Application of LiDAR-Derived Data using Multi-Criteria Evaluation (MCE) and Stochastic Modelling; A Flood Risk Analysis of the Mersey River, Nova Scotia

Almuina Pica, D.E., Nieto Rodriguez, A., Stange, T.

Department of Geography, Environment & Geomatics, University of Guelph (2021) Submitted 16/04/2021

Abstract

The Maritime province of Nova Scotia has seen coastal flooding become a more frequent phenomenon during the past decades due to the changing climate regime. This has influenced the interest provincial and federal governments have on flood risk modelling, who often incorporate Geographic Information Systems (GIS) as useful tools in their analysis. Incorporating LiDAR-derived digital elevation models (DEMs) in their workflows is the next step in hydrological analysis, as LiDAR offers a unique pathway for the analysis of flood risk without the need to rely on biotic or hydrological data. This study aims to follow this theme in order to model the effects of inland flooding in the low relief landscape of the Mersey River, located in Queen's County, Nova Scotia, and its effects on the infrastructure built along the river network. The analysis included multi-criteria evaluation (MCE) methods coupled with a stochastic simulation approach in order to determine areas where vulnerability is the most certain. Five criteria are derived and included in this analysis, them being Height Above Nearest Drainage (HAND), Landscape Slope, Land Use/Cover, Proximity to Hydroelectric Dams, and Downstream Distance to the River. The overall results derived from the MCE and sensitivity analysis workflows indicate that high flood risk is present in urbanized areas along the Mersey River embankment at high confidence intervals, while the Mersey River floodplain appears to flow laterally towards surrounding wetland areas and into drainage basins. The accuracy provided by LiDAR-derived DEMs supported a high-quality workflow for the MCE and uncertainty analysis, proving their utility for floodplain delineation. The addition of historical and hydrological data to future projects could build on the results presented in this study, adding more to the literature on flood risk modelling along the Mersey River.

Keywords: Flood risk, LiDAR, multi-criteria evaluation, hydroelectric dams, stochastic simulation, Monte-Carlo method.

Table of Contents

1. Introduction and Context

1.1 Field of Work

Floods represent one of the costliest environmental hazards to coastal communities, threatening infrastructure and human capital alike in case of a flooding event (Jha, Bloch, & Lamond, 2012, p. 21). The cited study indicates these are issues that are accentuated in an urban setting when contrasted to rural land, as population density peaks in cities where property and assets have a higher economic cost and use (Jha, Bloch, & Lamond, 2012, pp. 21-22). Furthermore, the changing climate regime is expected to increase flood intensity in the following decades, making this an extremely important study area in the near future (World Meteorological Organization & Global Water Partnership, 2009, p. 5).

Flood risk modelling has gained traction in the last decade as a key tool for predicting flood inundation zones and providing reliable information on risk associated with flooding events. Governments and some private institutions often use Geographic Information Systems (GIS) for this purpose, where aided by computer-generated models they can improve damage estimation in case of a natural disaster. LiDAR-derived data can be quite useful for this purpose, as high-resolution digital elevation models (DEMs) allow for the creation of more accurate floodplains, predicting flood risk to a powerful degree of certainty (Haile & Rientjesb, 2005).

Here the integration of GIS with use of multi-criteria evaluation (MCE) comes into play. By using these techniques, GIS specialists are able to evaluate complex spatial problems where more than one variable is involved (Carver, 1991). Although MCEs are more commonly used for creating suitability maps (Eastman, 1999), there is extensive evidence in the literature showing their importance in flood risk modelling (Hazarika et al, 2018, Khan et al, 2018, and Rahmati et al, 2018).

There are, however, legitimate concerns regarding MCEs. The fluctuations in real elevation values, known as the root-mean-square-error (RMSE) can lead to results being very different from the truth, therefore increasing uncertainty in the analysis. In order to assess this, a probabilistic approach can be taken, using stochastic (Monte-Carlo) simulation to run a predetermined number of iterations of the MCE workflow, subjecting its criteria to the fluctuations expressed in the RMSE. Stochastic processes are sometimes used in flood risk modelling and MCE independently (Celik, Gul, Yucesan, & Mete, 2019), but there is a void in literature which discusses their application to both topics combined.

1.2 Research Purpose

This study intends to create a flood risk model for the area surrounding the Mersey river, in Queens County, Nova Scotia, using MCE methodology. A stochastic simulation is then performed in order to analyze the sensitivity of the MCE output to RMSE in the DEM, differentiating at-risk areas with varying degrees of uncertainty.

2. Research Objectives

Our research purpose will be met by meeting the following research objectives:

1) Determine criteria and constraints associated with inland flooding in Nova Scotia.
2) Assign criteria weights using a pairwise comparison matrix, based on reviewed literature.
3) Develop a flood risk model using MCE output.
4) Perform a stochastic simulation at varying degrees of uncertainty to verify the legitimacy of the MCE findings.
5) Conjoin the MCE and stochastic maps to assess flood risk in the study site.

3. Study Area

The base location of this study is located in the southwestern corner of Nova Scotia. The chosen strip of the Mersey river extends for 17 kilometers and borders two major Urban townships, Milton, and Liverpool, while touching on the periphery of another, Bristol, as seen in figure 1. The combined population of these three towns is around 3,500 residents (Peterson, 2015). Along this low relief strip of river also are roadways containing peri-urban development along with automotive and railway bridges stretching over the river and spillways. The Mersey river contains Nova Scotia's largest and second most productive hydroelectric network, consisting of 6 generating stations, 33 dams, 17 spillways and 3 canals. This hydroelectric system is a critical part of Nova Scotia's electricity network, ensuring power supply for a large part of the southern counties. This was one additional reason for selecting the river, as damage

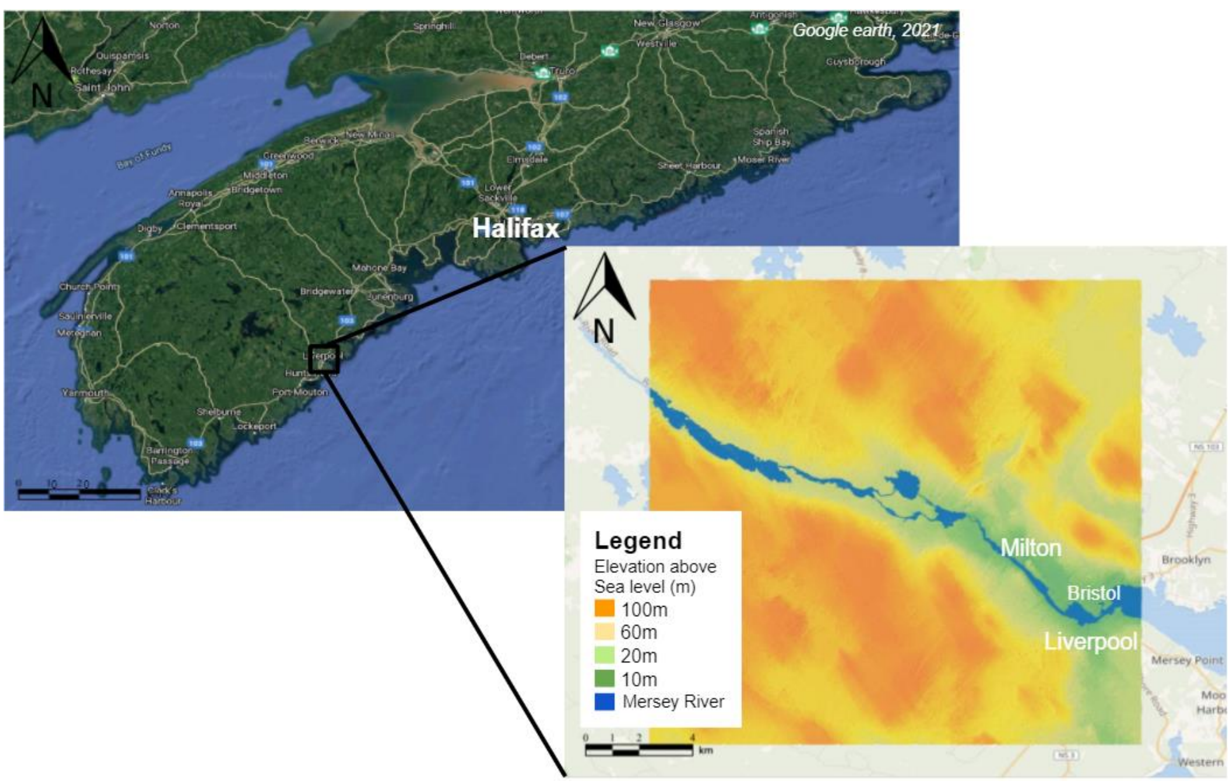

Figure 1 - The study site encompasses a subsection of the Mersey River, located in proximity to Liverpool, Queens County, along the southern coast of Nova Scotia. A DEM of the study area is overlaid to show the local topography.

to the hydro infrastructure could put the energy security of the surrounding cities at risk in case of a flooding event. Furthermore, deforestation in the study site is not an uncommon feature, exemplified by several “bare land” patches in proximity to the riverbank. These patches are susceptible to having lower infiltration rates than forested land, thus increasing the frequency and intensity of potential floods (Regüés et al., 2017).

4. Methods and Materials

4.1 Data Needs

LiDAR datasets help provide a high-resolution representation of elevation data, something which is particularly important when modelling complex topography, according to Haile et. al (2005). The cited report indicates that this characteristic of LiDAR datasets makes them an invaluable tool for modelling drainage networks, representing land-use and infrastructure in 3D view and mapping floodplain extent (Haile et. al 2005). Six DEM raster tiles at a ~ 1-meter resolution were used in this study, all derived from LiDAR data gathered by a third-party geomatics company. Another required layer, land use, was obtained through Agriculture and Agri-Food Canada, who in 2010 created the Canada-wide land use dataset at a 30-meter resolution using classified satellite imagery. The last data component used in the study was a vector polygon which represented the extent of the Mersey River from the Port of Liverpool all the way up to Sandy Bottom Lake.

4.2 Data Cleaning and Pre-processing Methods

Each of the layers described above was reprojected to the corresponding coordinate system of NAD_1983_UTM_Zone_20N, which was used by every layer created onwards in our report. The six DEM tiles were mosaicked and then hydrologically conditioned using breaching to ensure flow across depressions. This breached DEM served as an input in the creation of the slope, HAND, and distance from river criteria.

4.3 Criteria Selection and Creation

The criteria included in the MCE workflow were influenced by the methodology used in Hazarika et al (2018), Khan et al (2018), and Rahmati et al (2018), which overall chose parameters that had a higher degree of influence in river floods. The addition of the proximity to dams criterion was made based on the unique characteristics of our study site when compared to other studies (see section 1); three dams affect water flow along the Mersey River, making it an important criterion to include in the analysis. Figure 2 shows a visual representation of these criteria.

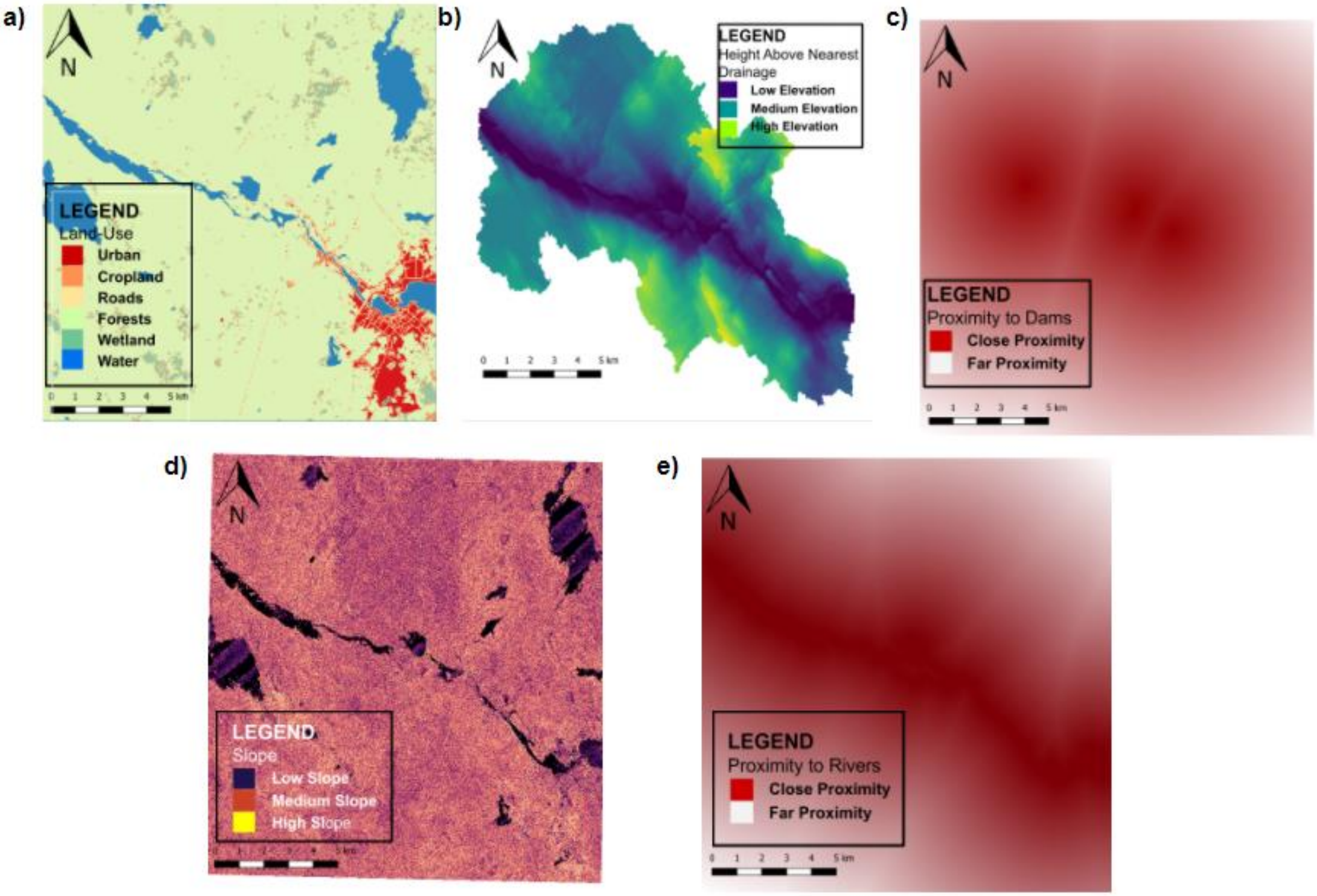

Figure 2 - The visual representation of the criteria to be used in the MCE analysis. Represented as a) land use layer, b) height above nearest drainage, c) proximity to dams, d) slope, and e) proximity to rivers.

Slope – Slope affects the velocity at which water travels through a drainage channel. The lower the slope, the flatter the terrain, and the more likely it is for water to flow through the determined location (Kandilioti & Makropoulos, 2011, p. 447). By contrast, steeper ascending paths will limit the extent of the floodplain, effectively reducing the impacts of the flooding event (Mohamed Elmoustafa, 2012, p. 328).

Proximity to rivers – Flooding is more common in areas closer to rivers. Therefore, the closer a certain location is to the river, the higher at risk it is (Rincón, Khan, & Armenakis, 2018). The rasterized river extent was used to generate a downslope distance to stream (DDTS) raster, which represents the distance from all cells in the raster to the closest point of the stream measured along the downslope flowpath of the water.

HAND – Height above nearest drainage (HAND) represents the difference in elevation between a location and its nearest stream cell. The higher the value associated with the HAND criterion, the lower the risk of flooding will be for a certain location (Souza Santos, Koenow Pinheiro, & Gallo Junior, 2021).

Proximity to dams – Dams help regulate water flow and are also a source of hydro-power for the people of Bristol, Liverpool, and Milton. In case of a flooding event, there is risk of dam failure which, depending on the water volume stored by the dam, will determine the degree of risk that dam poses to the neighboring lands (CVCOG, 2012). Dams in the Mersey River were digitized and rasterized and used to derive a Euclidean distance raster from their location to the rest of the cells in the study site.

Land use – Due to the impervious nature of asphalt, urban areas tend to carry more water as overland flow during a flooding event. Permeable soils, such as forested areas and bare land, on the other hand, have a way higher infiltration rate than asphalt, leading to a significant percentage of water being lost to infiltration in case of a rainfall or flooding event (Markovič, Zeleňáková, Káposztásová, & Hudáková, 2014). This raster was resampled to match the resolution of the other layers.

4.4 Multi-Criteria Evaluation (MCE)

Two key steps were performed prior to running the MCE for this study.

Rescaling of criteria factors – This step consisted of rescaling all criteria to the same scale, which was determined to be from 0 to 100. Values approaching 100 would be considered higher risk while values approaching 0 would be considered lower risk. All criteria were rescaled using a linear stretch, as shown in equation 1.

$$\boxed{OUTVAL = (INVAL - INLO) \times \frac{(OUTUP - OUTLO)}{(INUP - INLO)} + OUTLO}$$

Equation 1

Where:

Value	*Criteria*
OUTVAL	Value of pixel in output map
INVAL	Value of pixel in input map
INLO	Lower value of 'stretch from' range
INUP	Upper value of 'stretch from' range
OUTLO	Lower value of 'stretch to' range
OUTUP	Upper value of 'stretch to' range

Determination of criteria weights – Weighting of the rescaled criteria was accomplished using a pairwise matrix, as shown in table 1. Rankings in the matrix were determined based on the literature.

Table 1 - MCE Table indicating the distribution of weights amongst our analysis constraints given by each researcher and applied to the flood delineation.

Our Criteria	**Almuina Pica, D. Weighting**	**Nieto, A. Weighting**	**Stange, T.: Weighting**	**Final Ranking**
HAND	0.231	0.120	0.320	0.221
LANDUSE/COVER	0.408	0.162	0.250	0.270
PROXIMITY TO DAMS	0.125	0.150	0.080	0.118
SLOPE	0.184	0.282	0.220	0.226
PROXIMITY TO RIVERS	0.252	0.122	0.130	0.165
TOTAL				1.0

After weights were determined, they were combined with the criteria to perform the MCE in a similar manner to that shown in equation 2.

$$\boxed{\sum_i^n C_n W_n = C_1 \times W_1 + C_2 \times W_2 + C_3 \times W_3 + \dots \dots \dots \dots + C_n \times W_n}$$

Equation 2

Where:

Code	Criteria
C	Criteria
W	Weight
n	Upper limit
i	Lower limit

4.5 Stochastic Simulation (Monte Carlo Method)

Stochastic simulations are useful for estimating probability distributions of an output when one or more inputs are allowed to vary randomly (Patidar, Haynes, Li, & Haynes, 2017;

Graham & Talay 2015). The RMSE of the DEM (6.6 cm) was taken as reference to apply this variation to the input DEM. The simulation workflow demonstrated in figure 3 was run for 50 iterations over a 14-hour period.

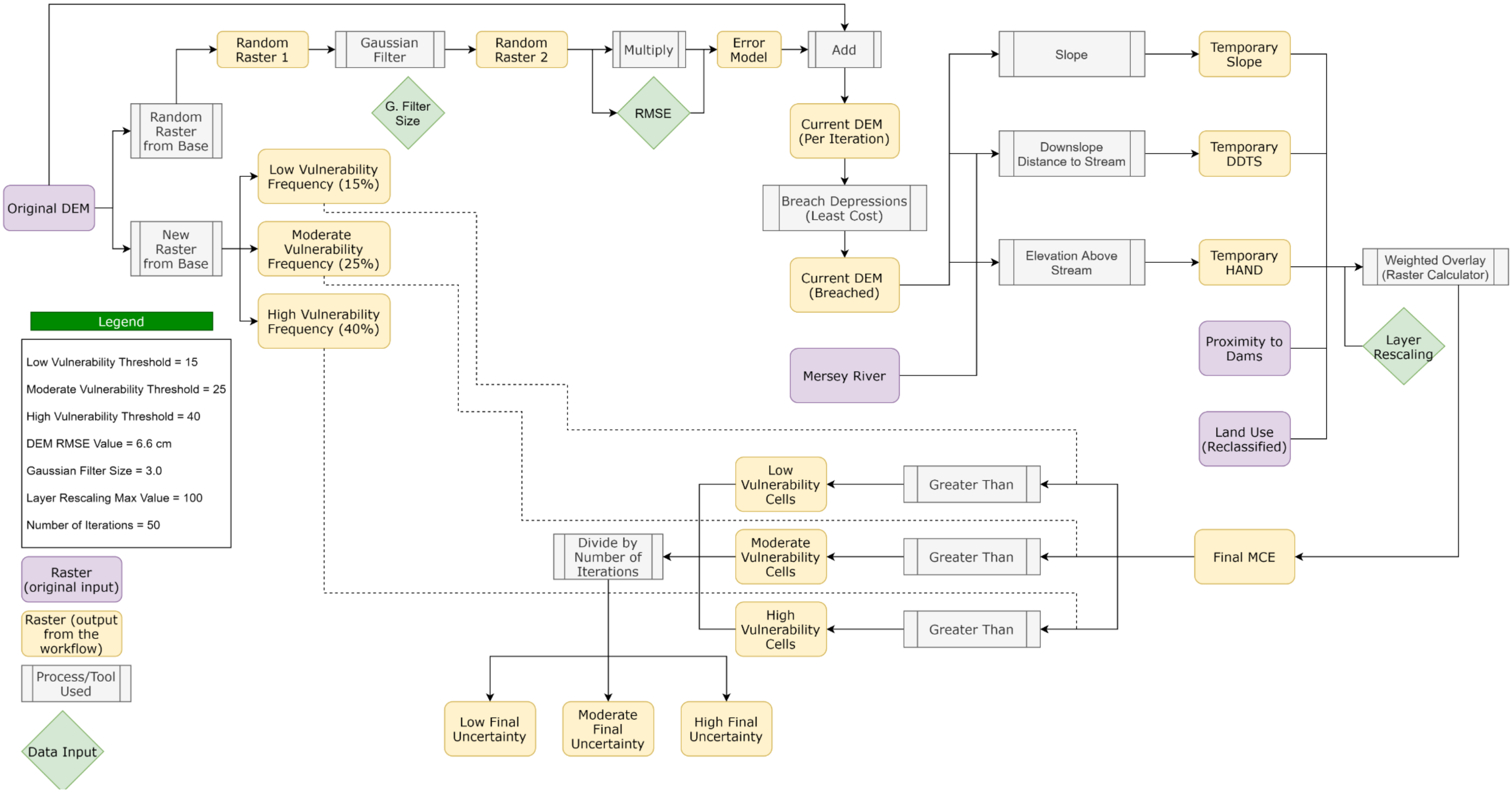

Figure 3 - Flowchart illustrating the steps and processes used to create the stochastic layers using a series of for loops.

5. Results

5.1 MCE Flood Risk Map

Flood risk calculated over the floodplain extent is shown in figure 4, the output of the MCE calculations shows areas of high risk in contrast to moderate risk using a color gradient.

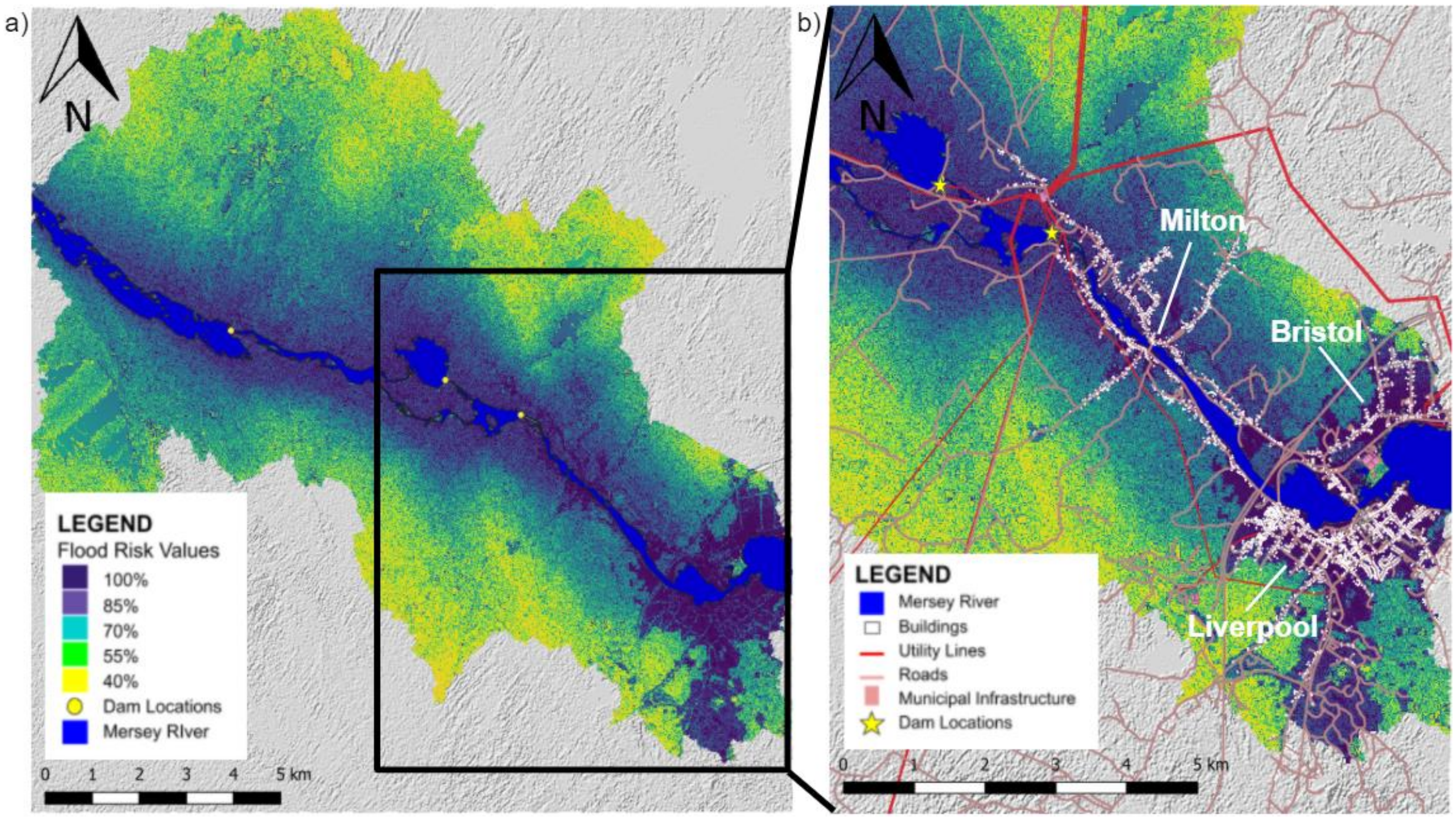

Figure 4 - Map a) displays the output of our MCE risk calculated over the floodplain extent, darker hues indicating higher risk while lighter colors indicate areas of lower risk. Map b) shows the flood delineation with respect to urban landmarks in the county.

5.2 Stochastic Sensitivity Maps

Figure 5 below shows how sensitive the MCE output was to variation in the original DEM due to the RMSE. The models below were generated by the stochastic simulation across three uncertainty levels.

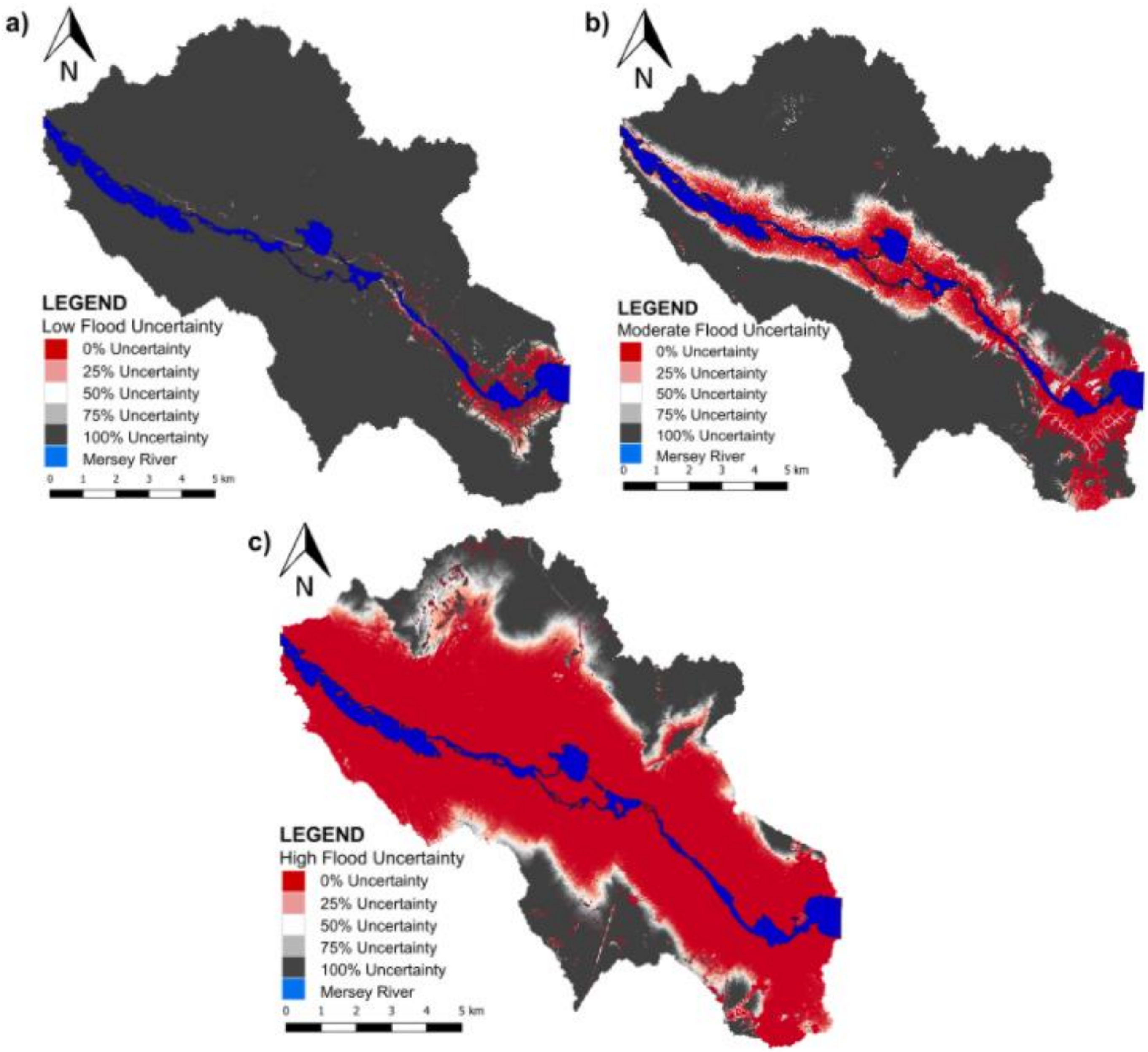

Figure 5 - Final output from the stochastic simulation indicating the levels of uncertainty in terms of confidence that a flood will reach and affect the surrounding Queen's County landscape. a) illustrates the lowest uncertainty threshold, which equals 15%, b) illustrates our moderate threshold value, which equals 25%, c) shows the maximum/highest uncertainty threshold, which equals 40%, which covers most of the HAND extent.

6. Discussion

6.1 Generation of the MCE Map

6.1.1 MCE Weights and LiDAR Discussion

Criteria values used in the MCE presented in table 1 emphasize land use as the heaviest weighed, as urban infrastructure is heavily impacted by flooding. These include roadways, urban centers and rural areas that hug the bank of the Mersey River. Slope played a crucial role in the containment of flooding, as demonstrated when reaching the outer edges of the HAND extent (~0.4 – 0.7 km perpendicular to the river direction). At this distance, it is seen that the relief of the landscape halts the lateral progression of floodwaters. A key component of this study revolved around simulating the effects flooding has on low relief landscapes and comparing them with similar literature on high-relief landscapes, specifically M. Besharat et. al (2016) and C.D Rennó et.al (2011), their results indicate that the high relief floodplain does not extend nearly as much as one in low relief areas. However, the volume of floodwater accumulated in the former would be greater, potentially causing more water damage to essential structures, such as power lines and housing zones. This analysis would require a greater emphasis to be put on hydrological and bathymetric data, something which was absent for our study.

6.1.2 Mersey River MCE Analysis

Results presented in the figure 4 maps a) and b) show significantly high flood risk mainly in the urban sprawl in Liverpool, Bristol, and Milton, with Liverpool being the area of highest vulnerability among the three. This is due to Liverpool being the lowest elevation town in the study site, sitting at ~22 – 31 m above sea level. A high-risk cluster occurs as the flood path continues south away from Liverpool along NS Highway 3, then flowing into the wetlands and marshlands that make up the Meadow, Round, Neck and Bar Ponds. This will most likely be a point of flooding as well, which will flow laterally into the surrounding wetland and could potentially overflow onto the highway.

The urban extent of the Bristol harbour also shows areas of 80 - 100 % risk. The vast majority of these were identified to be the locations for parking lots and yards, identified mostly as the locations for parking lots and yards. Flooding extent can be accentuated by overland flow passing over impermeable surfaces, as the distance traveled by water is proportional to the respective surface roughness coefficient of land under it (Arcement et. al, 1989). This variable is dependent on the channel width, length, and induced drag on the fluid across the medium (see section 4.3.2). The reverse also occurs in vegetated areas, where water passing over the surface is lost to infiltration. Areas away from urbanized land can still have values greater than 40% risk, as flooding can occur all the way to the edge of the floodplain but will be stopped by the upslope portion of the landscape relief. Milton shows an 80 - 100% risk value due to its proximity to two dams upstream from it. Milton is also at a narrow point in the river, bottlenecking the accumulation of floodwater, which eventually could spill out becoming overland flow.

6.2 Analysis of Floodplain Sensitivity Maps

6.2.1 Low threshold uncertainty

Low threshold map Figure 5 a) (threshold = 15%) indicates a low uncertainty region of the urban landscapes along the Mersey River embankment, indicating that at the highest possible confidence level we are assured that Liverpool, Milton, and the Bristol harbor areas will be the most at risk, coinciding with the initial analysis of the MCE based floodplain map in figure 4. Outside of these urban areas along the riverbank, model uncertainty increases to 50% when distancing from urban areas and the river, and changing abruptly to 100% uncertainty shortly after.

6.2.2 Moderate threshold uncertainty

The moderate threshold in Figure 5 b) for a 25% threshold shows a delineation output that is nearly identical to the flood map in figure 4. Low uncertainty areas with values of 0-25% reach down into the southern highway 3 networks, including the multi basin/pond network along the wetlands. With the exception of the elevated roads and bridge networks north and within south Liverpool which indicate areas of 50% uncertainty, a considerable amount if not all of the urban scape is at 0% uncertainty of flood risk occurring in these areas. Regions of higher uncertainty ~50% coincide with areas of 75-80% flood risk in the MCE, reinforcing the risk assessment made using the determined criteria.

6.2.3 Higher threshold uncertainty

Highest threshold output in Figure 5 c) (threshold = 40%) shows the full extent of the certainty that potential flood risk will occur. Areas in the MCE map (figure 4) with risk values less than 50% are grouped and counted as non-flooding areas or areas with 100% uncertainty indicating that at the highest threshold level we can assume these areas to be the least impacted in terms of lateral movement in fluid flow. Now, this is not to say that the water accumulation from flooding in areas closer to the river will not affect and impact these low-risk areas, but in terms of mitigation, this confidence level shows that prioritization for prevention should be less focused in this region. The high threshold map also indicates that risk values of 70 - 100 % all appear to be within the 0 - 25% uncertainty range, further reinforcing the validity of the MCE which counted these regions as high risk. The results of the stochastic simulation therefore proved it to be a helpful tool to ensure the validity of the initial MCE analysis, properly modelling areas at risk where flood mitigation measures could and should be implemented.

6.3 Future Work

The floodplain delineation analysis presented in this study only shows one of many existing methods for assessing flood risk. An all-encompassing model of the Mersey river floodplain would require additional historical and hydrological data for the river, information on soil type and biotic data of the neighboring lands, and industry data describing the logging and fishing operations present through the entirety of the study site (see figure 1). Additionally, information about bank height and surface roughness would aid in the estimation of flood timing.

7. Conclusion

Urban areas surrounding the Mersey River in Nova Scotia are expected to be at a higher risk of flooding events than any other land type in the region. The importance of land use for determining flood delineation patterns lies in that impervious areas receive higher levels of overland flow and less infiltration during a flooding event. On top of this, urban areas have higher economic value than other land types, as well as a higher population density, further accentuating the associated risks coming from floods. This conclusion was supported and reinforced by the MCE model and the stochastic simulation analysis. Operating these two methods in conjunction allowed for this study to expand on the limited literature on the topic while also pioneering on their application to flood risk modelling. The results gathered put the cities of Liverpool, Bristol, and Milton at a high risk, making them the best targets for the development of risk mitigation programs. It is intended that the combination of MCE and stochastic processes used in this study could serve as reference for flood risk work performed in different locations, as assessing uncertainty in the source data is of key importance for conducting a robust analysis.

Bibliography

Arcement , G. J ., Schneider , V. R., (1989) *Guide for Selecting Manning's Roughness Coefficients for Natural Channels and Flood Plains.* U.S. Department of Transportation, Federal Highway Administration.

Casas, A, G. Benito, V.R. Thorndycraft & M. Rico. (2006). *The topographic data source of digital terrain models as a key element in the accuracy of hydraulic flood modelling.* Centro de Ciencias Medioambientales – CSIC, C/Serrana 115 Dpdro, 28006 Madrid, Spain

C.D.Rennó, A.D.Nobre, L.A.Cuartas, M.Hodnett, G.Rodrigues, A.Silveira, M.Waterloo, S.Salesk. *Height Above the Nearest Drainage – a hydrologically relevant new terrain model.* Journal of Hydrology, Volume 404, Issues 1–2, 29 June 2011, Pages 13-29

Celik, E., Gul, M., Yucesan, M., & Mete, S. (2019). Stochastic multi-criteria decision- making: An overview of methods and applications. *Beni-Suef University Journal of Basic and Applied Sciences, 8*(1). doi:10.1186/s43088-019-0005-0

Concho Valley Council Of Governments (CVCOG). (2012). Hazard Mitigation Plan Update - Dam Failure. Retrieved March 30, 2021, from

Eastman, J. R. (1999). Multi-criteria evaluation and GIS. *Geographical information systems*, *1*(1), 493-502. Carver, S. J. (1991). Integrating multi-criteria evaluation with geographical information systems [Abstract]. *International Journal of Geographical Information Systems, 5*(3), 321-339. doi:10.1080/02693799108927858

Graham, C., & Talay, D. (2015). *Stochastic Simulation and Monte Carlo Methods Mathematical Foundations of Stochastic Simulation*. Berlin, Berlin: Springer Berlin Heidelberg.

GRASS Development Team. (2021, February 05). GRASS GIS - Bringing advanced geospatial technologies to the world. Retrieved March 30, 2021, from https://grass.osgeo.org/

Haile, A.T. & Rientjesb, T.H.M. (2005). *Effects of LiDAR DEM Resolution in Flood Modelling: a Model Sensitivity Study for the City of Tegucigalpa, Honduras. Isprs wg iii/3, iii/4, 3,* 12-

jackie_pc (2021), Updated Mersey River shapefile up to Sandy Bottom Lake (Version 1), Rights: jackie_pc, ArcGIS Online.

Kandilioti, G., & Makropoulos, C. (2011). Preliminary flood risk assessment: The case of Athens. *Natural Hazards, 61*(2), 441-468. doi:10.1007/s11069-011-9930-514

Lamichhane N, Sharma S. Development of Flood Warning System and Flood Inundation Mapping Using Field Survey and LiDAR Data for the Grand River near the City of Painesville, Ohio. *Hydrology*. 2017; 4(2):24. https://doi.org/10.3390/hydrology4020024

Lindsay J.B., Evans M.G., (2007) The influence of elevation error on the morphometrics of channel networks extracted from DEMs and the implications for hydrological networks UpERU, School of Environment and Development, University of Manchester, Hydrol. Process. 22, 1588– 1603 (2008)

Lindsay, J. (2021). Whiteboxtools. Retrieved March 30, 2021, from https://jblindsay.github.io/ghrg/WhiteboxTools/index.html

MacDonald, C., Webster, T. (2016). Flood Risk Analysis of the Halifax Harbor to Support Evacuation Modeling. Technical Report, Applied Geomatics Research Group, NSCC Middleton, NS.

Markovič, G., Zeleňáková, M., Káposztásová, D., & Hudáková, G. (2014). Rainwater infiltration in the urban areas. *WIT Transactions on Ecology and The Environment, 181*, 313-320. doi:doi:10.2495/EID140271 http://www.cvcog.org/cvcog/docs/Public%20CVCOG%20Hazard%20Mitigation%20Plan%20U pdate%202012-2017.pdf

McGuigan, K., Webster, T., & Colins, K. (2015). *A flood risk assessment of the lahave river watershed, Canada using gis techniques and an unstructured grid combined river-coastal hydrodynamic model*. *Journal of Marine Science and Engineering, 3*(3).https://doi.org/10.3390/jmse3031093

Nova Scotia Data Explorer (2019), 201901_RAW_DEM.tif (Version 2019) [GeoTIFF DEM dataset] Producer: Leading Edge Geomatics

Nova Scotia Environment. (2017, December 10). Flooding: Climate Change. Retrieved January 26, 2021, from https://novascotia.ca/nse/climate-change/nsfaf-flooding.asp

Nova Scotia Power Incorporated Hydro Asset Study. (2018). 1-622. https://irp.nspower.ca/files/key-documents/background-materials/20181221-NS-Power-Hydro- Asset-Study-REDACTED.pdf

Omid Rahmati, Hossein Zeinivand & Mosa Besharat (2016) Flood hazard zoning in Yasooj region, Iran, using GIS and multi-criteria decision analysis, *Geomatics, Natural Hazards and Risk*, 7:3, 1000-1017, DOI: 10.1080/19475705.2015.1045043

Open Source Geospatial Foundation (OSGeo)). (2021). QGIS. Retrieved March 30, 2021, from https://qgis.org/en/site/

Patidar, S., Haynes, H., Li, J., & Haynes, R. (2017). Stochastic modelling approach for future flood risk modelling. In *Math Foresees General Assebly 2017 Presentation*. Retrieved March 30, 2021, from http://www1.maths.leeds.ac.uk/mathsforesees/presentations/Patidar.

Peterson, Jean. "Liverpool". The Canadian Encyclopedia, 04 March 2015, Historica Canada. https://www.thecanadianencyclopedia.ca/en/article/liverpool. Accessed 30 March 2021.

Regüés, D., Badía, D., Echeverría, M., Gispert, M., Lana-Renault, N., León, J., . . . Serrano-Muela, P. (2017). Analysing the effect of land use and vegetation cover on SOIL infiltration in three CONTRASTING environments in northeast Spain. *Cuadernos De Investigación Geográfica, 43*(1), 141-169. doi:10.18172/cig.3164

Rincón, D., Khan, U., & Armenakis, C. (2018). Flood risk mapping using gis and multi-criteria analysis: A Greater Toronto area case study. *Geosciences, 8*(8), 275th ser., 1-27. doi:10.3390/geosciences8080

Souza Santos, E. D., Koenow Pinheiro, H. S., & Gallo Junior, H. (2021). Height Above the Nearest Drainage to Predict Flooding Areas in São Luiz do Paraitinga, São Paulo. *Floresta E Ambiente, 28*(2), 1-10. doi:10.1590/2179-8087-floram-2020-00705

Tutton, M. (2018, March 5). Growing frequency, ferocity of Nova Scotia storm surges worries local politicians. *Global News - Canada*. Retrieved January 26, 2021, from https://globalnews.ca/news/4063940/nova-scotia-storm-surges/

World Meteorological Organization, & Global Water Partnership. (2009). *Flood Management in Changing Climate - A Tool for Integrated Flood Management* (pp. 1-28, Tech. No. 14). World Meteorological Organization.

Yalcin, G., & Akyürek, Z. (2002). *Analysing flood vulnerable areas with multicriteria evaluation* (Master's thesis, Thesis for the degree of Master of Science in the Department of Geodetic and Geographic Information Technologies, 2002) (pp. 1-6). Ankara: Middle East Technical University METU.pdf