributed if no data is available to calibrate them. For example, many more cars will likely opt to turn onto a highway than a small side street, and these proportions need to be reflected in the model. For this reason, we introduce a matrix of proportions, $\mathbf{P}$, whose entries give p_{ij}, the proportion of cars from street i who are expected to turn onto street j. Note that this probability might not sum to equal 1 in real life as some travelers might meet their destination on a particular street, however we are going to use this as an assumption to constrain the model later. Note that this matrix is also likely to be highly sparse.

Lastly, we have to account for the fact that if a street is full, e.g. there is no more room, then the flow into that street has to be zero. With all of these models in mind, we have the following formula for the flow of traffic into a street:

$$V_{in}^i(t + \Delta t) = \begin{cases} 0, X_i \geq X_i^{max} \\ \psi_i + \sum_{j=1}^{m} \min([\mathbf{V_{max}}]_{ij}, (V_{out}^j(t) \cdot p_{ij})), \text{otherwise} \end{cases}$$

Where ψ_i is the influx of vehicles (vehicles / 10 min) from either the boundary or somewhere else into this street that do not come from the connecting streets. We can think of ψ as an input to the model that we can vary over time to reflect rush hour traffic patterns, seasonal events, etc.

Lastly, we need to quantify the outflow, V_{out}^i of a given street, i. Initially, it seems to be quite similar to the inflow until we realize that we have to include some sort of delay. Some streets are much longer than others and some have very different speed limits, making the time that it takes cars to traverse the street quite variable. For example, if a large influx of cars entered an empty street, V_{out}^i would be 0 until that influx of cars reached the end of the street. For this reason, V_{out} needs to equal V_{in} after the time it takes to cross the street. Hence, we need some metric to determine travel time, T_v across the street. We will adopt and slightly modify the approach used in Li et al. which uses the BPR (U.S. Bureau of Public Roads, 1964) to approximate travel time:

$$T_v(X_i) = T_0^i[1 + \alpha(X_i/X_i^{max})^\beta]$$
$$T_0^i = \vec{L}_i/\vec{S}_i$$

- $T_v(X_i)$: Congested travel Time for street i.
- T_0^i: Free-flow travel time for street i.
- $\vec{L}_i$: Length of street i.
- $\vec{S}_i$: Speed limit of street i.
- α, β: Parameters to be calibrated.

If we use a time-delay to denote how long it takes cars to travel down the street at a particular congestion level, denoted by X_i, the number of vehicles on street, i, then we arrive at the following formula:

$$V_{out}^i(t + \Delta t) = \sum_{j=1}^{m} \begin{cases} 0, X_j \geq X_j^{max} \\ \phi_i + \min([\mathbf{V_{max}}]_{ij}, V_{in}^i(t - T_v(X_i(t)))) \cdot p_{ji}, \text{otherwise} \end{cases}$$

Similar to ψ_i, ϕ_i is the outflux of vehicles that are not leaving to go to other streets. We will use this to simulate cars "leaving" the city. When the street ends and there are no connections $p_{i,j}$ will be zero since there is no probability of going to a different street.

Problem Statement

To simulate the introduction of a flash flood, we can set some of the entries of $\mathbf{V_{max}}$ and $\mathbf{P}$ to 0 (and make minor adjustments to keep proportions equal to 1). The objective then becomes altering $\mathbf{P}$ to maximize traffic flow which can be denoted as: $||\frac{dX}{dt}(t)||$.