

**A Stochastic Framework
for
Urban Flood Hazard Assessment:
Integrating SWMM and HEC-RAS Models to Address
Watershed and Climate Uncertainties**

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Statement of Contributions

This research was conducted at the University of Waterloo by Sayed Abedin under the supervision of Dr. Bruce MacVicar.

Important contributions to this thesis were made by my supervisor, Dr. Bruce MacVicar, through his knowledge, experience, and wisdom.

Sayed Abedin contributed to developing the research ideas presented in the thesis, executing them, and preparing the draft of the manuscript. Dr. Bruce MacVicar provided guidance in developing the research ideas, assisted in their execution, and reviewed and edited the manuscript draft. Kimisha Ghunowa contributed by assisting with the reach definitions used in Chapters 3 and 4. The Credit Valley Conservation authority agreed to share the calibrated hydrologic and hydraulic models that were used as the inputs to the developed stochastic framework and other relevant data on land use and building footprints within the watershed.

I certify that I am the sole author of all the Chapters presented in this thesis. Of which, Chapters 2, 3 and 4 were written for publication.

Abstract

Urbanization significantly alters natural hydrological processes, leading to increased flood risks in urban areas. The potential damages caused by flooding in urban areas are widely recognized, making it crucial for urban residents to be well-informed about flood risks to mitigate potential losses. Flood maps serve as essential tools in this regard, providing valuable information that aids in effective planning, risk assessment, and decision-making. Despite floods being the most common natural disasters in Canada, many Canadians still lack access to high-quality, up-to-date flood maps. The occurrence of recent major flood events across the country has sparked renewed interest among government officials and stakeholders in launching new flood mapping initiatives. These projects are critical for enhancing flood risk management across communities.

Traditional flood hazard mapping methods, based on deterministic approaches, often fail to account for the complexities and uncertainties inherent in urban flood dynamics, especially under rapidly changing climate conditions. Uncertainty affects every stage of flood mapping, influencing accuracy and reliability. Recognizing this, recent studies advocate for stochastic approaches to explicitly incorporate these uncertainties. However, there is a lack of industry-standard tools that allow for a convenient and comprehensive analysis of uncertainty, making it challenging to routinely incorporate uncertainty into flood hazard assessments in practice. This underscores the need for a robust framework to model flood uncertainty. While various models have been proposed to address the uncertainty, many remain conceptual or lack the necessary automation. Despite no "perfect models", the Storm Water Management Model (SWMM) and the Hydrologic Engineering Center's River Analysis System (HEC-RAS) are widely used for urban hydrology and channel hydraulics modeling, respectively, due to their robust physics-

based approaches. Both SWMM and HEC-RAS models have been enhanced with commercial and open-source extensions, built on algorithms written in various programming languages, to improve their utility, particularly for automating workflows to handle complex urban flood scenarios. While SWMM has more robust extensions, most available HEC-RAS extensions are designed for one-dimensional (1D) steady state models, which lack the complexity needed for accurate urban flood modeling. The release of HEC-RAS 6.0, which allows for two-dimensional (2D) unsteady flow modeling and incorporates structures like bridges and weirs, marks a significant advancement for urban flood modeling. The current research was motivated by the perceived benefits of designing such extensions for automating workflows in recent versions of SWMM and HEC-RAS, as well as automating the coupling of these two models in a stochastic framework to facilitate the integration of uncertainty into existing flood hazard mapping workflows. This thesis introduces the SWMM-RASpy framework, a novel automated stochastic tool built using the open-source Python programming language. SWMM-RASpy integrates SWMM's detailed urban hydrologic capabilities, such as dual-drainage modeling, with HEC-RAS's 2D unsteady hydraulic modeling, coupled with stochastic simulations through Latin Hypercube Sampling (LHS) to analyze the uncertainty in flood hazard mapping. The framework was demonstrated on the Cooksville Creek watershed, a highly urbanized area in Mississauga, Ontario, known for its susceptibility to flooding. An entropy map was successfully produced for the case study site, which better reflects the uncertainty of flooding and could be used to develop tailored flood planning and preparedness strategies for different zones within the site.

This thesis also presents a detailed application of the SWMM-RASpy framework to assess flood hazards, with a specific focus on topography-based hydraulic uncertainties in the watershed, particularly surface roughness variability, which affects pedestrian safety during

flood events. The study highlights that traditional hazard models, which focus mainly on residential buildings, do not adequately account for the risks to pedestrians who are a significant source of fatalities in flood events, especially in densely populated urban areas with high mobility. Three flood hazard metrics were developed and used to evaluate the flood risks to pedestrians given the uncertainty surrounding surface roughness: FHM1, based on inundation depth; FHM2, combining depth and velocity; and FHM3, incorporating depth, velocity, and duration. Key findings from the assessment indicate that surface roughness significantly affects pedestrian hazard estimation across the floodplain, making it a critical factor in flood hazard management. The FHM2 metric, which incorporates depth and velocity, was found to be highly sensitive to roughness variation, potentially leading to the misclassification of hazardous zones as safe and *vice versa*. The inclusion of velocity in the hazard assessment, while improving accuracy, also increased variability, emphasizing the need for a balanced approach in flood risk evaluations. In contrast, the FHM3 metric, which includes flooding duration, showed minimal sensitivity to surface roughness uncertainty. The research also suggests that confidence maps, produced as part of the analysis and accounting for estimated uncertainties surrounding the hazard metrics propagated from surface roughness, can offer a more reliable alternative to traditional deterministic hazard maps. Lastly, the study, through this analysis, emphasizes the importance of combining grid-level and zonal-level analyses for a more comprehensive understanding of flood hazards at different scales, thereby supporting more robust flood risk assessments.

This thesis extends the application of the SWMM-RASpy framework to assess the impacts of climate change on flood hazards within the Cooksville Creek watershed. It examines how projected changes in rainfall intensity from Global Climate Models (GCMs) affect flood

risks, particularly for urban buildings, as well as the importance of incorporating uncertainties from these projections into flood hazard assessments. The same hazard metrics used for pedestrian hazard assessment, FHM1, FHM2 and FHM3, were used to evaluate building hazards. The study predicts a significant increase in flood hazards within the watershed, with a substantial expansion of inundation areas affecting up to 40% more buildings when uncertainties are considered. The analysis shows that without considering uncertainties, FHM1 and FHM3 predict a higher number of damaged buildings than FHM2, with FHM1 predicting the highest number of affected buildings. This suggests that relying solely on FHM1 to estimate building hazards may be sufficient in similar climate change scenarios, although further investigations are needed. However, when uncertainties are included, FHM2 shows a greater increase in the number of buildings at risk compared to FHM1 and FHM3, due to the larger uncertainty associated with velocity versus depth and duration. This underscores the need to incorporate uncertainty into flood hazard assessments to ensure a more comprehensive understanding of potential future damages.

Overall, this study has made significant contributions to the field of urban flood hazard assessment by developing a robust method for incorporating and analyzing uncertainties, thereby supporting more effective flood management and resilience planning. Future research should apply the SWMM-RASpy framework to other watersheds and investigate additional hydrologic and hydraulic variables to further improve flood risk assessments.

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CHAPTER 1: INTRODUCTION

1.1 Synopsis

Urbanization refers to the conversion of rural and natural land cover into urban land cover. Urban areas are distinguished by buildings, roads and parking lots that are built with concrete and asphalt surfaces. In the early 19th century, less than 10% of the world's population resided in urban areas, but by 2008, this number had exceeded 50% and is projected to increase further in the coming decades (Seto & Shepherd, 2009). Despite urban areas covering only about 3% of the world's land surface, their expansion to accommodate a growing population often leads to urban sprawl, encroaching into suburban and rural areas (Güneralp, Reba, Hales, Wentz, & Seto, 2020). Urbanization directly impacts the water balance due to a reduction of pervious land cover (e.g., open/green space) and an augmentation of impervious land cover (e.g. concrete and asphalt). Imperviousness modifies the watershed's hydrology such that rainfall events produce higher volume of runoff, which tends to exceed the existing capacity of the areas' drainage system. The local streams also receive more runoff or flow from the surrounding area, which leads to flooding.

Flooding is the most common natural disaster globally over the last 20 years, accounting for a significant portion of all catastrophic events. Studies indicate that floods are responsible for a substantial number of disasters, with the frequency of such events increasing over time due to various factors, including climate change (Ward, P. J., Kumm, & Lall, 2016). In 2012 alone, global flood damages exceeded \$19 billion, and floods continue to be a major contributor to economic losses from natural disasters (Ward, Philip J. et al., 2013). In Canada, floods are the most common natural disasters, posing a significant risk to low-lying, flood-prone urban areas. Given the potential damages from flooding, it is crucial for people to know whether they live in a

flood zone and to understand the extent of their properties' vulnerability. The best current practice to anticipate flooding is to consult local flood maps, which typically show areas prone to flooding from nearby streams, such as rivers and creeks. These maps, produced, managed, and utilized by local flood management and other concerned authorities, are critical tools for decision-making in flood mitigation, land use planning, and emergency management (Natural Resources Canada & Public Safety Canada, 2018). They also serve as vital tools for raising public awareness, providing information that allows individuals to make informed decisions related to flood risks (Natural Resources Canada & Public Safety Canada, 2018).

Unfortunately, most Canadians lack access to high-quality, up to date flood maps. Public map availability is grossly uneven among the ten provinces, and most of those have a median age of 18 years (Henstra & Thistlethwaite, 2018). Recent major flood events in the country mean that 92% of the people living in high flood risk area want up-to-date flood maps accessible to the public and there is a renewed interest among the government officials and stakeholders in initiating flood mapping projects (Henstra & Thistlethwaite, 2018). A vision for flood guidance has been developed by the Government of Canada for enhancing community resilience pertaining to flood mitigation based on the key principles of accessibility and collaboration (Natural Resources Canada & Public Safety Canada, 2018). Accessibility means that necessary data, information and knowledge should be available to the practitioners. Collaboration means that process should be transparent and done in cooperation with the community, including through the incorporation of local and traditional knowledge. Such an approach is thought to be vital for establishing community-level understanding of flood risk and increasing the accuracy and effectiveness of the flood maps. A series of community engagement activities on flood mapping in Canada has been put into motion including town hall and public meetings,

information booths, website and social media updates, workshops and focus groups (Natural Resources Canada & Public Safety Canada, 2018).

Flood mapping can be classified into three categories: flood hazard maps, which display information about flood parameters such as depth; flood vulnerability maps, which depict the consequences of floods on the economy, society, and the natural environment; and flood risk maps, which show the spatial distribution of risk based on a combination of hazards and vulnerability (Di Baldassarre, Schumann, Bates, Freer, & Beven, 2010). These maps are produced from flood models using either a deterministic or probabilistic (stochastic) approach. A flood model comprises a hydrologic model, transforming rainfall into runoff, and a hydraulic model, routing the runoff through streams. Traditionally, flood maps have been produced using deterministic models that do not consider uncertainty. In Canada, existing flood maps are typically created with deterministic models, such as those recommended by the Federal Flood Mapping Framework Version 2.0 (Natural Resources Canada & Public Safety Canada, 2018). Deterministic maps use a binary system to indicate whether a property is flooded (1) or not (0), requiring the same level of emergency response for all flooded properties, which can be time- and resource-consuming. Conversely, stochastic flood models consider uncertainty and produce maps that depict the probability (between 0 and 1) of a property being flooded, along with the uncertainty zone around the flood inundation boundary. Since uncertainty is involved in every stage of flood modeling, recent studies advocate for using probabilistic maps in flood mitigation and emergency response strategies, as they account for uncertainty and are more realistic and effective (Di Baldassarre et al., 2010; Merwade, Olivera, Arabi, & Edleman, 2008; Papaioannou, Vasiliades, Loukas, & Aronica, 2017).

The uncertainties can be considered as either natural, which originates from the natural/random variability of underlying processes, or epistemic, which originates from deficient information about the processes and factors (Beven, Lamb, Leedal, & Hunter, 2015; Teng et al., 2017). Sources of epistemic uncertainty can include: i) choice of model structures or processes, ii) model parameter values, iii) model inputs/boundary conditions, iv) change in floodplain landscape or characteristics over time and space, and v) change in climate conditions (Bales & Wagner, 2009; Beven et al., 2015; Liu, Merwade, & Jafarzadegan, 2019; Stephens & Bledsoe, 2020; Teng et al., 2017). In the case of uncertainty assessment related to the hydraulics of flood modeling/mapping, the uncertainties from the surface friction of the channel/floodplain are commonly evaluated since the friction is found to have considerable impact on the accuracy of hydraulic models (Kuta, Annable, & Tolson, 2010). The friction resists the flow in the channel/floodplain, and it increases with the increase in the surface roughness and *vice versa*. The friction values for different surfaces, i.e. land covers are represented by a roughness coefficient called Manning's n , which is used as an input parameter to a hydraulic model. This parameter (known as either roughness or friction parameter) is considered an uncertain model input because no definite information is usually found available for the parameter (Castro-Bolinaga & Diplas, 2014). Studies have shown that the n values are either estimated for a site using empirical formulas based on the data collected from the field, or selected from a recognized land cover dataset such as National Land Cover Dataset (NLCD) where a range of n values are provided for a specific land cover (Castro-Bolinaga & Diplas, 2014; Kuta et al., 2010; Papaioannou et al., 2017). The n values do not only differ between the channel and the floodplains, they can also differ along the channel itself due to the presence of hydraulic structures such as bridges (Jung, 2011). In addition, the roughness parameter can also change

with the type of model used (1D vs 2D), the resolution of the input topographic data, and boundary conditions (Lim, 2018). Thus, the multifaceted variability nature of the roughness parameter makes it the most influential uncertain hydraulic parameter (Teng et al., 2017). However, the uncertainty propagation into the model outputs from this input parameter has traditionally been analyzed using relatively simple (1D) models. Given the increasing availability of accurate topographic data and availability of more advanced and accurate models, more research is warranted to allow the assessment of uncertainty from surface friction to be easily included in flood mapping.

Uncertainty in flood mapping can also arise from changes in climate, which have altered the normal balance of our earth's hydrological cycle (Solaiman & Simonovic, 2011) and impacted weather events. 'Normal' weather events have become more extreme in recent times, and extreme events are occurring more frequently, even in areas that do not have past history of such events (Hettiarachchi, Wasko, & Sharma, 2018). Accordingly, more regions in the world have higher numbers of heavy rainfall events leading to the increase in frequencies of flooding (Hettiarachchi et al., 2018). There has also been a notable increase in damages associated with the intensification of flood frequency resulting from climate change in major urban municipalities of Canada (Simonovic, Schardong, Sandink, & Srivastav, 2016). Considering the impacts of climate on flooding, flood management authorities around the country have started to recognize their effects in the flood mapping practices (Feltmate, 2016), but there is no consensus on the methodology for estimating floods in the context of climate change. Moreover, the existing practices do not acknowledge the uncertainties associated with the climate change projections (Beevers, Collet, Aitken, Maravat, & Visser, 2020) that may come from the following three sources: i. selection of climate models; ii. greenhouse gas (GHG) emission

scenarios; and iii. random internal variability of the climate system (Deser, Phillips, Bourdette, & Teng, 2012; Gaur, S., Bandyopadhyay, & Singh, 2021; Wu et al., 2022). The relative significance of the three sources of uncertainty will vary depending on the temporal scale (e.g. yearly, seasonal or monthly), the climate variable under consideration (e.g., temperature, precipitation, or other variables), and the geographic scale (e.g. at the continent-scale or country-scale). The majority of investigations have identified that projections from different climate models, also referred to as ‘model uncertainty’, are the main sources of uncertainty, and opinions regarding the relative contributions of the other sources are divided (Senatore et al., 2022). Since model uncertainty can directly impact precipitation projections to a great extent (Gaur, A., 2013), neglecting them could significantly degrade the quality of any flood-related assessment (Zahmatkesh, Han, & Coulibaly, 2021). To address uncertainties in practice, they should be efficiently quantified and communicated to flood management professionals (Zahmatkesh et al., 2021). However, addressing uncertainties is often challenging and computationally expensive (Byer & Yeomans, 2007). While some frameworks have been developed for this purpose by researchers such as Beevers et al. (2020), Zahmatkesh et al. (2021), Ahmadisharaf et al. (2018) and Alipour et al. (2024), there is a gap in creating comprehensive models that integrate H&H modeling and can successfully meet industry requirements for flood hazard assessments considering climate change. For these reasons, authors like Beevers et al. (2020) have advocated for the development of alternative frameworks for flood hazard assessments from climate change that can be utilized as part of the routine practices in the industry.

Mapping of flood hazard parameters and their uncertainties has been evaluated using steady flow conditions inside a one-dimensional (1D) hydraulic model (Di Baldassarre et al., 2010). The 1D steady-state (i.e. time invariant) hydraulic models have been favoured because

they are easy to implement and require less time and resources (Hosseinipour, Vargas, O'Brien, & Kasraie, 2012; Merwade et al., 2008). These models are effective in simulating flood hazard parameters, namely flood depth, for different flood scenarios (Ahmadisharaf et al., 2018). However, they have limited capacity in understanding flood behavior. For example, the spatial domain of a 1D hydraulic model is limited to the channel and its overbanks. Steady models use a single attribute, such as peak discharge, as an upstream (u/s) boundary condition, assuming to fill the floodplain instantaneously, which fails to capture the reality of flood dynamics and may produce unreliable information (Ahmadisharaf et al., 2018). Additionally, flood depths provide limited information for planning against different types of hazards, which may also require information about water velocity, flood timing, and the duration of inundation for effective emergency management (Luke et al., 2018). The 1D approach also limits the ability to evaluate hazards on a spatially distributed scale, particularly for flood flows where flow patterns may be complex and include extensive lateral flows or the formation of secondary channels (Farooq, Shafique, & Khattak, 2019). The limitations of 1D steady models can be overcome with two-dimensional (2D) unsteady hydraulic models. A 2D model encompasses overland areas in addition to the channel and overbanks. Unsteady flow models can capture both spatial and temporal changes in flooding since a fully developed flow hydrograph is provided as an upstream boundary condition for unsteady flow modeling (Ahmadisharaf et al., 2018). New research and flood management authorities are increasingly relying on 2D unsteady hydraulic models for developing multi-variable hazard models, which can provide time-varying and spatially distributed information about flood depth, velocity, duration of inundation, and other variables such as shear stress (Bertsch, Glenis, & Kilsby, 2022; Bhola, Leandro, & Disse, 2020; Lazzarin, Viero, Molinari, Ballio, & Defina, 2022; Luke et al., 2018; Ongdas, Akiyanova,

Karakulov, Muratbayeva, & Zinabdin, 2020; Zhang, Shao, Sun, Huang, & Yang, 2022).

Although these models can assist in capturing the spatio-temporal characteristics of uncertainties in flood mapping variables, only a few recent researchers, like Ahmadisharaf et al. (2018), Oubennaceur et al. (2018), Liu et al. (2019), Gao et al. (2021), and Dalledonne et al. (2019) have used 2D unsteady models for uncertainty assessment in flood mapping. This signifies that there are still substantial gaps in understanding the detailed nature of uncertainty in flood mapping. A suitable framework, particularly based on 2D hydraulic models, for modeling flood uncertainty inherent at different steps of the flood mapping procedure is needed.

1.2 Research Objectives

The goal of this thesis is to contribute towards the improvement of the current practices of flood hazard mapping in urban environments for mitigating flood related risks. Hence, the thesis focuses on developing and implementing advanced methodologies for enhancing the accuracy and reliability of flood hazard assessments, with a specific emphasis on the uncertainties inherent in hydrologic and hydraulic modeling. The research objectives are to:

1. **Construct an automated stochastic flood hazard modeling framework** that integrates hydrologic and 2D unsteady hydraulic models to generate stochastic flood hazard maps.
2. **Investigate the impacts of hydraulic uncertainties on urban flood hazard mapping with a focus on pedestrians** by extending the flood hazard assessment to include the hazards posed to pedestrians in urban areas, particularly considering uncertainties related to a hydraulic modeling parameter, surface roughness, using the novel framework.

3. Evaluate the impacts of climate change and its uncertainties on urban flood

hazard mapping by incorporating rainfall projections from Global Climate Models (GCMs) and the associated uncertainties into flood hazard assessments using the novel framework, with a particular focus on flood hazards for buildings.

1.3 Research Scope and Approach

The proposed research is part of a larger effort to improve the science, communications and outcomes surrounding land use decision making related to stream networks. In particular it aims to work on improving the outcomes from an Spatial Decision Support System (SDSS) called the Risk and Return on Investment Tool (RROIT) that was developed by Credit Valley Conservation (CVC) authority in co-operation with other academic and private partners (<https://sustainabletechnologies.ca/home/urban-runoff-green-infrastructure/rroit/>) through a program supported by Natural Resources Canada to help municipalities across Canada for making evidence-based, cost-effective decisions to reduce flood risk. The RROIT tool helps users to identify flood risk areas considering current and future climate, estimates socio-economic impacts, and manifests return on investment of flood management options using GIS data and/or H&H modeling data. However, the RROIT uses a deterministic modelling approach to establish the flood levels from which damage estimates are calculated. It is therefore envisioned that the proposed research will be able to contribute to the improvement of the tool in addition to the contribution towards the effectual flood management by refining the present-day flood mapping practices. The methods used are also common to many areas around the world because they are based on well supported and documented open-source codes. For this reason, it is envisioned that the framework could be widely adopted for flood hazard analysis.

To achieve Objective 1, we describe and demonstrate a novel stochastic framework named SWMM-RASpy, which is based on multi-variable hazard modeling and capable of analyzing the impact of hydrologic and hydraulic uncertainty on flood hazard mapping in urban areas. The framework is a Python-based tool that utilizes Latin Hypercube Sampling (LHS) method for stochastic simulations, in combination with the US Environmental Protection Agency's Storm Water Management Model (SWMM) for urban watershed hydrology and the Hydrologic Engineering Center's River Analysis System (HEC-RAS) model for channel hydraulics. To accomplish the second objective, we consider the uncertainties of parameters critical to flood damage assessments, such as flood depth, velocity, and duration. The propagation of uncertainty from surface roughness to these flood hazard variables is assessed through sensitivity analysis. While the focus is on pedestrian hazards, the SWMM-RASpy framework used to achieve this objective can also assess other types of hazards, such as vehicle and building hazards. To accomplish the third objective of the research, we consider the uncertainty around the rainfall intensity parameter of the Intensity-Duration-Frequency (IDF) curve, which is induced by the difference in projections from the available climate models. Similar to the second objective, the uncertainties of critical flood damage assessment parameters are estimated, and the propagation of uncertainty surrounding the estimation of rainfall intensity to these flood hazard variables is assessed via sensitivity analysis. The SWMM-RASpy framework is employed to achieve this objective. Cooksville Creek watershed is used as a demonstration site for the research. The watershed is fully urbanized with known urban flooding problems in the City of Mississauga, Ontario, Canada. Detailed topography and land use maps are available for the site as are calibrated SWMM and HEC-RAS models. The watershed was also used as a study site for previous works that helped to add erosion risk to RROIT tool.

1.4 Thesis Outline

This thesis is organized as a series of research papers that will be submitted for review in academic journals. Chapter 1 provides the overall view of the research, a short review of background material, and introduces the research objectives. Chapter 2 reviews additional background material, describes the SWMM-RASpy framework, the Cooksville Creek study site, and demonstrates the utility of the framework. Chapter 3 and 4 review relevant additional background material, and describe the methods and results related to research objectives 2 and 3, respectively. Chapter 5 summarizes the thesis, and provides conclusions and recommendations based on the limitations of the research work.

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CHAPTER 2: SWMM-HECRAS COUPLED FRAMEWORK FOR STOCHASTIC FLOOD HAZARD MAPPING

This chapter is prepared to be submitted in Environmental Modelling & Software journal

2.1 Introduction

Flood mapping is essential for determining potential hazards for people and infrastructure. Mapping can be classified into three categories: i. flood hazard maps, which display information about the flood parameters used to evaluate hazards such as flood depth; ii. flood vulnerability maps, which depict the consequences of floods on the economy, society and the natural environment; and iii. flood risk maps which show the spatial distribution of risk based on a combination of hazards and vulnerability (Di Baldassarre, Schumann, Bates, Freer, & Beven, 2010). Among these, flood hazard maps are the key hydrotechnical requirement (Bales & Wagner, 2009; Natural Resources Canada & Public Safety Canada, 2018). Research on the methods to model floods has rapidly increased in recent years (Mudashiru, Sabtu, Abustan, & Balogun, 2021; Teng et al., 2017) due to the opportunities created by technical advances (Dottori, Di Baldassarre, & Todini, 2013; Noh, Lee, Lee, Kawaike, & Seo, 2018), a deeper understanding of the uncertainty of the underlying hydrologic and hydraulic (H&H) models (Merwade, Olivera, Arabi, & Edleman, 2008; Teng et al., 2017), and increased evidence of the impacts of climate and land use change on flooding (Alipour, Engeland, & Leal, 2024; De Moel, Aerts, & Koomen, 2011; Qiang, Lam, Cai, & Zou, 2017). Floods remain the most expensive natural hazards (Jongman et al., 2014; Tellman et al., 2021), and legal actions resulting from incorrect predictions are a strong financial incentive to invest in accurate mapping (Stephens & Bledsoe, 2020). Despite a common perception of neutrality (Ajibade, McBean, & Bezner-Kerr, 2013), flooding intersects with demographic factors that include gender, age, income, and culture

(Doocy, Daniels, Murray, & Kirsch, 2013; He et al., 2024; Sharif, Jackson, Hossain, & Zane, 2015), which means accurate maps are also important for addressing the equity of flood protections. Governments around the world have renewed their interest in flood mapping for a range of regulatory analysis and communication purposes (Cattoën et al., 2022; De Moel et al., 2011; Merwade et al., 2008; Mudashiru et al., 2021; Nkwunonwo, Whitworth, & Baily, 2020; Speckhann, Borges Chaffe, Fabris Goerl, Abreu, & Altamirano Flores, 2018).

In Canada, the availability of flood mapping is highly uneven (Henstra & Thistlethwaite, 2018) and the federal government has made significant investments in programs such as the Flood Hazard Identification and Mapping Program (FHIMP), which began in 2021 (and has been extended to 2028) with a goal to create or update flood hazard maps for areas at higher risk of flooding (Natural Resources Canada & Public Safety Canada, 2018; Natural Resources Canada, 2024). However, while the federal government helps to ensure that flood management is approached in a broadly consistent manner, the Canadian provincial and territorial governments remain ultimately responsible for flood mitigation efforts and programs such as FHIMP are necessarily collaborative with lower levels of government (Natural Resources Canada, 2024). Provincial governments may produce their own guidance, for example with the ongoing update to the Technical Bulletin for Flooding Hazards (Government of Ontario, 2024), but typically they delegate the responsibility for flood mapping to municipal governments or water agencies. For example, watershed conservation authorities (CAs), which are responsible in Ontario for the areas where 95% of the population live, were created with a core mandate to protect life and property from flood hazards (Government of Ontario, 2024). The CAs may have the expertise to develop the H&H models themselves, but more often hire private consulting firms to create or update the models as needed. In this decentralized regulatory and professional environment,

there is a need for a collaborative approach to flood modeling, one that emphasizes the co-production of knowledge (Luke et al., 2018). Academic advances that use H&H models with which the regulatory and consulting industries are already familiar will be most likely to be rapidly adopted.

The H&H models used in flood mapping are subject to significant sources of uncertainty. The uncertainty can be considered as either natural, which originates from the natural/random variability of underlying processes, or epistemic, which originates from deficient information about the processes and factors (Teng et al., 2017). Sources of epistemic uncertainty can include: i) choice of model structures or processes, ii) model parameter values, iii) model inputs/boundary conditions, iv) change in floodplain landscape or characteristics over time and space, and v) change in climate conditions (Bales & Wagner, 2009; Liu, Merwade, & Jafarzadegan, 2019; Stephens & Bledsoe, 2020; Teng et al., 2017). The representation of uncertainty and the development of flexible tools for scenario analysis that can be used to support decision making is thus an important need for floodplain mapping and an area of active research (Liu et al., 2019; Mudashiru et al., 2021). Though they are fundamentally different, both types of uncertainty can be quantified using probabilistic or stochastic approaches (Di Baldassarre et al., 2010; Stephens & Bledsoe, 2020). A gap remains, however, because deterministic H&H approaches remain the standard for inundation mapping in many jurisdictions (Ahmadisharaf, Kalyanapu, & Chung, 2016; Stephens & Bledsoe, 2020). The need to communicate uncertainty is well known, as evidenced by the recent Ontario guidelines (Ontario Ministry of Natural Resources and Forestry, 2023), for example, which cites the study by Dottori et al. (2013), but the lack of tools to easily complete an objective analysis makes the routine assessment of uncertainty difficult in practice.

A suitable framework for modelling flood uncertainty will require the ability to loop through multiple simulations with coupled H&H models so that the parameter uncertainty inherent at different steps of the procedure can be propagated through the framework. However, few automatic tools are available for this purpose (Annis, Nardi, Volpi, & Fiori, 2020). Merwade et al. (2008) proposed a generic floodplain modelling information system (FMIS) that would result in a probabilistic flood inundation map, but the framework was more conceptual than practical at the time. More recently, Aronica et al. (2012) coupled a relatively simple rational hydrologic model and a 2D flood propagation model in a Monte Carlo based framework to assess uncertainty, Ahmadisharaf et al. (2018) coupled a semi-distributed Gold Sim hydrologic model and a 2D unsteady Flood2D-GPU hydraulic model, and Liu et al. (2019) used the hydraulic LISFLOOD-FP model with the ability to simulate uncertainty around hydraulic parameters and the input flow time series. Annis et al. (2020) developed a novel tool that couples stochastic hydrologic sampling from Intensity Duration Frequency (IDF) curves, the Curve Number method for estimating runoff, and instantaneous unit hydrographs, all of which are fed as input to the FLO-2D hydrodynamic software. There is no such thing as ‘perfect models’ (Teng et al., 2017), but the Storm Water Management Model (SWMM), developed and maintained by the United States Environmental Protection Agency (EPA) is widely used to simulate urban hydrology due to its physics-based approach for dynamics rainfall-runoff simulation of either event-based or continuous simulation (Lewis & Michelle, 2022). The Hydrologic Engineering Center’s River Analysis System (HEC-RAS), developed and maintained by the United States Army Corps of Engineers is widely used to simulate open-channel flow hydraulics for flood inundation modelling due to its physics-based approach and the ability to solve both steady (time-invariant) and unsteady (time-variant) flow in one and two dimensions (Brunner, 2022).

The current research was motivated by the perceived benefits in coupling these two models in a stochastic framework to make it easier to add uncertainty to the existing workflows of flood mapping.

Both the SWMM and HECRAS core modelling functions have been enhanced with commercial and open access extensions. For instance, developed commercial software such as PCSWMM and InfoWorks ICM allow for integration of SWMM simulations with GIS and other analysis options, enhancing its utility. Additionally, toolboxes of algorithms facilitate the automation of steps like the generation of subwatersheds (Niemi, Kokkonen, Sillanpää, Setälä, & Koivusalo, 2019; Warsta et al., 2017) and the selection of management strategies (Ghodsi, Zhu, Matott, Rabideau, & Torres, 2023). Extensions to the core algorithms of HEC-RAS are somewhat less common than for the SWMM model, but standalone geospatial capabilities for hydraulic analyses are available through its module RAS Mapper, and commercial software such as GeoHECRAS and the Watershed Management System (WMS) have also been developed. Program automation is also possible through the HEC-RAS Controller, which holds the largest collection of programming tools, such as classes and functions, of the HEC-RAS Application Programming Interface (API) (Goodell, 2014; Leon & Goodell, 2016). The controller can be accessed via a variety of programming languages, and some algorithms have been developed for automation of model calibration (Desrochers, Trudel, Peters, Siles, & Leconte, 2020; Dysarz, 2018) and comparison of scenarios (Worley et al., 2022). However, this controller and many extensions available for HECRAS are developed for older or simpler HECRAS versions such as 1D steady-state models (Desrochers et al., 2020; Leon & Goodell, 2016). 1D models are constrained by their network structure, the lack of lateral exchange of flow and momentum (Kalyanapu, Judi, McPherson, & Burian, 2012), and the assumption that a primary flow direction

can be defined a priori, even at complex channel confluences (Bales & Wagner, 2009). 2D models are preferred in relatively complex flows such as urban settings (Hosseini pour, Vargas, O'Brien, & Kasraie, 2012; Vojtek, Petroselli, Vojteková, & Asgharinia, 2019) and large floods where conveyance in the floodplain is relatively important (Liu et al., 2019). The assumption of steady flow for inundation modelling similarly suffers from error, particularly in areas such as urban rivers where the flows rise and fall quickly (Costabile, Costanzo, De Lorenzo, & Macchione, 2020) and precludes the ability to explore spatio-temporal characteristics of a flood and its uncertainties (Ahmadisharaf et al., 2018). HEC-RAS version 6.0 (released in 2020) now allows structures such as bridges and weirs to be modeled in the 2D domain via a combination of weir and pressure flows, an advancement that is critical for its application to urban areas where conveyance constraints due to civil infrastructures is common.

In this study we describe and demonstrate a novel stochastic framework, named SWMM-RASpy, that was developed to analyze the impact of hydrologic and hydraulic uncertainty on flood hazard mapping in urban areas. The main innovation is a Python based tool that uses stochastic sampling in combination with a SWMM model for watershed hydrology and a HEC-RAS model for channel hydraulics. These H&H models were selected because they are: i) free to download, ii) actively maintained by US government agencies, iii) applicable to urban areas with mixed drainage systems, modern stormwater management facilities, and complex in-channel flows. The selected models are also supported by watershed authorities in Ontario for floodplain mapping, which is important because the framework is intended to be immediately applicable in this jurisdiction. In particular, the new tool will build on previous work conducted with municipal governments and watershed authorities to add erosion modeling methodologies (Ghunowa, MacVicar, & Ashmore, 2021; Papangelakis, MacVicar, Montakhab, & Ashmore,

2022) to a decision support tool, called the Risk and Return on Investment Tool (RROIT) (Credit Valley Conservation, 2019), which calculates the financial, social, and environmental costs and benefits of municipal investments in stormwater management. A current weakness of the RROIT system is that it uses deterministic H&H models as part of the stochastic financial risk calculations, which means that the risk may be inaccurate. The widespread use of SWMM and HECRAS also means that SWMM-RASpy could be easily applied to other urban areas.

2.2 SWMM-RASpy Framework

The SWMM-RASpy framework was developed within the Jupyter Notebook environment using the Python programming language (Figure 2.1). The procedure is orchestrated by the **masterpy** script, which calls the **inputs_frameworkpy** script to initialize input parameters, and then calls the four core scripts (all codes developed for the SWMM-RASpy framework are highlighted in **bold** font). The algorithms stored in the four core scripts are: i. AutoSAMPpy, which generates samples for the parameters of interest; ii. AutoSWMMpy, which controls the operation of the hydrologic modeling module, including the execution of the SWMM model, iii. AutoRASpy, which controls the hydraulic modeling module including the execution of the HECRAS model; and iv. AutoRAS-HDFpy, which extracts the required outputs from the HEC-RAS model. These outputs are processed outside the framework, and used to construct stochastic flood hazard maps that help to visualize the uncertainty. **rasexecute.py** acts as a subsidiary script that is externally invoked by the AutoRASpy script; the rationale for which is explained later in the document. The following sections describe the methodologies of the four core scripts.

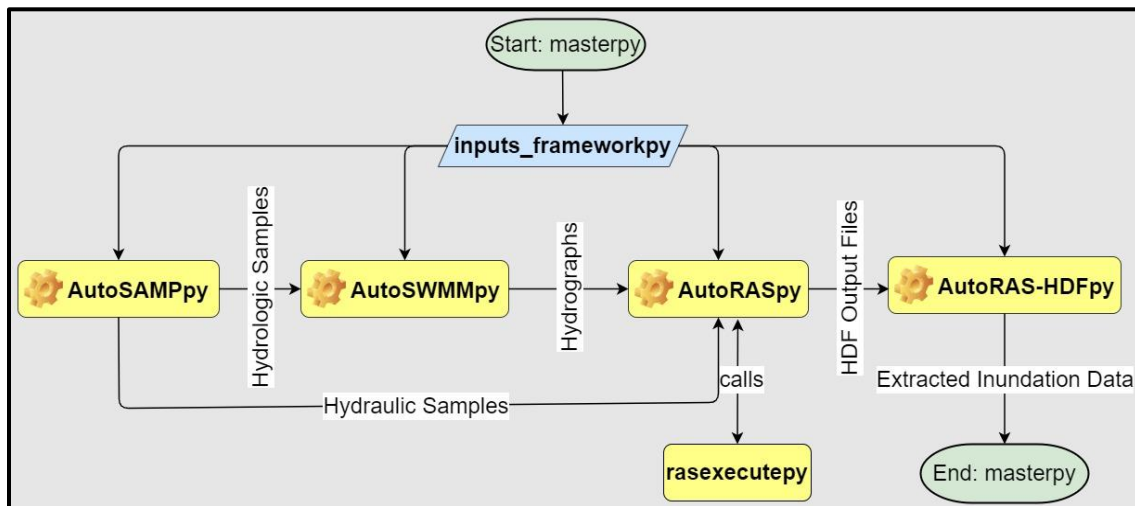


Figure 2.1: Flowchart of the automation processes of the SWMM-RASpy framework

2.2.1 Stochastic Sampling Module (AutoSAMPpy)

The stochastic sampling module generates samples for the parameters of interest using Latin Hypercube Sampling (LHS), a stratified sampling approach for which the sample set points are distributed evenly across the range of the input distribution (Papaioannou, Vasiliades, Loukas, & Aronica, 2017). Alternative approaches were considered, including fully randomized technique such as Monte Carlo Sampling (MCS), where any sample value may fall anywhere within the range of the probability, but LHS was employed because it is thought to require smaller sample sizes to attain the same precision in outcomes (Papaioannou et al., 2017).

The AutoSAMPpy script includes three sub-functions: i) **latin_hypercube_sampling**, which requires the upper and lower bound of the input parameter and the number of desired samples as arguments and returns a sample set of parameter values, ii) **generate_raindataset**, which invokes **latin_hypercube_sampling** to produce samples of rainfall intensity; and iii) **generate_lcmdataset**, which invokes **latin_hypercube_sampling** to produce samples of n values. Samples sets are stored as *.CSV files for ingestion into other sub-functions of the framework. A copy of AutoSAMPpy is provided in Appendix A.

2.2.2 Hydrologic Modeling Module (AutoSWMMpy)

The hydrologic modeling module is built around the execution of a SWMM model. A SWMM model has two main computational components related to surface-water hydrology: i. the rainfall/runoff component, which operates on the collection of a watershed's subcatchment areas that receive precipitation and generate surface runoff through an infiltration model, and ii. the flow routing component, which simulates the movement of this runoff through the watershed's drainage network system over time, encompassing a combination of pipes, streets,

storage/treatment units and diversion structures (Lewis & Michelle, 2022). The model typically takes in rainfall data, topography, soil characteristics, land uses, and drainage networks as its inputs. Any of the parameters or process models may have significant natural or epistemic uncertainty associated with them and hence, may be relevant for stochastic modelling. For the current framework, rainfall intensity was selected to represent hydrologic uncertainty due to its dependence on return period estimation, which is highly uncertain for extreme floods given limited data records and effects of climate change.

To run a SWMM model, a text '*.inp' file lists the study catchment characteristics and model user commands. A practical method to update the SWMM model is to directly modify this input file, especially when repeated executions of the model are warranted. Rainfall data is provided as a hyetograph that is either entered manually or stored external *.DAT file that is specifically formatted for use with the SWMM program. The latter is the viable option when a series of rainfall hyetographs need to be inputted sequentially, as is common in stochastic modeling. Following the execution of a SWMM model, the results are written to an output file denoted by the extension '.out'. This file is in a binary format, indicating that its contents can only be read using SWMM's built-in tools or other programs capable of interpreting the binary structure. SWMM does not have built-in features for automating a workflow, so all automation steps must occur using programming languages and external tools.

The AutoSWMMpy script allows users to use an existing deterministic SWMM model for stochastic simulation by running a loop to convert sample rainfall intensities to a rainfall hyetograph, update a SWMM model with a new hyetograph, execute the updated model, and extract hydrographs from the output file. Version 5.2.2 of SWMM was used for tool development. Functions/methods from two external Python toolboxes were used: i) PySWMM,

which designed for interacting with the SWMM *.inp file (McDonnell, Ratliff, Tryby, Wu, & Mullapudi, 2020), and swmmtoolbox, which is designed to extract information from the output binary file created by SWMM (Cera, 2013). Both the PySWMM and swmmtoolbox packages work with versions 5.0 or newer of SWMM and require Python version 3.6 or newer.

In AutoSWMMpy, hyetographs are created using Python's built-in functionalities. The **RainfallSimulator** class, which consists of several functions, was constructed for this step. This study used Chicago Storm Distribution (CSD) method for producing rainfall hyetographs. The CSD method is particularly noted for its application in designing urban drainage systems to withstand a specific storm event by providing a realistic temporal distribution of rainfall. This method takes in design rainfall intensities (derived from an IDF curve) and distributes them over the storm's duration, typically placing the peak intensity at or near the storm's center to create a non-uniform distribution with concave upward rising and falling limbs. The method is widely used to simulate storm events in urban drainage design, including in Ontario (Ontario Ministry of Transportation, 1997). Equations 2.1 and 2.2 were considered in this study to estimate instantaneous rainfall intensities for designing the Chicago Storm event.

$$i_b = \frac{A \left[\frac{(1-C)(t_p - t)}{\gamma} + B \right]}{\left(B + \frac{t_p - t}{\gamma} \right)^{1+C}} ; t < t_p \quad (2.1)$$

$$i_a = \frac{A \left[\frac{(1-C)(t - t_p)}{1-\gamma} + B \right]}{\left(B + \frac{t - t_p}{1-\gamma} \right)^{1+C}} ; t > t_p \quad (2.2)$$

where i_b and i_a are the instantaneous rainfall intensities (mm/hr) at time t before and after the peak of a hyetograph respectively, t_p is the time to reach the hyetograph's peak (hr), and A, B

and C are IDF coefficients. t_p is estimated by multiplying the total duration of the event with a time-to-peak factor (γ) that ranges between 0 and 1. More details on the CSD method can be found in the article by Keifer and Chu (1957). The **RainfallSimulator** class takes in the necessary parameters for the CSD method as inputs, and stores the outputs in corresponding DAT files. Following the creation of the hyetographs, the SWMM *.inp file is updated with these new rainfall hyetographs using **update_swmm_input_file**. The SWMM model is executed through **run_swmm_simulation** function which calls ‘Simulation’ function and ‘execute’ method from PySWMM. Following the execution of the model, the **extract_and_save_node_data** function from swmmtoolbox is called to read the binary '.out' files produced by SWMM simulations and convert the data into CSV format for transferability to subsequent steps within the framework. A copy of AutoSWMMpy is included in Appendix A.

2.2.3 Hydraulic Modeling Module (AutoRASpy)

The AutoRASpy script allows users to use an existing deterministic HEC-RAS model for stochastic simulation by updating a HECRAS model with Manning’s n values retrieved from *CSV files created by AutoSAMPpy, updating the HEC-RAS inflow hydrographs with the output hydrographs from *CSV files created by AutoSWMMpy, and running the HEC-RAS model. Version 6.1 of HEC-RAS was used in the current study. More details about all HECRAS procedures and computations can be found in the HEC-RAS Hydraulic Reference Manual (Brunner, 2022). Assuming no lateral inflows, the 2D continuity equation can be written as:

$$\frac{\partial(hu)}{\partial x} + \frac{\partial(hv)}{\partial y} + \frac{\partial h}{\partial t} = 0 \quad (2.3)$$

where h is the water depth (m), t is time (s), u and v are the water velocity components (m/s) in the x and y cartesian directions. Assuming negligible surface wind, atmospheric pressure gradients, and Coriolis effects, the 2D momentum equations can be written as:

$$\frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} + v \frac{\partial u}{\partial y} = -g \frac{\partial z_s}{\partial x} + \frac{1}{h} \frac{\partial}{\partial x} \left(\nu_{t,xx} h \frac{\partial u}{\partial x} \right) + \frac{1}{h} \frac{\partial}{\partial y} \left(\nu_{t,yy} h \frac{\partial u}{\partial y} \right) - \frac{\tau_{b,x}}{\rho R} \quad (2.4)$$

$$\frac{\partial v}{\partial t} + u \frac{\partial v}{\partial x} + v \frac{\partial v}{\partial y} = -g \frac{\partial z_s}{\partial y} + \frac{1}{h} \frac{\partial}{\partial x} \left(\nu_{t,xx} h \frac{\partial v}{\partial x} \right) + \frac{1}{h} \frac{\partial}{\partial y} \left(\nu_{t,yy} h \frac{\partial v}{\partial y} \right) - \frac{\tau_{b,y}}{\rho R} \quad (2.5)$$

where g is gravitational acceleration (m^2/s), z_s is the water surface elevation (m), $\nu_{t,xx}$ and $\nu_{t,yy}$ are the horizontal eddy viscosity coefficients in the x and y directions (m^2/s), $\tau_{b,x}$ and $\tau_{b,y}$ are the bottom shear stresses in the x and y directions (N/m^2), and R is the hydraulic radius (m). For the above, τ_b is written as:

$$\tau_b = \rho C_D |V| V \quad (2.6)$$

where C_D is a drag coefficient, calculated as:

$$C_D = \frac{n^2 g}{R^{\frac{1}{3}}} \quad (2.7)$$

where R is the hydraulic radius (m) and n is Manning's roughness coefficient ($\text{s}/\text{m}^{1/3}$). ν_t is computed as the sum of two terms, with the first a function of user-specified mixing coefficients in the longitudinal (D_L) and transverse directions (D_T), and the second a function of the $x - y$ strain rate and the Smagorinsky coefficient (C_s). Of these parameters, Manning's n , D_L , D_T , and C_s are all empirical coefficients and so are relevant for stochastic modelling. For the current framework, Manning's n was selected to represent hydraulic uncertainty due to its natural variability in heterogeneous urban environments.

Updating the Manning's n values as part of a stochastic simulation requires the program to modify the HEC-RAS geometric data file. The geometric data file is created as part of the generation of the model computational mesh, which needs to be created manually prior to the execution of the SWMM-RASpy framework based on a Digital Elevation Model (DEM). As part of the computational mesh, the extent of the computational domain or flow area, the location of break lines where the mesh cells will align, the location of boundary conditions (BCs), and the initial values for Manning's n must be defined following recommendations from Brunner (2022). The Manning's n values are then stored in a geometric data file, which is encoded in a binary HDF5 (Hierarchical Data Format version 5) format. HDF5 files are efficient for handling large, diverse, and complex datasets because of the hierarchical structure that allows users to access specific data segments without having to process the entire file (Brunner, 2022). In the geometry file, the raster map of roughness values is accessible via the path "/Geometry/Land Cover (Manning's n)/Calibration Table". HDFView was used to view the HEC-RAS HDF5 geometric files (downloaded from <https://www.hdfgroup.org/downloads/hdfview/>) during program development. Functions from the external Python toolbox 'h5py' were used to retrieve data from HDF5 files during AutoRASpy execution.

Updating the flow as part of a stochastic simulation requires the program to modify the inflow hydrographs, which may include upstream BCs defined on main channel where water enters the flow area, and all internal BCs where flow changes due to tributary inputs or stormwater outlets. Inflow hydrographs are stored in external DSS (Data Storage System) files, which is designed for managing larger datasets, in a format that is unique to the HEC-RAS. These HEC-DSS databases can be managed through an external application called HEC-DSSVue, which is a Java-based program created for this purpose by the U.S. Army Corps of

Engineers' Hydrologic Engineering Center. Version 3.2.3 of HEC-DSSVue was used for tool development.

The AutoRASpy script automates the workflow of the hydraulic modeling module, which involves updating the 2D HEC-RAS model with new hydrographs and Manning's n values, and then executing the updated model. In terms of the logical flow of the script, it first calls **read_csv_data** to read CSV hydrograph files produced by AutoSWMMpy. Subsequently it calls **write_to_dss** to update the boundary conditions of the HEC-RAS model using these files, employing HEC-DSSVue's 'hec' module for data manipulation and analysis. For these updates, AutoRASpy needs to operate within the HEC-DSSVue environment, necessitating the temporary move of **inputs_frameworkpy** and the script itself to the HEC-DSSVue directory. This requirement derives from HEC-DSSVue's use of Jython, which allows for Python scripting on its Java platform but is based on the older Python 2.7 version. This environment is incompatible with the rest of the SWMM-RASpy environment, which uses Python 3.6 or newer. For this reason, AutoRASpy runs the function **rasexecutepty** externally by invoking **run_external_script** (shown in Figure 2.1). This setup ensures that the data manipulation dependent on HEC-DSSVue can be included in an automated workflow within SWMM-RASpy. **rasexecutepty** also calls **update_mannings_n** to update the HEC-RAS geometry HDF5 file with samples of n values. Finally, **run_simulation** is called to run the HEC-RAS model using HEC-RAS Controller commands as an executable within the script (Dysarz, 2018).

2.2.4 Data Extraction Module (AutoRAS-HDFpy)

The data extraction module was designed to acquire the inundation data needed from the model simulation to create flood hazard maps. It extracts data based on user-defined flood parameters from the 2D HEC-RAS model's output file and stores this data in the CSV file

format. Similar to its geometry file, HEC-RAS stores all its 2D model computation results in an HDF5 file. The data pertaining to 2D flow area computations can be accessed within the file structure at: '/Results/Unsteady/Output/Output Blocks/Base Output/Unsteady Time Series/2D Flow Areas/'. By default, an HDF output file includes water surface elevation data for a 2D flow area; however, information about additional variables such as flood depth and velocity can also be written to the file. In order to retrieve such information, a user need to select the relevant parameters from the program's 'HDF5 Write Parameters' tab, accessible via the program's graphical user interface under **Run → Unsteady Flow Analysis → Options → Output Options → HDF5 Write Parameters**. Further details about reading and writing these output HDF files can be found in the '2D Output File (HDF5 binary file)' section of the HEC-RAS 2D User's Manual (Brunner, 2022).

The AutoRAS-HDFpy script streamlines the operations of the data extraction module. The two key functions are **find_hdf_files_with_output**, which locates the HDF output files in a directory specified by the user, and **extract_and_save_data**, which uses functions from the 'h5py' library to extract data for variables specified by the user and stores this data in CSV format. A copy of the script is provided in Appendix A.

2.3 Inundation Uncertainty Quantification and Mapping

The uncertainty of inundation was quantified by calculating the flooding probability (P_f) and the analogous entropy (E) following the methods described by Horritt (2006) and Lim (2018). The state of inundation for the cells within a 2D flow area was determined based on their water surface elevations. At the start of the simulation all cells were assumed to be dry and given a value of 0. If a cell exhibited a positive water surface elevation at any time interval during a HEC-RAS simulation, it was considered to be wet and given a value of 1. P_f at a location (x, y) was then calculated as:

$$P_{f(x,y)} = N_{w(x,y)} / N \quad (2.8)$$

where $N_{w(x,y)}$ is the number of simulations in which the cell was wet, and N is the total number of simulations. The probability of remaining dry ($P_{d(x,y)}$) was calculated as:

$$P_{d(x,y)} = 1 - P_{f(x,y)} \quad (2.9)$$

The concept of analogous entropy was used to describe the uncertainty surrounding flood inundation (Horritt, 2006). With this approach, E is high if cells are wet in some simulations and dry in others, and low when cells are consistently either wet or dry. In the current study the entropy ($E_{(x,y)}$) was calculated as a specific type of Rényi entropy (Singh, 2013) defined as:

$$E_{(x,y)} = -\log_2 P_{f(x,y)} \quad ; \quad P_{f(x,y)} \leq 0.5 \quad (2.10)$$

$$E_{(x,y)} = -\log_2(1 - P_{f(x,y)}) \quad ; \quad P_{f(x,y)} \geq 0.5 \quad (2.11)$$

With this formulation, a value of $P_{f(x,y)} = 0.5$ corresponds to the highest level of uncertainty, where $E_{(x,y)} = 1$, as shown in Figure 2.2. Equations 2.10 and 2.11 result in a peaky relation between probability and entropy, which is called ‘minimum entropy’ because it highlights the

most probable outcome and discounts less probable outcome (Singh, 2013). Thus, it is considered a conservative estimate of entropy that is particularly suited to situations where the worst-case scenario needs to be considered (Singh, 2013). For visualizing the uncertainty through maps, cells that were wet at least once throughout the N simulations were selected for inclusion in the map. Their coordinates and P_f values were imported into the ArcGIS program in a CSV file. Through the required geoprocessing, a flood probability map was first produced, which was then further geoprocessed to produce the entropy map using Equations 2.10 and 2.11.

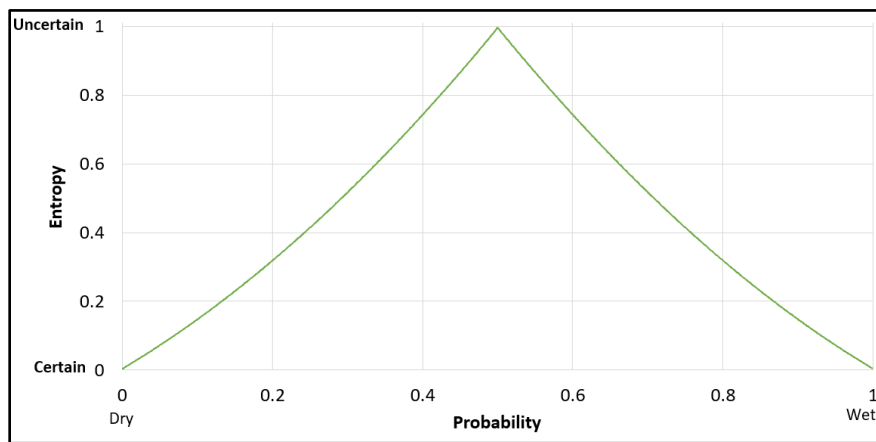


Figure 2.2: Entropy plot demonstrating Equations 2.10 and 2.11

2.4 Case Study: Cooksville Creek

2.4.1 Site description

Cooksville Creek watershed has a drainage area of 33.9 km² that outlets to Lake Ontario and is located entirely within the City of Mississauga (Figure 2.3). The watershed is highly urbanized as current land use is comprised of ~60% residential, ~34% commercial/industrial, ~5% institutional/other, and less than 1% of natural land cover (Randall, Perera, Gupta, & Ahmad, 2017). Most of the watershed area was developed over an approximately 40 year period from the mid 1950's to the 1990's, during which time the focus was on rapid drainage and conveyance of stormwater (Credit Valley Conservation, 2020). The urban nature of the watershed combined with steep slopes in some channel reaches has led to channel degradation and widespread reconstruction/stabilization efforts in the creek (Credit Valley Conservation, 2020; Tinkler, Parish, & Wohl, 1998). Notable floods occurred in 2009 and 2013 when approximately 70 mm of rainfall fell over 10-12 hours (Randall et al., 2017). Up to 60 mm fell within a 1-hour period in the 2009 event such that the recorded flows exceeded the modelled flows for a synthetic 100-year storm (Aquafor Beech Ltd., 2012) and peak intensities were even higher for the 2013 event (Randall et al., 2017). Significant flooding and damage due to erosion occurred in both events (Credit Valley Conservation, 2020). The watershed is expected to become more susceptible to flooding as high intensity rainfall events increase due to climate change (Credit Valley Conservation, 2020).

After the 2009 flood, a Flood Evaluation Master Plan study was conducted by the local watershed authority, Credit Valley Conservation (CVC), which works with the municipal government to maintain the river and mitigate potential flood hazards (Aquafor Beech Ltd., 2012). In the study/report, several strategies were recommended to mitigate future flooding in

the area, including creating storage in the upper watershed, increasing capacity of the watercourses and channels, constructing flood levees in some locations, and implementing Low Impact Development (LID) source and conveyance control measures. After the 2013 flood, a resolution was passed by the City of Mississauga that mandated the use of LID for flood management in the watershed and an updated flood mitigation plan was produced based on updated modelling, financial risk analysis, and SWM infrastructure investment scenarios (Credit Valley Conservation, 2020). The risk and return on investment tool (RROIT) was developed by the CVC to help address this new mandate. Amongst other analyses, RROIT uses inundation mapping generated with a SWMM model based on current and future land-development and climate scenarios in combination with a steady state 1D HECRAS models to assess risk scenarios. This information is used to help the authority determine the recommended level of service for flood management and support investment from the municipality in flood management infrastructure. Construction projects involving new retention basins and LID have begun as the CVC and the City of Mississauga continue to try to reduce flood hazard and risk in the watershed (Credit Valley Conservation, 2020).

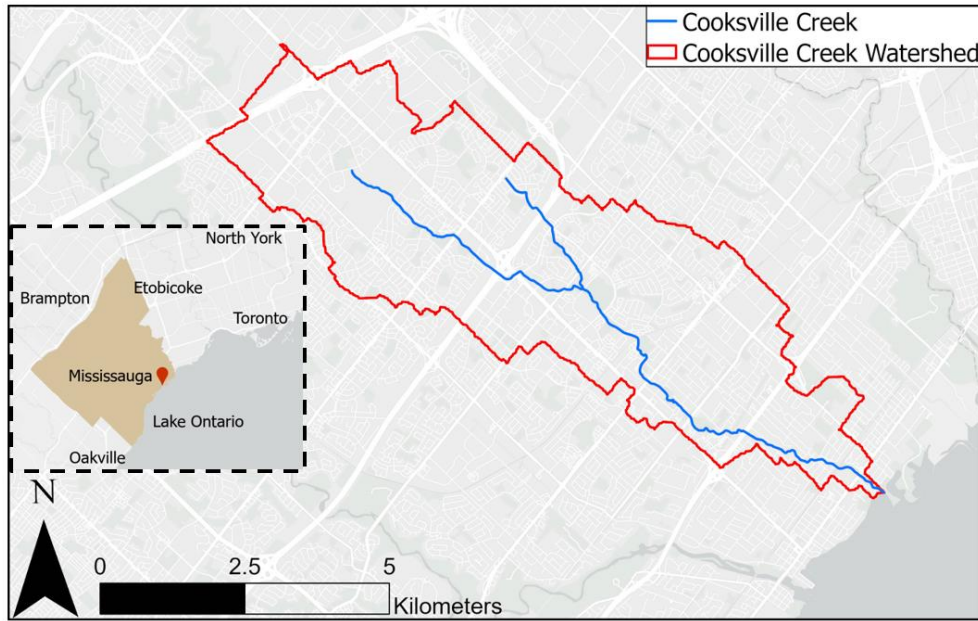


Figure 2.3: Map of Cooksville Creek watershed with its location inside the City shown in the inset map

2.4.2 Hydrologic Model

A semi-distributed dual drainage model developed for the Cooksville Creek watershed was developed for the CVC following the 2009 and 2013 floods (Randall et al., 2017). The model is highly detailed and includes more than 4000 subcatchments, a near-complete minor drainage network of subsurface pipes, and all major drainage components such as open-channels and overland routes such as roads. Channel geometry and bridge information was also imported to create a comprehensive model of the watershed all the way to the outlet with Lake Ontario. The Green and Ampt method was used to model infiltration. Twelve of the largest rainfall events (duration ranging from 10 hours to 30 hours) during the snow free period of the years 2009 and 2013 were used to calibrate the model. Validation was completed using another 12 rainfall events during the same period. The model showed a very good agreement between the computed outputs and observed data, with Nash–Sutcliffe coefficients of 0.86 and 0.82 for the peak and total flow volumes in the calibration events and 0.90 and 0.80 for the same metrics in the

validation events (Randall et al., 2017). Since the model was already well calibrated and validated for the study site, no further calibration/validation was performed as part of the current study.

For the current study, a single CSD-based design storm was simulated to evaluate the hydrologic modeling module of the framework. The design storm adhered to the guidelines from the Ontario Ministry of Transportation (MTO) drainage manual (Ontario Ministry of Transportation, 1997). The time of concentration (T_c) was estimated to be between 2 and 3 hours based on the method originally introduced by R.W Carter (1961), which is suitable for highly urbanized watersheds with significant pipe flow (Salimi, Nohegar, Malekian, Hoseini, & Holisaz, 2017; Sharifi & Hosseini, 2011). Given that the duration of the design storm should be equal to or greater than T_c , the duration of the synthetic storm was set at 3 hours. A 100-year return period was chosen for the rainfall event because it is used for risk analysis, evaluation and flood management in the Cooksville watershed (Credit Valley Conservation, 2020). The storm event's intensities were estimated using the IDF data obtained from City of Mississauga's Development Requirements Manual (City of Mississauga, 2020). The duration of the SWMM simulation event was set at twice of the rainfall duration (i.e. 6 hours) with a computational step of 5 minutes.

2.4.3 Hydraulic Modeling in the Case Study Site

A 1D steady state hydraulic model developed in HEC-RAS software for Cooksville Creek was provided by the CVC for the current project. As part of the research, the 1D steady model was converted to a 2D unsteady model to better estimate flood hazards. This conversion process was time consuming and complex, particularly due to the existence of numerous

hydraulic structures such as bridges and culverts along the creek and the calibration process. The following paragraphs describe the conversion and calibration process for this hydraulic model.

Topographical information for the site included a digital elevation model (DEM) and the cross-section and bridge geometry information stored within the existing 1D HECRAS model. The available DEM was a relatively coarse (30m x 30m) grid with a spatial projection of NAD 1983 UTM Zone 17N. This initial DEM was resampled to a resolution of 1 meter based on bilinear interpolation. Within the channel area, available surveyed bathymetry data was interpolated onto the 1 m grid and used to replace the DEM-derived elevations. Blocked obstructions, which are defined as floodplain structures that obstruct the conveyance of flow were represented in the 2D topography of the DEM following the method recommended in the HEC-RAS Mapper User's Manual (2020).

A modelling challenge with Cooksville Creek is that it has 37 bridges locations (Figure 2.4a). All bridges were defined using data from the CVC's 1D model, following the guidelines outlined in Brunner (2022). During this process, a potential source of error was noted based on the differences between recorded bridge topographies and the available DEM. One example (Central Parkway) is shown in Figure 2.4b, where some discrepancies are visible in the bridge opening between the 1D and 2D models. The problem is that the topographic data in the bridge sections were not considered while creating the creek's DEM, and the 2D grid elevation data at the location of the structures was calculated based on the interpolated elevation between the u/s and d/s external cross sections. The discrepancies can significantly affect the flow conveyance through the bridge. The discrepancies were eliminated or minimized manually where it was not possible to do so using the software's built-in tools inside its RAS-Mapper. Regardless, special

attention needs to be paid to the channel geometry around bridge locations.

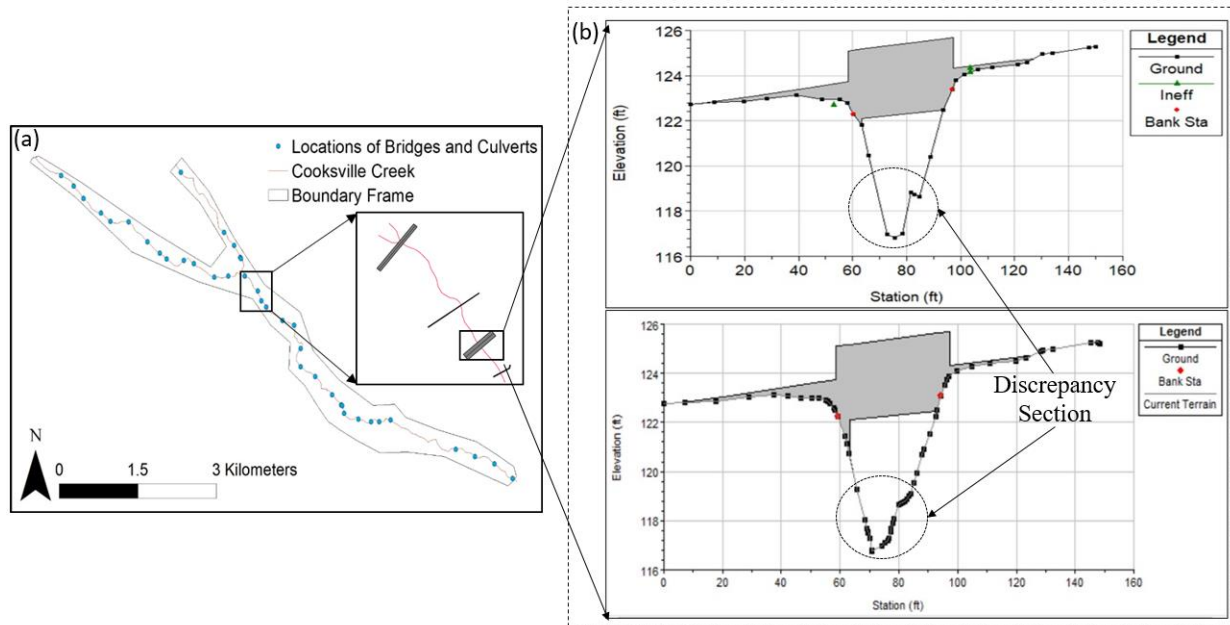


Figure 2.4: (a) Location of bridges along the Cooksville Creek and (b) section of discrepancy visualizing the disparity between the upstream cross sections from 1D model (at the top) and 2D model (at the bottom) of a bridge located near the Central Parkway of the study site

The computational mesh was created from the final updated DEM and manually defined breaklines and boundary conditions as shown in Figure 2.5a. The mesh was created using Triangulated Irregular Network (TIN) algorithm with an initial assumption of a 1m x 1m grid (i.e. the resolution of DEM), but this mesh size was later increased as part of the calibration process described in later in this section. Breaklines were defined at all bridges and the channel centerline to ensure the alignment of flow cells as shown in Figure 2.5b. The Manning's n raster map, used in the 2D modeling, was generated from a land cover raster map of the watershed and four broad classifications of i) developed, ii) floodplain, iii) channel, and iv) wetland. The n values for each land cover class was set at the midpoint of their respective ranges. The land cover map was based on a 2010 map produced by Agriculture and Agri-Food Canada that was resampled to create a raster map that matched the resolution of the DEM. Internal and external boundaries were defined at all outlets from major or minor watershed drainage systems to the

open channel of Cooksville Creek in the SWMM model. The local bed slope at each boundary location was used as the slope of the Energy Grade Line for these boundary conditions.

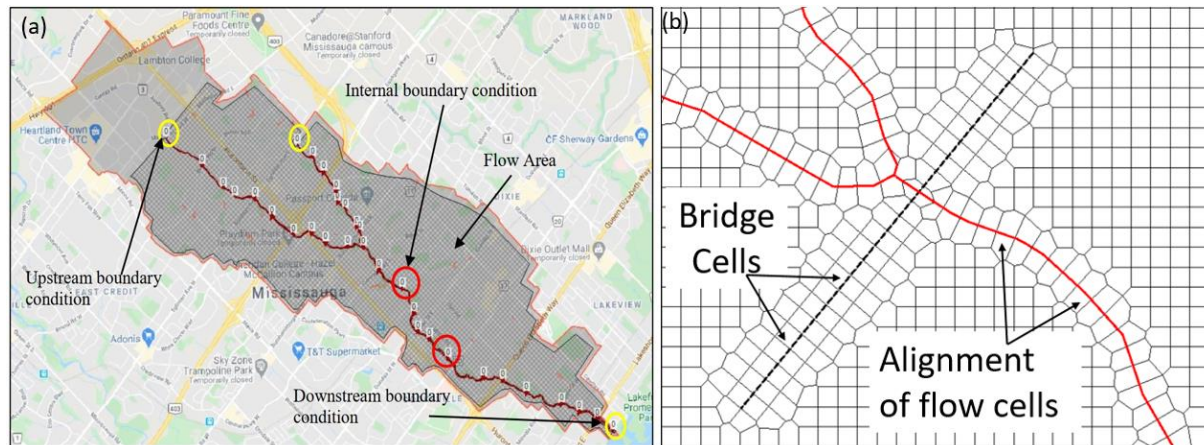


Figure 2.5: (a) Flow area and boundary locations for hydraulic modeling inside the study site and (b) alignment of the mesh grids inside the flow area

A base HEC-RAS 2D model was optimized for computational cost prior to its use within the stochastic framework. As part of this step, the computational method and preliminary values for the mesh size and time step were chosen. For the computational method, the dynamic wave or Full Momentum (FM) approach is generally assumed to produce more accurate results (Brunner, 2022), but the Diffusion Wave (DW) approach is often relatively stable and is computationally less expensive. Following testing of both methods, the DW approach was used because the results were not significantly different than the FM results. The choice of mesh (grid) size of the flowarea is a key parameter for optimizing the accuracy and computational time (Brunner, 2022). Small cell sizes are generally necessary where the topography/terrain changes rapidly, but large cell sizes can sometimes be used, even in highly uneven terrain (Abedin & Stephen, 2019). Accurate model results depend on the ratio of the computational time step (ΔT) and the product of the water velocity (V) and the cell size (ΔX), commonly written as the Courant number (C):

$$C = V * \frac{\Delta T}{\Delta X} \quad (2.12)$$

For the current analysis, the HEC-RAS option called ‘Variable Time Step’ was selected with a Maximum Courant value of 1.0, which is suitable for models where depth and velocity change rapidly. With this option, ΔT is adjusted automatically to ensure an optimum trade-off between computation time and model accuracy.

The model was calibrated to further adjust the cell size if needed and select values for the turbulence coefficients (D_L , D_T and C_s). The calibration followed a trial and error procedure with an objective of minimizing the difference in inundated extent between CVC’s calibrated 1D model (Papaioannou et al., 2017) and the 2D model. The difference was characterized using the Feature Agreement Statistic, also known as F-statistic, which is widely used for this purpose (Lim, 2018). F-statistic has several variations, and the one used in the research is given by the following equation (Horritt, 2006):

$$F_i = \frac{CA_i}{CA_i + OA_i + UA_i} \quad (2.13)$$

where i is the simulation number; F is the value of F-statistic, CA is the area common to both the observed (i.e. the 1D model) and the modelled (i.e. 2D model) flood extent for simulation i , and OA and UA are the areas that are over- and under-predicted, respectively, by the 2D model for the simulation i . F ranges between 0 and 1, with a higher value indicating superior accuracy. All the simulations that showed a F value greater than 0.90 were selected and ranked according to their computational time in ascending order. Among them, the one with the lowest rank was selected, and thus, the optimum values for the calibration parameter set were obtained. Default ranges of parameters and final calibrated values are shown in Table 2.1. The range of values for

the mixing coefficients was taken from HEC-RAS 2D User's Manual (Brunner, 2022), assuming gentle meanders and moderate surface irregularities in the Cooksville Creek.

Table 2.1: List of calibration parameters, their ranges and optimum values used in the research

Calibration Parameter (unit)	Range of Values	Calibrated Value
Computation Method	DW, FM	DW
Mesh Cell Size (m)	1-10	10
Time Step (min)	1-10	1
Longitudinal Mixing Coefficient (D_L)	0.3-1	0.5
Transverse Mixing Coefficient (D_T)	0.1-0.3	0.3
Smagorinsky Coefficient (C_s)	0.05-0.2	0.1

2.4.4 Stochastic sampling

To demonstrate the SWMM-RASpy framework in Cooksville Creek, stochastic sampling using LHS method was conducted by varying the hydraulic roughness, Manning's n . A uniform probability distribution was applied to the parameter, reflecting the lack of prior assumptions about its uncertainty (Ahmadisharaf et al., 2018). The initial ranges of n values for the existing land covers in the study watershed are provided in Table 2.2 (Brunner, 2022). Adjusted n values for these land covers, are also shown, which assumed an additional variation of -20% to +20% from their original values to provide a larger span of n values in order to better capture their impacts on flood modeling/mapping (Castro-Bolinaga & Diplas, 2014). At bridge locations, the original n values from the 1D model, which were used in the initial 2D model setup, were replaced by the corresponding new n values at their upstream (external and internal) and downstream (external and internal) cross sections. The distribution of these n values between the

distances of a bridge's external and internal cross sections on its both ends was considered to be uniform, as is standard for bridge hydraulics in HEC-RAS.

Table 2.2: Original and adjusted n values for land covers of the study site used in sampling

Land Cover Name	Original Manning's n Range	Adjusted Manning's n Range
Developed	0.06-0.20	0.048-0.24
Floodplain	0.035-0.08	0.028-0.096
Wetland	0.045-0.15	0.036-0.18
Channel	0.025-0.055	0.02-0.066

The ideal number of model runs to describe uncertainty is affected by the type of hydraulic model (1D or 2D), model resolution, study area size, and the type of outputs (Lim, (2018)). 100 simulations were run for the current study to demonstrate the utility of the SWMM-RASpy tool for calculating the impact of hydraulic uncertainty on flooding. The initial set of n values from which roughness samples were selected for each run was created using the LHS method, with five sample values from each of the four different land covers at the study site to make a set of different n value combinations. For each of the 100 runs, the creation process began with applying the LHS method to the adjusted n value ranges specific to each land cover type. The LHS method produced 100 distinct samples for each land cover class. Next, from these 100 unique samples for each land cover, one sample was selected. These chosen samples, one from each land cover type, were then compiled to form a complete sample set. Therefore, each sample set contained four samples, each corresponding to one of the four distinct land cover types, culminating in a total of 100 sample sets. Out of 100 hydraulic simulations, 96 simulations were accepted for which the calibrated 2D HEC-RAS model ran successfully without any stability issue based on its threshold volume accounting error of 2% (Brunner, 2022). Each time

a simulation was run, the Manning's map i.e. the HDF geometry file of the model, was updated with the new n values. Following the procedure described in Section 2.3 of this document, the inundation probability and entropy maps were produced for the case study.

2.5 Results

The probability of inundation is shown for the study area in Figure 2.6., which demonstrates the flood prone areas using the H&H analysis. The map was created using only the grid cells that were flooded in at least one of the stochastic simulations. The inundation extent is relatively narrow in most areas, due to relatively deep valleys and anthropogenic creek modifications to reduce the flood risk. However, despite this general impression of a limited flooding hazard, the two insets maps show that the uncertainty is potentially significant for neighbouring buildings and properties. Near the junction between the east and west branches of the creek (Zone A), the highest flooding probability is largely restricted to a narrow zone near the creek where the valley is locally quite deep. In most simulations, no houses or properties are at risk in Zone A. However, flooding is uncertain, as indicated by the areas with red and orange colouring, where flood inundation limits in the stochastic simulation did sometimes overlap with house and property boundaries. There is also a moderate probability of an overflow channel (purple shaded) flowing from the west branch of the creek upstream of the confluence through to the main branch of Cooksville Creek. In Zone B, which is the widest inundation area in the system, both the high and low probability inundation zones included properties and buildings. The area to the south-west side of the channel where relatively a large inundation area was observed is particularly vulnerable, with some buildings and properties showing a high probability of flooding, with others showing a reduced but still positive inundation probability.

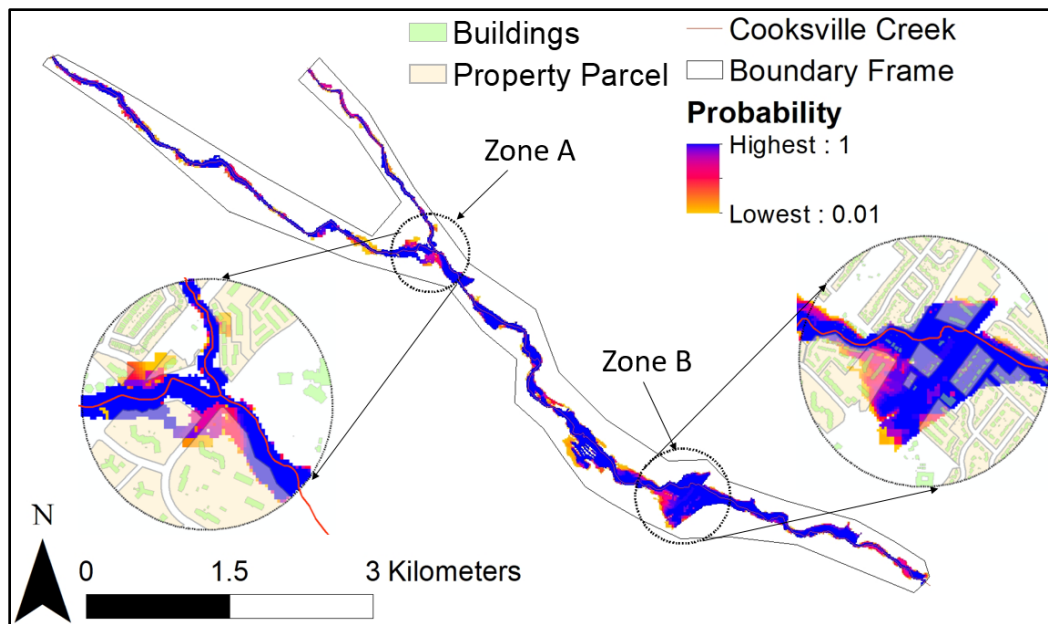


Figure 2.6: Probability map showing the spatial distribution of inundation probabilities at the grid cells that were flooded in at least one of the simulations Building footprints and property parcels are used with permission from the CVC.

A comparison of the inundation maps/extents within the two identified flood zones from the 1D model, the 2D deterministic model and the stochastic modeling of the framework are shown in Figure 2.7. The 1D deterministic model refers to the 1D HEC-RAS model provided by CVC where the 2D deterministic model is the HEC-RAS 2D unsteady model which was developed and calibrated as part of testing the framework for the case study. In Zone A the 2D deterministic model resulted in slightly more flooding than the 1D model, which led to more properties potentially flooded. When uncertainty from roughness is considered, the potential inundation area and numbers of affected properties increased considerably. In Zone B a similar phenomenon is observed. Although it was not possible to depict flooding in other areas at these resolutions due to space limitations, similar discrepancies were observed in several other regions of the study area.

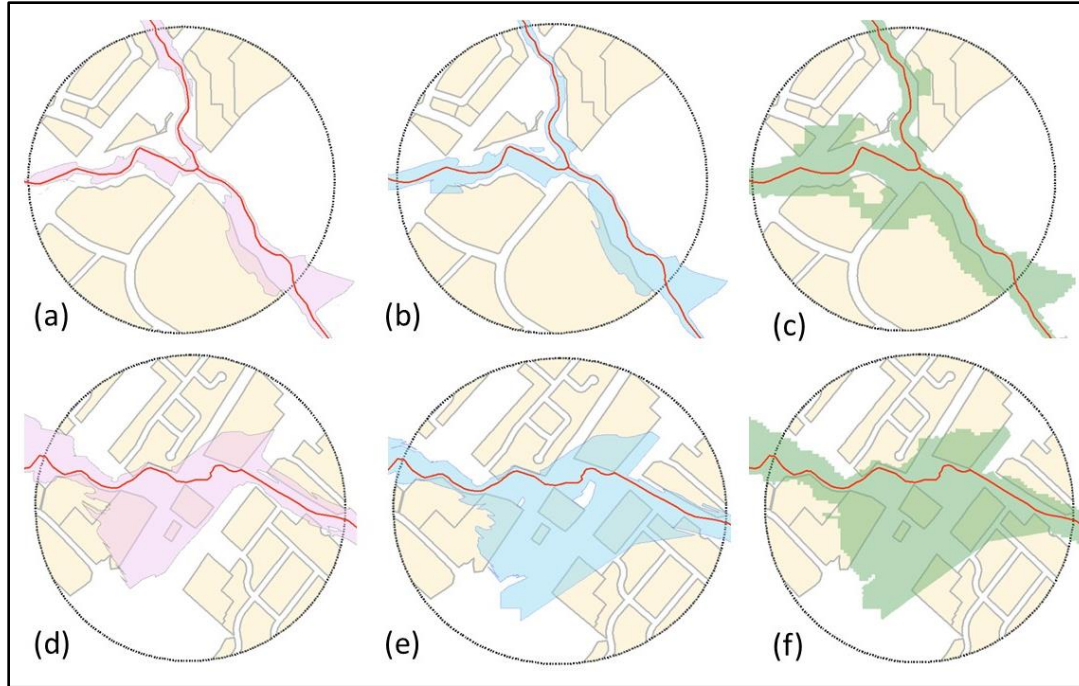


Figure 2.7: Inundation in Zone A from (a) 1D model (b) 2D deterministic model and (c) 2D stochastic framework, and Inundation in Zone B from (d) 1D model (e) 2D deterministic model and (f) 2D stochastic framework. Zones A and B are defined in Figure 2.6. Inundation from the stochastic framework considered flooding at the grid cells that were flooded in at least one of the simulations. On the background of the inundation extents, property parcels are displayed.

The total inundation area (IA) was computed for the study site for each model option and each run of the stochastic simulations. With the 1D deterministic model, the inundation area was 1.15 km², while the 2D deterministic approach was slightly larger (1.25 km²) and the maximum area inundated under any of the stochastic 2D model runs was 1.45 km², or ~4.5% of the total watershed area. In comparison, the inundated area from any single 2D simulation varied from ~1.14 km² to ~1.32 km². A normal distribution was fit to the distribution of inundation areas from the 2D stochastic simulations.

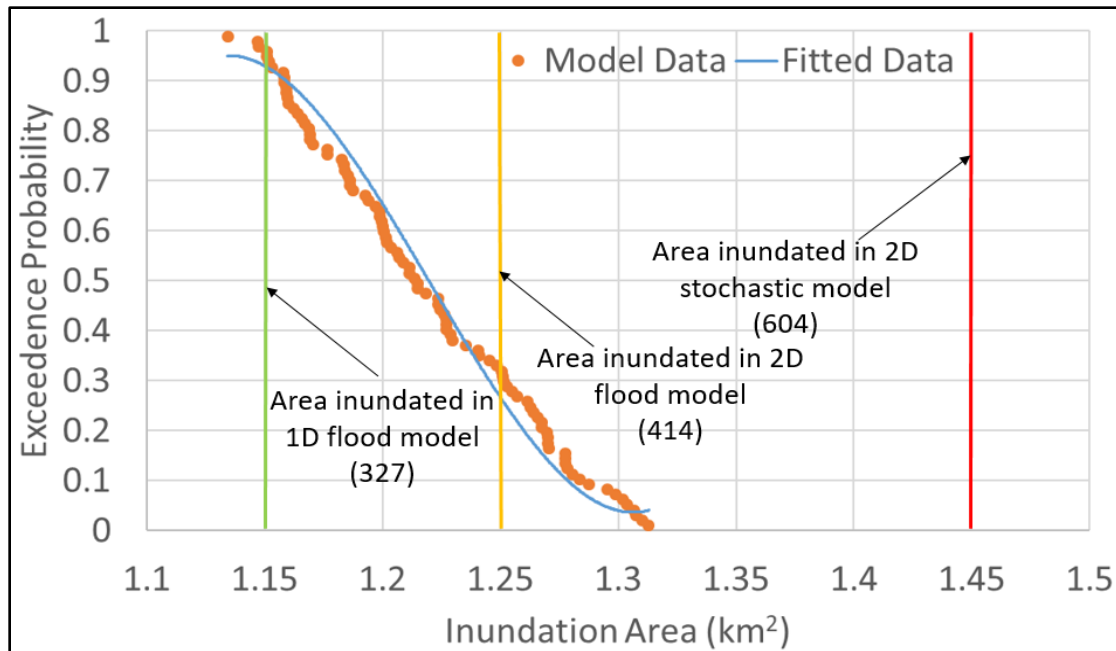


Figure 2.8: Probability distribution of inundation area (IA) in comparison with the IA from the 1D flood map, the 2D deterministic flood map, and the probabilistic map where the total number of buildings affected by each of flood mapping approach are also provided in the parentheses

To further assess the significance of the variability on flood risk, the number of buildings affected by the flooding in different scenarios was also assessed. Regardless of the level of the flood relative to the building's height, a building was deemed to be flooded if it was situated inside an inundated region. Figure 2.8 also provides the flooded area and the number of affected buildings by each of the model. It was estimated that the width of the IA distribution would result in an additional 130 buildings being flooded. This was calculated by subtracting the number of inundated buildings when IA is 1.13 km² (the lower limit of the distribution) from the number of inundated buildings when IA is 1.31 km² (the upper limit of the distribution). This reflects a 40% increase in flooded buildings. Given the uncertainty from surface roughness included in this analysis, the stochastic map (depicted in Figure 2.6) would result in the highest number of flooded buildings. When comparing the stochastic map to the 1D and 2D models, the

number of flooded buildings increases by 323 and 213 respectively.

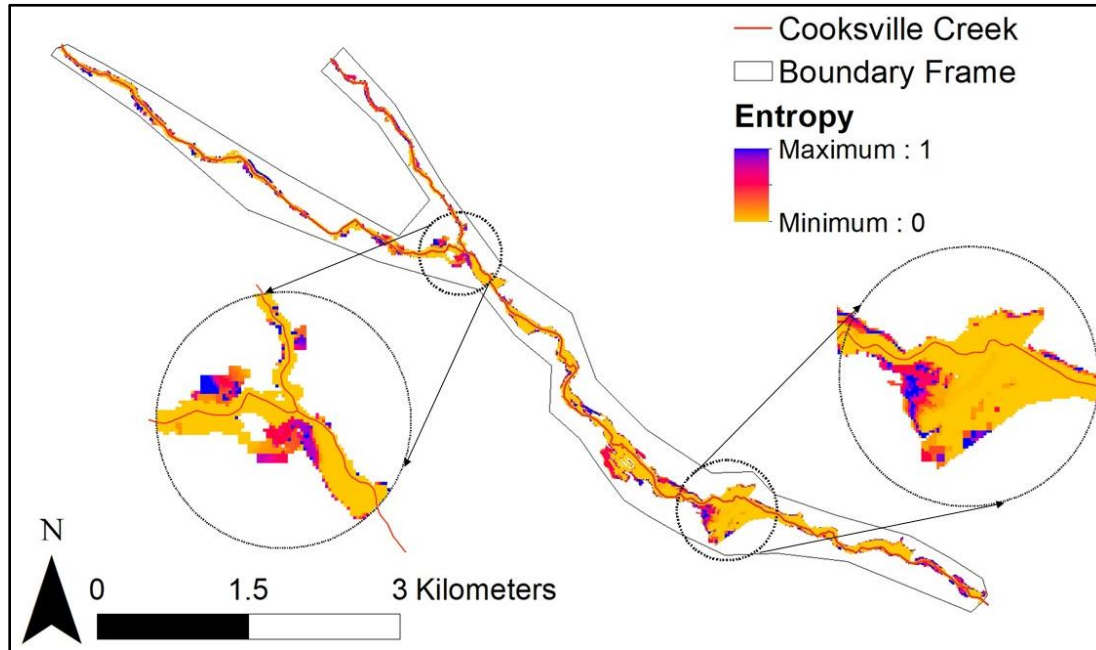


Figure 2.9: Entropy map showing the spatial distribution of inundation uncertainties

Figure 2.9 shows the entropy map of inundated locations in the study site originating from the variation of its surface roughness. Only the entropy for areas that were flooded in at least one simulation are shown (other areas have zero entropy). With this presentation, the high-entropy areas are generally located in the floodplain away from the main channels. As shown in Zones A and B, the high entropy areas are clustered within the floodplain where pockets of high uncertainty are visible.

2.6 Discussion

In this research, a stochastic framework for assessing uncertainty related to flooding was successfully constructed and tested at the case study location. The main novelty of the research is the automated coupling of the SWMM and HECRAS models inside the framework, which offers computational efficiency, and reduces both the time to complete such an analysis and the data storage requirements because of temporary file deletion during execution. The coding of the framework had to overcome several challenges, particularly due to a scarcity of related literature and the HEC-RAS program's reliance on HEC-DSSVue for data importation. The use of HECRAS was necessary because it is the hydraulic model that is currently used in the study site by the watershed authority, and this program remains widely used in the province of Ontario and other jurisdictions. The previously 1D model was converted to a 2D model for reasons of accuracy in complex urban flows where the concern is the uncertainty of the flood inundation area. This conversion was possible due to advances in bridge and weir modelling within HECRAS, allowing the inclusion of many bridges within the study site, which is crucial for accurate urban flood modelling (Costabile & Macchione, 2015). The SWMM-RASpy framework that integrates the hydrologic SWMM model and the hydraulic HEC-RAS models and its demonstration within the Cooksville Creek watershed in Mississauga, Ontario are thus the main contributions of the research.

The main advantage of the coupled model framework is that it can be used to complete an uncertainty analysis. This outcome allows the type of result envisioned by Merwade et al. (2008), which conceived of a two-zone flood inundation definition, with a relatively certain floodplain and an uncertain area near the limit. Various researchers have been able to produce these maps with a range of H&H modelling strategies (Annis et al., 2020; Aronica et al., 2012;

Kalyanapu et al., 2012) including some that emphasize the key role of roughness uncertainty (Ahmadisharaf et al., 2018; Papaioannou et al., 2017), as was done in the current study. Channel change and hydrologic inputs are additional sources of uncertainty (Stephens & Bledsoe, 2020), both of which could be tested within the existing framework, the former by modifying the channel geometry file similar to what was done for the roughness, and the latter by modifying the rainfall hyetographs that are input to the SWMM model. Similar to Ahmadisharaf et al. (2018) the use of the 2D unsteady hydraulic model could also be used to quantify the magnitude and uncertainty of velocity and duration, both of which are important for damage estimation for buildings, vehicles and people (Kreibich et al., 2009; Wagenaar, 2012), simply by changing the parameters that are extracted from the model results of each simulation. This ability to connect directly with the hydrologic simulation model using the same framework used to generate the input hydrographs allows the uncertainty inherent in different steps of the analysis to propagate through to the results in a seamless way that would make it suitable for adoption as part of current efforts to incorporate sensitivity and uncertainty in flood inundation mapping (Natural Resources Canada, 2023; Ontario Ministry of Natural Resources and Forestry, 2023). The inclusion of uncertainty in flood hazard mapping would also likely benefit the Risk and Return on Investment Tool (RROIT), which was developed in part to address the flooding of Cooksville Creek. Currently the RROIT uses a deterministic 1D HECRAS flood model to calculate water depths and velocities that are then used to estimate building and erosion damage. Inclusion of the 2D modelling results and the uncertainty of those estimates would likely improve the financial risk assessment results.

A novelty of the current work was to transform the probabilistic map to an entropy map, which visualizes the uncertainty surrounding inundation at the wet cells. As expected, the

uncertain cells were primarily situated at the edge of the flood limit where the flood boundaries tend to overlap with building/property footprints. These locations are not within the deterministically determined regulatory floodplain, but communicating the uncertainty of the floodplain limit would help to prepare for extreme events or climate driven changes to flood inundation probabilities, which suggests that these locations require updated management solutions. To develop such an approach, the entropy map was discretized based on a criteria of $e=0.5$, as shown in Figure 2.10, based on the principle that a discretized map is better for communication with stakeholders and emergency managers (Lim, 2018). Uncertainty was thus divided into three ‘priority’ zones, with zones 1 and 3 having high and low probabilities of flooding, respectively, but both with low uncertainties, while zone 2 has only a moderate flood hazard but a high uncertainty.

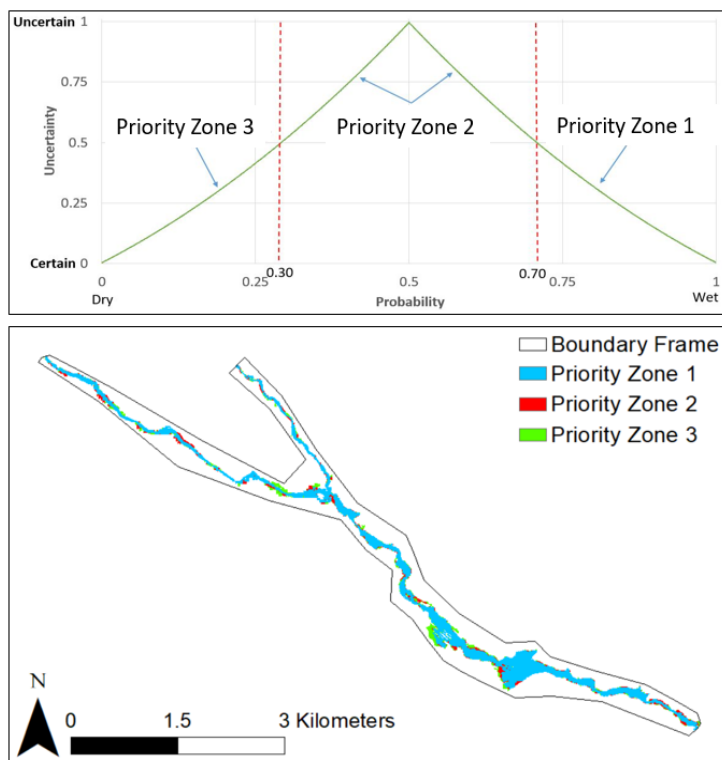


Figure 2.10: The uncertainty plot exhibiting the demarcation of uncertain/certain zones (at the top) and the discrete uncertainty map (at the bottom)

The resulting discrete map could be used as a three-category flood preparedness map to allocate resources more efficiently than a standard deterministic map, which would provide equal priority to all flooding locations. In addition to aiding in the site's reliable flood control, the map can also assist other stakeholders in making better, more informed decisions. For example, in terms of financial perspective such as for fixing an insurance rate, the properties at the uncertain locations would be rated equally as other identical buildings that are certain to be flooded if a deterministic model/approach is used. However, the map illustrates that the properties should be rated differently, and perhaps, an effective approach would be to utilize their entropy values when determining the insurance rate. This could result in reducing relevant financial losses for both the insurers and insured parties in the site. Because the map was built on a 2D model based on a relatively detailed topographic input, the map also provides scope for microscale flood management and analysis of associated losses even within a single property. At a municipal scale, the mapping may also help to allocate resources. For example, the discrete map also revealed that only 9% of the inundation area showed uncertainty. If other watersheds had higher values, then this watershed could be envisioned as a 'low-entropy' system, which would require less management efforts than a 'high-entropy' one. The maps can then be utilised to define and rank each watershed system in accordance with their estimated entropy.

The framework is not all-encompassing, and there are limitations associated with it and the approaches used in building it. For example, the framework was only tested in one study site and an application to more sites would be beneficial for generalization of the results. The utilization of SWMM and HEC-RAS was also a motivation for the work, but the results will be limited by the assumptions and methods built into this software. The framework was also only tested with the hydraulic uncertainty from surface roughness, but the integration of the

hydrologic and hydraulic models into a single framework means that other sources of uncertainty, such as bridge hydraulic routing parameters, turbulence coefficients or rainfall intensities, could be tested with this framework by modifying the attached scripts accordingly.

The main utility of the research is its demonstration of the critical need to factor in uncertainty when conducting flood mapping in the watershed. The stochastic map from the 2D model showed more areas where inundation is a possible result for the same flood that was used to derive the existing map based on a deterministic and steady 1D model. These areas should be prepared for this risk of flooding, even if it is relatively small, particularly because buildings, pedestrians and traffic are more common in these areas. Despite the fact that the uncertainty only increased the possible flooding areas by 9%, the number of potentially flooded buildings would rise by up to 100%. Given that the source of the uncertainty is roughness, efforts could be made within these zones to reduce the roughness and allow flow to pass. This consideration could be manifested in street alignments, parking restrictions, or even re-scheduling of garbage pickups to avoid placing objects in the flow pathway. Regardless, it should be made clear to stakeholders and decision makers that the delineation of a single line to designate an inundation boundary or a binary number to designate an inundation status are fictions that are used for convenience but obscure the true flood hazard. Such demarcation practices should be scrutinized for better and reliable management.

2.7 Conclusions

In this study a novel stochastic framework (SWMM-RASpy) was developed to take existing hydrologic and hydraulic models (with some modifications if the hydraulic model needs to be converted to a 2D model) and use them to generate a stochastic assessment of flood inundation risk. This framework was tested for feasibility in the study site, Cooksville Creek watershed, and the following conclusions were drawn:

1. The SWMM-RASpy framework is suitable for calculating and communicating both the magnitude and uncertainty of the flood inundation hazard in an urban area;
2. An entropy map was produced that can replace a conventional flood inundation map for flood hazard identification. The entropy map better reflects the uncertainty of flooding and could be used to develop different flood planning and preparedness strategies for different zones.
3. The framework could be used to improve the analysis of flood inundation hazards within the Risk and Return on Investment Tool (RROIT) and other similar financial risk assessment tools, and could be adopted as part of ongoing efforts to incorporate sensitivity and uncertainty in flood inundation mapping in Canada (Bazoge, 2024; Natural Resources Canada, 2023; Ontario Ministry of Natural Resources and Forestry, 2023) and in other jurisdictions around the world.

Future work should test the framework on additional watersheds and further demonstrate the capabilities of the system for understanding uncertainties related to hydrology, bridge hydraulics, turbulent flow mixing parameters, and channel change.

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CHAPTER 3: FLOOD HAZARD ASSESSMENT FOR PEDESTRIANS IN THE PRESENCE OF SPATIALLY DISTRIBUTED HYDRAULIC UNCERTAINTY

This chapter is prepared to be submitted in Natural Hazards journal

3.1 Introduction

Flood hazard assessment, a crucial component of 'integrated flood risk management,' has greatly advanced in recent decades thanks to comprehensive and sophisticated hazard modeling (Lazzarin, Viero, Molinari, Ballio, & Defina, 2022). Initially limited to residential buildings, current models now enable hazard assessments for a range of assets, including people, vehicles, crops, and industrial sites. However, the assessment across different exposed assets has been uneven, with the primary focus continuing to be residential structures (Lazzarin et al., 2022). Flood hazard assessment for pedestrians is either not updated to the latest available methods or is not considered at all in many countries (Musolino, Ahmadian, & Falconer, 2020), including Canada. This mischaracterization of the pedestrian risk could potentially be attributed to the tendency of pedestrians themselves to underestimate the severity of flood effects on the human body, particularly when confronted with shallow water depths and high flow velocities (Musolino et al., 2020). Such conditions are not uncommon during floods in urban areas, where floodwater interacts with common urban infrastructure such as sidewalks, roads, and buildings to create perilous and unfamiliar flow conditions for pedestrians. Additionally, many individuals mistakenly believe that flood hazard defense schemes offer complete protection against flooding, whereas in reality, these measures often provide only partial safeguard (Musolino et al., 2020). Pedestrians walking in flooded areas are one of the two leading causes of death related to flood events (Arrighi, C., Pregnotato, Dawson, & Castelli, 2019; Musolino et al., 2020). The risk is higher in urban areas with high mobility and dense populations. With climate change projected

to further increase the magnitude and frequency of extreme events such as flooding, determining the risks that floods pose to pedestrians should be one of the core components of urban flood risk management. The inclusion of pedestrian hazard maps via collaborative flood hazard mapping will enhance the relevance and utility of commonly produced urban flood risk maps (Luke et al., 2018).

Flood hazard maps are typically based on inundation models created using a combination of hydrologic and hydraulic (H&H) models. 1D steady-state hydraulic models are often applied for flood hazard modeling due to their simplicity in simulating flood depth for different flood scenarios (Ahmadisharaf, Kalyanapu, & Bates, 2018). However, flood depths provide limited information for planning against hazards such as pedestrian hazards, which will also require information about water velocity, flood timing and the duration of inundation for effective emergency management (Luke et al., 2018). The 1D approach also limits the ability to evaluate hazards on a spatially distributed scale, particularly for flood flows where flow patterns may be complex and include extensive lateral flows or the formation of secondary channels (Farooq, Shafique, & Khattak, 2019). New research and flood management authorities are increasingly relying on 2D unsteady hydraulic models for developing multi-variable hazard models, which can provide time-varying and spatially distributed information about flood depth, velocity, duration of inundation and other variables such as shear stress (Bertsch, Glenis, & Kilsby, 2022; Bhola, Leandro, & Disse, 2020; Farooq et al., 2019; 2024; Luke et al., 2018; Ongdas, Akiyanova, Karakulov, Muratbayeva, & Zinabdin, 2020; Zhen et al., 2022). The multi-variable hazard models allow the investigation of the role of various crucial hazard variables, both individually or collectively, in shaping flood-related risks (Lazzarin et al., 2022).

Despite their better representation of a suite of hazard parameters, the hydrologic models used to estimate their boundary conditions and the 2D hydraulic models themselves are inherently uncertain (Luke et al., 2018). Uncertainty arises at each stage of flood mapping, posing significant challenges to achieving accuracy (Dong et al., 2022). Consequently, making reliable decisions is difficult without considering the uncertainties associated with the models (Warmink, Van der Klis, Booij, & Hulscher, 2009). The presence of uncertainty should be properly addressed by conducting uncertainty analyses, utilizing multiple models, or combining deterministic models with probabilistic approaches (Dong et al., 2022). Uncertainties propagate to the flood hazard parameters; therefore, these uncertainties surrounding the parameters should also be presented alongside their hazard maps when proper resources are available (FEMA, 2020). Integrating uncertainty into the mapping of pedestrian hazards from flooding will enhance the effectiveness of risk management strategies, support the development of safer urban environments, and improve the resilience of pedestrians against flood-related disasters. Therefore, particularly with the increased availability of post-flooding data and innovative modeling techniques, advanced stochastic approaches that allow for the consideration of uncertainty are now being promoted (Lazzarin et al., 2022).

Academic studies have significantly advanced the identification and categorization of pedestrian stability thresholds when subjected to flood water through laboratory testing and empirical methods (Cox, R., Yee, & Ball, 2004; Cox, R. J., Shand, & Blacka, 2010; HR Wallingford, Flood Hazard Research Centre, & Risk & Policy Analysts Ltd., 2006; Jonkman & Penning-Rowsell, 2008; Martínez-Gomariz, Gómez, & Russo, 2016; Russo, Gómez, & Macchione, 2013). The development of physics-based models has also advanced the assessment of these stability thresholds (Arrighi, Chiara, Oumeraci, & Castelli, 2017; Chen, Xia, Falconer,

& Guo, 2019; Milanese, Pilotti, & Ranzi, 2015; Xia, Falconer, Wang, & Xiao, 2014). Other significant contributions include assessing pedestrian hazard conditions by coupling hydrodynamic models with criteria for pedestrian stability (Dong et al., 2022; Li, Q., Xia, Dong, Liu, & Wang, 2023; Wang et al., 2021), as well as exploring remedial measures such as designing evacuation routes for pedestrians during floods (Musolino et al., 2020). In regards to presenting and communicating the outcomes of a hazard assessment, classical flood maps showing the spatial distribution of hazard variables like flood depth and velocity have been used as an effective tool (Lazzarin et al., 2022; Lazzarin et al., 2024). Recent studies have employed color maps to convey the spatial distribution of hazards, categorizing them based on their severity to the object, which allows for the effective communication of the degree of hazard in an intelligible way (Lazzarin et al., 2024). For example, Luke et al. (2018) and Houston et al. (2019) produced water depth maps for pedestrians, where color categories corresponded to the ankle, knee, waist, and head levels of a human body, with 'ankle' representing the least severe and 'head' the most severe. The Hazard-Rating (HR) index, presented by HR Wallingford et al. (2006), has also been widely used in recent studies for categorizing and mapping pedestrian hazards (Lazzarin et al., 2024). In their review of quantitative flood hazard assessment methods, Maranzoni et al. (2023) found that flood depth and flow velocity are the most commonly used parameters for assessing pedestrian hazards, which is appropriate due to their significant impact on flood consequences, but other important variables such as the arrival time and duration of flooding are rarely considered, despite their potential impact on safety. It was also noted by Maranzoni et al. (2023) that, while multi-variable hazard models are increasingly preferred for detailed assessments of pedestrian hazards, there remains a notable gap in models that effectively account for the uncertainties associated with these variables.

Despite uncertainties in flood hazard estimation that stem from various sources, those related to model information—such as input data, parameters, and methodologies—predominate due to the critical role of hydrologic and hydraulic modeling in flood hazard mapping (Maranzoni et al., 2023). Some studies address uncertainties in both hydrologic and hydraulic models, primarily to analyze the relative impact of each for specific case studies. Surface roughness is commonly used to model hydraulic uncertainty in flood hazard assessments, and given that pedestrian hazards can be greatly influenced by the local conditions of the underlying surface (Dong et al., 2022), it is reasonable to consider also roughness uncertainty for pedestrian hazard assessments. Oubennaceur et al. (2018), Liu et al. (2019), Gao et al. (2021), and Dalledonne et al. (2019) are among the recent researchers who have investigated its impact on the estimation of flooding using 2D models. Their research does differ with respect to a number of key methodologic choices. For example, Oubennaceur et al. used the H2D2 model to quantify the uncertainty of flood depth, Liu et al. (2019) used HEC-RAS 2D and LISFLOOD-FP models to quantify the uncertainty of inundated areas, Gao et al. (2021) used HEC-RAS 2D to quantify the uncertainty of inundated area, flood depth, and arrival time, and Dalledonne et al. (2019) used TELEMAC-2D to quantify the uncertainty of velocity. There remains a need to quantify the uncertainty of pedestrian hazards using a coupled SWMM and HEC-RAS 2D H&H approach.

The goal of the current research is to develop a robust and reproducible framework that advances pedestrian hazard assessment in urban flooding conditions. This will be achieved through the following specific objectives:

- 1) **Propose a stochastic flood modeling framework for pedestrian hazards** that incorporates multi-variable hazard modeling, integrating both widely used variables—such as flood depth and flow velocity—and underexplored variables like the duration of

flooding, while effectively accounting for the associated uncertainties through a stochastic approach.

- 2) **Investigate the impact of surface roughness on pedestrian hazards** by conducting a detailed case study and employing advanced 2D modeling to analyze how variations in surface friction influence the hazards across different spatial scales.
- 3) **Enhance pedestrian hazard communication and decision-making** by deploying constructive color-coded mapping techniques to produce hazard maps and analyzing them at different spatial scales.

To achieve the first objective, we considered the novel SWMM-RASpy framework. This framework not only supports 2D hydraulic and stochastic modeling but also allows for dual-drainage modeling through SWMM, which can significantly enhance hazard assessment in urban areas (Dong et al., 2022). The second objective was met by utilizing this novel framework and presenting the outputs at various spatial scales, with Cooksville Creek watershed serving as the case study site. The third objective was accomplished by generating and analyzing maps of hazards and their uncertainties using advanced techniques adapted from existing literature. While the focus of this chapter is on pedestrian hazards, other types of hazards, such as vehicle and building hazards, can also be assessed using the general methodology employed here. The hope is that the work presented here will provide a useful perspective on the estimation of flood hazards, particularly in the presence of uncertainty, which can be used to better inform flood risk management.

3.2 Methodology

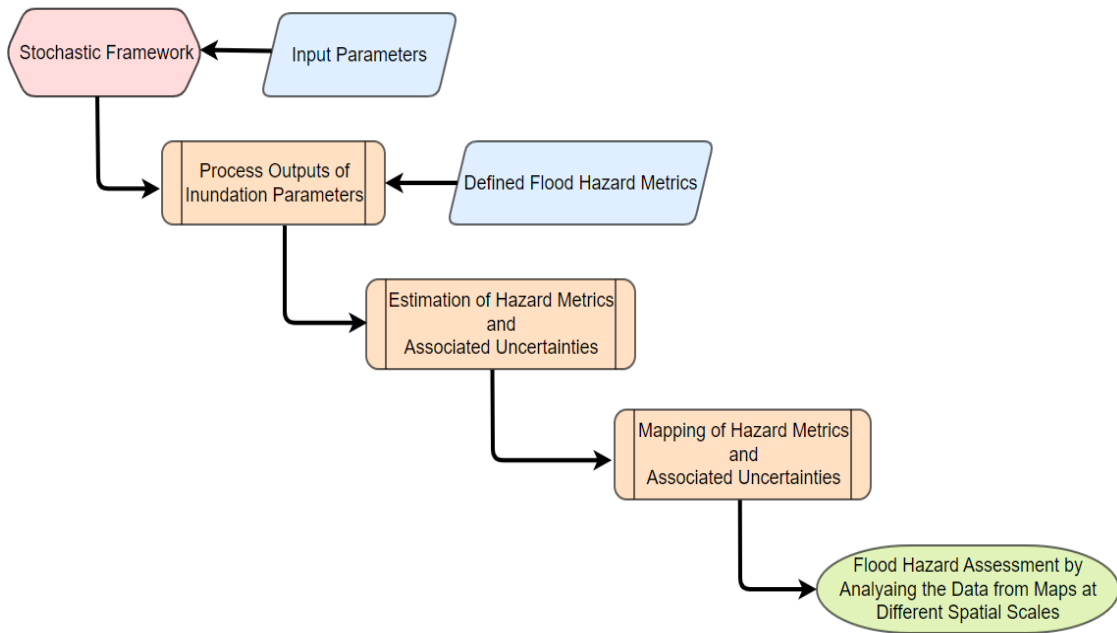


Figure 3.1: Generic approach for estimating flood hazard metric and their uncertainties using the novel framework

The approach used in the research to achieve the objectives is illustrated in Figure 3.1. This methodology is generic and can be applied to assess flood hazards of any nature. Detailed descriptions of the various steps involved are provided in the subsequent sections.

3.2.1 Stochastic Flood Modelling Framework

The stochastic modeling was carried out within the SWMM-RASpy framework developed as part of this thesis. The framework is fully automated and allows hydrologic and hydraulic uncertainties to be propagated from the input variables such as surface roughness to the output variables such as flood hazard metrics. The framework is coded with a set of four main Python algorithms (see Figure 2.1) as follows:

1. AutoSAMPpy uses a stratified sampling approach (Latin Hypercube Sampling - LHS) to generate unique sample sets of input datasets for either the hydrologic EPA-SWMM

model, the hydraulic HEC-RAS model, or both. The program relies on a control file for execution and passes parameters to sub-programs as listed below;

2. AutoSWMMpy controls the execution of a pre-existing SWMM model for a study watershed. The program receives the parameters for each run from AutoSAMPpy and generates hydrographs at given locations within the watershed, which are passed to AutoRASpy;
3. AutoRASpy program utilizes the hydrographs at select nodes, designated as the boundary conditions, to integrate the hydrologic model with a pre-existing 2D HEC-RAS hydraulic model. It also receives parameters from AutoSAMPpy, requires outputs from AutoSWMMpy and generates data sets of spatially varied time series of inundation variables such as flood depth, velocity and duration.
4. AutoRAS-HDFpy retrieves the necessary inundation variable data from the AutoRASpy output files and collects the data for flood hazard and uncertainty analysis.

The current study is based on an analysis of Cooksville Creek in Mississauga, Ontario. A calibrated SWMM model of sewer and surface drainage was available for this site through a partnership with the local watershed authority (Credit Valley Conservation), as was a calibrated 1D HECRAS model. The 1D model was converted to a 2D model for the current study. More detail on the site, the available models, and the 2D model creation is available in section 2.4 of this thesis. For the current study, a 100-year, 3-hour Chicago storm event was modelled and discretized into 5-minute time intervals. The coupled SWMM and HECRAS models were run for a total duration of 6 hours with a computational step of 5 minutes. Guidelines were not available for selecting the optimal number of samples for conducting a stochastic simulation, so a total of 100 simulations were run for the Monte Carlo style analysis. Each run had a unique set of surface

roughness (n) values for the different land covers. The n values were assumed to vary between -20% and +20% of their original values and are provided in Table 2.1 of Chapter 2. Of the total, 96 simulations were accepted for which the HEC-RAS model ran without any stability issue based on its 2% threshold volume accounting error (Brunner, 2022).

3.2.2 Inundation Variables

The maximum water depth for each simulation run, which represented each sample set of n values, was used to define the flood depth, which can be presented by the following equation:

$$Y_{F(x,y),i} = \max \left[\bigcup_{t=0}^{t=T} Y_{(x,y),t,i} \right]; \quad Y_{(x,y)} > 0 \quad (3.1)$$

where $i=1,2,3 \dots N$ represents the number of times the simulation runs, N is the number of total accepted simulation runs, $Y_{(x,y)}$ is the flood depth at time t for simulation, i , at a cell located at (x,y) coordinate (m), T is the duration of simulation, i (hr) and $Y_{F(x,y)}$ is the cell's flood depth. The peak flood depths from each simulation were chosen to represent the hazards from flood depth because they represent the maximum hazards.

The maximum water velocity from a given simulation (i) at a given location (x,y) is referred to as the local flood velocity ($V_{F(x,y),i}$). Maps of $V_{F(x,y),i}$ were produced for each simulation i using the following equations, following the method described by Brunner (2022), where the velocity of each cell is calculated from the normal velocities of its adjacent faces:

$$V_{(x,y),i,t} = \frac{1}{A_{c(x,y)}} \sum_{m=1}^M d_{k(x,y),m} * L_{k,m} * (u_{n,i,t})_{k,m} \quad (3.2)$$

$$V_{F(x,y),i} = \max \left[\bigcup_{t=0}^{t=T} V_{(x,y),i,t} \right] \quad (3.3)$$

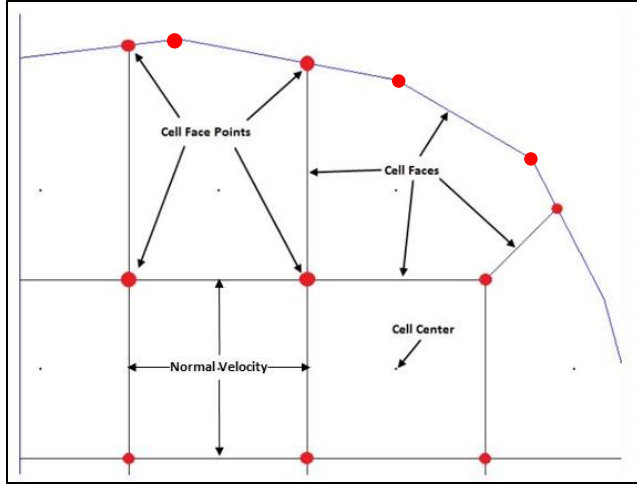


Figure 3.2: Geometric properties of a cell inside a 2D mesh of HEC-RAS (modified from HEC-RAS 2D User's Manual)

where $V_{(x,y),i,t}$ is the local flow velocity at any given time t of simulation i (m/s), $A_{c(x,y)}$ is the area of the cell (km^2), $m=1,2,3 \dots M$ is the number of edges/faces of the cell, $d_{k(x,y),m}$ is the distance from the center of the cell to the center of its face k (m), L_k is the length of the face k (m), and $u_{n,i,t}$ is the normal velocity at the given time t of simulation i at face k (m/s). The geometric properties of a cell introduced in Equation 3.2 are illustrated in Figure 3.2. Similar to the flood depth, the maximum flood velocity during a simulation was chosen to represent flood velocity because it maximizes the hazard.

A cell's overall flooding duration was calculated by adding up all the times that the cell was submerged during the simulation. The cell was considered flooded as long as there was water over its surface, i.e., water depth > 0 . Table 3.1 demonstrates the approach for estimating flood duration (D_F) at a given location (x,y) for a simulation, i .

Table 3.1: Estimation of flood duration using sample data

Time of Simulation (min)	Time Interval (min)	Water Depth (m)	Flood Status (1=wet; 0=dry)	Status * Interval (min)
0	0	0	0	0
5	5	0.5	1	5
10	5	1	1	5
15	5	0.5	1	5
20	5	0	0	0
Flood duration, $D_{(x,y),i} : \sum \text{Status} * \text{Interval} =$				15 minutes

3.2.3 Hazard Metrics

Flood hazard metrics were defined based on inundation depth, velocity, and event duration. The metrics that were considered in this research are: i. flood depth, which is the Flood Hazard Metric 1 (FHM1), ii. Flood Hazard Metric 2 (FHM2) which is a combination of flood depth and velocity and iii. Flood Hazard Metric 3 (FHM3) which is a combination of flood depth, velocity and duration. FHM1 was considered as a key metric because stakeholders often quantify flood hazards using depth alone (Luke et al., 2018). FHM2 is also a key metric because it is widely used for hazard assessments involving pedestrians, vehicles, and buildings (HR Wallingford et al., 2006). The use of FHM3, in contrast, is relatively limited (Lazzarin et al., 2022; Wagenaar, 2012).

To compute FHM2, the methods used generally followed the ‘Flood risks to people - phase 2: managing risks and dangers’ report (referred as FRP report hereafter), authored by researchers at HR Wallingford, Flood Hazard Research Centre of Middlesex University (2006).

$FHM2_{F(x,y),i}$ represents the value of FHM2 located at (x,y) coordinate for simulation i , calculated as follows:

$$FHM2_{F(x,y),i} = Y_{F(x,y),i} * [V_{F(x,y),i} + V_c]; \quad Y_{F(x,y)} > 0 \quad (3.4)$$

where V_c is a velocity coefficient used to ensure that FHM2 does not approach zero when there is no velocity in the flood water. Based on experimental data, a value of $V_c = 0.5$ was recommended (HR Wallingford et al., 2006) and this value was applied herein.

FHM3 metric was estimated by adding a duration factor to account for the impact of duration on the risk to people in a flood. This duration factor was conceptualized from the work of HR Wallingford et al. (2006) and Wagenaar (2012), where the authors added a similar factor to their depth and velocity-based damage assessment to account for things like debris in the water. According to Lazzarin et al. (2022), the likelihood of being swept away by floodwaters depends on the duration of the flooding because: i) the longer a person remains in floodwaters, the weaker their resistance becomes, and ii) the probability that a disruptive event such as an energetic turbulent eddy or floating debris occurs also increases with time. In this study, a duration factor for a given location and simulation ($DF_{(x,y),i}$) to account for both of these possibilities is expressed as fraction of time the location was inundated during the simulation:

$$DF_{(x,y),i} = FTI_{(x,y),i} \quad (3.5)$$

where $FTI_{(x,y),i}$ is the fraction of time the cell was inundated during simulation i . The FHM3 metric for a given location in simulation i can then be calculated as:

$$FHM3_{F(x,y),i} = FHM2_{F(x,y),i} + \alpha * DF_{(x,y),i} \quad (3.6)$$

where α is a constant scaling factor (m^2/s) which ensures that the impact of the duration is proportionately included without overshadowing the contributions of velocity and depth. This constant is introduced to maintain the unit consistency and to ensure that the combined effect of duration does not dominate the FHM3 hazard metric. The value of α used in this thesis is based on an adaptation from the work of Tingsanchali and Promping (2022) where α was set to 0.67 for building flood hazards. However, for this analysis, which focuses on pedestrian hazards, α was considered to be 0.33. This adjustment was made under the assumption that shorter durations will have a more significant impact on pedestrian hazards compared to building flood hazards. However, it is important to note that this value is open to further investigation and adjustment as future research may refine or validate the scaling factor for different contexts or conditions.

3.2.4 Uncertainty Quantification

The concluding steps of the generic approach involved utilizing the acquired inundation variable data to quantify uncertainties associated with the flood hazard metrics. Quantification and analysis of uncertainty for spatially distributed data is challenging and there are many ways that have been developed to express uncertainties including probability distributions, standard deviation and range. In this study, standard deviation was used because it is a simple measure that is easily determined as part of stochastic simulations. The standard deviation of a flood variable such as depth was estimated as:

$$\sigma(S_{(x,y)}) = \sqrt{\frac{\sum_{j=1}^{j=J} (S_{(x,y),j} - \bar{S}_{(x,y)})^2}{J - 1}} \quad (3.7)$$

where σ represents standard deviation, S represents the flood variables used in the study, i.e. depth, velocity and duration, j is the simulation number out of a total of J simulations, and the overbar indicates the mean. The uncertainty of FHM1 was then calculated as:

$$\xi FHM1_{F(x,y)} = \sigma(Y_{F(x,y)}) \quad (3.8)$$

where ξ represents uncertainty.

Since FHM2 and FHM3 depend on multiple independent parameters like depth, velocity, and duration, uncertainties were estimated using the multiplication (applicable to FHM2 since it is the product of depth and velocity) and addition (applicable to FHM3 since it is the addition of FHM2 and DF) laws of propagation of uncertainty, as described in Loucks and Van Beek (2017). Both laws rely on the standard deviations of the independent parameters to estimate the uncertainties surrounding them (Loucks & Van Beek, 2017) as follows:

$$\xi FHM2_{F(x,y)} = FHM2_{F(x,y)} * \sqrt{\left[\frac{\sigma(Y_{F(x,y)})}{\bar{Y}_{F(x,y)}}\right]^2 + \left[\frac{\sigma(V'_{F(x,y)})}{\bar{V}'_{F(x,y)}}\right]^2} \quad (3.9)$$

$$\xi FHM3_{F(x,y)} = \sqrt{\xi(FHM2_{F(x,y)})^2 + \sigma(DF_{(x,y)})^2} \quad (3.10)$$

3.2.5 Mapping of Flood Hazards and Associated Uncertainties

The representation and communication of flood hazards and their uncertainties are challenging due to their continuous nature. Continuous variables can be categorized, as has been done in numerous studies for categorizing hazards and uncertainties, to effectively communicate results to stakeholders (Lim, 2018). However, there isn't a single, standardized method for such categorization, which leads to different scholars using various discretization strategies (Lim, 2018).

3.2.5.1 Hazard Classification

Generally, aside from flow and terrain features, an individual's physical attributes such as height and weight also play a significant role in determining the level of hazards they may encounter (Dong et al., 2022). In this study, a pedestrian was defined as an adult person who has a Height(H)-Weight (W) index greater than or equal to 50 m-kg ($H*W \geq 50$ m-kg) (Lazzarin et al., 2022; Russo et al., 2013; Shand, Smith, Cox, & Blacka, 2011). Hazards to pedestrians were classified based on each hazard metric, utilizing relevant literature, which is described in subsequent paragraphs.

Flood depths were discretized using the typical reference heights of various segments of a human body living in the United States and Canada (Luke et al., 2018). The discrete categories of the depths were later translated to their corresponding hazards based on the literature reviews provided in Russo et al. (2013), Shand et al. (2011), and Lazzarin et al. (2022). Water depths at or below knee height (0.45 m) were considered to pose a minimal threat to pedestrians and were classified as 'low hazard.' It is generally safe for pedestrians to move cautiously in these areas. Depths exceeding knee height but not reaching the waist were labeled as 'moderate hazard.' While generally safe, pedestrians should exercise increased caution in these areas compared to low hazard zones. Water depths that extend above the shoulder (1.3 m) pose the greatest risk, potentially leading to life-threatening situations, and were therefore classified as 'extreme hazard.' Pedestrians must avoid these areas during flooding, as they are extremely unsafe. Water depths between the waist and the shoulder of a pedestrian were considered 'significant hazard.' Although these areas present a reduced risk of life-threatening situations compared to extreme hazard zones, pedestrians should still avoid them during flooding.

Although it is not feasible to quantify the exact potential hazards from velocity without the corresponding depth at a given location, it was observed from the experimental data provided in Russo et al. (2013), Shand et al. (2011), and Lazzarin et al. (2022) that velocities below 0.5 m/s were incapable of destabilising (either through sliding or toppling) the pedestrians (subjected to the experiments) at any depth. The studies also showed that some of their pedestrians started to destabilize when velocities became greater than 0.5 m/s. Velocities greater than 1 m/s destabilised the majority of pedestrians, while a velocity higher than 2 m/s was found to destabilise the vast majority of them. In this research, a velocity between 0 m/s and 0.5 m/s was considered a low-intensity velocity that has a low degree of destabilising potential, and velocities greater than 0.5 m/s were considered to be high-intensity velocities that were assumed to be unsafe for pedestrians. Since there were no credential guidelines found in the literature reviews on classifying the parameter, flood duration, it was classified utilizing hourly intervals.

The metric values of FHM2 and FHM3 were translated to their corresponding pedestrian hazards following the guidelines from the FRP report (HR Wallingford et al., 2006). In the context of analysing the FHM2 and FHM3 hazards, low hazards were assumed to present a wary/cautious situation to all the pedestrians residing in the watershed. Moderate hazards were assumed to be dangerous for some pedestrians while the significant and extreme hazards were assumed to be dangerous for most and all of the pedestrians of the watershed, respectively.

3.2.5.2 Uncertainty Classification

The quantile classification method was used to categorize the uncertainties of the hazard parameters since the approach ensures uniformity when classifying data for different variables (ESRI, 2024). The 33rd percentile of the distribution of uncertainty data for a hazard metric was deemed to fall under the low category, while the 33rd–67th percentile of the distribution was

considered to fall under the moderate category, and the data above the 67th percentile were labeled as being in the high category.

3.2.5.3 Visualization of Information

There are no universally mandated standards for color coding in flood hazard maps, but there are widely accepted best practices that are commonly used to ensure clarity and effectiveness in communication (Lim, 2018). Typically, diverging color schemes are chosen to intuitively represent levels of risk. Some studies suggest using a gradient or a clear progression of colors from cool to warm to visually represent the increasing level of flood risk. In this study, low-hazard areas were colored in shades of green, indicating minimal threat and safer zones for pedestrians. As the risk increases, the colors transition to shades of yellow and orange, with extreme-hazard areas depicted in shades of red. This color scheme, used in numerous studies, is believed to be an effective means of visualizing pedestrian hazards. The same color scheme was also used to visualize uncertainties.

3.3 Results

3.3.1 Flood Hazard Metric Maps

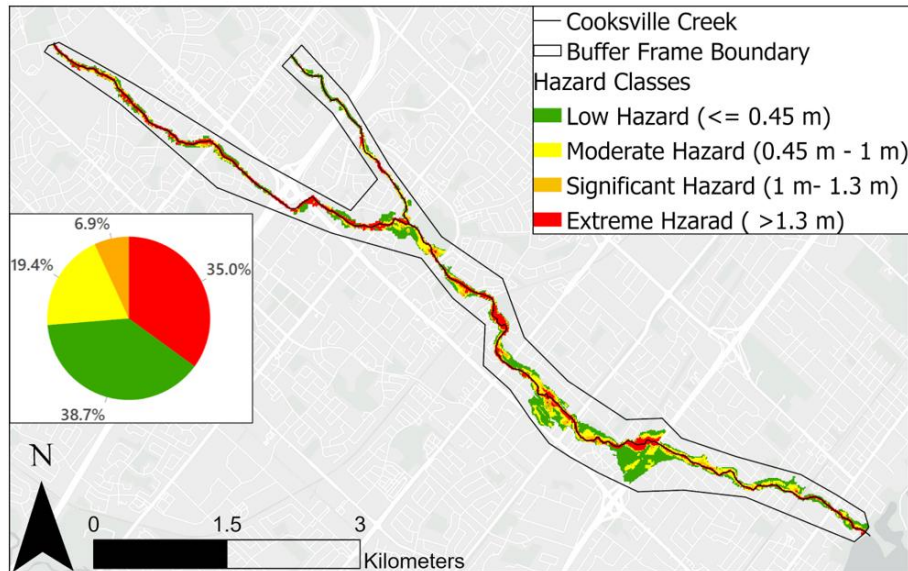


Figure 3.3: Spatial distribution of hazards for FHM1 metric along with the histogram of the distribution (in the inset)

Figure 3.3 shows the map of the distribution of FHM1 hazards resulting from flood depths at the study site. The depth at each cell is the mean of its peak flood depths computed for each stochastic simulation using Equation 3.1. A quick visual inspection of the map shows that the extreme hazards mainly occurred along the creek and in its immediate surroundings, as expected. However, as the distance from the creek increased, noticeable variations in hazards were observed. The histogram shown in the inset of the figure illustrates that approximately 55% of the flooded areas at the study site showed at least significant hazards, indicating that these places pose threat to the mobility of the pedestrians. Based on a zonal analysis in ArcGIS, 85% of the total hazards occurred outside of the creek banklines defined in HECRAS, and approximately 40% of those were at least significant FHM1 hazards.

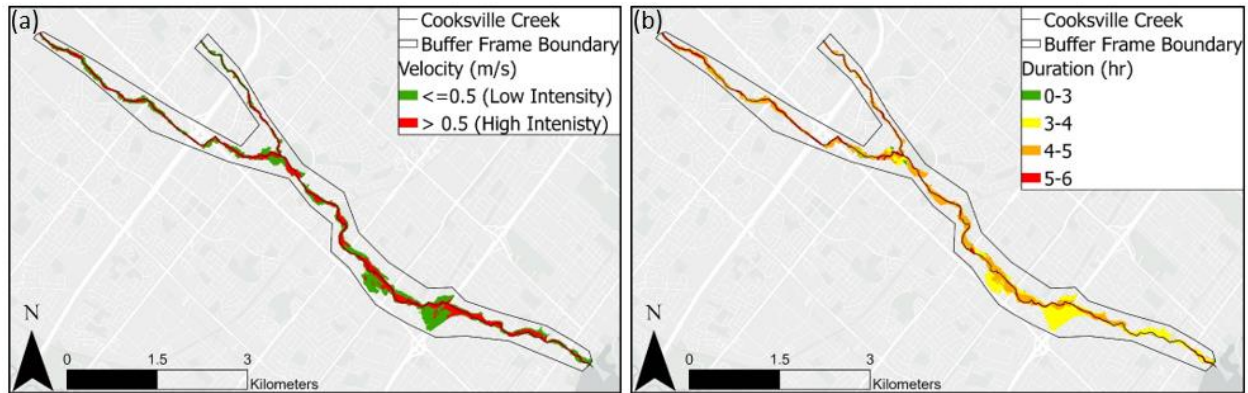


Figure 3.4: (a) Spatial distribution of flood velocities in the site and (b) spatial distribution of flood duration in the site

The distributions of flood velocities and durations are presented in Figure 3.4. The velocity plot represents the mean of the peak flood velocities of all stochastic simulations computed using Equations 3.2 and 3.3. High-intensity velocities were present in approximately 70% of the area that was flooded and, based on an ArcGIS zonal analysis, over 75% of these areas are outside the creek banklines. Velocity was moderately correlated with depth (correlation coefficient of 0.30 calculated using the Band Collection Statistics tool of ArcGIS), which suggests that deep areas also have high velocities, but not exclusively such that there are clearly many areas with low depth and high velocity and *vice versa*. Figure 3.4b shows the map of inundation duration in the study site where duration at each cell is the mean of its flood durations computed for each stochastic simulation using the approach provided in Table 3.1. A visual inspection of the map illustrates that the flooding in the majority of the site lasted between 4 and 5 hours. Flooding that lasted more than 5 hours primarily occurred either inside the creek. Inundation areas were generally wet for at least 3 hours.

Figure 3.5 shows the map of the distribution of hazards for the FHM2 metric at the study site. A visual inspection of the map indicates that the degree of hazard is greatest in the surroundings of the creek and is considerably dominated by the presence of hazard from flood

depth. The histogram of hazards on the inset of the figure demonstrates that nearly 50% of the flooded areas are under the threat of at least moderate pedestrian hazards. Based on an ArcGIS zonal analysis, 85% of the flooding areas were outside the creek banklines, and 67% of the flooded area outside the creek presented at least a moderate hazard. A comparison of the areas of extreme hazards (unsafe for any pedestrian) found outside the creek for the FHM1 and FHM2 metrics reveals that velocity increased the flood risks by 4%, which represents 58,000 m² of flooded area where, though not extremely dangerous based on flood depth alone, should be considered extremely dangerous for pedestrians due to the combination of depth and velocity. Due to the position of Cooksville Creek within the high-density corridor of the city surrounding it, this increase in area will affect many urban residents.

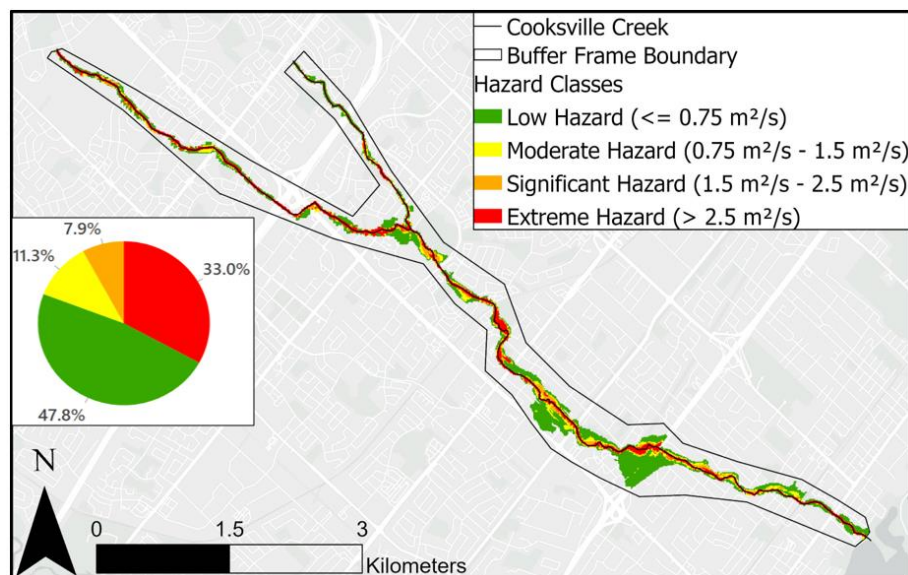


Figure 3.5: Spatial distribution of hazards for FHM2 metric along with the histogram of the distribution (in the inset)

The distribution of FHM3 metric in the study site is shown in Figure 3.6 using the same criteria from the FRP report as the FHM2 parameter. As per the report, the classes were configured to have the same range of values as the FHM2 parameter, which allows the impact of the duration on hazard estimation to be assessed by comparing with Figure 3.5. Overall, the

spatial distribution of FHM3 hazard is similar to FHM2, although a net difference was noted based on the respective histograms of cumulative hazard categories. As shown, approximately 52% of the flooded area displayed at least moderate hazard for the FHM2 metric, but approximately 67% of the area reached this level for the FHM3 metric, which indicates that the inclusion of duration does increase the overall hazard level.

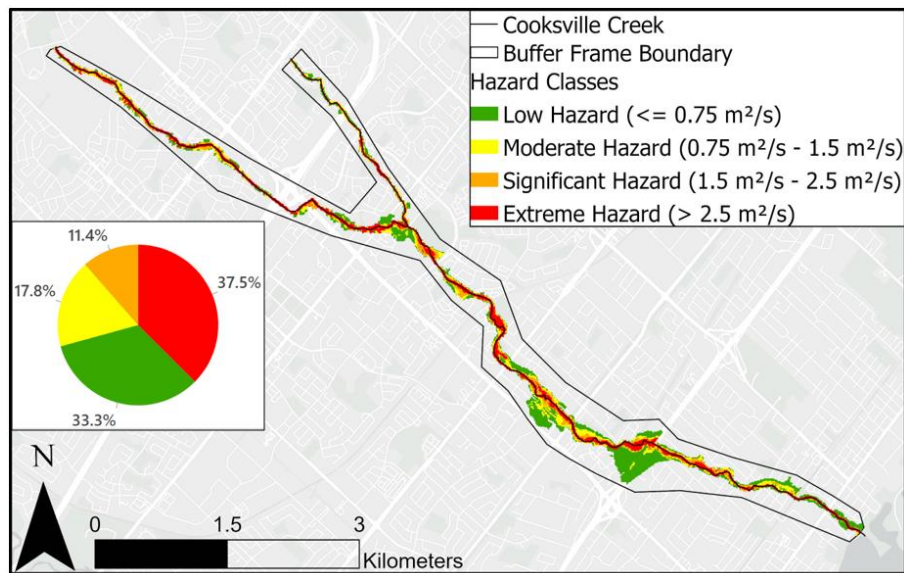


Figure 3.6: Spatial distribution of hazards for FHM3 metric along with the histogram of the distribution (in the inset)

3.3.2 Uncertainty of Flood Hazards

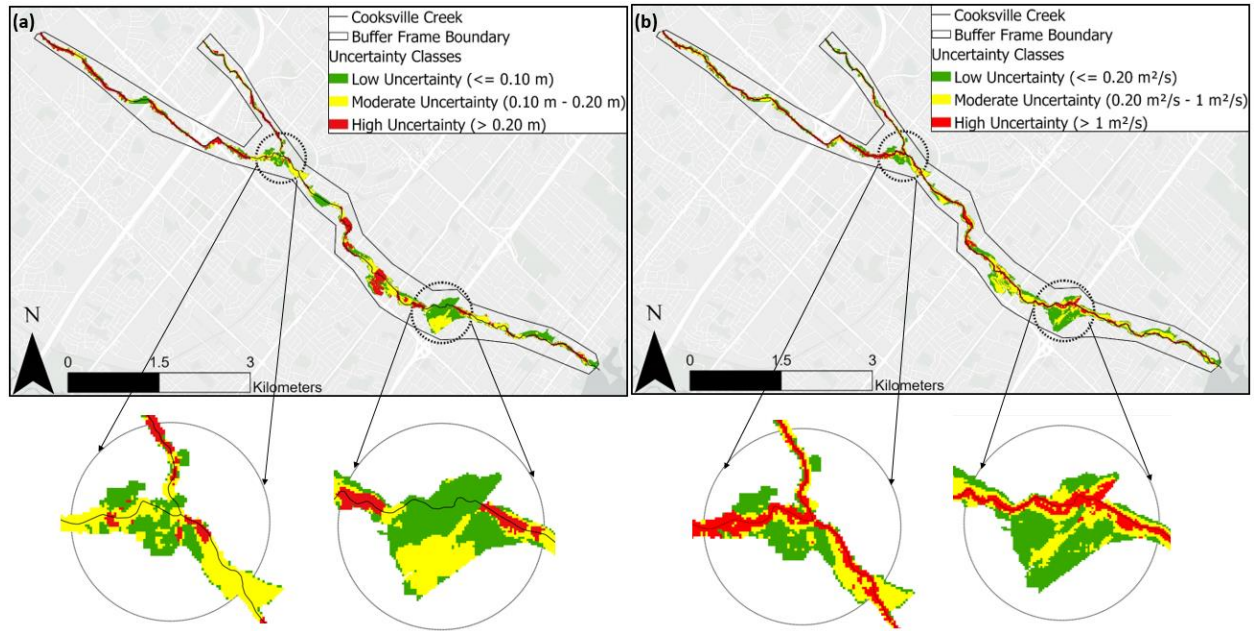


Figure 3.7: Spatial distribution of uncertainties surrounding hazards from (a) FHM1 metric and (b) the FHM2 metric

Based on the set of simulations run for the study site, the variability and therefore the uncertainty of the hazard classifications is spatially variable. Based on the spatial distribution of ζ_{FHM1} and ζ_{FHM2} , high-moderate-low categories were assigned. As shown the spatial distribution of uncertainty is different depending on the metric under consideration. ζ_{FHM1} tends to vary in the streamwise direction along the length of the creek, with pockets of high uncertainty showing up as red patches that seem to stretch across the entire inundation zone (Figure 3.7a). In contrast, ζ_{FHM2} appears to vary primarily as a function of the distance from the creek (Figure 3.7b). The spatial patterns are thus contrasted for Zones A and B, where ζ_{FHM1} is predominantly low or moderate, while ζ_{FHM2} is consistently high through the channel where depth and velocity are high. ζ_{FHM3} is not shown because it is identical to ζ_{FHM2} .

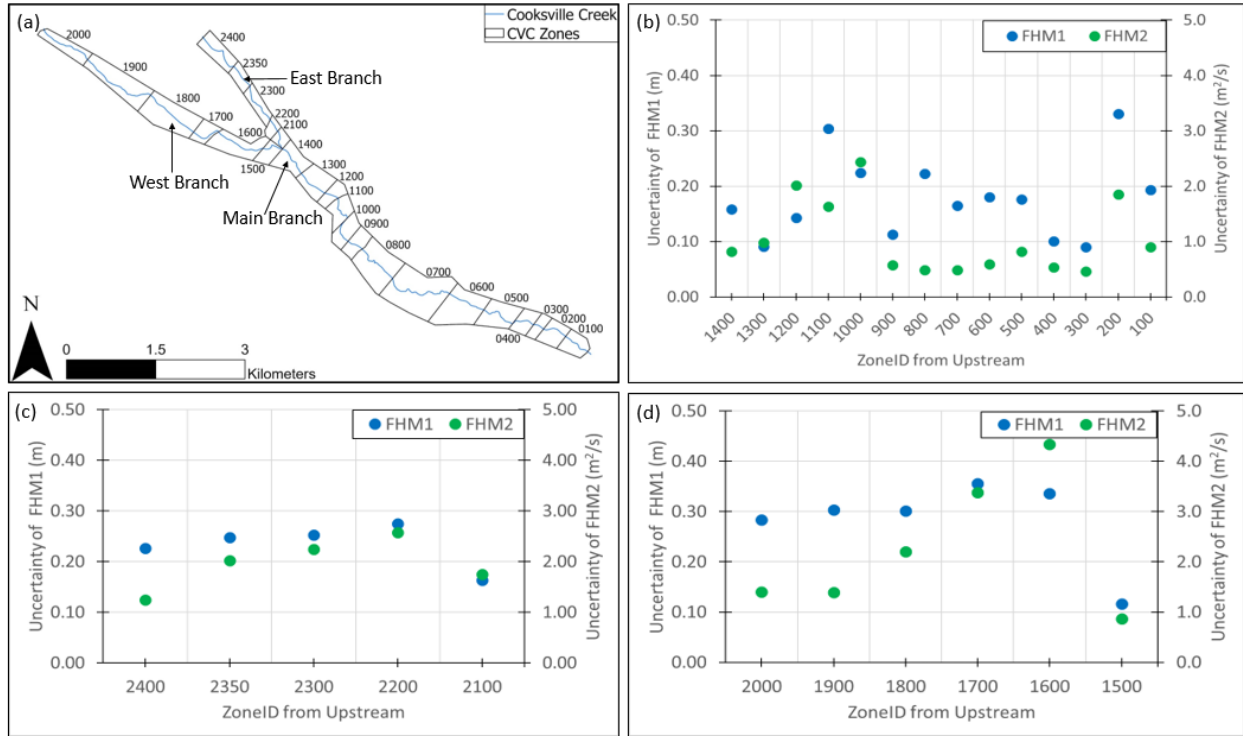


Figure 3.8: (a) Division of the Cooksville creek according to the zones defined by CVC; (b) variation of uncertainties of FHM1 and FHM2 metrics along the creek's Main branch; (c) and (d) variation of uncertainties of FHM1 and FHM2 metrics along the creek's East and West branch, respectively.

To better represent variation of uncertainty along the length of the creek, the spatially distributed data was aggregated into zones numbered 0100 to 2400 (Figure 3.8a) which follow reach demarcation lines provided by the CVC and generally align with critical infrastructure such as bridges. Figures 3.8b, 3.8c, and 3.8d show the mean magnitude of ζFHM1 and ζFHM2 in each zone along the Main, East and West branches of the creek, respectively, as calculated using ArcGIS's Zonal Statistic tools (ESRI, 2021). ζFHM1 was highest (> 0.30 m) in reaches 200 and 1100 of the main branch and 1600-1900 of the West branch, and lowest (< 0.15 m) in reaches 300, 400, 900, 1200, and 1300 of the main branch and 1500 of the West branch. ζFHM2 generally followed similar patterns with strong positive correlation (coefficient of 0.72) between the two metrics. ζFHM2 was highest (> 2.0 m²/s) in reaches 1000 and 1200 of the main branch, 1600-1800 of the West branch, and 2200-2350 of the East branch. In general, it was noted that

uncertainty was generally higher where inundation areas were relatively narrow (e.g. zone 1600), and lower in areas where inundation areas were relatively wide (e.g. zone 700). Wide inundation areas may have been influenced by bridges with relatively low capacity such that the roughness of the upstream reach was less critical than conveyance values at the bridge.

For the purpose of the current analysis, the most relevant consideration was to evaluate whether the hydraulic uncertainty was sufficient to affect flood hazard classifications. For this purpose, the hazard metrics were compared across two cross sections labelled XX' and YY' passing through relatively wide inundation areas located within Zones A and B, respectively (Figure 3.9). Both sections are characterized by relatively low and broad floodplain to the right of the main channel (Figure 3.9a and 3.9b). Peak values of FHM1 and FHM2 occur within the limits of the defined channel for both sections, where depths and velocities are known to be highest. Peak values are higher along YY' due to the increased flow, depth and velocity at this downstream location. In both cases, inundation outside of the main channel largely occurs to the right of the channel in the floodplain. In these areas, the low depths, low velocities and relatively high variability mean that the uncertainty is high relative to the mean (Figure 3.9c - 3.9f). To better show the relative uncertainty, the coefficient of variation (CV) was calculated as the ratio of the standard deviation to the mean. A CV map of the study site for flood depth revealed that 67% of the distribution fell below 0.25, and this threshold was used to identify the most significant locations. As expected, CV is low in the channel but high in the floodplains, peaking at values of CV = 1.0 or above at the edge of the flood inundation area (Figure 3.9g and 3.9h). Critically, the uncertainty is high enough that the delineation of hazards changes if it is included. For FHM1, for example, 3/10 floodplain pixels on the XX' section and 31/61 pixels on the YY' section increase their hazard level if $FHM1 + \zeta FHM1$ is used to classify the hazard level instead

of FHM1 (Figure 3.9g and 3.9h). For FHM2, 90% of the XX' and 30% of the YY' pixels increase their hazard level with a similar analysis. Overall, the CV values were found to be substantial for both cross sections and indicated that roughness uncertainty has a significant impact for floodplain hazard conditions.

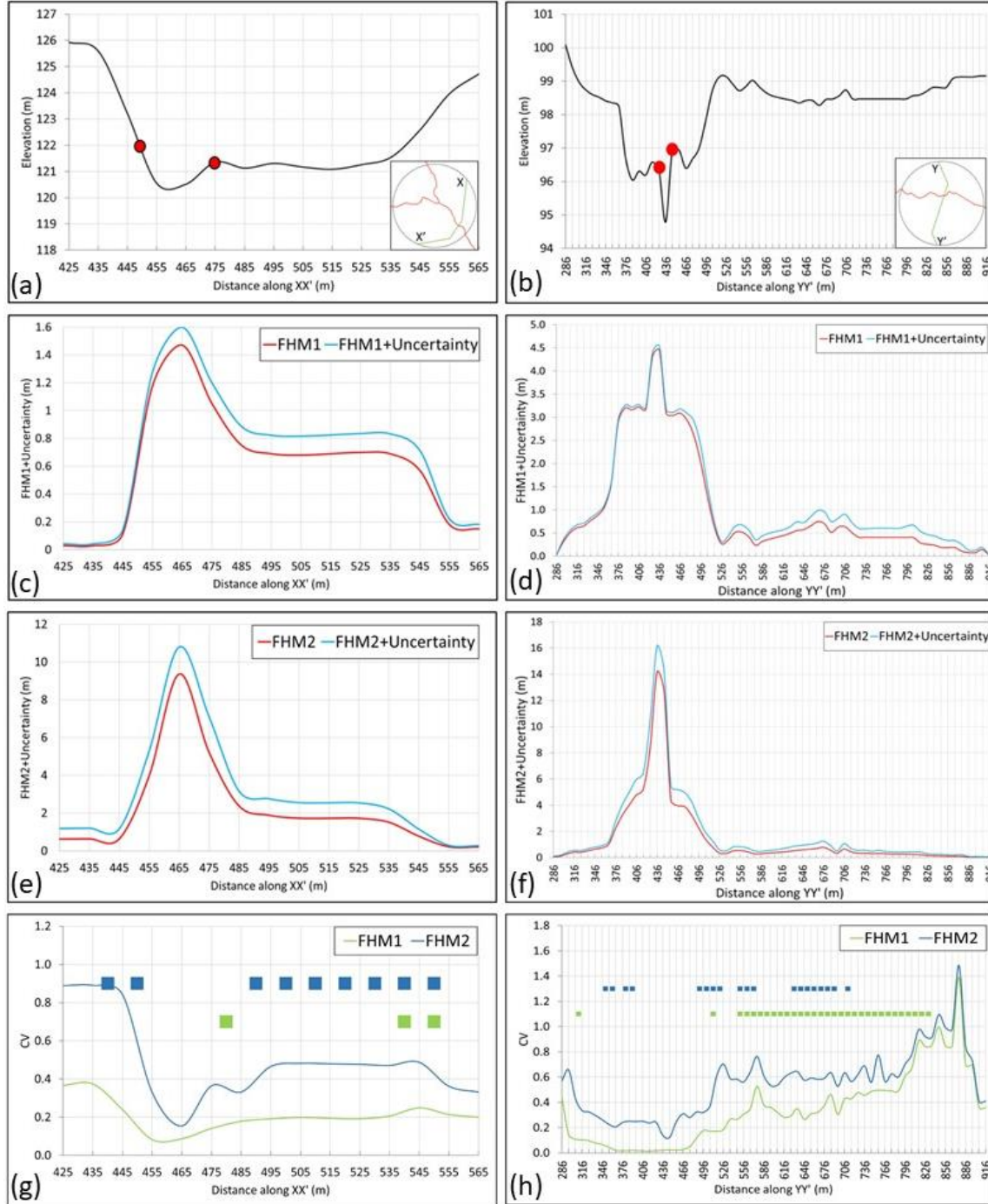


Figure 3.9: (a) and (b)--Elevation profile of XX' and YY' where the 'red' dots represent the creek's banks; (c) and (d)--Spatial variation of FHM1 and its uncertainty along XX' and YY'; (e) and (f)--Spatial variation of FHM2 and its uncertainty along XX' and YY'; (g) and (h)--Spatial variation in CV values of FHM1 and FHM2 metrics along XX' and YY' where the 'blue' and 'green' squares represent the center location of cells that experienced the hazard level change considering uncertainty from FHM1 and FHM2 respectively.

3.4 Discussion

This study aimed to evaluate flood hazards related to pedestrians in an urban watershed by explicitly representing the temporal and spatial variability of modelling parameters and boundary conditions while also considering the uncertainty of the key hydraulic parameter, the surface roughness. This study is novel because it used the SWMM-RASpy framework for multi-variable hazard modeling, which is a new stochastic tool that allows the commonly used SWMM model and a 2D HECRAS model to be coupled seamlessly in a single platform. Although significant progress has been made towards automating the SWMM model (Behrouz, Zhu, Matott, & Rabideau, 2020; Cera, 2013; McDonnell, Ratliff, Tryby, Wu, & Mullapudi, 2020) and the HEC-RAS model (Desrochers, Trudel, Peters, Siles, & Leconte, 2020; Dysarz, 2018; Goodell, 2014; Leon & Goodell, 2016; Philippus, Wolfand, Abdi, & Hogue, 2021) separately for various tasks, the automatic integration of SWMM and HEC-RAS through a framework like SWMM-RASpy better supports the design and analysis of integrated water management solutions because it eliminates the need for manual iterations to assess uncertainty. The novelty of the study also lies in the fact that flood hazard metrics related to pedestrians were included within the SWMM-RASpy framework. This latter step is important because it assesses uncertainty, which has been consistently excluded in pedestrian hazard assessments (Maranzoni et al., 2023).

Decision makers make less than optimal decisions without information on the uncertainties in outcomes of a model (Warmink et al., 2009). There may be circumstances, nevertheless, in which decision-making does not actually need to take the uncertainties into account, such as where uncertainties are small in magnitude, are large but located in places that are not important to the decision makers, or when they are large but do not exceed values that would trigger a change in managements. This focus of the current research was on the question of whether the

uncertainties surrounding flood hazard metrics were significant enough to be considered in flood hazard management. It was shown that, in an absolute sense, the uncertainty of the FHM1 metric varied by longitudinally defined reach, which would indicate that pedestrians in certain areas of the system would be more at risk. In contrast, the FHM2 metric was more uncertain in the channel in comparison with the floodplain, which would suggest a lower uncertainty of risk in the areas where pedestrians may come into contact with floodwaters. However, in a relative sense, the uncertainty of both metrics was consistently higher in the floodplains. This sensitivity to the change in surface friction is likely due to lower absolute flow depths and velocity, where slight changes in the conveyance of the floodplain cells can lead to a greater proportion of the overall flow passing through the floodplain rather than through the channel. Overall, the uncertainty of this process of lateral exchange and the division of flow between the channel and floodplain is one of the biggest challenges for hydrodynamic modelling.

A key result from the study is that although the inclusion of velocity in hazard models, as highlighted by Kim et al. (2012) and Kreibich et al. (2009) can improve the accuracy of flood risk assessments by providing a more comprehensive understanding of flood dynamics, hazard metrics that incorporate this parameter are also likely to have higher variability. This trade-off indicates that the chances of misrepresenting pedestrian hazards using these metrics are greater than with metrics that do not consider velocity. At the watershed scale, uncertainties around flood hazard metrics were found to vary longitudinally and laterally along a creek. The FHM2 metric, which includes velocity, was found to be the most uncertain along both directions, as evidenced by higher coefficients of variation (CV) compared to the FHM1 metric. This is due to the fact that velocity was determined to be the most uncertain flood variable at the site given the variation in surface roughness; a comparable finding was also observed by Dalledonne et

al.(2019). A comparison of CV maps among the flood variables revealed that the spatial mean of velocity for the study site was approximately 2.2 times greater than depth while depth's spatial mean was approximately 3.3 times greater than duration. An uncertainty map of velocity revealed that approximately 30% of the inundated area outside the channel showed high magnitude of uncertainty (> 0.50 m/s), predominantly in regions with high-intensity velocity (> 0.5 m/s). Given that the stability of a pedestrian is more influenced by flood velocity than water depth alone in urban areas (Dong et al., 2022; Li, Q. et al., 2023; Li, Y., Zhou, & Shen, 2022), it is crucial to consider the uncertainty of velocity, and thus of the FHM2 metric, for effective planning against pedestrian hazards in areas like the Cooksville Creek.

Flood duration also plays a significant role in altering hazard levels. Specifically, the inclusion of duration in the FHM3 metric resulted in a 15% increase in higher-level hazards. This change is consistent with findings from Wagenaar (2012) and Lazzarin et al. (2022), particularly given the urban nature of the study site and the shorter simulation period. Despite its impact on hazard levels, duration was the least-affected flood variable by variations in surface roughness. This may be attributed to the predominant urban land cover, such as surface imperviousness, and the relatively flat topography of the inundated floodplains (Schubert, Burns, Fletcher, & Sanders, 2017). Duration was included as a factor in estimating the FHM3 hazard metric, which further mitigated the impact of its uncertainty. Studies using 2D models for uncertainty analysis, such as Ahmadisharaf et al. (2018), also found duration to be the least uncertain parameter. Therefore, unlike the FHM2 metric, the uncertainties surrounding the FHM3 metric were not significantly influenced by the addition of uncertainty from duration.

2D unsteady hydraulic models generate a large amount of information, and managing data from multiple simulations of models running inside a stochastic framework can be a massively

challenging issue (Luke et al., 2018). In this regard, the research considered averaging the maximum values derived from stochastic simulations for each hazard metric at each inundated location of the study site to represent the hazards. The intended outcome of the analysis is to be able to produce hazard maps that include the impact of the estimated uncertainties on the hazard metrics. A ‘confidence’ map of FHM1 metric such as the one shown in Figure 3.10 can be produced with this method.

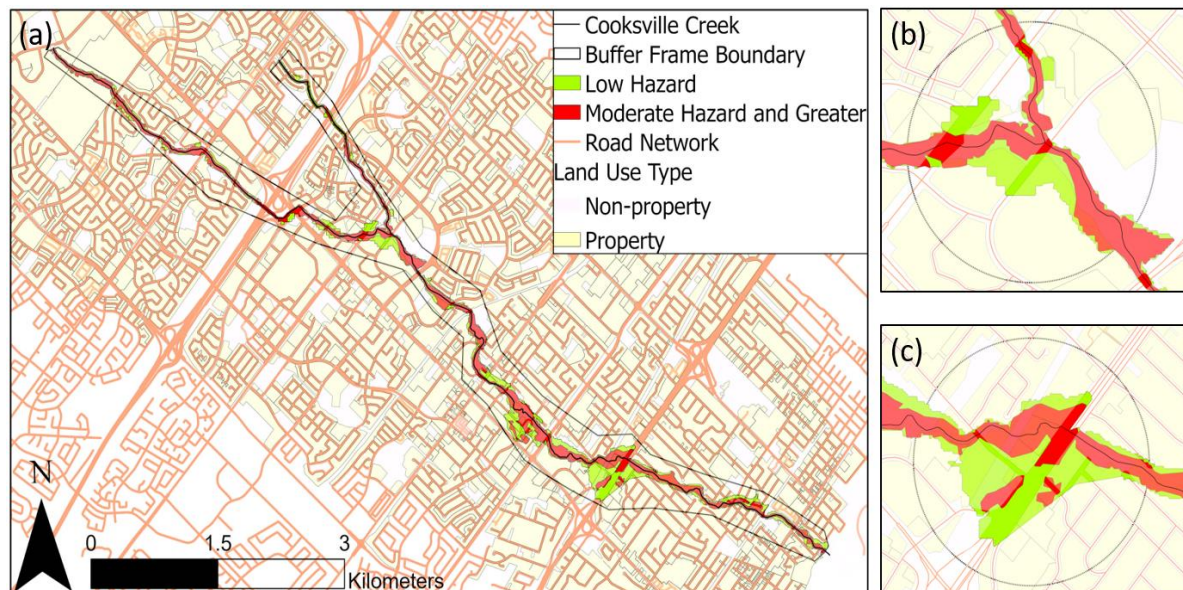


Figure 3.10: A confidence map of the FHM1 hazard metric overlaid with the property boundaries and road network in the watershed (a) focusing the full Cooksville Creek, (b) focusing Zone A and (c) focusing Zone B. The hazards are categorized as low hazard (where $FHM1 \leq 0.45$ m) and moderate hazard and greater (where $FHM1 > 0.45$ m). FHM1 is the original(mean) value plus the margin of error of its distribution at a 95% confidence level.

This map shows the hazard level based on the mean FHM1 value plus the margin of error of its distribution at a 95% confidence level. Such a map could be used as a substitute for traditional deterministic maps. In this case, red is used to indicate areas of moderate hazards or above, while green zones indicate areas that are not free of flood risk, but would likely only experience relatively low hazard flooding. The map is advantageous because it would make it easier for management authorities to communicate flood hazard. A probability distribution map

of depth-related hazard would in general depict the probability of exceeding a certain level of hazard at a given location, and such probabilistic information are typically challenging for authorities to utilize. Di Baldassarre et al. (2010), for example, note that decision makers often prefer a deterministic hazard map for setting floodplain management rules despite the more accurate representation of hazard in a probabilistic map. The transfer of probabilistic information to general stakeholders is also difficult (Di Baldassarre et al., 2010). For a flood-hazard confidence map, the displayed values appear similar to deterministic estimations, and the authorities could therefore regard them similarly to how they would a deterministic hazard map.

Spatially distributed uncertainty maps were analyzed using both grid-level and zonal-level approach. Grid-level analysis captured the impact of local topographic variations on hazard assessment. For example, analyzing the grids/pixels along cross sections XX' and YY' revealed in details how the floodplain behaved differently from the channel, given the uncertainty in surface roughness for both FHM1 and FHM2 hazard metrics. On the other hand, zonal-level analysis, which involved larger areas or zones of the watershed along the creek, provided a broader perspective on flood hazards. This analysis identified which zones are more susceptible than others to the uncertainty in roughness using the grid-level data. For instance, Zones 2100, 1500, and 1400, located around the confluence point of the creek, showed relatively low uncertainty for both hazard metrics. Although one might assume that areas directly connected to the junction point would be highly uncertain, the zonal analysis, reflecting the cumulative effects of topographic variations at each zone, revealed otherwise for the watershed. Utilizing the grid data to conduct zonal analysis offers a more reliable and comprehensive view for large-scale flood management in the watershed compared to using semi-distributed or lumped data (Zhang, Shao, Sun, Huang, & Yang, 2022). Thus, combining grid-level precision with zonal-level

comprehensiveness would facilitate better-informed decision-making for flood management strategies in the watershed.

The findings discussed in this section are based on an analysis of a single watershed for a single hydrologic event. Our study watershed is predominantly urban with a creek at its center which is narrow and shallow and has a moderate slope. Narrow valleys in the upstream of the watershed reduce the extent of possible flooding, while the flatter areas and bridges increase the extent of possible flood hazard at the downstream end. In addition, the findings are based on a single hydrological event. The single hydrograph should also be considered as a significant source of uncertainty, so pedestrian hazard should also consider this source if decisions are being made based on a return period type analysis. Although the modelling approach used in this study could be applied to other types of watersheds in the future and compared with machine learning-based geophysical approaches for assessing flood risk, caution should be exercised when applying it in settings that might still employ 2D models. One recommendation for conducting similar analyses on other watersheds is to decrease computational time. The Latin Hypercube Sampling method used in this study for stochastic modeling is computationally expensive, particularly with complex hydraulic modeling like 2D modeling. For example, each hydraulic simulation for a sample set of n values took approximately 15 minutes on average, resulting in a total of approximately 26 hours of simulations. The amount of time might be decreased in a variety of ways, either by increasing the processing power of computing machines or by using an alternate approach like PEM that would take fewer sample sets and possibly produce results that are comparable (Oubennaceur et al., 2018). The latter one seems more feasible, and can be used in future investigations. In future research, given that velocity was greatly impacted by the uncertainty in surface roughness, it would also be worthwhile to compare the conventional 1D

and 2D deterministic models with our SWMM-RASpy framework, particularly for estimating the FHM2 metric. Such a comparison would assist flood management authorities in making more informed decisions.

3.5 Conclusions

This study aimed to comprehensively evaluate flood hazards related to pedestrians in an urban watershed by explicitly representing the temporal and spatial variability of modeling parameters and boundary conditions while also considering the uncertainty of the key hydraulic parameter, surface roughness. The innovative use of the SWMM-RASpy framework, which couples the commonly used SWMM and HEC-RAS models in a single platform, enabled a detailed and automated analysis of flood hazards. This novel framework facilitated the incorporation of stochastic analysis in hazard assessment, a critical step often overlooked in pedestrian hazard evaluations. Although additional research and case study applications are required to establish more general conclusions about the uncertainty of the hazard metrics and their impacts on pedestrian hazard assessment, focusing on a single case study enables certain conclusions to be formed (Ahmadisharaf et al., 2018). The following conclusions were drawn from this study:

1. The SWMM-RASpy framework was successfully applied to describe pedestrian hazard using SWMM and HEC-RAS models. These models are widely used, and hence, this framework will facilitate the incorporation of such analysis into decision-making processes.
2. The uncertainty related to surface roughness had a significant impact on pedestrian hazard estimation. This is particularly relevant for floodplains where the roughness is highly uncertain and pedestrians are likely to be during floods.
3. FHM2 metric, incorporating depth and velocity, is highly sensitive to the stochastic analysis such that certain zones may be misclassified as safe that are in fact hazardous for pedestrians. This is because the uncertainty related to roughness had the greatest impact on velocity estimation.

4. The duration of flooding altered the pedestrian hazard level; however, it was minimally affected by the uncertainty in surface roughness. Consequently, the FHM3 metric demonstrated negligible sensitivity to stochastic analysis, in contrast to FHM2.

5. Confidence maps can be incorporated into decision-making and disaster planning as an improvement over traditional deterministic maps. These maps provide a more reliable representation of hazard metrics by including the impact of estimated uncertainties.

6. Given the availability of a grid-based model, the scopes for both grid-level and zonal-level analyses should exist as part of effective flood management. Combining these approaches enhances the understanding of flood hazards at different scales, facilitating more robust flood risk assessments.

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Chapter 4: ASSESSING THE IMPACTS OF CLIMATE CHANGE AND ITS UNCERTAINTIES ON FLOOD HAZARD

4.1 Introduction

Climate change is forecasted to increase precipitation frequency, rainfall intensity, and flood hazards in most regions across Canada (Oubennaceur et al., 2021). A notable increase in the damages associated with climate change has already been observed in major urban municipalities in Canada (Oubennaceur et al., 2021), and this trend is expected to continue worldwide in the coming decades (Wasko et al., 2021). In an effort to better prepare for flood-generated hazards, numerous flood management authorities across the globe have started to incorporate the effects of climate change into their flood design guidelines. However, these guidelines differ across countries and jurisdictions, and there is no consensus methodology for estimating floods in the context of climate change (Wasko et al., 2021). In Canada, there is no single established method or best practise for incorporating climate change projections into flood maps (Natural Resources Canada, 2023). A review of flood estimation guidance by Wasko et al. (2021) highlighted the common use of scaling factors applied to the peak flow rate or to the flood-producing rainfall to account for climate change, which is simple with a low computational cost, but does not capture the non-linear response of model inputs to climate forcing. Accurate assessment of flood hazard and risk will require that hydrologic and hydraulic processes be more accurately represented and parameterized.

Global Climate Models (GCMs) are currently one of the most useful instruments for studying climate change because of their capacity to replicate previous climatic characteristics and anticipate future climate change. However, projections of future climate change are inherently uncertain (Gaur, A., 2013), and neglecting the associated uncertainties can

significantly degrade the quality of the projections (Zahmatkesh, Han, & Coulibaly, 2021). The uncertainty can be attributed to our imperfect understanding of the climate, inadequate representation of the climate system, and limited computer resources (Wu et al., 2022). Uncertainty can emerge from both natural uncertainty, which originates from the variability of underlying processes, and epistemic uncertainty, which originates from deficient information about the processes and factors (Beven, Lamb, Leedal, & Hunter, 2015; Teng et al., 2017). For climate change in particular, Hawkins and Sutton (2009) proposed three categories, including: i. model uncertainty, which arises from different climate models (i.e. GCMs) yielding different predictions of climate change despite being subjected to the same radiative forcing; ii. scenario uncertainty, which arises from incomplete knowledge of external factors influencing the climate system (e.g. future trajectories of emissions of greenhouse gases); and iii. internal variability, which arises from the natural variability/fluctuations of the climate system occurring in the absence of external forcing (Deser, Phillips, Bourdette, & Teng, 2012; Gaur, S., Bandyopadhyay, & Singh, 2021; Wu et al., 2022). Many studies have tried to measure the degree of uncertainty from each source and found that their relative significance depends on the temporal scale (e.g. yearly, seasonal or monthly), the climate variable under consideration (e.g., temperature, precipitation, or other variables), and the geographic scale (e.g. at the continent-scale or country-scale) (Meresa, Murphy, Fealy, & Golian, 2021). Model uncertainty, however, is frequently identified as the main source of uncertainty, while evidence on the relative contributions of the other sources is mixed (Senatore et al., 2022). Since distinct climate models have the potential to produce entirely different climate projections, it is reasonable to use an ensemble of climate models rather than a single model in order to enhance the reliability of climate predictions (Gaur,

S. et al., 2021). A stochastic output from an ensemble of GCMs can therefore improve the representation and management of uncertainties and climate impact assessment.

GCM-based conventional or top-down approaches for climate change impact assessments in flood hazard studies generally adhere to a modelling chain in which GCMs forced with one or several scenarios of future greenhouse gas (GHG) concentrations and the outputs such as temperature and precipitation are extracted (Meresa et al., 2021). These GCM outputs are then scaled for a study catchment and fed into hydrological models, which are generally calibrated for the existing condition, to model future GHG scenario discharge series. A flood frequency analysis is then conducted using the discharges of extreme events to evaluate changes to flood inundation hazard. The GCM outputs from an ensemble of models, emission scenarios and/or other entities such as downscaling methods can be used to create uncertainty bounds for flood hazards (Meresa et al., 2021). Several other researchers such as Gaur et al. (2021) and Lawrence et al. (2013) included flood frequency analysis, which required estimating runoffs/flows using a hydrologic model, into their frameworks in order to achieve a similar goal. However, flood frequency analysis is not spatially explicit and therefore not a reliable approach for estimating design floods, particularly in urban watersheds (Ahmadisharaf, Kalyanapu, & Bates, 2018). The studies also defined flood hazards in terms of peak flow and flood volume alone, which is not sufficient where water systems are modified by human intervention and managed by structures such as weirs and dikes (Lawrence, D. et al., 2012). In such cases, and despite the complexity and computational cost of the task, a combination of hydrological and hydraulic (H&H) models will typically be needed to model the potential impacts and uncertainties of climate change.

Some studies have built frameworks that couple H&H models for the purpose of analyzing the impacts of climate change and its associated uncertainties on flood hazards. An

integrated framework was implemented by Beevers et al. (2020), for example, though their analysis was limited to the impacts of climate change on the areal extent of flooding. The authors also acknowledged that the framework did not meet the industry needs, and they advocated for investigating alternative approaches that can be integrated with standard practices in industry. Zahmatkesh et al. (2021) used a HEC-HMS and HEC-RAS framework to understand the impact of climate change on the uncertainties surrounding flooding. However, the hydrologic model only accounted for surface flow, ignoring the sub-surface system commonly used for urban drainage, and used a 1D steady state hydraulic model, which is regarded as less accurate than 2D models for smaller and more heavily urbanized watersheds (Hosseinipour, Vargas, O'Brien, & Kasraie, 2012; Vojtek, Petroselli, Vojteková, & Asgharinia, 2019). Ahmadisharaf et al. (2018) developed a framework to quantify the impact of uncertainty from a hydro-climatic variable on both the spatial and temporal uncertainty of a range of flood hazard parameters. However, their framework was mainly tested for one scenario in a rural setting, and the authors advocated for additional research and case studies. Using a 2D hydrodynamic model, Alipour et al. (2024) have investigated three different sources of uncertainty related to rainfall intensity including RCP scenario, climate model, and probability distribution function on flood depth only. Collectively, these studies highlight the significant progress made in coupling H&H models to assess climate change impacts on flood hazards. However, they also reveal persistent gaps and limitations, particularly in the accurate representation of urban flooding and the comprehensive consideration of uncertainties. There remains a critical need for the development of more robust and integrated frameworks that can address both surface and sub-surface flows, meet industry standards, and account for a wider range of uncertainties across different scenarios and settings.

Communicating flood risks has traditionally relied on methods like regulatory flood lines and river setback distances. While effective for existing hazards, these approaches are inadequate for addressing the increased uncertainty of flood risks under climate change. As climate change intensifies the stochastic nature of floods, new strategies are needed to effectively convey these evolving risks and ensure communities are better prepared (Zahmatkesh et al., 2021). Currently, there is no consensus on the best means to communicate uncertainty to water policymakers (Kundzewicz et al., 2018). Refsgaard et al. (2013) and Kundzewicz et al. (2018) developed generic qualitative frameworks that were geared towards policymakers on how to accommodate and reduce the effects of uncertainty in climate change adaptation strategies for water resources. However, the authors noted that developing suitable approaches for handling uncertainties in preparing for climate change remains a research challenge (Wasko et al., 2021). It is recommended that, despite the increased complexity and computational cost, adaptive planning should be based on ensembles of projections rather than a single-value future prediction (Kundzewicz et al., 2018) because they better represent the uncertainty surrounding climate change (Byer & Yeomans, 2007; Lawrence, J. et al., 2013). Flood hazard maps produced by integrating a visualization program such as ArcGIS with the coupled H&H computer programs can be used as a great resource to visualize the effect of climate change and its uncertainties on future flood hazards (Lawrence, D. et al., 2012). Once made available to the public, these maps can help stakeholders and the broader public in their future planning. Using an online platform, the maps may be displayed side by side with the most recent flood hazard map, making the comparison process more interactive (Lawrence, D. et al., 2012).

The goal of the existing research is to advance a method to effectively represent the impact of future climate change on both the magnitude and uncertainty of flood hazard in cities.

The novel SWMM-RASpy framework (Chapter 2) is applied because it allows for a high degree of fidelity in the physical representation and relevant processes in an urban watershed, and it couples an industry standard hydrologic model (Storm Water Management Model -SWMM) with an industry standard 2D unsteady hydraulic model (Hydrologic Engineering Center's River Analysis System - HEC-RAS). Specific objectives of the research are to: i) adapt the novel SWMM-RASpy framework to model the impact of climate change on flood hazard; ii) assess the impact of forecast changes to rainfall intensity on building flood hazard in an urban watershed; and iii) demonstrate the utility of flood hazard metrics for communicating the risk of flooding as a result of climate change. The urban Cooksville Creek watershed was used to demonstrate the methodology and assess the impacts. The rainfall intensity was considered to be uncertain due solely to the estimates of GCMs for a given GHG emission scenario. The analysis considered three flood hazard metrics (FHM) applied in Chapter 3 including: i) FHM1 –flow depth; ii) FHM2 – FHM1 and flow velocity; and iii) FHM3 – FHM2 and flood duration. The hope is that the work presented here will provide a useful method to estimate flood hazards and inform flood risk management given the uncertain nature of climate change projections.

4.2 Methodology

The generic approach used in the research to achieve the chapter's objectives is shown in

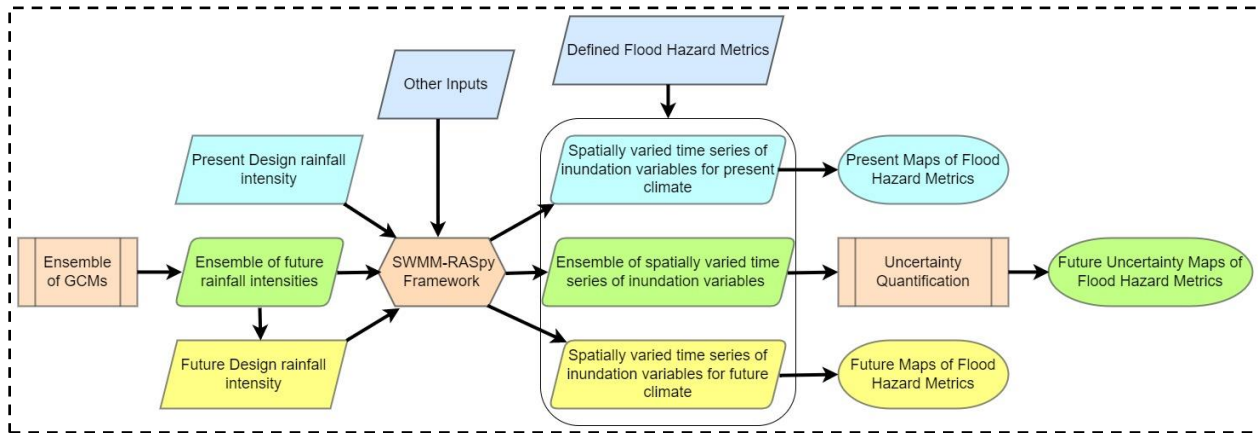


Figure 4.1: Process diagram showing how the impacts of climate change and its uncertainties on flood hazard assessment are estimated using the SWMM-RASpy framework. The 'cyan' and 'yellow' shapes represent stationary processes involved with existing and future climate, respectively, while the 'green' shape represents non-stationary processes involved with future climate only

Figure 4.1. This chapter has focused on the flood hazards in relation to buildings. In this analysis, the level of potential structural damage caused by flooding to a building was used to estimate its level of hazard. A building was considered to be flooded if floodwater came into contact with its footprint, and flood depth was measured relative to the building's first-floor elevation (Natural Resources Canada & Public Safety Canada, 2021). The footprints of the buildings within the study watershed, along with their first-floor elevations, were provided by CVC. The analysis was conducted over a 30-year period, from 2040 to 2070, using a 100-year, 3-hour rainfall event, discretized at 5-minute intervals. The following sections describe the generic approach in detail. While the approach discussed in this chapter has been applied to buildings, it can also be used to evaluate flood hazards connected to other types of structures.

4.2.1 Ensemble of Global Climate Models (GCMs)

Over 100 GCMs have reportedly been developed by various organizations worldwide (Schardong, Gaur, Simonovic, & Sandink, 2024). The main inputs to these GCMs are GHG emission scenarios, with four GHG emission scenarios, or Representative Concentration Pathways (RCP), generally used for climate projection studies (Schardong et al., 2024). The four RCPs vary from low (RCP 2.6) to high (RCP 8.5) with high emission scenarios generally resulting in high climate change impacts (Schardong et al., 2024). For the existing analysis, the high severity scenario was analysed using an ensemble of GCMs from the IDF_CC tool (Simonovic, Schardong, Srivastav, & Sandink, 2015). This tool was chosen because it has the built-in capability to downscale the GCMs both spatially and temporally for analysis inside Canada. Additionally, the tool can be used to create Intensity-Duration-Frequency (IDF) curves for ungauged stations whose locations are supplied by the users, as well as gauged rainfall stations like those run by Environment Canada. If there are more than one gauged rainfall station lies inside a watershed, it spatially interpolates the stations' data to produce a single IDF curve for the entire catchment. Another advantage of the tool is that it allows users to use either a single GCM or ensemble of its GCMs available for each RCP. For the existing analysis, the RCP 8.5 scenario was modelled because it is thought to be the most severe. One limitation is that the IDF_CC tool only permits the use of only 24 of the GCMs for RCP 8.5, and only 22 GCMs could be used to produce the rainfall data due to technical challenges that prevent downloading information for certain GCMs.

4.2.2 Ensemble of IDF Curve Parameters

The Sherman formula has been shown to accurately representing rainfall data in North America (Chin, 2019) and was used to generate an IDF curve as follows:

$$i = \frac{A}{(t_d + B)^C} \quad (4.1)$$

where i is the rainfall intensity (mm/hr) of a design storm event for a given return period, t_d is the duration of the event (hours), and A , B and C are fitted coefficients. Coefficient values are calculated within the IDF_CC tool by fitting a theoretical probability distribution to an annual maximum precipitation (AMP) time series (Schardong, Simonovic, Gaur, & Sandink, 2020). The Gumbel probability distribution was selected as an option for the existing study because it is widely used and recommended by Environment Canada (Schardong et al., 2020). The A , B , and C coefficients for the 22 GCMs used in the existing analysis are listed in Table 4.1. The GCMs differ only in the value of A . Coefficient values for the existing climate are shown for comparison obtained from City of Mississauga's Development Requirements Manual (City of Mississauga, 2020).

Table 4.1: A, B and C coefficients used by the GCMS and used for existing climate condition for the station located inside the study watershed

A, B and C coefficients (in hours) used by GCMS			
Climate Model Name	A	B	C
bcc-csm1-1	91.1	0.168	0.821
bcc-csm1-1-m	89.3	0.168	0.821
BNU-ESM	74.5	0.168	0.821
CanESM2	69.5	0.168	0.821
CCSM4	65.9	0.168	0.821
CESM1-CAM5	78.4	0.168	0.821
CNRM-CM5	76.8	0.168	0.821
CSIRO-Mk3-6-0	79.3	0.168	0.821
FGOALS_g2	58.1	0.168	0.821
GFDL-CM3	81.1	0.168	0.821
GFDL-ESM2G	73.6	0.168	0.821
GFDL-ESM2M	73.8	0.168	0.821
HadGEM2-AO	71.8	0.168	0.821
HadGEM2-ES	71.8	0.168	0.821
IPSL-CM5A-LR	82.1	0.168	0.821
MIROC5	79.9	0.168	0.821
MIROC-ESM	89.1	0.168	0.821
MIROC-ESM-CHEM	80.6	0.168	0.821
MPI-ESM-LR	80.1	0.168	0.821
MPI-ESM-MR	87.2	0.168	0.821
MRI-CGCM3	86.8	0.168	0.821
NorESM1-M	81	0.168	0.821
A, B and C coefficients (in hours) for existing climate condition			
Existing Condition	57	0.10	0.78

4.2.3 Implementation of the SWMM-RASpy Stochastic Framework

The SWMM-RASpy framework uses the Chicago Storm Distribution (CSD) method to generate design hyetographs. To apply this method, peak intensities (i_{peak}) were calculated using Equation 4.1 for each value of coefficient A in Table 4.1 using a t_d of 5 minutes, which represents the time interval (Δt) of the desired hyetographs. Using the ensembles of i_{peak} , their uncertainty bound was constructed and then sampled using the Latin Hypercube Sampling (LHS)

based module of the framework (AutoSAMPpy). A total of 100 samples of i_{peak} were generated to define the set of model simulations. To allow the full CSD to be constructed, the coefficient A was calculated from a rearranged version of Equation 4.1 for each value of i_{peak} . The midpoint of the sample distribution, (i_{mean}) was used to represent a deterministic future rainfall intensity.

The hyetographs, representing rainfall distribution over time, were generated using the coefficient values (A , B , and C) corresponding to the sampled i_{peak} values using the following CSD equations for the rising and falling limbs adapted from Silveira (2016):

$$P_t = \gamma * P_{tot} - \frac{A(t_p - t)}{\left(B + \frac{t_p - t}{\gamma}\right)^C} ; t < t_p \quad (4.2)$$

$$P_t = \gamma * P_{tot} + \frac{A(t - t_p)}{\left(B + \frac{t - t_p}{1 - \gamma}\right)^C} ; t > t_p \quad (4.3)$$

where P_t is the cumulative rainfall (mm) at time t (hr) from the beginning of the hyetograph, t_p is the time to peak (hr), γ is the time-to-peak factor (t_p/t_d), and P_{tot} is the total rainfall (mm). P_{tot} was calculated from Equation 4.1 with t_d set to the total duration of the event. Rainfall depth during the time interval where $t = t_p$ was set by multiplying the corresponding i_{peak} by the time interval Δt . In this analysis, t_d was fixed to 3 hours, Δt was set at 5 minutes, and γ was set at 0.35. The duration of each SWMM simulation event was chosen to be twice of the rainfall event, i.e. 6 hours, with a computational step of 5 minutes. The AutoSWMMpy script of the framework was invoked to automate this process.

The framework's AutoRASpy script was invoked to automate the hydraulic modeling procedure. The script updates the SWMM hydrographs stored in the CSV files, controls their

ingestion into a HEC-RAS data file the using HEC-DSSVue program and then executes a 2D HEC-RAS model for each of the 100 simulations. Each simulation of HEC-RAS was run for a duration of 6 hours. 97 of the 100 simulations did not encounter any stability concerns, as determined by its volume accounting error threshold of 2% (Brunner, 2022), and so were deemed acceptable. The AutoRAS-HDFpy script of the framework was invoked to collect spatially varied time series outputs for three flood variables—depth, velocity, and duration—following each successful RAS model execution.

4.2.4 Uncertainty Quantification

Standard deviation was used as the primary statistical measure to quantify uncertainty of the flood hazard metrics under projected climate change. The outputs of the flood variables were transformed to create the data for these flood hazard metrics by employing Equations 3.1 through 3.6., while the uncertainties surrounding the metrics were estimated by employing Equations 3.8 through 3.10. The hazard metrics obtained for i_{mean} were used to create a deterministic future hazard map, which was used to compare with the existing hazard map and the uncertainty data for the hazard metrics.

4.3 Results

The results of the mapping and estimation of the flood hazard metrics, along with their uncertainties resulting from the future climate (i.e. the future rainfall) projected at the study site within the given timeframe, are presented in this section. In addition, the future hazard metrics are compared with the hazard metrics of the existing climate to evaluate the impact of projected climate change. Both the future metrics (generated for i_{mean}) and the existing metrics were estimated using the SWMM-RASpy framework. This was done by setting the 'runs_hydrologic' and 'runs_hydraulic' parameters in its 'inputs_frameworkpy' script to 1.

4.3.1 Rainfall

The rainfall data, specifically the IDF coefficients, was the only input requirement that differed between the climates of the existing and the future. It was determined that the existing peak intensity of rainfall, i_{exist} , as determined by the existing IDF parameters of the study site, was lower than i_{mean} . The value of i_{exist} was estimated to be 214 mm/hr while i_{mean} was estimated as 253 mm/hr. The range of peak intensities for future climate, as estimated from the GCMS, varied between 180 mm/hr and 283 mm/hr. The average intensity for the existing condition was calculated as 23.6 mm/hr, while the mean of the average intensities from each of the GCMs was 30.5 mm/hr. The average intensities were estimated using Equation 4.1 with t_d equals to 3 hours. Consequently, the total depth of rainfall projected for the future climate condition (91.5 mm) was higher compared to the existing condition (70.8 mm).

4.3.2 Inundation Extent

The inundation areas for the existing and future climates are shown in Figure 4.2.

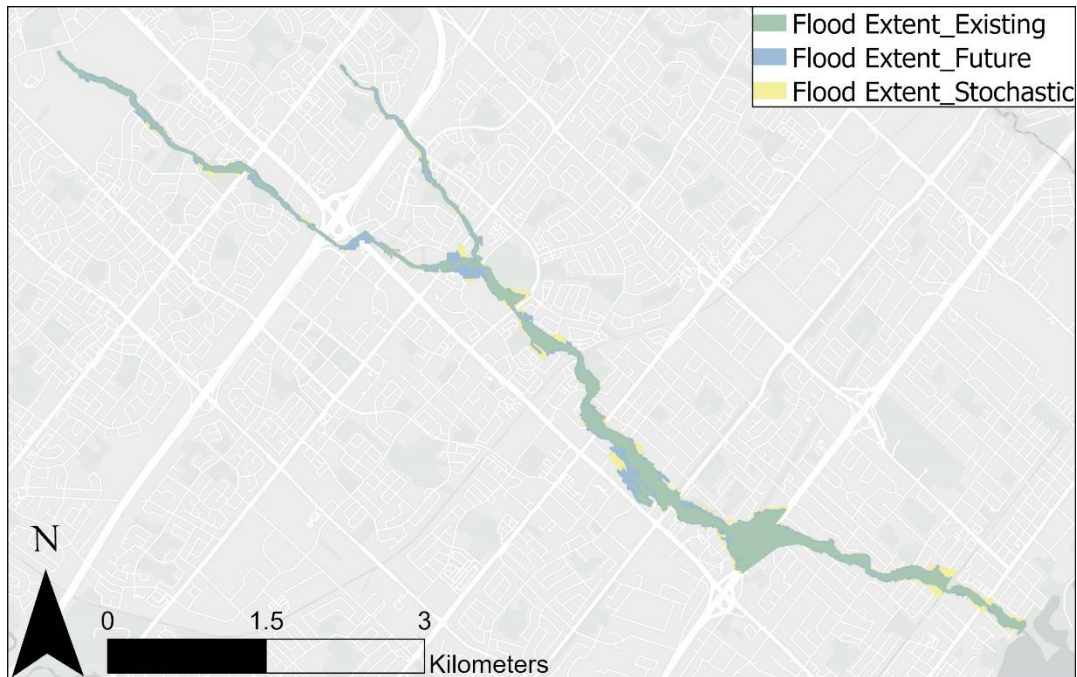


Figure 4.2: Inundation extents generated for existing climate, *Flood Extent_Existing* and future climate, *Flood Extent_Future*. *Flood Extent_Existing* was produced using the rainfall hyetograph with a peak intensity of i_{exist} , whereas *Flood Extent_Future* was produced using the one with a peak intensity of i_{mean} . *Flood Extent_Stochastic* was produced using the ensemble of hyetographs that corresponding to the sampled intensities

In the figure, *Flood Extent_Existing* and *Flood Extent_Future* represent the deterministic inundation areas for existing (i_{exist}) and future climate (i_{mean}) conditions, respectively. Meanwhile, *Flood Extent_Stochastic* represents the inundation area generated from the ensemble of inundation areas produced by the sampled hyetographs corresponding to the sampled intensities. *Flood Extent_Future* is estimated to increase from 1.10 km² (*Flood Extent_Existing*) to 1.50 km². Along most of the creek's course, the width of the inundation extent in the future will be greater than its existing extent. The *Flood Extent_Stochastic*, which is 0.20 km² larger than the *Flood Extent_Future*, covers the largest inundation area in the watershed. This is because it accounts for any location that was flooded at least once in any of the stochastic simulations.

The increase in inundation area due to climate change and the uncertainty of climate change will significantly increase the number of flooded buildings. The locations of these flooded buildings were categorized into three distinct regions to differentiate between the varying levels of flood risk under different climate scenarios: (i) **A1**: buildings already at risk under existing conditions (inside the Flood Extent_Existing), (ii) **A2**: buildings newly at risk due to future climate change impacts (outside the Flood Extent_Existing but within the Flood Extent_Future), and (iii) **A3**: buildings additionally at risk due to stochastic or uncertain climate variations (outside the Flood Extent_Future but within the Flood Extent_Stochastic). Under the existing climate conditions, 308 buildings are at risk of flooding in A1. The increase in inundation area results in an additional 157 inundated buildings in A2, representing a ~50% increase, with the majority (~90%) located along the Main branch of the creek. A further 185 buildings were identified as potentially at risk of flooding in A3, bringing the total number of buildings at risk within the watershed to 650—more than double the number under the existing climate scenario.

4.3.3 Hazard Evaluation via FHM1 metric

Flooding always increased in future climate scenarios due to the higher rainfall, and the mean of flow depth (FHM1) in A1 region increased by ~0.50 m for i_{mean} . The spatial distribution of differences in flow depth between the existing and future climate within A1 is shown in Figure 4.3. The mean of increased depth was calculated as 0.54 m within the area defined by the creek banks in the HECRAS model and 0.47 m in the area outside the channel, which demonstrates that variation in the direction perpendicular to the primary flow direction was relatively minor. What is more apparent was that the spatial variation in the primary flow direction was very high (Figure 4.3). Along the Main Branch, for example, ~90% of the A1

region will see an increase in flood depth greater than 0.15 m, with 60% will see an increase of greater than 0.30 m, while only 70% and 60%, respectively, of the East Branch had similar increases in depth, and the West Branch was even lower, with only 40% and 10%, respectively, of the area showing increases in depth of 0.15 and 0.30 m.

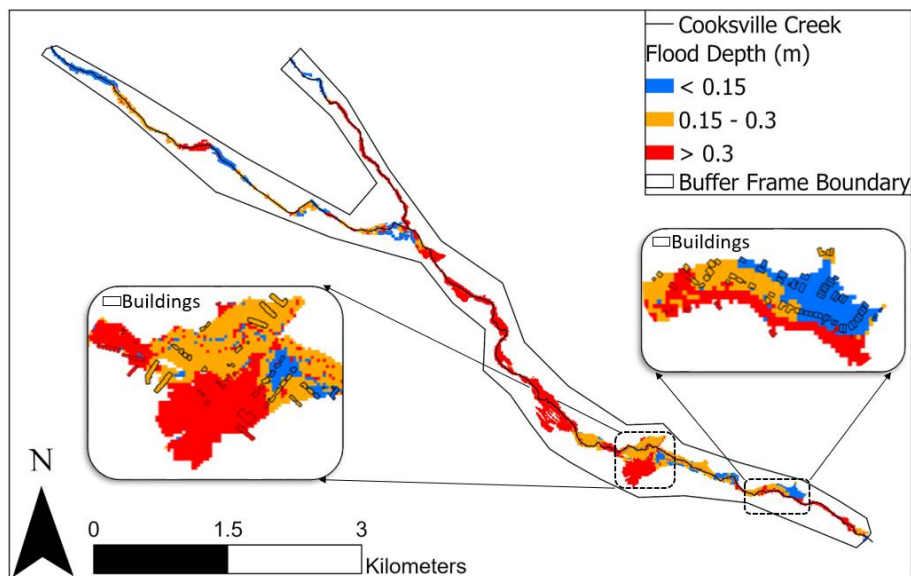


Figure 4.3: Spatial distribution of flood depth differences between the existing climate and future climate scenarios inside A1 region; the inset images display the distribution of flooded buildings classified by the magnitude of flood depth differences

To understand the spatial variation of uncertainty along the creek, a zone-based approach was applied to Cooksville creek using the reach demarcation lines provided by CVC (Figure 4.4a). The magnitude of uncertainty of FHM1 in each zone was discretized based on percentiles, with 0.20 and 0.32 m representing the 33rd and 67th percentiles. Uncertainties of each zone along the Main, East and West branches of the creek are shown in Figures 4.4b, 4.4c, and 4.4d, respectively. The clearest result from this analysis is that Zones 1000-1400, which are on the Main Branch immediately downstream of the confluence of the East and West Branches, is a

highly uncertain area, with all five zones higher than any other zone in the system. Along the

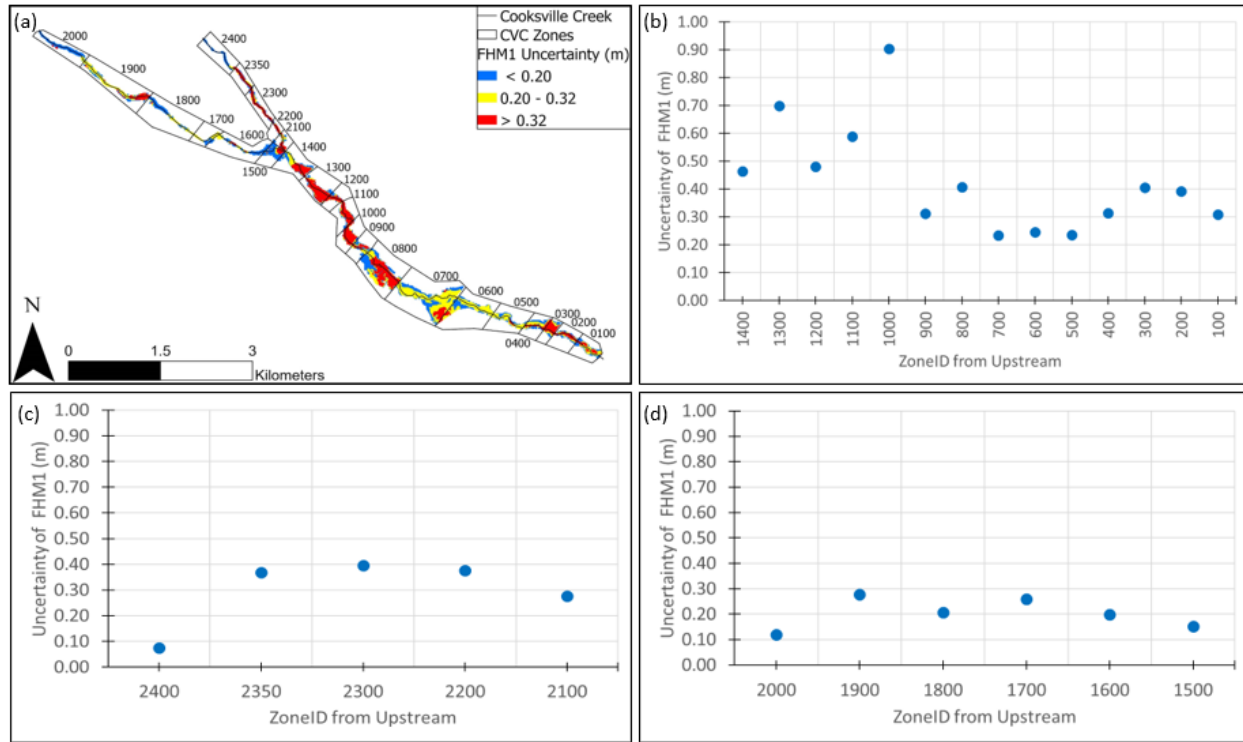


Figure 4.4: (a) Uncertainty map of FHM1 metric showing the distribution of uncertainties at each CVC zone along the creek; (b) Distribution of uncertainties at the CVC zones along the Main branch; (c) and (d) Distribution of uncertainties at the CVC zones along the East and West branch, respectively.

Main branch, several zones, particularly Zones 700, 600 and 500 showed lower magnitudes of uncertainty compared to their surrounding ones. The West Branch has higher uncertainty than the East branch, with Zones 2200-2350 all above 0.32 m, which places them in the upper third class based on percentiles. Uncertainty is relatively low at the upstream limits of both the East and West Branches (Zones 2000 and 2400). A correlation analysis found that the inundated areas with low FHM1 values also had low uncertainties and *vice versa*.

The mean of the flood elevation distribution around a building footprint was used to calculate hazards for buildings. The hazard metric, FHM1 was then calculated for the buildings

based on the difference between the flood and the first-floor elevation (Figure 4.5a).

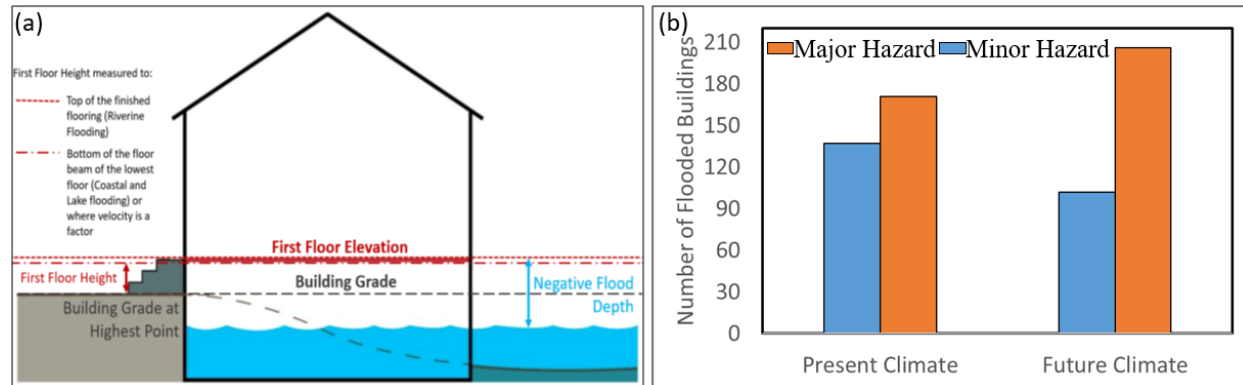


Figure 4.5: (a) Visualization of flood level demarcation, adapted from Natural Resources Canada (2021) and (b) total number of inundated buildings under each hazard category for both existing and future climate scenarios inside A1 region

If a building's flood elevation was greater than the first-floor elevation, it was classified as a 'major hazard'; otherwise it was considered a 'minor hazard'. Based on this classification system, 167 buildings were classified to fall under major hazards within A1 under the existing climate, representing 55% of the total 308 flooded buildings. This number increased by 35 in the future climate, representing 66% of the flooded buildings in A1. Most of these that are predicted to have a change in hazard classification were located along the Main branch, and majority of them will be subjected to a change in depth of greater than 0.3 m. Within A2, 93 buildings were identified as major hazards, increasing the total number of buildings with a major hazard classification from 167 to 295 due to the projected average increase in future flooding from climate change.

Beyond the average increase in future flooding, the uncertainty of the depth value means that additional buildings may be subject to flooding and others may change their hazard level, depending on the GCM model used. Table 4.2 provides a summary of the distribution of buildings affected by the uncertainty in the FHM1 metric. Buildings whose existing hazard ratings will not change are called 'Status-Unchanged', while the 'Status-Up' and 'Status-down'

columns denote buildings whose existing hazard ratings will increase and decrease, respectively. For buildings inside A1, a total of 58 buildings will have their hazard status changed. 21 of them will see their status changed to ‘major hazard’ from ‘minor hazard’ and the rest will see *vice versa*. Approximately 26 of the 157 buildings located inside A2 will see their status changed when the uncertainty surrounding future climate induced rainfall is considered. 21 of these 26 buildings will see their status changed to ‘major hazard’ from ‘minor hazard’ and the rest will see *vice versa*. Based on the analysis of the most extreme flooding case, 185 buildings that were estimated to be flooded within A3 region, only 13 of these will see their flood hazard status changed due to uncertainty.

Table 4.2: Estimation of the impact of uncertainty of FHM1 on building hazards

Location of Flooded Buildings	Status-Unchanged	Status-Up	Status-Down	Total
A1	250	21	37	308
A2	131	21	5	157
A3	172	10	3	185
Subtotal=	553	52	45	650

4.3.4 Hazard Evaluation via FHM2 Metric

Figure 4.6 shows the difference in the distribution of flood hazards at the study site for FHM2 metric under existing climate (i_{exist}) and future climate (i_{mean}) conditions. It is evident that after a distance of few kilometres along the Main branch of creek, the hazards are predominantly low outside the channel. It signifies that the (flooded) buildings situated beyond this distance (henceforth referred to as the inflection point) will sustain less damage in the future compared to those situated upstream, particularly up to the confluence between the East and West Branches.

This may be because the difference in depth and velocity between the existing and future climates was found to be low downstream of this inflection point.

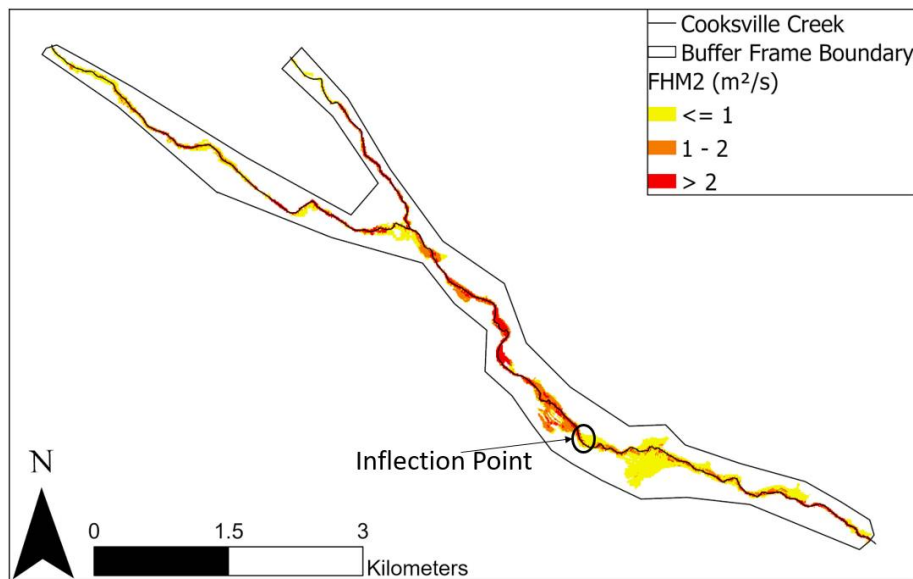


Figure 4.6: Spatial distribution of differences in FHM2 metric within the study watershed's A1 region

Since the FHM2 metric is a combination of flood depth and velocity, the way its uncertainties are spread out will show a mix of traits from these two parameters. Figure 4.7a shows the future distribution of uncertainties surrounding the FHM2 metric. The magnitude of uncertainty was found to be higher in the vicinity of the creek and decreased with lateral distance from it. This pattern is due to the higher flow velocities in or near the channel banks, which contribute to greater uncertainty close to the creek. To better understand the spatial variation of uncertainty along the creek, the zonal/segmental approach was applied. The magnitude of uncertainty of FHM2 in each zone was discretized based on percentiles, with 0.25 m^2/s and 0.70 m^2/s representing the 33rd and 67th percentiles. Figures 4.7b, 4.7c, and 4.7d show the

uncertainties of each zone along the Main, East and West branches of the creek, respectively.

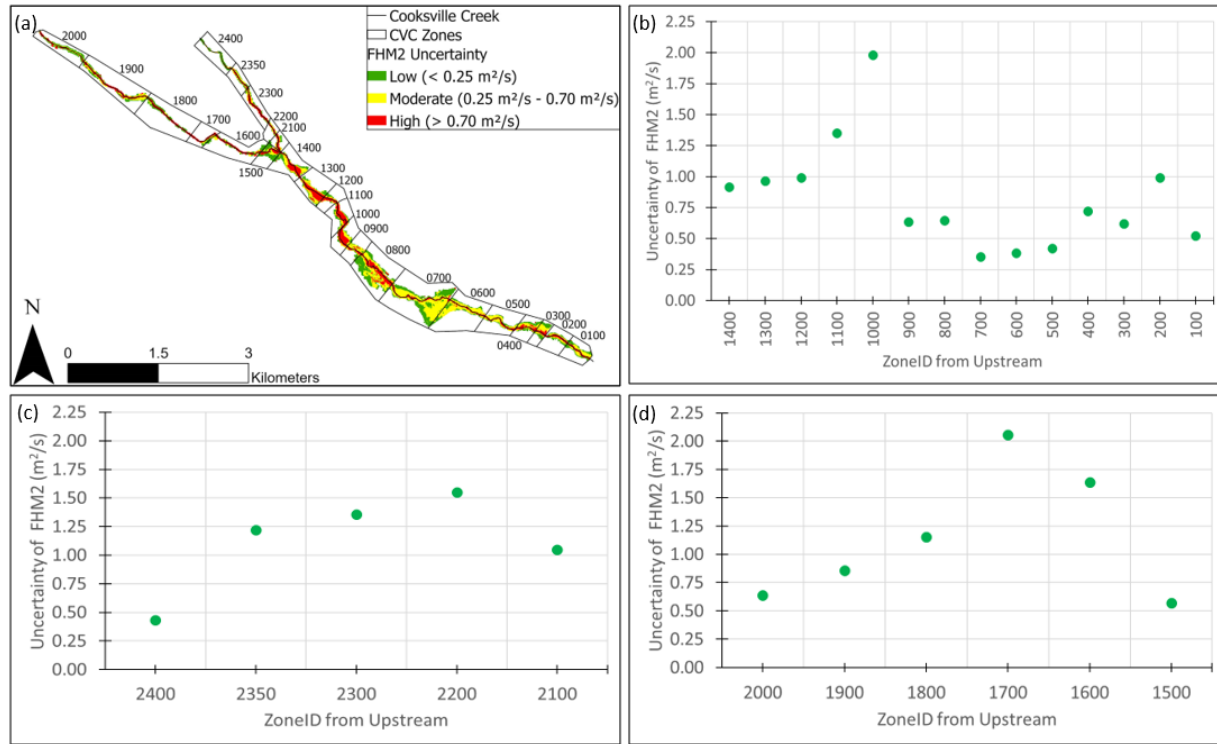


Figure 4.7: (a) Uncertainty map of FHM2 metric showing the distribution of uncertainties at each CVC zone along the creek; (b) Distribution of FHM2 uncertainties at the CVC zones along the Main branch; (c) and (d) Distribution of uncertainties at the CVC zones along the East and West branch, respectively.

The West branch of the creek was projected to be slightly more uncertain, averaging 0.03 m²/s more, than the East branch. Similar to the FHM1 metric, zones encompassing the junction, i.e., Zones 1500 and 2100, where the topography is relatively flat, showed lower magnitudes of uncertainty compared to those further upstream. Along the Main branch, zones such as Zones 700 (where the inflection point lies), 600, and 500 also exhibited lower magnitudes of uncertainty compared to their surrounding zones, consistent with the FHM1 metric. This could be attributed to various factors, including topographical differences and the capacity of the existing bridges at the zones. However, unlike FHM1, the uncertainty of FHM2 was found to be substantially lower overall in the Main branch of the creek compared to the East and West branches.

For buildings, the hazards were categorized or rated for buildings using the ‘Flood Hazard Matrix for Buildings’ guidelines from FRP report (HR Wallingford, Flood Hazard Research Centre, & Risk & Policy Analysts Ltd., 2006). As per the report, a more comprehensive examination is required to fully quantify the extent of damage to buildings based on various factors that may impact the structure during a flood such as its footprint, construction materials and number of storeys, but the matrix is intended to provide a preliminary assessment of the damage that may occur to a building situated on a floodplain under various combinations of flood depth and velocity. According to HR Wallingford et al. (2006), buildings with an FHM2 < 1 are anticipated to sustain no damage. They will be subjected to some damage if their FHM2 is between 1 and 3, and they will sustain severe damage if their FHM2 is between 3 and 5. For FHM2>5, the buildings are expected to experience irreparable damage. Table 4.3 provides the status of buildings affected by existing and future climate using FHM2 metric. The projected mean future climate is anticipated to result in the inundation of 465 building at the site, meaning a 157-building increase in comparison to the existing conditions. Within region A1, the number of inundated buildings subjected to damage will increase from 56 to 98, while in region A2, only eight (8) buildings are projected to experience at least some degree of damage.

Table 4.3: Estimation of building hazards using FHM2 metric

FHM2 Hazard Rating	Number of Flooded Buildings			
	Existing Climate inside A1	Future Climate inside A1	Future Climate inside A2	Future Climate Total
No Damage	252	210	149	359
Some Damage	52	88	8	96
Severe Damage	2	6	0	6
Irreparable Damage	2	4	0	4
Total	308	308	157	465

Future climate uncertainty means that additional areas and additional risks need to be considered for building hazard assessments. As shown in Table 4.4, a significant proportion (~37%) of the existing 465 buildings will see a modification in their hazard classification for the FHM2 metric. Furthermore, the uncertainty will affect an extra 177 buildings concerning the FHM2 metric. Out of the total 177 buildings for which the FHM2 hazard class was affected by the uncertainty from future climate projections, the majority had an increase in hazard, but many actually had their hazard status decreased. This decrease is explained by a lower velocity at higher flow depths.

Table 4.4: Estimation of the impact of uncertainty of FHM2 on building hazards

Location of Flooded Buildings	Status-Unchanged	Status-Up	Status-Down	Total Flooded Buildings
A1	166	79	63	308
A2	128	22	7	157
A3	179	4	2	185
Total=	473	105	72	650

4.3.5 Hazard Evaluation via FHM3 Metric

When comparing the distribution maps of the FHM3 metric within A1 region between existing and future climates, the resulting map appears somewhat similar to Figure 4.6. Compared to the existing climate, the majority of flooded locations within A1 were found to experience only a slight increase in flood duration in the future. When considering the uncertainty distribution for the FHM3 metric, it was determined that the DF parameter exhibited minimal uncertainty. This is due to the fact that the duration uncertainty was determined to be rather low. As a result, no map showing the distribution of differences between the existing and

future climate scenarios, and no uncertainty map, is provided for the FHM3 metric, as they would be identical to those provided for the FHM2 metric.

Table 4.5 provides the status of buildings affected by existing and future climate using FHM3 metric. The hazards for this metric were categorized or rated for buildings using the same hazard matrix as the FHM2 metric. Approximately 31% of the total 465 buildings subjected to future flooding will sustain at least some degree of damage. In comparison to the existing situation, the number of flooded buildings inside A1 that will sustain at least some damage will increase by 34. There are comparatively few buildings inside A2 that are susceptible to damage. However, none of them will sustain severe or greater damage. The influence of uncertainty on buildings was not calculated, given that the uncertainty of the metric would be minimal. As a result, it was assumed that their existing hazard ratings would remain unchanged.

Table 4.5: Estimation of building hazards using FHM3 metric

FHM3 Hazard Rating	Existing Climate inside A1	Future Climate inside A1	Future Climate inside A2	Future Climate Total
No Damage	219	185	135	320
Some Damage	80	106	22	128
Severe Damage	6	11	0	11
Irreparable Damage	3	6	0	6
Total=	308	308	157	465

4.3.6 Comparison between the Hazard Metrics

Given that three distinct hazard measures were employed to assess flood hazards at the research site, it is pertinent to conduct a comparative analysis of them to determine their relative importance. To simplify the analysis, the flooded buildings inside A1 region for future climate

were the subject of the investigation. To compare the flood hazard levels from the three matrices (FHM1, FHM2 and FHM3), a common scoring system ranging from 0 to 5 was developed. In this system, a score of 0 represents no hazard, while a score of 5 represents the most severe or irreparable damage. For FHM1, buildings are classified as a Major Hazard if the flood elevation exceeds the first-floor elevation, resulting in a score greater than 4. This score covers scenarios ranging from severe to irreparable damage. If the flood elevation is below the first-floor elevation, the building is considered a Minor Hazard, with a score of 2. This reflects a moderate hazard level where some damage might occur but is not severe. For FHM2, buildings with an FHM2 value of less than 1 are expected to sustain no damage, corresponding to a score of 0. Buildings with FHM2 values between 1 and 3 are likely to experience some damage, which aligns with a score of 2. Buildings with FHM2 values between 3 and 5 are predicted to sustain severe damage, resulting in a score of 4. Finally, buildings with FHM2 values greater than 5 are anticipated to experience irreparable damage, receiving the highest score of 5. The same scoring system applied to FHM2 is also applicable to the FHM3 metric. With this scoring system, 106 buildings were assigned a score of 2 for FHM1, while 88 and 106 buildings received the same score for FHM2 and FHM3, respectively. For buildings with a score greater than 4, FHM1 identified 202 buildings, whereas FHM2 and FHM3 identified only 10 and 17, respectively. However, when considering their respective uncertainties, it was estimated that 84 more buildings within A1 are impacted by the uncertainty of FHM2 compared to FHM1.

4.4 Discussion

The novel SWMM-RASpy framework was successfully adapted to allow users to easily incorporate the impact of climate change and its uncertainty on flood hazard. This was achieved by using the IDF_CC tool to generate a range of precipitation projections for an ensemble of climate scenarios under the current ‘worst-case’ RCP 8.5 emissions scenario. The framework’s novelty lies in its capacity to seamlessly integrate climate change projections into industry-standard hydrologic and hydraulic models (SWMM and HEC-RAS), which are widely recognized in flood hazard regulation. Unlike other tools that may only consider surface flows or employ simpler 1D hydraulic models, the SWMM-RASpy framework integrates SWMM for both surface and sub-surface flow modeling, while utilizing a 2D unsteady-state hydraulic model in HEC-RAS. This combination allows for a more accurate and spatially explicit representation of flood hazards. The 2D unsteady modeling capability of HEC-RAS is particularly valuable for capturing the complex hydraulic behavior around critical infrastructure such as bridges and culverts, enabling more detailed and realistic assessments of flood risks. Although demonstrated for a particular case study, the framework is flexible enough to be applied to other watersheds and regions, provided that appropriate models for existing conditions are available.

An application of the SWMM-RASpy tool to the Cooksville Creek urbanized watershed in Ontario illustrates that changes to rainfall intensity anticipated because of climate change will have a significant impact on inundation areas, the numbers of flooded buildings, and the hazard level for those buildings. For instance, the results indicate an approximately 50% increase in the number of buildings at risk due to increased inundation extent under future climate conditions, with most newly at-risk buildings located along the Main branch of the creek. A comparison of the distribution of hazard metrics between existing and future climates showed that increased

rainfall under future climate scenarios will elevate hazard levels, resulting in the flooded buildings becoming more vulnerable to damage. Specifically, the number of buildings subjected to major hazards according to FHM1 increased by 80% compared to existing conditions, while FHM2 and FHM3 showed an increase in buildings experiencing at least 'some damage' by 90% and 60%, respectively. These findings highlight the need for proactive flood management and planning and underscore the tool's utility in identifying and managing future flood risks.

Cooksville Creek watershed is projected to be significantly impacted by future climate conditions, although rehabilitation works along the creek's overbanks (Credit Valley Conservation, 2020; Tinkler, Parish, & Wohl, 1998) have limited the variation between current and future flood extents. Despite the rehabilitation works, the predicted increase in rainfall intensity and subsequent flood risks highlight the importance of understanding the role of topography and hydraulic structures in flood management. A comparison with Mimico Creek, a neighboring watershed which has a similar physiography and a comparable number of hydraulic structures such as bridges, reinforces this point. Both Cooksville and Mimico Creeks have undergone significant human interventions to make them flood-resistant, such as channel modifications and the construction of hydraulic structures like bridges and culverts. The predicted flood extent in Cooksville Creek is expected to expand by 0.40 km² under future climate conditions, compared to an estimated 0.44 km² increase for Mimico Creek under similar conditions (Zahmatkesh et al., 2021). This similarity in flood extent expansion may result from comparable topographical characteristics and human interventions. The presence of hydraulic structures with limited capacities, such as bridges, exacerbated flooding in specific locations. In both watersheds, a greater degree of inundation was observed downstream where hydraulic structures were more frequent.

The significance of topographical variability is further evident in the projected changes in flood depth across different branches of Cooksville Creek. The Main branch is expected to experience a larger rise in flood depth compared to the East and West branches. This difference can be attributed to its lower terrain, larger catchment area, and a greater concentration of hydraulic structures that are more susceptible to capacity limitations under increased flow conditions (Aquafor Beech Ltd., 2012). Zahmatkesh et al. (2021) reported a comparable finding in the Mimico watershed. Their analysis found that the mean water level at sample cross sections increased by 0.54–0.98 m in upstream reaches and 1.21–1.55 m in downstream reaches. The East branch of our study creek was projected to show higher depth differences than its West branch which can be due to the fact that the West branch is slightly flatter in topography than the East branch. This comparison highlights that while flood hazards are site-specific, there are common patterns and challenges, such as the critical role of bridge capacities and topography in influencing flood extent and depth, that can inform management strategies across similar urban watersheds.

The inclusion of climate uncertainty introduces significant variability in the prospective inundation area, potentially altering the number of flooded buildings and the hazard levels for those buildings. The stochastic framework within SWMM-RASpy effectively captures this uncertainty by generating a range of future flood scenarios. For example, the Flood Extent_Stochastic was observed to be 0.20 km² larger than the Flood Extent_Future, covering the largest inundation area in the watershed and affecting 40% more buildings. The hazard analysis revealed that 15% of the total inundated buildings experienced a change in their hazard rating according to FHM1, with most changes occurring along the creek's Main branch (95 out of 516 buildings) compared to the East and West branches (only 2 out of 134 buildings). Similarly, the

hazard rating for FHM2 changed for 27% of the total inundated buildings, highlighting a significant change in risk levels due to uncertainty. Most of the affected buildings for both metrics were concentrated in A1 region, the nearest inundated areas to the creek, where uncertainty in flood hazards is most pronounced. The zonal analysis further highlighted critical areas of concern. Zones with low uncertainty (Zones 500-700) did not show changes in hazard levels for either FHM1 or FHM2 metrics, suggesting that these areas are less sensitive to variations in rainfall projections. In contrast, zones 1000-1400 along the Main branch are expected to experience high uncertainty, indicating a higher likelihood of changes in flood hazard levels for buildings in these zones. Overall, the findings highlight the critical importance of accounting for climate uncertainty in flood hazard assessments, as it can significantly alter hazard levels and the extent of inundation. The results also underscore the value of localized assessments, given that the impact of uncertainty varies across the watershed, particularly in areas with high-risk factors such as proximity to watercourses. Understanding these spatial variations in uncertainty is essential for developing effective flood risk management strategies that are responsive to the specific conditions and risks present in each area.

Given that the impact of flooding on building hazards can be a function of depth, velocity, and duration, it is necessary to represent this hazard in a simple yet accurate way for decision-makers. The flood hazard metrics utilized in this study—FHM1 (flow depth), FHM2 (flow depth and velocity), and FHM3 (flow depth, velocity, and duration)—provide different perspectives on estimating potential flood hazards. The results of the comparison among these metrics indicate that the estimated number of buildings at risk was greater for FHM1 compared to FHM2 and FHM3. Although no direct correlation analysis was conducted between the metrics and hazard ratings, this finding is consistent with some of the results from Kreibich et al. (2009),

who found that flood depth (particularly when exceeding 2 m) had a more significant impact on the damage to residential buildings than intensity (a combination of velocity and depth, similar to the FHM2 metric). When considering the effect of flood duration, the number of buildings projected to be damaged by FHM3 was notably higher than for FHM2. This aligns with the idea that duration is a critical factor in estimating building hazards, particularly for more extensive flood events, as suggested by Wagenaar (2012). Given the brief duration of the flood in our analysis, the influence of duration may become even more pronounced for longer-duration floods.

The analysis also showed that more buildings were projected to sustain damage due to the greater uncertainty associated with FHM2 compared to FHM1. This can be attributed to the higher degree of uncertainty in velocity relative to depth. The coefficient of variation (C_v), a unitless statistical measure used to compare uncertainty magnitudes, was highest for velocity at 1.31, compared to 0.82 for depth. This suggests that future uncertainties arising from climate-induced rainfall will be amplified more in velocity than in depth. While this finding contrasts with Ahmadisharaf et al. (2018), who found that depth uncertainty had the greatest influence on flood hazard (followed by velocity and duration uncertainty), it is consistent with the study by Kreibich et al. (2009). The difference from Ahmadisharaf et al. (2018) may be partly explained by other factors, such as differences in grid resolution (10m vs. 30m) and the duration of the flood event (6h vs. 120h), as well as the fact that our study site is heavily urbanized compared to their rural watershed. Kreibich et al. (2009), who studied a more urbanized area, also found that areas with high flood velocity, such as roadways with high imperviousness, exhibited a higher C_v for velocity than for depth, leading to greater uncertainty in intensity. Overall, the results indicate that while each metric has its own criteria for hazard categorization, together they offer a

more comprehensive understanding of the risks. This multi-metric approach enhances the communication of flood risks to stakeholders by illustrating the varying degrees of hazard across different scenarios and uncertainties.

The findings for the hazard metrics discussed in this section are based on a 100-year 3-hour Chicago Storm design event with a 5-minute rainfall interval. It is anticipated that alternative design storm techniques, sampling strategies, and data sources will provide different rainfall hyetographs, which may lead to differing conclusions regarding the site's hazard metrics (Ahmadisharaf et al., 2018). The framework used for this analysis was built on the integration of SWMM and HEC-RAS models, both of which have underlying assumptions and limitations that affect the results. In this analysis, 2D unsteady hydraulic modelling inside HEC-RAS was used, but the outcomes could be different if a different kind of model (e.g. a 1D steady model) had been used. A different urban watershed could also have generated different results, indicating that the findings should be used with caution in other settings.

4.5 Conclusions

This study has provided a comprehensive assessment of the impacts of climate change and its uncertainties on flood hazards within the Cooksville Creek watershed. Using the SWMM-RASpy framework, we were able to model the influence of future climate projections on flood hazard metrics, emphasizing the need for more sophisticated approaches to account for climate uncertainties in urban flood management. Although additional research and case study applications are required to establish more concrete conclusions about the hazard metrics and their uncertainties given the climate change, focusing on a particular case study enabled us to draw the following conclusions:

1. The SWMM-RASpy framework is useful for characterizing the uncertainty of urban floods as a function of rainfall intensity. This tool is novel because it allows Chicago storm distributions to be generated and run through SWMM and routed through HECRAS models following the recommended H&H modelling procedure supported by Canadian flood management protocols.

2. Climate change is expected to significantly increase flood hazards in the study area. Our analysis projects a substantial rise in both the magnitude and extent of flooding due to higher rainfall intensities in future climate scenarios. The inundation area is predicted to expand, affecting an additional 157 buildings under deterministic conditions and an extra 185 buildings when considering uncertainty. The increased rainfall will also significantly elevate the hazard levels for the flooded buildings.

3. This study demonstrates that incorporating climate uncertainty into flood hazard assessments is crucial, as it significantly affects both inundation extents and hazard levels for inundated buildings. The findings also reveal that the impact of uncertainty varies across

different zones of the watershed, with some areas showing high sensitivity to changes in rainfall projections, while others are less affected. Effective flood risk management strategies must consider these spatial variations when conducting localized assessments.

4. The comparative analysis of the flood hazard metrics demonstrates that the estimated impact on buildings varies significantly depending on the metric used and whether uncertainties are considered. FHM1 predicts the highest number of buildings at risk when uncertainties are not accounted for, suggesting it may be a sufficient metric for assessing building hazards in the study area under similar climate scenarios. However, once uncertainties are included, FHM2 shows a greater increase in the number of buildings at risk due to the higher uncertainty associated with velocity compared to depth and duration. These findings highlight the importance of using multiple metrics to capture different aspects of flood risk and the need to account for their associated uncertainties to ensure comprehensive and effective flood risk management.

This study highlights the need to update flood mapping practices, refine hydrologic and hydraulic methodologies, and adapt policies for defining flood hazards in an effective manner and for incorporating uncertainty to better reflect the evolving flood risks considering climate change. Thus, the Ontario government's ongoing review of natural hazard technical guides (Government of Ontario, 2024) is critical in the context of climate change because it addresses the increasing flood hazards anticipated due to climate variability. This includes evaluating flood standards for their sensitivity to climate change, assessing the hydrologic and hydraulic methodologies in existing technical guides, and re-examining policies and approaches for designating and defining floodplains. The government is also focusing on the use of floodway and flood fringe concepts, particularly in the context of future development. These initiatives are

critical for aligning flood management practices with evolving climate challenges and ensuring resilient urban planning.

The findings of this study have important implications for flood management practices. The increased flood hazards projected for the Cooksville Creek watershed call for urgent action to enhance flood resilience. Moreover, the significant uncertainties associated with future flood hazards necessitate the adoption of adaptive management approaches. Utilizing an ensemble of climate models, as demonstrated in this study, can provide a more comprehensive understanding of potential future scenarios, and help in developing flexible and adaptive flood management strategies.

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CHAPTER 5: SUMMARY AND CONCLUSIONS

This research focuses on developing and implementing a novel stochastic framework, SWMM-RASpy which is capable of assessing hydrologic and hydraulic modeling uncertainties inherent to flood hazard mapping in urban areas. The framework integrates the Storm Water Management Model (SWMM) for watershed hydrology and the Hydrologic Engineering Centre's River Analysis System (HEC-RAS) for channel hydraulics, utilizing Latin Hypercube Sampling (LHS) for stochastic simulations. The study was applied to the Cooksville Creek watershed in Mississauga, Ontario, a highly urbanized area prone to flooding. It provides a comprehensive review of existing methodologies for flood hazard mapping, highlighting their limitations and recent advancements. Traditional one-dimensional (1D) hydraulic models often fail to account for complex urban flood dynamics and associated uncertainties, emphasizing the need for advanced multi-variable hazard models. These models should provide detailed information on water velocity, flood timing, and duration of inundation. The SWMM-RASpy framework addresses these gaps by integrating industry standard hydrologic and two-dimensional (2D) hydraulic modeling with stochastic methods to provide a comprehensive analysis of flood hazards. The development of this framework is the key contribution of Chapter 2. The automatic integration of SWMM and HEC-RAS model inside the framework represents a significant and novel advancement in flood hazard mapping, allowing for more detailed assessments of flood risks in urban areas with a reduced computational burden.

The key contribution of Chapter 3 was the demonstration of the utility of the SWMM-RASpy framework for flood hazard assessments, particularly focusing on hydraulic uncertainty in relation to pedestrian hazards. While current hazard models often consider the impact of floods on residential buildings, there is a growing need to assess hazards for other assets and

pedestrians. Pedestrians themselves often underestimate flood risks, especially in urban areas where shallow water depths and high flow velocities can create dangerous conditions during extreme events in areas where hazards are not typically encountered. Given the uncertain pathways of flow on the floodplain in extreme events, it is crucial to estimate areas of potential hazard using methods that incorporate that uncertainty. Our study defined flood hazard metrics based on inundation depth (FHM1), a combination of depth and velocity (FHM2), and a combination of depth, velocity, and duration (FHM3) following methods recommended in the literature and quantified the uncertainty of each that can be attributed to surface roughness, which is the key hydraulic variable. The spatially distributed results were used to provide both grid-level and zonal-level spatial analysis to assess flood hazards. Grid-level analysis captures local topographic variations, while zonal-level analysis provides a broader perspective on flood hazards across larger watershed areas. This combined approach can allow both specific information on hazard limits and allow a broader priority mapping to enhance the reliability and comprehensiveness of flood hazard protection and disaster resource allocations. The study also discusses the effective communication of flood hazards through color-coded maps, which are crucial for stakeholders' understanding and decision-making. It used a gradient color scheme from green (low hazard) to red (extreme hazard) to visualize pedestrian hazards and their uncertainties. Key findings from Chapter 3 include:

1. Surface roughness significantly impacts flood hazard variation in the floodplain areas of the Cooksville Creek watershed. Uncertainty is high enough to change hazard levels, indicating that mapping without uncertainty analysis may underestimate the risk to people and infrastructure in flooded areas.

2. The inclusion of velocity in hazard models, particularly the FHM2 metric, will improve the accuracy of pedestrian flood hazard assessments because it more accurately represents the conditions under which a pedestrian may lose their footing in flooded areas. However, it also introduced higher variability, underscoring the trade-off between comprehensiveness and uncertainty. The study found that velocity had the greatest impact on flood hazard metrics compared to depth and duration, making it crucial for effective flood management in urban areas like Cooksville Creek watershed.
3. Duration played a significant role in altering hazard levels when included in the FHM3 metric. Although it was the least affected by surface roughness variations, its inclusion reduced the number of low-level hazards and increased higher-level hazards. This finding highlights the importance of considering duration in flood hazard assessments, especially in urban watersheds with significant impervious surfaces and flat topography.
4. The research employed both grid-level and zonal-level spatial analysis to capture the impact of local topographic variations on hazard assessments. This dual approach provided a more reliable and comprehensive view for large-scale flood management, identifying zones more susceptible to uncertainties.

Chapter 4 of the thesis focuses on the application of the SWMM-RASpy framework to assess the impacts of climate change on flood hazards, taking into account uncertainties in rainfall intensity projections. The ability to account for climate change within the SWMM-RASpy framework and to develop uncertainty bands from an ensemble of Global Climate Models (GCMs) following different Representative Concentration Pathways (RCPs) is the key contribution from Chapter 4. Given recent flooding such as the July 16, 2024 event in Cooksville Creek, which has been described as another ‘100 year’ event and the third that has occurred since

2009 (Lim, 2024), this research and the development of a tool to better understand the risks is timely work. Key findings from the chapter include:

1. The inundation area is predicted to significantly expand in an average future scenario, affecting approximately 50% more buildings under deterministic conditions and 40% more when the uncertainty of climate projections is considered.
2. There was significant variation in the hazard metrics, with FHM1 and FHM3 predicting higher hazards for buildings in comparison with FHM2. Real data from flood scenarios would help to assess which of the metrics are most applicable under different conditions.
3. It is important to include uncertainty when assessing risk. When uncertainties are included, FHM2 shows a greater increase in the number of buildings at risk compared to FHM1 and FHM3.

The results show that the use of average future scenarios may be deceiving. This conclusion is particularly relevant to the Risk and Return on Investment Tool being applied to support decision making with respect to stormwater management and flood preparedness. The use of a deterministic flood model in tools such as this represents a significant problem that may lead to misallocation of municipal resources and put residents and infrastructure at risk.

This research highlighted the limitations of traditional one-dimensional models in capturing the complexities of urban flooding and emphasized the need for advanced, multi-variable hazard models. The research has advanced the field of urban flood hazard assessment by developing and demonstrating the utility of the SWMM-RASpy framework. The framework effectively integrates hydrologic and hydraulic models to provide a detailed and stochastic analysis of flood hazards. This integration allows for the propagation of uncertainties from both

random hydrologic and hydraulic input variables, such as surface roughness and rainfall intensity, to output flood hazard metrics, enhancing the reliability of flood risk assessments. Consequently, the research demonstrated the utility of the SWMM-RASpy framework in providing comprehensive flood hazard assessments in the presence of hydrologic and hydraulic model uncertainty. The findings from the application of the framework to the Cooksville Creek watershed, demonstrated significant impacts of hydrologic and hydraulic uncertainties on flood hazard metrics underscoring the need for adaptive planning and robust flood risk management strategies that incorporate these uncertainties. The research also showed that considering multiple variables, such as depth, velocity, and duration, in flood hazard assessments provides a more comprehensive understanding of flood risks. Overall, this study has advanced the field of urban flood hazard assessment by providing a robust method to incorporate and analyze uncertainties, ultimately supporting better flood management and resilience planning. Future research should apply the SWMM-RASpy framework to other watersheds, integrate it within financial risk assessment tools, explore additional hydrologic and hydraulic variables to further enhance flood risk assessments, and collect spatially-distributed information about inundation and flood damages to better parameterize and validate the framework and underlying models.

Beyond the immediate findings, a deeper consideration of the modeling techniques and parameters is essential for refining and expanding the capabilities of the SWMM-RASpy framework. Addressing key aspects such as data quality, calibration, and parameter uncertainties will ensure the framework remains flexible and applicable across various watersheds and flood scenarios. Several important factors, such as topographic accuracy, calibration data, and model adjustments, warrant further exploration to enhance the precision and utility of the framework.

For example, in developing the HEC-RAS model for the framework, the use of a 30m resolution DEM for the overland areas beyond the floodplain was a necessary choice due to the unavailability of higher-resolution data at the time. The 1m resolution DEM of the creek and floodplain was created by interpolating surveyed bathymetric data, ensuring detailed representation in these critical areas. To maintain consistency, the 30m DEM was refined to 1m resolution using interpolation techniques within ArcGIS. While this approach improved spatial resolution, it is acknowledged that using a 30m DEM, even with refinement, introduces limitations, as some fine-scale terrain details may not be fully captured. Research such as that conducted by Abedin and Stephen (2019) indicates that while higher-resolution data often enhances model precision, it does not always result in significant changes in flood modeling outcomes depending on factors such as terrain complexity and model calibration. Nevertheless, the developed framework can use higher-resolution datasets, should they become available, to further improve model accuracy. It is recommended that future models begin with high-resolution data, such as LIDAR, across both the floodplain and overland areas to minimize interpolation needs and ensure a more detailed representation of terrain. Nevertheless, even high resolution DEMs may lack bathymetric data. The best available channel bathymetric surveys remain the relatively sparse HEC-RAS data.

Calibrating and validating the HEC-RAS 2D model using recent flood events would have been ideal to enhance the accuracy of the model. However, inundation extent data from real flood events was not available at the time of analysis. As a result, the study relied on the inundation extents from a previously calibrated 1D HEC-RAS model provided by the Credit Valley Conservation (CVC) authority. This 1D model served as a reference point to adjust the computational parameters of the 2D model, ensuring computational efficiency for the subsequent

stochastic analysis. While this approach was necessary due to data limitations, it is acknowledged that using the 1D model's inundation extents for such adjustments may affect the accuracy of the 2D model, particularly in capturing more complex flood dynamics. Future studies should prioritize adjusting the 2D model using actual inundation data from recent flood events, as such data becomes available. This could further improve the model's accuracy and enhance its predictive capabilities in urban flood hazard assessments in the study site.

While the focus of this research was primarily on uncertainty stemming from surface roughness and rainfall projections from climate models, there are other significant sources of uncertainty. Topographic uncertainty, for instance, can arise from inaccuracies in the digital elevation models (DEMs) used to represent terrain features. The precision of the DEM, particularly in urban settings, is critical, as inaccuracies may lead to errors in flood hazard predictions. Additionally, developmental uncertainty, which relates to the unpredictability of future land-use changes, could also impact flood hazard predictions. Future work could explore this effect by adjusting the percentage of impervious surfaces in the SWMM model to simulate potential urban developments. Hydrological uncertainties, such as those related to initial conditions of soil, further add complexity to flood predictions, as they influence the runoff response to rainfall events. In a similar manner, the significance of such parameters could be tested with some slight modifications to the framework developed in this thesis.

Another key source of uncertainty lies in the modeling of hydraulic structures, particularly bridges. Bridges can significantly alter flow patterns during flood events, and the accuracy of the HEC-RAS model is highly dependent on the proper calibration of bridge coefficients, such as entry and exit loss coefficients. These parameters, if not adequately represented, could result in considerable discrepancies in the model's flood predictions.

Furthermore, there is uncertainty surrounding the data used for model calibration. This study utilized a 2D model that was computationally adjusted based on the results from an existing 1D model due to the lack of available inundation data from recent flood events. This approach adds further uncertainty to the results, underscoring the importance of including these uncertainties in future analyses. In terms of sampling methods, while Latin Hypercube Sampling was employed to efficiently sample the uncertain parameters in this study, alternative sampling techniques, could be explored in future research to further assess their impact on uncertainty propagation. Future research can aim to incorporate these additional uncertainties into a comprehensive stochastic framework to enhance the robustness of flood hazard assessments.

As a final statement, it is hoped that the SWMM-RASpy framework will be used for future modelling studies of urban flooding where the uncertainty may lead to the refinement of a wholesale revision of management strategies. To ensure that the method to use the framework is clear, a short summary is provided here. To begin, a user must first ensure that the necessary installation requirements are met. The framework relies on several key tools, including SWMM (version 5.0 or greater), HEC-RAS (version 5.0 or greater), and HEC-DSSVue (version 3.0 or greater), along with Python (version 3.6 or greater). Additionally, Python packages such as PySWMM and swmmtoolbox are required for the framework's operation. Once the environment is set up, the user can proceed by adjusting the input parameters in the **inputs_frameworkpy** script, which initializes the inputs for the stochastic simulations. If a user wishes to investigate other sources of model parameter uncertainties beyond surface roughness and rainfall, they can modify the framework's core scripts accordingly, provided they have a working knowledge of the SWMM and HEC-RAS models as well as Python programming. This flexibility allows users to tailor the framework to their specific needs.

References

- Abedin, S. J. H., & Stephen, H. (2019). GIS framework for spatiotemporal mapping of urban flooding. *Geosciences*, 9(2), 77.
- Lim, R. (2024). 'Instant action plan': More than 100 evacuated from nursing home amid flood. Retrieved from https://www.thestar.com/news/ontario/instant-action-plan-more-than-100-evacuated-from-nursing-home-amid-flood/article_0b073b4f-5ecf-5e7b-a9bf-9ca0a74c6b8b.html

APPENDICES

APPENDIX A

```

1  # This is masterpy script #
2
3  import subprocess
4  import shutil
5  import os
6
7  #Define Python path and its version #
8  python = r'C:\Users\sjabedi\AppData\Local\Programs\Python\Python38\python.exe'
9
10 # Get current working directory of the Framework's python programs #
11 current_directory = os.getcwd()
12
13 # Define paths to the python programs #
14 inputs_framework_path = os.path.join(current_directory, 'inputs_framework.py')
15 autosamppy_path = os.path.join(current_directory, 'AutoSAMppy.py')
16 autoswmpy_path = os.path.join(current_directory, 'AutoSWMPy.py')
17 autoraspy_path = os.path.join(current_directory, 'AutoRASpy.py')
18 rasexecutefile_path = os.path.join(current_directory, 'rasexecutepy.py') #called
    inside AutoRASpy#
19 autorashdfpy_path=os.path.join(current_directory, 'AutoRAS-HDFpy.py')
20
21 # Define the HEC-DSSVue program path and the target directory for AutoRASpy #
22 hecdss_program = r'C:\Program Files\HEC\HEC-DSSVue\HEC-DSSVue'
23 target_dir = r'C:\Users\sjabedi\AppData\Roaming\HEC\HEC-DSSVue\scripts'
24
25 # Function to run python scripts #
26 def run_python_script(script_path):
27     subprocess.run([python, script_path], check=True)
28
29
30 # Function to move and run AutoRASpy within HEC-DSSVue #
31 def run_in_hecdss(script_path, inputs_framework_path, target_dir, hecdss_program):
32     original_file = os.path.join(current_directory, os.path.basename(script_path))
33     inputs_framework_current_directory = os.path.join(current_directory,
34     os.path.basename(inputs_framework_path))
35
36     shutil.copy(inputs_framework_current_directory,
37     os.path.join(target_dir,os.path.basename(inputs_framework_path)))
38     shutil.move(original_file, target_dir)
39
40     os.chdir(target_dir)
41
42     subprocess.run([hecdss_program,
43     os.path.join(target_dir,os.path.basename(script_path))], shell=True) #AutoRASpy
    script is run#
44
45     shutil.move(os.path.join(target_dir,os.path.basename(script_path)),
46     current_directory)
47     os.remove(os.path.join(target_dir,os.path.basename(inputs_framework_path)))
48
49     os.chdir(current_directory)
50
51 # Call the functions to run python scripts in order #
52 if __name__ == "__main__":
53     run_python_script(inputs_framework_path)
54     run_python_script(autosamppy_path)
55     run_python_script(autoswmpy_path)
56     run_in_hecdss(autoraspy_path, inputs_framework_path, target_dir, hecdss_program)
57     run_python_script(autorashdfpy_path)
58
59 # Process to move all the data files except python scripts from the current directory
    to the directory where the files will be eventually stored #
60
61 current_directory = os.getcwd()
62 datatransfer_dir = os.path.join(current_directory, 'Data')
63
64 if not os.path.exists(datatransfer_dir):

```

```
61     os.makedirs(datatransfer_dir)
62
63     for filename in os.listdir(current_directory):
64         file_path = os.path.join(current_directory, filename)
65
66         if os.path.isfile(file_path) and not filename.endswith('.py'):
67             shutil.move(file_path, os.path.join(datatransfer_dir, filename))
68
69     print('\n\nFramework is successfully run')
```

```

1  # This is inputs_frameworkpy script #
2
3  framework_directory =
4  r'C:\Users\sjhabedi\sjhabedi_old\Research_Document\pycode\Framework_pycodes\Framework_pyc
5  odes_v03' # reinitiating the parent directory for the framework where all the scripts
6  are located #
7
8  # directory of parent SWMM model #
9  directory_model=r'C:\Users\sjhabedi\sjhabedi_old\Research_Document\PCSWMM_Models\SimpleTe
10 stModel'
11
12 # call the input format file of the SWMM model #
13 org_swmmfilename='SWMMmodel.inp'
14 org_swmmfile=directory_model+'\\'+org_swmmfilename
15
16 dummySWMM_model=r'C:\Users\sjhabedi\sjhabedi_old\Research_Document\PCSWMM_Models\SimpleTe
17 stModel\DummyModels'
18
19 # directory of files containing flow/stage information extracted from the output files
20 of SWMM models #
21 directory_SWMMoutfiles=framework_directory
22
23 # raingage information of SWMM model #
24 raingagename='Waterloo_CHICAGO'
25 rainformat='VOLUME'
26 raininterval='0:05'
27 snowfactor='1.0'
28 raindatasourcetype='FILE'
29 rainunit='MM'
30 rain_gage_params = {
31     'raingagename': raingagename,
32     'rainformat': rainformat,
33     'raininterval': raininterval,
34     'snowfactor': snowfactor,
35     'raindatasourcetype': raindatasourcetype,
36     'rainunit': rainunit
37 }
38
39 nodes=["US_BC2", "US_BC1", "DS_BC"] #SWMM model nodes #
40 nodes_ras=['USleft','USright','DS'] #HEC-RAS model nodes #
41
42 #Parent HEC-RAS model's project file specification #
43 rasprojectfilename='RASmodel.prj'
44 rasprojectfilepath=r'C:\Users\sjhabedi\Framework\RASmodel'
45 rasprojectfile=rasprojectfilepath+'\\'+rasprojectfilename
46
47 # geometry file of the parent HEC-RAS model #
48 org_rasgeomfile=rasprojectfilepath+'\\'+RASmodel.g01.hdf'
49 name_flowarea='FlowArea'
50
51 # output file of the parent HEC-RAS model #
52 org_rasoutfile=rasprojectfilepath+'\\'+RASmodel.p01.hdf'
53
54 lcndata = "lcndataset.csv" #initiate an empty landcover dataset to be filled with
55 sampled n values from the sampling process #
56 land_cover_ranges = {'Developed': (0.048, 0.24), 'Wetland': (0.036, 0.18),
57     'ChannelBanks': (0.02, 0.096), 'Channel': (0.012, 0.054)} #
58     manning's n range for landcovers#
59
60 # specify the number of desired simulation runs for hydrologic and hydraulic models#
61 runs_hydrologic=1 # the number of simulation runs for hydrologic model, i.e the number
62 of rainfall intensity samples #
63 runs_hydraulic=3 # the number of Manning's n sample sets for the land covers #
64
65 # inpus for rainfall generator class #
66

```

```

59 intensitydata="intensitydataset.csv"
60 low_rainfallintensity=100
61 high_rainfallintensity=120
62 intensity_range=(low_rainfallintensity,high_rainfallintensity)
63
64 directory_rainfiles=framework_directory
65 rainfall_duration=3
66 B=0.334
67 C=0.837
68 R=0.35
69 rainfall_interval=5
70 year_rainfall=2020
71 month_rainfall=6
72 day_rainfall=1
73
74 org_rasHECDSS=rasprojectfilepath+'\\'+ 'RASmodel.dss' #HECDSS file of the parent HEC-RAS
model#
75
76 # HEC-RAS model computation parameters #
77 comp_startdate='31May2020'
78 comp_starttime='24:00'
79 comp_timeline='31May2020-01Jun2020'
80 comp_interval='5minute'
81 comp_identifier='v01'
82
83 directory_infiles = framework_directory #directory where the HEC-RAS HDF output files
are saved before they are moved to the datatransfer_dir#
84 name_outvar = ['Water Surface','Cell Invert Depth'] # variable for whihc data will be
extracted from HEC-RAS HDF output files #

```

```

1  # This is AutoSAMPpy script #
2
3  from __future__ import division
4  import numpy as np
5  import pandas as pd
6  import random
7  import os
8  import csv
9  from inputs_framework import *
10
11  # latin_hypercube_sampling is a function created to perform Latin hypercube Sampling of
    input parameters #
12
13  def latin_hypercube_sampling(n, min_range, max_range):
14
15      low = np.arange(0, n) / n
16      high = np.arange(1, n + 1) / n
17      points = np.random.uniform(low, high, n)
18      pointval = list((points * (max_range - min_range)) + min_range)
19      return pointval
20
21  # generate_raindataset is a function created to generate datasets containing samples of
    rainfall intenisty #
22
23  def generate_raindataset(runs):
24
25      intensity_samples = latin_hypercube_sampling(runs, low_rainfallintensity,
        high_rainfallintensity)
26      df = pd.DataFrame(intensity_samples, columns=['Intensity'])
27      df.to_csv(intensitydata, index=False)
28
29  generate_raindataset(runs_hydrologic)
30
31  # generate_lcndataset is a function created to generate landcover datasets #
32
33  def generate_lcndataset(runs, lcndata, land_cover_ranges):
34
35      land_cover_data = {}
36
37      #Generate samples for each land cover type#
38      for land_cover, range_values in land_cover_ranges.items():
39          samples = np.around(latin_hypercube_sampling(runs, *range_values), decimals=3)
40          land_cover_data[land_cover] = samples.tolist()
41      # shuffling and prepare dataset #
42      for samples in land_cover_data.values():
43          random.shuffle(samples)
44
45      lc_manningsn_records = list(zip(*land_cover_data.values()))
46      lcndarray = np.array(lc_manningsn_records)
47      lcndataset = pd.DataFrame(lcndarray, columns=land_cover_data.keys())
48      lcndataset_unq = lcndataset.drop_duplicates()
49      lcndataset_unq.to_csv(lcndata, index=False)
50
51  generate_lcndataset(runs_hydraulic, lcndata, land_cover_ranges) #generate landcover
    dataset#

```

```

1  # This is AutoSWMMpy script #
2
3  import pandas as pd
4  import numpy as np
5  import subprocess as sp, os, shutil
6  import pyswmm
7  from pyswmm import Simulation
8  import swmmtoolbox
9  import csv
10 from inputs_framework import *
11
12 # RainfallSimulator is a class created to generate Chicago Storms #
13
14 class RainfallSimulator:
15     def __init__(self, directory, ttot, b, c, r, precip_interval, year, month, day):
16         self.directory = directory
17         self.ttot = ttot
18         self.b = b
19         self.c = c
20         self.r = r
21         self.precip_interval = precip_interval
22         self.year = year
23         self.month = month
24         self.day = day
25
26     def load_intensity_data(self):
27         # Load intensity data from CSV file
28         intensities = []
29         with open(intensitydata, "r") as f:
30             reader = csv.DictReader(f)
31             for row in reader:
32                 intensities.append(float(row['Intensity']))
33         return intensities
34
35     def generate_rainfall_events(self):
36         # Load intensity data
37         intensities = self.load_intensity_data()
38
39         # Simulate rainfall events and save data to files
40         time_int_hrs = round(self.precip_interval / 60, 3)
41         A = [x * ((time_int_hrs + self.b) ** self.c) for x in intensities]
42
43         for i, a in enumerate(A):
44             iprcp, hours, minutes = self.calculate_rainfall(a, intensities[i])
45             self.save_rainfall_data(i, iprcp, hours, minutes, a)
46
47
48     def calculate_rainfall(self, a, max_intensity):
49         #Calculate incremental rainfall#
50         tp = self.r * self.ttot
51         t = 0
52         tprcp = []
53         while t <= self.ttot:
54             t += round(self.precip_interval / 60, 3)
55             if t < tp:
56                 prcp = round(max_intensity - ((a * (tp - t)) / (((tp - t) / self.r) +
57                     self.b) ** self.c), 3)
58             else:
59                 prcp = round(max_intensity + ((a * (t - tp)) / (((t - tp) / (1 -
60                     self.r)) + self.b) ** self.c), 3)
61             tprcp.append(prcp)
62
63         iprcp = [tprcp[j + 1] - tprcp[j] for j in range(len(tprcp) - 1)]
64         hours, minutes = self.calculate_time_sequence(len(iprcp))
65         return iprcp, hours, minutes
66
67     def calculate_time_sequence(self, length):

```

```

66         #Calculate the time sequence for rainfall data#
67         hours = [0]
68         minutes = [self.precip_interval]
69         for _ in range(1, length):
70             next_minutes = minutes[-1] + self.precip_interval
71             if next_minutes >= 60:
72                 hours.append(hours[-1] + 1)
73                 minutes.append(next_minutes - 60)
74             else:
75                 hours.append(hours[-1])
76                 minutes.append(next_minutes)
77         return hours, minutes
78
79     def save_rainfall_data(self, index, iprcp, hours, minutes, a):
80         #Save rainfall data to a file#
81         stid = f'chicago_{self.ttot}hr{index + 1}'
82         sid = [stid for _ in range(len(iprcp))]
83         yy = [self.year for _ in range(len(iprcp))]
84         mm = [self.month for _ in range(len(iprcp))]
85         dd = [self.day for _ in range(len(iprcp))]
86         comp_array = np.column_stack([sid, yy, mm, dd, hours, minutes, iprcp])
87         #out_array = np.insert(comp_array, 0, ('', '', '', '', '', '', ''), axis=0)
88         out_array=comp_array
89         filename = f'chicago{self.ttot}hr_a{round(a,2)}.dat'
90         with open(os.path.join(self.directory, filename), 'w') as f:
91             for item in out_array:
92                 f.write(' '.join(map(str, item)) + '\n')
93
94 if __name__ == "__main__":
95     simulator = RainfallSimulator(
96         directory=directory_rainfiles,
97         ttot=rainfall_duration,
98         b=B,
99         c=C,
100        r=R,
101        precip_interval=rainfall_interval,
102        year=year_rainfall,
103        month=month_rainfall,
104        day=day_rainfall
105    )
106    simulator.generate_rainfall_events()
107
108
109 def update_swmm_input_file(dummy_swmmfile, directory_rainfiles, file_name,
rain_gage_params, var='[RAINGAGES]'):
110     #Updates the SWMM input file with new rainfall data#
111     rainfile = os.path.join(directory_rainfiles, file_name)
112     is_raingages_section = False
113     raingage_index = None
114     with open(dummy_swmmfile, "r") as file:
115         elements = file.readlines()
116
117     for n, element in enumerate(elements):
118         if element.strip() == var:
119             is_raingages_section = True
120             continue
121         if element.strip().startswith '[' and element.strip() != var:
122             is_raingages_section = False
123         if is_raingages_section and rain_gage_params['raingagename'] in element:
124             raingage_index = n
125             print(raingage_index)
126             break
127     if raingage_index is None:
128         print(f"Raingage {rain_gage_params['raingagename']} not found in the
[RAINGAGES] section.")
129     else:
130         elm_index = elements[raingage_index].split()

```

```

131     elm_index = list(filter(None, elm_index))
132     elm_index[0] = rain_gage_params['raingagename']
133     elm_index[1] = rain_gage_params['rainformat']
134     elm_index[2] = rain_gage_params['raininterval']
135     elm_index[3] = rain_gage_params['snowfactor']
136     elm_index[4] = rain_gage_params['raindatasourcetype']
137     with open(rainfile, "r") as rfile:
138         next(rfile)
139         rainfile_line = rfile.readline().split()
140         stationid = rainfile_line[0]
141     elm_index[5] = os.path.join(directory_rainfiles, file_name) + ' ' + stationid +
142     ' ' + rain_gage_params['rainunit']
143     elements[raingage_index] = ' '.join(elm_index[:6]) + '\n'
144     with open(dummy_swmmfile, "w") as file:
145         file.writelines(elements)
146     print ('fine')
147
148 def run_swmm_simulation(dummy_swmmfile):
149     #run a SWMM simulation#
150     sim = Simulation(dummy_swmmfile)
151     print ('running')
152     sim.execute()
153
154 def extract_and_save_node_data(outfile, node, directory_SWMMoutfiles, iter_number):
155     #extracts and saves node data from the SWMM output file#
156     filename = f"{outfile.split('.')[0]}_{node}.txt"
157     sp.call(f'swmmtoolbox extract {outfile} node,{node},>{filename}', shell=True)
158     destfile = os.path.join(directory_SWMMoutfiles,
159     f"{org_swmmfilename.split('.')[0]}{iter_number}_{node}.txt")
160     {org_swmmfilename.split('.')[0]}
161     shutil.move(filename, destfile)
162     return destfile
163
164 def process_node_data(destfile, node, nodes):
165     #Processes node data and returns a DataFrame#
166     datetime = []
167     nodedata = []
168     with open(destfile, "r") as dfile:
169         elements = dfile.readlines()
170         for e,element in enumerate(elements):
171             if element.strip():
172                 split_element = element.split(",")
173                 datetime.append(split_element[0])
174                 data_element = split_element[5] if node != nodes[-1] else
175                 split_element[1]
176                 if e==0:
177                     nodedata.append(data_element)
178                 else:
179                     nodedata.append(round(float(data_element), 2))
180     nodedata[0] = f"{node}_{'flow' if node != nodes[-1] else 'depth'}"
181     datetime_index = pd.Index(datetime, name='datetime')
182     return pd.DataFrame(nodedata,index=datetime_index)
183
184 def main(directory_model, org_swmmfile, directory_rainfiles, nodes,
185 directory_SWMMoutfiles, dummySWMM_model, rain_gage_params):
186     filearray = [f for f in os.listdir(directory_rainfiles) if f.endswith('.dat')]
187     for i, item in enumerate(filearray):
188         dummy_swmmfile = os.path.join(dummySWMM_model,
189         f"{org_swmmfilename.split('.')[0]}{i}.inp")
190         shutil.copyfile(org_swmmfile, dummy_swmmfile)
191         update_swmm_input_file(dummy_swmmfile, directory_rainfiles, item,
192         rain_gage_params)
193         run_swmm_simulation(dummy_swmmfile)
194         outfile = os.path.join(dummySWMM_model,
195         f"{org_swmmfilename.split('.')[0]}{i}.out")
196         all_node_data = []
197         for node in nodes:

```

```

191         destfile = extract_and_save_node_data(outfile, node,
192         directory_SWMMoutfiles, i)
193         node_data = process_node_data(destfile, node, nodes)
194         all_node_data.append(node_data)
195         # Combine and process all node data and save to csv file #
196         combined_df = pd.concat(all_node_data, axis=1)
197         columnname_new = combined_df.iloc[0]
198         combined_df = combined_df[1:]
199         combined_df.columns = columnname_new
200         combined_df.iloc[:, -1] = pd.to_numeric(combined_df.iloc[:, -1], errors='ignore')
201         combined_df.iloc[:, -1] = combined_df.iloc[:, -1] + 117.50
202         combined_df.to_csv(os.path.join(directory_SWMMoutfiles,
203         f"{org_swmmfilename.split('.')[0]}{i}.csv"), index=True)
204     print('\n\nSWMM simulation finished')
205
206 if __name__ == "__main__":
207     main(directory_model, org_swmmfile, directory_rainfiles, nodes,
208     directory_SWMMoutfiles, dummySWMM_model, rain_gage_params)

```

```

1  # This is AutoRASpy script #
2
3  # All hec modules from HEC-DSSVue #
4
5  from hec.script import Plot
6  from hec.heclib.dss import HecDss, DSSPathname
7  from hec.io import TimeSeriesContainer
8  from hec.heclib.dss import HecDss
9  from hec.heclib.util import HecTime
10
11 # python modules compatible with Jython #
12 import java
13 import os
14 import sys
15 import subprocess as sp
16 import csv
17 import time as tm
18 import re
19 from datetime import datetime as dt
20
21 # Set working directory for 'inputs_framework' to be recognized by HEC-DSSVue program #
22 roaming_dir = os.environ.get('APPDATA')
23 part_path='HEC\HEC-DSSVue\scripts'
24 temp_dir=roaming_dir+'\\'+part_path
25 sys.path.append(temp_dir)
26 from inputs_framework import *
27
28
29 def read_csv_data(filename, column_index):
30     data_csv = []
31     with open(filename, "r") as datafile:
32         csv_reader = csv.reader(datafile)
33         next(csv_reader)
34         for row in csv_reader:
35             if not row:
36                 continue
37             data_csv.append(float(row[column_index]))
38     return data_csv
39
40 def write_to_dss(theFile, bclines, file):
41     tsc = TimeSeriesContainer()
42     tsc_parta = 'BCLINE'
43
44     print(file)
45
46     for i, item in enumerate(bclines):
47         full_path, tsc_units = construct_full_path(tsc_parta, item, comp_timeline,
48             comp_interval, comp_identifier, i == len(bclines) - 1)
49         tsc.fullName = full_path
50         tsc.units = tsc_units
51         start = HecTime(comp_startdate, comp_starttime)
52         tsc.interval = int(re.findall(r'\d+', comp_interval)[-1])
53         bcdata = read_csv_data(file, i + 1)
54
55         times = [start.value() + tsc.interval * e for e in range(len(bcdata))]
56
57         tsc.times = times
58         tsc.values = bcdata
59         tsc.numberValues = len(bcdata)
60         tsc.type = "INST-VAL"
61         theFile.put(tsc)
62
63     print("Processed file")
64
65 def construct_full_path(part_a, item, part_d, part_e, part_f, is_stage):
66     part_b = item

```

```

67     part_c = 'STAGE' if is_stage else 'FLOW'
68     tsc_units = "m" if is_stage else "CMS"
69     full_path = '{}/{}/{}/{}/{}/{}/{}/'.format(part_a, part_b, part_c, part_d, part_e,
70     part_f)
71     return full_path, tsc_units
72
73 def record_count(count, directory):
74     counts = str(count)
75     with open(os.path.join(directory, 'countsfile.txt'), 'w') as countsfileout:
76         countsfileout.write(counts)
77
78 def run_external_script(script_path, count):
79     starttime = tm.time()
80     sp.call(['python', script_path, str(count)], shell=True)
81     endtime = tm.time()
82     return round((endtime - starttime), 2)
83
84 def main():
85     theFile = HecDss.open(org_rasHECDSS)
86     bclines = [name_flowarea + ": " + node for node in nodes_ras]
87     filearray = [os.path.join(directory_SWMMoutfiles, file) for file in
88     os.listdir(directory_SWMMoutfiles) if file.endswith('.csv') and
89     file.startswith(os.path.splitext(org_swmmfilename)[0])]
90
91     for f, file in enumerate(filearray):
92         write_to_dss(theFile, bclines, file)
93         record_count(f, framework_directory)
94         rasexecute_path = os.path.join(framework_directory, 'rasexecute.py')
95         rasrun = run_external_script(rasexecute_path, f) # the rasexecute script is
96         called #
97
98     theFile.close()
99
100     #print('\n\nHEC-RAS model run completed. Computational time:', rasrun)
101
102 if __name__ == "__main__":
103     main()

```

```

1  # This is rasexecutepy script #
2
3  import h5py
4  import win32com.client as win
5  import os
6  import shutil
7  import pandas as pd
8  import sys
9  from inputs_framework import *
10
11
12  lcndata = pd.read_csv(framework_directory+'\\'+lcndataset.csv') # Load landcover data
    from the csv file #
13
14  count = 0
15  if len(sys.argv) > 1:
16      count = int(sys.argv[1])
17  #count_suffix = str(count)
18  #file_name_with_count = f"filename_{count_suffix}.txt"
19
20
21  def update_mannings_n(gfile, lcndata_row):
22
23      # updates Manning's n values in the HEC-RAS geometry HDF file #
24
25      gdset = gfile.get("/Geometry/Land Cover (Manning's n)/Calibration Table")
26      items = []
27      for item in gdset:
28          land_cover_name = item[0].decode('utf-8').replace("b'", "").replace("'", "")
29          if land_cover_name in lcndata_row.index:
30              item[1] = lcndata_row[land_cover_name]
31              items.append(item)
32
33      del gfile["/Geometry/Land Cover (Manning's n)/Calibration Table"]
34      gfile.create_dataset("/Geometry/Land Cover (Manning's n)/Calibration Table",
        data=items)
35
36  def run_simulation_and_copy_output(x):
37
38      # Runs the HEC-RAS simulation and copies the output to a new file for each trial #
39
40      #Run the parent HEC-RAS model#
41      hec = win.Dispatch("RAS610.HECRASController")
42      hec.project_open(rasprojectfile)
43      hec.Compute_CurrentPlan(None, None, True)
44      hec.quitras()
45      del hec
46
47      #copy the output information from the model's run to a new HDF file#
48      if x==count:
49          dummy_rasoutfile = os.path.join(framework_directory,
            f"{rasprojectfilename.split('.')[0]}{x}_output.hdf")
50          shutil.copy(org_rasoutfile, dummy_rasoutfile)
51      if x>count:
52          dummy_rasoutfile = os.path.join(framework_directory,
            f"{rasprojectfilename.split('.')[0]}{x}_output.hdf")
53          shutil.copy(org_rasoutfile, dummy_rasoutfile)
54      if x<count:
55          dummy_rasoutfile = os.path.join(framework_directory,
            f"{rasprojectfilename.split('.')[0]}{count}_output.hdf")
56          shutil.copy(org_rasoutfile, dummy_rasoutfile)
57
58
59  for x in range(len(lcndata)):
60
61      #update the parent geometry file with new Manning's n#
62      with h5py.File(org_rasgeomfile, "r+") as gfile:

```

```
63         update_mannings_n(gfile, lcndata.iloc[x])
64
65     run_simulation_and_copy_output(x)
66
67     print('\n\nRAS simulation finished')
```

```

1  # This is AutoRAS-HDFpy script #
2
3  import numpy as np
4  import pandas as pd
5  import os
6  import h5py
7  from inputs_framework import *
8
9  def find_hdf_files_with_output(directory, keyword='output'):
10
11     return [file for file in os.listdir(directory) if file.endswith('.hdf') and keyword
12             in file]
13
14  def extract_and_save_data(directory, filenames, flow_area_name, output_variable_names,
15                             output_file_prefix):
16     path_to_results = '/Results/Unsteady/Output/Output Blocks/Base Output/Unsteady Time
17                       Series/2D Flow Areas'
18
19     for output_variable_name in output_variable_names:
20         path_to_outvar = f"{path_to_results}/{flow_area_name}/{output_variable_name}"
21
22         for i, infile in enumerate(filenames):
23             with h5py.File(os.path.join(directory, infile), 'r') as rfile:
24                 data_ccc = np.array(rfile.get(f'/Geometry/2D Flow
25                 Areas/{flow_area_name}/Cells Center Coordinate'))
26                 data_outvar = np.transpose(np.array(rfile.get(path_to_outvar)))
27                 data_merged = np.column_stack((data_ccc, data_outvar))
28
29                 df = pd.DataFrame(data_merged)
30                 output_filename = f"{output_file_prefix}{i}_{output_variable_name}.csv"
31                 df.to_csv(os.path.join(directory, output_filename), index=False)
32
33  def parent_process(directory, project_filename, flow_area_name, output_variable_names):
34
35     hdf_files = find_hdf_files_with_output(directory)
36     output_file_prefix = project_filename.split('.')[0]
37     extract_and_save_data(directory, hdf_files, flow_area_name, output_variable_names,
38                           output_file_prefix)
39
40  parent_process(directory_infiles, rasprojectfilename, name_flowarea, name_outvar)

```