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Developing Blue Spots Model for Tennessee Using GIS, and Advanced Data Analytics: Literature Review

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Abstract

Climate change and global warming results in natural hazards, including flash floods. Flash floods can create blue spots; areas where transport networks (roads, tunnels, bridges, passageways) and other engineering structures within them are at flood risk. The economic and social impact of flooding revealed that the damage caused by flash floods leading to blue spots is very high in terms of dollar amount and direct impacts on people's lives. The impact of flooding within blue spots is either infrastructural or social, affecting lives and properties. Currently, more than 16.1 million properties in the U.S are vulnerable to flooding, and this is projected to increase by 3.2% within the next 30 years. Some models have been developed for flood risks analysis and management including some hydrological models, algorithms and machine learning and geospatial models. The models and methods reviewed are based on location data collection, statistical analysis and computation, and visualization (mapping). This research aims to create blue spots model for the State of Tennessee using ArcGIS visual programming language (model) and data analytics pipeline.

Keywords

Blue Spots, Floods Risks and Management, GIS, Hydrological Models, Geospatial, Model Builder, LiDAR Data, Remote Sensing, Data Analytics Pipeline

1. Introduction

The constant and erratic nature of the global weather pattern and global warming results in the occurrence of several natural hazards including flooding. While flooding can occur because of engineering failures (dams and levee breaches), most occurrences are linked to weather extremes. According to U.S. Global Change Research Program (USGCRP) in 2017 (USGCRP, 2017), there are more flooding events occurring in the Mississippi River Valley, Midwest, and Northeast region of the United States. Floods can occur with little or no warning, particularly flash floods; in addition to the hazardous nature of floods is the occurrence of flash floods with speed and unpredictability, heavily impacting lives, and infrastructures. Among the infrastructures impacted are the transport networks (road stretches, bridges, tunnels, water passageways) and other engineering structures constructed to aid transportation. Flash floods result in the creation of blue spots; these are the areas vulnerable to flooding during fill or overflow water conditions, putting the lives and infrastructure within it at flood risk.

The weather channel (2018), reports on the economic impacts of flooding; annual flood fatalities in the United States is over 100 lives and vast property damage. According to Nation Resourced Defense Council (NRDC) in 2019 (NRDC, 2019), Federal Emergency Management Agency (FEMA), estimated the cost of repairing and replacing flood-damaged transport networks (roads, bridges), utilities, and other public infrastructure within the blue spots areas between 1998 and 2014 to be $48.6 billion. Generally, the economic impact of flooding particularly in blue spots has been the concern of the states and federal governments, as well as the flood experts. The endeavor of the science world to solve complex problems such as climate change among many others has driven researchers to embrace interdisciplinary approach; some of the recent methods used for flood impact assessment and predictions combine the knowledge from applied sciences and computer science. This article reviews the existing methods and models created for flood impact assessment and predictions in blue spots areas.

2. Literature Review

Historical records of floods are essential tools for predicting current and future flood levels and their economic impacts. Urban areas flood when drainage exceeds their storm water sewer system's capacity, causing surcharging. Water in flooded areas will follow flow paths such as roads, local depressions (blue spots) and other available pathways that allow the flow of water. Flooding is a natural hazard that has been directly linked to climate change. During and after a heavy rainfall, water flows downhill into adjacent streams. Some water may also collect in sinks belonging to catchments. Excess water can collect in blue spots: locations that can flood, usually with significant consequences. Infrastructure that can be damaged when blue spots fill, and overflow include adjacent buildings and roads (Baby et al., 2021). According to Pregnolato et al. (2016), lives and infrastructures threatened by flooding, including transport networks such as roads, water passageways, tunnels, and bridges, can be protected through preventive measures developed from the analysis of climate change data.

2.1. Economic Impacts of Flooding

The disastrous impacts of weather extremes, particularly flooding, affect transport infrastructures like roads, tunnels, and bridges. The economic impacts of flood events can be weighty. According to Marques (2021), annual flood losses cause billions of dollars in annual property damage. Flood Factor (2022) notes that more than 16.1 million properties in the U.S are subject to flooding, including approximately 389,000 in Tennessee; it projects an increase in risk "by 3.2% within 30 years due to constantly changing environmental factors." According to NCEI (2018), flood events along the Mississippi, Missouri, and Arkansas Rivers in 2018 caused $20.3B in damage, impacting multiple infrastructures, including roads. A 2020 report from the Tennessee Advisory Commission on Intergovernmental Relations stated that "on the average, the annual cost of flooding in Tennessee is $234 million." (PEW, 2022).

2.2. Social Impacts of Flooding

Winter et al. (2016) note that flooding has social impacts, including delays to transportation during flood events and impacts employment, health, education, and social activities. The assessment of flooding events has become more important due to population increase, migration, and urbanization; the makes it more important to the state governments and other stakeholders. In 2016, Michielsen et al. (2016) discussed the need for improved means for evaluating flood risks for critical transport infrastructures and communicating these to these infrastructures' stakeholders. According to these authors, "improved methods for estimating current and potential flood risks should be adopted by the department of transportation and environments; this method should provide precise location and the extent of potential infrastructure damage." (ibid.) The authors cite land use, soil types, topography, and geology as important factors to consider in analyzing current and potential flood risk, along with seasonal changes in the environment due to changing climatic factors.

2.3. Flood Risks Mitigation and Management

According to Miller, Hughes and Whitlock (1996), the Tennessee Valley Authority (TVA) is responsible for flood management in the Tennessee River Basin. Historically, the TVA treats the December-April time frame as the Basin's major flood season, with the frequent storms occurring in March. Flood events have also been recorded outside major flood seasons. After a devastating storm hit Waverly, Tennessee in late August 2021, Tennessee Coalition (Flood Ready Tennessee) asked Tennessee's governor and policy makers "to commit to state level resilience planning, technical assistance for local governments and projects that will mitigate the impact of flood events." (PEW, 2022).

Federal Emergency Management Agency (FEMA) provides National Flood Insurance Policies (NFIP) to alleviate the socio-economic impact of floods. Still, flood management and mitigation strategies remain important practices. The

Tennessee state government is concerned about funding mitigation planning as an act of preparedness. Bliss (2020), responding to a 2010 flood that cost the state up to $4 billion, noted that flood mitigation could save the state money in the future; thereafter, the federal government allocated $85.5 million to Tennessee for flood hazard mitigation. Most states in the United States engage in five-year cycles of hazard mitigation planning. FEMA (2022) notes that such planning can "identify natural disaster risks and vulnerabilities and develop long term strategies" that "reduce[s] loss of life and property by minimizing the disasters' impact." The government's proactive planning, readiness and involvement of flood experts has generated several flood models.

2.4. Models Used in Flood Risk Analysis and Management

2.4.1. FloodStroem Model

According to Teng et al. (2017), commonly used flood models include the 1D (one dimensional) distributed drainage model, the 2D (two dimensional) distributed surface overland flow model and the dynamical coupling model (1D-2D). The large computational time demand of the 1D-2D flood model renders it useless for large areas requiring multiple simulations and more running time.

Thrysøe et al. (2021) developed a dynamic urban pluvial flood and damaged assessment model termed FloodStroem, which requires no calibration being a surrogate mechanistic model. The research's goal was to investigate FloodStroem model's ability to emulate overland processes. The model is comprised of five sub-model components; these include M1—Dynamic distributed input e.g., from 1D model, M2—Generation of flow network, M3—Dynamic mechanism modelling of surface flows, M4—Conversion of conceptual results to 2D floods maps, and M5—Damage assessment; each of which models a specific aspect of flooding. One component, which identifies local blue spot, pour points and downstream flow paths from a digital elevation model (DEM), uses a surface flow network generated using Arc-Malstroem; an open-source software application by Balstrøm and Crawford (2018). Thrysøe et al.'s model postprocesses the blue spots identified by Arc-Malstroem to reduce the sub-model's number of elements and computational costs.

According to Thrysøe et al. (2021), FloodStroem was 33 times faster than the MIKE21 flood model and 60 times than the MIKE FLOOD model. FloodStroem supports the reuse of results from some of its modules when evaluating multiple simulations for the same catchment. The surface routing simulations of the FloodStroem model consumed the least time and performed better when applied to multiple scenarios and large-scale modelling. Other advantages of FloodStroem include support for generating simulated flooding times, patterns, and water levels. Floodstroem's limitations include its rigid surface network model, which does not allow for multidirectional spilling and dynamic adjustments to its surface network, its subpar performance for modeling flat (low-lying depression areas) catchments (Jamali et al., 2019; Zhang & Pan, 2014).

2.4.2. PCD, PLS and ANN Prediction Models

Michielsen et al., developed a model of a region of Sweden that "predict[s] flood hazard probability using roads, railways, and catchment characteristics [along with] a method to effectively interpret and communicate results of flood risk analysis to stakeholders." Geographic information systems were used to calculate physical catchment descriptors (PCDs) for land use, soil type and road characteristics. Five flooded areas and 10 non-flooded road stream intersections areas were selected for the first study area; 9 flooded locations and 15 non-flooded stream road-intersections were selected for a second. The authors' dataset which included a digital elevation model, road and stream shapefiles, land use data, and soil data, was acquired from the Geological Survey of Sweden.

The PCD calculations for flooded and the non-flooded areas for the two study areas were used in combination with partial least square (PLS) regression, binomial logistics regression, and artificial neural networks (ANN) to predict vulnerable locations (floods risks). A cut-off value of 0.5 was selected as the threshold for flood risk using the PLS regression model. Locations with values above 0.5 were identified as "flooded" and values 0.5 were identified as "non-flooded". The authors found that "PLS correctly predicted the outcome of the flooding events selected in an 85% of the catchments within each study area." (ibid.). Using binomial logistic regression, the authors identified urban land use and local channel slope as this model's most important variables for predicting flooding, i.e., "the model correctly predicted the outcome in 72% of catchments following the results of the cross-validation." (ibid.).

The study locations used for the ANN cross-validation were newly introduced into this statistical model (they were not used in the other statistical models); five networks were combined into one for the purpose of visualization. The outcomes of flooding events for each location were assigned "flooded" and "non-flooded" depending on the most common outcome of the five best networks selected. i.e., 3 times flood prediction and 2 times non-flood predictions for a location identified that location to be at flooding risks (ibid.). Overall, the ANN model outperformed the PLS and binomial logistic regression models, correctly predicting flooding in 97% of the catchments. The authors noted that flood risk predictions from the models matched the actual events selected in the model design. For example, some blue spot areas (road-stream intersection) that were flooded in real life were also predicted to be at risk of flooding by the 3 models and an additional blue spot analysis. Similarly, locations that were not flooded (in reality) were predicted not to be at risk of flooding by the 3 models.

2.4.3. Integration Framework (City Catchment Tool and GIS)

In 2016, Pregnolato et al. (2016) introduced an integrated framework to assess the economic impact of disruptions to transport networks and the use of adaptive measures to reduce flood risk in adverse rainfall climates. Pregnolato et al.'s framework "combines information from climate and flooding simulations, with transport networks' exposure analysis while also considering moving vehicles at flood risks." (ibid.). The framework uses flood model tool, City Catchment Analysis Tool, to simulate high resolution pluvial rainfall events based on the calibrations applied on other cities. This tool was augmented with "rainfall (duration and intensity) [and] terrain and boundary conditions". Road networks were omitted to simplify these computations. It uses geographic information system (GIS) data to simulate a region's transport networks. The model "simulated traveling across a transport network, following the spatial and nodes' definitions using least cost and shortest path tool within the GIS environment."

Using this data, the framework creates a vulnerability curve by calculating traffic disruption. The calculation accounts for flood depth for any given flooding scenario, translating this into delays in travel time and economic impact. Pregnolato et al. applied their framework to 2012 data from a flash flood in Newcastle upon Tyne in United Kingdom. This flood was described as series of connective storms, locally referred to as Toon Monsson or Thunder Thursday. The authors acquired their data from the Tyne and Wear Road Traffic an Accident Data Unit (TADU). Based on their previous assessments of the vulnerability of Newcastle upon Tyne's Road network to flooding, Pregnolato et al. suggested link hardening to improve the resilience of transport network infrastructures. Link hardening is a process of making a transportation link completely invulnerable to flooding, This, for example, would include constructing a better drainage system and road elevation to make the transport networks adapt to changing climate conditions.

Pregnolato et al. (2016) characterize their framework as a cost-effective prioritization framework developed to introduce more interventions at the critical road network stretches i.e., in terms flows and flood depth; including more intervention options reduced flooding risks. Overall, the method can be used in quantifying indirect impacts of flooding on transport delays when available flood risk management resources are minimal.

2.4.4. Geospatial Models

Also, spatial models that estimate infrastructures at risk in flooded areas can support decision-making for land-use and development. Creating flood awareness and planning policy requires a business workflow, data collection and spatial database (Baby et al., 2021). While an area's topography can determine the behavior of floods, the geographical extent and flooding time can be determined using precipitation-runoff models. According to Sultana et al., flash floods in geographically small areas can cause more severe damage to infrastructures in blue spot regions than riverine floods because of little or no warning time; the authors developed a method to screen buildings and roads in areas prone to flood risks.

Combining GIS (Geographic Information Systems) and hydrological modelling can also give insights into local flooding and flood risk areas when considering new infrastructure. Currently, geoscientific research collects a wide variety of field and laboratory observations, including outcrop locations, aerial image and photographs, maps, demographic data, and data on land use, climate, and natural hazards. The enormous amounts of geospatial data generated by geoscientific research is becoming increasingly challenging to manage. According to Le et al. (2014), most current geoscientific research now requires "the use a computer or an interaction with some software [system]." These geospatial information systems are being used for processing and analyzing geospatial data, including aerial images, point and polygon data, and other location data.

In 2011, Kourgialas and Karatzas (2011) discuss the use of GIS technologies "to access the complexity in flood data and also to map the relationships between floods and the elements at risk." The authors note that GIS applications are appropriate for "natural hazards such as floods, are multi-dimensional processes with spatial components." (ibid.). Over the last three decades, GIS technologies have been combined with remote sensing to obtain insights into complex geospatial datasets. In 2020, Hall J. et al. (2020) discuss the use of maps and impervious sources in studies of Greater Chattanooga to determine "net spatial growth across watershed and related streams."

Esri's ArcGIS applications are common tools for processing geospatial data. ArcGIS includes model builder, a visual programming language for automating GIS workflows. According to Esri (2022), data processed during an interaction with the ArcGIS software and the analysis done are documented by model builder: a model for the workflow is created visually as a diagram, which can be accessed with model builder. The model created can be saved, shared, and manipulated with python scripting. Uses of model builder in geospatial research include work by Hidayat and Andajani (2018) on "a Modified Universal Soil Loss Equation (MUSLE) model to calculate soil annual loss for Citepus watershed", by Uddin K. et al. (2013) on flood hazard zone and flood shelter maps models using GIS and remote sensing techniques; and by Madurika H.K. et al. (2017).

Sultana et al. identified flooded areas and their associated watersheds using ArcGIS geoprocessing tools. The blue spots model (BSM) was used to determine blue spots on the DEM (digital elevation model), analyze the results, highlight building footprints for spatial selection, and identify buildings within or adjacent to the blue spots. The main processes were carried out using a model builder.

The results before the LiDAR data clean up indicated that approximately 20.5% of the roads within the study area were prone to flood risks during a rainstorm. After the cleanup, the updated results indicated that 14.4% (149 roads) were within or adjacent to blue spots and were at risk of flooding in the event of a downpour. The results also indicated that the effect of floods could affect other infrastructures, such as buildings and highways present in blue spot areas.

According to Sultana et al., the risks posed to infrastructures by floods differ from one blue spot region to another. Also, the rate of filling and overflowing of a sink during a rainfall event depends on its depth, catchment size, or local watersheds; these factors determine the overall impact on the infrastructure. The

BSM calculated the amount of water to fill each blue spot, which can be used to assign relative degrees to flood risks.

Sultana et al. suggested that the inclusion of infrastructural features in the model could improve the outcome. Modeling the infrastructure's location permeability (soil property) and whether large sections of river basins are lined was also suggested for assessing risk to infrastructure in blue spot regions.

3. Conclusion

Flash flood creating blue spots is a national problem directly affecting lives and states' infrastructures. The combination of existing models and tools can be used to produce blue spots maps and actionable insights can be drawn from the data. ArcGIS's model builder application, together with datasets that characterize a region's flow accumulation, slope, elevation, rainfall intensity, land use and geology, will be used to generate a blue spot model for the state of Tennessee beginning with Davidson County. According to Kourgialas & Karatzas (2011), "these datasets were selected and used in the study because of their relevance to flood hazards and they can be modelled using ArcGIS-ArcMap." This model, once developed, should also be applicable to the counties Tennessee and the maps will be available to government, public and private organizations, especially construction companies.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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