INTEGRATING PROBABILISTIC WEATHER FORECASTING FOR FLOOD EARLY WARNING IN DOMINICA

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June, 2024

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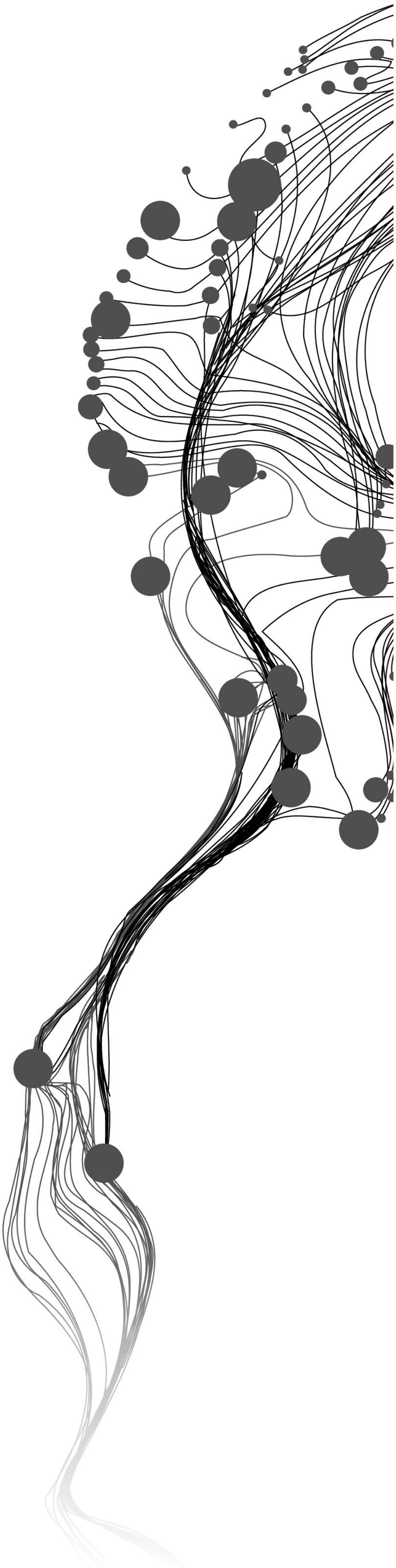

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Enschede, The Netherlands, June, 2024

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Specialization: M-SE

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ABSTRACT

Extreme weather events are projected to increase in magnitude due to climate change, especially tropical cyclones. One of the hazards associated with tropical cyclones is flooding, which can be devastating, especially in populated, mountainous regions. As a result, there is an urgent need for accurate and reasonably fast flood forecasting tools that can ascertain the certainty of approaching weather events, especially for climate-vulnerable regions such as the Caribbean. Many flood forecasting tools exist, but it is rare to find one that provides helpful visualisations for decision-making and quantifies the uncertainty of forecasts.

This research aims to address these research gaps by integrating the use of probabilistic (ensemble) forecasts as precipitation input in the rapid flood model, FastFlood. It selects the case study area island of Dominica, as intense hurricanes have recently impacted it and it urgently needs improved forecasting techniques. This study uses historical ensemble forecasts from the Global Ensemble System from the forecast period of Hurricane Maria (2017) as precipitation inputs for FastFlood.

The findings of the research indicate that the use of ensembles for early flood warnings in Dominica is promising moving forward. There is an inverse relationship between lead times and forecast uncertainty, which supports the use of ensemble forecasting to aid in the assertion of event probability. Further, the flood model outputs from FastFlood were reasonably accurate when compared to historical records and reports. The use of quantiles for extreme precipitation prediction is especially promising, as lead times of up to eleven days were observed. A needs identification of local stakeholders in Dominica indicated that many elements of the applied methodology would be advantageous to them, including the derivation of rainfall thresholds and options for exposure predictions within the flood model.

While the use of ensembles as precipitation inputs in FastFlood appears to be promising for flood early warning, there are many obstacles to implementation. It is recommended that additional applications of the method be carried out, to strengthen the internal consistency of the method, as well as the strength of the findings. It is advised these additional applications include tests in different catchments of varying characteristics, as well as with precipitation events of varying severity.

In conclusion, this research presents promise for the use of probabilistic forecasting to improve flood early warning and could serve as a foundation for more thorough studies moving forward.

Keywords

flood forecasting, ensembles, lead time, rainfall thresholds, early-warning

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Chapter 1

Introduction

The effects of extreme weather are felt globally and are becoming increasingly more relevant as climate change progresses. Not only will events become more powerful in their intensity, but some will also become more frequent (Knutson et al., 2021). These changes could also lead to shifts in hazard interactions or new hazards altogether. One type of hazard that is essential to keep monitoring is flooding. Flooding, globally, is one of the most destructive and most common natural disasters. It can have adverse effects for long-stretching periods after the initial event, creating harmful health, economic, and social problems (WHO, 2022). Moreover, the impacts of flooding have been exacerbated by both anthropogenic factors as well as climate change.

Anthropogenic factors have made the impacts of flooding on society greater. According to the World Health Organisation, the global population living in river basins and flood plains has risen by 114% and those living on vulnerable coast areas by 192% in the last 40 years (WHO, 2012). Moreover, technological advancements have made it easier and more common for settlements to occur around mountainous areas (Sene, 2013). Both factors, encroaching into flood plains and moving into more mountainous regions, increase the risk factor of flash flooding, as more structures and people become exposed to the hazard. Additionally, changes in the global climate have meant that for many regions, precipitation will become more extreme and frequent, leading to increased flood risk (Wilby & Keenan, 2012). This is particularly relevant for flooding as a product of tropical storms, as they are predicted to become more severe in the near future as a result of climate change (Koninklijk Nederlands Meteorologisch Instituut, 2023).

This change in risk has enhanced the need for quick and accurate flood forecasting. Traditionally, the forecasting of floods has proven one of the most laborious tasks in hydrology. Many aspects make this task especially difficult: the uncertainty within input data, the assumptions within the hydrological model, and the calibrating of the forecasting model. Often, models exist within a nexus of computational time, lead time, and accuracy (Fotovatikhah et al., 2018; White et al., 2021). For, models that run quickly are usually not as high in accuracy, while those that are accurate either require an unrealistic amount of detailed input data, take too long to compute, or occur so close to the predicted event that action cannot be taken. A general gap that has arisen in the field because of this nexus is the need for a reasonably accurate flood forecast that does not take a lot of computational power and makes predictions with sufficient lead times.

1.1 BACKGROUND

The subsequent section will expand on the complexities of flood forecasting and explore the current state concerning many related components.

1.1.1 Flood Forecasting

A variety of simulation strategies have been developed to be able to handle real-time simulation as well as forecasting. These include faster models, models that simplify physical processes, and models that utilise statistical or machine-learning approaches.

To improve upon losses of spatial resolution and variability within traditional lumped models, semi-distributed hydrological models emerged. Instead of treating a catchment as a single, homogenous unit, these models divide the catchment into smaller sections, with varying parameters (Sitterson et al., 2017). An example of this kind of model is the HBV model, which conducts runoff simulations for the subbasins it defines, taking soil moisture, snow melt, and changes in the river discourse into account (Saelthun, 1996). The further applications of this model to flood forecasting are extensive, as the model does not possess an extensive amount of input data and has a simple structure that makes it reasonable to understand (Saelthun, 1996). The model has been used to simulate flash flooding, explore the impacts of climate change, as well as investigate runoff process formations (Driessen et al., 2010; Kobold & Brilly, 2006; Lupakov et al., 2021). Although, unfortunately, these models do not create 2D flood maps, making visualisation for decision-making difficult. These models also require large amounts of input data for calibration (Parra et al., 2018).

Machine learning within the field attempts to develop results faster with minimal inputs (Mosavi et al., 2018). Often, the use of machine learning can bridge gaps in data or areas where data is not available, like ungauged catchments (Dawson et al., 2006). Machine learning has been applied to different methodologies in various ways. For instance, some reports discuss the application of machine learning models for the determination of rainfall thresholds (Chu et al., 2022; Ke et al., 2020). This allows for quicker and simpler threshold predictions, facilitating an increase in decision-making and warning times. Other methods call for machine learning to assist with predicting flood susceptibility, or the floods themselves (Munawar et al., 2021; Towfiqul Islam et al., 2021). The use of machine learning and statistics for flood prediction has its drawbacks, as it requires large amounts of training data to ensure biases are eliminated, and once trained for a certain area, algorithms and rules are difficult to transfer (Kumar et al., 2023).

To ease the difficulties of interpreting flood model results, numerous flood simulation tools have been created. A good example of a flood simulation tool is the HEC-RAS software, which allows users to select among many different tasks; one-dimensional steady or two-dimensional unsteady flow calculations, sediment transport computations, or modelling for water quality (US Army Corps of Engineers, 2023). In summary, the software facilitates simpler interpretation as it simplifies the entry of data and allows for easier understanding of results, through graphical observation or exportation into tables (US Army Corps of Engineers, 2023). This tool is especially accessible, as it is free and can be used within geographic information systems (GIS) like ArcGIS, which many users will already have access to (Marina et al., 2015). HOWAD is another simulation model that eases the results interpretation process. However, instead of focusing on flood hazard modelling as seen with HEC-RAS, HOWAD concentrates on high-resolution flood damage simulation, also in a GIS-based environment (Neubert et al., 2016). Flood simulation tools like HEC-RAS and HOWAD have some limitations, though, as they struggle with computational speed and in catchments with complex drainage and urban areas (Betsholtz & Nordlöf, 2017).

Real-time numerical weather predictions were first used as input for flood models as they can account for situations where in-situ discharge data fails or is not available, as well as provide updates for models operating with shorter lead times (Das et al., 2022). This input of singular rainfall values into flood modelling creates a deterministic result. While deterministic results using numerical weather predictions are useful, they can, at times, give a false sense of certainty as they do not explore any aspects of risk or uncertainty. Thus, the field has seen a keenness toward exploring probabilistic forecasting, by use of ensemble forecasts. Ensemble forecasts are weather predictions where instead of running the numerical weather prediction model once, the model is run multiple times while varying initial conditions (WHO, 2012). This means that instead of one outcome that possesses no uncertainty information, several outcomes (or members) are produced, which can be analysed and compared to ascertain a sense of uncertainty.

Many factors motivate the use of ensemble forecasts in flood forecasting. The first is that they can provide a probabilistic assessment of potential flooding that can, unlike deterministic forecasts, offer information about uncertainty (Das et al., 2022; Wu et al., 2020). Additionally, the use of numerical weather prediction, in general, mitigates issues with the sparseness of rain/river gauge networks globally as well as their decaying quality over time (Das et al., 2022; Paz et al., 2020; Wu et al., 2020). Moreover, the vast swath of information the use of ensembles can provide can make the results more useful for decision-making and perhaps indicate potential flooding earlier (Cloke & Pappenberger, 2009; Dale et al., 2014; Hawcroft et al., 2021). The Global Flood Awareness System (GloFAS) is an example of a tool that makes use of ensemble forecasts to facilitate anticipatory action for flood events across the globe. By making use of medium and extended-range ensemble forecasts from the European Centre for Medium-range Weather Forecasts (ECMWF), GloFAS can give results concerning accumulated precipitation, precipitation probabilities, and rapid flood estimations (Copernicus, 2023).

Though, the use of ensembles in flood forecasting specifically still has some limitations. With the shift from deterministic to probabilistic forecasts, the responsibility of interpreting uncertainty and probability of a forecast shifts from experts to the end-users of the model (Demeritt et al., 2016). Additionally, the useful visualisation of ensembles is still a debated topic across the field. One of the most popular ways to interpret ensemble results is through the use of spaghetti hydrographs, but these are not multi-dimensional and do not offer any kind of visualisation in regards to the real terrain (Demeritt et al., 2016). Choropleth maps showing the probability of flooding are also used, but these maps are often very coarse in resolution (Demeritt et al., 2016).

There are still quite a few gaps within the use of ensemble forecasting for flood warnings. It is integral that the results of ensemble flood forecasts are communicated effectively, especially from experts to non-experts, who are often in charge of making decisions (Cloke & Pappenberger, 2009; Das et al., 2022). Large amounts of information can be derived from ensemble flood forecasts, and it is thus essential to ensure the forecasts are sufficiently understood to facilitate informed decision-making. Detailed research into the identification and training of end-users of these forecasts can aid in the mitigation of this issue. With further research into this area, it can become clear, based on forecast results, how an impending flood is likely to develop, along with its severity and to what extent the population may be impacted where (Dale et al., 2014; Das et al., 2022). Finally, there is also a gap within the field regarding the validation of ensemble flood forecasting for real-world events and locations (Cloke & Pappenberger, 2009; Das et al., 2022). Most research for ensemble flood forecasting has occurred in geographic clusters, leaving places like the continents of Africa, South America, and Australia, as well as the South Atlantic and Caribbean outside of the ensemble flood forecasting study locations in the past twenty years (Das et al., 2022).

Another development in the forecasting field that is important to note is the emergence of rapid flood forecasting models. As many in-depth models have low simulation speeds, rapidly performing flood models assist to mitigate this problem and produce model results quickly. Many of these fast-computing models exist with a plethora of different focuses- some depicting a low-resolution representation of potential flood events for decision-makers, others integrate real-time information for small urban catchments (Bellos et al., 2023; Bout et al., 2022; Jamali et al., 2019; Nkwunonwo et al., 2020).

FastFlood Simulation Model

One example of a super-fast simulation tool for flooding is FastFlood. It uses the super-fast flood simulation method to achieve high accuracy whilst modelling results with rapid simulation speed (Bout et al., 2022). This method utilises several innovative concepts to create a model that is up to 1500 times faster than traditional models (Bout et al., 2022). Moreover, the in-browser tool is free to use and can aid in quick calculations to facilitate decision-making based on real-time, current weather conditions (Bout et al., 2023). The model currently does not have a clear methodology for the use of ensembles, but it has been specified as an area of interest for future research (Bout et al., 2022). Fortunately, the fast simulation speed of the model allows for multiple simulations in a short period, which will be necessary for the exploration of ensembles within the tool.

1.1.2 Problem Definition

Upon exploring the current state of flood forecasting and other relevant elements, it can be seen that there is a lack of application of probabilistic forecasting in rapid flood models with a focus on climate-vulnerable Caribbean countries. Advancements in this field are important as they can assist in the mitigation of harmful flooding impacts, especially for areas particularly vulnerable to climate change. Reduction of potential impacts could occur because of new tools/models by arming local stakeholders with more information to facilitate informed decision-making.

The exploration of this topic could also address additional research demands. As previously mentioned, research in the probabilistic flood forecast field has not often been extended to the general area of the Caribbean. Disaster risk reduction for the areas that are to be highly impacted by climate change, such as small island nations in the Caribbean, is at the forefront of research priorities across the field. The island of Dominica has been selected for this study as it is extremely vulnerable to the impacts of the changing climate and has been affected by hurricane-induced flooding, most recently in 2017, with Hurricane Maria. It possesses extreme topography and hundreds of rivers, making for a complex physical system that is vulnerable to hazards. As the island has experienced many heavy and destructive flooding events in the last decade, there are sufficient records and data to also explore the validity of flood forecasts derived from ensemble inputs concerning real flooding events. Further, the exploration of the use of ensembles in fast flood models would address two main needs within the field of flood forecasting; the need for flood results that can be retrieved quickly and the need to interpret uncertainty within flood forecasts.

1.1.3 Research Objectives

The previous sections outlined a clear research gap and motivation for the selection of the overall objective:

Overall objective: To assess the potential of using probabilistic forecasting (ensembles) as an input to a rapid flood model to facilitate informed decision-making and anticipatory action in the climate-vulnerable Caribbean island nation of Dominica.

To achieve this general objective, three sub-objectives and subsequent research questions are defined:

Sub-objective #1: To analyse how the use of ensemble forecasts in FastFlood can provide information about the certainty of possible flood events.

1. What is the impact of the lead times of the ensemble on the uncertainty of the forecast?
2. What is the effect of the variance in precipitation on the spatial variance of FastFlood results?

Sub-objective #2: To evaluate the potential of using probabilistic forecasting in FastFlood for forecasting a real, extreme flooding event in Dominica.

1. To what extent are the flood maps generated by the tested method in FastFlood accurate to the recorded information from Hurricane Maria?

Sub-objective #3: To investigate how the input of ensemble forecasts into FastFlood can be best tailored for decision-makers and end-users in Dominica.

1. What are the specific needs of decision-makers and end-users in the study areas concerning the utilisation of FastFlood results?
2. How can the initial tested method be altered to best fit the needs of local end-users and what are its implications for local stakeholders?

1.1.4 Academic Contributions

This research contributes to the existing field of research by:

1. Testing the novel application of ensemble forecasts as input in FastFlood
2. Examining the use of probabilistic weather prediction specifically in the climate-vulnerable island of Dominica
3. Estimating the element of certainty associated with the flood model results
4. Offering a foundational analysis of the current state of the chosen case study location, Dominica, and providing meaningful additions as to how the tested method could be tailored and made useful for local needs and contexts

Chapter 2

Study Area & Data

2.1 STUDY AREA SELECTION

The nation of Dominica is a small island (750km^2), located in the Lesser Antilles of the Caribbean, about 500 kilometres north of the coast of Venezuela. It is mostly covered in rainforests and possesses 365 rivers and over 26 mountain peaks (Gazol et al., 2019). Dominica's physical characteristics mean that it is particularly prone to flooding and landslide activity due to prolonged precipitation (World Bank, 2021). It has been identified as a Small Island Developing State by the United Nations, as it is extremely vulnerable to the impacts of the changing climate. Not only is the island vulnerable to slow, onset effects of climate change like sea level rise, but it is also challenged by the increasing intensity of tropical cyclones (United Nations, 2023).

The catchment that this research focuses on specifically is that of the Roseau River. The catchment is located in the southwest of the island, as seen in Figure 2.1, and has quite a few tributaries in addition to the Roseau River. Additionally, the catchment is quite mountainous, and downtown Roseau sits directly in the alluvial fan of upstream volcanoes. This has created a very flat floodplain that borders a steep, mountainous region on one side, and the ocean on the other. This catchment was selected specifically because it houses most of the buildings integral to the island's function, like government buildings and the hospital, as well as being the most populated city on the island.

2.1.1 Hurricane Maria on Dominica

Dominica, along with many other small Caribbean islands, was heavily impacted by the 2017 storm season. On September 19th, the island was hit by Hurricane Maria, the strongest hurricane to hit Dominica in recent history (ReliefWeb, 2018b). Maria brought extremely heavy winds and rain (Folger, 2017). A hallmark of the storm was how quickly it developed. On September 16th, the storm was upgraded to a tropical storm, and only within twelve hours of its landfall on Dominica, was it classified as a Category 5 hurricane (Pasch et al., 2023). While a hurricane warning was issued two days before Maria's arrival, on the 17th, the actual level of danger the storm presented was only available in the hours before its arrival on the 19th. Maria made landfall on Dominica at around 01:15 UTC, leaving complete devastation behind before moving northwest towards the Greater Antilles. The rapid intensification of the storm caused many communities across the Caribbean, especially those in Dominica, to be caught off guard by the severity of the storm and its impacts. The exact timing of the event can be seen in Table 2.1.

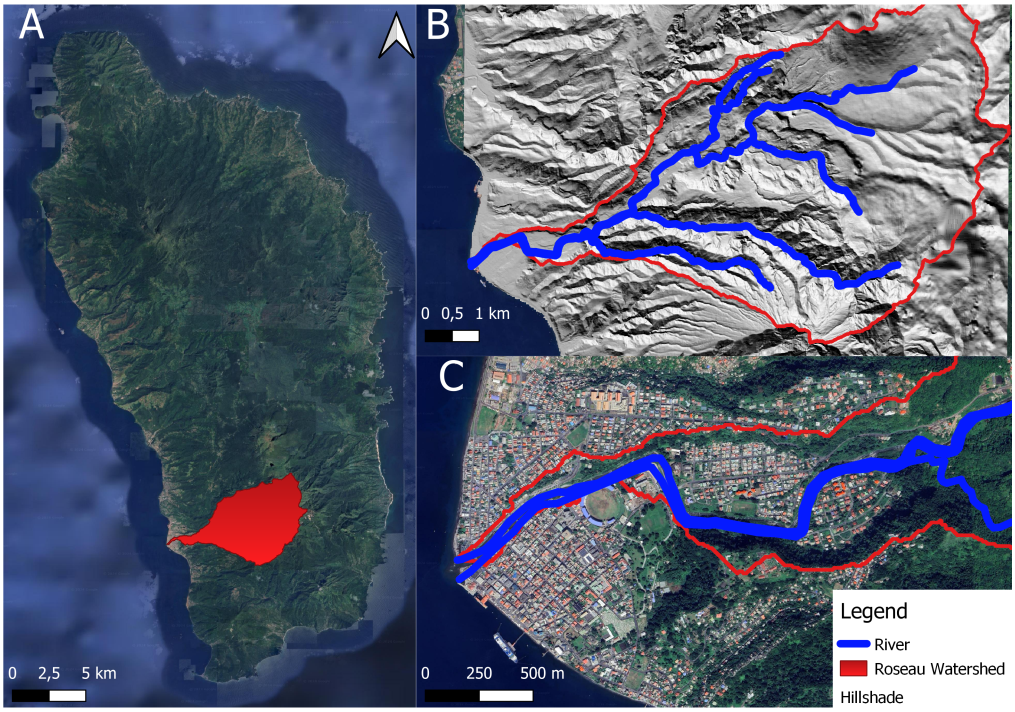


Figure 2.1: A: Watershed's location relative to the country of Dominica B: Catchment hillshade with river and watershed outlines C: Downtown Roseau with the location of Roseau River

Table 2.1: The events relevant to this research's study of Hurricane Maria

Date	Time (UTC)	Event
September 4th	00:00	Start of forecast study period
September 15th	12:00	Thunderstorms show signs of structure and organisation
September 16th	12:00	Tropical depression formation
September 16th	15:00	Tropical storm watch issued
September 16th	18:00	Tropical cyclone formation
September 17th	09:00	Tropical storm watch upgraded to hurricane watch
September 17th	15:00	Hurricane watch upgraded to hurricane warning
September 17th	18:00	Hurricane formation
September 19th	00:00	Category 5 hurricane classification
September 19th	01:15	Landfall on Dominica
September 19th	18:00	End of forecast study period

The highest amount of precipitation on the island was recorded Within the Roseau River catchment (referred to as the Copthall Catchment locally). The island began to receive rain at about 21:00 UTC while peak precipitation occurred just after midnight, with the Roseau catchment receiving 289.2mm in just one hour (Dominica Meteorological Service, 2017). This peak behaviour is seen in Figure 2.2, which shows the rain gauge information for the Roseau catchment from the Dominica Meteorological Service (2017). In total, the catchment had the largest amount of rainfall (579mm) of the entire island. This had devastating repercussions for the heavily populated capital of Roseau downriver. The river widened greatly, approximately tripling, overflowing and flooding downtown areas. All bridges in the city were overrun. Large debris, like tree trunks and boulders, were left piled on top of bridges after the passing of the storm, causing widespread suspension of travel and supply chain disruption (Dominica Meteorological Service, 2017). Examples of the devastation can be seen in Figure 2.3. Nearly all buildings on the island sustained

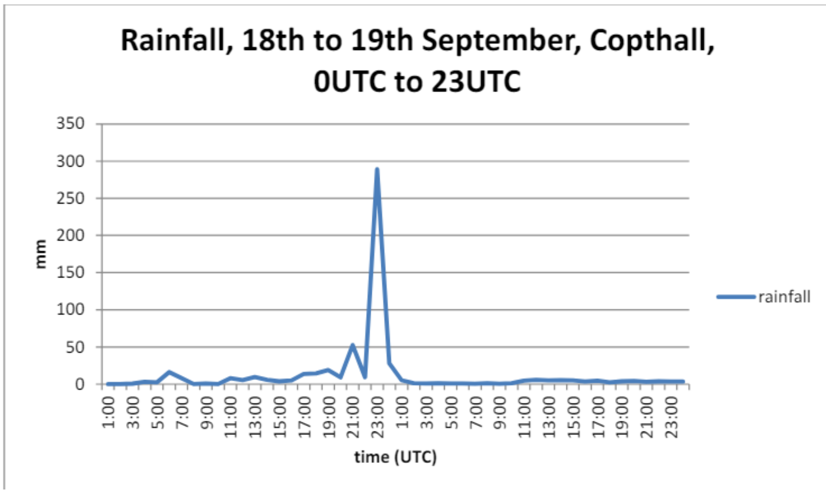


Figure 2.2: Rainfall behaviour depiction from Hydro-Meteorological Report (Dominica Meteorological Service, 2017)

damage because of the storm. Furthermore, as many essential buildings like hospitals and health centres were destroyed, the communities on the island suffered for many months after the storm (International Federation of the Red Cross, 2020). To make matters worse, the country faced many challenges throughout the relief phase; running out of construction materials on the island (increasing rebuilding costs exponentially), experiencing a shortage of local rebuilding expertise, as well as a strong subsequent storm season the following autumn, delaying relief projects even longer. In sum, the Government of Dominica estimates that around $95 million was lost in their general income with an approximate double in the amount of individuals experiencing poverty as a direct result of the storm (Commonwealth of Dominica, 2018).

(a) Hurricane Maria's impact on downtown Roseau, the capital of Dominica (Phipps, 2017)

(b) Bridge in Downtown Roseau with debris (Fagan, 2018)

Figure 2.3: Photos of the devastation Hurricane Maria caused

As a result of this catastrophic storm, the government of Dominica shifted many of their priorities toward creating a safer future for the island. It passed its Climate Resilience Act in 2018, just a year after Maria. The act establishes Dominica's intention to become the first 'climate resilient' country in the world, where it will withstand climate-induced disasters with "minimal loss of life and minimal damage to infrastructure, property, and livelihoods" by 2030 (Commonwealth of Dominica, 2018, p. 270). It also establishes the CREAD, the Climate Resilience Execution Agency of Dominica to ensure the goals specified in the act are properly achieved. The act being approved and the agency being established showed the nation's clear priority to ensure that their island is never impacted as severely as it was during the 2017 hurricane season.

2.2 DATA

The overview of the data used in this study can be found in Table 7.2 of the Appendix.

2.2.1 Historical Ensemble Data

Various facilities across the globe produce ensemble prediction products, like the national weather services of France, the UK, and Japan, as well as organisations like the Environment and Climate Change Canada (Bouttier & Buizza, 2019). The product that is most logical for use in this study is the Global Ensemble Forecast System (GEFS) product from the National Centres for Environmental Information (NCEI). This product was selected because it has historical archives and can be accessed through the platform for free. The GEFS product produces up to 16-day forecasts at a 6-hour temporal resolution and 1.0-degree horizontal resolution (NOAA, 2023).

The ensemble from GEFS consists of 21 members, one original, unperturbed member, and 20 perturbed members. The control (original) member is derived from the measured initial conditions, whilst all other members differ by applying perturbations to the initial conditions to capture the uncertainties in the forecast.

The data was downloaded through the NCEI Dataset Order. Grid GENS3 is selected as the data is of higher resolution and the period 04.09.2017-19.09.2017 was selected because it encapsulates the period 16 days from the arrival of Hurricane Maria's landfall on Dominica.

The datasets from NCEI were downloaded as TAR files, as the ensemble consists of many different archived files. Each TAR file represented the data for one of 21 ensemble members, and of each ensemble member, there were 64 time steps available (6-hour intervals among 16-day outlooks). Additionally, the ensemble forecast was updated four times a day. This structure is displayed in Figure 2.4. There is one flaw in the availability of GEFS data, though, and this does have a rather significant impact on the study. All data points at the first available time step, (step 0 out of 384), were empty, as the relevant precipitation variable within the archive was based on 6-hour intervals. This means that there was not a projection for the 6-hour interval, as, at the first time step, no time had passed yet. To account for this missing value, an average calculation based on the performance of other forecasted days was made, to fill the value reasonably. This missing value only impacted the last forecast day within the forecast period, as no other days used this empty time step in their average calculations. Another disadvantage of using the ensemble product from GEFS was that the resolution of the available historical ensembles is quite coarse, especially for the case study of a small island, at 1.0-degree horizontal resolution ($\sim$100 km). Other products on

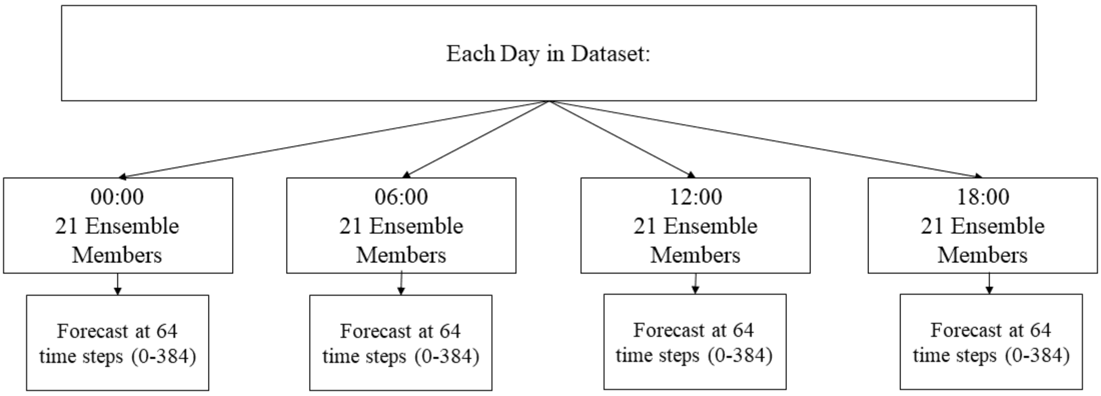


Figure 2.4: Structure for a dataset for each day in forecast period

the market, like that of the European Centre for Medium-Range Weather Forecasts (ECMWF), have higher resolutions and depending on the product, a higher amount of ensembles.

However, the GEFS product possessed some advantages as well. Unlike the ECMWF product and others, this product is free and available to download globally, which is essential for use in small developing island states like Dominica. Further, specifically for Hurricane Maria, the performance of data from the global forecast system (GFS) outperformed the ECMWF in accuracy for lead times from 48 to 120 hours of the storm's track, even though the ECMWF usually outperforms the GFS predictions (Pasch et al., 2023).

2.2.2 Field Data

For the aspects of this research that pertained to the specific catchment area selected, data collection occurred in February 2024. In-person interviews with various local organisations were conducted to investigate what the current state regarding flood forecasting and disaster risk reduction was for the island, as well as what the requests were for emerging forecasting tools.

2.2.3 Data Management and Ethical Considerations

The ethics of this research, specifically the aforementioned fieldwork conducted in February 2024, was assessed and approved by the ITC GEO Ethics Committee. The approval came before the fieldwork occurred and the assessment was based on the GEO Ethics online questionnaire. The data utilised in the research, from historical GEFS ensembles to interview notes, is stored in a secure SurfDrive folder that is available upon request to ensure repeatability.

2.2.4 Software

The software used for this research is as follows:

- **QGIS 3.28.14** for ensemble pre-processing and analysis

- **Microsoft Power Automate 2.42** for the automation of flood model runs and analysis
- **FastFlood Pro (v 0.12)** for the flood model runs (Pro version was used but none of the Pro features were used. Pro simply ensured that the automation loop did not encounter a "Consider FastFlood Pro" advertisement every 500 runs)

Chapter 3

Research Methodology

All processes used in this study are discussed further in subsequent sections and can be summarised in Figure 3.1.

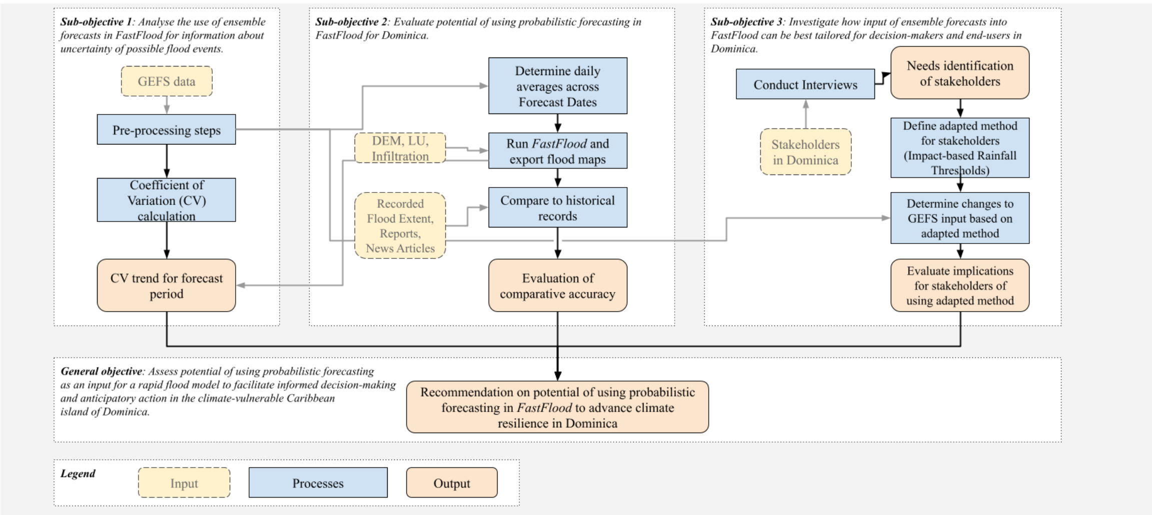


Figure 3.1: Conceptual framework

All inputs in yellow are discussed in Section 2.2, all processes in blue will be discussed in the subsequent sections, and all outputs in red will be discussed in Chapter 4.

3.1 USE OF ENSEMBLES IN FASTFLOOD

The forecast needed to be processed for input into FastFlood. From the original TAR files downloaded, a GRIB2 file that contains multiple weather variables, including precipitation, was extracted. This GRIB2 file from NCEI needed to be converted to GeoTIFF, and the extent of the forecast needed to be warped to the extent of the elevation models used. This step was completed with the use of code executed in the command line.

Due to the sheer vast amount of data that needed to be pre-processed before use, it was advantageous to complete these steps with the use of an automation tool; Microsoft Power Automate. With this tool, the workflows needed for these pre-processes were automated, reducing the amount of time needed to individually process each ensemble member's forecasts. Once pre-processed, it was also advantageous to use such an automation tool for the actual model runs of FastFlood, including the uploading of relevant inputs and downloading of outputs. The scripts used in Power Automate, as well as the command line batches, are linked in Section 7.3 in the Appendix.

3.1.1 FastFlood Settings

The FastFlood model was run with the same initial settings for all flood runs (Tab. 3.1), with the only changing variable being precipitation, which was determined by the GeoTIFF precipitation files derived from the GEFS data.

Table 3.1: The settings for FastFlood per different parameters in the model

Relevant Tab	Setting/Input
Elevation	Choose File: dem_roseau.tif
Land Cover	Land use class map: Auto-Download
Rainfall	Rainfall Intensity Map: final_gens-a.tif
Infiltration	Include infiltration: Auto-Download

The *Auto-Download* function was used for two parameters; Land Cover and Infiltration. This function retrieves data with world coverage and clips it specifically for the relevant extent of the project, in this case, for the extent of the catchment as delineated by the Roseau DEM GeoTIFF. The land cover download option retrieves ESA WorldCover land cover data at a 10-metre resolution. The infiltration parameter downloads soil information from SOILGRIDS, at 250-metre resolution. These maps can be found in Section 7.4 in the Appendix. The selection of these parameters to use the *Auto-Download* function was both due to availability and reproducibility purposes. Data availability for Dominica is sparse, so retrieving the necessary soil and land use maps from Dominica was not possible. Additionally, using these settings allows for the method to be more easily extended to other catchments or regions, where data availability may also be sparse, while the world coverage datasets implemented within FastFlood continue to have coverage.

The Power Automate script is available within the SurfDrive reproducibility folder, along with the input precipitation files, so one does not even have to select these settings individually. The use of the automation script ensures that all the same settings are selected.

3.1.2 Exploration of Uncertainty

Two different analyses were used to explore the impact of lead time on the forecast's uncertainty. In this study, the variance of the ensembles at the same time step was used as a proxy for uncertainty, as uncertainty can be observed by studying the forecast spread (ECMWF, 2024).

First, the spread of the precipitation amounts was calculated using the coefficient of variation (CV). The selection of the use of CV instead of a normal variation calculation was justified because the CV is a unitless value that will not be swayed by variation in the amounts of precipitation predicted. This means that variations among predictions in higher ranges, in the tens or hundreds, are comparable to variations among the values under ten, for example. CV is calculated by dividing the standard deviation by the mean of the sample, as seen in Equation 3.1.

$$CV = \frac{\sigma}{\mu} \tag{3.1}$$

Practically, the precipitation values were extracted from the GeoTIFF files by using the GDAL_INFO command in the command line. This command was used in conjunction with a Power Automate script, that automated the running of the batch GDAL command in the command line and exported the values to Microsoft Excel for analysis. From Microsoft Excel, the standard deviation and mean for each ensemble was calculated. CV was then plotted across the date of the forecast and interpreted.

Further, the variance across cells of the flood model results was compared to interpret the impact of lead time on the forecast's uncertainty spatially. Essentially, the output flood map results across different lead times were compared to see where, spatially, they differ. Flood maps were compared across forecast days and the period by creating spatial variance maps. These variance maps were calculated through a script that makes use of the GDAL_PROCESS executable. All of the executables used in the command line script were and can be downloaded during the installation of the QGIS application. The combination of the CV analysis and variance maps both indicated the uncertainty among the ensemble members' results, but also in which areas of the catchment, spatially, the uncertainty originates.

3.2 TESTING ENSEMBLES IN FASTFLOOD FOR CASE STUDY

This section will detail the methods relevant to the second research objective, which investigates the potential of the proposed method specifically for real extreme flooding events in Dominica. A few different aspects of the observations from Dominica during Hurricane Maria will be explored. They are flood extent and buildings and road exposure.

The recorded flood extent from Maria was compared to the predicted flood extent from FastFlood predictions. While the extent does not nearly give as good of an accurate picture as comparing predicted flood depths would, there were no records of flood height available for the event.

The flood exposure maps from FastFlood were compared to eyewitness accounts and the Hydro-Meterological Report from the meteorological service (2017). The flood exposure maps from FastFlood took Open Street Map (OSM) data and overlaid it on the flood maps, for both buildings and roads.

3.3 STAKEHOLDER INVOLVEMENT IN FASTFLOOD & FIELDWORK

The main way that end-user needs and requests were identified was through the interviewing of end-users and stakeholders from Dominica. Interviews with members of many organizations were conducted during the fieldwork described in Section 2.2.2.

The main purpose of the interviews with the stakeholders is to present the tested method and record their varying opinions on the following main areas:

- To what extent would FastFlood results using ensembles be of use to you?
- Which aspects of the FastFlood tool are most useful to you and why?
- If you could make any changes to the tool, what would you suggest and why?

Table 3.2 Overview of interviewed organizations and their functions

Name of Organization	Function	Function of Interviewees
Red Cross Dominica	Disaster Risk Reduction and Provision of Aid	Director General
Climate Resilience Execution Agency for Dominica	Leads and coordinates strategic initiatives across sectors in Dominica	Chief Development Planner
Office of Disaster Management	Prevention and mitigation of disasters, disaster preparedness, and disaster response and recovery	Natural Disaster Coordinator
Physical Planning Division	Executing arm for physical planning	GIS Analyst
Ministry of Public Works	Responsible for the upkeep of physical infrastructure and waterways	Engineer

It is also important to briefly note that these organisations are closely linked, as they interact often. Three of the organisations are direct functions of the government, as the Office of Disaster Management (ODM) is an office that responds directly to the Ministry of National Security and Legal Affairs, the Office of Public Works responds to the Ministry of Public Works, Public Utilities, and Digital Economy, and the Physical Planning Division (PPD) reports to the Ministry of Housing and Urban Development. Moreover, these organisations often work closely together, whereas the ODM and Red Cross often work together. The Red Cross focuses specifically on local capacity building and ODM tries to help facilitate this. Moreover, the Physical Planning Division tries to align its mitigations with what the public works delineates as well. The Climate Resilience Execution Agency (CREAD) is not necessarily attached to any one specific ministry as it exists as an agency to ensure the achievement of the points outlined in the Climate Resilience Act. While the knowledge of other organisations' functions is high within each respective organisation, data dissemination between the organisations surprisingly is not. Moreover, due to the small size and development of the island, many responsibilities regarding forecasting and storm watches are handled off the island. For instance, regional organisations hold responsibility for Dominica regarding the dissemination of hurricane watches and warnings from the National Hurricane Center (Pasch et al., 2023). Further, Dominica itself is not responsible for forecasting, as it relies on the Caribbean Meteorological Organisation for Meteorology & Hydrology for this (Caribbean Institute for Meteorology & Hydrology, 2024). The Dominican Meteorological Office does conduct some of its analyses of forecasts, but the forecasts usually originate from the American National Oceanic and Atmospheric Administration (NOAA) (Dominica Meteorological Service, 2024a).

3.3.1 Rainfall Impact Thresholds

In line with the research objectives, the tested method was altered to better fit the stakeholders, as identified in the needs identification. While the justification for how and why the method was altered will be discussed in Chapter 4, the method for how this altered method will be detailed in this sub-section, which describes a method to calculate impact-based rainfall thresholds for the catchment. This will essentially outline values of rainfall that would cause certain amounts of damage in the catchment.

To derive the rainfall thresholds in a way that is useful for the local area, results were adjusted to the vigilance levels that the Meteorological Office currently uses. The levels are as displayed below; No Severe Weather, Be Aware, Be Prepared, and Take Action as seen in Table 3.3.

Table 3.3 Flooding Vigilance Levels (Dominica Meteorological Service, 2024c)

Risk Level	Impact
No Severe Weather	• Rainfall does not cause disruptions • Small possibility of isolated cases of temporary flooding due to blocked drains
Be Aware	• Localised flash flooding, flooding of low lying areas • Some overflowing of drains and blocked/silted rivers • Flooding of a small number of homes and businesses • Possibility of water accumulation on roads
Be Prepared	• Some flooding of homes, businesses • Some overflowing of drains and rivers • Disruption to electricity, water supplies, and telecoms • Accumulated water on roads • Some evacuations may be required
Take Action	• Widespread flooding of property • Several rivers overflow their banks • Travel suspension due to blocked roads • Evacuation expected • Significant risk to life

By utilising the same OSM overlay option as discussed in Section 3.2, the flood heights across even intervals were calculated. For this project, it was decided to start with 4mm/hr for a 6-hour interval. 4 millimetres was selected as the Meteorological Office indicated that this was the starting value at which very small amounts of localised flooding first starts to become possible for the island (Dominica Meteorological Service, 2024b). The 6-hour interval was chosen so the rainfall intensities match those given by the ensembles from GEFS, facilitating a simple comparison of the two. Beginning at 4mm/hr, every interval from 4-80mm was simulated, at 4mm interval steps. The OSM data was then exported from FastFlood, resulting in JSON files that possessed max flood height values attached to each building ID. These flood heights were then reclassified into flood height classes that match the existing vigilance levels as described in the Dominica vigilance guide, as seen in Table 3.4. The specific heights were based on water depth safety levels defined by multiple sources(Ministerie van Infrastructuur en Waterstaat, 2024; Musolino et al., 2020; Swiss Federal Council, 2020). For instance, a flood height of $0.0897m$ was reclassified into the Be Aware category, indicating a minor amount of flooding.

Table 3.4: The relevant flood types and flood depths assigned to each vigilance level (Dominica Meteorological Service, 2024c)

Vigilance Level	Flood Type	Flood Height
No Severe Weather	None	0-0.05m
Be Aware	Minor	0.05-0.5m
Be Prepared	Moderate	0.5-1.0m
Take Action	Severe	1.0m+

After sorting each flood height of each building/road ID over the different rainfall intensity intervals into the vigilance classes, the occurrences of each risk class per rainfall intensity were counted. The number of instances can be seen in Table 3.5. These occurrences were used as input for various analyses in Chapter 4: Results.

Buildings																				
	Rainfall Interval (mm/hr for 6 hr)																			
Flood Type	**4**	**8**	**12**	**16**	**20**	**24**	**28**	**32**	**36**	**40**	**44**	**48**	**52**	**56**	**60**	**64**	**68**	**72**	**76**	**80**
No Flooding	9507	9250	9024	8883	8752	8634	8523	8422	8311	8214	8214	7989	7894	7793	7744	7657	7611	7565	7521	7490
Minor Flooding	248	452	629	717	808	872	934	992	1075	1136	1136	1268	1326	1381	1407	1434	1434	1455	1454	1443
Moderate Flooding	26	53	77	102	119	150	166	181	180	182	182	234	248	274	280	315	345	352	373	392
Severe Flooding	8	34	58	86	109	133	165	193	222	257	257	297	321	340	357	382	399	416	441	464
Roads																				
	Rainfall Interval (mm/hr for 6 hr)																			
Flood Type	**4**	**8**	**12**	**16**	**20**	**24**	**28**	**32**	**26**	**40**	**44**	**48**	**52**	**56**	**60**	**64**	**68**	**72**	**76**	**80**
No Flooding	1155	1066	1013	971	942	909	891	870	844	831	813	795	789	774	763	750	739	728	708	702
Minor Flooding	121	185	216	244	267	285	287	302	320	324	332	335	327	337	343	350	349	353	367	370
Moderate Flooding	0	24	43	39	36	45	55	47	44	47	51	60	68	70	73	75	83	83	85	85
Severe Flooding	0	1	4	22	31	37	43	57	68	74	80	86	92	95	97	101	105	112	116	119

Table 3.5: Number of occurrences of each flooding type across different rainfall intensity intervals

Chapter 4

Results

This chapter details the results from the analyses described in the methodology chapter. All results, unless specified, discuss the forecast from the 00:00 publishing moment only. While the research had initially planned to incorporate data across all publishing steps, it was discovered that there is a degradation of forecast accuracy throughout the day. This trend is probably due to the timing of the incorporation of current conditions into the model. Seemingly, the midnight time step uses current conditions, leading to the day's highest accuracy, where the longer the model goes without refreshing current conditions, the poorer the predictions become. The differentiation among different publishing moments within the model cycle organisation can be seen highlighted in Figure 4.1.

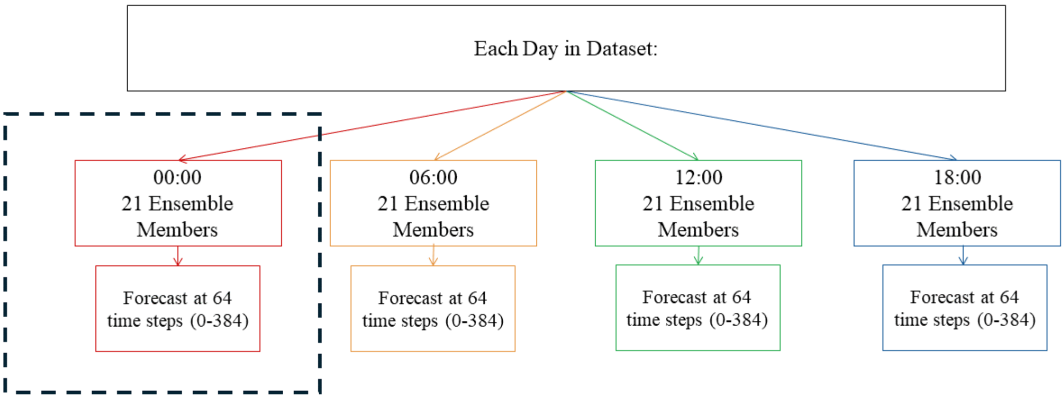


Figure 4.1: Different publishing moments during model cycle per day. Relevant publishing moment (00:00) marked with dotted box

This degradation can be seen in Figure 4.2, where the later the time step is in the day, the farther the prediction is from the actual total amount of precipitation recorded in the catchment (579mm), as defined by the Dominica Meteorological Service (2017). Furthermore, Figure 4.2 displays the total precipitation predicted for the storm arrival date, September 19th, per forecast across the daily model cycle. This means that for all points, all ensemble members were averaged together for their prediction for the 24-hour period on the 19th. It is for this reason that the additional time steps are not used further in the following analyses, as they do not provide a good estimation of the recorded precipitation. In total, it took around 56 hours to run all the 00:00 ensemble members through FastFlood, whereas indexing all of the members for their precipitation inputs took around 7 hours.

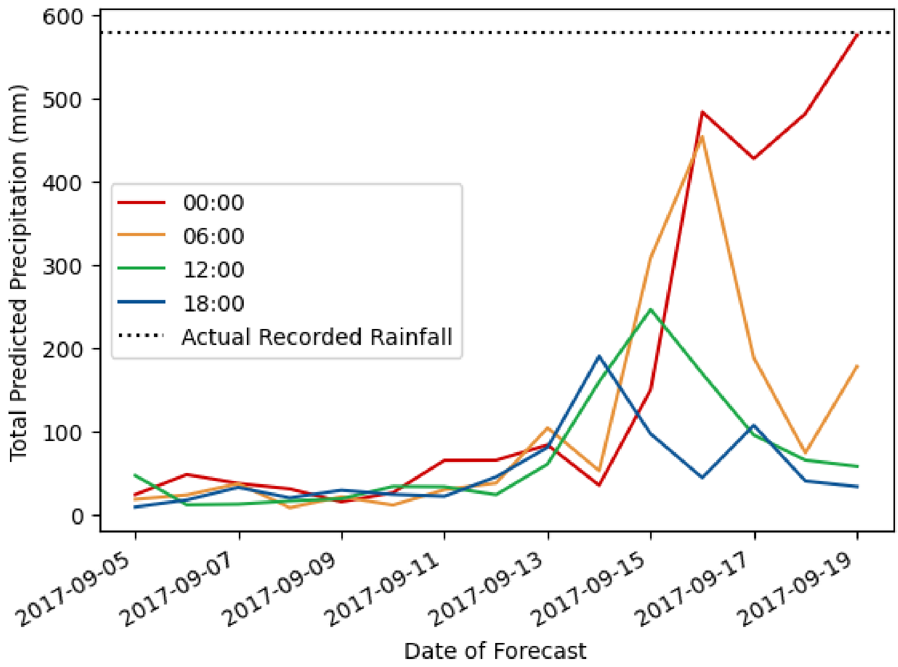


Figure 4.2: Degradation of forecast accuracy across time steps in forecast day

4.1 EXPLORATION OF UNCERTAINTY

The exploration into the uncertainty of the forecast was to ascertain the general relationship between the lead time of the forecast and forecast uncertainty. Regarding the relationship between lead time and forecast uncertainty, the coefficient of variation for each forecast step was calculated and graphed over the forecast date, producing Figure 4.3. According to Figure 4.3, the coefficient of variation had an inverse linear relationship with lead time across the forecast period, but this relationship is not statistically significant, with the R^2 value of 0.52. However, when shifting the forecast period from the entire 16-day forecast to the last six days of the forecast, when the storm's path and predicted behaviour are more known, the inverse relationship between the average CV and lead time is much clearer and is statistically significant. This relationship is described in Figure 4.4.

The spatial variance across the flood maps was also determined, as seen in Figure 4.5.

As can be seen, the areas that varied most across the entire 16-day forecast period were those of the river course, especially in the higher elevations. This spatial variance gives a good idea of where the flood model is the most uncertain. For this specific catchment and storm, it appears that the model does not have a lot of uncertainty in the urban areas or near the coast.

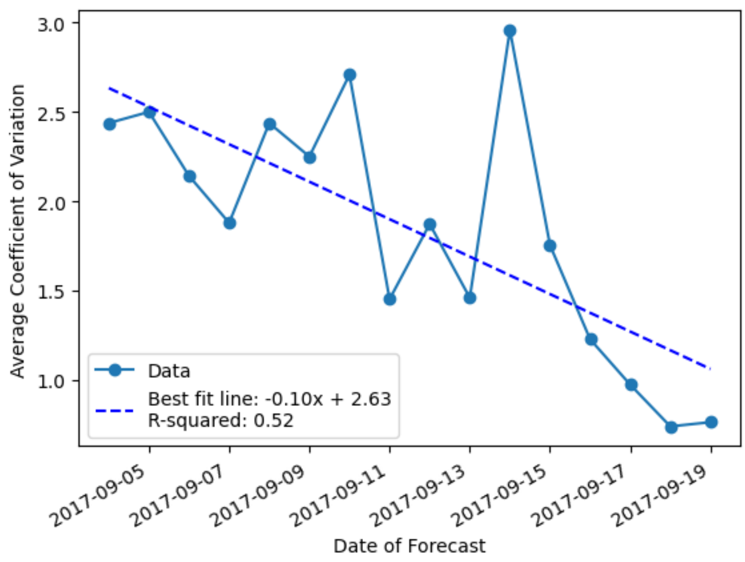


Figure 4.3: The coefficient of variation across the forecast period

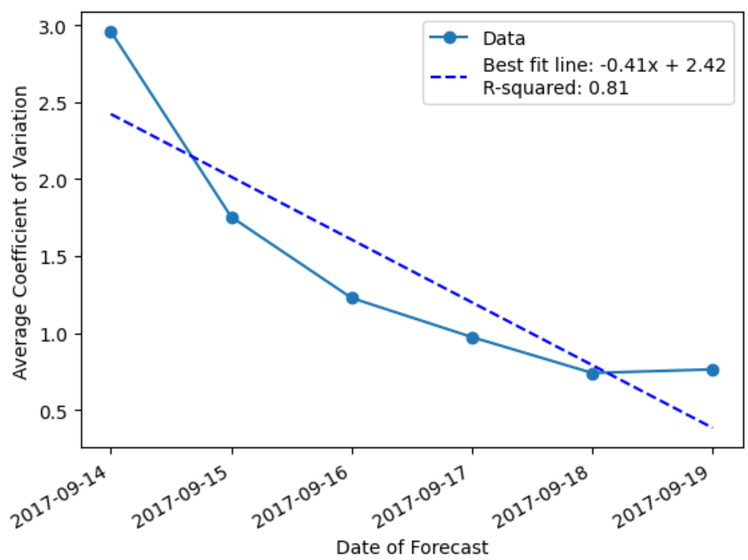


Figure 4.4: The coefficient of variation across the last six days of the period

4.2 POTENTIAL OF THE METHOD

This section will address the investigation prompted by the second research question, on how the ensembles performed and how the results compared to the limited records from Maria.

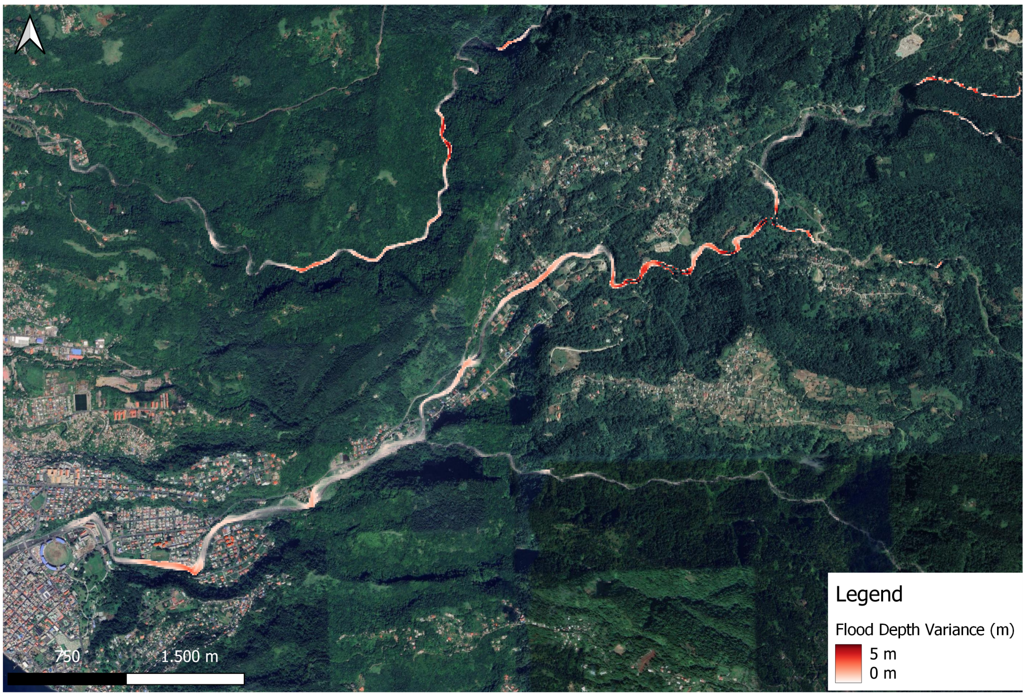


Figure 4.5: The spatial variance across the forecast period

4.2.1 General Forecasted Behavior

In addition to the quantification of uncertainty, literature dictates that an additional advantage of using ensemble forecasting is the potential for longer lead times for extreme events (Cloke & Pappenberger, 2009; Dale et al., 2014; Hawcroft et al., 2021).

This potential for longer lead times can be seen in Figure 4.6, which displays the daily average of each ensemble member for the day of Maria's arrival, and even clearer, in Figure 4.7, which indicates this behaviour of the ensembles as a group, by analysing the performance across the 25th, 50th, and 75th quantile.

While the ensemble members greatly differ in trend behaviour on a fine scale, when comparing member to member, the behaviour of the members as a group indicates a strong trend. As early as September 6th, large amounts of rainfall were predicted, well before the storm was detected as a tropical storm. However, what is difficult to ascertain from this figure is whether this increase is due to the members picking up on the nuances within initial conditions to predict the intensity of the storm correctly, or if those members generally have a tendency to overestimate the amount of precipitation.

The use of quantiles, as seen in Figure 4.7, assists to clear up this uncertainty. Here, the quantiles of the ensembles offer a much clearer indication of the overall behaviour of the ensemble. A clear increase of predicted precipitation can already be seen at the beginning of the forecast period, on the 6th of September. If this method had been implemented in real-time, this increase would

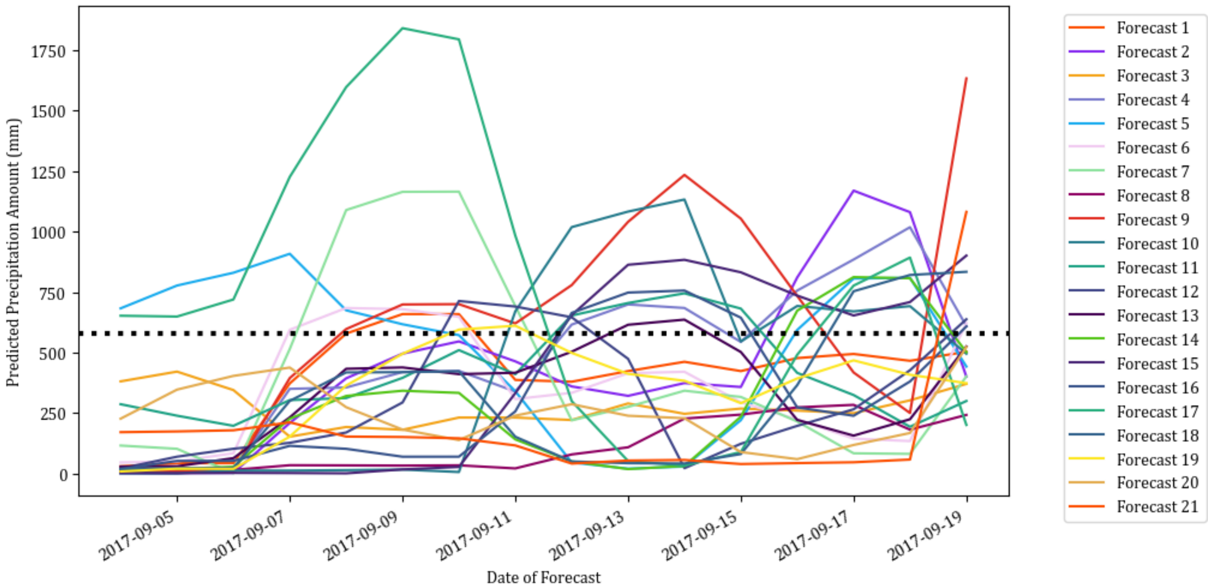


Figure 4.6: The behaviour of each ensemble member over the forecast period. The actual recorded amount of precipitation is displayed in the dotted, black horizontal line across the figure.

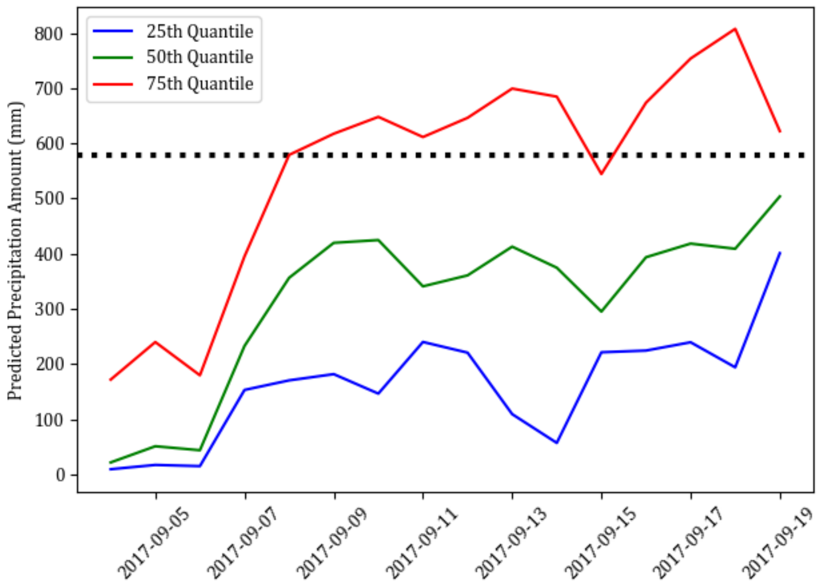


Figure 4.7: 25th, 50th, and 75th quantile trends derived from all individual ensembles, with recorded actual rainfall in catchment shown in dotted black line

stabilise on the 8th of September, at which the majority of the members are predicting amounts higher than 200mm for the storm's arrival, which arguably could already trigger the need for anticipatory action. This could be reinforced with the integration of the rainfall thresholds as derived in Chapter 3, where 200mm for the day would already cross the threshold for all types of flooding in the conservative, 15th quantile scenario. The precise values for each quantile are available in Section 7.5 in the Appendix.

Using this analysis could have raised concern about what would become Hurricane Maria around 10 days before it would become a Category 5 storm, which could facilitate anticipatory action over a week before the storm's rapid intensification. Moreover, the fact that the 75th quantile trend appears to be the closest indicator of what was recorded in the catchment supports the conclusion that the ensemble across the forecast period generally underestimated the storm's intensity, as a majority of members predictions (~75%) fell below the 75th quantile trendline, which hovered around the recorded amount of precipitation for a large portion of the forecast period. This underestimation is discussed in Chapter 5 as well, as it has greater implications for stakeholders and the greater field of study.

The lead time gained as a result of using the quantile analysis is a function of the analysis, though, as the ensemble data can create less useful analyses as well. This is well exemplified by the average behaviour of members across the forecast period, as seen in Figure 4.8. In this trend, as members are averaged against each other, and across the daily time steps, the longer early warning is lost. Thus, this trend more closely follows Maria's actual recorded behaviour, with the rapid intensification displayed in Figure 4.8 beginning on September 15th, closely preceding the tropical storm classification. This figure best estimates the actual recorded amount of precipitation, with the averages indicating 575mm and the Coptfall rain gauge indicating a total of 579mm (Dominica Meteorological Service, 2017). However, this correct prediction would not have been of much use, where the forecast was published at 00:00 UTC on the 19th, and Maria arrived at approximately 01:15 UTC the same day (Pasch et al., 2023).

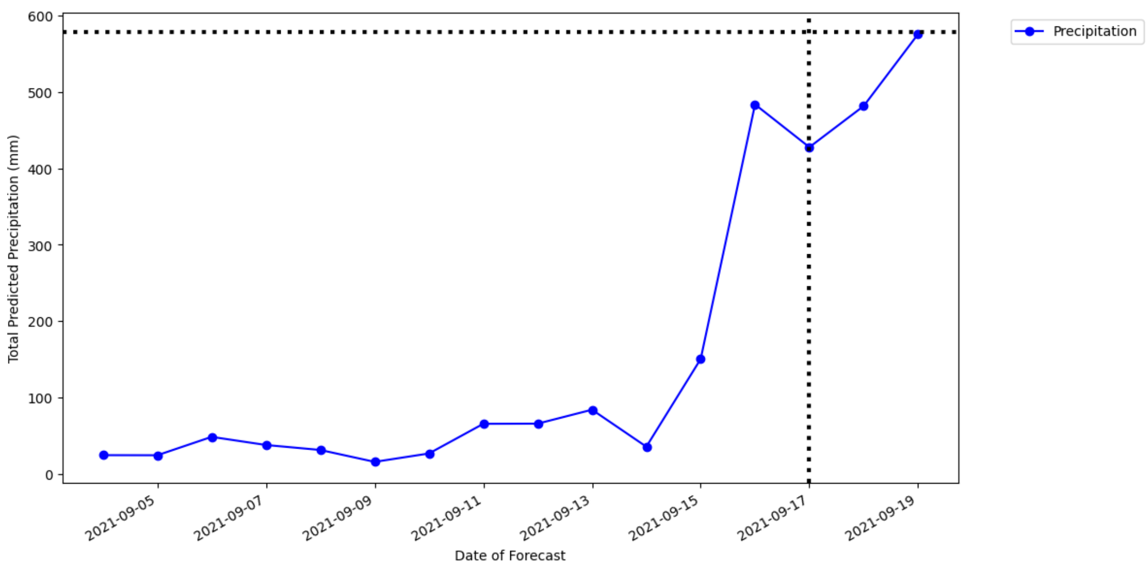


Figure 4.8: The daily precipitation averages of the ensemble forecasts for Hurricane Maria. The storm was classified as a tropical storm on September 17th, as marked as the dotted line on the y-axis, and the actual recorded amount from the Coptfall Precipitation Gauge is marked as the dotted line across the x-axis.

4.2.2 Flood Map Validation

Upon analysis of the average flood maps, produced by running FastFlood with the daily average precipitation values, the map that gets the closest to the flood extent mapped after Hurricane Maria is that of September 19th, where the daily precipitation was closest to the recorded value. The flood map from September 19th can be seen in Figure 4.9. As is seen in Figure 4.9, the flood extent of

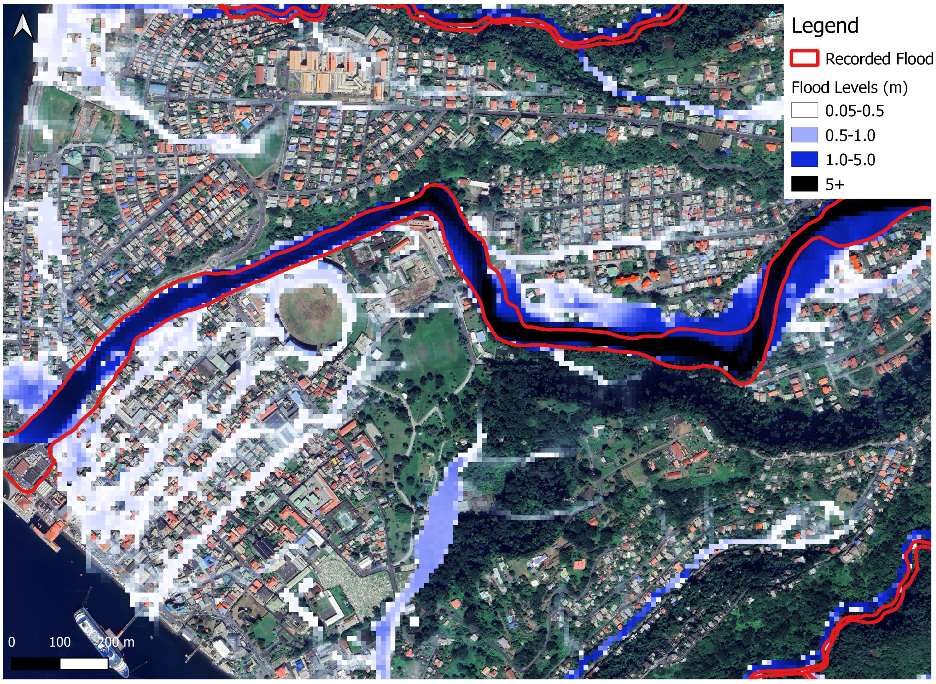
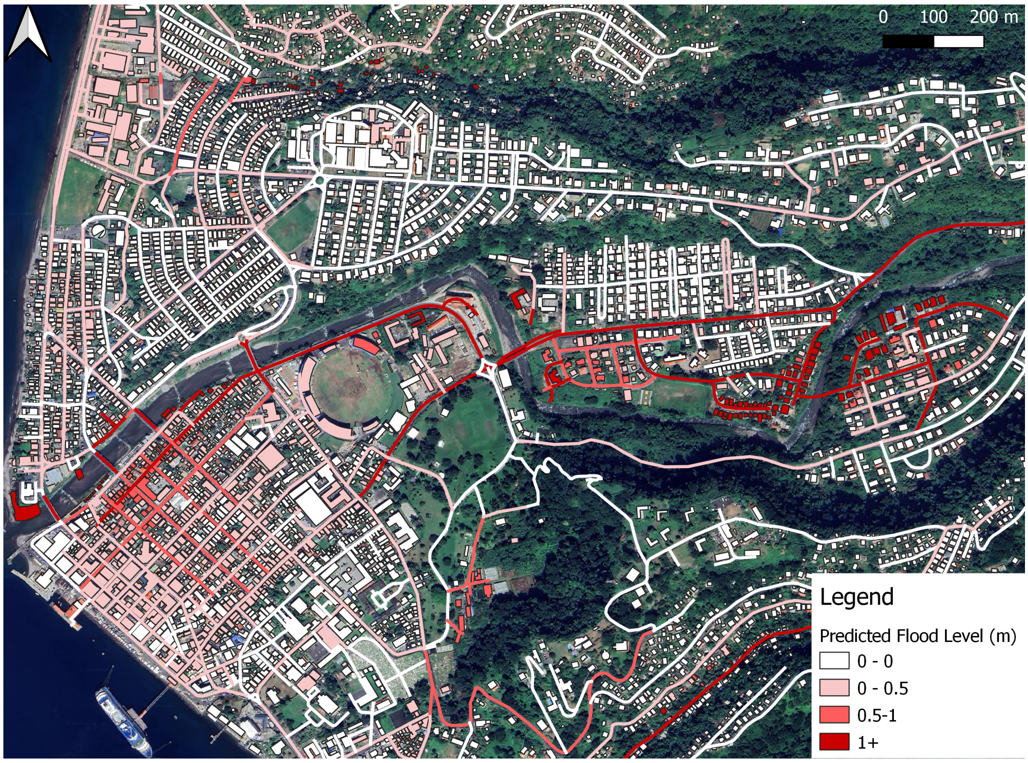


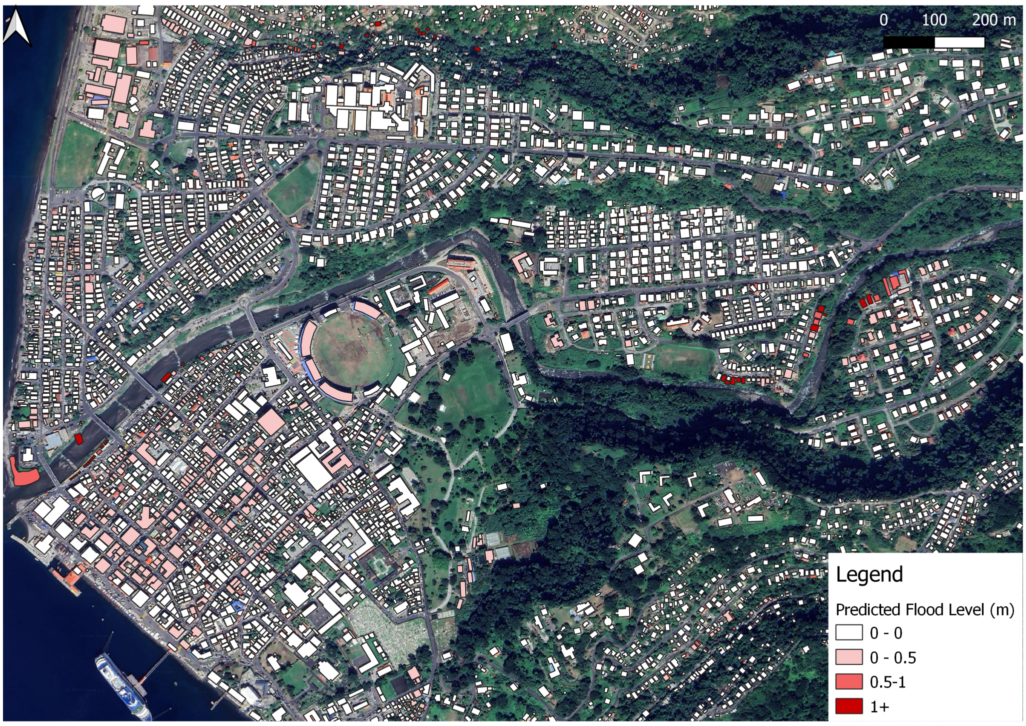
Figure 4.9: Historical flood extent in red vs. FastFlood produced flood map from the September 19th ensemble forecast average

the Roseau River is fairly accurate in downtown Roseau, but the FastFlood flood predictions deviate a bit outside of the regular river course. This is likely due to the recorded flood extent being delineated based on leftover sediment visible in high-resolution satellite imagery and no sediment evidence in the more urban areas visible at the time of analysis (van Westen & Zhang, 2018). Eyewitness statements as well as the damage assessment report confirm the flooding behaviour that FastFlood predicts in the downtown area; flood waters diverting at the bridge and overflowing into the streets downtown (Dominica Meteorological Service, 2017; “Fieldwork Meeting: Physical Planning Department”, 2024). In addition to the flood maps, exposure maps based on the flood depths and extent were created. In Figure 4.10a, the flooding levels in downtown Roseau are displayed. From this forecast, it can be seen that with the predicted precipitation levels, the peak flood moment is projected to completely flood buildings directly adjacent to the Roseau River, whereas more urban floodplain areas farther from the river will be moderately flooded.

For context on how rapidly the storm intensified, Figure 4.10b can be referenced. This is the exposure map based on the average daily forecast of September 15th, four days before Maria’s arrival. With this amount of lead time, it is still possible for last-minute measures, like the distribution of emergency supplies, reinforcing infrastructure, and preparing emergency shelters to be implemented (Dookie & Spence-Hemmings, 2022). However, given the predicted flood levels at this point on September 15th, it is understandable that such measures did not take place.



(a) Exposure map for Roseau based on 19/09 daily average flood map



(b) Exposure map for Roseau based on 15/09 daily average flood map

Figure 4.10: Exposure maps for buildings and roads created from daily average FastFlood runs

While local stakeholders, of course, did not have access to the map displayed in Figure 4.10b in 2017, the amount of precipitation predicted in reality did not warrant any anticipatory action, especially when just analysing the behaviour of the deterministic forecast. The exposure map indicates hardly any flooding across the downtown area of the catchment, only with minor flooding levels towards the coast.

4.3 STAKEHOLDERS

To recap, there were three main themes that the five interviewed organisations were questioned about. The first was regarding what extent the tested methodology could/would be useful to them, the second was about which aspects of the tool were most useful, and the third was involving if there were any suggested changes to the tool. The following paragraphs summarise the general findings of each organisation across each of the three question themes.

4.3.1 Interview Results

This sub-section details the general findings of each interview conducted during fieldwork.

Red Cross Dominica

The Red Cross indicated that the FastFlood tool and proposed methodology would be of use to them. As they currently use satellite imagery via Google Maps, additional maps, especially those specific for flooding would be a useful addition to supplement their current decision-making process. The aspects of the method and tool most useful to them would be the spatial component of the flood maps, as well as the OSM overlay. The only concern they expressed about the methodology and tool would be ensuring that information is correct, as they do not want to disseminate incorrect information or false positives.

Climate Resilience Execution Agency for Dominica

The CREAD also agreed on the positive potential of the proposed method and FastFlood. The agency stated that FastFlood could aid them in tailoring weather forecasts specifically for the local Dominican context, help facilitate informed decision-making for *local* users, and empower local citizens with information. They noted that the tool would be useful in allowing them to explore how much rainfall would flood certain areas of the community, which is further explored in Section 4.3.3. They also indicated that it would be important to keep small rainfall events in mind as well, as with the topography of the area, a small precipitation event can cause transportation delays for days.

Office of Disaster Management

The ODM shared the same positive outlook on the potential of the method using FastFlood, but was sceptical about the need to invest time and human capital required to use the method. An idea for a pre-built version of FastFlood was then proposed, which they agreed would be much more useful than the existing model infrastructure. They also mentioned that this pre-built version could include an option to sort by location and storm type, which would be additionally useful to them.

Physical Planning Division

The PPD stated that the most relevant part of the methodology for them would be the information pertaining specifically to roads and their impact on the local population. They would be able to use both the forecasting aspects of the methodology as well as the planning portion of the FastFlood tool for planning and decision-making. They indicated a desire for the tool to be based in the cloud or online as it assists in facilitating accessibility. Interestingly, they are the only organisation that explicitly indicated that the accessibility of the tool and the results of the method would not be a problem for the general public, as the pros of having such information public outweigh the cons.

Ministry of Public Works

The Ministry of Public Works was also most interested in the implications the method could have for the road network on the island. They indicated that the general results and timing described by the results of the method, as discussed in Section 4.2.1, seem generally correct in their timing and extent. They also stated that the tool could offer assistance in more efficient road improvement selection. The ministry did have doubts about the ability to use the tool, though, as they have limitations in graphics output abilities.

4.3.2 Needs Identification

Upon reflecting on all the individual responses of the organisations, the following general needs were identified:

1. The need for a method that is not needy in terms of processing power, time, and human capital to use it
2. The need for a tool that has a visualisation component, where organisations can interpret results spatially and see what implications exist for their local areas
3. The need for a tool that can be specialised specifically for catchment or neighbourhood levels of detail, so agencies can make decisions for different citizens across the country
4. The need for a cloud-based or online tool, so that the method is accessible on most devices across organisations and does not require local data storage
5. The need for the methodology to quantify the certainty of the results, as multiple stakeholders wanted the ability to outline false positive possibilities and/or incorrect results

Luckily, the tested methodology and the nature of the FastFlood tool can already address many of the needs identified. The tool allows for spatial visualisation and is currently a web-based model.

Additionally, the tool can be run at very fine resolution, so flood maps specifically for a neighbourhood are possible to create. Finally, the tested methodology attempts to give an estimate of general uncertainty within the forecast, as well as estimate the probability of certain rainfall thresholds being reached (explored in Section 4.3.3), something explicitly requested by the CREAD during the interview.

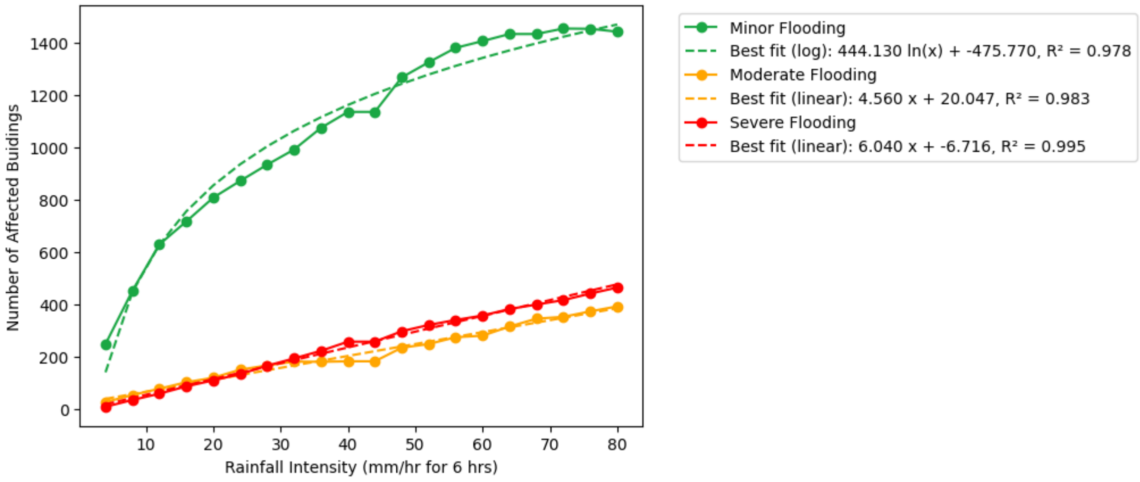
4.3.3 Methodology Suggestions

This section focuses specifically on how the tested method could be specifically tailored to the local context in Dominica and the needs identified through the interviews at the organisations.

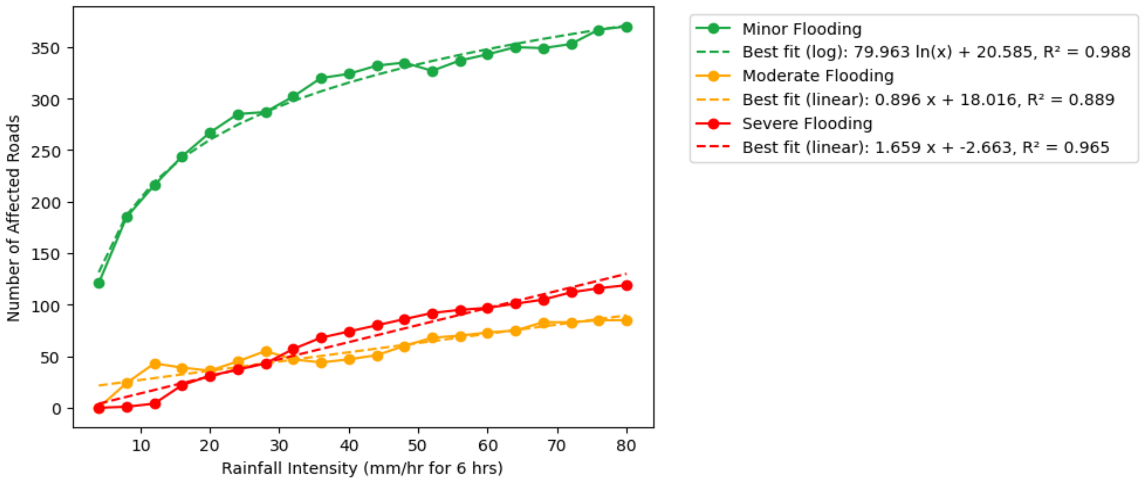
Impact-Based Rainfall Threshold Derivation

As requested by a few stakeholders, both in the interviews and follow-up emails, rainfall thresholds are something that agencies across Dominica need, but do not currently have access to. The only rainfall value that does exist is that after 25 millimetres (approximately 1 inch) of precipitation across 24 hours, the Meteorological Office indicated that localised flooding becomes possible. This, in turn, would average around 6 millimetres over a 6-hour interval. Unfortunately, there is no available information on how this threshold was derived, so a method for an impact-based derivation using FastFlood was determined. From the number of occurrences identified in Chapter 3, the corresponding occurrence value was plotted against increasing rainfall intensity. Further, a best-fit line was created based on the relationship so an equation for each severity of flooding could be derived. This equation describes the amount of damage that could be expected for the amount of rainfall that is predicted, as seen in Figure 4.11.

It is important to mention the biases that slight mistakes in the mapping of OSM data create in the rainfall trendlines. As can be seen in Figure 4.11, the minor flooding curve starts at a value higher than zero when rainfall intensity. This is due to slight errors in the OSM projection over the flood model, where some buildings and road items overlap with the extent of the Roseau River, causing them to be minorly flooded even when there is no rainfall. This is a mistake in the projections or mapping, but was decidedly not within the scope of this project and thus, was not addressed. Further biases within the projection are discussed in Chapter 5: Discussion. Another flaw in the way OSM interacts with FastFlood is that road segments are treated in the same way as building items. This means that in the case that there is flooding on a part of the segment, the entire segment is upgraded to the highest severity of flooding. This creates an overinflation of the flooding for the roads in the exposure maps, which also impacts the rainfall thresholds derived for roads. In an ideal scenario, the number of flooded metres of road should be taken into account, not the number of road segments.



(a) Number of affected *buildings* for rainfall intensity across types of flooding



(b) Number of affected *roads* for rainfall intensity across types of flooding

Figure 4.11: Number of affected items for rainfall intensity across types of flooding

Finally, to create different confidence scenarios, quantiles were calculated from the number of occurrences that describe how much rainfall will lead to how much flooding of each type. To determine the relevant rainfall thresholds from the quantile values of the number of impacted buildings/roads, the quantile values were plugged back into the equations to calculate the thresholds. For example, the 15$^{\text{th}}$ quantile value that was calculated from the number of occurrences of minor flooding for buildings was 816.7. This value was then plugged back into the equation $y = 444.130ln(x) - 475.770$, where $y = 816.7$. This returned the rainfall threshold of 18.35mm/hr for 6 hours for minor flooding. Quantile values 15, 50, and 85 were selected to simulate a conservative, median, and worst-case scenario. For instance, if stakeholders have a conservative outlook for flooding, they could select thresholds derived based on only 15% of buildings and roads flooding. All final rainfall thresholds are found in Table 4.1.

Table 4.1 The number of rainfall thresholds (mm/hr for 6-hour intervals) per each type of flooding for each scenario (quantiles)

Buildings			
Type of Flooding	Q15	Q50	Q85
Minor Flooding	18.35	37.6	68.58
Moderate Flooding	20.90	35.51	59.59
Severe Flooding	22.85	45.82	66.08
Roads			
Type of Flooding	Q15	Q50	Q85
Minor Flooding	11.51	44.40	61.47
Moderate Flooding	20.57	34.57	71.20
Severe Flooding	9.43	48.00	63.71

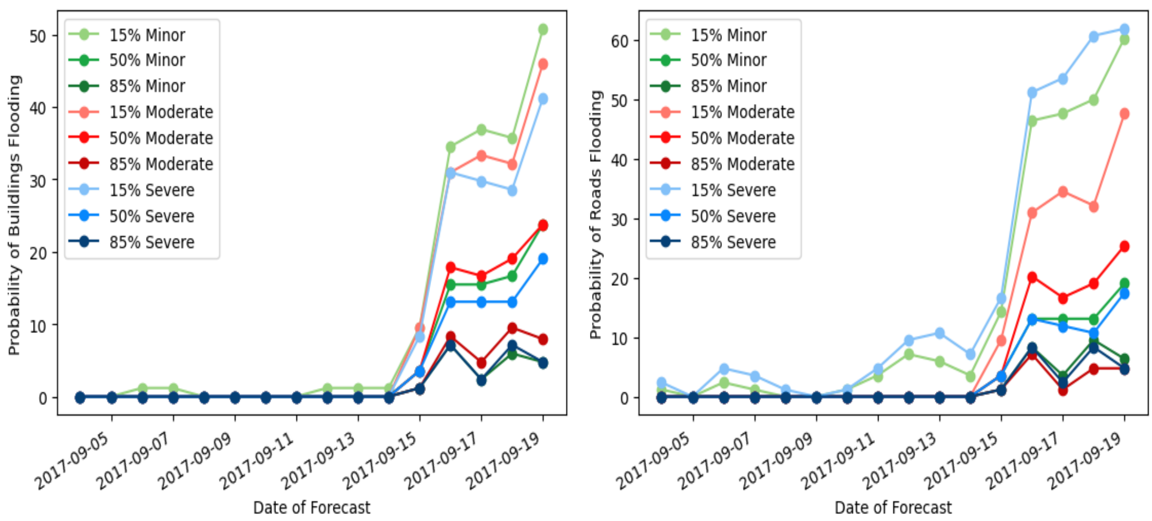
Based on the derived rainfall thresholds, the number of forecasts that meet or exceed these thresholds can be calculated. Further, with this information, the amount of FastFlood runs needed to be run with this threshold as an entry requirement could be determined. Given the defined rainfall thresholds, the amount of FastFlood runs for the entire forecast period is described in Table 4.2. The largest number of runs can be seen defined in the 15^{th} quantile scenario, as only 15% of buildings or roads need to be flooded in this scenario, and thus, has the lowest rainfall thresholds.

Table 4.2 The number of runs that would be required if the rainfall thresholds needed to be exceeded in the precipitation input to run the model

<table>
<tr><th colspan="4">Buildings</th></tr>
<tr><td></td><th colspan="3">Minor Flooding</th></tr>
<tr><th rowspan="6">Amount of FastFlood Runs Required</th><th>15Q</th><th>50Q</th><th>85Q</th></tr>
<tr><td>135</td><td>58</td><td>17</td></tr>
<tr><th colspan="3">Moderate Flooding</th></tr>
<tr><td>118</td><td>63</td><td>25</td></tr>
<tr><th colspan="3">Severe Flooding</th></tr>
<tr><td>108</td><td>48</td><td>18</td></tr>
<tr><th colspan="4">Roads</th></tr>
<tr><td></td><th colspan="3">Minor Flooding</th></tr>
<tr><th rowspan="5">Amount of FastFlood Runs Required</th><td>193</td><td>48</td><td>23</td></tr>
<tr><th colspan="3">Moderate Flooding</th></tr>
<tr><td>120</td><td>66</td><td>15</td></tr>
<tr><th colspan="3">Severe Flooding</th></tr>
<tr><td>230</td><td>44</td><td>20</td></tr>
</table>

As the tested method of running all ensembles in the FastFlood model was extremely time-consuming, this is a conceivable way of reducing the number of runs required. This specific example takes a look at only the forecasts from the midnight time stamp, and only the relevant time steps, so the original total amount of runs required was 1323. Comparatively, suppose one decided to run *all* scenarios for each flooding type for both buildings and roads. In that case, they would still only need to make 230 runs, as all inputs exceeding the lowest threshold (roads, severe flooding, 9.30 mm/hour) would also be run. Generally speaking, most of the predicted precipitation amounts for this storm were insignificant, where about 85% of them did not meet the minimum requirement to even flood 15% of roads (11.51mm/hour).

The inclusion of these impact-based derivations, depending on the stakeholders' priorities regarding confidence level (quantile) and severity of flooding, would see major reductions in the number of relevant runs required, which would save in both processing power and time. Additionally, these amounts of relevant runs required could indicate how probable a certain amount of flooding would be within the forecast. For instance, the probability of a severe amount of flooding across roads, which possesses the highest likelihood of all elements and confidence levels, can be seen in Figure 4.12b. To clarify, this probability is dependent on the probability of threshold exceedance based on the forecasts of each respective day, meaning the percentages are calculated from the 84 individual ensemble member predictions across the forecast period day. For instance, the probability of minor flooding exceedance for the conservative (Q15) scenario on September 18^{th} is 50% as 42 out of 84 cases exceed the threshold value of 11.51mm. Further, this *impact-based* threshold derivation quantifies the predicted flood amounts per number of buildings and roads, which assists in making the thresholds more easily understood by stakeholders across all agencies, regardless if they have a background in hydrology.



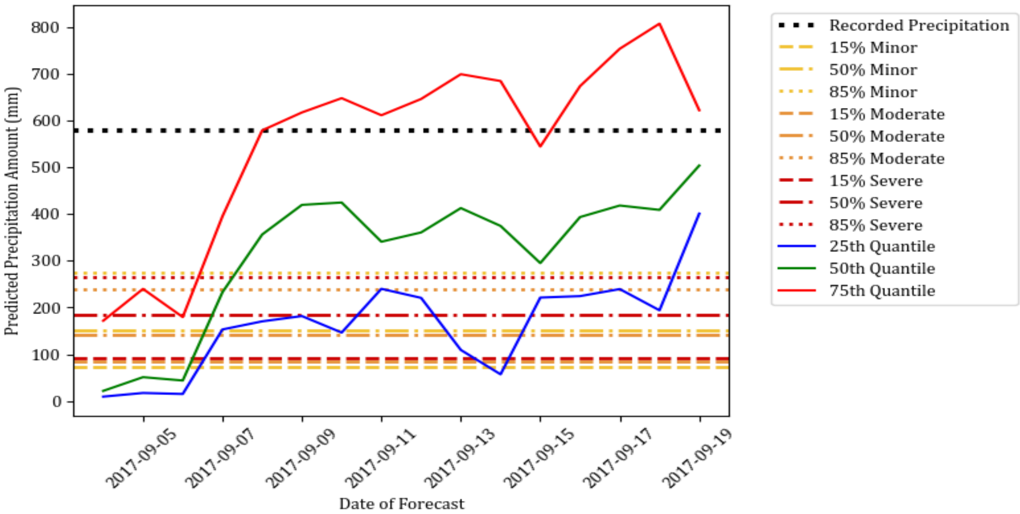
(a) The probability of threshold exceedance for buildings

(b) The probability of threshold exceedance for buildings

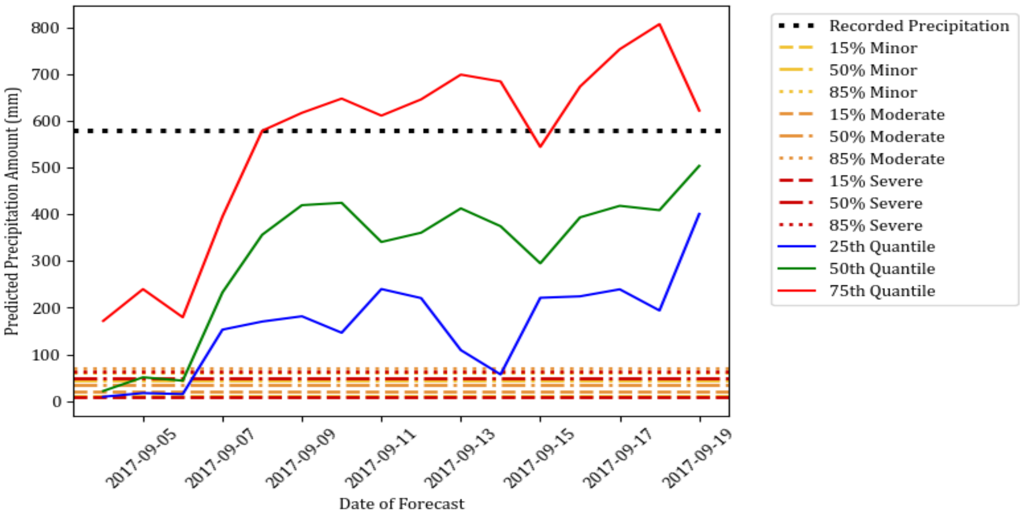
Figure 4.12: Probability curves based on probability of rainfall exceedance within ensemble forecast daily averages

An element of utilising impact-based rainfall thresholds that is especially useful to stakeholders is that while the dramatic increase in precipitation predictions is seen across many different analyses, the exact repercussions of this increase are quantified for the local context.

According to Figure 4.12, it is clear by September 15th that there is an extensive amount of damage expected for both roads and buildings with reasonably high probability. This increase in probability coincides with the reduction in CV seen in the exploration of uncertainty, as discussed in Section 4.1. This explains why this increase is only seen on the 15th, whereas the quantiles from the ensembles (Figure 4.7), show the increase on the 8th. The quantiles do not take variation or certainty into account, as the probability curves do. While the quantiles indicate a large increase in precipitation on September 8th, the exact implications of this amount of rainfall can only be discovered upon utilising the impact-based approach, and certainty using the probability curves.



(a) The quantiles from ensemble members with rainfall thresholds for *buildings* in the Roseau catchment



(b) The quantiles from ensemble members with rainfall thresholds for *roads* in the Roseau catchment

Figure 4.13: The same quantile figure as displayed in Figure 4.7, but with the derived rainfall thresholds overlaid on the figure as well. The recorded amount of precipitation of the catchment is marked in the black dotted line.

As seen in Figure 4.13, the quantiles of the ensembles exceed the derived rainfall thresholds already at the beginning of the forecast period, almost ten days before the increase is seen in the probability curves. This figure helps to contextualise how severe the intensity of the storm actually was, as can be seen, the derived thresholds are quite low in comparison to what was predicted and what was actually recorded. Furthermore, this analysis, if used in conjunction with the rainfall thresholds, creates a well-rounded picture of the ensemble data, and could assist in facilitating informed, real-time decision-making. The dramatic increase seen in the ensemble quantiles could, in the case of Hurricane Maria, trigger alarm bells in stakeholders around 10 days before Maria's arrival. Later, by using the probability and exposure maps, local agencies could ascertain exactly where efforts need to be focused and how certain they can be of the probability of storm intensity. The combination of methods would address the need for ensemble forecasts to be able to be used by local end users for their specific context.

Chapter 5

Discussion

5.1 EVALUATION OF RESULTS

This section aims to evaluate the results based on their generalisability and validity.

5.1.1 Generalisability of Results

While this research offered a thorough exploration into the use of ensembles as a precipitation input in FastFlood specifically for the Roseau river catchment on the island of Dominica, many of the results discussed may not be generalisable.

It is difficult to attach any kind of degree of certainty to any of the results as there were no other catchments or islands taken into account nor were any other storms analysed. Because Dominica has such severe topography and steep, narrow valleys, the flooding behaviour of other islands or areas would perform completely differently. Perhaps in a less mountainous island, like Sint Maarten for example, the same kind of predicted storm would lead to less flooding and as a result, less flood-related damages, as a result of a slower river flow rate and gentler mountain slopes. Additionally, an island like Sint Maarten has no permanent rivers, so it would be less susceptible to large amounts of flooding as a result of blockages of the main river course, as seen with Hurricane Maria in the Roseau River.

The level of development of a catchment may have influence as well. The Roseau River catchment studied in this case possesses a saturated hydraulic conductivity (KSAT) value of $\sim 0\mu m/s$ for the urban areas but has a KSAT up to $\sim 2\mu m/s$ in the more, grassy, forested areas. Logically, a different catchment of a higher development may differ in infiltration rates. For instance, in a much more developed urban area, infiltration rates across the catchment may be closer to zero on average, but could, on the other hand, also possess a developed drainage system across the catchment.

Furthermore, the impact of the selected storm could also cause the results from this study to differ. Hurricane Maria was very unique in its behaviour, with its rapid intensification and a large amount of rainfall specifically in the Copthall catchment. A storm that progresses at a slower, more traditional pace, or one of a lesser magnitude could create different results. It is logical to think that a storm that intensifies at a slower pace may be more predictable, and could result in a more linear relationship between CV and forecast date, across the forecast period, not just the last six days of the forecast. Further, a storm that varies less over a twenty-four-hour period may produce more accurate forecasts at the other publishing time steps, (06:00, 12:00, and 18:00). Additional time steps that perform at a similar level as the 00:00 time step could facilitate a more accurate general picture of the storm predictions, as calculations could be conducted across time steps as well as across ensemble members. However, in defence of the exploration of this storm specifically, Hurricane Maria was one of the most powerful hurricanes to ever hit Dominica, and it was historically one of the most difficult storms to forecast, due to the failure of global models to predict the formation of the tropical cyclone until just before it formed (Folger, 2017; Pasch et al., 2023).

The resolution of the GEFS data could also have had a major influence on the results. The 1.0-degree horizontal resolution of GEFS meant that in the current study, there were no variations in the amounts of rainfall across the catchment and that there was a constant rainfall amount across all areas. This happening in actuality is improbable, as the distribution of rainfall in a hurricane can vary significantly spatially. Whether due to the asymmetry of the storm, caused by wind or general storm motion, or topographical interference from mountainous terrain and shielding, variability in rainfall amounts in the storm can be large (Dollan et al., 2022). The input of a constant as a precipitation value for the entire catchment could mean that many of the nuances and intricacies of Hurricane Maria were not captured by the predicted precipitation values from GEFS, nor properly captured across the flood modelling investigation in FastFlood.

The temporal resolution of the GEFS data may have also played a role in the results. While GEFS publishes a new forecast four times a day, three of these forecasts were not used due to their degradation, as discussed in Chapter 4. The implication of this exclusion meant that the temporal resolution of the forecast updates was reduced from 6-hour to 24-hour intervals. This could have ramifications for the final results as higher temporal resolutions allow the rapid shifts in precipitation intensities to be captured. Furthermore, higher temporal resolutions would be even more relevant for urban catchments, like the Roseau River catchment used in this study, as finer temporal resolutions are integral in the issuing of timely emergency response for vulnerable populations (Zhang et al., 2023).

The exploration of the use of a higher resolution ensemble, like the historical ensemble product from the ECMWF has the potential to address these concerns, as the improvement from 100km horizontal resolution of the GEFS to 9km could facilitate the potential for a more accurate precipitation forecast, as well as the possibility for variation across a case study catchment. The temporal resolution in the shift from GEFS to ECMWF would also increase, as the resolution of the global coverage product is produced every three hours.

The recommendations for the exploration of all of these aspects are included in Section 6.1.

5.1.2 Lead Times and Magnitudes

It is also important to note the relationship between lead times and forecasted hurricane intensity, and the impact it could have on the results of this research.

According to Xue et al. (2013), there is a tendency for global models, especially those with coarser resolution, such as GEFS, to underestimate hurricane intensity as forecast lead time increases. Further, this relationship is especially relevant for lead times longer than 3-4 days (Hazelton et al., 2023).

This would further support the results found in the exploration of the daily averages and CV for this specific case study. The general uncertainty in the model's behaviour for the first 10 days of the forecast in the daily average exploration may be partially attributed to the underestimation of hurricane intensity. The same can be said for the general underestimation seen in the quantile analysis, as the 75th quantile was most accurate, not the 50th.

In defence of the results of this study, though, forecasts understandably still greatly struggle with predictions that include the rapid intensification of storms (Hazelton et al., 2023). Moreover, the underestimation of hurricane intensity has been observed to be present in any lead time over 1 to 2 days, so perhaps the current state of forecasting is not advanced enough to accommodate the needs of local stakeholders yet (Hazelton et al., 2023). While ensembles in general, as well as those observed in this research, do show promise of indicating strong storms and hurricanes earlier than a deterministic forecast, the exact timing and correct intensity of the predictions still require improvement.

5.2 ASSESSING POTENTIAL OF THE METHODOLOGY

To fully assess the potential of the tested methodology, the validity and feasibility of the method will be discussed. Analysing the reliability of results would have also been useful, to help map the internal consistency of the method, but repeating the method was not within the scope of this thesis research.

5.2.1 Internal Validity of the Research

The internal validity of the research pertains to whether the outlined method measures what it was intended to measure.

The first issue is the gap for the first time step in the GEFS data. This has repercussions for the accuracy of the forecast, as for the forecast of September 19th, the relevant time steps, as seen in Table 7.1 in the Appendix, include this first-time step for its averages calculation. This issue of completeness has obvious implications for the validity of the final CV and daily average projections, but has little impact on the stakeholder aspects of the project, as likely, anticipatory actions would need to be carried out with longer lead times, rendering the accuracy this 'day-of' forecast less significant. This problem with the archived GEFS could be mitigated by using a different ensemble archive, such as the one offered at the ECMWF.

Further, another aspect that pertains to internal validity is whether testing effects may have resulted in biases across the data retrieved from interviews. Stakeholders may have been biased by the nature of the questions that were asked, which is discussed in more detail in the following Subsection 5.5.2. This possibility of researcher bias or testing effects could be mitigated by conducting more interviews and increasing the sample size.

5.2.2 Feasibility of Implementation

The feasibility of implementation is a main source of assessing if the results have potential for the local stakeholders.

To quickly recap the findings of the needs identification for end-users in Dominica, they needed a visualisation tool that was capable of mapping floods at a small, neighbourhood level that was also low in cost and computing time, as well as easy to use. Emphasis was also placed on the ability to ascertain levels of certainty surrounding the projections. The original tested method met some of these needs, as it provided interpretable and interactive flood maps within the FastFlood tool. However, this method was extremely time-consuming. Of course, the total amount of time could be cut down with the use of computers with more processing power, but this is not available to local stakeholders, so the method does not seem probable for implementation.

As a result of this finding, an altered method tailored specifically for stakeholders in Dominica was designed. While this method would still need to complete the indexing of all forecasts for their precipitation amount, it attempts to cut down on processing power and computation time by creating a pre-requisite to run the flood model, by use of impact-based rainfall thresholds. This alteration would help cut down on the amount of runs needed in total, as small values and zeros are no longer run through the flood model. This method is something that seems more probable to be of use to stakeholders. For instance, the number of runs regarding severe flooding for the 15% quantile scenario of buildings went from 1261 to 230 runs for the 00 publishing step, an 81% reduction. This would eliminate around 45 hours of flood modelling computation time for this scenario. Moreover, the impact-based rainfall thresholds derived as a result of this method would be of major use to the local context, as they do not currently have any thresholds designed for the island (Dominica Meteorological Service, 2024b). Further, this method's use of exposure maps to quantify the meaning of the flood projections could have a real impact on stakeholders, as expertise in forecasting is not something they feel confident in (Dominica Meteorological Service, 2024b).

While the altered method would see a large decrease in computational time and processing power by filtering out irrelevant precipitation values, the current state of the method still has quite a few nuances that could present obstacles for stakeholders. The current automation of flood modelling utilises data scraping to input new data and run the model for each iteration, and this is inefficient overall and prone to errors. Even after adding additional error-mitigation code to the automation script, there were still a few times when the script stopped without explanation. This current state of the method is not yet ready for implementation for stakeholders and requires further research on how best to incorporate it into the architecture of FastFlood, if at all.

In sum, while the tested method shows potential for the future, it still requires further research across multiple aspects, to test its validity, reliability, and feasibility. A result that does show promise for the local context is the derivation of impact-based rainfall thresholds, as it both fulfils a gap in the current state, one that is specifically requested from stakeholders, as well as translates more complex flood modelling results to an interpretable manner that could assist in the facilitation of informed decision-making. Realistically, upgrading the promising elements from a single catchment to a system that covers the entire island would have repercussions, though. The amount of data and processing power and time required to conduct analyses would vastly increase.

5.3 IMPLICATIONS FOR STAKEHOLDERS

There are many aspects of the results of this research that could have implications for stakeholders in the local Dominican context.

While it is improbable that the original tested method using all ensembles from GEFS in Fast-

Flood would be immediately implemented and utilised by local users, there are a few aspects of the method that could have implications further down the line. First, the idea of using ensemble forecasts to ascertain the uncertainty of forecasts has the potential to be extremely useful for the stakeholders. Local agencies, even on the day before the arrival of Hurricane Maria, experienced quite a lot of uncertainty surrounding what was going to happen (Commonwealth of Dominica, 2017). According to the Post-Disaster Needs Assessment report (2017), residents received notification of an impending hurricane over 24 hours before Maria's landfall, but the storm's potential intensity was not realised until within two hours of arrival.

The use of ensemble forecasting would give local agencies insight into the uncertainty of the current forecasts, and if they could do so, could track the variation over time. While the CV on the day of the most accurate of the forecast (September 19 th) is not quite an acceptable value ($\sim$0.6), stakeholders could identify an inverse pattern accelerating towards the arrival of the storm.

The variance of a few aspects within the altered method would have different implications for the local end users.

A higher resolution ensemble forecast could have interesting implications for the stakeholders. While there is a tendency for global forecast systems to underestimate the prediction of storm intensity, using a higher-resolution dataset could still have positive implications for local stakeholders. A higher resolution dataset could give variance in the rainfall input across a single catchment. A variance in precipitation rates across the catchment has the potential to create more accurate flooding estimations in FastFlood. Not only would this mean stakeholders would have access to flood maps with higher accuracy, but the exposure maps created as a result of the flood height projections could also be more accurate. More accurate exposure maps could lead to better disaster preparedness.

For instance, flood and exposure maps with a higher amount of accuracy could encourage decision-making at a finer level. Local agencies could make scenarios of various rainfall intensities and their associated flood risk zones, and use these for evacuation planning. It could become clearer if a neighbourhood needs to be fully evacuated or just requires a stay-at-home action. It is these kinds of nuances that the Dominican government could have access to given flood and exposure maps with high relative accuracy, perhaps as a result of the use of higher-resolution ensemble data.

Further, the variance of lead times could have implications for stakeholders as well. While longer forecast lead times, ideally above 4 days, would be instrumental in anticipatory action and disaster preparedness (Hurffman, 2023), the current results of the study do not support the kind of certainty that local stakeholders would need to make decisions. The coordination of evacuation off the island would require forecasts that have lead times of closer to a week, with a large amount of certainty (Hurffman, 2023). However, even the certainty that was seen in the research with the tested method, where there was a reasonable degree of certainty that there was going to be a large event, could be of use to stakeholders. Dominica has invested in large emergency centres on both the eastern and western sides of the island, and it would have been helpful to know the certainty of the hurricane predictions before Maria's arrival (Office of Disaster Management, 2019). Even a lead time of 12 to 24 hours could have been integral to getting vulnerable populations out of harm's way. This is certainly something, at least in the specific case that was studied in this research, that could have been possible in the case of Maria.

Of course, something that local stakeholders would have to investigate is at which thresholds of certainty or predicted flooding or exposure they decide that action is needed, but many options within the proposed altered method could aid them in decision-making. Having the ability to use a visualisation tool to view predicted flood heights and damages, as well as the potential certainty surrounding these scenarios, could arm local Dominican stakeholders with a large swath of information that could facilitate informed decision-making in future storms. Furthermore, the translation of forecasts to exposure maps that they can interact with quantifies the predictions in a way that is arguably more useful for the local context.

Moreover, the ability to select different confidence intervals at which certain damages can be expected, through the use of different quantiles, could assist them in creating a more well-rounded action plan in the preparation for storms. For example, for the context of the studied catchment and storm, knowing on the 17^{th} that there was already a $\sim$60% likelihood of 15% of all roads in the catchment were going to be severely flooded and/or destroyed, could have sparked preparations. Especially for the local context in which, if certain bridges or roads are destroyed, entire regions of the island are then unreachable, this knowledge with 48 hours of lead time would have been integral to preparedness. Provisions could have been made for the communities that were expected to be cut off, and perhaps alternative routes could have already been ideated upon. Further, for this case, it was predicted with almost 20% probability that at least 50% of buildings would be moderately flooded, meaning up to 1 metre of flooding. With this information, the government could have indicated citizens to prioritize moving their important documents and property to safe locations, and or, began to prepare for the potential lack of water, electricity, and internet connection.

It is essential to mention that rainfall, and later, flooding, is only one component that is associated with hurricanes, as the impact of wind should not be underestimated. For Hurricane Maria, high wind speeds were detrimental to the island. With maximum wind gusts registering at over 250 kilometres an hour ($\sim$160 miles per hour), over 90% of roofs were damaged or destroyed, leaving debris scattered across the island (ReliefWeb, 2018a). Debris from wind and landslides also caused blockages in river courses, leading to higher flood waters and clogged bridges. Furthermore, high wind speeds thoroughly damaged essential infrastructure, like electricity and water lines (ReliefWeb, 2018a). Thus, the exposure maps presented in Chapter 4 do not begin to capture the full scope of the destruction that Roseau faced, as in actuality, while flood waters were dangerously high, extreme winds affected most, if not all houses in Roseau, advancing and amplifying the damage the capital city experienced.

In conclusion, there are a few suggestions on how to integrate the results of this research into the local context in Dominica. First, the derivation of rainfall thresholds should be expanded to the entire island. This would assist in hypothesising about which scenarios of rainfall would be associated with which levels of flooding, and can be done on a small, neighbourhood level, as originally requested by stakeholders. The biases and errors within the interaction between FastFlood and OSM data should understandably be mitigated before the expansion of the derivation to a larger region. Downloading daily ensembles and running FastFlood for any prediction that exceeds a threshold is not realistic for stakeholders to reasonably implement, but a system that utilises some of the elements could be implemented. Rainfall values could be extracted, and a warning could be alerted if a certain percentage of values exceeded a threshold. Then, stakeholders could decide to run FastFlood or keep alert of the progress of the storm depending on their current situation. Ideally, a balance of data could be found, where agencies are not overwhelmed by the amount of data to be processed and analysed, but empowered by the existence of such data, as it is available upon request.

5.4 UNCERTAINTIES

Two main kinds of uncertainties are relevant for this study, epistemic and ontological uncertainty. Both will be discussed, including how they may impact the results of the research and how they could be mitigated in future studies.

5.4.1 Epistemic Uncertainty

Epistemic uncertainty in this research arises from the limitations in knowledge, data, and modelling capabilities.

An aspect that adds uncertainty to the known uncertainty of the model is the use of OSM data as an overlay in FastFlood. Because OSM data is often mapped by local citizens and volunteers, there is a degree of uncertainty about the house locations and sizes. The implications of this can be seen on the exposure maps presented in the Flood Map Validation section of Chapter 4, as there are a few buildings that appear to lie directly in the course of Roseau River, and as a result, are always severely flooded, despite the precipitation input. While this fact was accounted for when counting occurrences for the quantile calculations (the always-severely-flooded building and road IDs were deleted), this is not something that was done for the visualisations and thus impacts the validity of the displayed exposure maps. The effects of the skewing can still be seen in the trendlines related to minor flooding, as these values were more difficult to filter out. The minor flooding trendlines begin with many building and road items flooded, even with no precipitation.

In sum, while the deletion of these misaligned items addresses any skewing in the threshold derivations, which was done in an attempt to reduce the uncertainty of the model results, these deleted items still represent real-life structures that need to be accounted for. Thus, a suggestion for future research could be analysing additional housing datasets that could be used to supplement the OSM data for this case, or developing a validation/exclusion automation technique.

A final aspect to mention is the impact hindsight bias had on the analyses conducted in this research. A key element in sorting through the ensemble data and filtering out thousands of irrelevant files was contingent on knowing when Hurricane Maria made landfall on Dominica. All analyses only selected the four relevant daily time steps (out of the 384 available from each forecast) as the arrival date was known, meaning that all other time steps could be sorted out. To practically implement the methods discussed, such a filter step would need to be completed for each forecast received, projecting for each forecast date in the future, without knowing exactly when an unknown storm may arrive. This offers many more analyses for comparison, which would complicate decision-making in the local context. This bias causes an oversimplification of the complexity of the architecture required to implement the discussed methods at a practical level, for real-time decision-making. Of course, there is still potential for the method, but its practical implementation is certainly more uncertain at a real-time level.

5.4.2 Ontological Uncertainty

Ontological uncertainty in this application is the uncertainty that comes as a result of trying to capture the many possible outcomes that could occur within nature with one quantity or model.

While, in general, the use of ensembles attempts to address this kind of uncertainty by quantifying it with forecast spread, it still exists within this research. The use of only 21 ensembles with varying initial conditions limits the infinite number of outcomes, and uncertainty arises from that.

It is difficult to estimate how exactly this kind of uncertainty impacts the results seen in this research. While the full mitigation of this uncertainty is impossible given the nature of its existence, this could further motivate the use of a more thorough ensemble forecast, like that of the ECMWF, where 50 members would be selected instead of 21, creating a wider swath of initial conditions to be tested in the flood model.

5.5 LIMITATIONS

There are a few limitations within the research that need to be discussed.

5.5.1 Methodological Limitations

First, the limitations regarding the tested method will be discussed, including data collection and time constraints.

The first to mention, regarding data collection, is that storm surge was not included in the flood model, despite there being an option to include it in the simulation. While it is known that storm surge affected Dominica during Hurricane Maria, there were no wave measurements available from the storm (Pasch et al., 2023), and thus its inclusion was not relevant for the analysis of modelling results. This decision was reinforced by the recorded flood extent being derived only from signs of sedimentation weeks after the storm, which meant that storm surge was not easily interpreted, along with flooding in urban landscapes. Thus, it was decided that this parameter was not within the scope of this research. The inclusion of this parameter can be explored in further case studies, even in different locations for the same storm, where more extensive data is available, in both historical flood extent and wave behaviour.

Similarly, the level of detail of the exposure maps was also limited by the data availability in Dominica. In an ideal case of mapping disaster impact, more detailed information about the exposed items would be included. For instance, a house in an informal settlement, often made of wood, is much less resistant to flooding than a permanent house made of brick or concrete (Fadhil et al., 2020). This spatial information was not available from the Physical Planning Division, as they did not possess any kind of spatial data regarding the building type and population distribution. A census was being conducted at the time of fieldwork, though, and thus, this kind of data may be available in the future ("Fieldwork Meeting: Physical Planning Department", 2024). The incorporation of more detailed datasets could advance the usefulness and accuracy of the exposure maps and is something that could be explored in future studies.

Also regarding a limitation in data collection was the level of depth of the stakeholder interviews. Because of the period of the fieldwork itself, as well as the limited availability of the various government agencies, the stakeholder interviews were only about an hour in most cases. Of course, as many relevant questions as possible were asked, but the results of the needs identification could certainly be affected by the amount of time devoted to each organisation. Perhaps with a more flexible schedule, more time could have been devoted to getting a handle on each organisation's function and specific needs and requirements for forecasting.

The same time constraints impacted the level of depth and generalisability of the results. With more time allotted for the research, the study's conclusions could have been strengthened greatly. Additional storms and catchments could have been studied, and additional explorations could have been conducted. The inclusion of additional catchments and storms has the potential to strengthen or weaken the findings of the current study. Many aspects could have been further researched to widen the scope of the study. For instance, a more deterministic forecast was never tested within the methodology, so it is impossible to say whether the ensembles truly outperform the deterministic forecast with the tested approach.

Finally, regarding the depth of data collection, Dominica is more limited in the existence of historical and spatial data records. Simply put, if the study was replicated in a location with a more detailed records system, the results could be impacted as well. The hydrograph records during the storm may have been more thorough, causing rainfall estimates to be more correct, and perhaps flood height and extent maps would have been created directly after the event through surveying, instead of one based on the sedimentation still visible by satellite weeks later.

5.5.2 Participant Limitations

There are certainly also some biases that exist as a result of interviewing members of the various agencies. The first to discuss is the response bias, as the fieldwork involved interviewers who are not a part of the in-group of the local community visited and interviewed local parties. It would be understandable, if, even subconsciously, respondents altered their responses based on the social desirability bias or recall bias. Recall bias is especially important to mention in this study, as participants at organisations were asked to speak about Hurricane Maria at times, an event that occurred just over five years prior at the time of the interviews. While stakeholder responses and eyewitness accounts were cross-checked with multiple reports published by the Dominican government, these biases probably persist.

Moreover, only one or two staff members at each organisation were available at each interview, so logically, the needs identification is biased to those employees' opinions as well. Again, the biases in these results could be mitigated with longer, more thorough interviews with across multiple sources within the same organisation.

Finally, the results of the needs identification are limited by the current state of forecasting development on the island. Many questions were asked throughout the interviews at each organisation regarding what agencies were looking for specifically regarding forecasting, but because Dominica does not conduct any flood forecasting of its own, their requests were vague and limited, as a result of their current development. If similar questions were asked in interviews with different countries, even nearby Caribbean islands, results could largely differ, depending on development.

5.6 THE WICKEDNESS OF THE STUDY

Advancing climate resilience in Dominica is a wicked problem. Hallmarks of wicked problems include the lack of definitive formulation of a problem, no clear solution, and no clear end goal (Marshall, 2008). In the instance of the problem discussed in this research, there is certainly no explicit definition of the problem that Dominica faces, as their overarching problem is multi-faceted. The island possesses severe characteristics that make it very susceptible to natural disasters, and it is a still developing nation. Moreover, it will face intensifying weather conditions as the climate shifts. Further, the island is restricted in its ability to combat the impacts of climate change as it is restricted by its geographical location as well as its resources, including monetary support. Additionally, there is no clear way forward to mitigate many of the problems that Dominica faces. Even if there was a clear solution, the island hangs in a complex system of jurisdiction and responsibility, with many different moving parts and actors.

Wickedness within complex problems can only decrease, traditionally by increasing knowledge surrounding the system and/or by increasing consensus among stakeholders about how to proceed or the efficacy of a solution (Marshall, 2008). This research aims to mitigate the wickedness of climate resilience in Dominica by supplementing both dimensions of wickedness; with stakeholders as well as the knowledge surrounding the system.

Regarding the dimension of knowledge within the system, the research aimed to decrease the uncertainty regarding the relationship of uncertainty across varying lead times in the 16-day ensemble forecast. While the results across the entire sixteen days were not significant, as they only displayed a reasonably strong relationship between the increase in lead time and uncertainty, the results of the analysis over the last six days showed more promising results.

It is logical that the shorter the lead time, the more certain the forecast would be, and this is seen in the last six forecast days before the storm. But what is almost more intriguing is how uncertain the first ten forecast days are in the prediction of the storm. What is especially interesting here are the results of the CV averages when compared to the daily precipitation averages. So even when the averages appear to be quite consistently predicting low amounts of rainfall, they vary greatly across their predictions.

Moreover, it is difficult to make any statements about whether this first 10 days vs. last 6 days relationships could be found in other storms when it is more probable that the turning point seen on the forecast of the 14^{th} of September is attributed to Hurricane Maria's rapid intensification. However, if more storms were studied, perhaps a more concrete and generalisable relationship could be derived so that the wickedness dimension of uncertainty would be decreased.

In addition to decreasing the uncertainty of knowledge, specifically regarding the knowledge surrounding the relationship between lead times and forecast uncertainty, this research also aimed to increase the knowledge among the stakeholders of the system. As discussed in Chapter 2: Study Area, the stakeholders in Dominica work together and rely on one another often, but information dissemination from one organisation to another is difficult at times. Furthermore, it is often unclear how the needs and wants of the stakeholders can be translated into real, actionable tasks.

As a result of the needs identification from the interviews with stakeholders, a few different specific forecasting needs were identified. First, they needed a method that is not time-consuming, or high in processing power or training. Further, the forecasting tool needs to be visual and tailorable for the small neighbourhood level, as well as quantify the certainty of the results. From these needs, a method for deriving impact-based rainfall thresholds was defined, which assisted in both cutting down the processing requirements and computation time of the tested method and gave a way for stakeholders to estimate predicted damages solely based on forecast predictions, without even needing to run the flood model.

In combination, both aspects attempt to mitigate levels of wickedness. To diminish uncertainty among the forecasts, the tested method defines the relationship between lead times and uncertainty. For the dimension of stakeholder consensus, thorough stakeholder research was conducted, and a needs identification was conducted. From this needs identification, a method for quantifying potential damages based on rainfall intensities was defined. A decrease in wickedness across both dimensions ideally leads to a system that is better defined, where local users in Dominica can continue towards their mission of climate resilience and disaster preparedness.

Chapter 6

Conclusion and Recommendations

This research has demonstrated the potential for the use of ensemble forecasts for facilitating early flood warnings in Dominica by using precipitation predictions as an input for a rapid flood model. Moreover, the study focused specifically on the southwestern Roseau catchment on the island, and its experience during the powerful Category 5 hurricane, Maria, in 2017. The relationship between the lead time of the forecast and its certainty was quantified and found to be inversely related, with a higher confidence in the last six days of the forecast. The use of individual ensemble members proved to grant early indications of an extreme event, up to ten days before the daily averages did. The flood maps produced by FastFlood appeared to be fairly accurate when compared to historical records and reports about Maria. The derivation of impact-based rainfall thresholds shows promise for minimising the computational time and processing power required to integrate the ensemble forecast, which would assist in meeting stakeholder needs. It should be stressed that the promise and potential discussed throughout this study are subject to change given the expansion of the application of the tested methods on other regions and storms. Through quantifying the certainty of precipitation forecasts and translating these predictions to interpretable flood visualisations for local stakeholders, the results of this research have the potential to assist in facilitating anticipatory action against extreme precipitation events.

6.1 RECOMMENDATIONS

There are quite a few research topics that are logical follow-ups or relevant to this research. They are, but are not limited to the following topics:

- Test the application of ensembles in FastFlood with the same tested methodology but with a higher resolution dataset. This would assist in determining if the performance of the method could be attributed to the lower 1.0-degree horizontal resolution of the GEFS data. ECMWF could be a good substitute, as the data for this storm has already been downloaded.

- Explore the application of ensembles in FastFlood with the same tested methodology for a more traditional (predictable) precipitation event. This would assist in seeing if the method's performance could be attributed to the rapid intensification of Hurricane Maria or to the method itself.

- Evaluate the validity of the tested methodology for different catchments and case study locations. This would make the conclusions described in this study more generalizable, or contradict them and offer a more well-rounded perspective on the tested methodology.

- Investigate the characteristic behaviour of ensemble members across different storms and catchments. This would assist in determining whether individual members, based on their initial conditions, were able to pick up on Hurricane Maria much earlier than the deterministic forecast or if they overestimated the amount of precipitation as a function of their behaviour.
- Research the practical needs of the stakeholders and identify the obstacles to implementation in Dominica and other climate-vulnerable regions. This would help shape the next steps of the research.
- Explore the impact-derived rainfall thresholds. There are a few aspects that could offer points of expansion here.
  - Test the validity of the method. This could test if the predicted amount of flood heights across building and road elements is accurate according to historical events
  - Investigate if the thresholds could be expanded to larger catchments and regions whilst remaining logical and functional
  - Evaluate what the use of the thresholds would be for local stakeholders in Dominica, and beyond. This could ascertain if this method could be helpful for stakeholders and if it was more useful than traditional rainfall threshold derivations.
  - Improve the errors seen in the OSM projection of the exposure maps. This would increase the usefulness of the maps and make them more accurate.

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Chapter 7

Appendix

In line with the AI guidelines from the University of Twente;

During the preparation of this work the author used ChatGPT to check the math for quantile calculations relevant to the derivation of rainfall thresholds. Further, the Copilot function of GitHub was used in Visual Studio Code to assist in code-writing for the production of figures and visualisations. After using these tools, the author reviewed and edited the content as needed and took full responsibility for the content of the work.

7.1 RELEVANT TIME STEPS FOR FORECAST PUBLISHING MOMENTS

Table 7.1: Relevant time steps across all four daily publishing moments throughout the model cycle. The 00:00 model cycle moment is the one used in this study.

	Publishing Time			
Date	00:00	06:00	12:00	18:00
19/Sep	n/a	6	12	18
	6	12	18	24
	12	18	24	30
	18	24	30	36
18/Sep	24	30	36	42
	30	36	42	48
	36	42	48	54
	42	48	54	60
17/Sep	48	54	60	66
	54	60	66	72
	60	66	72	78
	66	72	78	84
16/Sep	72	78	84	90
	78	84	90	96
	84	90	96	102
	90	96	102	108
15/Sep	96	102	108	114
	102	108	114	120
	108	114	120	126
	114	120	126	132

14/Sep	120	126	132	138
	126	132	138	144
	132	138	144	150
	138	144	150	156
13/Sep	144	150	156	162
	150	156	162	168
	156	162	168	174
	162	168	174	180
12/Sep	168	174	180	186
	174	180	186	192
	180	186	192	198
	186	192	198	204
11/Sep	192	198	204	210
	198	204	210	216
	204	210	216	222
	210	216	222	228
10/Sep	216	222	228	234
	222	228	234	240
	228	234	240	246
	234	240	246	252
09/Sep	240	246	252	258
	246	252	258	264
	252	258	264	270
	258	264	270	276
08/Sep	264	270	276	282
	270	276	282	288
	276	282	288	294
	282	288	294	300
07/Sep	288	294	300	306
	294	300	306	312
	300	306	312	318
	306	312	318	324
06/Sep	312	318	324	330
	318	324	330	336
	324	330	336	342
	330	336	342	348
05/Sep	336	342	348	354
	342	348	354	360
	348	354	360	366
	354	360	366	372
04/Sep	360	366	372	378
	366	372	378	N/A
	372	378	N/A	N/A
	378	N/A	N/A	N/A

7.2 DATA OVERVIEW

Data	Use	Resolution/Source	File Type
Ensembles	Historical precipitation input	1.0-degree horizontal, 4/day, 16 days	TAR
Roseau Catchment DEN	To define the extent of the study area and as elevation input in FastFlood	10 metres, ITC	geoTIFF
Flood Extent Roseau	To validate FastFlood maps	ITC	SHP
Stakeholders Input	To assist in stakeholder needs identification	Fieldwork Interviews	N/A
Land Cover	Land cover input in FastFlood (downloaded w/in tool)	FastFlood (WorldCover)	N/A
Soil Infiltration	Infiltration input in FastFlood (downloaded w/in tool)	FastFlood (SOILGRIDS)	N/A
Buildings and Roads	To create exposure maps	FastFlood (OSM)	N/A

7.3 REPRODUCIBILITY

In addition to the SurfDrive folder containing all relevant data and scripts, the Power Automate and command line scripts can also be found **here**.

7.4 FASTFLOOD INPUT INFORMATION

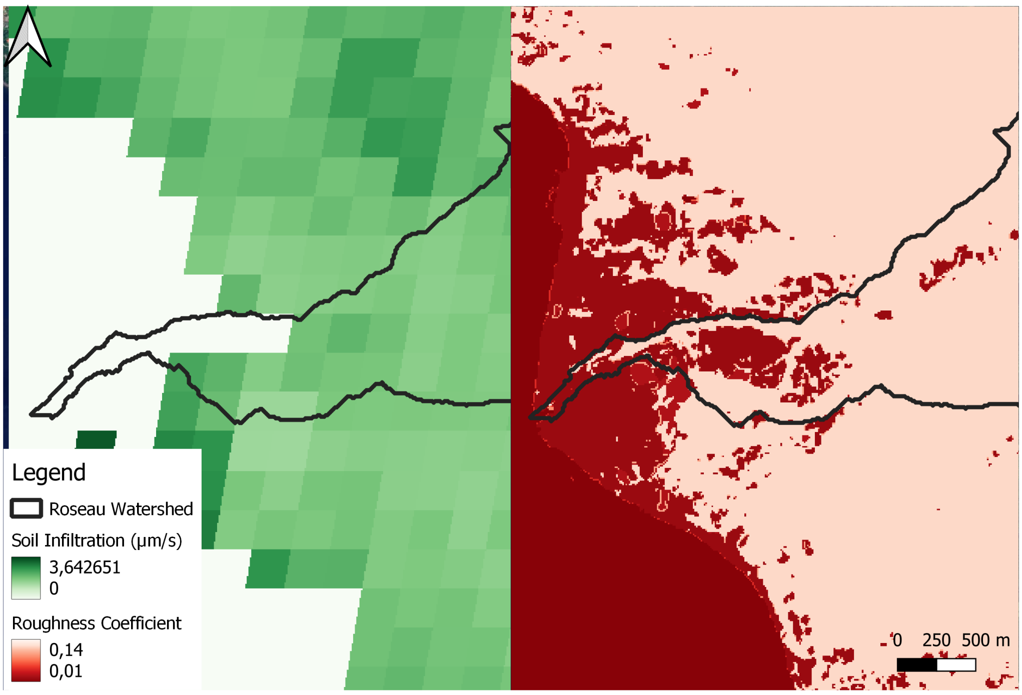

Figure 7.1: The soil infiltration and roughness coefficient (Manning's) maps, as created by the Auto Download of FastFlood, for Downtown Roseau

7.5 RAINFALL QUANTILE VALUES

Table 7.2 The quantiles of the ensemble member values

Date	25Q	50Q	75Q
September 4th	9.36	21.66	171.78
September 5th	17.16	51.00	239.82
September 6th	15.00	43.80	179.58
September 7th	153.06	232.80	395.16
September 8th	170.40	356.28	579.00
September 9th	181.68	419.64	617.40
September 10th	146.40	424.68	647.94
September 11th	240.00	340.80	611.40
September 12th	220.62	360.66	646.20
September 13th	109.20	412.74	699.24
September 14th	57.06	374.58	684.60
September 15th	221.28	295.08	544.44
September 16th	224.40	393.54	673.62
September 17th	239.46	418.26	752.66
September 18th	194.04	408.90	807.42
September 19th	400.86	503.76	622.14