Creating a Model to Predict High-Risk Areas for Pluvial Flash Flooding in the Urban Areas of Houston, Texas

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Abstract

Floods are unpredictable, and current flood maps have some flaws. One of their major flaws is the lack of consideration towards pluvial flooding, precipitation flooding that can turn into a flash flood. This type of urban flooding has not been explored in depth because urban infrastructure varies, and much research focuses on coastal flooding. However, urban flash flooding does happen, and more often than not, residents are not ready or well-informed. In particular, the prominence of impervious surfaces — artificial structures that do not absorb water like asphalt and concrete — makes urban areas particularly vulnerable to pluvial flooding. This research addresses the use of previous data related to elevation, precipitation, and flash flooding in Houston, Texas. The data, collected by several sources including the GLOBE Observer land covers, OpenTopography elevation data, and QGIS analysis features, is developed into a program that predicts areas at high risk for severe flash flooding by simulating water flow direction and accumulation based on terrain elevation. The model analyzes global 10m/1/3 arc second Digital Elevation Model rasters and visualizes the various analyses using Python's matplotlib library. In particular, the model uses the popular D8 flow raster algorithm to identify the direction of water flow at every given elevation point throughout a select AOI's elevation raster. Then, it runs a flow accumulation function on the raster to find specific elevation points that many other cells flow into, indicating areas particularly vulnerable to water accumulation in a flash flood. The data examined centered around Houston, Texas, but users can apply this technology to any area covered by GLOBE Observer in the United States.

Introduction

Flooding is a common global natural disaster in areas near water. Flooding can be caused by both natural and man-made factors. A more common type of flood is coastal floods, which often cause severe damage and numerous casualties. Nevertheless, with the proper research and tools developed by environmental scientists and meteorologists, these coastal areas are warned with time to evacuate. However, several flooding tools and maps are flawed: they lack information and data on pluvial flash flooding. Flash flooding is a type of flooding that comes with minimal warning, and it desecrates cities as it happens. This type of flooding occurs commonly in urban areas due to factors such as pavement and poor drainage. The pavement and other impervious surfaces do not allow water to be absorbed into the ground, thus resulting in pooling water and flooding. In addition, many urban areas do not have the proper drainage systems for flash floods, and this oversight can harm their residents. This lack of precautionary efforts puts several groups in danger, including small children, the elderly, and animals, who are vulnerable to the sudden strength of flash floods. Currently, there are limited tools that can help predict areas of vulnerability in the event of a pluvial flood. However, several databases can aid in identifying high-risk areas for pluvial flooding, serving to develop ways to warn the public on time. This paper will address the combination of databases to create a model that will predict high-risk areas for flash flooding in urban areas. The locations for this case study are several areas in Houston, Texas, which will be used for a flood simulation using previous elevation and flood data. The anticipated result of this model is to become a tool used to predict areas with a high risk of pluvial flash flooding by simulating a pluvial flood at any AOI point(s) supported by GLOBE Observer in the United States.

Literature Review

<u>Pluvial Flood Risk and Opportunity for Resilience</u>

One of the main reasons for the difficulties in predicting pluvial flooding and identifying high-risk areas is the limited data collected in urban cities. More often than not, it is due to indifference or misleading assumptions about pluvial flooding. One incorrect assumption is that pluvial flooding causes minimal damage. However, there is evidence that the effect of several small floods is much more destructive than a few severe floods. Additionally, several city infrastructures neglect to maintain and expand their storm drainage in response to previous pluvial floods, further endangering the residents and properties.

<u>FEMA Flood Maps Fail to Show Flood Risk of More Extreme Flooding Events</u>

In recent years, there has been a surge of online videos of flash floods destroying cities and neighborhoods in areas absent in FEMA flood maps to be high risk for floods. This has cost thousands of people to pay for flood repairs because there have been no indicators to buy flood insurance in past years. This model could aid in protecting the residents from paying for unexpected flood damage that could be covered by insurance.

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Methodology

We used two channels to generate accurate and clean data to enter into a flash flood model simulator. The first channel is from OpenTopography. The second channel we plan to use is from the AOI points collected as a team. These points contain images of the North, West, East, and South GLOBE Observer data. We run a series of steps to extract slope data from these images: first, we perform semantic segmentation using the UNET architecture. This segmentation algorithm separates the ground from all other objects. Once we have identified the ground, we run a SIFT feature extraction algorithm that gives us a series of "important" points in the image. We run a monocular depth estimation algorithm, ZoeDepth, which provides the 3D information of these ground features. Finally, we interpolate the points around the features, ultimately building a dataset of elevation nuances on the ground.

With the elevation data found from the AOI points, we then use QGIS to create a Digital Elevation Model (DEM) to run the flood simulations on. Since the data is in XYZ or point form format, the comma-separated values (CSV) file was added as a delimited text layer, allowing for the X mode and Y mode to be longitude and latitude, respectively. As the AOI points are scattered, we fill in the blank spots to improve the DEM's accuracy by interpolating elevation data from OpenTopography with the AOI data using IDW interpolation. Then, using the elevation as the interpolation attribute, TIN interpolation is applied to create a DEM that is exported as a Tag Image File Format (TIFF) file (Figure 1).

Using Google Colab as a notebook, we designed a Python program to extract and visualize the elevation data from the DEM files. This program performed a D8 flow analysis on the dataset, a type of raster analysis used to find the direction of the steepest flow. For the D8 method, each coordinate or cell directs flow to its steepest downward neighbor. The program calculates this steepness or descent using the formula shown in Figure 2. Furthermore, cells in a D8 analysis have a maximum of eight neighbors to flow into. Based on the direction of a cell to its steepest neighbor, each cell is assigned a new direction code from 1-128 using the grid shown in Figure 3. When a cell has two or more directions with the same maximum descent slope, the corresponding direction codes are added. For example, if a cell had a maximum descent of 5m directly east and south, it would have a code 1 + 4 = 5. Because the base codes are all powers of 2^n, all 255 unique combinations of directions correspond to one code and vice versa. The advantage, therefore, of this labeling system is that a particular cell's flow information is represented by an 8-bit integer. This program performed this analysis on each DEM raster for the Houston AOIs selected, with each DEM leading to a new "directions_grid" numpy array that stores the direction codes for the AOIs. Next, the program performed another analysis based on the flow accumulation, highlighting important cells where many other cells would contribute water. Then, three topographical plots (shown in Results) were generated using Python's matplotlib library. The first was a color-based elevation topographical map using the raw DEM data that visualized raw elevation data for each AOI and identified the areas with lower elevation that could be at higher risk of flooding. The second depicted the same AOI but under the D8 flow analysis where each color corresponds to a particular direction code. Finally, the third plot showed which locations were at the highest risk of flooding.

To make this tool accessible, we made a website that allows users to select areas in Houston to simulate the flash flooding. We built the front end of the website using Python and HTML, specifically using Flask and the Javascript library Leaflet. We used Leaflet to build the interactive map where users could select and deselect AOI points (Figure 4). The points were imported into the website via a CSV file in SQLite. After confirming their points, a DEM of the selected points would appear on the website, and users can simulate flash floods on the model which would reflect how flash floods would occur at that AOI location. The website is a very useful tool to publicly implement the resource we created and aid with flash flood preparation for those living in that AOI area. For now, we are focused on the Houston area, but we hope to expand the website and implement it globally.

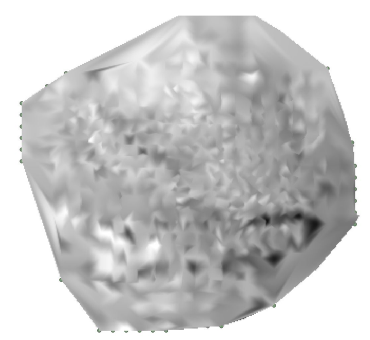

Figure 1

$$Steepness = \frac{E_{cell} - E_{neighbor}}{distance}.$$

Figure 2

32	64	128
16	Cell	1
8	4	2

Figure 3

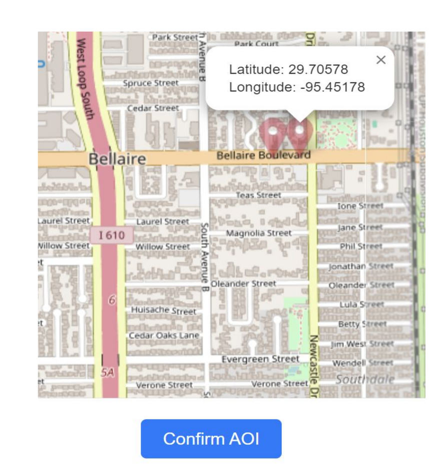

Figure 4

Results

The result of this research is a model for a certain area in Houston, TX, that displays the water flow and its flow direction, encompassed into a front-end (Figure 5) for accessibility. On the front-end, the user will select an AOI point, and confirm it. The Python back-end will then generate the two topographical plots, the filled DEM (Figure 6) and the D8 Flow Direction (Figure 7), resulting in a map for predicting high risk areas for flash flooding. The Flow Accumulation map (Figure 8) highlights specific areas that are at highest risk of flooding.

Figure 5

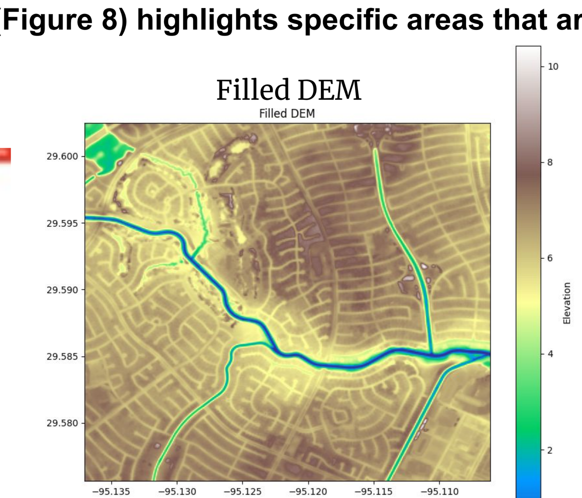

Figure 6

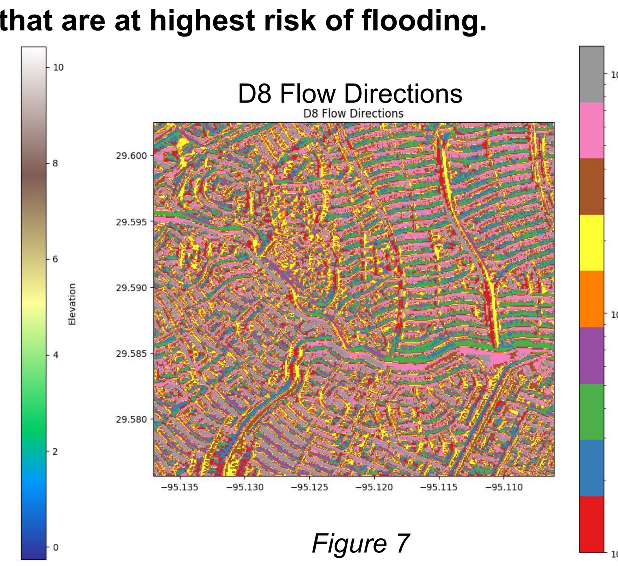

Figure 7

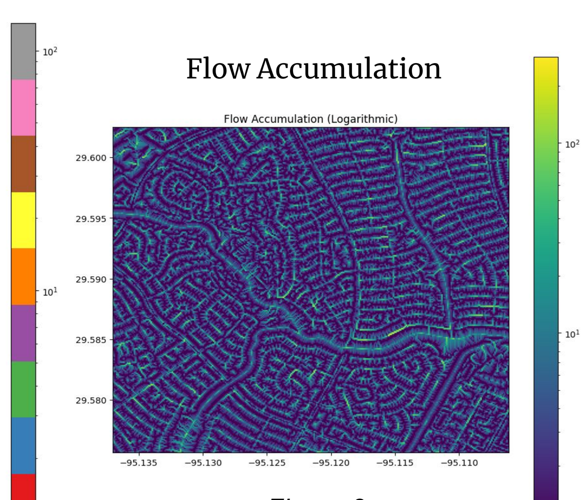

Figure 8

Discussion & Conclusion

There are several ways to interpret this model, but the one thing that remains true is that this model is intended to aid scientists and residents of high-risk areas to predict how a flash flood will affect the area in which they live. In comparison to data and previous models, the data types collected are very similar, and the models both take a very closely related approach to mapping areas. However, our model takes into account elevation and fluid mechanics as the primary data source, whereas this model (Figure 9) from Fondazione CMCC Centro Euro-mediterraneo sui Cambiamenti Climatici (CMCC) takes precipitation levels and previous damage as the primary data source.

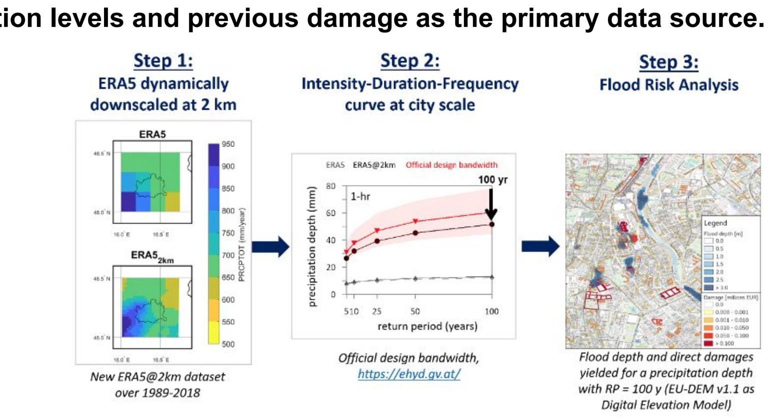

Figure 9 (Source: Copernicus)

Our newly developed model suggests that precipitation flows into the streets, possibly because they are built slightly lower than the elevation level of urban infrastructure. These results could be influential to policymakers in improving the storm drainage system on roads, advocating for policies that keep the roads free of excess water. With these policies, more studies on pluvial flash flooding could be funded or approved by the government or private companies, as they become more relevant to the world of politics.

Our model has potential for errors and oversight due to the limitations of our research. As high school students, we did not have monetary funding to conduct our research. Another limitation involved the virtual nature of our internship, which interfered with concise and timely communication. Additionally, the timeline for the research process was limited to two weeks, which influenced the quality of our work.

As a research team, we hope that our model is used and advanced with more research from the scientific community, eventually becoming a solution to the flaws in flood mapping. The research conducted in the future could be crucial to advancing cities, preventing severe damage, and, most importantly, improving residents' lives.

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