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Modeling and Mapping Flood Hazard with a Flood Risk Assessment Tool: A Case Study of Austin, Texas

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Abstract

As a hazard, flood is an extremely important indicator of how a city is resilient to waterborne diseases and epidemics. Over many decades, flood as a hazard has been a major factor in inducing displacement of marginalized section of the people. Austin city within Central Texas has been identified as one of the major hotspots for flooding in recent decades. Thus, the objectives of the paper are two folded: 1) Empirically, we analyzed and mapped out the susceptibility levels from the factors of physical environments to assess the risk of urban flooding (rainfall data, surface water bodies and topography); in Austin, Texas and 2) Methodologically, we created a re-useable ArcGIS scripting tool that can be used by researchers to automate the process of flood risk modelling with certain criteria. The paper showcases a novel time sensitive building of a tool which will enable better visibility of flood within the city of Austin.

Keywords

Mapping, Texas, Flood Risk, Susceptibility, Vulnerability, GIS, ArcPy

1. Introduction

Flooding is one of the most widespread hazards around the globe. Atmospheric anomalies are responsible for the creation of flooding [1]. Central Texas has witnessed one of the highest recorded floods in any other region in the U.S. Between 2011 and 2020, statewide, central Texas experienced three 100-year floods [2]. The City of Austin lies in the heart of Central Texas and is prone to inland floods characterized by excessive precipitation and high-water runoff volumes within the watershed of river or stream. The area's rocky, clay-rich soil and steep terrain make it uniquely vulnerable to major flooding. In addition, the geographical location places the city at a meteorological disadvantage from flooding due to the major storms from west (from the Pacific Ocean) and southeast (from the Gulf of Mexico), and strong frontal boundaries coming in from the Great Plains. At times, such as with the "perfect storm" of 1998—known as, the Great Central Texas flood—more than 20 inches of rain fell too fast, for too long, leading to significant overburdening of streams and rivers [3]. Furthermore, new meteorological data, known as Atlas 14 [2] (NCEI/NOAA, n.d.), have now revealed that parts of Austin will experience, on average, three inches more rain in major storm events than the National Oceanic and Atmospheric Administration had calculated with old rainfall data back in 1961 [4].

The metropolitan area has experienced at least six major flood events throughout the twentieth century, including the 1900 Austin Dam Break, the 1935 Upper Llano River flood event, the 1981 Memorial Day Flood, the 2013 Halloween Floods on Onion Creek, the Memorial Weekend Flood of 2015, and the Hill Country Flood of 2018. Therefore, with the construction of concrete structure the area becomes more urbanized, including adverse repercussion on biodiversity, property damage, and increasing loss of homes to flooding for people lying at the bottom of the economy [5].

Austin (**Figure 1**) is situated within the Hill Country of Central Texas. The city has geographical coordinate(s) extending from 30.2672 North to 97.7431 West. The city is covered majorly by the county of Travis, followed by some of the sub-urban regions by Hays and Williamson counties. Additionally, Austin is represented as the capital city of Texas State. According to the official website of

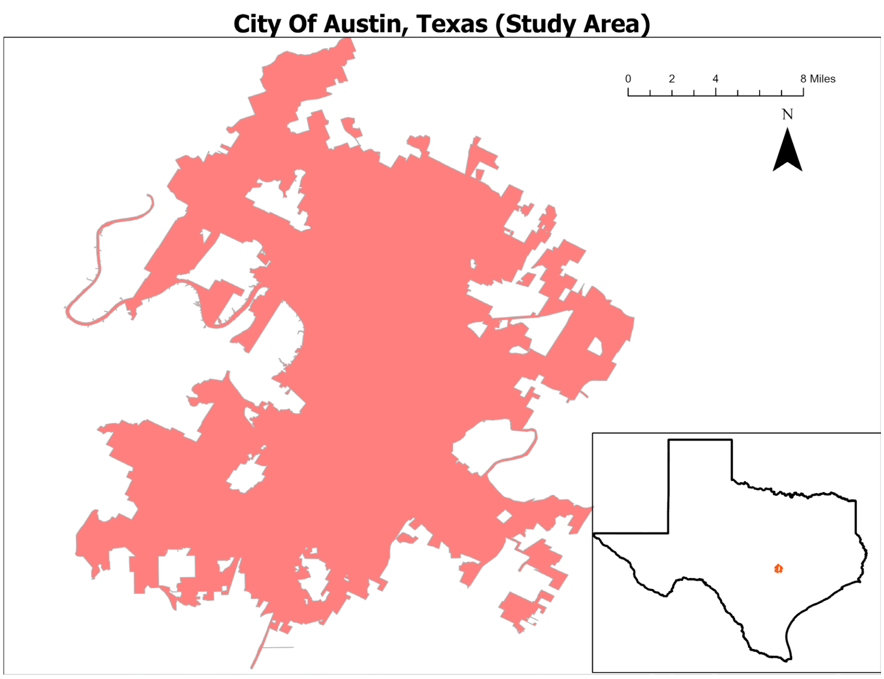

Figure 1. Map of the study area.

Austin, Texas, the city has been experiencing population explosion over the last five years. The city remains the source of numerous lakes and waterways such as Lady Bird Lake, Lake Travis on the Colorado River, Barton Springs and Lake Walter E. Long, etc.

Presently, with the advent of population growth, and changes in climatic conditions, the city is now experiencing urban flooding at recurrent intervals. Therefore, it is significant to delve deeper into two sides of the coin. There exists a lot of research flood vulnerability/risk assessment as well as literature on the development of re-useable scripts for modeling purposes. However, there exists no literature that can specifically cater to flood risk modeling. One of the major ideas is to perceive the factors impacting the possibilities of flooding in a booming city like Austin and one of the other aspects will be to perceive the aftermath of the disaster. This will help in the creation of geospatial analytical tool using Python programming that can model flood susceptibility levels of a location based on a set of weighted criteria. This will serve as a base for the automation of future flood modelling research and projects without having users go through the manual struggles of carrying out each step to generate a susceptibility map. Also, depending on the criteria of interest, GIS (Geographic Information System) developers can build upon this model to factor in more variables pertinent to their risk assessment.

The aim of this paper is to create a re-useable scripting tool that can be executed within ArcGIS Pro for flood risk modelling, that automates the analysis of and mapping out of the susceptibility levels to flood risk from a physical environment perspective within Austin, Texas. Several studies have implemented flood risk mapping based on a multi-criteria approach to determine regions most susceptible to flooding [6] [7] [8]. However, we do see the need to generate a means of automating the modelling process with little to no alterations of criterion. With this, components of the physical environment that are sensitive to or influence flood levels are merged to produce an overall physical vulnerability assessment tool. This could prove very useful in the automation of analytical procedures when dealing with flood risk modelling as well as aiding flood mitigation efforts and serving as a guide towards zoning and development in not just this study area, but other cities as well. As such, the following are the major objectives of this study:

1) Map out the susceptibility level from the factors of physical environments to assess the risk of urban flooding: rainfall data, surface water bodies and topography; in Austin, Texas.

2) Create an ArcGIS tool that can automate the process of flood risk modelling with certain criteria.

2. Literature Review

Marginalized populations disproportionably inhabited the hazard-prone areas; they are more susceptible to the impact and have extremely low coping mechanisms with socio-natural disasters [9]. The adverse impacts of flooding [are] experienced disproportionately by the poor [10]. Their research simulates the interactions of flood events with flood response models to examine flood impact in socially heterogeneous communities. With the advent of increasing climate crisis: urban flooding concerns the cities of the West, will need to focus on adapting to sophisticated methods to manage land use, infrastructure, and service provision" [11]. Lastly, Natural hazards have relatively more impact on people who are exposed to social inequality [12].

Flood risk evaluation is approached using catastrophe theory [13], however, they lay a conceptual framework for considering flood risk that featured four categories used in the current research. Disaster Drivers include the weather patterns of a region, most importantly the average precipitation. Disaster Environment refers to the geography of a region, examining slope and other physical features. Disaster Bearers consider the socio-economic factors of an urban environment, and Disaster Bearing Capacity examines the environment's ability to hold water. A Weighted Linear Combination technique to develop a GIS-aided urban flood hazard zoning map within Argentina by focusing on the analysis of the variables that control routing at times when high-peak flows surpass drainage system capacity [14]. The weight values were assigned to each variable based on local characteristics of each layer as well as engineering geology development.

Another group of researchers adopted GIS and remote sensing techniques to arrive at a flood vulnerability map for the city of Ibadan, Nigeria by taking into consideration 7 contributing variables [15]. Each variable was introduced into the model one after the other to monitor the effects they had on the overall analysis. A comparative approach was taken between a Weighted Linear Combination method and an Analytical Hierarchy Process to demonstrate the importance of decision makers in the weight determination process and selection of appropriate techniques in decision making [16]. A more complex approach was taken with the combination of 3 multicriteria decision rules; Weighted Linear Combination, Analytical Hierarchy Process and Ordered Weighted Averaging; to produce an overall flood risk map to deal with uncertainties in criteria values and how they influence the overall assessment [17].

A customized GIS tool within ArcGIS software using Python scripting, that could construct the minimum spanning tree of a connected, undirected, and weighted road network by considering all important network junction points as well as distance and time as the cost factors [18]. A GIS tool was created for infinite slope stability analysis using a PISA-m algorithm based on the infinite slope model and the Fist Order Second Moment (FOSM) method, to assess the potential of seismic triggers in slope instability [19]. Another GIS tool was generated with Python scripting to support scale-dependent analysis of spatial heterogeneity with a focus on landscape ecology with results showing that valuable information can be obtained from the spatial distribution of gaps in the input data at different scales [20].

3. Data

Based on existing literature centered around flood risk assessment 6 variables are considered for the assessment of flood risk using the GIS tools [21] [22] [23]. All the data for this analysis was obtained from secondary sources. For understanding water data for the city of Austin, the National Oceanic and Atmospheric Administration website has been selected. Nineteen stations were identified across the city of Austin; these Gage Stations encounter precipitation/rainfall data in the region.

For the purposes of secondary data collection, monthly rainfall/precipitation data (19 stations) was obtained for the city of Austin from January 2021 to December 2021 from the National Oceanic and Atmospheric Administration (NOAA). Mean precipitation for the year is averaged across all 12 months for each station. A Digital Elevation Model (DEM) of Austin was taken from the United States Geological Survey (USGS) in a 10 m-by-10 m TIFF 32-bit format. This serves as a source to obtain not just the elevation of the study area, but also the slope, fill, and flow accumulation. Updated hydrology polygons are obtained from the City of Austin's Open Data portal representative for all the lakes and rivers in the city as well as other inland water bodies. Land Cover/Land Use data is also derived from the city of Austin's Open data portal representative of land use inventory used for regional land use modelling and prediction as well as growth management and watershed modelling.

4. Methodology

Upon extensive review of research done by [21] [22] [23], the 6 factors used for analysis in this study are precipitation, slope, flow accumulation, elevation, Euclidean distance, land use/land cover. All analysis will be done with ArcPy using a set of tools from the ArcGIS Pro Toolbox (**Figure 2**). Using the elevation raster, four important variables will be needed to determine risk levels from a hydrology and elevation perspective. The steepness of each cell of the elevation raster is calculated to obtain the slope of the study area. This works with the notion that the steeper the slope, the lower the flood risk level of that area whereas a gentle slope is indicative of a higher risk of flood. Sinks within the DEM are filled to ensure a proper outline of the streams and basins before the flow direction downslope and flow accumulation can be taken into consideration (in the event of rainfall). Flow accumulation is simply the accumulated flow of the weight of all cells flowing downslope in each cell in the output raster. Cells with high accumulation values have concentrated flows and are more likely to be susceptible to flooding. An inverse weighted distance (IDW) technique is used to interpolate the rainfall data, thus producing a raster surface representative of rainfall levels. Higher rainfall levels are representative of higher flood risk levels and vice versa. It is also important to take into consideration the distance from water bodies in

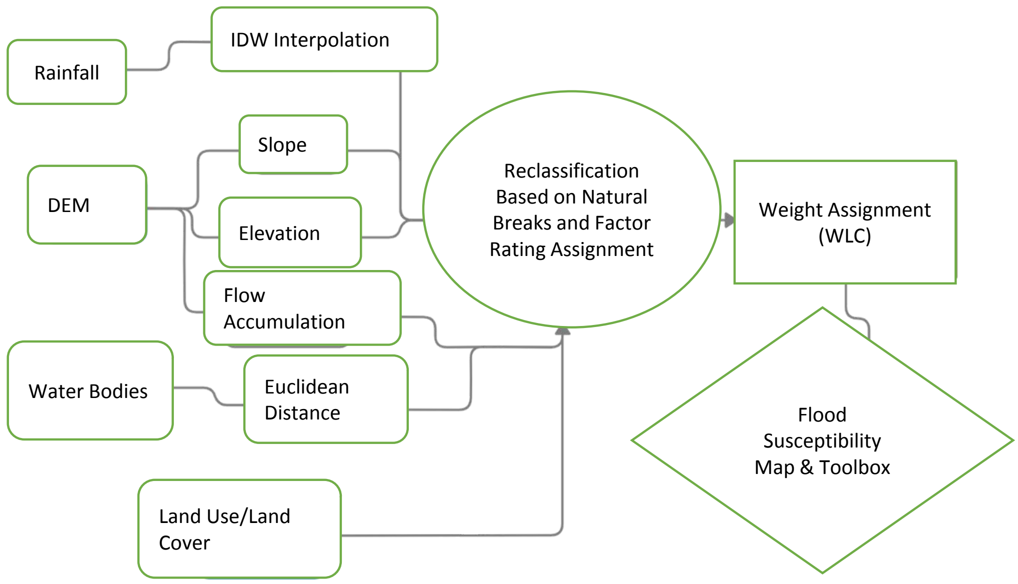

Figure 2. Methodological framework.

the study area to every other point within the defined processing extent. For this study, the straight-line distance (Euclidean distance) is calculated for each point away from an existing water body. The closer a point on the ground is to an inland water source or lake, the higher the flood risk potential and vice versa. Data from the land use/land cover will be separated and classified based developed/impervious cover and undeveloped/pervious cover, the notion behind this being that places with impervious cover tend to fall at a higher risk to flooding than places of pervious cover.

A weighted linear combination method will then be used to assign weights as percentages to all the variables used in this analysis with the total weight summing up to 100.

Weighted Linear Combination

A weighted linear combination works based on the concept of a weighted average of continuous data that are standardized on a common numeric range and then combined by means of a weighted average. Weights are assigned to each criterion by decision makers based on their relative importance to each attribute considered for the analysis. These attribute criteria are then combined by applying the respective weights and are summed up to produce one composite overall suitability/susceptibility map as represented in Equation (1) [8],

$$S = \sum \omega_i \chi_i \tag{1}$$

where S is the suitability, w_j is the weight assigned to factor i, and x_i serves as the criterion score of factor i.

This technique can be implemented on both vector data and raster data. For this analysis, four experts in flood hazard modelling were consulted in the weight derivation process for a better understanding of the influence of each factor to flood risk exposure. To do this, the weights were evaluated and generated using two techniques according to [24]:

- Ranking method: Every criterion is ranked based on the experts' preferences. This is the simplest method for assessing the importance of weights.
- Rating method: Weights are estimated based on a predetermined scale.

Using ArcPy, the methodology for this project will be used to create a separate new tool within the ArcGIS Pro toolbox to enable its use by other researchers. Each variable will be reclassified into 3 classes based on a Natural breaks (Jenks) classification scheme) and also on a criteria value range with a factor rating assigned (**Table 1**). For the purpose of this study, five experts in the field of flood risk assessment were consulted individually, with the aim of having them rank/ weight each variable based on the perceived level of importance. Results from each expert were collated and averaged out to produce the final weighting system that guides the rest of this study.

5. Results

5.1. Tool Interface and Design

The underlying principle of this work, to decipher flood susceptibility, is that

Table 1. Weight linear combination classification criteria.

Weights	Rank	Variables	Range (Natural Breaks Classification)	FactorRating/ Reclassification Value
0.47	1	Rainfall	0.075 - 0.099	Low Risk (3)
			0.1 - 0.111	Moderate Risk (2)
			0.112 - 0.135	High Risk (1)
0.15	2	Flow Accumulation	0.001 - 175,361.941	Low Risk (3)
			175,361.942 - 631,302.988	Moderate Risk (2)
			631,302.989 - 1,277,637	High Risk (1)
0.11	4	Euclidean Distance	0.001 - 0.005	High Risk (1)
			0.006 - 0.012	Moderate Risk (2)
			0.013 - 0.035	Low Risk (3)
0.05	6	Elevation	116.232 - 187.537	High Risk (1)
			187.538 - 244.93	Moderate Risk (2)
			244.931 - 337.976	Low Risk (3)
0.10	5	Slope	0.001 - 4.276	High Risk (1)
			4.277 - 12.59	Moderate Risk (2)
			12.591 - 60.574	Low Risk (3)
0.12	3	Land Use	0-Pervious cover	Low Risk (2)
			1-Impervious cover	High Risk (1)
1				

several geographic factors work in unison to create varying levels of flood risk in a region. All these factors do not contribute to flooding in a uniform way. Rather, some factors have more weightage/relative strength towards causing floods vs others. The tool attempts to generate relevant data with regard to each identified geographic factor. In order to generate such data, the tool takes user input of the location of several files (.tif, .shp, .csv) which describe the region under investigation (**Figure 3**) and feeds them into the tool based on the data prompts of the user interface (**Figure 4**).

With the tool interface in ArcGIS, users provide the location of shapefiles for 1) boundary under observation, 2) water bodies in that area 3) the land use and land cover of the area 4) the raster describing the DEM of the region 5) a .csv describing the precipitation of the region (**Figure 5**). Once the factors are quantified for the region, the tool then reclassifies every factor into a uniform scale (**Figure 6** and **Figure 7**).

Finally, the tool superimposes the flood risk levels into a unified overlay based on user defined weightage assigned to each factor. The final outcome is an overlaid map (.img file) of the project area, showing the risk of flood in each region.

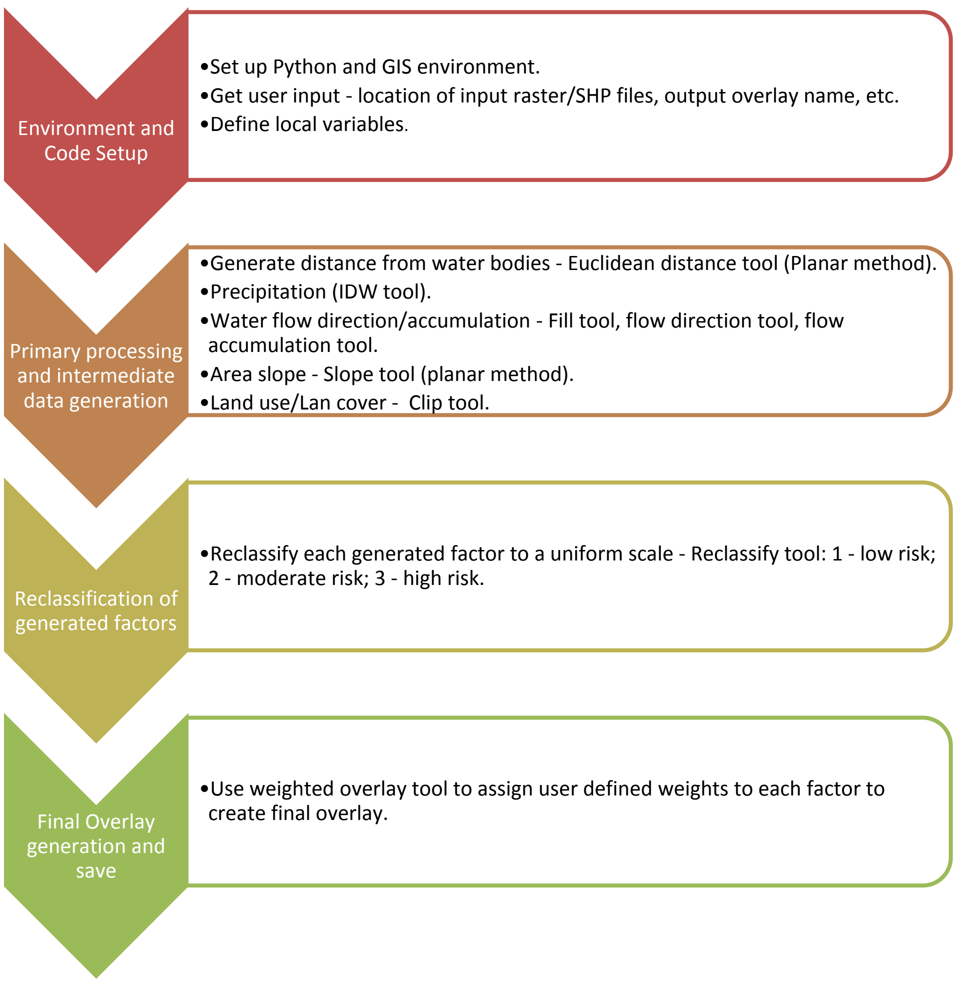

Figure 3. Python code organization.

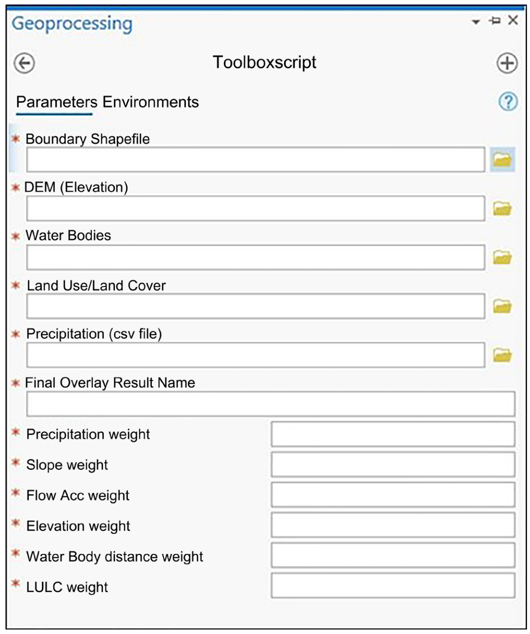

Figure 4. User interface with weighted overlay tool in ArcGIS.

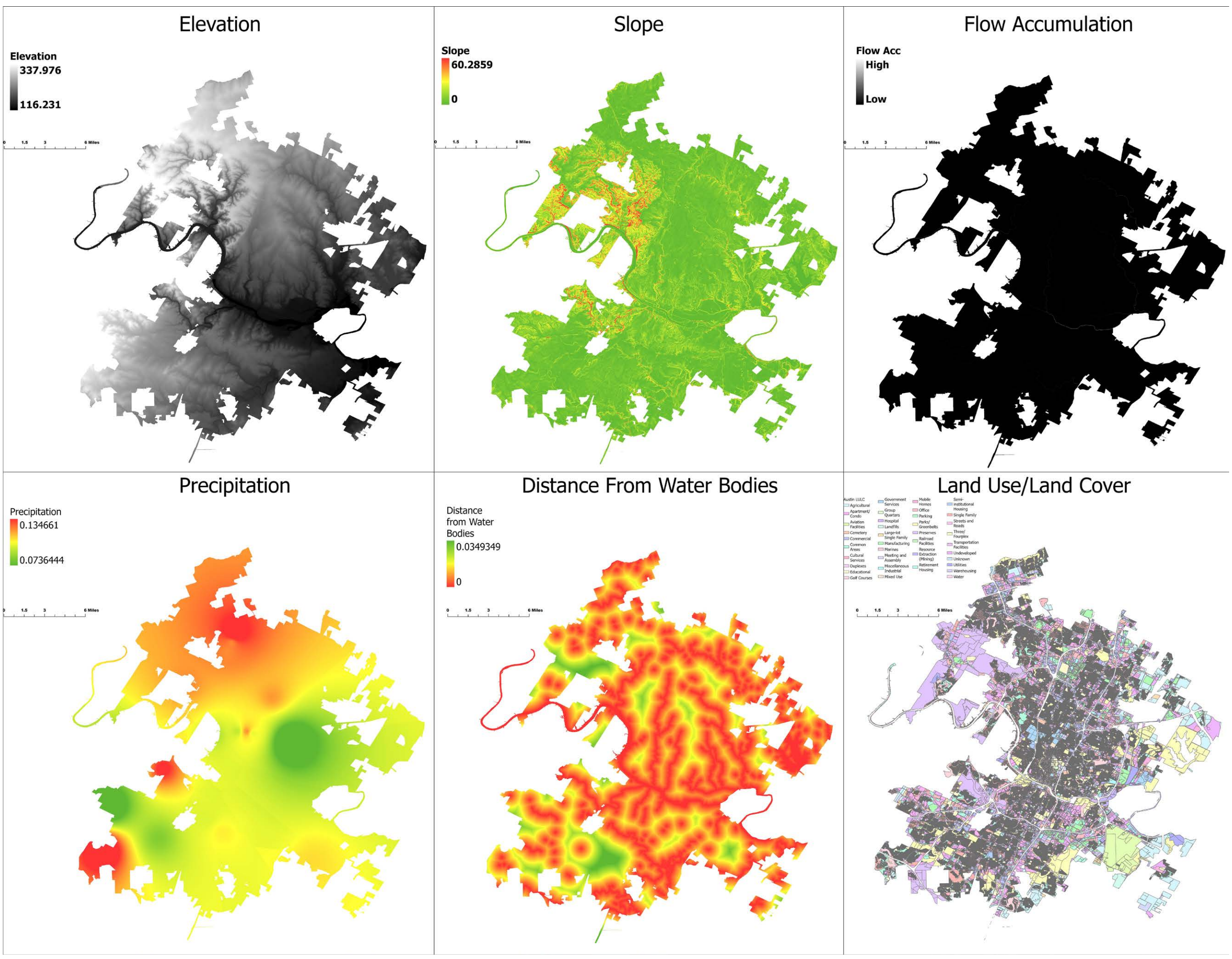

Figure 5. Methodological variables/criteria.

Figure 6. Reclassified criteria values.

The cumulative risk level of the region is computed using the Weighted Overlay tool in ArcGIS, which provides the weighted sum of the risk levels contributed by each individual factor (**Figure 7**). The final product denotes the highest risk of flooding in the northern region of Austin, with small, isolated regions of relatively low risk trending toward the southwest.

5.2. Analytical Results and Maps

Figure 4 is the user interface of the newly created tool within ArcGIS Pro. The parameters marked with an asterisk are the necessary variables as well as weighted values that are plugged in to generate the final risk map (**Figure 7**), show the relative susceptibility of parts of Austin. A greater portion of the high-risk areas falls within North-west Austin with sparing patches in the South-west. Downtown Austin all the way to the south fall within the medium risk parts and a small part of South-east Austin lies in a low-risk area. It is however important to note that results may vary with the difference in weighted values. The experts for these types of studies could have certain factors of particular interest to them that could influence their weighting decisions. Some could be focused on emergency

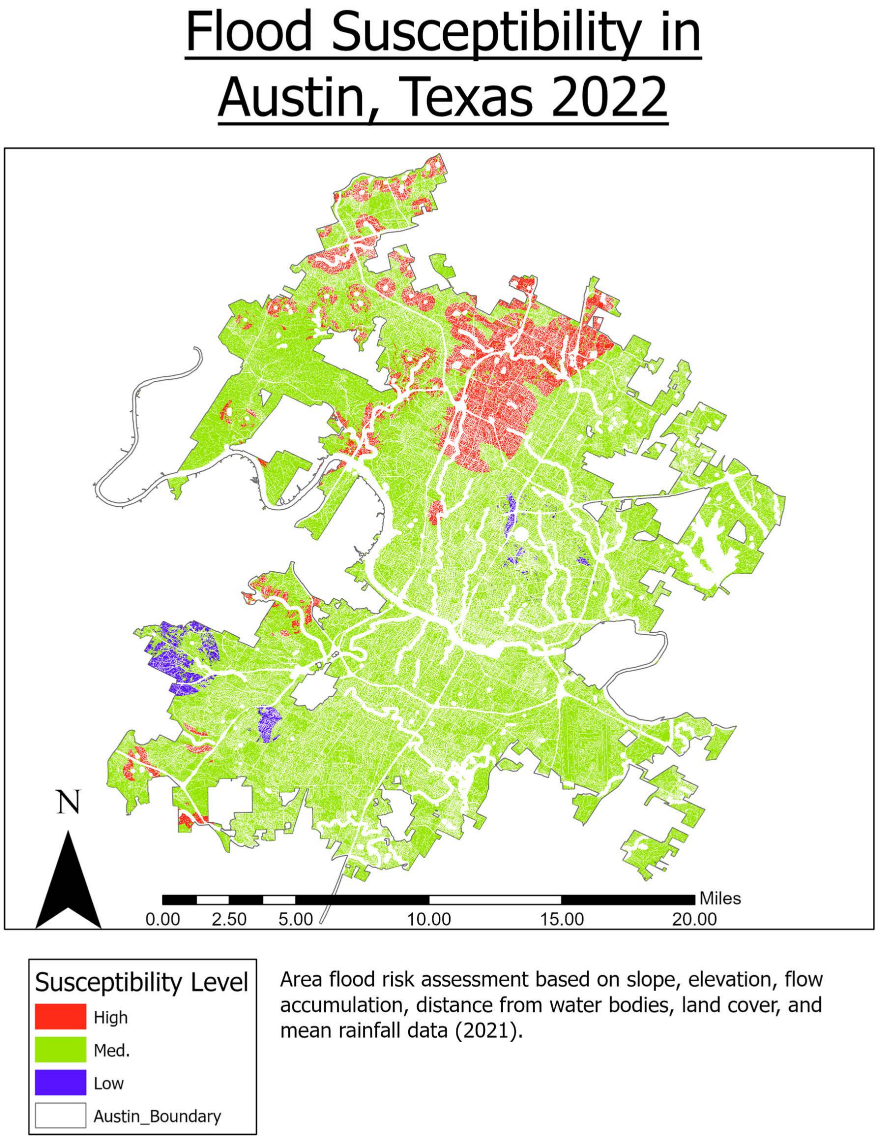

Figure 7. Final combined map for overall susceptibility.

management and hazard mitigation; others could be focused on resource allocation and urban development. These factors influence the risk trends that we will see in the overall susceptibility map. This tool can be used in other flood modelling studies and projects to map out susceptibility levels for different intervention schemes.

6. Conclusion

Flood hazards have proven over time to be one of the deadliest natural phenomena with an abundance of literature from researchers trying to establish and implement susceptibility models that can highlight the high-risk areas in an attempt to aid mitigation efforts as well as urban planning, carry out environmental justice studies, to mention but a few. The cumbersome task of having to go through the flood modeling process step by step can be automated in a way that all the necessary/selected variables can serve as inputs into a single tool, that enables the users to plug in weighted values for each criterion based on their level of importance while reducing computational time. This study attempted to create a Python tool that can be implemented in a geospatial environment to model flood risk levels using Austin, Texas as a case study. Existing literature has highlighted elevation, slope, flow accumulation, rainfall/precipitation, land use/land cover and distance from water bodies as major factors that influence flood levels, however they vary based on the environment and scope of the study. As such, developers can advance this tool in more complex ways to suit their research needs. With this tool, analysis with a weighted linear combination (WLC), Analytical Hierarchy Process (AHP) and even computational programming can be carried out once experts have been consulted on a pairwise comparison and the determination of criteria weights, and the maximum and minimum values per variable are known.

This study is however not without limitations with the most prominent being the classification scheme. Ideally users should be able to set the determined ranges for each variable that fit specific needs or requirements. However, for this study, a natural breaks (Jenks) classification scheme was used to segment the different variables but the range of values for this scheme was gotten manually and hard coded into the tool, thus forcing users to hard code their ranges within the script. Future studies in this regard will be centered on adopting the array of classification schemes from ArcGIS Pro into python to make this process seamless.

Authors' Contributions

Conceptualization: Chikodinaka V. Ekeanyanwu, Priyanjali Bose, Matthew Beavers; Methodology: Chikodinaka V. Ekeanyanwu, Priyanjali Bose, Matthew Beavers, Inioluwa Obisakin; writing—original draft preparation: Chikodinaka V. Ekeanyanwu, Priyanjali Bose, Matthew Beavers; writing—review and editing: Chikodinaka V. Ekeanyanwu, Priyanjali Bose, Matthew Beavers, Yihong Yuan, Inioluwa Obisakin; supervision: Yihong Yuan. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest regarding the publication of this paper.

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Appendix

Table A1. Rainfall and precipitation data source: national oceanic and atmospheric administration (NOAA); accessed: 22nd March 2022.

STATION	NAME	LATITUDE	LONGITUDE	ELEVATION	DATE	PRCP(INCH)S
US1TXTV0044	AUSTIN 1.0 N 45TH AND SHCRK, TX US	30.320713	−97.750208	196.9	12/31/2021	0.116275072
US1TXTV0293	AUSTIN 1.0 NNE, TX US	30.318536	−97.743766	196	12/31/2021	0.106740331
US1TXTV0111	AUSTIN 10.8 WSW, TX US	30.195271	−97.90217	277.1	12/31/2021	0.134660767
US1TXTV0332	AUSTIN 2.1 WNW, TX US	30.316692	−97.782559	176.8	05-02-2021	0.102
US1TXTV0334	AUSTIN 2.8 E, TX US	30.310035	−97.7043067	189.3	12/31/2021	0.073644315
US1TXTV0087	AUSTIN 3.9 NNE, TX US	30.3574	−97.72355	229.2	12/31/2021	0.115766871
USW00023907	AUSTIN 33 NW, TX US	30.6222	−98.0846	414.8	12/31/2021	0.09260274
US1TXTV0122	AUSTIN 5.6 WSW, TX US	30.280817	−97.839183	240.8	12/31/2021	0.125328185
US1TXTV0164	AUSTIN 4.1 SW, TX US	30.2277973	−97.793987	205.4	12/31/2021	0.105666667
US1TXTV0117	AUSTIN 5.9 NW, TX US	30.372069	−97.81338	217.6	12/31/2021	0.116920821
US1TXTV0333	AUSTIN 6.6 SSW, TX US	30.21334	−97.77586	189	12/31/2021	0.109378531
US1TXTV0318	AUSTIN 7.0 N, TX US	30.404979	−97.770507	258.5	12/31/2021	0.116704871
US1TXTV0113	AUSTIN 7.3 SW, TX US	30.207183	−97.843988	229.2	12/31/2021	0.097270195
US1TXTV0292	AUSTIN 7.6 W, TX US	30.295181	−97.877516	239.9	12/31/2021	0.091263158
US1TXTV0320	AUSTIN 8.2 N, TX US	30.424167	−97.763333	282.9	12/31/2021	0.131732026
US1TXTV0228	AUSTIN 9.8 WSW, TX US	30.24137878	−97.89620209	313	12/31/2021	0.080864553
USW00013904	AUSTIN BERGSTROM INTERNATIONAL AIRPORT, TX US	30.18311	−97.67989	146.5	12/31/2021	0.110739726
USW00013958	AUSTIN CAMP MABRY, TX US	30.3208	−97.7604	204.2	12/31/2021	0.103369863
USC00410433	AUSTIN GREAT HILLS, TX US	30.4144	−97.7664	268.2	12/31/2021	0.116821918