DEVELOPMENT OF A WEB APPLICATION THROUGH A MOBILIZED CROWDSOURCING PLATFORM TO ENABLE PARTICIPATORY RISK SENSITIVE URBAN DEVELOPMENT

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DECLARATION

I declare that this is my own work and this thesis does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

11/03/2025

Signature: Date:

The above candidate has carried out research for the Master's thesis under my supervision. I confirm that the declaration made above by the student is true and correct.

Name of Supervisor:

22/03/2025

Dr. Chathura De Silva

Dr. Nayomi Kankanamge

22/03/2025

Signature of the Supervisors: Date:

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ABSTRACT

Flooding remains the most frequent and destructive natural disaster in Sri Lanka, exacerbated by rapid urbanization and evolving precipitation patterns, leading to extensive socio-economic damage. Despite the availability of technological tools for disaster management, community engagement in early warning systems and risk mitigation remains minimal. This study addresses this gap by developing an integrated platform comprising a crowdsourcing-based mobile application and a web-based geospatial decision support system, aimed at fostering participatory risk-sensitive urban development. The mobile application enables real-time flood data collection from affected communities, while the web platform visualizes and validates this data, providing actionable insights for disaster response authorities. A flood vulnerability assessment model was developed using 30 years of historical flood data, nine key conditioning factors—including topography, weather patterns, hydrology, land cover, and soil type—and Sentinel-2 satellite imagery to enhance prediction accuracy. The methodological approach integrates machine learning techniques for crowdsourced data verification, participatory workshops for system validation, and mobilization strategies for community engagement. The research makes significant contributions to both theory and practice. Theoretically, it advances the discourse on participatory disaster management by integrating community-based crowdsourcing with remote sensing analytics. The study also refines geospatial modelling techniques for flood vulnerability assessment, incorporating novel indicators such as Night-Time Light (NTL) data to measure human exposure to flooding. In practice, the developed platform enhances disaster preparedness by providing a scalable, cost-effective solution for real-time flood risk assessment. The findings demonstrate that combining crowdsourced data with remote sensing can bridge critical information gaps in disaster management, empowering communities and authorities to respond proactively to flood hazards. The study's framework can be adapted to other flood-prone regions, contributing to global efforts in urban resilience and risk-sensitive development.

Keywords: Community engagement, Crowdsourcing, Flood vulnerability assessment, Remote sensing.

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LIST OF ABBREVIATIONS

Abbreviation	Description
AI	Artificial Intelligence
CBDM	Community-Based Disaster Management
CBS	Community-Based Solutions
DEM	Digital Elevation Model
DRR	Disaster Risk Reduction
GDP	Gross Domestic Product
GEE	Google Earth Engine
GIS	Geographic Information System
IoT	Internet of Things
ML	Machine Learning
NDVI	Normalized Difference Vegetation Index
NTL	Night-Time Light
NUACI	Normalized Urban Area Composite Index
P-RSUD	Participatory Risk Sensitive Urban Development
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SRTM	Shuttle Radar Topography Mission
TWI	Topographic Wetness Index
UAV	Unmanned Aerial Vehicles

LIST OF APPENDICES

CHAPTER 1 – INTRODUCTION

This chapter introduces the study by highlighting the increasing risks of urban flooding in Sri Lanka due to rapid urbanization and climate change, emphasizing the socio-economic impacts and the gaps in existing disaster management approaches. The chapter begins with an overview of the study, discussing urban flooding trends, the importance of participatory disaster risk reduction, and the technological innovations being explored. It then presents the research objectives, focusing on the development of a flood vulnerability assessment model and a crowdsourcing-based disaster response system. The research questions outline key inquiries into integrating crowdsourced data, remote sensing, and real-time stakeholder engagement. The scope of the study details its geographical focus on the Kelaniya watershed, the technological tools employed, and the critical areas of disaster management explored. Finally, the limitations acknowledge technological and logistical constraints, data accuracy challenges in crowdsourcing, and the varying levels of digital literacy affecting community participation. This chapter sets the foundation for the study by defining its research focus, problem statement, and significance in advancing flood resilience through geospatial technologies.

1.1.Overview of the Study

Urbanization is an undeniable global phenomenon as of 2021, more than 55% of the world's population resides in urban areas (Geekiyanage et al., 2021) and this figure is expected to rise to over 66% by 2050 (Ni et al., 2019). While urban development is crucial for socio-economic progress, it also presents significant challenges in regard to natural disasters. Moreover, a significant number of cities worldwide, namely those with populations exceeding 500,000, are at a high risk of being affected by various disasters such as floods, droughts, earthquakes, tsunamis, and wildfires (Junhua et al., 2023; Saja et al., 2021). Urban flooding was documented as the predominant natural disaster, which accounts for 44% of all disaster occurrences between 2000 and 2019 Over 2 billion people worldwide are exposed to the risk of flooding (UNDRR, 2021). Over the years, there has been an increase in the frequency of urban flood events in Sri Lanka, resulting in significant socio-economic consequences and posing challenges to countless lives. Urban floods caused the most property damages, with a numerical value of 243,655, between the years 1965 and 2019 (Abeysinghe et al., 2021).

According to the World Bank (2017), approximately 50% of Sri Lanka's population is residing in areas that are flood vulnerable, while the economic damage from flooding is estimated at about 1% of the country's GDP yearly (Walsh & Hallegatte, 2019). Colombo, Gampaha, Kalutara, and Rathnapura are districts in Sri Lanka that have seen significant urban flooding. This flooding has been exacerbated by the increased rainfall brought on by the activation of the South-West monsoon (Gunathilaka & Harshana, 2023). The rapid process of urbanization, coupled with the influence of changed precipitation patterns resulting from climate change, are factors that contribute to the escalating occurrence and severity of floods (Xu et al., 2024). The urban population of Sri Lanka is expected to rise to 60% by 2030, up from 14% in 2010 (SerasinghePathiranage et al., 2018). The rapid growth of cities into flood-prone areas without sufficient planning and infrastructure exacerbates the impact of floods. This leads to the formation of informal settlements in vulnerable sites, increasing the risk to lives and property during flood occurrences.

Although there are technology-based solutions available for enhancing disaster awareness and management, they are not widely utilized within Sri Lankan communities. Jayasinghe et al. 2023 emphasize the pressing problem of inadequate awareness and the absence of official early flood alert systems in the country. This gap leads to limited participation from the community in disaster management, which reduces the level of preparedness and resilience of vulnerable populations in the face of disasters. Recent technological breakthroughs provide communities with the opportunity to share early crisis warnings throughout their networks. Mobile applications and crowdsourcing platforms are being recognized as useful means to improve community involvement (Alhaffar et al., 2023; Franco et al., 2019; Leventhal et al., 2024).

However, while platforms like Ushahidi have successfully demonstrated the power of participatory data in disaster response (Krishna et al., 2020), there is still insufficient integration of crowdsourced data with advanced remote sensing techniques like satellite data, which remains underexplored in the context of Sri Lanka. Furthermore, there is a noticeable shift from conventional relief-focused strategies to more progressive methods that highlight Disaster Risk Reduction (DRR) and Community-Based Solutions (CBS). The trend towards more decentralization and participation is facilitated by the use of advanced technological tools like GIS mapping, artificial intelligence (AI), and the Internet of Things (IoT). These tools improve the efficiency of community-based initiatives. These technologies enable the collection and distribution of data in real-time, allowing communities to actively engage in disaster preparedness and response operations (Kaur, 2024; Roy et al., 2023).

To fill this gap, the study develops a platform integrating a mobile application based on crowdsourcing with a web application. The platform aims in promoting inclusivity in disaster management and response by including the community and utilizing remote sensing technologies. A flood vulnerability assessment model has been developed by utilizing 30 years of historical flood data and nine conditioning elements, such as topographic features, weather-related variables, hydrological networks, land cover, and soil type etc. The smartphone application enables the instantaneous gathering of data from persons residing in flood-prone regions, enabling them to report flood levels, impacted areas, and other vital information. The crowdsourced data is subjected to verification using machine learning model to assure its accuracy. After being confirmed, the information is displayed on a web application, which serves as an essential communication tool for both the community and disaster response authorities. The methodology encompasses the formulation of a vulnerability assessment model, the construction of a mobile application including crowdsourcing methodologies, and the execution of trial workshops to involve the community and authenticate the platform with the participation of pertinent authorities. Mobilization techniques are suggested using the knowledge gained from these community contacts. This research makes a substantial contribution to the development of resilient and proactive urban communities in Sri Lanka by placing a high priority on community engagement and leveraging advanced geo-information technology. The results illustrate the significant capacity of integrating crowdsourced data with remote sensing to improve disaster management and community resilience.

Inspired by the insights gained during my undergraduate Individually Supervised Research Project, this study seeks to address the critical gap identified in the availability of updated flood-related data within the Sri Lankan context. During my previous research, I concentrated on assessing flood risk and encountered the substantial obstacle of insufficient and antiquated databases, especially about precipitation trends and flood-prone areas. This event underscored the pressing necessity for a comprehensive and current data management system to facilitate successful disaster management. Theoretically, this research contributes to the evolving discourse on participatory disaster management by integrating community-based crowdsourcing with advanced geospatial technologies, such as Sentinel-2 satellite imagery and machine learning algorithms. This approach refines existing flood vulnerability models by incorporating real-time, crowdsourced data, and provides a more scalable, cost-effective framework for urban flood management. In practice, the developed platform enhances disaster preparedness by providing an efficient solution for real-time flood risk assessment, empowering communities and authorities to respond proactively to flood hazards. The study's findings offer an innovative, cost-effective approach for integrating crowdsourced data with remote sensing, bridging information gaps in disaster management, and can be adapted to other flood-prone regions globally, contributing to urban resilience and risk-sensitive development efforts.

Objectives of the Study

1. To develop a web application with complementary volunteer crowdsourcing-based mobile application that enables real-time flood data collection and dissemination, enabling Participatory Risk Sensitive Urban Development (P-RSUD)
2. To create a flood vulnerability assessment model using historical flood data remote sensing technologies and Night-time light data to accurately identify and map flood-vulnerable areas

1.2.Research Question

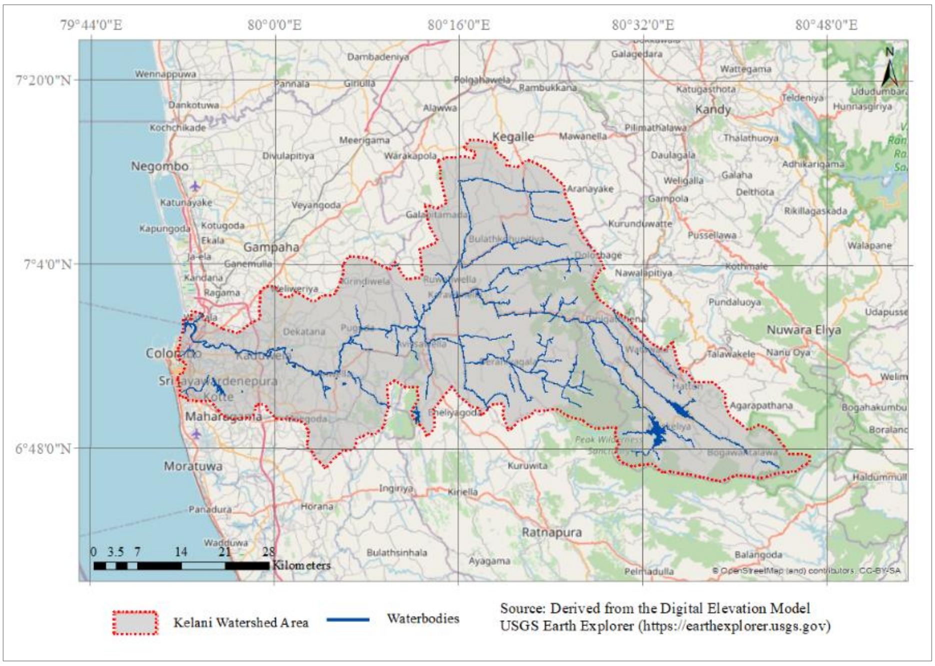
1. How to develop a web application, integrated with a volunteer crowdsourcing-based mobile application, facilitate real-time flood data collection and support

effective stakeholder engagement in Participatory Risk Sensitive Urban Development (P-RSUD)?
2. How can historical flood data, remote sensing technologies, and night-time light (NTL) data be integrated to create a comprehensive flood vulnerability assessment model?
3. How to mobilize the developed volunteer crowdsourcing application to efficiently gather reliable, real-time disaster information?

1.3.Scope of the Study

1.3.1. Geographical Scope

The Kelaniya watershed area has been selected as the case study for this study considering its significant relevance to urban flooding in Sri Lanka. The study area covers approximately an area of 2,298.9 km^2 and is subjected to rapid urban growth and frequent flooding. The Kelani River, across this watershed basin, undergoes annual flooding, mostly during May, and occasionally in February and November, with water levels rising to an average elevation of 3-4 meters near the two main gauging stations, Nagalagamweediya and Hanwella. The Hanwella station has been identified as the location with the highest risk of flooding in the basin. Over the previous decade, water levels at this station have risen by 19.7 meters, which represents a significant increase of 89.3% (Dushyantha & Ptuhina, 2020) Furthermore, the rapid urban expansion as seen in time-lapse satellite pictures, emphasizes the need to investigate this area to assess the extent of human vulnerability to urban flooding. The study area was defined using the Digital Elevation Model (DEM) generated from the Shuttle Radar Topography Mission (SRTM) data, acquired from the USGS Earth Explorer.



Source: Derived from the Digital Elevation Model, USGS Earth Explorer

Figure 1: Study Area (Kelaniya Waterhsed Basin)

1.3.2. Technological Scope

The technological scope of this study consists of the design and implementation of a mobile application and its complementary web application that allow collecting and sharing flood data in real time. In developing these tools, open-source or non-paid versions of software and platforms were used. This reflects the commitment of the project toward cost-effective and accessible technology solutions. Real-time data synchronization between the mobile and web applications is managed manually due to budgetary constraints within a window of about 5-10 minutes. Critical data gets updated in time, which would not have been possible with manual processes, even in the absence of paid servers or platforms.

1.3.3. Content Scope

The scope in the content of the research covers the most critical disaster management aspects oriented around community engagement, roles of crowdsourcing in real-time flood data collection, and flood vulnerability assessment using historical data, remote-sensing technologies, and night-time light data. Additionally, the study proposes mobilization strategies for the developed applications based on available literature and existing mobile applications. It recognizes the limitations of the currently available disaster management apps in stakeholder integration and mobilization as one of the key areas for further future research.

1.4.Limitations

There are few limitations in the study, significantly the technological and logistical limitations. The mobile and web applications were developed in open-source software and platforms that are non-paid, hence with very limited capabilities and scalability. Another challenge is data accuracy and quality issues innate in any crowdsourced data. This can be partially allayed by the development of a machine learning model to further enhance data validation. In Sri Lankan context the community engagement and participation are considerably low. This may be furthered by the different levels of digital literacy among the various communities. Furthermore, the crowdsourcing efforts are carried out inconsistently due to the developing volunteering culture in Sri Lanka itself. Factors that underline the need for further research and development in order to enable the overcoming of the above-mentioned limitations, particularly in data quality, and the diffusion of technological solutions.

1.5.Organization of the Thesis

This thesis is structured into four main chapters, systematically guiding the reader through the research process. **Chapter 1 - Introduction** provides an overview of the study, highlighting the significance of urban flooding, research objectives, questions, scope, and limitations. **Chapter 2 - Methodology** details the research design, data sources, and analytical techniques used, including the development of the mobile and web applications, integration of crowdsourced and remote sensing data, and the application of machine learning for data validation. **Chapter 3 - Results and Discussion** presents the findings from the study, including the refinement of the mobile application, user feedback analysis, and insights gained from bibliometric and systematic literature reviews. It also discusses the effectiveness of integrating community-driven flood data with geospatial modelling to enhance disaster management. **Chapter 4 - Conclusion and Recommendations** summarizes the key findings, evaluates the study's contributions to participatory risk-sensitive urban development, and provides recommendations for further improving community engagement and technological integration in disaster management. The thesis concludes with an assessment of its broader implications and potential applications in other flood-prone regions, reinforcing the need for scalable and cost-effective disaster resilience strategies.

CHAPTER 2 - METHODOLOGY

Chapter 2 outlines the research methodology used to develop a participatory flood risk management system. The study follows an inductive approach, identifying the problem and iteratively testing solutions. The methodology is structured into three stages: first, the development and testing of a mobile application for real-time flood data collection through crowdsourcing; second, a bibliometric and systematic literature review to analyse disaster management trends and assess existing mobile applications; and third, the integration of the mobile app with a web-based platform that utilizes remote sensing, night-time light data, and machine learning for data validation and flood vulnerability assessment. Statistical models, including the Frequency Ratio Model, are used to analyse flood susceptibility. This chapter establishes the technical foundation for the study, ensuring the accuracy, scalability, and effectiveness of the proposed flood management solution.

2.1. Research Approach

This study employs an inductive research methodology, commencing with the identification of a practical issue in flood management in Sri Lanka. Subsequently, solutions are formulated based on empirical data and subjected to iterative testing. The inductive technique is well-suited for this research as it enables the step-by-step development of a technology-driven solution, based on real-world observations and input from stakeholders.

2.2. Research Design

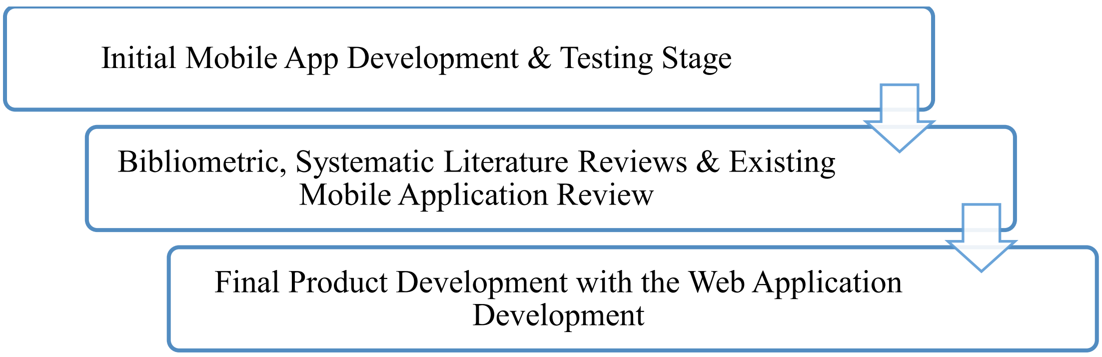


Figure 2: Research Design

The study comprises three primary phases, each utilizing separate submethodologies to accomplish the objectives of the study. The initial phase encompassed the development and testing of a prototype mobile application aimed at gathering real-time flood data through crowdsourcing. 30 individuals participated in the initial testing session to test and improve the functionality and data accuracy of this app. In the second phase, bibliometric and systematic literature reviews were conducted, as well as an evaluation of existing mobile applications, to identify any deficiencies and acquire valuable ideas for improving engaging communities in disaster management approaches. The last phase involved the development of mobile and web applications.

2.2.1. Stage 01 – Initial Mobile App Development & Preliminary Testing Stage

During the initial development phase of the mobile application, the study utilized a systematic methodology to ensure the app's significance and efficacy in the context of flood management within the Kelaniya watershed basin area. The app was developed utilizing web-based, freely available platforms, which enabled cost-efficient deployment (Figure 03). The testing phase encompassed a diverse set of volunteers, selected randomly, who represented a broad spectrum of age groups, gender, educational backgrounds, and employment positions. This ensured that the app's usability could be evaluated across a wide range of user demographics.

Participants were involved in practical trial session to evaluate the app's performance, which encompassed tasks such as data input, navigation, and the overall user experience. A structured questionnaire was filled out after testing to assess the app's performance and identify any potential difficulties (Figure 04). This questionnaire (Annexure 01) specifically examined important factors such as the ease of use for users, and the willingness of participants to contribute to crowdsourcing and volunteer activities. The feedback played a crucial role in improving the application, ensuring that it effectively meets both technical and user engagement requirements. prototypes and testing photographs from this phase were recorded and examined to provide guidance for the following development stages.

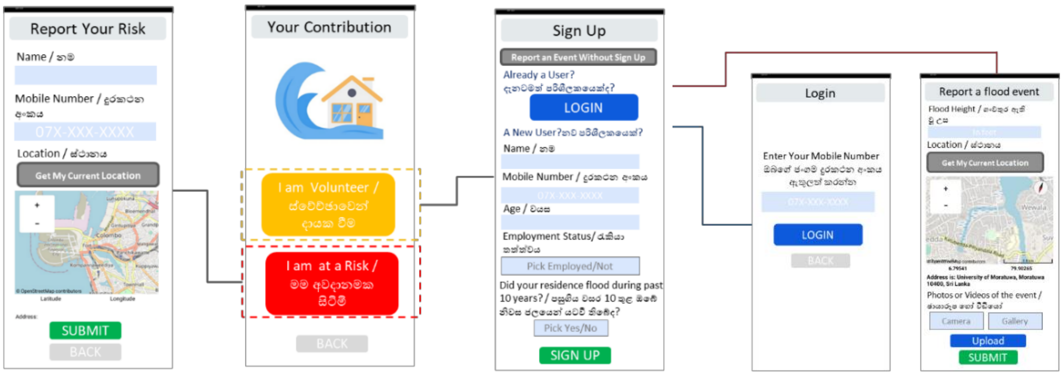


Figure 3: Initially Developed Mobile App

Figure 4: Photographs of the Initial Testing Session

2.2.2. Stage 02 – Bibliometric, Systematic Literature Reviews & Existing Mobile Application Review

Initially, a thorough bibliometric study was carried out by scanning relevant academic databases, such as Web of Science and Google Scholar. A total of 525 articles were retrieved using meticulously chosen keywords, including "Risk Sensitive Urban Development". The articles were analyzed to determine word frequency and temporal trends, which revealed valuable information about the development of important concepts and the distribution of study within the discipline. Then a systematic literature review was done using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) standards. Out of the original set of publications, 56 were chosen using a few criteria that considered their relevance (Figure 5), and recent contributions to this topic. This systematic review integrated current information and provided the basis for the conceptual framework that will guide the next phases of the study.

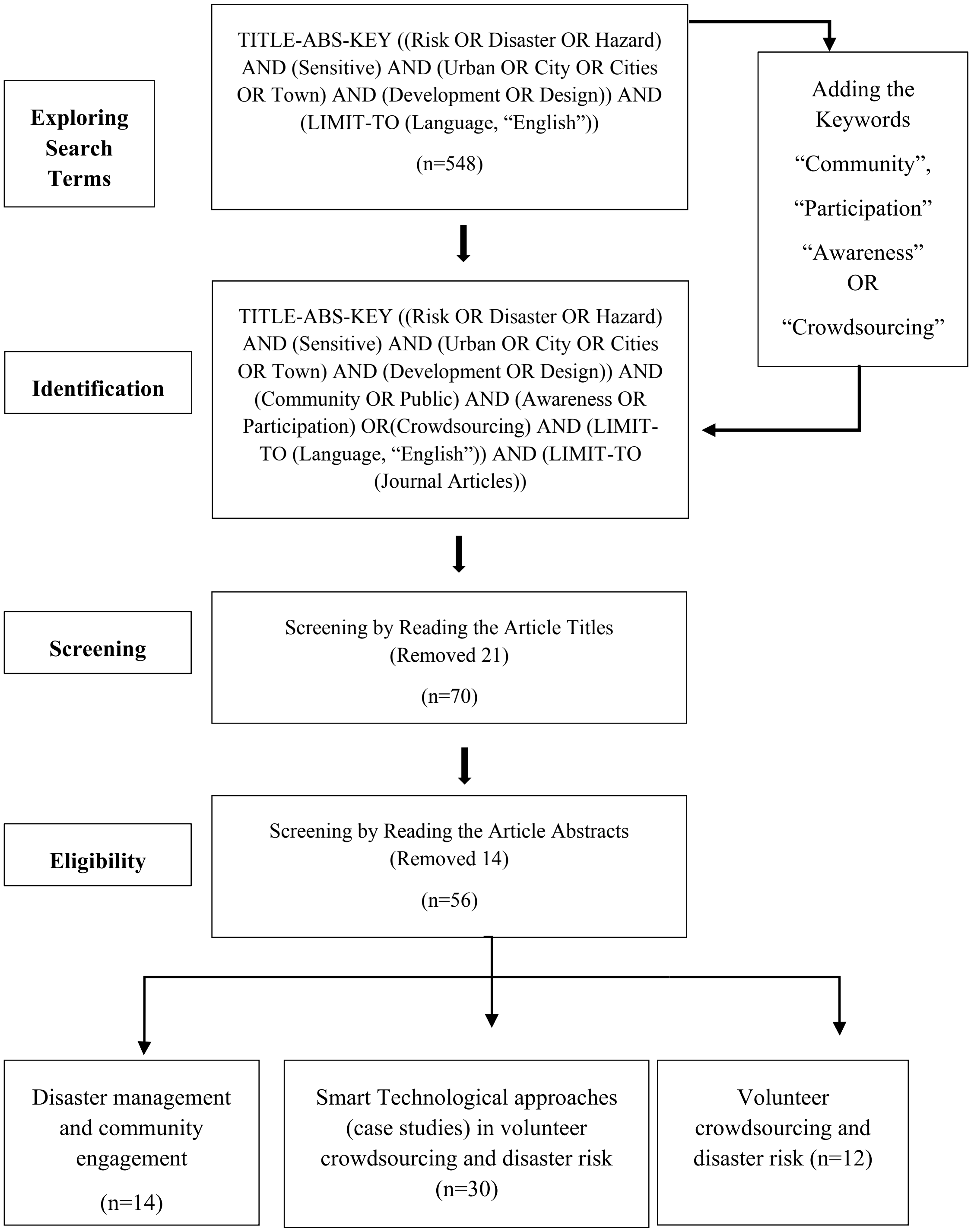


Figure 5: The PRISMA Flow Diagram (Adapted From Pérez-Gañán et al., 2023; Kankanamge et al., 2019)

Furthermore, a comprehensive examination of current mobile applications pertaining to disaster management was conducted, in addition to the bibliometric and systematic reviews. This assessment was limited to the Google Play Store due to constraints on data extraction, thereby eliminating the Apple App Store from the analysis. The selection criteria for this assessment encompassed mobile applications on disaster management, awareness, and alarm systems, with a specific emphasis on apps relating to floods. A total of 78 applications were identified for examination by searching for keywords such as "Disaster Management," "Disaster Awareness," "Disaster Alert," "Flood Apps," and "Flood Alert Apps." The data sources utilized for this evaluation encompassed user reviews from the Play Store, personal installation and testing of the programs, and extra secondary internet searches. The review procedure evaluated the applications by considering their functionality, user engagement, technical integration, and the alignment of their features with the requirements of disaster management.

2.2.3. Stage 03 - Final Product Development integrating with the Web Application.

The third phase of the study is conducted under two sub-stages. In the first sub-stage, the basic mobile application built and tested during Stage 1 was refined in the first sub-section. The refinement process was informed by the comments provided by participants, the insights obtained from comprehensive literature research, and the study of existing mobile applications in disaster management. The objective was to optimize the user experience, boost data precision, and ensure that the application's functionality is in line with the current technology landscape in disaster management.

The second sub-section concentrated on the development of an interconnected web application intended to assess the degree of susceptibility to flooding and the level of human exposure to flooding in Kelaniya watershed area. The development of this web application was done under the below-demonstrated methodology (Figure 6).

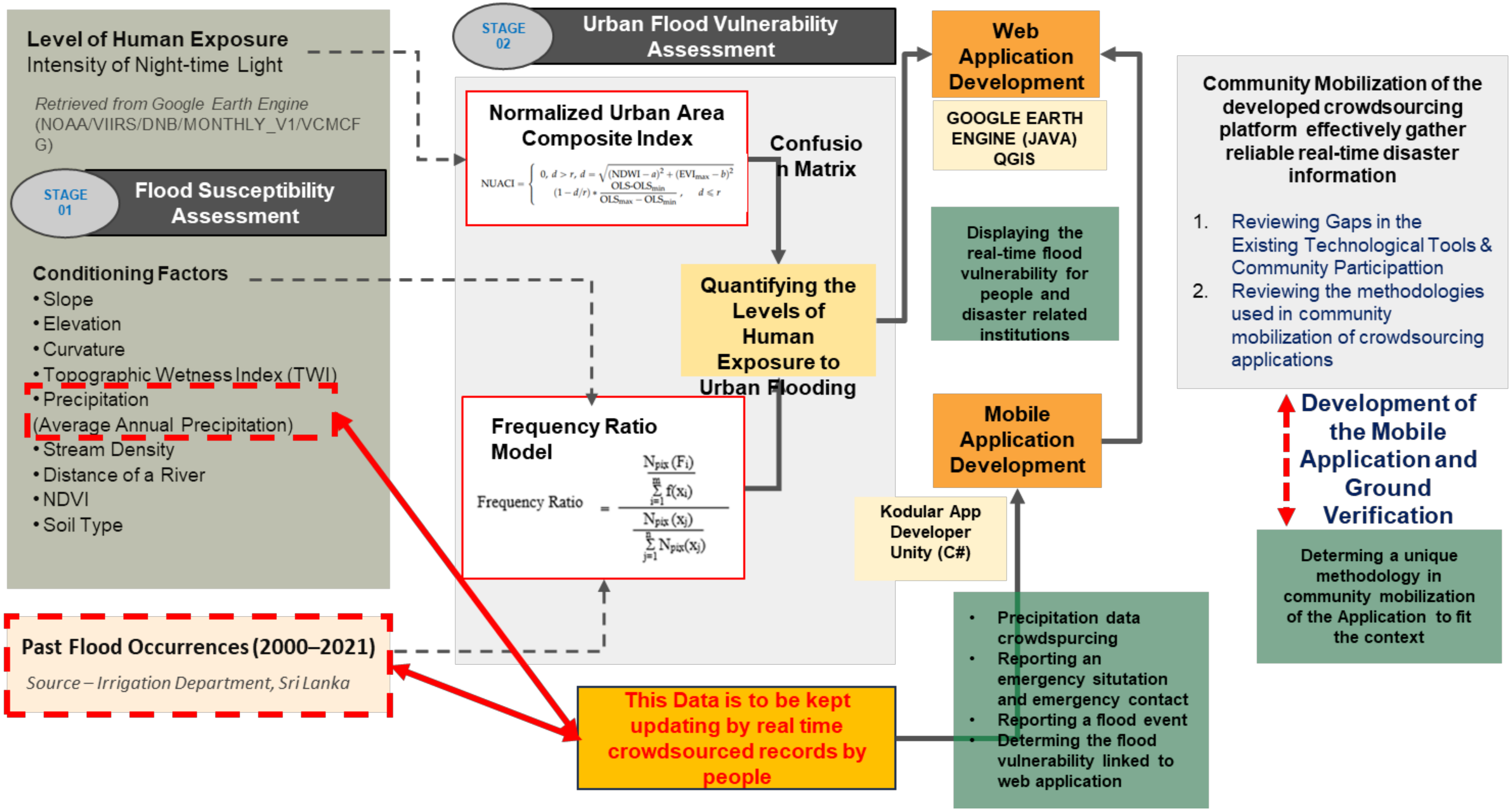


Figure 6: Stage 03-Methodology

Step A: Urban Flood Vulnerability Assessment

I. **Level of Human Exposure; Intensity of Night-time Light**

NTL data is the main source of data used in the study to examine the human exposure levels, which records the brightness of the light emitted artificially from the human activity features. Even though non-urban activities such as agriculture and burning can produce light emissions that can be detected by NTL sensors, urban areas are the primary source of light associated to habitation, land, energy consumption, and other development-related activities. This is because urban regions are where most of these activities take place (Ferreira & Condessa, 2012). The NTL is captured using two satellites currently, The Défense Meteorological Satellite- Program Operational Line Scan System (DMSP-OLS) and Suomi National Polar-orbiting Partnership visible IR Imaging Radiometer Suite (NPP-VIIRS). In the study, NPP-VIIRS has been used in which data is available from 2012 to 2022.

II. Urban Flood Susceptibility

According to Khosravi et al. (2018) magnitude of the flood depends on the duration and the intensity of rainfall while catchment characteristics such as topographic features, land cover, soil characteristics, and river network are the factors affecting flood susceptibility. Accordingly, the following are the conditioning factors and the attributes considered under each factor for the study.

Table 1: Conditioning Factors & Attributes

<table>
<tr><th>Conditioning Factor</th><th>Attributes</th><th>Source of Data</th></tr>
<tr><td rowspan="4">Topographic Features</td><td>Slope</td><td rowspan="3">Derived from DEM,
SRTM Data from USGS Earth Explorer</td></tr>
<tr><td>Elevation</td></tr>
<tr><td>Curvature</td></tr>
<tr><td>Topographical Wetness Index (TWI)</td><td>Derived from Flow Accumulation, SRTM Data from USGS Earth Explorer</td></tr>
</table>

Weather Related Factors	Precipitation (Average Annual Precipitation)	Meteorological Department, Sri Lanka
Hydrological Network	Stream Density	Survey Department, Sri Lanka
	Distance of a River	
Land Cover	NDVI	Remote Sensing, Landsat 8 data from USGS Earth Explorer
Lithology	Soil Type	National Building Research Organization

1. *Slope*

Slope is one of the key factors in regional flood analysis, in which the slope angle is the main parameter of study, as the steeper slope results in increased runoff (Tehrany et al., 2014). The slope angle has been categorized into five main classes as, 0-5^0, 5^0 – 12^0, 12^0 – 18^0, 18^0 – 30^0, and 30^0 – 70^0.

2. *Elevation*

The probability of flood occurrence is lower in high elevations is comparatively higher in low elevations (Meybeck et al., 2001). Accordingly, the elevation map has been taken into analysis and classified into five classes as, 0-200m, 200m – 500m, 500m -1000m, 1000m – 1500m, and 1500m – 2500m.

3. *Curvature*

Curvature is also another key indicator in regional flood susceptibility analysis, which reflects the shape of the ground surface (Khosravi et al., 2019). Therefore, a curvature map is derived from the DEM classified into five classes as -4.6 – -0.5, -0.5 - -0.1, -0.1 – 0.2, 0.2 – 0.6, and 0.6 – 7.5.

4. Topographical Wetness Index (TWI)

TWI is a qualitative representation to evaluate the runoff, which is also a geometric parameter of soil moisture (Rahmati et al., 2016).

As = (flow accumulation+1) * cell size

Equation 1: Cumulative Upslope Area Draining through a Point

$TWI = \ln (As/\tan (\beta))$

Equation 2: Topographic Wetness Index

'As' is the cumulative upslope area draining through a point (per unit contour length) and $\tan\beta$ is the slope angle at the point (Mitra & Das, 2022). ArcGIS software was used to produce TWI as classified into 6 classes as, 0 - 8, 8 - 10, 10 - 12, 12 - 15, and 15 – 25.

5. Precipitation

Precipitation is the main factor affecting the magnitude and duration of the flood. Therefore, in flood susceptibility annual average rainfall for the past five years from 2017 to 2022 has been taken into consideration under five classes as 2000 – 3500 mm, 3500 – 4000 mm, 4000 – 4500 mm, 4500 – 5500 mm. 5500 – 8500 mm.

6. Stream Density

Stream density is also, one of the main conditioning factors that contribute to flood occurrence (Rahmati et al., 2016). The density was determined using ArcGIS software which calculates the stream links per unit area, which is classified into five classes as, 1 – 0.12, 0.12 – 0.3, 0.3 – 0.5, 0.5 – 0.75, and 0.75 – 1.3.

7. Distance of a River

Hydrological network is a key determinant of flooding therefore, the distance from a river link buffer map was also considered in the analysis and classified into five classes as, 0 – 200m, 200 – 500m, 500 - 1000m, 1000 – 2500m, and 2500 – 5000m to assess the effect of its extent of flooding.

8. NDVI

The land cover, which determines the level of infiltration and runoff is a critical factor in urban flooding (Khosravi et al., 2019). NDVI was calculated using the equation below using Google Earth Engine.

$$\text{NDVI} = \frac{\text{NIR Band} + \text{RED Band}}{\text{NIR Band} - \text{RED Band}}$$

Equation 3: Normalized Difference Vegetation Index

The NDVI map was created using Operational Land Imager (OLI) sensor images from the Landsat 8 satellite, which were classified into five classes as, -0.32 – 0, 0 – 0.3, 0.3 – 0.5, 0.5 – 0.6, and 0.6 – 0.8.

9. Lithology

Soil type also plays a key role in the rate of infiltration which directly affects the magnitude and extent of flooding, which are classified into the following categories as extracted from the National Building Research Organization soil type mapping, (a) erosional remnants steep rock (b) Latosols and regosol red and yellow sands (c) Reddish brown latosolic soils, (d) Red-Yellow podzolic soils and mountain regosol (e) Red-Yellow podzolic soils strongly mottled sub-soils, and (f) Red-Yellow podzolic soils with prominent A1 or semi-prominent A1.

Past flood occurrence; River gauge data from 2000-2021

Past flood occurrence, the extent, and the return period are mandatory to analyse future flood susceptibility (Manandhar et al., 2010). Therefore, the source of past flood occurrences in the Kelani River basin is the daily readings of the river gauges of Kelani River, Hanwella, and Nagalagam Weediya. The data was obtained from the Irrigation Department, Sri Lanka for the past 21 years from 2000 to 2021. The flood was identified with the daily gauge reading according to the table below (Table 2: Flood Identification).

Table 2: Flood Identification

Gauging Station	Location	Alert Level	Minor Flood Level	Major Flood Level
Hanwella	6.9079, 80.0630	7.00 ft	8.00 ft	10.00 ft
Nagalagam Weediya	6.9579, 79.87862	4.00 ft	5.00 ft	7.00 ft

The average daily water levels from 2000-2021 is depicted in the figure below (Figure 7: Average water level of gauging stations (Hanwella & Nagalagam Weediya), Source: irrigation Department, Sri Lanka), extracted from the hourly water levels of the Hanwella and Nagalagam Weediya gauging stations.

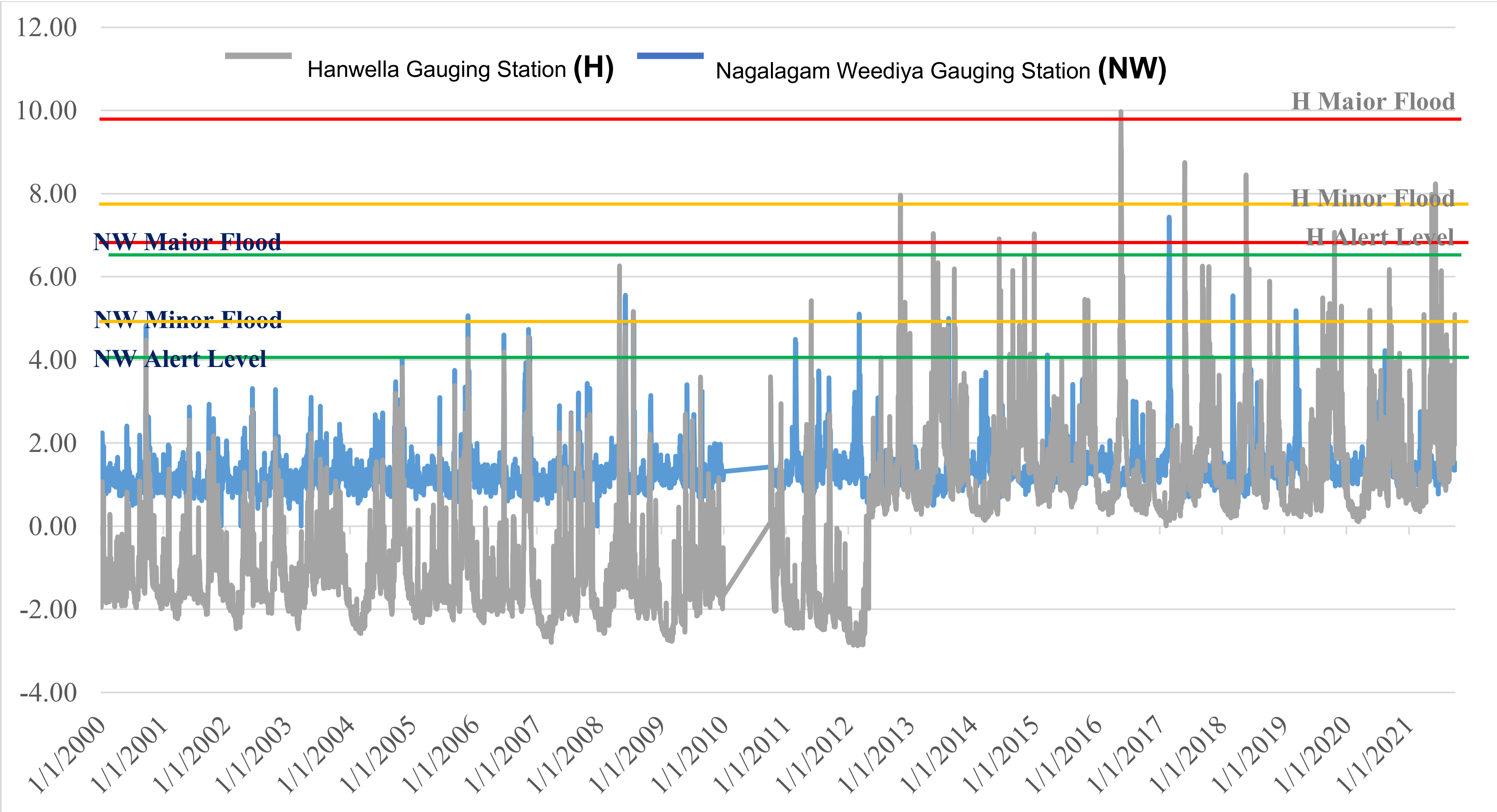


Figure 7: Average water level of gauging stations (Hanwella & Nagalagam Weediya), Source: irrigation Department, Sri Lanka

Sentinel-1 SAR GRD: C-band Synthetic Aperture Radar

After identifying the flood occurrence, the flood extent is to be identified using Sentinel-1 SAR GRD: C-band Synthetic Aperture Radar. SAR is capable of acquiring data in any weather condition during both daytime and night-time. Therefore, in identifying the previous flood events with higher accuracy, Sentinel 1 SAR data has been used in the study which is retrieved from the GEE.

Function of the Crowdsourced Data

The application integrates various geospatial datasets, such as night-time light (NTL) data and satellite images, to dynamically map flood vulnerability in the Kelaniya watershed area. Two key dynamic variables critical to assessing flood vulnerability were identified: precipitation and past flood occurrences. These variables are known to change rapidly over time and significantly impact the flood risk profile of urban areas. Real-time precipitation data is vital in predicting flood risk, as the magnitude and duration of rainfall are directly correlated with flooding events while Accurate historical flood data is essential for predicting future flood risks and understanding flood patterns (Khosravi et al., 2018; Manandhar et al., 2010).

The innovative aspect of this approach lies in the utilization of crowdsourced data for these two dynamic variables. The mobile app enables users to report real-time observations related to local precipitation levels and any recent flood events. To facilitate user participation, the mobile app offers a simplified interface where users can input rainfall data categorized into predefined levels for ease of use. These categories, as shown in the table below, are mapped to standardized precipitation rates per hour based on established literature:

Table 3: Average amount of precipitation according to categories

Input options for the users	Average amount of precipitation
Not raining	(0 mm/h)
Slight Drizzle	0.5 mm/h

Drizzle	2.5mm/h
Average Rain	10 mm/h
Heavy Rain	33 mm/h
Thunderstorm	50 mm/h

Since general public have limited understanding on measuring precipitation and do not have access to measuring equipment, the app simplifies data entry by offering a set of predefined categories that users can choose from based on their perception of the rainfall intensity. Each category corresponds to an estimated precipitation rate per hour, which is derived from relevant studies and literature on precipitation measurement. By transforming the qualitative input from users into quantitative precipitation rates, the application can more effectively integrate this data into its flood vulnerability models.

Secondly, the occurrence of flood events the users can input flood heights and upload images if available. The app automatically detects the location of the report through the device's GPS, ensuring accurate and precise data collection. This method is particularly valuable in regions like Sri Lanka, where comprehensive and up-to-date flood event datasets are lacking.

This data is then continuously fed into the web application, allowing for near-instantaneous updates to the flood vulnerability models. By incorporating real-time crowdsourced data, the web application provides a more accurate and up-to-date representation of flood risk. While static variables, such as topography (slope, elevation, and curvature), land cover, hydrological network characteristics, and soil type are already integrated into the GEE platform, these datasets do not require frequent updates as they represent relatively stable, long-term conditions (Rahmati et al., 2016; Tehrany et al., 2014). The static datasets, sourced from reliable repositories like the USGS Earth Explorer and local meteorological and survey departments, form the foundational layers of the web application's flood vulnerability assessment framework. By combining these stable datasets with dynamic, real-time data on precipitation and past flood occurrences sourced directly from community members, the web application offers a more comprehensive and current analysis of flood vulnerability. This integrated approach also facilitates stakeholder collaboration in validating data accuracy, enhancing trust in the platform's findings, and encouraging ongoing community engagement.

By incorporating these real-time, crowdsourced inputs, the web application dynamically adjusts its analysis to reflect the latest conditions, thereby offering a robust tool for disaster preparedness and response. This model demonstrates how utilizing community-sourced data can bridge gaps in traditional disaster management frameworks and enhance the resilience of urban areas to climate-related hazards.

III. Overlaying

Normalized Urban Area Composite Index (NUACI)

According to Liu et al. (2015), the NUACI proposes a new approach to depicting urban activities comparing with a number of indices (Human Settlement Index, Vegetation Adjusted NTL Urban Index) whereas NUACI accounts for the highest accuracy. Therefore, in validating the use of NTL Data in measuring human exposure to urban flooding, NAUCI is utilized.

$$\mathrm{NUACI} = \begin{cases} 0,\ d > r,\ d = \sqrt{(\mathrm{NDWI} - a)^2 + (\mathrm{EVI_{max}} - b)^2} \\ (1 - d/r) * \dfrac{\mathrm{OLS\text{-}OLS_{min}}}{\mathrm{OLS_{max}} - \mathrm{OLS_{min}}}, \quad d \leqslant r \end{cases}$$

Equation 4: Normalized Urban Area Composite Index

NDWI – Normalized Difference Vegetation Index,

[NWDI (Sentinel 2A) = (NIR - MIR) / (NIR + MIR)]

EVI – Enhanced Vegetation Index,

[EVI (Sentinel 2A) = (2.5 * ("NIR Band - "RED Band")) / ("NIR Band " + (2.4 * " RED Band ") + 1)]

a – Average Value of NDWI,

b – Average Value of EVI,

r - Radius of the circle region aggregated with urban samples

d - Distance to the center of the circle

OLS_{min} - Minimum values in the DMSP-OLS image (VIIRS has been used)

OLS_{max} - Maximum values in the DMSP-OLS image (VIIRS has been used)

Accordingly, NUACI ranges between 0 – 1, which can be utilized in validating the accuracy of using VIIRS in extracting the human activities in an urban area to measure the human exposure to urban flooding.

Frequency Ratio Model

For the study, Frequency Ratio Model has been used as the bivariate statistical technique, that builds up a qualitative relationship between the frequency of flood occurrence and different conditioning factors (Samanta et al., 2018). The Frequency Ratio is calculated using the following Equation (Equation 5)

$$\text{Frequency Ratio} = \frac{\text{Urban Flood Occurrence Ratio}}{\text{The Ratio in each Class in Conditioning Factors}} \quad \text{---------} \quad \text{Equation 5: Frequency Ratio Application}$$

Accordingly, the weighted value of the classes used to categorize each parameter is determined based on urban flood occurrence in each class. This method depends on the selection of the required parameters and their categorization into a number of classes, overlaid with the previous flood occurrences in higher frequency, finally, the level of susceptibility to flooding in the selected area is determined. Further, the following equation (Equation 6: Frequency Ratio) is used in weighing each class of the selected conditioning factors that qualitatively determine the level of flood susceptibility.

$$\text{Frequency Ratio} = \frac{\dfrac{N_{pix}(F_i)}{\sum_{i=1} f(x_i)}}{\dfrac{N_{pix}(x_j)}{\sum_{j=1} N_{pix}(x_j)}} \text{ --------- Equation 6: Frequency}$$

$N_{pix}(F_i)$ = The number of pixels with flood within class i of conditioning factor variable X,

$N_{pix}(x_j)$ = The number of pixels within conditioning factor variable,

m = The number of classes in the parameter variable,

n = The number of factors in the study area.

According to Pradhan & Youssef, (2010), the conditional probability of an event to occur, when another past occurrence has been recorded is the likelihood of that event to happen as said in the probability theory. Therefore, in calculating the Flood Susceptibility, the conditioning factor layers are reclassified according to the weights obtained by the frequency model and all the factors are summed-up as in the below equation (Equation 7), where *fr* is the reclassified conditioning factors based on the determined Frequency Ratio weights.

$$\textit{Flood Susceptibility} = fr_1 + fr_2 + fr_3 + fr_4 + \ldots + fr_n \text{ -------- Equation 7: Flood Susceptibility}$$

Confusion Matrix

The confusion matrix is used in the study to assess the accuracy of using NTL as the indicator of human activities, with the Normalized Urban Area Composite Index (NUACI), which accounts an accuracy of 96% according to a study by Tong et al., (2018) that reviews different indices to derive the urban areas using remote sensing. Accordingly, the confusion matrix can be simplified as below.

Table 4: Confusion Matrix

	Actual Positive	Actual Negative
Predicted Positive	True Positive (TP)	False Positive (FP)
Predicted Negative	False Negative (FN)	True Negative (TN)

Equation 8: Accuracy Assessment (Confusion Matrix)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

4.1

According to the above discussed methodology the web application was developed utilizing Google Earth Engine (GEE) using Java programming language. This platform facilitated the examination and representation of geospatial data, namely in monitoring immediate human exposure to urban flooding. The application utilized real-time night-time light (NTL) data and other satellite pictures, effectively incorporated via GEE. The utilization of this approach was crucial in monitoring alterations in flood vulnerability and human proximity, taking into account the ever-changing character of urban expansion and climate trends. The web program was developed with the capability to easily change to various locales, necessitating very minimal input data layers and modifications to the watershed border.

The web application integrated with the crowdsourced data gathered via the mobile app. The data underwent processing using a machine learning model, specifically the DBSCAN method, in order to eliminate outliers and guarantee the dependability and precision of the supplied information. Furthermore, the platform is expected to collaborate with the stakeholders in the disaster management disclosure and a mechanism to validate data through those organizations is also open for further procedure. The incorporation of these components results in a comprehensive platform for assessing flood susceptibility in real-time and promoting urban planning that is sensitive to risks.

CHAPTER 3- RESULTS AND DISCUSSION

This chapter presents the results and discussion of the study, analysing the effectiveness of the developed mobile and web-based flood risk management system. It evaluates user feedback from mobile application testing, highlighting engagement levels, usability challenges, and improvements made based on participant input. The findings from the bibliometric and systematic literature review are discussed, emphasizing trends in disaster management and the role of community participation. The integration of crowdsourced flood data with remote sensing and machine learning techniques is assessed, demonstrating the accuracy and reliability of the developed flood vulnerability model. The chapter also explores the potential of participatory approaches in disaster management, addressing key challenges such as data validation, stakeholder collaboration, and technological constraints. The results validate the feasibility of combining crowdsourced data with geospatial analysis to enhance real-time flood monitoring and response.

3.1.Initial Mobile App Development & Preliminary Testing

The initial testing stage of the mobile application included a diverse sample of 30 individuals from the Kelaniya watershed basin region. The participants were three-wheeler drivers within the flood prone areas, considering the high mobility within disaster prone area and as a group of local residents with an understanding on the disaster situations, chosen randomly to ensure a diverse range of demographic factors, including age, gender, educational background.

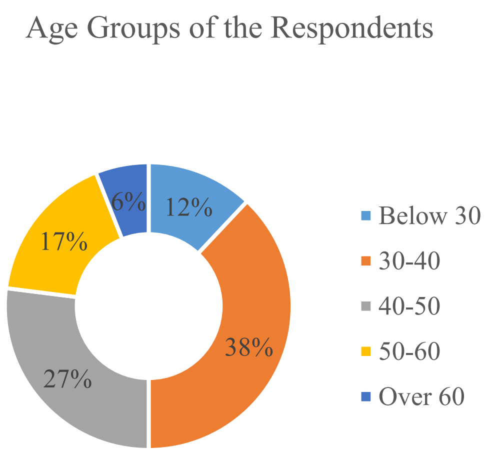


Figure 8: Age Groups of the Respondents

The majority (38%) of the respondents were in between the age of 30 – 40 years, and over 50% of them were in the income group Rs.50,000 – Rs. 70,000. While only 22 of them had smart phones in working condition. The participants were inquired about their past flood experiences, there 26 participants out of the 30 have faced flooding in their residential areas or workplaces.

The survey was comprised of two sections other than their profile discussed above, the first section focused on participants' general opinions regarding mobile applications that employed crowdsourcing for various purposes, such as the Fuel Distribution App (Mobile app, where people updated the location of the fuel stations where fuel is available and the other people who use the app can easily find the stations where fuel is available) used during the economic crisis in Sri Lanka and the Train Schedule App. They were aware of the Fuel Distribution App, and they highlighted its efficacy and use. However, a minority (less than 10%) of individuals were unaware of these applications and instead relied on information obtained from people in general, platforms such as Facebook, and their WhatsApp groups. Accordingly, there is a majority that are willing to use crowdsourcing and mobile platforms as a tool in disseminating information.

The second section focused on the aftermath of the trial mobile app that was developed to gather information about flood disasters through crowdsourcing. The application was installed to the respondents' mobile phones, and they were asked to use the application for 10 days during monsoonal rain during September 2023. Initially, they were inquired about their present method of receiving early warnings or information regarding flooding. More than 90% of the respondents highlighted the absence of an early warning system for flooding in their respective localities. The majority of individuals emphasized that residents in flood-prone regions having local knowledge regarding river water levels, continuous rainfall during the monsoon season and the subsequent filling up of nearby wetlands. As a result, they are aware about the situation and make the decision to evacuate for a period of 2-3 days. However, a few individuals indicated that they were unfamiliar with the area and their domestic equipment was damaged and faced extensive damage due to flooding. Finally, they were inquired on the application introduced to them for crowdsourcing flood events, majority of the people appreciated the initiative while few respondents mentioned that they do not have a motivation to use such apps as they are already aware on the situation and evacuate accordingly. Therefore, emphasizing the social benefit of the initiative as well as implementation of a robust mechanism in mobilizing with individual benefit is up for further exploration in the next stages of the app development. Following with important comments on the app functions and user interface of the mobile application, the requirement of contacting emergency help for people in disaster situation, allowing people to communicate with their local neighbourhoods within the app, and complexity in the user interface.

3.2. Analysis of the trends of keyword behaviour in the Disaster Management Domain: Bibliometric review

As discussed extensively in the methodology, the research followed an inductive approach, therefore as the second stage a review of literature was conducted, establishing the observed gap in the current practice studying the conventional and contemporary approaches in the disclosure. Accordingly, 525 papers were included in the bibliometric literature survey from the keyword search. Below table presents the summary of the number of papers employed in the survey under each keyword search.

Table 5: Number of articles under each Search Command

Search Command	Number of articles
IN TITLE “risk AND sensitive AND urban AND design”	93
IN ABSTRACT “risk AND sensitive AND urban AND design”	121
IN TITLE “risk AND sensitive AND city* AND design”	33
IN TITLE disaster AND sensitive AND city* AND design	203

IN TITLE hazard AND sensitive AND city* AND design	24
IN TITLE vulnerability AND sensitive AND city* AND design	51
TOTAL	525

Initially, a keyword analysis and a temporal analysis of the keywords was performed to understand the trends related to risk-sensitive urban development. The keyword analysis, depicted in Figure 9, is a visual representation of the connections and occurrence rate of different terms related to risk-sensitive urban development. The network map illustrates that significant discussions are concentrated around numerous prominent topics, including "community," "data," "process," "change," "water," and "exposure." The significance and magnitude of the nodes, such as "community," "data," and "change," signify their substantial impact within the study area, implying that these concepts are fundamental to discussions on disaster risk reduction and urban growth.

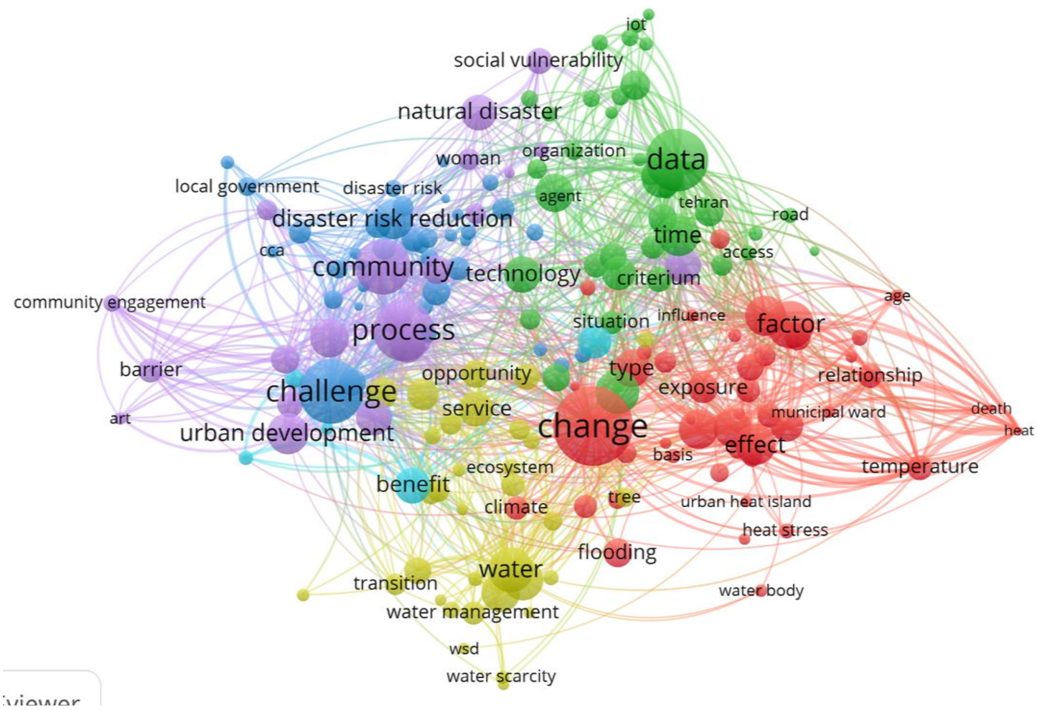


Figure 09: Most Frequent Keywords (Abstract Analysis)

Specifically, the frequent use of words such as "community" and "process" highlights the continuous focus on involving the community and adopting participatory methods in managing disaster risks. The recurring use of the terms "data," "exposure," and "change" emphasizes the growing dependence on data-driven approaches to analyze and address the constantly evolving urban risks. The interrelation of these issues with concepts like as "natural disaster," "technology," and "challenge," implies the shift towards technology-driven approaches. This approach considers social, technological, and environmental variables together to effectively manage urban risk sensitivity.

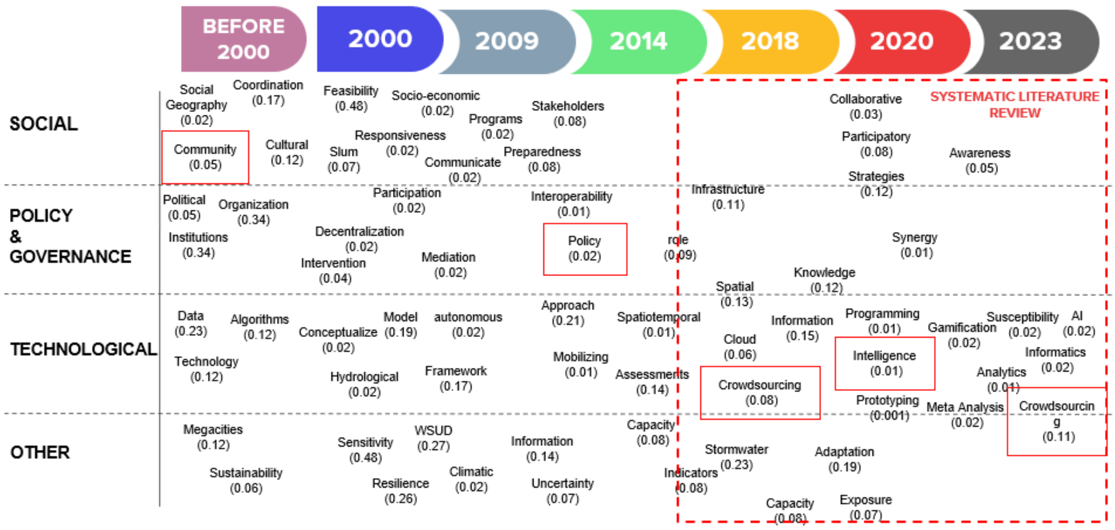


Figure 10: Temporal Analysis of the Keywords

The temporal analysis, depicted in Figure 10, provides additional insights into the evolution of the risk-sensitive urban development disclosure. Accordingly. before 2000, the initial conversations primarily revolved around social geography and the synchronization of urban development endeavors. The term "community" was identified in the literature, but its significance was low compared to the last decade. Nevertheless, as we progress into the 2000s and beyond, there is a noticeable transition towards more intricate and interconnected concepts, such as "feasibility," "socio-economic" considerations, "stakeholders," and "preparedness."

Starting in 2018, the literature has been placing more emphasis on technical breakthroughs and how they are used in urban risk management. The terms "crowdsourcing," "cloud computing," "AI," "gamification," and "programming" are becoming important subjects, indicating the increasing interest in using technology to collect and analyze real-time data and engage with communities. The frequent occurrence of the terms "policy," "infrastructure," and "collaboration" during this time period emphasizes the crucial importance of governance and institutional frameworks in facilitating technology solutions and assuring their efficacy in disaster management. During the last five years, the conversation has already shifted towards more specific domains such as "meta-analysis," "machine learning," and "gamification," which are anticipated to significantly influence the future direction of research and application in this discipline.

Concluding, the bibliometric study indicates a distinct progression in the discussion surrounding risk-sensitive urban development, with an increasing focus on technology, data-driven methodologies, and community engagement. These findings highlight the necessity for ongoing interdisciplinary research and collaboration in order to address the issues presented by urbanization and climate change.

3.3. Role of Crowdsourcing in Disaster Management: Systematic Literature Reviews

Following with a systematic review conducted comprehensively investigating the evolution of community involvement in disaster management, analyzing both conventional and contemporary methods. The environment depicted showcases the coexistence of conventional Community-Based Disaster Management (CBDM) practices and rising technological technologies, which typically vary in terms of effectiveness and community participation.

Accordingly, scholarly literature has identified two main approaches that effectively utilize strategies and resources at various stages of the disaster management process, (1) approach prioritizes community engagement, (2) approaches depending on data-driven techniques including remote sensing, historical events, predictions, artificial intelligence, machine learning, and other novel technologies, without requiring community involvement. Additionally, some methodologies include both the principles of community engagement and the efficient utilization of smart techniques. The second strategy has been the focus of substantial discussion in case studies over the past decade, among the two basic categories. Out of the 30 case studies, more than 20 are focused on the intelligent strategies employed in disaster management. As discussed by Singh et al. 2024 and Varsha et al. 2024, there is a current trend toward using unmanned aerial vehicles (UAVs), IoT Networks, Artificial Intelligence, and Machine Learning to process large datasets, identify patterns, and improve predictive models in disaster management.

Significantly, the review examined the reasons behind the lack of consideration given to community engagement in the current disaster management approaches. The lack of attention given to community engagement in the crisis management process may be traced back to historical circumstances and governmental priorities throughout the 2010-2012 timeframe. Traditionally, disaster management strategies have frequently followed a hierarchical approach, prioritizing centralized decision-making and coordination of response efforts (Mayer, 2019). The centralized approach has unintentionally disregarded the vital participation of local communities in achieving disaster resilience and recovery.

The dominant frameworks that shape disaster management strategies often emphasize a hierarchical and regulatory structure, prioritizing formal institutions and procedures. Consequently, these inflexible systems often neglect community engagement, which depends on local expertise, connections, and grassroots initiatives (Comfort & Dunn, 2023). The inherent rigidity of crisis management methods could hinder the active engagement of communities, hence constraining their efficacy. Inadequate resources and funding dynamics exacerbate the disregard for community engagement in disaster management (Mohammad & Huq, 2016).

One significant issue contributing to the absence of community engagement is the existence of communication gaps and challenges in the transmission of information between authorities and local communities(Paton, 2019). Efficient community engagement relies on transparent and easily available communication channels. Nevertheless, bureaucratic institutions and centralized decision-making can impede the prompt distribution of crucial information to individuals who are directly affected by disasters. Hence, it is crucial to integrate potential intelligent technology to address these deficiencies. During the 2018 Sulawesi earthquake and tsunami in

Indonesia, individuals encountered substantial difficulties caused by the delayed spread of information (Wang & Tsai, 2022), as observed in the incidents documented by Prawenti et al. (2023) and Wang & Tsai (2022). To fill these deficiencies, intelligent technologies such as mobile applications, crowdsourcing platforms, and social media integration might be employed. Mobile applications have the capability to deliver real-time notifications directly to users, while platforms such as Ushahidi can provide immediate awareness of the current situation by utilizing data contributed by a large number of people(Raja & Thomas, 2019). By integrating these technologies, the speed and accessibility of catastrophe communication can be greatly improved, leading to more effective community involvement.

The challenge of including the community in crisis management is made much more difficult by cultural and socioeconomic disparities. Vulnerable and marginalized communities sometimes face challenges that impede their active participation in decision-making processes. These challenges include linguistic challenges, lack of trust in authority, and economic barriers (Teo et al., 2019). To overcome these obstacles, it is crucial to implement inclusive strategies grounded in a thorough comprehension of the specific local circumstances. Mobile applications that support several languages can deliver catastrophe information and alerts in various languages. Additionally, community-based crowdsourcing platforms such as Ushahidi enable citizens to communicate their real-time observations and demands (Basak et al., 2020). Artificial intelligence (AI)-driven chatbots and easily available information portals can provide user-friendly interactions and information in desired languages, hence improving accessibility (Karyotaki et al., 2024). In addition, the implementation of interactive public forums and digital literacy efforts can effectively increase community involvement and optimize the use of these technologies, hence reducing barriers and promoting active participation in disaster management (Nkombi & Wentink, 2022).

To effectively involve these communities in disaster management, this review highlights three essential aspects that must be upheld for a Smart CBDM Strategy: (1) Trust in the crowd and trusting the crowd, to share data. It involves trusting both the community's data and the organizations and mediators who utilize that data in disaster management (Fornalé et al., 2023; Järvihaavisto & Öhman, 2022; Mehta et al., 2017). These variables are important factors to consider in real-time data-sharing platforms used for disaster management: (2) Digital Divide, which refers to inequalities in technology access and digital literacy levels within the community. This aspect highlights the disparity between community members who possess modern information and communication technology (ICT) resources, such as smartphones, computers, and broadband connectivity, and those who have limited or no access. The availability of these resources is influenced by factors such as socioeconomic status, geographic location, education, and age (Madhavaram et al., 2017; Zangana, 2022). In the context of sharing data in real-time during disasters, individuals or communities who have no access to these technologies may not be able to contribute or benefit from important information exchanges (Gaire et al., 2020; Meesters & Wang, 2021; Ravi et al., 2020). (3) cultural sensitivity, which involves involving culturally and linguistically diverse communities in disaster management (Teo et al., 2018, 2019). This is a crucial issue in guaranteeing community involvement and the approval of the measures implemented in the disaster management process. Moreover, it is not only a moral obligation, but also a practical requirement to share real-time data during disasters (Moghaddam et al., 2023; Pratama & Sariffuddin, 2018; Saja et al., 2021).

3.4. Review of the Existing Mobile Applications in Disaster Management Domain: User Interface, Features and Mobilization Strategies.

The next phase of the review focuses on the existing mobile applications in disaster management. The emergence of mobile technology has drastically transformed disaster management approaches. Mobile applications provide a flexible platform for distributing important information, improving communication, and organizing emergency responses (Leventhal et al., 2024). Due to the extensive utilization of smartphones and the wide accessibility of mobile internet, a significant section of the population can easily access these apps. As a result, community preparedness and responsiveness to disasters are improved (Rawsthorne et al., 2023).

Accordingly, 77 Disaster Management related apps were identified in the systematic search carried out utilizing keywords such as "Disaster Management", "Disaster Awareness", "Disaster Alert", "Flood Apps", and "Flood Alert Apps". The selected apps were then categorized based on their type and functionality and the main objectives of the review.

Table 06: Categorization of the Mobile Apps in Disaster Management

	Type	**Total Number of Apps**
01	Crowdsourcing-Based Disaster Management Apps	07
02	Non-Crowdsourcing Disaster Management Apps	11
03	Earthquake-specific Apps (Non-Crowdsourcing)	14
04	Flood Disaster Apps	12
05	General Weather Apps	16
06	Other Disaster Management Apps	17
Total		77

According to the findings from the review, the efficiency of flood-related applications can be greatly improved by using techniques used in successful disaster management systems such as MyShake and Zello PTT Walkie Talkie. These applications excel in promoting community involvement through interactive and user-friendly interfaces, which motivate users to contribute to data collection and actively participate in emergencies. Engaging users in this manner not only increases their level of involvement but also improves the trustworthiness of the acquired data (Habib et al., 2023). Flood applications can enhance community engagement by incorporating elements such as discussion forums, educational materials, and live communication capabilities. This fosters a collaborative atmosphere that encourages users to actively contribute.

Flood-related apps can integrate smartphone capabilities, which is a crucial aspect. The utilization of accelerometers in MyShake to identify seismic activity presents a blueprint for flood applications, which may use comparable sensors to observe water motion or vibrations that signify landslides. In addition, GPS data can be utilized to monitor the real-time locations of users, offering vital information about places that are susceptible to flooding. Furthermore, barometric pressure sensors have the potential to forecast weather fluctuations that could result in floods (Krommyda M et al., 2019; Madhu et al., 2019; Spaargaren, 2012).

Ensuring continuous user involvement, particularly during non-crisis periods, is crucial for the long-term viability of these applications. Methods such as push notifications, gamification, and frequent updates ensure that consumers are well-informed and actively involved. For instance, the act of earning points for providing data or receiving badges for community engagement can enhance the user's experience by making it more dynamic and pleasant. This, in turn, promotes continued participation (Doğan-Südaş et al., 2023; Escolano et al., 2023; Watini & Setyowati, 2023).

Ensuring a consistent and long-term source of funding is crucial for the continuous effectiveness of disaster management applications. Monetization options such as freemium models, adverts, sponsorships, and crowdsourcing can offer essential financial backing. These methods guarantee that the app remains easily available to users while also producing income to support ongoing enhancements (Caputo et al., 2022; Deng et al., 2023; Kawaguchi et al., 2023; Tan et al., 2020).

Ultimately, it is crucial to include modern technologies like artificial intelligence, machine learning, and blockchain into flood-related apps to maintain their effectiveness. AI and machine learning can improve the analysis of data in real time and provide more accurate forecasts about disasters (Devi et al., 2024). By implementing these principles, flood-related applications can enhance their functionality, resulting in more resilient tools that greatly enhance disaster preparedness, response, and recovery activities, engaging the vulnerable communities in the process.

3.5. Final Product Development integrated with the Web Application & Operation.

This section discusses the findings of the third phase of the study, which examines the process of refining the mobile application developed to collect real-time flood data utilizing crowdsourcing. The initial prototype, which was constructed and evaluated in Stage 1, underwent a thorough refinement process based on feedback from participants, insights gained from a systematic assessment of relevant literature, and an examination of existing mobile applications in the field of disaster management. The objective was to improve the app's user experience, increase data precision, and connect its capabilities with current technical breakthroughs in disaster management.

Taking into account the cultural sensitivity indicated in the literature research, the app was modified to accommodate both Sinhala and English languages. The inclusion of multilingual support not only improved the app's usability but also expanded its accessibility to a wider range of individuals, hence increasing its usefulness in real-time disaster management. Furthermore, Participants emphasized the user interface's complexity as a major concern. A significant number of users encountered challenges in navigating the initial architecture, potentially impeding the efficient utilization of the system during crucial flood occurrences. In order to tackle this issue, the application underwent a redesign process that resulted in a more streamlined and user-friendly layout, ensuring that even individuals with less technological proficiency may easily navigate and utilize it

In response to the digital divide identified in the literature review, which stressed insufficient digital literacy and limited access to modern technology among certain users, the application was developed as a user-friendly Android app. This technique guarantees that the application is compatible with a diverse array of devices, including less sophisticated smartphones, thus facilitating the participation of people with different levels of digital expertise. The software was enhanced to be more accessible and culturally sensitive by streamlining the user interface and offering multilingual help in both Sinhala and English. This improvement further contributes to narrowing the digital literacy divide. In order to establish confidence in the reliability of data collected from a crowd, a DBSCAN machine-learning model was utilized (Annexure 02). This model plays a crucial role in identifying and removing abnormal data points, guaranteeing that the data gathered from users is accurate and dependable. This strategy ensures the reliability of the information gathered from the public, with the goal of instilling greater trust among users.

Participants also stressed the need of having an emergency contact function incorporated into the application. Many individuals believed that incorporating such a characteristic was crucial, especially in circumstances where users could potentially encounter in the event of a flood. As a result, the app was upgraded to incorporate an emergency contact feature, enabling users to promptly seek assistance via the platform. The incorporation of this modification greatly enhanced the app's functionality in situations involving disasters, so transforming it into a more all-encompassing tool for the control of floods.

Although the crowdsourcing endeavour was well-received, certain participants voiced a lack of motivation to consistently utilize the program. In response to this issue, the application was enhanced with an incentivization mechanism, whereby users have the opportunity to accumulate points by providing flood event occurrence data. These points can be exchanged by collaborating with a private enterprise, offering a constant motivation for engagement. In addition, the app incorporated gamification aspects, such as the inclusion of badges for top contributors, to enhance user engagement. These elements were derived from effective strategies utilized in other crisis management applications and were created to promote continuous user involvement.

Furthermore, the significance of push notifications was stressed in the existing mobile applications for disaster management and during the review of the existing mobile applications in disaster management to enable users to make well-informed decisions. As a result, the app now incorporates real-time flood and weather alerts, which are delivered to users as notifications. In order to maintain user engagement even in situations where they are not directly impacted by floods, a weather update feature was implemented. This feature utilizes crowdsourced inputs to deliver precise information.

In conclusion, the improvements made to the mobile application were based on user feedback and aimed to address the issues and requirements highlighted during the trial period. The incorporation of a more streamlined user interface, support for two languages, data verification that enhances trust, tools for emergency contact, incentivization through points, and real-time warnings have collectively converted the app into a powerful tool for disaster data crowdsourcing. The app interfaces with the functionalities, backend saving and analysis are depicted in the below diagrams.

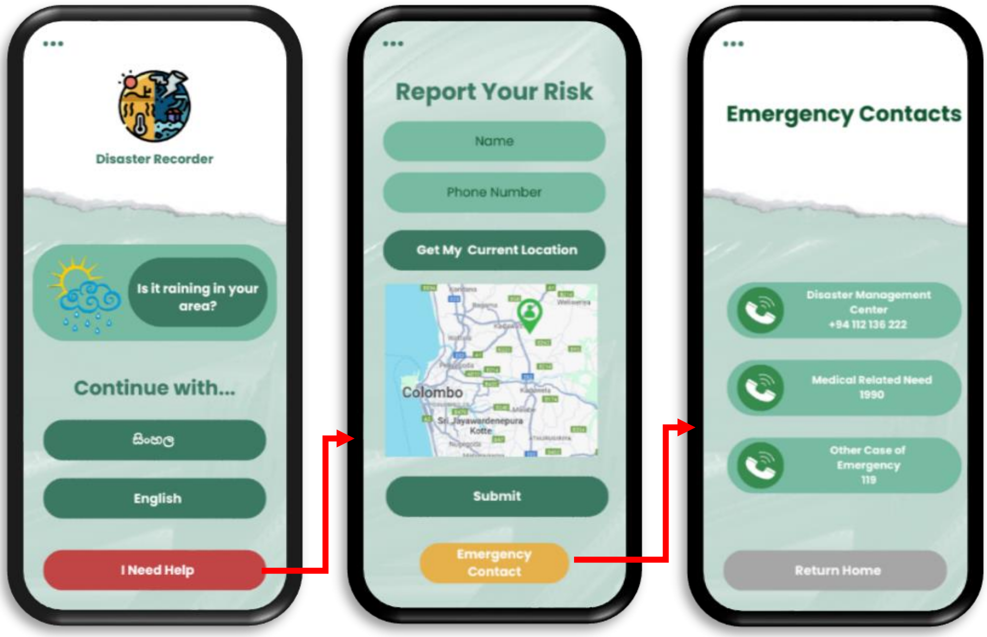


Figure 11: Welcome screen, reporting risk & emergency contact

People at risk (Responses)

	A	B	C	D	E
1	Timestamp	Name	Mobile Number	Latitude	Longitude
2	9/12/2024 12:38:45	Name 1	07x xxx xxxx	6.795943	79.90157
3	9/13/2024 11:09:04	Name 2	07x xxx xxxx	6.794283	79.92443
4					
5					

Figure 12: Back end of Risk Reporting

This functionality is designed to connect directly with disaster management authorities, such as the Disaster Management Centre, thereby facilitating prompt communication and response. If an individual is at a risk, this option allows them to report to the app they are in need of help thereby provide people with evacuation guidance or if in critical cases send relevant relief groups to the location immediately. Figure 14 depicts how the data is saved at the backend. This option is crucial in saving the lives of people during disaster situations linking people with authorities.

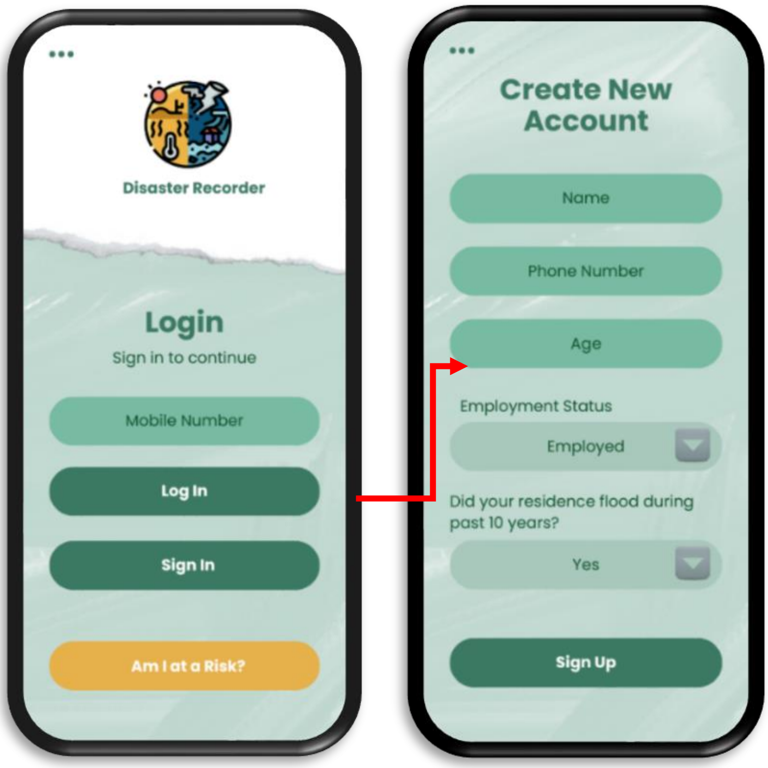


Figure 13: Login & Sign in Screen

Sign Up (Responses)

Timestamp	Name	Mobile Number	Age	Employment Status	Did your residence flood
9/13/2024 10:55:54	Name 1	07x xxxxxxx	27	Employed	No
9/13/2024 12:41:43	Name 2	07x xxxxxxx	26	Employed	Yes
9/14/2024 12:03:49	Name 3	07x xxxxxxx	25	Student	Yes
9/14/2024 12:30:32	Name 4	07x xxxxxxx	25	Employed	No

Figure 14: Back end of Sign in

The sign in information is saved as represented in Figure 14, which is expected to create risk profiles for each individual based on their age, employment status, etc. with further research. At this extent of the study this information is gathered from individuals as a profile for further study and incentivization purpose.

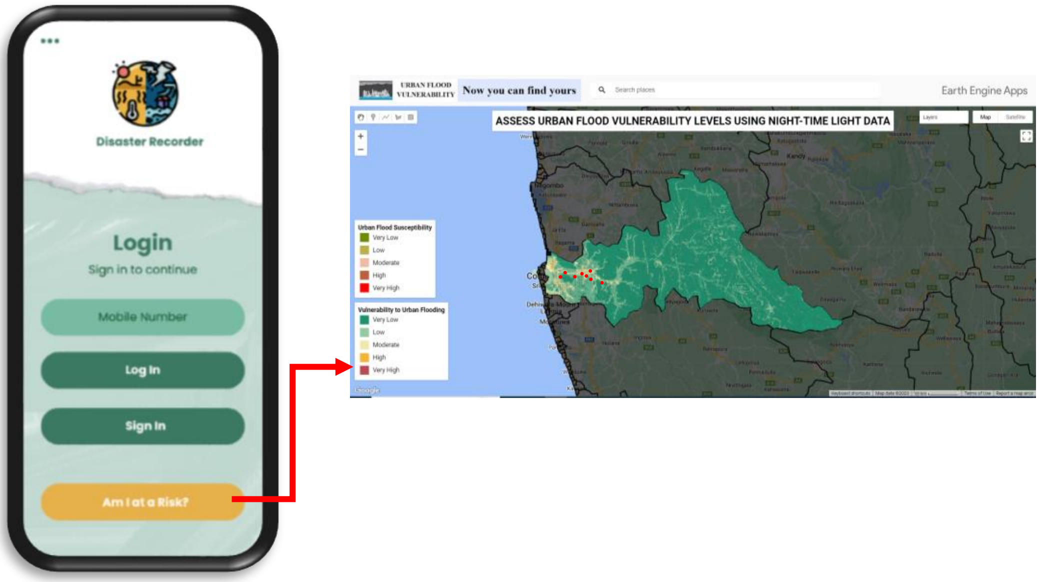


Figure 15: Am I at a risk option linked to Web Application

Figure 15 represents one of the most crucial aspects of the mobile application, which directs the user to the web application allowing them to know their level of vulnerability to flooding.

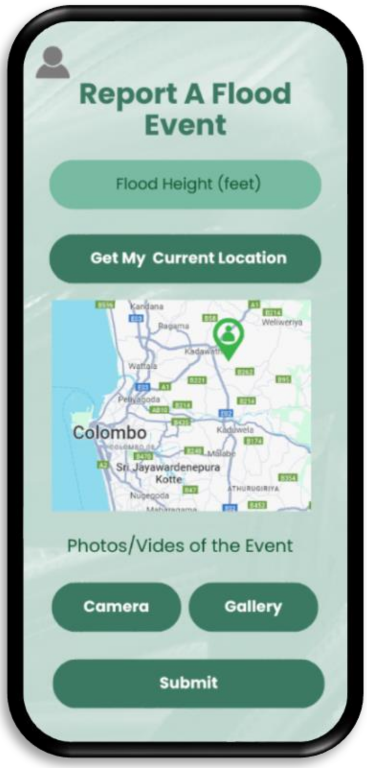
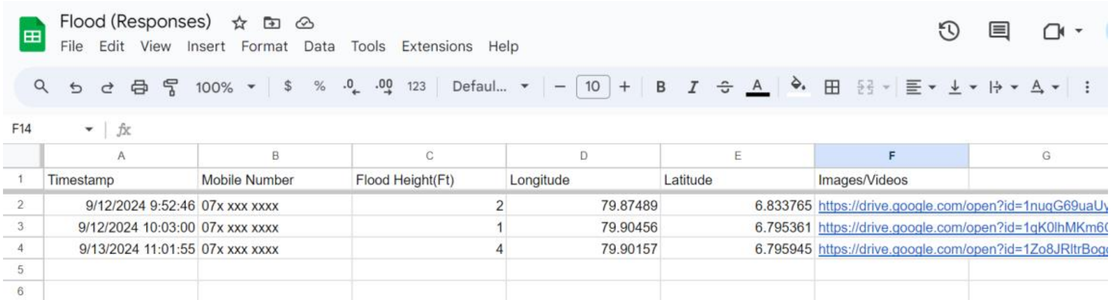


Figure 16: Reporting a Flood Event



	Timestamp	Mobile Number	Flood Height(Ft)	Longitude	Latitude	Images/Videos
2	9/12/2024 9:52:46	07x xxx xxxx	2	79.87489	6.833765	https://drive.google.com/open?id=1nuqG69uaU
3	9/12/2024 10:03:00	07x xxx xxxx	1	79.90456	6.795361	https://drive.google.com/open?id=1qK0lhMKm6
4	9/13/2024 11:01:55	07x xxx xxxx	4	79.90157	6.795945	https://drive.google.com/open?id=1Zo8JRltrBo

Figure 17: Back end of the flood event report

The figures above (16 and 17) depict how the crowdsourcing function of the mobile app works. The data is saved under the user's mobile number which they have logged into the app, the approximate flood height and the location, while photos/videos of the event can be uploaded if available. This data is used to detect the flood events occurring in the area as a vital crowdsourced input from people. Below figure (Figure1 18) represents how the events reported by people are visualized in the web application.

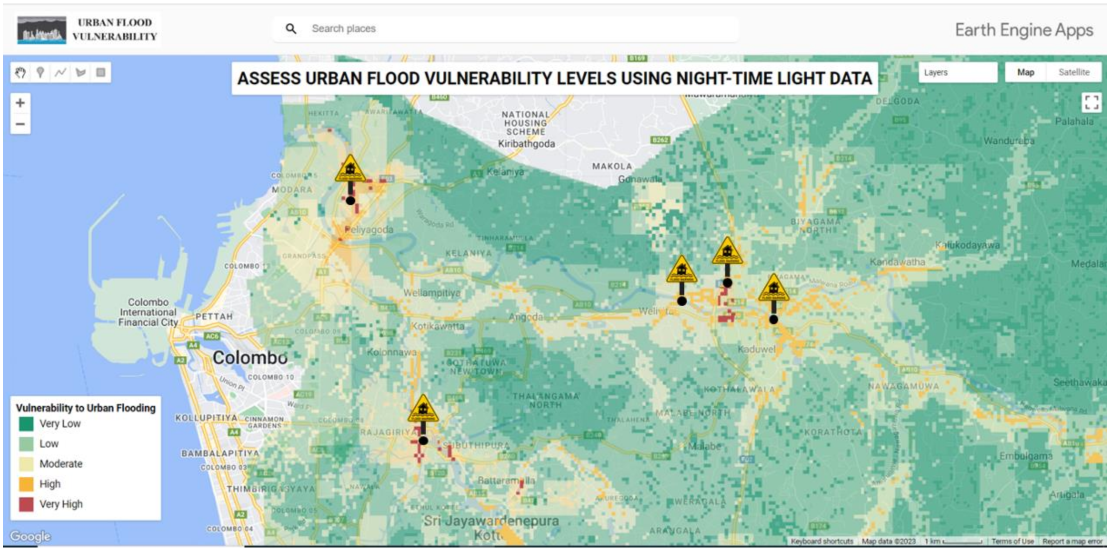


Figure 18: Precipitation Data Crowdsourcing Function

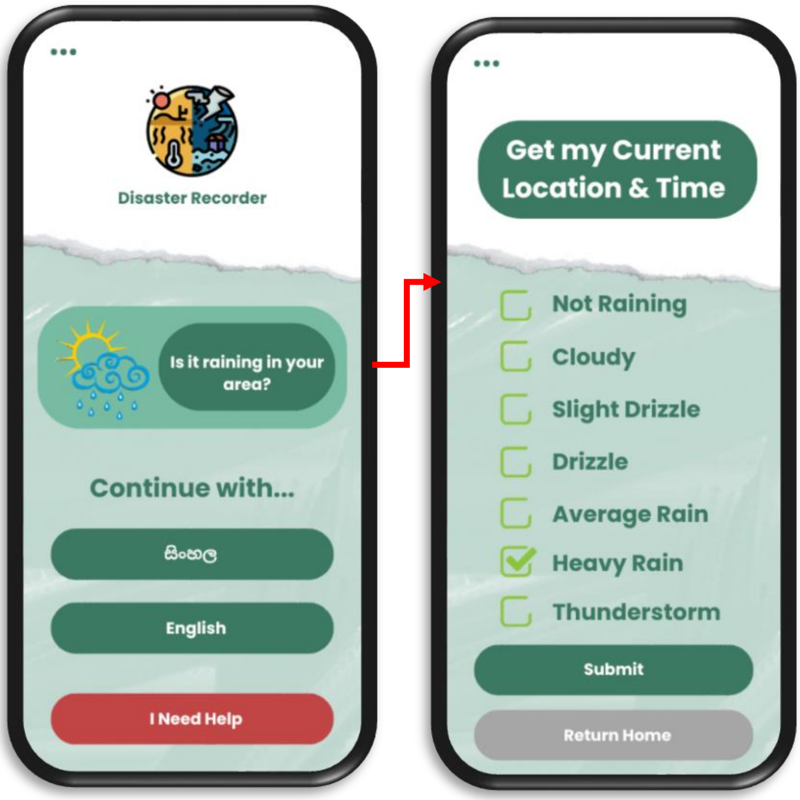


Figure 19: Precipitation Data Crowdsourcing Function

	Timestamp	Longitude	Latitude	Not Raining (0 mm/h)	Slight Drizzle (0.5 mm/h)	Drizzle (2.5mm/h)	Average Rain (10 mm/h)	Thunderstorm (50 mm/h)	Heavy Rain (33 mm/h)
2	9/11/2024 12:55:13	79.90157	6.795945	Yes	No	No	No	No	No
3	9/11/2024 12:55:55	79.87489	6.833765	Yes	No	Yes	No	No	No
4	9/13/2024 10:54:36	79.90154	6.79594	Yes	No	No	No	Yes	No

Figure 20: Back end of Precipitation Data Crowdsourcing Function

The precipitation data crowdsourcing is the most vital aspect in the mobile application, that keeps updating the most crucial variable in determining flood vulnerability and constantly engaging the users in the mobile application. For the ease of users, the following commands have been included and the precipitation values for the categories for each category has been retrieved from (*MANOBS - Manual of Surface Weather Observations*, 2013). Whereas Figure 18 depicts the visualization of the crowdsourced precipitation level data in the web application.

Table 07: Categorization of the Precipitation Levels

Command in App UI	**Data input taken**
Not raining	(0 mm/h)
Slight Drizzle	0.5 mm/h
Drizzle	2.5mm/h
Average Rain	10 mm/h
Heavy Rain	33 mm/h
Thunderstorm	50 mm/h

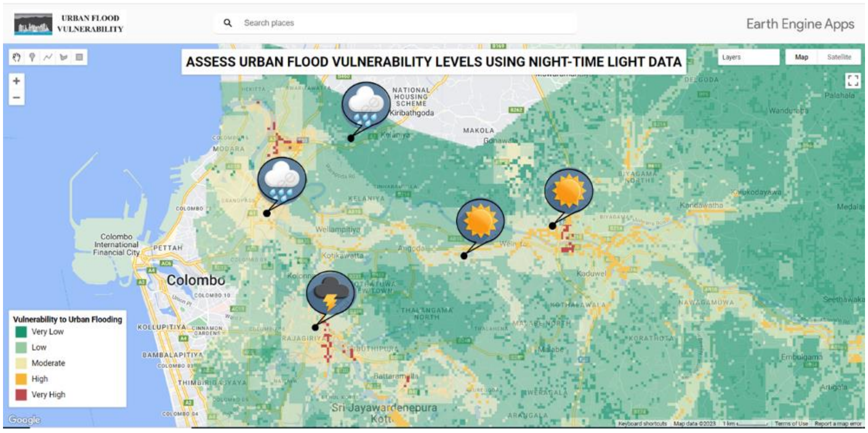
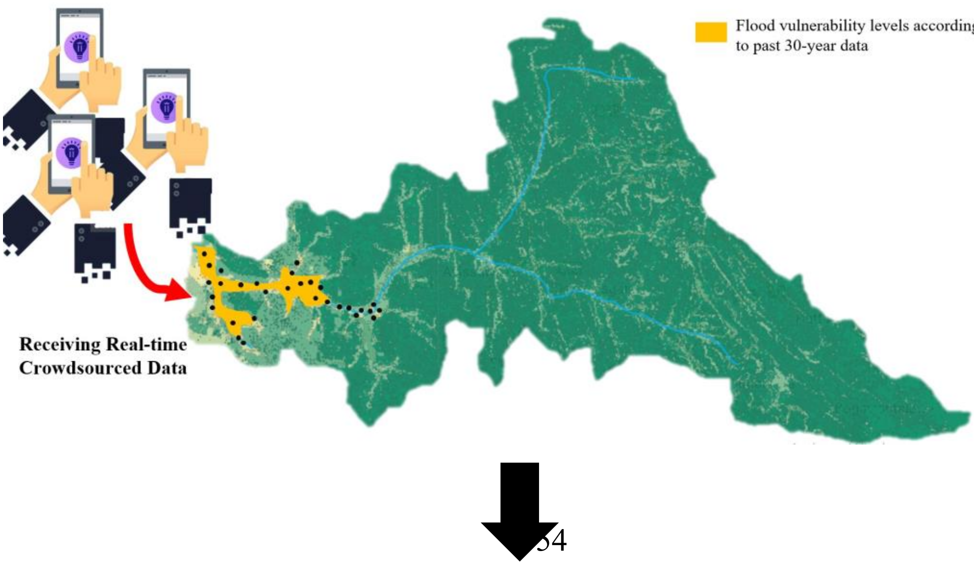


Figure 21: Visualizing Precipitation Levels (Crowdsourced Data)

Accordingly, the below is a representation of how the crowdsourced data from the mobile app is visualized and the web app is updated with the level of vulnerability (Figure 19).



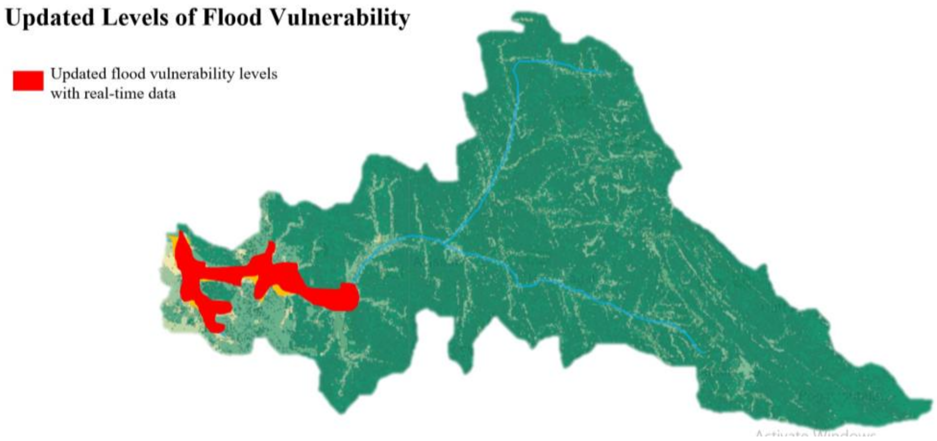


Figure 22: Functioning of the Mobile and Web App

Then according to the number accurate data inputs given by the user, the profile of the user is updated with the number of points earned and the level of contribution by the user. This functionality is expected to be in cooperated with an organization for incentivization and enhance the community participation.

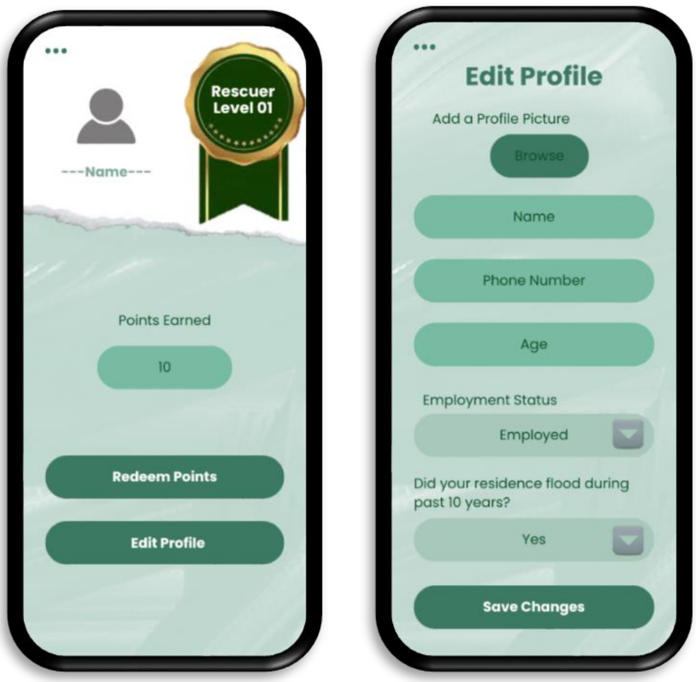
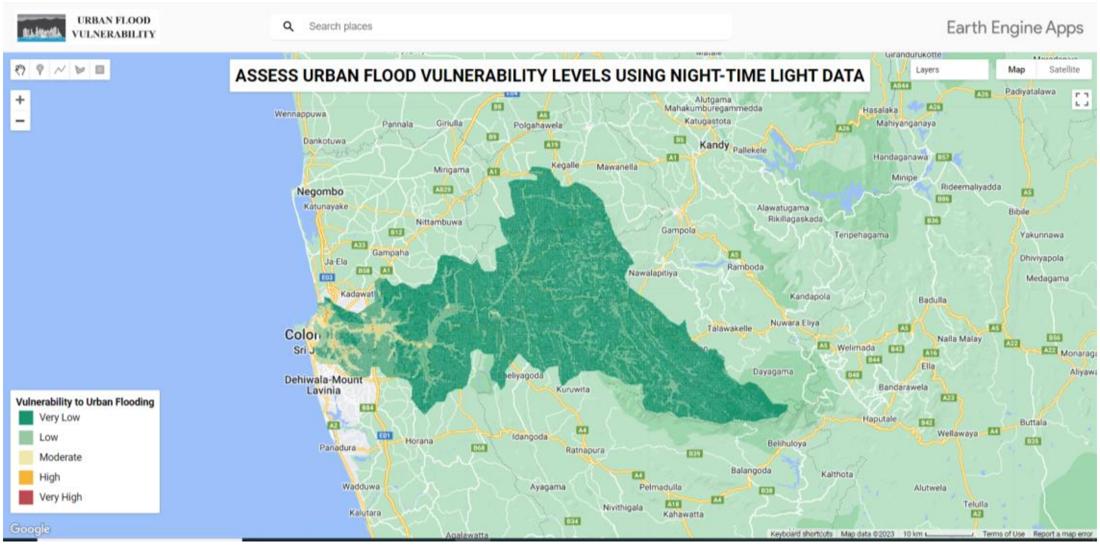


Figure 23: User Profile and Edit Profile

Building upon developing and improving the mobile application, which concentrated on collecting real-time flood data and engaging users through crowdsourcing, the next stage entailed developing a complementing web application, the platform to completely analyse and visualize the level of human exposure to flooding, disseminating the collected information. The web application is available at:

https://ee-researchnuwani.projects.earthengine.app/view/floodexposure

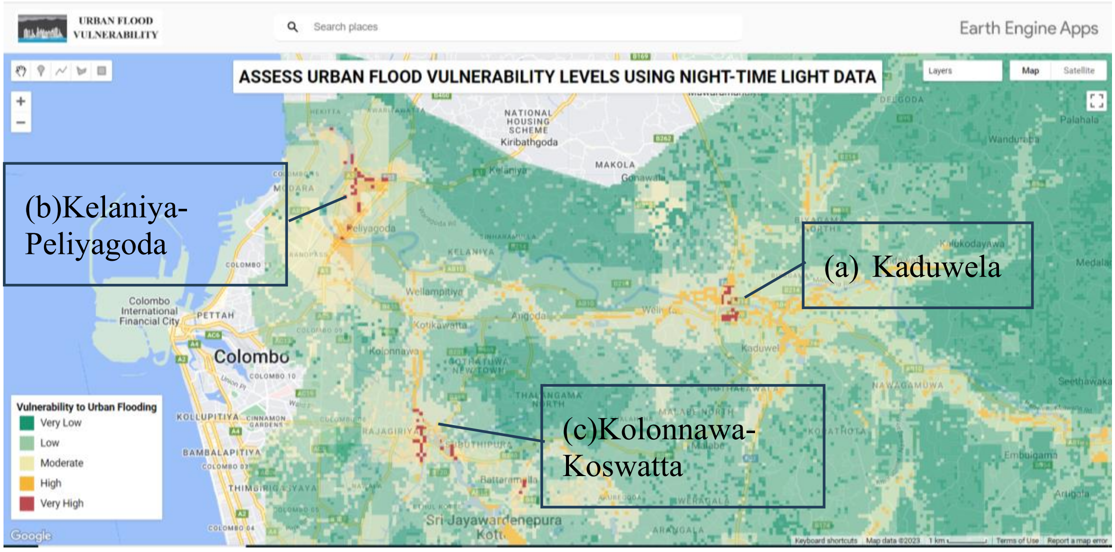
According to the result of the stage 02 of the study, the levels of flood vulnerability was mapped for Kelani watershed area (Map 1), overlaying the flood susceptible areas and the concentration of human activities which was derived from the intensity of Night-time Light Data.



Map 1: Urban Flood Vulnerability Levels

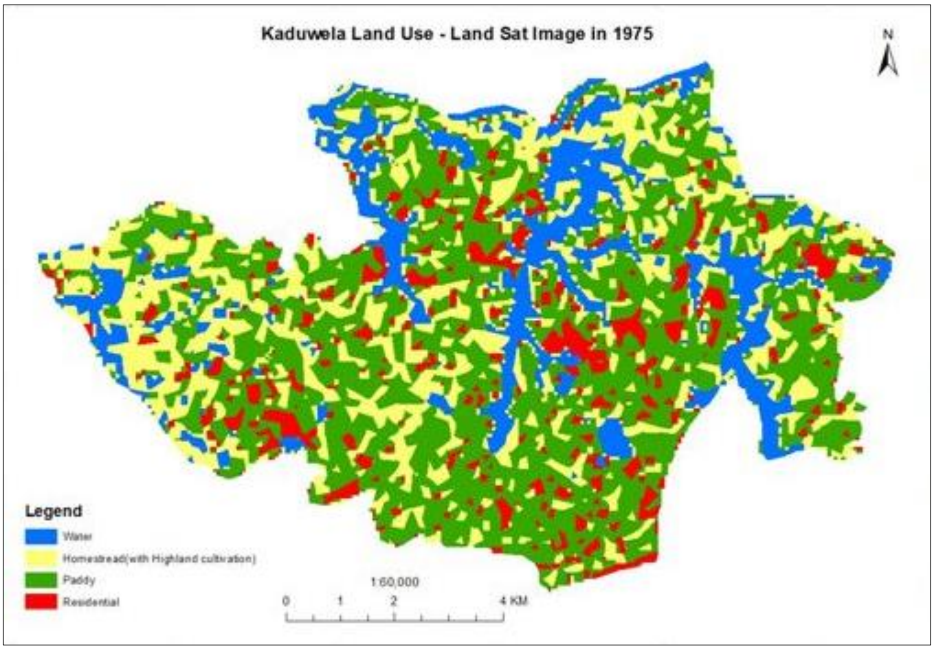
Urban areas with very high vulnerability

As per the results of the study, three highly urban flood vulnerable urban spots were identified, (a) Kaduwela, (b) Kelaniya-Peliyagoda, and (c) Kolonnawa- Koswatta corridor.

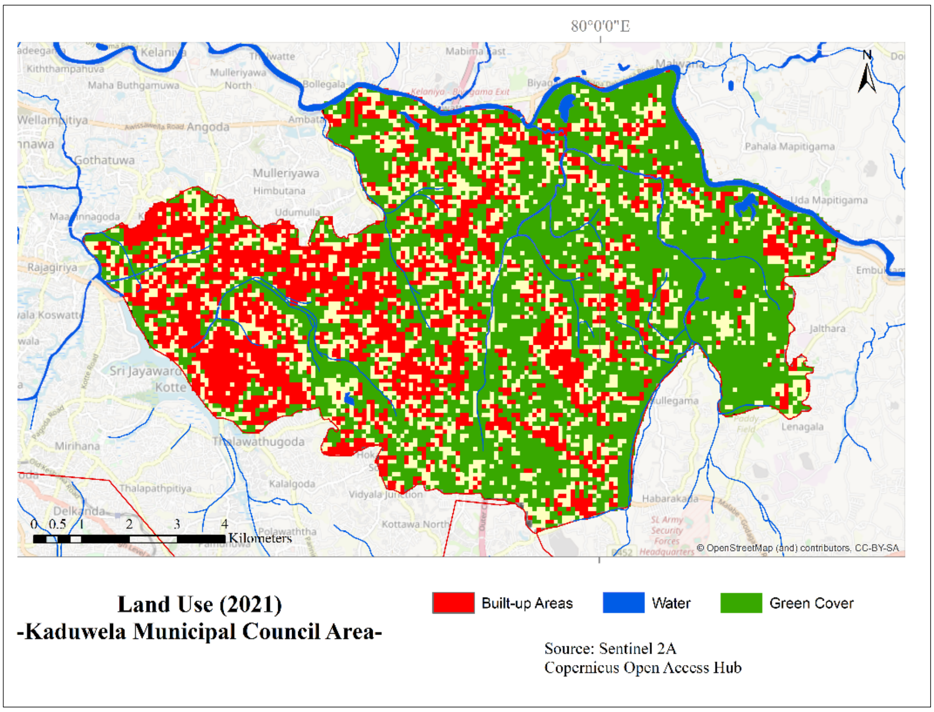


Map 2: Areas with very high urban flood vulnerability

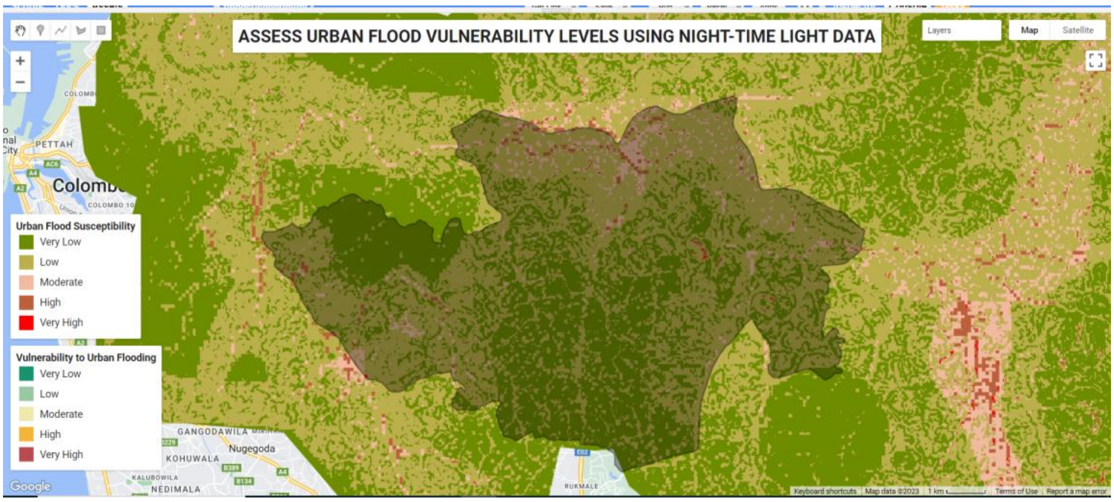
Kaduwela Municipal Council area is a frequent flood recorded urban area in which the magnitude and extent has been increased according to the Hydrological Report on the Kelani River Flood in May 2016 by Irrigation Department, Sri Lanka. According to Ranaweera & Ratnayake, (2017), the built-up areas of Kaduwela area have been increased from 8.6% to 22.9% from the total land use types from 1975 to 2016, that can be clearly observed from the maps below (Map 3: Land Use of Kaduwela MC – 1975 (Source- Ranaweera & Ratnayake, (2017)) & Map 4: Land Use of Kaduwela MC – 2021) The population increase accounts for +168.9% within that time.



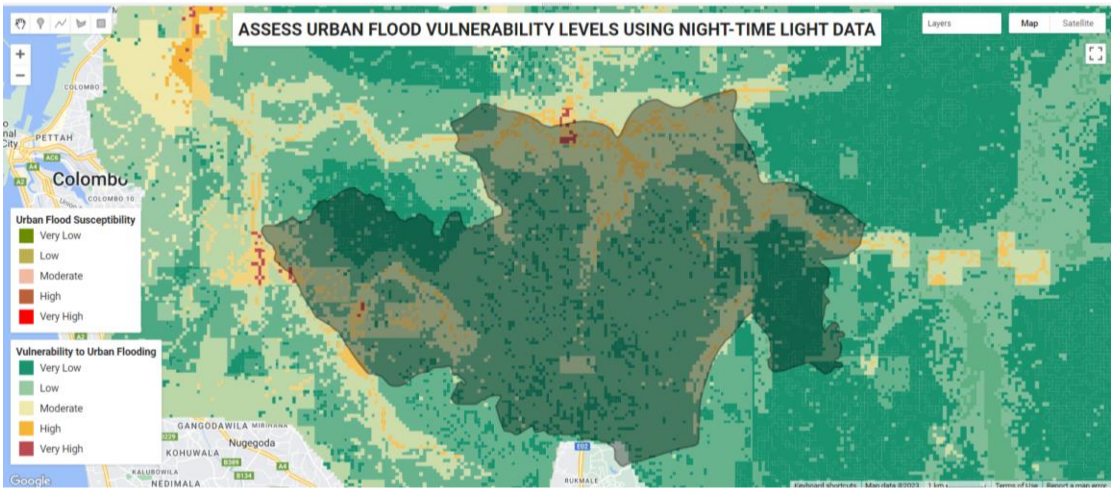
Map 3: Land Use of Kaduwela MC – 1975 (Source- Ranaweera & Ratnayake, (2017))



Map 4: Land Use of Kaduwela MC – 2021

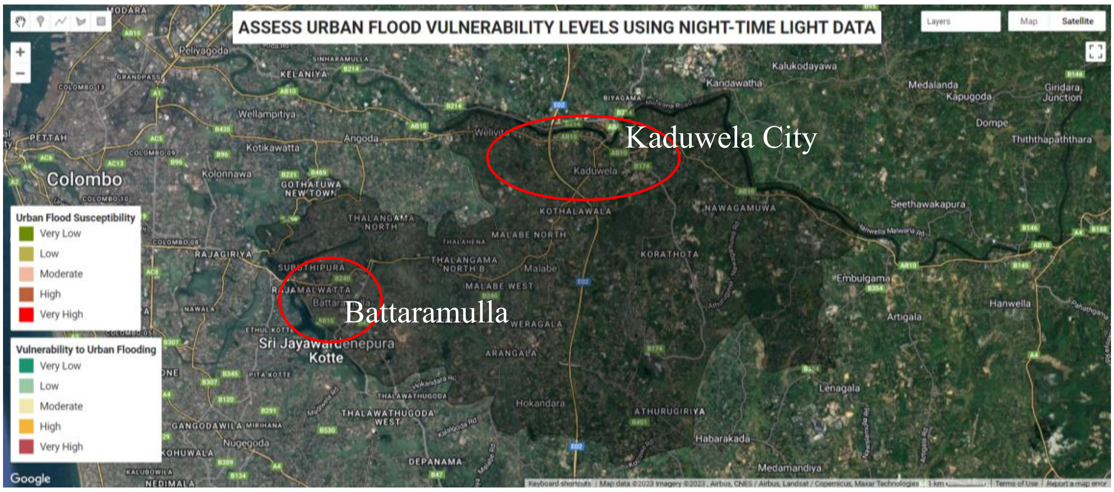


Map 5: Urban Flood Susceptibility - Kaduwela



Map 6: Human Exposure to Urban Flooding – Kaduwela

Map 5 and 6 provide a comparative assessment of flood vulnerability in Kaduwela. Map 5 illustrates urban flood susceptibility based on environmental and topographic conditioning factors, highlighting natural flood-prone areas. In contrast, Map 6 integrates human exposure by overlaying urban activity indicators such as population density and night-time light intensity. This comparison reveals that while natural flood-prone areas are concentrated in low-lying regions near water bodies, human exposure is significantly higher in dense urban settlements, commercial hubs, and industrial zones, emphasizing the role of land-use transformation in increasing flood risk.

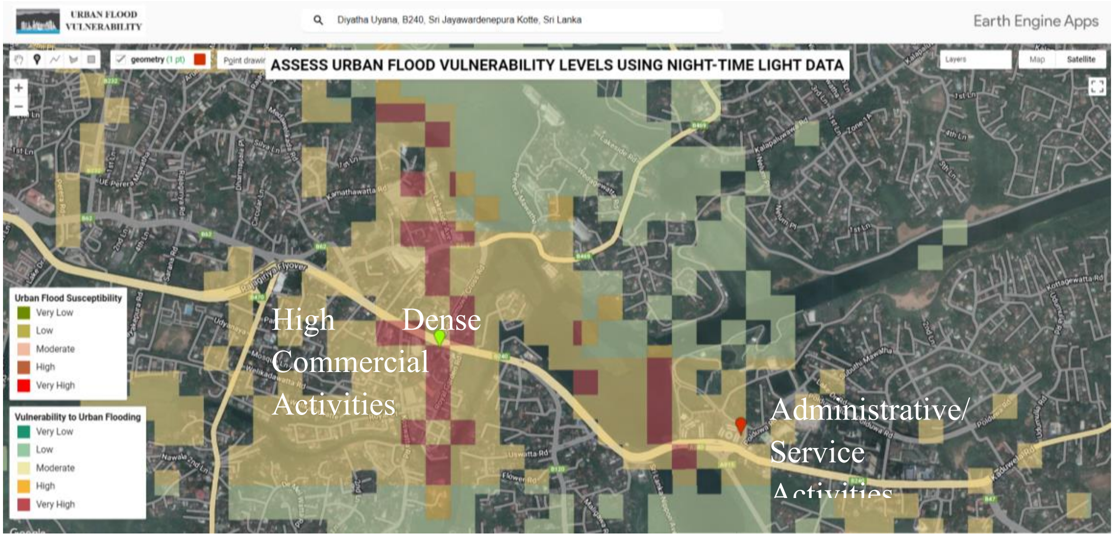


Map 7: Urban Flood Affected Urban Centres

Specifically with the construction of the outer-circular expressway, in 2014.

Kaduwela is a rapidly growing urban hotspot in the Colombo-Kandy corridor. At the same time, Kaduwela-Malabe corridor has been identified as an Information Technology, High-Tec business development zone with the existing economic setting of the area which attracts thousands of professionals to the city, according to the studies done for Colombo Megapolis Development Plan.

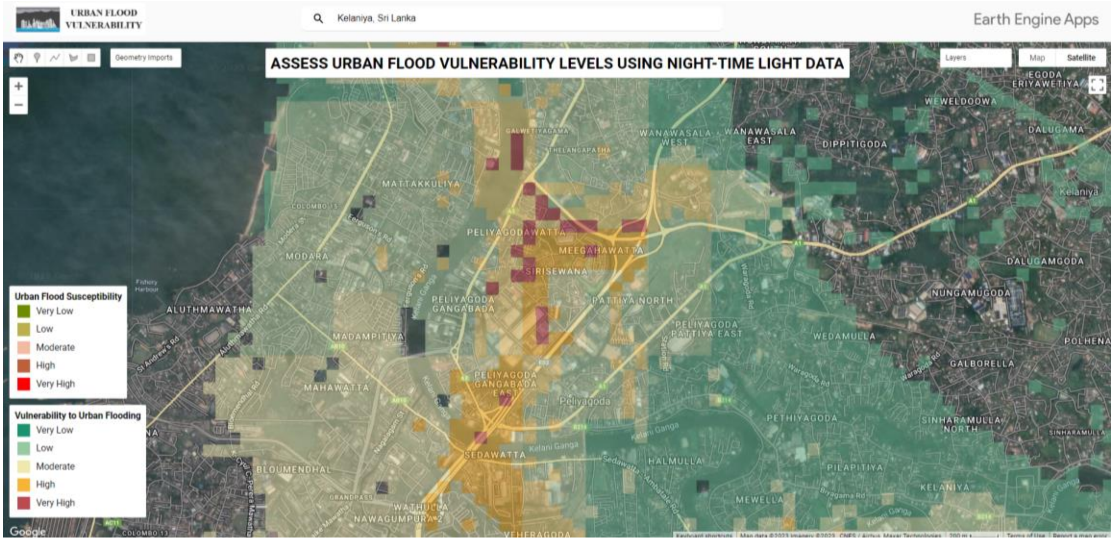
Similarly, Kolonnawa-Koswatta area is a developing economic-service centre for Colombo with the location of administrative activities.



Map 8: Battaramulla - High Urban Flood Vulnerable Area

While the local population of the area also has been recorded a growth of +172.5% from 1975 to 2016. While Kolonnawa is comprised of a majority of low-income housing. Where frequent flooding has been recorded impacting a larger population. Significantly, during the 2022 October flood event the highest number of displaced people from each division was recorded from Kolonnawa, which is numerically 3,666.

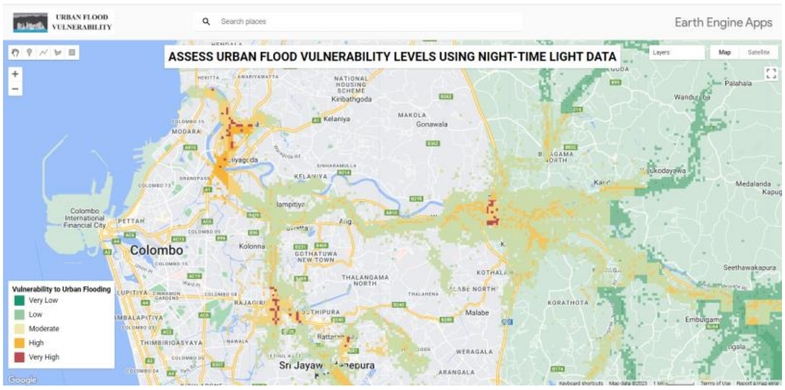
When it comes to the Kelaniya-Peliyagoda area, that area is also subjected to frequent flooding.



Map 9; Peliyagodawatta- High Urban Flood Vulnerable Area

The population change is +57.1% from 1975 to 2016 that is comparatively lower to the other two identified very high flood vulnerable hotspots according to the study. The human exposure is not merely the residential locations; therefore, the findings also indicate the new infrastructure and economic activity developments taking place in the Peliyagoda-Kelaniya area.

Urban areas with high vulnerability



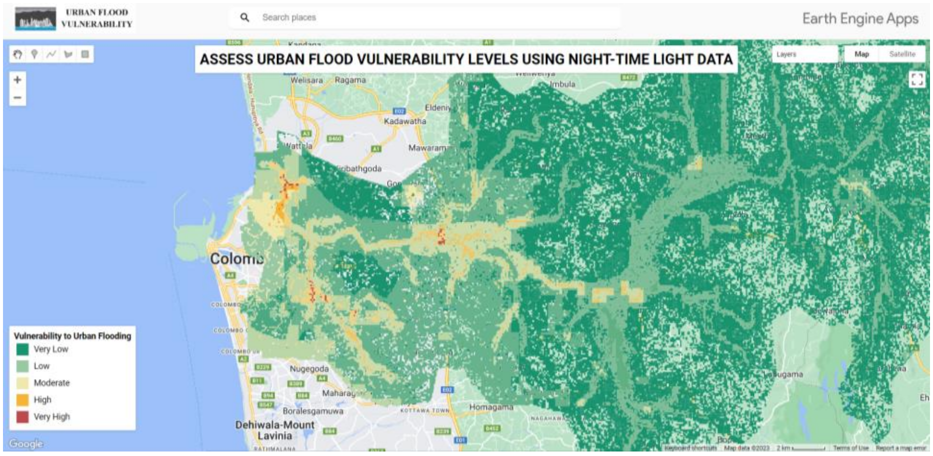
Map 10: Areas with high urban flood vulnerability

The map above (Map 10: Areas with high urban flood vulnerability) depicts the high urban flood vulnerable areas in orange colour, the areas include the adjacent areas to the city cores of Peliyagoda-Kelaniya, Kolonnawa-Koswatta and Kaduwela.

The high flood vulnerable areas include, Madiwala, Pelawatta, Sedwatta, Biyagama, Ranala, Bomiriya, and Hanwella areas according to the results of the study.

When it comes to Hanwella, which is another highly vulnerable hotspot for urban flooding, the population change in Hanwella from 1975 to 2016 accounts for 25.1%, which is comparatively lower than the above discussed main three very high flood vulnerable hotspots, which clearly implies that the results of the study have categorized the human exposure to urban flooding in its scale of severity affecting the density of human activities.

Urban areas with moderate vulnerability

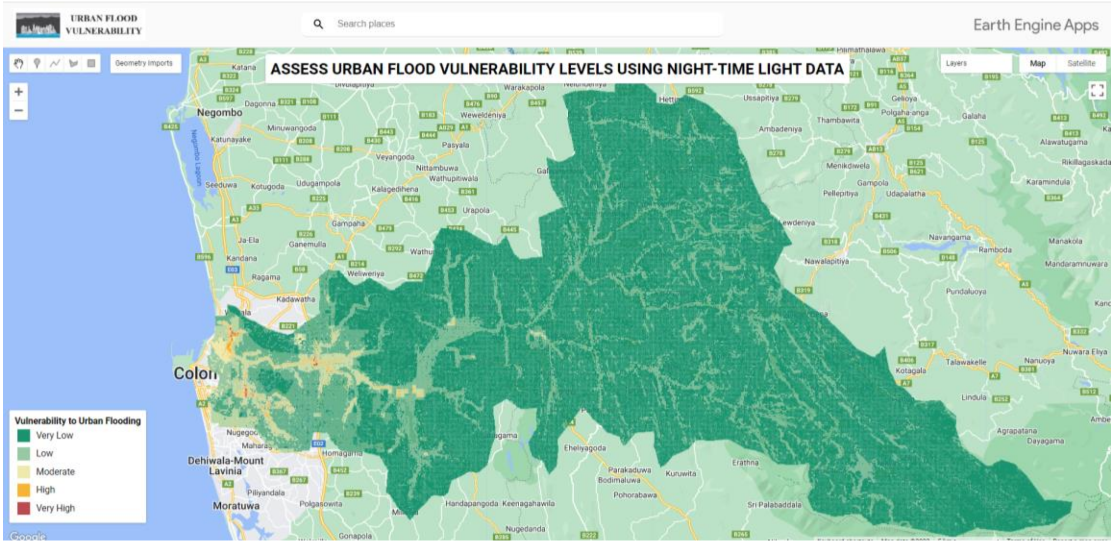


Map 11: Areas with moderate flood vulnerability

The map above (Map 11: Areas with moderate flood vulnerability) indicates the areas with moderate flood vulnerability in yellow colour. When it comes to the moderate urban flood vulnerability, which includes the flood susceptible areas and the intensity of hight light that represents the concentration of urban activities. The moderate flood vulnerable areas include the high and moderate flood susceptible areas with moderate concentration of urban activities according to the intensity of night time light. That mainly includes the adjacent area to high urban flood vulnerable areas.

Urban areas with low and very low vulnerability

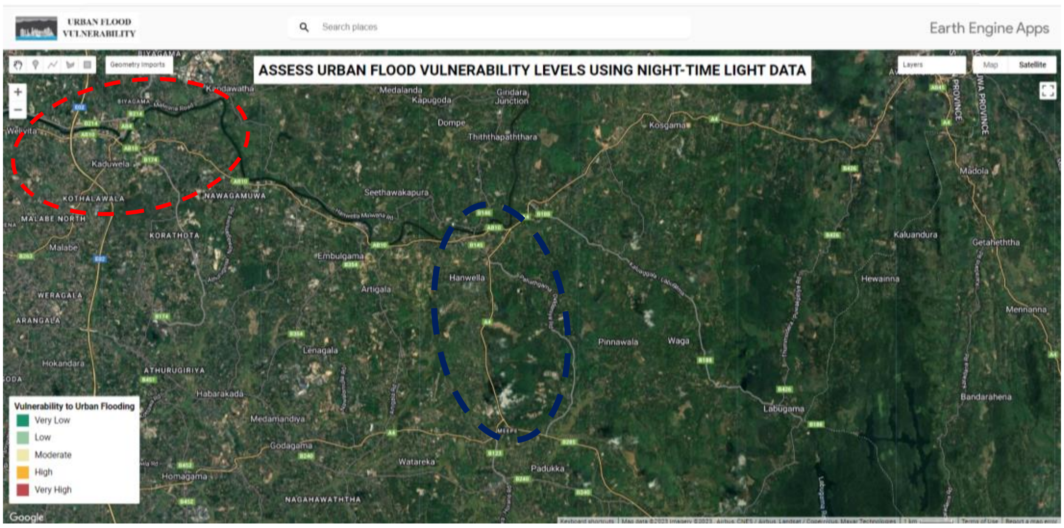
When it comes to the low and very low flood vulnerable areas, it includes the high flood susceptible areas with no urban activities or very lower concentration of human activities and the lower and very low flood susceptible areas with high and low urban activity concentrations according to the study. The areas in light green and dark green in the map below indicated the low and very low urban flood vulnerable areas in Kelani River watershed.



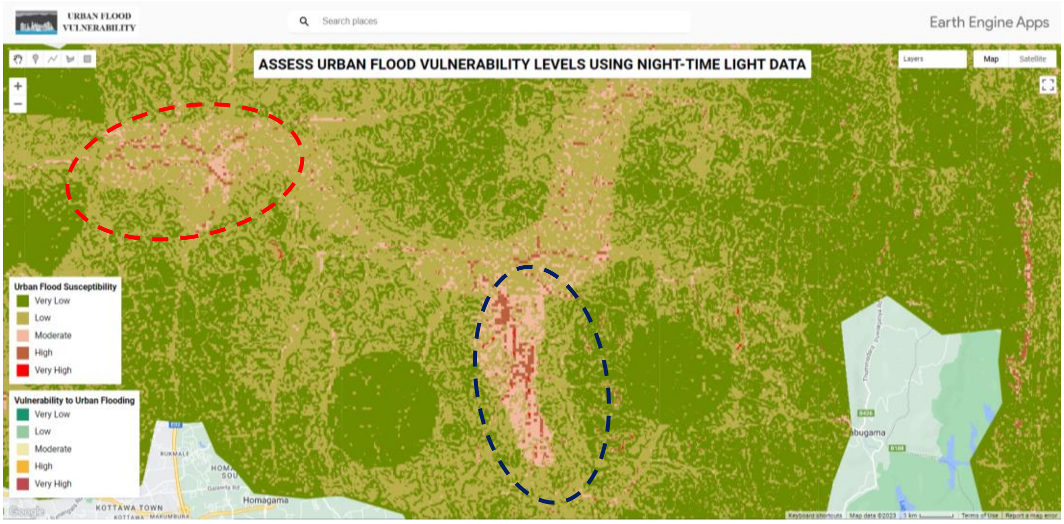
Map 12: Areas with low and very low vulnerability

The higher elevations of the watershed area are obviously recorded with low flood susceptibility at the same time, the lower concentration of human activities therefore, the flood vulnerability is low.

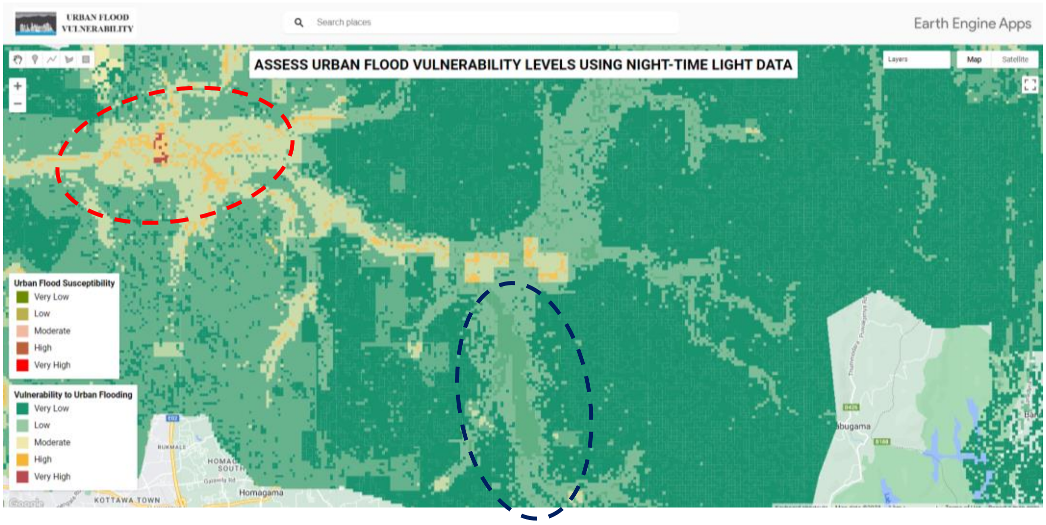
The significance of this study can be explained as in the below instance at Hanwella, the three maps depict the satellite view, flood susceptibility and the human exposure respectively.



Map 13: Satellite View- Hanwella Area



Map 14: Flood Susceptibility-Hanwella Area



Map 15: Human exposure to urban flooding-Hanwella Area

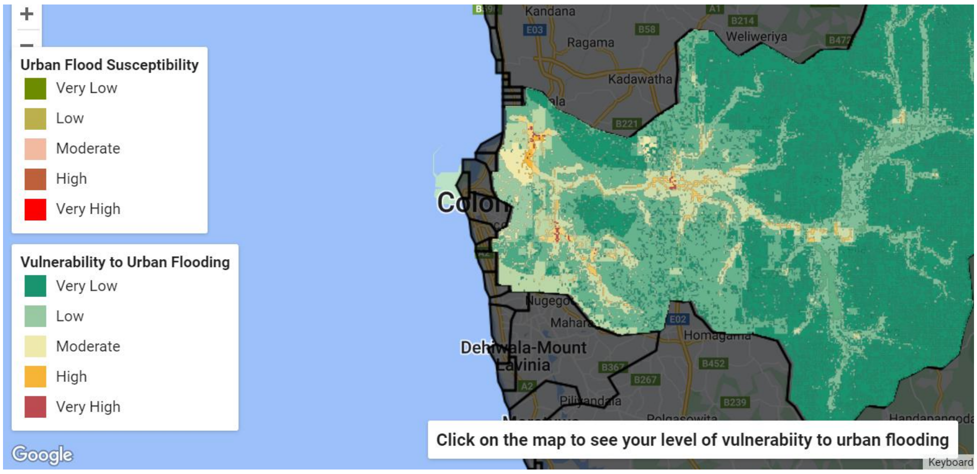
Both the areas marked in the above maps are diagnosed with higher flood susceptibility, but the area marked in red shows a higher vulnerability to urban flooding while the area marked in blue shows a lower vulnerability to urban flooding. The concentration of urban activities retrieved from the intensity of Night-time Light has affected in the result that, the blue marked area, where there are no human activities are recorded according to NTL is with a lower flood vulnerability compared to the area in red with higher concentration of urban activities although both the areas are highly susceptible to urban flooding.

The results and discussions are based on the analysis of 30 years of historical flood data and relevant Sentinel-2 satellite images. This comprehensive approach provides a strong basis for comprehending flood patterns and susceptibility. Nevertheless, to uphold the validity and precision of this analysis, the system has been designed to dynamically update with real-time data collected through the mobile application. By incorporating data acquired from people, the flood vulnerability assessments are kept up-to-date, allowing for the synchronization of historical data with present conditions. This continuous updating process not only enhances the precision of the analysis but also empowers users to make informed decisions based on the most recent flood data available.

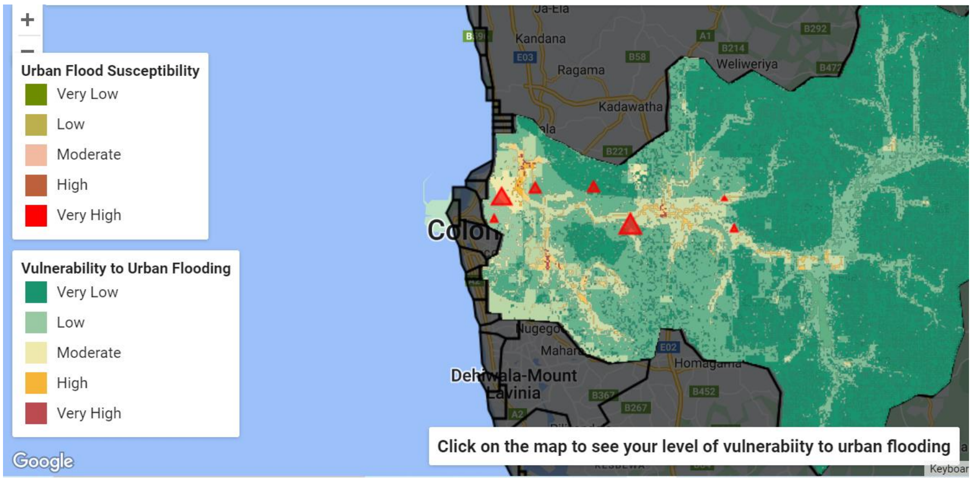
CHAPTER 4 – CONCLUSION AND RECOMMENDATIONS

This chapter concludes the study by summarizing its key findings and providing recommendations for future improvements and practical applications. It first presents a summary of the research, highlighting the integration of crowdsourced data, remote sensing, and machine learning in flood risk management. The study validates the effectiveness of the developed mobile and web-based applications in enhancing real-time flood monitoring and community participation. Next, recommendations for future developments are provided, suggesting expansion to other river basins, improved validation of crowdsourced data, and stronger private sector partnerships for technological sustainability. Lastly, recommendations for practitioners offer guidance for disaster management authorities and urban planners, emphasizing the adoption of participatory flood monitoring, integration into policy frameworks, and enhanced stakeholder collaboration for risk-sensitive urban development.

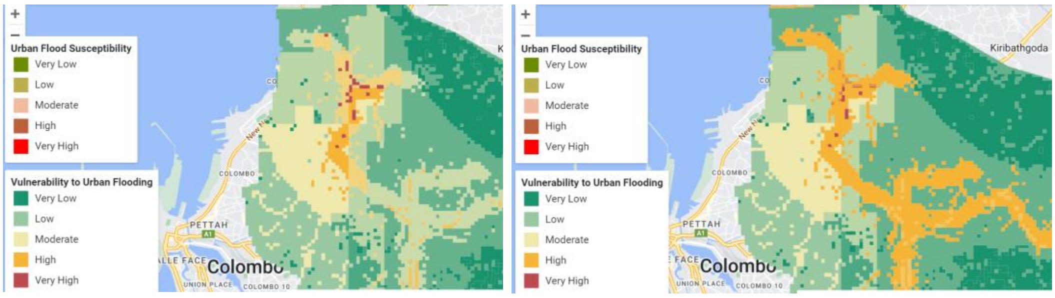
4.1 Impact of Real time crowdsourcing data on readily available data



Map 16: Web application with readily available data



Map 17: Receiving real-time crowdsourced flood event reports



Map 18: Comparison of the flood vulnerability analysis with readily available data vs real-time crowdsourced data

The two figures under Map 18 display the comparative flood vulnerability levels. The figure on the left represents flood vulnerability levels using only readily available data, while the figure on the right incorporates real-time crowdsourced inputs, merging real-time crowdsourcing information with historical data. Without crowdsourced data, the map illustrates flood risks based solely on historical flood events, average annual precipitation, and the nine conditioning factors. However, with the integration of crowdsourced data, the second map reveals a refined depiction of moderate vulnerable zones and enhances real-time responsiveness. The contribution from people on the flood risk locations and rainfall intensity captures subtle yet critical updates on level of flood vulnerability, thus enabling a more dynamic and precise representation offering actionable insights for both local authorities and communities, promoting targeted interventions. Conventional disaster management, predominantly reliant on historical data and fixed variables, provides insufficient adaptation to current circumstances, often resulting in generalized vulnerability assessments. However, with real-time community inputs, flood risk maps can dynamically capture current conditions like localized rainfall and flood patterns, leading to more accurate and responsive depictions of vulnerable zones.

The distinct shift in disaster management highlighted from the literature review, with a growing preference for adaptive, community-inclusive, and data-driven models. Traditionally, disaster management frameworks predominantly depended on hierarchical rigid procedures, frequently neglecting community involvement and constraining adaptability to changing vulnerability to disasters. Integrating real-time crowdsourcing data represents a transformative method that improves the accuracy of flood vulnerability assessments by capturing situational variables such as rainfall intensity and flood occurrences. Recent literature underscores that advancements in Community-Based Disaster Management (CBDM) prioritize local participation, fostering a trust-based connection between authorities and communities. This involvement enhances conventional data with real-time insights, promoting resilience through active participation in disaster management activities. The implementation of technologies like AI, UAVs, and IoT facilitates extensive data processing, allowing authorities to shift from static to dynamic mapping and respond to quickly evolving conditions with increased accuracy.

However, these changes raise additional inquiries regarding equity, sustainability, and inclusivity. As literature emphasizes that communities do not possess equal access to digital resources, highlighting the necessity to bridge technical barriers to enable all the individuals to contribute and gain. The growing focus on intelligent disaster management systems in the literature necessitates deeper exploration of how these technologies might be adapted to various socioeconomic contexts while maintaining accessibility.

This study marks a significant progress in utilizing crowdsourced data along with flood vulnerability analysis developing a platform with a mobile and a web application. By utilizing 30 years of past flood data and Sentinel-2 images of the identified flood occurrences, along with up-to-date crowdsourced data, the platform offers a comprehensive tool for monitoring and evaluating the level of human exposure in flood susceptible areas. The mobile application effectively involves in crowdsourcing disaster data and, disseminating disaster alerts, while the web application provides robust visualization and analytical features, allowing users to gain a deeper understanding of and respond more effectively to flood hazards.

The platform highlights the capacity of crowdsourcing as an efficient approach for collecting specific, real-time information. By integrating historical data, this approach greatly improves the precision and significance of flood vulnerability evaluations. By integrating machine learning techniques, such as DB SCAN, to verify crowdsourced data, the reliability of the acquired information is significantly enhanced. In addition, the mobile app's inclusive design caters to a diverse user base, including individuals with less sophisticated devices. This approach helps bridge the digital gap and promotes wider engagement.

However, the study highlights a significant obstacle: the need to continually motivate people to actively participate on the site. Although the program is technically strong and provides significant advantages, enhancing long-term user engagement is a crucial aspect that needs to be further strengthen. The results indicate that while a significant number of users value the effort, there are individuals who do not possess the drive to consistently provide data. This is frequently attributed to the presence of pre-existing local knowledge or a strong inclination towards self-reliance in managing flood hazards.

In order to address this obstacle, the study suggests the implementation of focused mobilization techniques. These could involve forming alliances with local government and private companies to provide concrete incentives and acknowledgment for individuals who actively contribute, thus motivating their engagement. Furthermore, increasing community awareness regarding the platform's wider societal advantages, such as its ability to enhance early warning systems and safeguard vulnerable populations, could serve as an additional incentive for active participation. To achieve continuous mobilization, it is crucial to implement community-based outreach activities, incorporate educational content within the app, and ensure that the platform stays user-friendly and responsive to criticism.

Ultimately, the effectiveness of this platform in participatory flood risk management is on its ability to effectively mobilize and retain user engagement. By tackling these difficulties, the platform may fully realize its promise as a crucial instrument for improving disaster resilience and promoting a proactive culture of flood risk management.

4.2 Recommendations for Future Developments

To enhance the effectiveness and scalability of the developed flood risk management system, several improvements and expansions are recommended. Firstly, the system should be extended to other river basins in Sri Lanka, particularly those prone to frequent flooding, such as the Mahaweli, Kalu, and Gin River basins. This will help in creating a nationwide flood vulnerability assessment framework that can be integrated into disaster management strategies.

Secondly, improving the validation of crowdsourced data is crucial for ensuring data accuracy and reliability. Implementing AI-driven verification mechanisms and integrating real-time hydrological and meteorological datasets can enhance data credibility. Incorporating sensor-based flood level monitoring alongside community-reported data will further improve model precision.

Another key recommendation is fostering private sector partnerships to support the long-term sustainability of the system. Collaborating with technology firms, telecommunication providers, and insurance companies can help enhance system infrastructure, ensure continued funding, and improve disaster response capabilities. Additionally, involving private organizations in community engagement initiatives can promote wider adoption of the platform.

Lastly, enhancing mobile application features by integrating multilingual support, interactive disaster preparedness modules, and reward-based incentives for active participation will improve community engagement. Strengthening cloud-based data storage and analysis can also facilitate more efficient and scalable operations.

4.3 Recommendations for Practitioners

For disaster management authorities in Sri Lanka, integrating the developed flood monitoring platform into national emergency response systems is recommended. Authorities such as the Disaster Management Centre (DMC), Department of Meteorology, and Irrigation Department should utilize crowdsourced data to enhance flood forecasting and real-time alerts. Establishing a centralized data-sharing platform among agencies will ensure timely disaster response and coordination.

For urban planners and planning agencies, leveraging the system for risk-sensitive urban development is crucial. The platform can provide critical insights into flood-prone areas, guiding land-use planning and infrastructure development. Authorities like the Urban Development Authority (UDA) and local municipal councils should adopt geospatial flood data for zoning regulations, ensuring that new developments are resilient to flood risks.

Moreover, community engagement strategies should be strengthened by incorporating citizen-led disaster preparedness programs. Conducting awareness campaigns and integrating the platform into local government disaster response plans will encourage active community participation.

Finally, government agencies should work towards policy-level integration of participatory disaster management. Adopting legislation that mandates the use of crowdsourced and remote sensing data in flood risk assessment can institutionalize these approaches, ensuring that they become a standard part of Sri Lanka's disaster resilience strategies.

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Annexure 01: Pre & Post Questionnaires

Disaster Recorder App - Survey Questionnaire 01

* Indicates required question

1. Name *

2. Age *

3. Employment Status

Check all that apply.

- [ ] Employed
- [ ] Unemployed
- [ ] Other:

4. Average Monthly Income

Check all that apply.

- [ ] Below Rs. 30,000
- [ ] Rs.30,000-50,000
- [ ] Rs. 50,000-70,000
- [ ] Rs. 70,000- 100,000
- [ ] Over Rs. 100,000

5. Do you have a smart phone

Mark only one oval.

- Yes
- Yes, but not in a good condition to use apps/internet etc.
- No, I don't

DISASTER VULNERABILITY

6. Have you ever experienced floods situation?

Mark only one oval.

- Yes
- No
- Can't specify

7. Does your home/work place subjected to flooding

Mark only one oval.

- Yes, frequently
- Yes, not frequently
- No

TECHNOLOGY & DISASTER AWARENESS

8. Do you use social media platforms (Facebook/Instagram/WhatsApp etc)

Mark only one oval.

- Yes
- No

9. Have you used any mobile applications related such Fuel App/ Train schedule App/ Dansal App etc. such crowdsourcing app.

Mark only one oval.

- Yes
- No
- May Be

10. What Motivated you to use such apps (crowdsourcing apps)

11. Have you ever used a mobile application to get or care disaster related information

Mark only one oval.

- Yes
- No
- Maybe

12. If yes Please specify the apps

13. How do you get to know about disaster information currently

Mark only one oval.

- News
- Social Media
- Through pre signs according to the local knowledge
- Any other risk sharing platforms
- Other: ____________

14. If, Other risk sharing platforms, Please Specify (Applications/ Early warning systems etc.)

15. What do you think about the accuracy and the reliability of the above mentioned existing method of risk data sharing

16. If you get to know reliable risk information, would you like to contribute to it and share information for people?

Mark only one oval.

- Yes
- No

Disaster Recorder App - Survey Questionnaire 02

1. Does this app consumes a lot of your time to report a disaster event?

   Mark only one oval.

   - Yes
   - No

2. Overall, how can you rate the convenience in handling the app

   Mark only one oval.

	1	2	3	4	5	
Not						Very Easy to handle

3. What issues you faced during handling the application?

4. What was your motivation to use the app

   Mark only one oval.

   - You have experienced flooding and think we need to share risk information for people
   - No experience in flooding but sharing risk information is for people to prevent from disasters
   - Motivation provided (With the financial benefit)
   - Other:

5. If other, Pls Specify

Suggestions to improve the Application

6. What are the general improvements/ suggestions you have to improve the app?

7. What are the visual aspects need to be improved in the app?

8. What are the technical aspects need to be improved in the app?

9. What do you think about using this kind of a platform to share risk information? Will people use it? And will people get the benefit?

10. Would you like to share this app with another one from the community?

Mark only one oval.

- Yes
- No

Annexure 02: DB Scan Model (Removing Outliers from the Data Set)

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import DBSCAN
import pandas as pd
# Step 1: Load dataset from CSV
df = pd.read_csv('/content/sample_data/Sample Dataset.csv')

# Assume the CSV file has columns 'x' and 'y'
X = df[['x', 'y']].values
# Step 2: Apply DBSCAN
db = DBSCAN(eps=0.3, min_samples=5).fit(X)
labels = db.labels_

# Step 3: Identify core samples, clusters, and noise
core_samples_mask = np.zeros_like(labels, dtype=bool)
core_samples_mask[db.core_sample_indices_] = True
unique_labels = set(labels)
n_clusters_ = len(unique_labels) - (1 if -1 in labels else 0)

# Step 4: Plot the results
plt.figure(figsize=(10, 6))
colors = plt.cm.Spectral(np.linspace(0, 1, len(unique_labels)))

for k, col in zip(unique_labels, colors):
    if k == -1:
        # Black color for noise
        col = 'k'


    class_member_mask = (labels == k)
    xy = X[class_member_mask & core_samples_mask]
      plt.plot(xy[:, 0], xy[:, 1], 'o', markerfacecolor=col,
markeredgecolor='k', markersize=14)
```

```
    xy = X[class_member_mask & ~core_samples_mask]
      plt.plot(xy[:, 0], xy[:, 1], 'o', markerfacecolor=col,
markeredgecolor='k', markersize=6)

plt.title(f'Estimated number of clusters: {n_clusters_}')
plt.xlabel('x')
plt.ylabel('y')
plt.show(
```

Annexure 03: List of Publications

Title	Journal	Progress
Development of a Web Application through a Mobilized Crowdsourcing Platform to Enable Participatory Risk Sensitive Urban Development https://acrs-aars.org/proceeding/ACRS2024/AB0030.pdf	Asian Conference on Remote Sensing	Published
Bridging Community Engagement and Technological Innovation for Creating Smart and Resilient Cities: A Systematic Literature Review https://doi.org/10.3390/smartcities7060147	Smart Cities	Published
Harnessing Mobile Technology for Flood Disaster Readiness and Response: A Comprehensive Review of Mobile Applications on the Google Play Store	Urban Science	Under Review
Development of a Web Application to Assess the Flood Vulnerability Levels Using Night-time Light Data	Disasters	Under Progress