



**College of Science and Technology**

**School of Architecture and Built Environment**

**Master of Science in Geo-Information Science for Environment and Sustainable  
Development (MSc GI-ESD)**

**Leveraging Crowd-sourced Social Sensing for Enhancing  
Remote Sensing-Based Real time Flood Mapping. Case Study  
of The Nile Nyabarongo Lower Level I, Rwanda**



**Source: Reuters (2023)**

**Olivier NIYOMUGABO**

**August 2025**



UNIVERSITY of  
RWANDA

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The Nile Nyabarongo Lower Level I, Rwanda**

By

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*A dissertation submitted in partial fulfilment of the requirements for the  
degree of Masters of Science in Geo-Information Science for Environment and  
Sustainable Development*

**Supervisor:** Assoc. Prof. Elias NYANDWI

Kigali, July, 2025

## DECLARATION

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I declare that this MSc dissertation entitled **“Leveraging Crowd-sourced Social Sensing for Enhancing Remote Sensing-Based Real time Flood Mapping. Case Study of The Nile Nyabarongo Lower Level I, Rwanda.”** submitted for an award of Master of Science’s degree in Geo-Information Science for Environment and Sustainable Development is my own original work and has never been submitted in any higher learning institution or elsewhere.

NIYOMUGABO Olivier

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Date: ...../August /2025

## **APPROVAL**

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This is to certify that the study entitled “**Leveraging Crowd-sourced Social Sensing for Enhancing Remote Sensing-Based Real time Flood Mapping. Case Study of The Nile Nyabarongo Lower Level I, Rwanda**” was conducted by Olivier NIYOMUGABO in partial fulfilment of the requirements for the award of the Degree of Master of Science in Geo-Information Science for Environment and Sustainable Development, in the School of Architecture and Built Environment.

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## **DEDICATION**

This work is dedicated with deepest love and gratitude to my family and loved ones.

To the entire Bidugu family, thank you for your constant love and support.

To my wife, Gaudence Uwase Niyomugabo; my mother, Judith Mukamugema Bidugu; my stepfather, Augustin Ruzirabwoba; my brother Honore Rwibutso; my sister Dinah Penouella Ineza and my daughter, Ivy Amarah Agwize Niyomugabo, thank you for your unconditional love, patience, and encouragement throughout this journey.

Finally, I honour the memory of the late Rose Uwimana Bidugu, who was a great inspiration and a beloved grandmother.

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Thank you!

Until next time

Olivier NIYOMUGABO, Kigali, July 2025

## ABSTRACT

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Flooding is a common natural catastrophe that can devastate communities by inflicting structural damage, loss of life, interruption of key services, and environmental degradation. In May 2023, Rwanda experienced intense flooding with notable socio-economic impacts, coinciding with peak rainfall in the study area as indicated by CHIRPS 5-day satellite data. This study assessed the flood extent, socioeconomic infrastructures and utilities at flood risk in the Nile Nyabarongo Lower Level I Catchment by integrating Sentinel-1 Synthetic Aperture Radar (SAR) data processed in Google Earth Engine with crowdsourced social sensing images. Flood detection employed an image differencing technique with Otsu's automatic thresholding, while social media images were filtered, geotagged, and overlaid with SAR-derived maps. The results showed an inundated area of approximately 21.34 km<sup>2</sup>, with VV polarization slightly outperforming VH, and strong agreement with UNOSAT reference data. Twelve unique geotagged images and four manually geolocated ones confirmed the SAR findings. Exposure analysis revealed that several critical infrastructures, including roads, water treatment plants, other utilities and socio-economic facilities, were at risk. The study demonstrates that combining satellite imagery with crowdsourced data strengthens real-time flood mapping and delivered capabilities of socio sensing platforms in real time flood mapping, particularly in data-scarce regions.

**Keywords:** GEE, SAR, Social Sensing, Floods, Change detection, Geotagging, and UNOSAT.

## LIST OF SYMBOLS AND ACRONYMS

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<b>AI</b>	Artificial intelligence
<b>CBD</b>	Central Business District
<b>CHIRPS</b>	Climate Hazards Center Infrared Precipitation with Stations
<b>CNN</b>	Convolutional Neural Network
<b>DEM</b>	Digital Elevation Model
<b>EO</b>	Earth observation
<b>ESA</b>	European Space Agency
<b>GEE</b>	Google Earth Engine
<b>GIS</b>	Geographic Information System
<b>IFRC</b>	International Federation of Red Cross and Red Crescent Societies
<b>ML</b>	Machine learning
<b>NASA</b>	National Aeronautics and Space Administration
<b>NDWI</b>	Normalized Difference Water Index
<b>NISR</b>	National Institute of Statistics Rwanda
<b>OSINT</b>	Open-source intelligence
<b>OSN</b>	Online Social Networking
<b>ROI</b>	Region Of Interest
<b>RS</b>	Remote Sensing
<b>S-1</b>	Sentinel 1
<b>SAR</b>	Synthetic Aperture Radar
<b>UAV</b>	unmanned aerial vehicle
<b>UNITAR</b>	United Nations Institute for Training and Research
<b>UNOSAT</b>	United Nations Satellite Centre
<b>USGS</b>	United States Geological Survey
<b>VH</b>	vertical transmit, horizontal receive
<b>VV</b>	vertical transmit, vertical receive

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## CHAPTER I: INTRODUCTION

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### 1.1. Background Information

Flooding is a common natural catastrophe that can devastate communities by inflicting structural damage, loss of life, interruption of key services, and environmental degradation (Bates et al., 2020). Despite breakthroughs in flood hazard mitigation methods, the frequency and severity of floods continue to grow, worsened by climate change, increasing urbanization with insufficient drainage systems. Globally, floods account for approximately one-third of all natural disasters and over half of disaster-related casualties (Huang, 2020). Floods, notably flash floods, have a substantial influence on food security in Africa, particularly in rural communities that rely heavily on agriculture. Flooding caused roughly 12% of all food insecurity instances between 2009 and 2020, damaging lives and economic stability (Reed et al., 2022).

Flood measuring has progressed from ancient Nilometers used by the Egyptians to contemporary remote sensing systems. Early techniques depended on manual water level measurements and stream gauges (El-Bestawi, 2021; Robinson & Ward, 2017). Satellite imagery, such as Landsat, improved flood mapping but required lengthy revisit periods (Wulder et al., 2022). The Sentinel-1 mission, with Synthetic Aperture Radar (SAR), revolutionized flood monitoring by providing cloud-penetrating, real-time data (Kuntla, 2021). Drones have recently improved flood assessment by providing high-resolution imagery and rapid deployment to supplement satellite data (Zakaria et al., 2019). The combination of UAVs, GIS, and remote sensing allows precise flood mapping, which strengthens disaster response and mitigation measures in flood-prone regions

Crowd-sourced social sensing data has emerged as a valuable tool for improving real-time flood detection and impact assessment by combining user-generated content from digital platforms such as social media, mobile applications, and Volunteered Geographic Information (VGI) systems. Social sensing, when integrated with remote sensing and GIS, improves the timeliness and spatial accuracy of flood mapping, thereby strengthening emergency response and disaster resilience efforts (Li et al., 2017). Several case studies have demonstrated the effectiveness of crowdsourcing in flood management. For example, during Hurricane Harvey, social media reports provided critical real-time information about flood-affected areas, supplementing satellite-based observations (Mohr et al., 2022). Similarly, the European Flood Awareness System (EFAS) integrates citizen reports to boost

flood forecasting accuracy (Mourato et al., 2021). Despite these advancements, challenges remain in extracting high-quality, reliable observational data from unstructured user-generated content (Akhtar et al., 2024).

Rwanda's geographical position just south of the equator exposes it to a tropical climate characterized by two distinct rainy seasons: a long rainy season from March to May and a shorter one from September to November. This climatic pattern contributes to the country's relatively high mean annual precipitation of 1,170.3 mm (The World Bank Group, 2021). Furthermore, the country's steep terrain and intense rainfall, is highly susceptible to floods, particularly in urbanized regions where rapid development has altered natural drainage patterns. For Rwanda, the intensity of heavy rainfall is projected to increase, leading to a higher risk of natural disasters such as floods and flash floods, which may in turn trigger landslides and mudslides. Recent population growth and worsening land scarcity have compelled many people to settle in flood-prone areas, further exacerbating their vulnerability to these hazards (The World Bank Group, 2021).

According to the IFRC (2018), the frequency and intensity of floods have dramatically increased over the past decades, more recently, the devastating floods of May 2-3, 2023, across the Western, Northern, and Southern provinces resulted in over 130 deaths and displaced more than 20,000 people (Nkurunziza, 2024; ReliefWeb, 2023). Moreover, the capital city of Kigali which is part of the Kigali Catchment, is especially vulnerable due to population growth, inadequate drainage systems, and land use pressures has experienced recurring floods, with the March 2020 event recording a maximum water depth of 2.56 meters and a peak velocity of 1.38 m/s, causing significant business losses in the Nyabugogo valley (Uwineza & Irie, 2022). These incidents underscore the urgent need for improved flood detection and management systems.

Although flood mapping has evolved from ancient traditional flood measurement techniques at the level of satellites and unmanned aerial vehicle (UAV) imagery as powerful tools for flood detection and mapping. these advanced, real-time techniques remain costly, particularly for developing countries like Rwanda. Therefore, there is a growing need to adopt crowdsourced data as a complementary approach, especially when access to remote sensing data is limited during flood events.

## 1.2. Problem Statement

Rwanda, with its steep topography and heavy rainfall, is highly prone to flooding particularly in urban areas where rapid development has disrupted natural drainage systems. The country's growing population and increasing land scarcity have driven many residents to settle in flood-prone zones, significantly heightening their vulnerability to flood hazards (The World Bank Group, 2021). According to the IFRC (2018), flood frequency and intensity have grown considerably in recent decades. More recently, within the catchment area, the devastating floods of May 2–3, 2023, across Rwanda's Western, Northern, and Southern provinces resulted in over 130 fatalities and displaced more than 20,000 people (ReliefWeb, 2023). The capital city of Kigali, also situated within this catchment, is particularly vulnerable to flooding due to rapid population growth, inadequate drainage infrastructure, and increasing land use pressures. The city has experienced recurring flood events, including the significant March 2020 flood, which recorded a maximum water depth of 2.56 meters and a peak velocity of 1.38 m/s, resulting in substantial business losses in the Nyabugogo Valley (Uwineza & Irie, 2022).

Heavy rainfall frequently triggers severe flooding in highly vulnerable areas within the catchment, such as Nyabugogo, which is situated downstream of Kigali's Central Business District (CBD) and the surrounding hills of Mount Kigali, Mount Jali, and Gisozi. Flooding in this area is a recurrent disaster, resulting in extensive property damage, loss of life, and significant economic hardship (Bizimana & Ndahigwa, 2020; Manizabayo et al., 2024). Among impacted locations, include Nyakabanda, Rwezamenyo, Kimisagara, and Gitega posing threat to homes nearly 8,035 vulnerable households and Nyabugogo valley (Uwizeye et al., 2022). Historical floods in 2019 killed six (6) people and damaged 110 homes, while in 2021, three people died, five were wounded, and 35 houses collapsed. The 2022 floods were the deadliest, killing seven people, injuring eight, and destroying 117 homes (Nkurunziza, 2024) Flood severity is growing as a result of urbanization and climate change, necessitating immediate drainage improvements, urban planning, and catastrophe risk mitigation techniques (Uwineza & Irie, 2022).

In recent years, flood mapping in Rwanda were done through combining hydrological models, remote sensing, and GIS approaches to improve flood risk assessment and disaster preparedness. Also, Hydrodynamic models such as HEC-RAS were used to predict water flow and flood extent

(Icyimpaye & Abdelbaki, 2022). Remote sensing, particularly Sentinel-1 SAR, were introduced to provides real-time flood detection, while now Landsat and MODIS imagery aid in long-term flood risk analysis as an advanced way of flood mapping.

However, its usefulness is hampered by ordering delays, satellite revisit cycles, data processing delays, and computing limitations (Manizabayo et al., 2024). But nowadays, Community-based mapping and UAV technologies further enhance flood estimates, giving high-resolution spatial data and prediction of the real-time flood impact mapping (Zakaria et al., 2019). Despite progress, obstacles in real-time detection exist, Integrating Artificial Intelligence, machine learning, and social sensing data could revolutionize flood mapping, strengthening Rwanda's resilience to flood disasters. These methods often require significant financial resources, technical expertise, and extended processing times in contrast, social sensing leverages user-generated data from social media and mobile platforms, offering a cost-effective and immediate alternative.

Real-time and cost effective flood information can be retrieved from X (former Twitter), Facebook, Instagram, WhatsApp, Flickr etc., using advanced data mining techniques such as natural language processing (NLP), geotagging, geolocating and machine learning algorithms. Social media users frequently share flood-related updates, images, and videos with location-specific hashtags, allowing researchers and disaster response teams to extract critical situational data (Li et al., 2017). Automated methods, such as Twitter APIs and machine learning classifiers, detect flood-related tweets using keywords like "flood," "heavy rain," and location-specific phrases (Arthur et al., 2018). Geotagged posts provide precise flood locations, and computer vision models analyze images to determine flood severity (Sadiq et al., 2022). Integrating crowdsourced data with GIS and remote sensing improves flood mapping, response strategies, and situational awareness in real time.

Social media can provide localized, on-the-ground real-time flood reports from affected communities, enabling rapid flood mapping, enhancing situational awareness, and supplementing remote sensing data with firsthand observations. While previous studies have contributed valuable insights into the use of remote sensing for flood detection, most have been limited to relying solely on satellite imagery and ground truthing. In contrast, this study integrates remote sensing techniques with crowdsourced data collected from areas affected by flooding. This combined approach not only enhances the accuracy and completeness of flood maps but also provides a more nuanced understanding of local

conditions and the challenges associated with flooding. Moreover, it demonstrates the potential to consider social media platforms in flood mapping in regions with limited access to high-quality remote sensing data, as Rwanda.

### **1.3. Objective of the study**

#### **1.3.1. Main objective**

The major goal of this research is to assess the contribution of crowd-sourcing social sensing data for real-time flood mapping.

#### **1.3.2. Specific objectives**

1. To identify flooded area, and element at risk of being flooded using SAR imagery.
2. To combine crowdsourced social sensing data from various social media with remote sensing map.
3. Evaluate the contribution (accuracy and reliability) of crowdsourced data for real-time flood mapping and emergency response.

### **1.4. Research questions**

1. How extensive in terms of area and basic infrastructures were the floods in the catchment?
2. How can crowdsourced social sensing data from social media produce flood maps?
3. How accurate and reliable is crowdsourced social sensing data in mapping real-time floods and supporting emergency response efforts?

### **1.5. Research Matrix**

The research matrix shown below summarizes the study's essential components, matching the research objectives to the related research questions, data sources, collecting methods, and data analysis procedures. This organized framework guarantees that the various parts of the research are consistent, allowing for systematic data collection and analysis for successful flood mapping in the catchment. The matrix also shows the predicted results for each study aim.

Table 1: Research Matrix

Research Objectives	Research Questions	Data Needed and Sources
1.To identify flooded area using SAR imagery.	How extensive in terms of area, were the floods in the catchment?	Sentinel-1 SAR images (from Google Earth Engine)
2.To combine crowdsourced social sensing data from various social media with remote sensing map.	How can crowdsourced social sensing data from social media produce flood maps?	Geotagged social media posts (Tweets, Instagram photos, Facebook posts, etc.) from social media platforms
3.Evaluate the contribution (accuracy and reliability) of crowdsourced data for real-time flood mapping and emergency response.	How accurate and reliable is crowdsourced social sensing data in mapping real-time floods and supporting emergency response efforts?	Flood area map will be compared with social sensing flood map
4.Identification of elements at risk of being affected by flood.	What are human beings, crops, and other environmental elements at flood risk?	Flood map will be assessed for elements at risk

### 1.6. Hypotheses

This research aims to improve the understanding of flood dynamics in Rwanda and support the development of proactive strategies to reduce impacts on people and the environment. It focuses on mapping the extent of a major flood event in the Nile Nyabarongo Lower Level I Catchment using satellite imagery, complemented by crowdsourced data. The study also evaluates the consideration of use of crowdsourced data in real-time flood mapping, particularly in vulnerable urban and agricultural areas in remote sensing data scarce areas. Combining these data sources enables more comprehensive, accurate, and timely flood assessments, strengthening decision-making for disaster management.

## 1.7. Conceptual Frameworks and research design

A conceptual framework with a set of concepts is developed to carry out this research in a structured manner and adequately explain the study. Active remote sensing and socio sensing require consideration of active sensors and socio sensors in mapping of flood dynamics. As shown in figure 1, flood drivers cause floods, sensors detect floods using active energy and socio sensors.

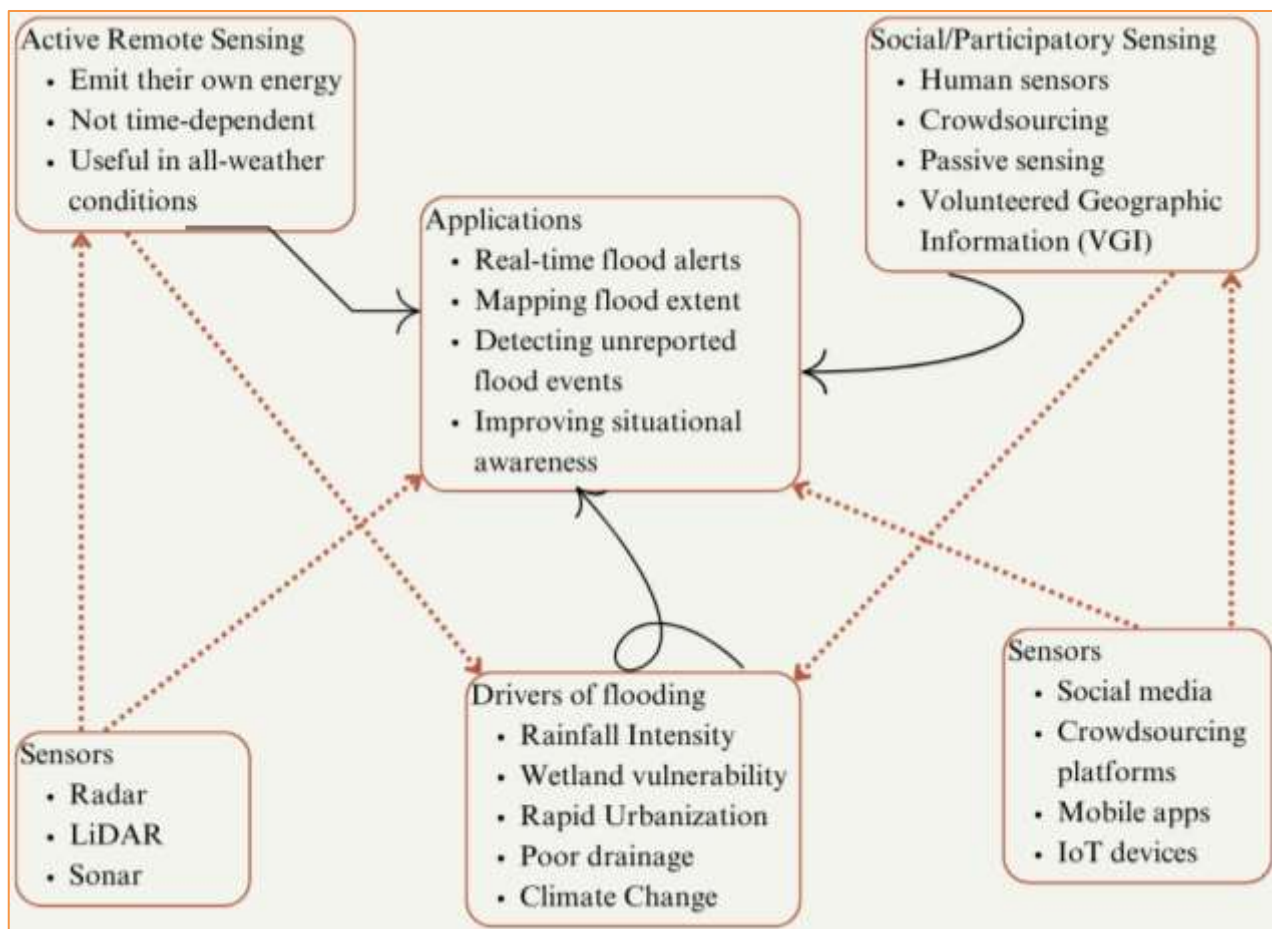


Figure 1: Conceptual framework

This study employed a mixed-methods research strategy (Figure 2), combining both qualitative and quantitative approaches to investigate real-time flood mapping in the catchment. The research process began with the formulation of research objectives and questions aligned with the identified problem. A review of existing literature was conducted to understand flood dynamics, SAR data analysis, image processing techniques, and flood segmentation methods. The findings were then presented using

maps, figures, and tables to effectively communicate the spatial and analytical outcomes for the study area.



Figure 2: Research process

### 1.8. Motivation and Significance of the Research

This study intends to enhance flood detection accuracy, emergency response, and disaster management by combining remote sensing and social sensing data sources, while also addressing time restrictions and spatial consistency difficulties in metropolitan environments.

Flooding in Rwanda, especially in the Lower Nile Nyabarongo Lower Level 1 catchment, continues to disrupt lives, destroy infrastructure, and endanger public health. The growing frequency of floods highlights the critical need for enhanced monitoring and response capabilities. Traditional flood mapping systems frequently rely on single data sources, resulting in delayed and sometimes erroneous estimates. The combination of social sensing and remote sensing provides a viable answer to these issues by merging real-time citizen reports with satellite-based data.

This study aims to contribute to the development of more efficient and accurate flood mapping techniques. The expected outcomes include:

- ✧ Improved accuracy and timeliness in flood detection and mapping.
- ✧ Enhanced flooding detection and its severity estimation.
- ✧ A scalable and adaptable methodology that can be applied to other flood-prone regions in developing countries.

## CHAPTER II: LITERATURE REVIEW

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This chapter reviews existing literature on flood mapping with a focus on the application of remote sensing technologies, the emergence and role of crowdsourced social sensing, and the integration of both approaches in real-time flood management.

### 2.1. SAR remote sensing applications for flood mapping

Satellite imagery, particularly Synthetic Aperture Radar (SAR), has become the preferred method for near real-time flood extent delineation, as its signals can penetrate cloud cover, an advantage over optical sensors especially when combined with flood detection algorithms (Sadiq et al., 2022). While there are many common techniques relying on thresholding methods to differentiate between water and surface pixels in satellite imagery, such as Otsu's thresholding method and the Normalized Difference Water Index (NDWI), deep learning algorithms have emerged to be reliable approaches in detecting floods due to their generalization capability over different geographic locations and geologies.(Akhtar et al., 2024). The use of Sentinel-1 SAR data via Google Earth Engine (GEE) for mapping flood extents in and around the city of Beira, Mozambique, following Cyclones Idai and Kenneth in 2019 (Nhangumbe et al., 2023), serves as a significant methodological inspiration for this study in producing flood maps.

Thresholding is one of the most commonly used techniques for flood detection in satellite imagery, as it enables rapid binary classification of water and non-water regions. However, this method faces significant limitations in terms of generalizability. For instance, flood detection in urban areas is particularly challenging because the imagery often exhibits unimodal or subtle bimodal histogram distributions, making it difficult to determine an optimal threshold (Zhan & Zhang, 2019). Moreover, the performance of thresholding techniques declines sharply when the proportion of water pixels is very low, especially in urban environments or areas with complex terrain. To overcome these limitations, researchers have increasingly turned to deep learning methods, which can learn from diverse image datasets and thereby generalize more effectively across different geographic regions and varying water coverage ratios (Nhangumbe et al., 2023).

A recent study on SAR imagery demonstrated that Fully Convolutional Networks (FCNs) outperform the Otsu thresholding method in segmenting temporary water bodies (Zhan & Zhang, 2019). The researchers reported their findings using various combinations of Sentinel-1 SAR bands, showing that

deep learning models such as U-Net and SegNet achieved superior performance compared to traditional thresholding approaches (Wulder et al., 2022). While many earlier studies relied solely on either optical or SAR imagery, more recent research has focused on the fusion of multi-source data. For example, some studies have analysed the integration of multispectral Landsat imagery (optical) and dual-polarized SAR data to assess the effectiveness of convolutional neural networks (CNNs) within data fusion frameworks for flood mapping (Sadiq et al., 2022). Other work has further explored the fusion of Sentinel-1 (SAR) and Sentinel-2 (optical) imagery to train water segmentation models using boundary-aware deep networks (Kuntla, 2021). These studies consistently indicate that deep learning approaches provide significantly better accuracy for flood water segmentation than traditional thresholding techniques.

## **2.2. Crowdsourcing in Flood Monitoring**

In flood monitoring, crowdsourcing has become a potential supplementary tool, especially when it comes to improving the temporal and spatial precision of flood data. Crowdsourcing is the act of collecting information freely provided by a large number of individuals, frequently using digital platforms. It uses social media's connection and mobile devices' widespread use to offer real-time, on-the-ground data during crisis events (Rosser et al., 2017). The use of crowdsourced data has been increasingly explored in the aftermath of flood events, particularly through the coordinated deployment of crowd contributors. Crowdsourcing platforms are employed to evaluate ground-level images captured using smartphones and other mobile devices. One notable example is the UNITAR-UNOSAT project GeoTag-X, which engages volunteers to categorize images taken during disaster situations and provide critical assessments such as floodwater extent, structural damage to buildings, and the condition or safety of temporary shelters for displaced populations (Li et al., 2017).

The use of geo-referenced citizen reports in relation to flood events has been examined through methods that assess the credibility of such reports using probabilistic models trained on data from previous flood events. These models are then applied to categorize the credibility of reports during subsequent events, demonstrating that volunteered information can be automatically ranked to facilitate faster integration into emergency management systems (Huang, 2020). Online Social Networking (OSN) platforms such as Twitter and Facebook offer valuable real-time insights during natural disasters. The large volumes of data generated from user interactions on these platforms have given rise to the field of Participatory Sensing which involves the use of user-contributed information

to observe and analyse physical phenomena, including events such as floods, earthquakes, and other natural hazards (Sadiq et al., 2022).

While participatory sensing offers the advantage of real-time information acquisition, it also presents the challenge of data verification. This limitation contrasts with the strength of remote sensing, where satellite imagery though not always immediate is generally considered reliable and accurate (Huang, 2020). Remote sensing and social sensing data complement each other effectively, as the strengths of one address the limitations of the other. Their integration offers a powerful approach for rapid flood mapping, particularly valuable for crisis response. While satellite imagery provides a broad, consistent spatial perspective, ground-level information from locally sourced textual and visual content adds contextual detail and immediacy. Together, these data sources enhance situational awareness and support more informed and timely emergency response planning (Reed et al., 2022).

### **2.3. Integrating Remote and Crowdsourced Data for Flood Mapping**

While social media sources alone can offer valuable insights, the integration of social media with remote sensing in disaster management has proven to be significantly more impactful. This fusion has been applied in various studies, primarily focusing on two key phases of a disaster: the monitoring phase during the event and the damage assessment phase afterward (Rosser et al., 2017). In the context of disaster monitoring, timely detection is critical to minimizing the severity of damage. Several studies have demonstrated the potential of integrating remote sensing with real-time social media data to enhance flood monitoring. For example, Gaussian kernel functions have been used to combine post-event optical satellite imagery with real-time Twitter data to generate near real-time flood likelihood maps. Other researchers have developed flood probability maps by integrating terrain data, socially sensed images, and satellite observations into Bayesian statistical models (Huang, 2020).

Additionally, time series maps of flood extent over multi-day events have been produced by fusing SAR imagery, Digital Elevation Models (DEMs), Twitter messages, geolocated photographs, and online news reports using geostatistical techniques such as kernel density estimation. The same technique has also been applied to generate flood hazard maps by combining social sensing data (including photos, videos, and news), remote sensing imagery, DEMs, meteorological data, and river gauge measurements (Kuntla, 2021). A study by Akhtar et al. (2024) found that the fusion of social

sensing and remote sensing data yielded highly consistent results, with 95% of Flickr images aligning with the spatial distribution of satellite-derived flood extents.

In the context of damage assessment, humanitarian organizations must quickly identify and prioritize emergency needs related to human safety, infrastructure, and the environment (Arthur et al., 2018). Much of the research in flood damage assessment has concentrated on the impact to transportation networks, particularly roads. One study employed a supervised machine learning model to detect water in optical satellite imagery, which was then complemented by geolocated tweets and photographs (Huang, 2020). These social media inputs were interpolated using a kernel smoothing technique to generate a damage assessment surface. By overlaying a road network on this surface, researchers were able to identify impassable roads. The findings demonstrated that, in situations where remote sensing data is limited or delayed, social media can offer valuable, localized information about flood damage at the street or block level (Sadiq et al., 2022).

#### 2.4. Data Governance and Privacy Regulations in Rwanda

Flood mapping research that integrates crowdsourced social sensing data must carefully consider the legal frameworks governing data protection, privacy, and access. In Rwanda, Law No. 058/2021 on the Protection of Personal Data and Privacy establishes clear rules for the collection, processing, storage, and sharing of personal data. It mandates lawful and transparent processing, informed consent, data minimization, and respect for data subject rights, guiding how geotagged imagery from social media can be ethically used in research (Mutimukwe et al., 2019). Complementing this, the Access to Information Law No. 04/2013 grants the public the right to request information from government agencies and certain private entities, facilitating transparency and access to relevant flood-related datasets (Bonde et al., 2015). These frameworks collectively ensure that flood mapping studies align with both scientific rigor and ethical/legal standards.

*Table 2: Data Legal framework*

Law / Regulation	Year	Key Provisions	Relevance to This Study
Law No. 058/2021 – Protection of Personal Data and Privacy	2021	Consent, data minimization, data subject rights, cross-border transfer restrictions, DPO requirements	Ensures responsible handling of social media and geotagged imagery used in flood mapping

Access to Information Law No. 04/2013	2013	Public right to request data from public institutions and some private bodies	Supports access to open datasets and government flood records
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Source: Mutimukwe et al. (2019) & Bonde et al. (2015)

## 2.5. Best Practices

This subsection reviews established some best practices in flood mapping that combine remote sensing and crowdsourced data, drawing from recent studies and operational frameworks. Emphasis is placed on approaches integrating remote sensing technologies, community-based data collection, and geospatial analysis to improve the accuracy and timeliness of flood detection and response.

### 2.5.1. European Flood Awareness System (EFAS)

The European Flood Awareness System (EFAS) represents a best practice in integrating social media into flood risk monitoring and early warning systems. EFAS leverages hydro-meteorological models to automatically trigger the collection of social media data when a flood risk warning is issued. A multilingual approach is employed to identify flood-related content, utilizing two advanced methodologies: language-agnostic word embeddings and language-aligned word embeddings. These methods enable the development of classifiers for detecting relevant flood-related messages across multiple languages, even in cases where labelled data is minimal or unavailable. To enhance operational value, EFAS incorporates a strategy for selecting and displaying the most relevant and representative social media messages directly within its interface, thereby improving situational awareness for decision-makers and emergency responders (Smith et al., 2021).

In early October 2018, severe flooding struck the Calabria region in southern Italy, resulting in fatalities, evacuations, infrastructure damage, and over 300 mm of rainfall in three days. The European Flood Awareness System (EFAS) successfully forecasted the event on October 4th, triggering a social media data collection that gathered over 14,000 tweets. Two classifiers cold-start and warm-start were used to identify flood-relevant tweets in Italian. The warm-start model, which incorporated 300 manually labelled tweets, outperformed the cold-start by detecting a greater number of relevant and geographically accurate messages. This case illustrates the potential of combining

EFAS forecasts with multilingual social sensing to enhance situational awareness during flood events (Zvolenský et al., 2023).

### **2.5.2. Hurricane Harvey in Texas and Louisiana, United States**

Hurricane Harvey (2017) served as a critical test of social media's role in disaster response and recovery. The absence of a government evacuation order and a public call for citizen-led rescues, combined with high social media usage in Houston, created ideal conditions to study online networks during crises. Using two original datasets and over 2.3 million social media interactions, researchers found that Houston's online social network became denser, more clustered, and more efficient during the disaster. Spatial and statistical analyses across 333 Next door neighbourhoods revealed that increased hyperlocal social media activity significantly predicted faster post-disaster rebuilding. These findings underscore the importance of strengthening hyperlocal online networks and supporting digital infrastructure as part of disaster preparedness and recovery policy (Page-Tan, 2021).

#### **2.2.1. United Nations Satellite Centre**

UNOSAT, the United Nations Satellite Centre, operates under the United Nations Institute for Training and Research (UNITAR). Established in 2001, it provides satellite imagery analysis and geospatial information to support humanitarian relief, development, peacekeeping, and disaster response efforts. Since 2003, UNOSAT has been conducting emergency mapping for various humanitarian crises including natural disasters, complex emergencies, and conflict situations (UNITAR, 2021). In Rwanda, UNOSAT has played a significant role in disaster risk management by providing satellite-based flood mapping during major flood events, notably in 2020 and 2023. Utilizing Sentinel-1 SAR imagery, UNOSAT delivered rapid flood extent maps for affected districts such as Rubavu, Nyabihu, Gakenke, Rulindo, Kigali and Musanze, aiding government agencies and humanitarian actors in damage assessment and emergency coordination. This study also explored the available mapping of UNOSAT on selected study event and assess the contribution from local community.

### **2.6. Gap in current research**

While previous studies have provided valuable insights into methodologies for integrating remote sensing and crowdsourced data, particularly through the use of SAR imagery and geotagged social media content, most have been conducted in developed countries. In contrast, this study focuses on a

developing country in sub-Saharan Africa, addressing a critical gap in the literature. By applying a combined approach of remote sensing and crowdsourced data within the Rwandan context, this research not only enhances the accuracy of flood mapping but also offers a more nuanced understanding of the local environmental conditions and challenges associated with flooding.

## CHAPTER III: MATERIAL AND METHODS

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This section will provide a comprehensive overview of the study area, remote sensing techniques, social sensing API retrieval and their combinations in flood mapping. We will delve into the materials used and outline the methodology adopted for combining remote sensing data and social sensing data in flood mapping in The Nile Nyabarongo Lower Level 1 catchment, Rwanda, as the case study.

### 3.1. Description of the Study Area

The Nile Nyabarongo Lower Level 1 catchment in Rwanda. Cover an area of approximately 3,313 km<sup>2</sup>, represents the main downstream section of the Nyabarongo River, located northwest of Kigali. It begins at the confluence of the Upper Nyabarongo and Mukungwa Rivers and extends about 70 km southeast to its downstream boundary at the confluence with the Akanyaru River, which feeds into the Nile Akagera Upper catchment. Three Level 2 sub-catchments feed into the Nyabarongo Valley sub-catchment: the Giciye/Mukungwa Sub-Catchment from the north, the Nyabarongo Upstream Sub-Catchment from the west, and the Nyabugogo Sub-Catchment from the east.

The primary inflows to the Catchment Valley originate from the Upper Nyabarongo (Nyabarongo Upstream) and the Giciye/Mukungwa sub-catchments. The Nyabarongo Valley sub-catchment comprises numerous Level 3 catchments that drain into the main valley, with the most prominent being the Base tributaries in the northwest and the Mambu tributaries in the west. Seven districts are partially located within the Nyabarongo Valley catchment: Burera, Gakenke, Gicumbi, Kamonyi, Muhanga, Nyarugenge, and Rulindo (Rwanda Water Board, 2025).

In addition to the catchment, the historically frequent floods occurring in the urban areas surrounding the Nyabugogo bus park and along the downstream section of the river (Rwanda Water Board, 2025). A defining characteristic of the Nyabarongo Valley catchment is the transformation of the Nyabarongo River from a mountain stream into a broad, meandering river valley that experiences annual flooding during the rainy seasons. The land cover within the catchment is primarily composed of urban areas, rainfed agriculture, irrigated agriculture, and scattered forest plantations (Mugiraneza, 2021).



### 3.2.Data Collection Methods

Two datasets were used in this study: Sentinel-1 SAR data for flood extent mapping, and crowdsourcing data from social sensing platforms.

#### 3.2.1. Remote Sensing Data

SAR data used for flood mapping in this study is sourced from the Copernicus Sentinel-1 (S-1) constellation. The original configuration of the constellation comprised two identical satellites operating in near-polar, sun-synchronous orbits at an altitude of 693 km, with a revisit cycle of 12 days and 175 orbits per cycle (Bergsma & Almar, 2020). Both Sentinel-1A (S-1A) and Sentinel-1B (S-1B) were positioned in the same orbital plane, separated by a 180-degree phase difference. However, on 23 December 2021, Sentinel-1B experienced a critical anomaly involving the failure of its power supply system, which subsequently rendered the satellite's instruments inoperable (Potin et al., 2022). Sentinel-1A (S-1A) remains in nominal operational status, while the launch of Sentinel-1C (S-1C) in the fourth quarter of 2024 has restored the constellation's intended functionality, reducing the revisit time back to six days (European Space Agency, 2025).

Due to the failure of Sentinel-1B and the delayed launch of Sentinel-1C, the May 2023 flood event in Rwanda was captured solely by Sentinel-1A. As a result, the monitoring of this and other time-sensitive flood events was constrained by limited temporal coverage, increasing the likelihood of missed observations due to the orbital parameters and reduced revisit frequency of the single operational satellite(University of Twente, 2025). Despite the limitations in satellite coverage, the May 2023 flood event was captured by Sentinel-1A during an ascending pass on 3 May 2023 and a descending pass on 5 May 2023. These acquisition times align well with the peak of the flood, which occurred during the night of 2 May 2023, and the subsequent days, thereby providing valuable imagery for assessing flood extent during and shortly after the event.

*Table 3: Technical data on the Sentinel-1 satellite*

SN	Satellite	Sentinel-1A
1	Temporal Resolution	12 days
2	Altitude	693 km
3	Inclination	98.2°

4	C-SAR center frequency	5.405 GHz
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Source: eoPortal (2025)

The primary instrument onboard Sentinel-1A used in this study is the C-band Synthetic Aperture Radar (SAR), which operates in four observation modes: Strip map (SM), Interferometric Wide Swath (IW), Extra Wide Swath (EW), and Wave (WV) mode. Each mode is designed for specific remote sensing applications, offering varying swath widths and spatial resolutions (European Space Agency, 2025). The IW mode, commonly used for land applications including flood mapping, provides a 250 km swath with a spatial resolution of  $5\text{ m} \times 20\text{ m}$ . The EW mode covers a 400 km swath at a coarser resolution of  $25\text{ m} \times 100\text{ m}$ , suitable for wide-area ocean and ice monitoring. The SM mode offers high-resolution imagery (5 m) over an 80 km swath, while the WV mode captures  $20\text{ m} \times 20\text{ m}$  images at 100 km intervals with a spatial resolution of  $5\text{ m} \times 20\text{ m}$ . Sentinel-1A supports both single polarization (VV or VH) in WV mode and dual polarization (VV+VH or HH+HV) in IW, EW, and SM modes (Potin et al., 2022). VV stands for vertical transmit, vertical receive, and VH for vertical transmit, horizontal receive.

*Table 4: Technical data on the Sentinel-1 satellite*

SN	Mode	Swath	Spatial resolution
1	SM	80 km	5 m
2	IW	250 km	$5\text{ m} \times 20\text{ m}$
3	EW	400 km	$25\text{ m} \times 100\text{ m}$
4	WM	$20\text{ m} \times 20\text{ m}$ images at 100 km intervals	$5\text{ m} \times 20\text{ m}$

Source: eoPortal (2025)

This study acquired pre-flood and post-flood imagery using the C-band SAR onboard Sentinel-1A and apply image differencing techniques to delineate the flooded area. The imagery was acquired in Interferometric Wide Swath (IW) mode, utilizing both VH and VV polarizations. The use of both polarizations was intended not only to enhance flood detection but also to enable a comparative analysis of their respective accuracy in flood mapping.

Table 5: Technical data on the Sentinel-1A bands

SN	Band	Units	Min	Max	Pixel Size	Description
1	HH	dB	-50*	1*	10 meters	Single co-polarization, horizontal transmit/ horizontal receive
2	HV	dB	-50*	1*	10 meters	Dual-band cross-polarization, horizontal transmit/vertical receive
3	VV	dB	-50*	1*	10 meters	Single co-polarization, vertical transmit/vertical receive
4	VH	dB	-50*	1*	10 meters	Dual-band cross-polarization, vertical transmit/horizontal receive
5	angle	deg	0*	90*	2000 meter	Approximate incidence angle from ellipsoid

Source: Earth Engine (2025)

### 3.2.2. Crowdsourced/ Social Sensing data

Real-time flood event data were collected from social media platforms such as Flickr, Twitter, and Instagram using search engines and filters based on flood-related keywords and hashtags. Where possible, geotagged posts were utilized directly; in cases where geolocation was not available, efforts were made to manually geo-reference social media content to derive spatially explicit flood observations. This participatory sensing approach complemented satellite-based data by providing localized validation of flood extents, identifying affected areas, and enhancing the accuracy of flood impact assessments.

### 3.2.3. Field observation

A field visit was conducted on 15 June 2025 to collect ground-truth data and verify flood-affected locations within the Nile Nyabarongo Lower Level I, including key areas in and around Kigali City. The visit focused on areas identified as high-risk or frequently flooded based on satellite-derived flood maps and crowdsourced social media data from the May 2023 flood event. Key locations visited included Kinamba, Gisozi, Kagugu, the Mpazi drainage system, the Nyabarongo wetland, and the Nyabarongo Essential Bridge. Additional sites in Kibumba, Nyabugogo, Nyarugenge District, and upstream areas in Rulindo District were also assessed.



of open-source geospatial datasets from agencies such as NASA and ESA, enabling efficient, large-scale image processing and analysis (Nhangumbe et al., 2023; Yang et al., 2022).

All maps produced in this thesis were made using the GIS software (ArcGIS 10.8 and ArcGIS Pro 3.1.0).

### 3.3.2. Imagery Selection and Data Processing – Sentinel 1 SAR

Synthetic Aperture Radar (SAR) is a form of active remote sensing that fundamentally differs from optical image acquisition. Rather than relying on reflected sunlight, SAR transmits microwave signals toward the Earth's surface and records the backscattered responses to construct images. The nature of the returned signal depends on surface properties such as roughness, moisture content, and geometry, making it essential to carefully select the appropriate radar frequency for specific applications (eoPortal, 2023). In this study, Sentinel-1A (S-1A) was used, which operates a C-band SAR sensor at a frequency of 5.405 GHz, thereby restricting the analysis to that specific range of the electromagnetic spectrum (University of Twente, 2025).

*Table 6: S-1A acquisition dates*

Flood event	Period	Orbit number	Date	Orbit direction	Polarization
3 May 2023	Pre-flood	174	21 April 2023	Ascending	VV, VH
	Post-flood	174	3 May 2023	Ascending	VV, VH
5 May 2023	Pre-flood	21	23 April 2023	Descending	VV, VH
	Post-flood	21	5 May 2023	Descending	VV, VH

This study employed a forked approach consisting of two parallel pipelines: one for generating a flood extent map using Sentinel-1 SAR data, and another for extracting crowdsourced flood information from social sensing platforms. These two outputs were subsequently integrated to produce a comprehensive flood map. By combining satellite-based observations with localized, real-time social media reports, the study was able to capture flood dynamics from multiple perspectives.

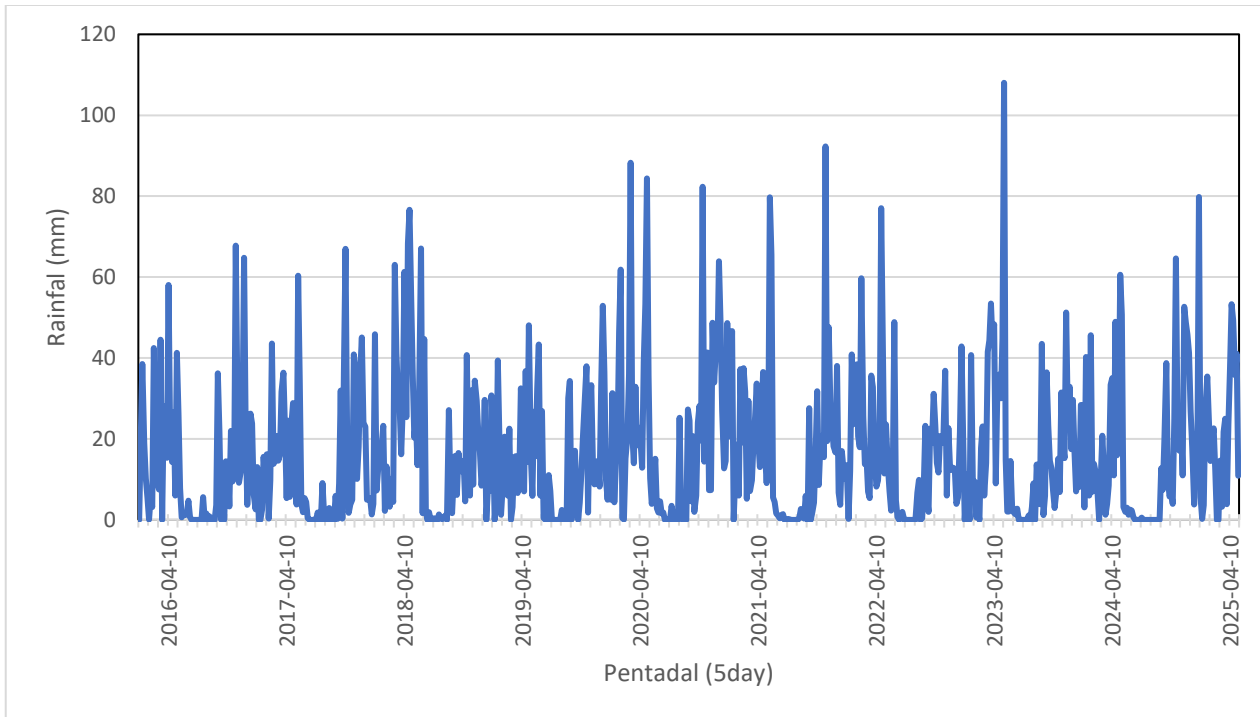
### **3.4.Data analysis**

#### **3.4.1. Detection of flood events by satellite imagery interpretation**

##### **3.4.1.1.Definition of temporal scope for flood detection**

Based on CHIRPS 5-day satellite rainfall estimates for the period from January 1, 1981, to February 26, 2024, the average annual precipitation over the Nyabarongo Valley catchment is approximately 1,126 mm. The most intense rainfall occurs during the two primary rainy seasons: April to June and September to December (REMA, 2020). The Nile Nyabarongo Lower Level 1 spans a large portion of central Rwanda, encompassing a variety of landscapes and climatic zones. The western parts of the catchment receive moderate to high rainfall with a relatively short dry season, whereas the eastern parts experience lower to moderate rainfall and a more pronounced dry season. Recent and ongoing urbanization in the catchment has led to increased rainfall-runoff, primarily due to the expansion of impervious surfaces. The uncontrolled discharge of this additional stormwater significantly impacts water quality throughout the catchment (Rwanda Water Board, 2025).

An analysis of CHIRPS 5-day satellite rainfall estimates for the period of around 10 years from 1 January 2016 to 29 May 2025 reveals a significant spike in rainfall during the first week of May 2023 (figure 4). The corresponding Excel raw data used for this analysis were annexed to the report. This anomaly corresponds to the major flooding events that occurred around 3 May 2023 and will therefore serve as the reference point for flood mapping and analysis in this study.



*Figure 5: Five-day precipitation in mm from CHIRPS satellite estimate over the last 10 years at NNYL-1, 10/01/2016 to 29/05/2025*

Source: USGS (2025)

### **3.4.1.2.Flood detection**

For flood detection and mapping, this study employed an image differencing method, a widely used approach for identifying changes in water and ice surfaces (Bergsma & Almar, 2020). This technique is well-established within the Google Earth Engine (GEE) platform, which was utilized for image processing in this research. The methodology adopted for flood mapping is based on, and inspired by, a previous report on flood mapping and damage assessment conducted in Mozambique, which demonstrated the effectiveness of image differencing in delineating flood extents using SAR data (Nhangumbe et al., 2023).

Flood mapping using image differencing is a pixel-based change detection technique, chosen in this study for its simplicity, ease of implementation, and suitability for cloud-based platforms such as

Google Earth Engine (GEE) (Yang et al., 2022). This method is not only intuitive but also computationally efficient, making it ideal for use within GEE's processing limits. Selecting a low-cost computational methodology helps minimize errors related to timeouts and performance lags. Effective change detection requires both pre-flood and post-flood images that meet specific criteria to ensure accurate analysis (Potin et al., 2022). These criteria include matching polarization, acquisition mode, orbit direction, and relative orbit number. Ensuring these parameters are consistent is essential for reliable pixel-level comparison. Additionally, a secondary objective of this study was to develop adaptable code that can be easily modified for flood mapping in other geographic regions. As such, the codebase includes modular components that, while potentially redundant for advanced users, enhance reusability and scalability.

To ensure consistency in viewing geometry and avoid discrepancies caused by different SAR sensor angles, this study adopted the standard practice of using identical orbit numbers for both pre- and post-flood image acquisitions over the same area. Orbit number calculation was integrated into the processing code and is automatically determined and displayed for the user, allowing for easy adaptation to different regions of interest (ROIs). In this case, a single Sentinel-1 image was selected for each time period one for the pre-flood and one for the post-flood phase. While acquisition times varied naturally between ascending and descending passes, the same image processing function was uniformly applied. This function accepted key parameters such as geometry, start and end dates, orbit direction, polarization, and orbit number. For each date, two images one for each polarization (VV and VH) were processed. A focal mean filter was applied to each image to reduce speckle noise and enhance image quality. The resulting images were then used as inputs for the flood detection algorithm.

In the flood mapping functions, this study specifically evaluated the performance of VV and VH polarizations for detecting flood extents within the Catchment. To facilitate this comparison, the flood mapping functions were implemented separately for each polarization, resulting in two distinct outputs. Both functions followed the same methodological approach, differing only in the polarization input. Each function applied Otsu's thresholding method to the log-ratio of pre- and post-flood SAR images as part of the image differencing technique. This automatic thresholding process enabled the extraction of flooded areas for both VV and VH polarizations, allowing for a comparative analysis of their effectiveness in flood detection. The processing interface of the change detection code used in

Google Earth Engine (GEE) is shown below with few syntaxes, while the full code was provided in the annex of this report.



Figure 6 GEE processing SAR Interface

Source: Google Earth Engine (2025)

### 3.4.2. Social sensing data filtering and geocoding

Posts that contain relevant information for humanitarian response and impact assessment, particularly those originating within the defined area of interest, are prioritized in this study. Given that only a small proportion of social media posts include precise geolocation data, it was necessary to georeference non-GPS-tagged posts to address the challenge of limited spatially-relevant content within the study area an issue noted in existing research. Additionally, social media content often includes noise and irrelevant information; thus, assessing the relevance and informational value of each post was a critical step. To ensure data quality, a rigorous filtering and processing workflow was applied, selecting only those posts that met predefined criteria for spatial, temporal, and thematic relevance. Furthermore, field observation was conducted to gain contextual understanding of local flooding dynamics and validate observations derived from social media and remote sensing sources.

Posts containing valuable information but lacking geotags were georeferenced using identifiable physical features visible in the content of the posts. These features were cross-referenced with field

observations to ensure spatial accuracy and alignment with real-world locations. Flood extent maps obtained from remote sensing data (satellite imagery) was overlaid with flood coordinates from flood events of social media platforms (e.g., Instagram, Flickr, Twitter and Facebook) to reveal geographical linkages, some of links explored were annexed to the report. This stage is crucial for enhanced validation of the locations of flood-impacted regions detected by remote sensing and confirming them with user-generated material. also flood map was overlaid to historical flood records, official catastrophe

### 3.4.3. Evaluate the contribution of crowdsourced data for real-time flood mapping

UNOSAT was activated in response to the flood and landslide event that occurred in May 2023 in Rwanda, producing flood maps covering the Study area. UNOSAT’s emergency mapping process is semi-automated, employing state-of-the-art technology and expert analytical methods. The flood extent maps produced by UNOSAT served as a reference dataset for the accuracy assessment of flood mapping results derived from Sentinel-1 SAR imagery processed in Google Earth Engine (GEE).The code for function of accuracy is based on the work on flood mapping and damage assessment in Mozambique (Nhangumbe et al., 2023). The metrics used for accuracy assessment are defined below (see equations (1), (2), (3), and (4)). These metrics are widely used for accuracy assessment in remote sensing (Nhangumbe et al., 2023).

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

Source: Nhangumbe et al. (2023)

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

Source: Nhangumbe et al. (2023)

$$F1 = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad (3)$$

Source: Nhangumbe et al. (2023)

$$\text{Overall accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (4)$$

Source: Nhangumbe et al. (2023)

TP stands for true positive; FP stands for false positive; TN stands for true negative and FN stands for false negative

Another common statistical method in remote sensing and accuracy assessment of change detection is kappa. The main formulas are as follows below (see equation (5)); however, for a deeper understanding and more details about the formulas see the written work specifically about this subject(van Vliet et al., 2011).

$$Kappa = \frac{P_o - P_e}{1 - P_e} \quad (5)$$

Source: Nhangumbe et al. (2023)

$P_o$  is the overall accuracy,  $P_e$  is the proportion expected to be correctly classified(van Vliet et al., 2011). In parallel, field observations conducted during the study were used to assess the spatial accuracy and reliability of the flood-related social sensing data.

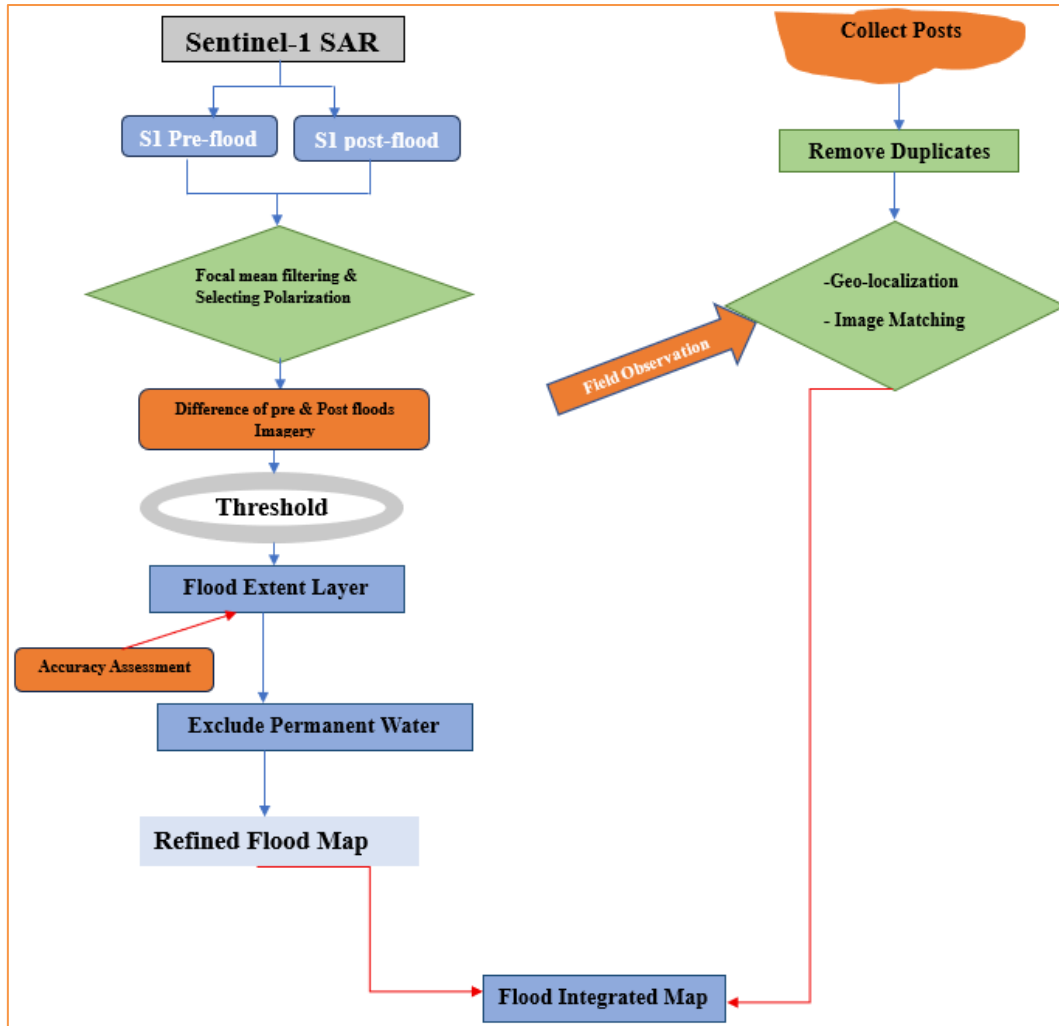


Figure 7: Methodology Flowchart

### 3.4.4. Identification of elements at risk of being affected by flood

The elements at risk of flood impact were identified by conducting an overlay analysis of the flood extent map, wetlands, high-resolution satellite basemaps, and critical infrastructure layers. The critical infrastructure geodatabases included roads, building footprints, bridges, culverts, schools, health facilities, power stations, hydropower plants, water pumping stations, drainage systems, and water treatment plants. This approach enabled a comprehensive assessment of exposure and vulnerability across the flood affected areas. Field observations and GPS data were used to validate and refine the analysis, ensuring accurate identification of at risk elements.

## **CHAPTER IV: RESULTS AND THEIR DISCUSSION**

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This chapter presents the results derived from the integration of remote sensing and crowdsourced social sensing data for flood mapping in the Nile Nyabarongo Lower Level I catchment, Rwanda. The findings are structured to reflect the study's objectives, beginning with the flood extent maps generated using Sentinel-1 SAR imagery and followed by the spatial insights extracted from social media data. The accuracy of both data streams is evaluated independently and then comparatively, using reference data from UNOSAT and ground-truth field observations.

### **4.1. Results**

#### **4.1.1. Flood map from SAR imagery interpretation**

VV and VH polarizations both give identical findings for flooded areas, with the same level of accuracy and the same calculated flood extent in square kilometres. Nonetheless, there is a slight variation between VV and VH polarization generally, and the accuracy evaluation yields comparable findings. Both polarizations yielded similar results, with the VH polarization estimating a flooded area of 21.34 square kilometers and the VV polarization estimating 22.03 square kilometers.

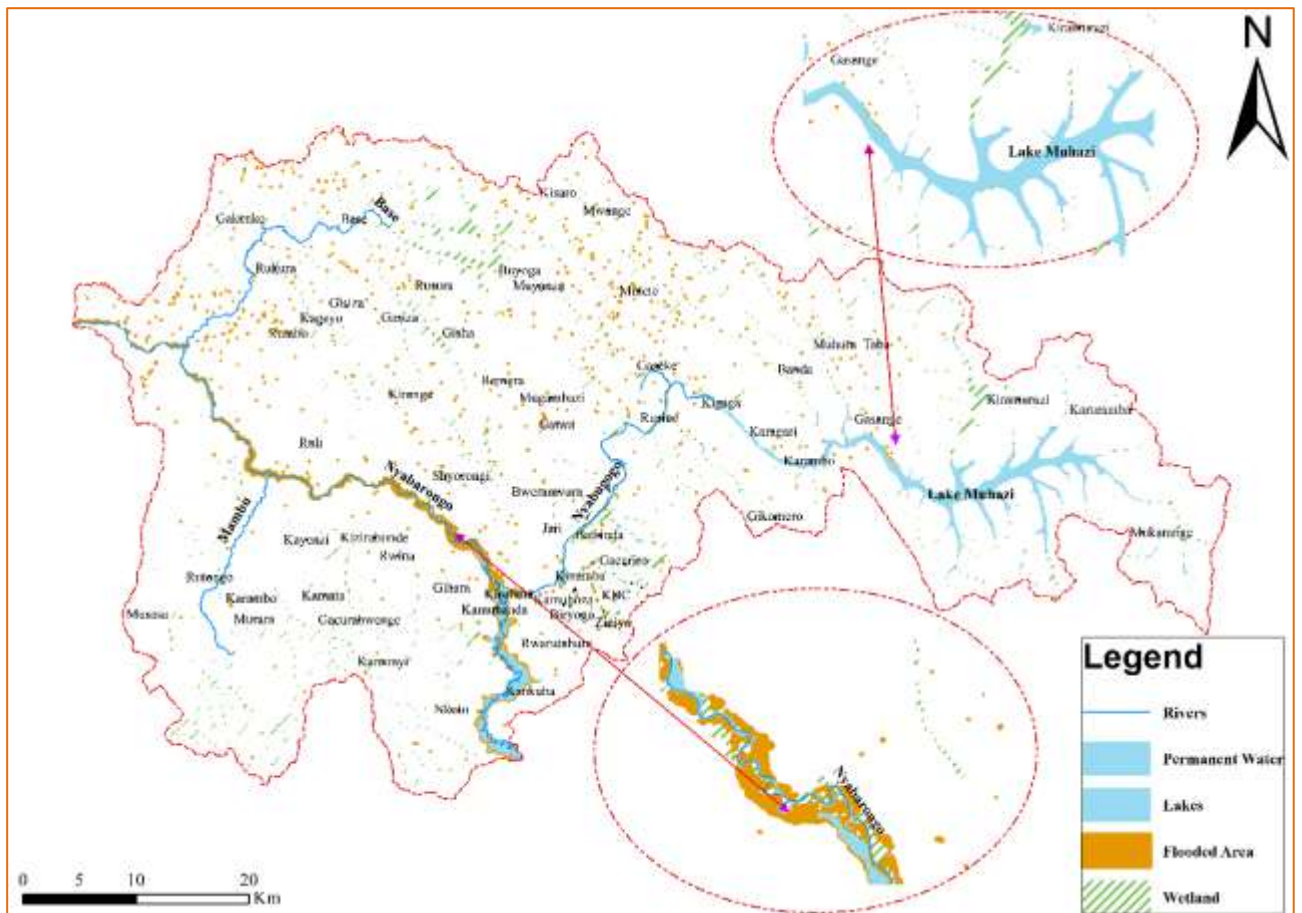


Figure 8: Flood map with polarization over Catchment

#### 4.1.1.1. Field Visit

The field visit conducted on 15 June 2025 began at key locations across Kigali, including Kinamba, Gisozi, Kagugu, the Mpazi drainage system, the Nyabugogo wetland, and the Nyabarongo Essential Bridge. These sites were identified as frequently flooded during the event period, based on crowdsourced data and produced remote sensing event flooding model. Observations focused on drainage infrastructure and bridge conditions, with particular emphasis on the Mpazi drainage system, which conveys runoff from large areas of Kigali into the Nyabugogo River. At the Nyabugogo Bus Park, substantial concrete retaining walls have been constructed to protect the terminal and surrounding businesses from floodwaters. Nonetheless, the drainage system accumulates significant sediment, requiring routine removal by municipal workers. These initial locations are presented in figure 9 below



*Figure 9: Left: Picture over Mpazi drainage. Right: View of the Mpazi Drainage facing northwest. In the distance, the confluence with the Nyabarongo River and the National Road 3 bridge can be seen.*

Source: Field Survey (2025)

Additional observation points included road junctions at Kinamba, Gisozi, Kagugu, Gakiriro which are adjacent or cross Kibumba and Nyabugogo wetlands, which are among five interlinked wetlands which are currently undergoing rehabilitation. Photographs from these locations are presented in the figure 10 below.



*Figure 10: Right up Kinamba bridge. Left up view of Kibumba wetland from Gakinjiro. Right down Kibumba wetland rehabilitation. Left down Nyabugogo wetland rehabilitation*

Source: Field Survey (2025)

The second location visited was along National Road 1, heading toward the Southern Province, in the Nyabugogo area. This national road runs parallel to the Nyabugogo River, which flows just to the north. On the southern side of the road lie rice fields, fish ponds, and other agricultural plots that rely on irrigation from the Nyabugogo River and its associated wetlands. These features are illustrated in Figure 11 below.



*Figure 11: Left: Sugar cane fields, and bamboo on the south side of the NRI. Right: rice fields and decorative flowers*

Source: Field Survey (2025)

The third location was a viewpoint situated just beyond the Skol Brewery and the Nzove Water Treatment Plant, which pumps water from the Nyabarongo River for distribution across Kigali (Figure 12). From this vantage point, a clear view of the surrounding wetlands and the Nyabarongo River was possible. The river is bordered by natural wetlands, although in some areas, patches of sugarcane plantations were observed either within the wetlands or along their edges, particularly near the road heading north.



*Figure 12: View looking upstream of the Nyabarongo Valley*

Source: Field Survey (2025)

The fourth location involved following the Nyabarongo River upstream, just beyond the boundary into Rulindo District in the Northern Province, where several settlements are situated along the river's course. A dirt road in this area serves as a boundary between the wetland and the sugarcane plantations located to the west, adjacent to the river. Most residential settlements are positioned east of the road at higher elevations, reducing their direct exposure to flooding. This spatial arrangement is illustrated in Figure 13.



*Figure 13: Left: Settlements in Rulindo district. Right: View from the road in Rulindo District looking west towards the Nyabarongo*

Source: Field Survey (2025)

The fifth location was the essential bridge on National Road 1 (N1) that crosses the Nyabarongo River which is boundary to southern province (Kamonyi District) with Kigali (Nyarugenge District). On the eastern bank, just before the bridge, a large clay factory is situated directly along the riverbank. Observations continued along the N1 road, overlooking the wetland. Notably, water was observed at the base of the sugarcane plants, indicating saturated soil conditions or residual surface flooding. (see Figure 14).



*Figure 14: Left: The bridge of the NRI crossing over the Nyabarongo River. Right: The clay factory near the Nyabarongo River.*

Source: Field Survey (2025)

To gain a better understanding of the landscape, a viewpoint was accessed from the eastern side of the Nyabarongo River valley in Nyarugenge District. This marked the sixth location of the field visit. From this vantage point, the upstream course of the Nyabarongo River is clearly visible, traced by a line of bamboo forest planted along its banks. The surrounding naturally formed wetland is also distinctly observable, with sugarcane cultivation occurring within and along its edges (see Figure 15).



*Figure 15: Left: View looking upstream of the Nyabarongo River valley. Right: View looking down on the wetlands south of the NRI bridge.*

Source: Field Survey (2025)

The seventh location visited was along National Road 3, heading toward the Northern Province (Gicumbi District), in the Nyabugogo area. This national road runs parallel to the Nyabugogo River, which flows just to the south. On the southern side of the road lie rice fields, fish ponds, and other agricultural plots that rely on irrigation from the Nyabugogo River and its associated wetlands. These features are illustrated in Figure 16



*Figure 16: Right: Rice fields on sides of river protected by bamboo plantation. Left: Bamboo protection till Nyacyonga bridge*

Source: Field Survey (2025)

#### **4.1.1.2. SAR Accuracy assessment**

The results of the accuracy assessment indicate a high overall accuracy, ranging from 0.993 to 0.996. VV polarization achieved a slightly higher accuracy of 0.996, while VH polarization yielded a marginally lower accuracy of 0.993. However, this difference is minimal and does not significantly affect the outcome of the flood maps. The variation between VV and VH polarizations is not statistically significant. The Kappa coefficient values, ranging from 0.983 to 0.991, further confirm an extremely strong agreement between the observed and predicted classifications.

Additionally, the F1 score which represents the harmonic mean of precision and recall demonstrates low false negatives (FN) and false positives (FP). Similarly, both producer and user accuracies indicate strong classification performance, confirming that both VV and VH polarizations are effective for flood mapping in the Nyabarongo catchment area. For thresholding, Otsu's method produced distinct thresholds for each polarization. A threshold of -2.799 was computed and applied for VH polarization, while a threshold of -4.935 was used for VV polarization.

*Table 7: Accuracy assessment of flood mapping using both VH and VV polarization*

<b>Statistics</b>	<b>May 3 VH</b>	<b>May 3 VV</b>
Producer Accuracy	0.9945	0.9945
User Accuracy	0.9953	0.9953
Overall Accuracy	0.9928	0.9961
Kappa	0.9828	0.9906
F1	0.9870	0.9934
Precision	0.9889	0.9998
Recall	0.9879	0.98716

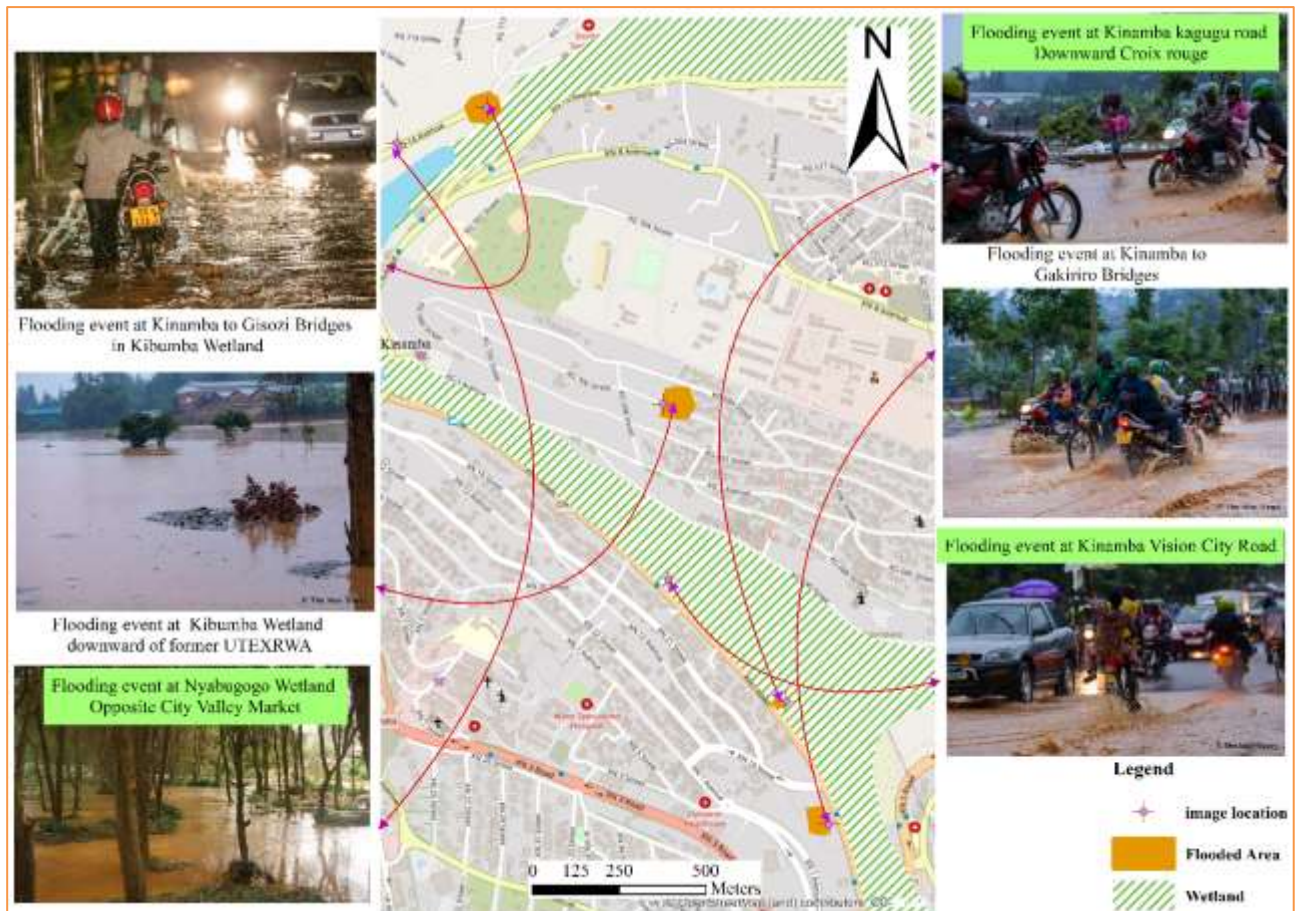
The results from the socio-sensing data show strong agreement between the calculated flood extent of May 2023 and the actual flooding social sensing platforms observed through collected images and geolocations. A total of 12 unique geotagged images collected from social media platforms were fully consistent with the flood map. Additionally, 4 images without embedded geotags were manually geolocated during the field visit using a handheld Garmin GPSMAP66i, which had a stated accuracy of 3.0 meters at the time of measurement. These also demonstrated strong agreement with the remote sensing-derived flood map.

#### **4.1.2. Flood sites and extent improved by combination of social sensing data**

The use of social sensing data to confirm events and locations has grown in parallel with the rapid expansion of the digital footprint, with a significant portion of the content being publicly accessible. A wide range of tools can be used to map the locations of flood-related events, including social media platforms such as Instagram, Flickr, and Twitter (X), along with news agencies, government reports, Google Maps, OpenStreetMap, and other open-source mapping resources. During the May 2023 flood event in Rwanda, particularly in the Catchment which include various parts of Kigali and parts adjacent Nyabarongo River, numerous photographs documenting the flooding were publicly shared. These images were spatially assigned using embedded geotags where available then overlaid to the flooding map generated using remote sensing.

A total of 100 images were collected from X (formerly Twitter) and Flickr, many of which contained embedded geotags that allowed for straightforward spatial referencing and overlay with the remote sensing-derived flood map. However, a significant number of these images were duplicates, reposted by different users with only 12 unique images being shared multiple times. Six unique images were identified in flooded road areas, including the Kinamba Gisozi Bridge, where significant flooding

was observed (figure 16). Additional flooded locations included the downstream section of the UTEXRWA Kibumba wetland, the Kinamba Kagugu Gakiriro road, particularly near the Croix-Rouge junction, Gakiriro bridge, the Vision City junction, and the Nyabugogo Kinamba section opposite City Valley Market.



*Figure 17: combines flooding map at Kinamba-Gakiriro-Kagugu using geotags*

Additionally, six unique images documented flooding in the Nyabugogo and Kibumba wetlands, where agricultural activities were significantly affected. The floodwaters impacted maize, rice fields, banana plantations, flower nurseries, and sugarcane crops. Severe flooding was also observed at the National Road 1 (NR1) Essential Bridge leading to the Southern Province (Kamonyi District), with images showing the complete submergence of wetland plantations in the Nyabarongo wetland, as illustrated in Figure 17.

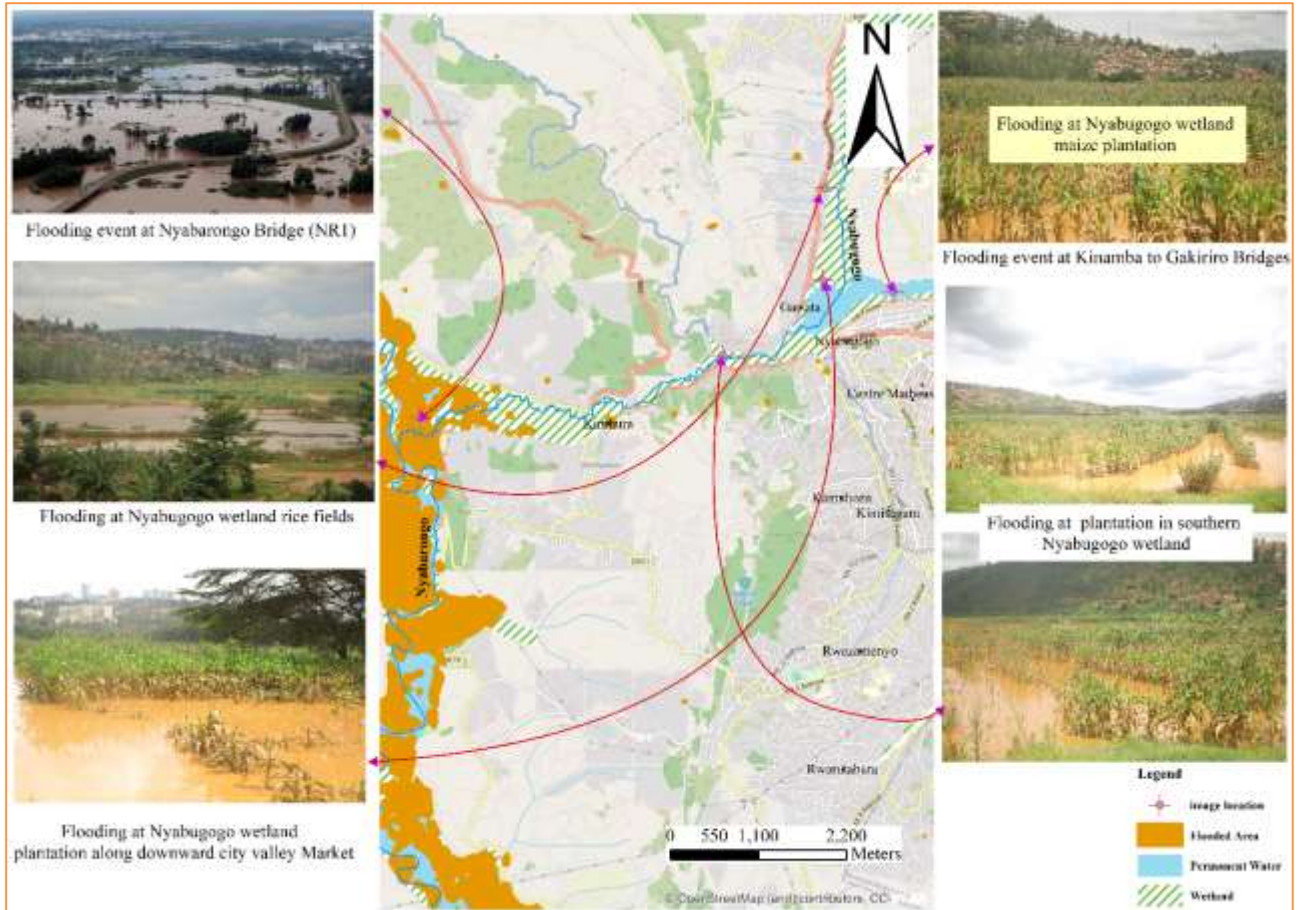


Figure 18: Combined Flooding map in Nyabugogo Valley using geotags

The results from the geotagged image data demonstrate a clear agreement between the flood extent derived from Sentinel-1 remote sensing on 3 May 2023 and the actual flood conditions, as confirmed through imagery and geolocated observations. In cases where geotags were absent, images were geolocated by identifying distinct features and landmarks such as infrastructure, buildings, and vegetation, enabling the mapping of flood occurrences with greater spatial accuracy.

The Giticyinyoni–Ruli–Nyabikenke Road (DR 51) is currently a mud laterite road that connects Kigali to Ruli in the Northern Province and Nyabikenke in the Southern Province. It serves as an alternative route when sections of National Road 1 (NR1), which links Kigali to the Southern Province, and National Road 2 (NR2), which connects to the Northern and Western Provinces, are blocked or impassable. DR 51 runs parallel to the Nyabarongo River, making it vulnerable to flooding. During the May 2023 flood event, several sections of this road were completely submerged as illustrated in table 8 and figure 18.

Table 8: Giticyinyoni-Ruli-Nyabikenke Road

Geolocated image 1, Giticyinyoni-Ruli-Nyabikenke Road (DR 51)	
 <p>(IGIHE, 2023)</p>	 <p>(Field Survey, 2025)</p>
 <p>(IGIHE, 2023)</p>	 <p>(Field Survey, 2025)</p>

The Nyabarongo Bridge along National Road 1 (NR1) is highly vulnerable to flooding due to its proximity to the Nyabarongo River. It has experienced flood events on multiple occasions, including the significant flooding in May 2023, during which the upstream Nyabarongo wetland was inundated, as illustrated in the figure 18 and table 10.

Table 9: NR1 Bridge over Nyabarongo River

**Geolocated image 3, NR1 bridge over Nyabarongo River**



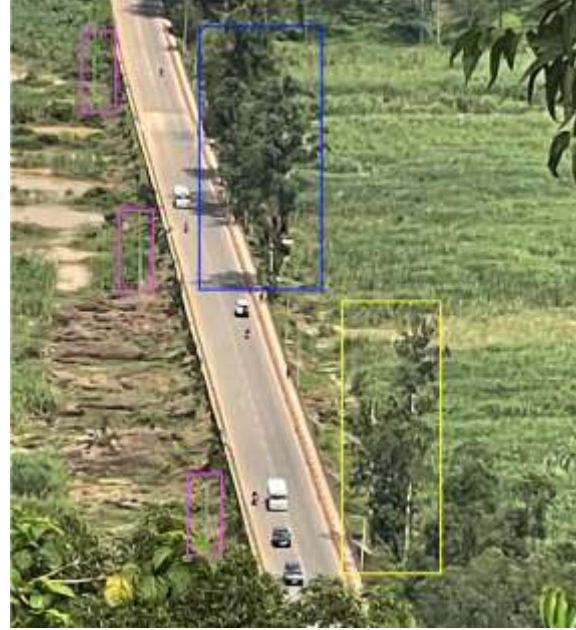
*(RedBlueJD, Instagram, 2023)*



*(Field Survey, 2025)*



(RedblueJD, Instagram, 2023)



(Field Survey, 2025)

Additionally, four unique images documented flooding at the Nyabarongo Bridge and the adjacent Nyabarongo wetland on the Rulindo side, where road infrastructure was significantly affected. The floodwaters inundated sugarcane plantations and blocked the Giticyinyoni Ruli Nyabikenke road, as illustrated in Figure 18. These images initially lacked embedded geotags; however, geolocation was manually assigned following a field visit by matching them with similar geo-referenced images collected on site.

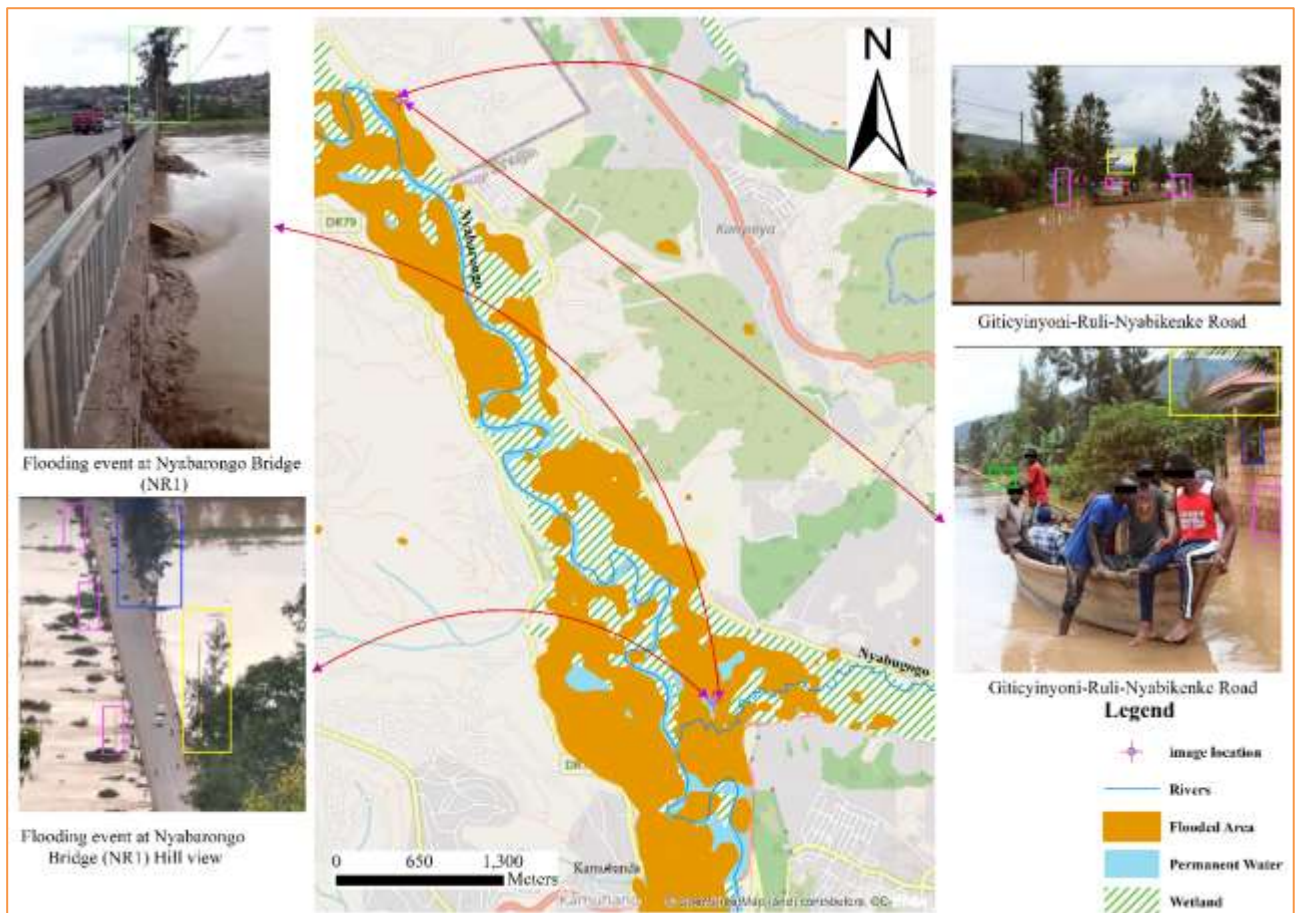


Figure 19: combined flooding map using matched image

The results from manually geotagged image data demonstrate a clear agreement between the flood extent derived from Sentinel-1 remote sensing on 3 May 2023 and the actual flood conditions, as confirmed through imagery and geolocated observations.

#### 4.1.3. Socio-economic infrastructures and utilities at high risk

This section presents the analysis of elements at risk affected by the flood event of May 3, 2023, within the Catchment. Using the flood extent map derived from Sentinel-1 SAR imagery and validated with field observations and socio-sensing data, key physical, socio-economic, and environmental assets were identified as being directly impacted. The analysis focuses on critical infrastructure, residential areas, agricultural land, and ecological zones vulnerable to inundation. Spatial overlay techniques in a GIS environment were employed to quantify the extent of impact on each category. These results provide insight into the severity of flood exposure and help inform future mitigation and response planning as illustrated in figure 20 and table 10.

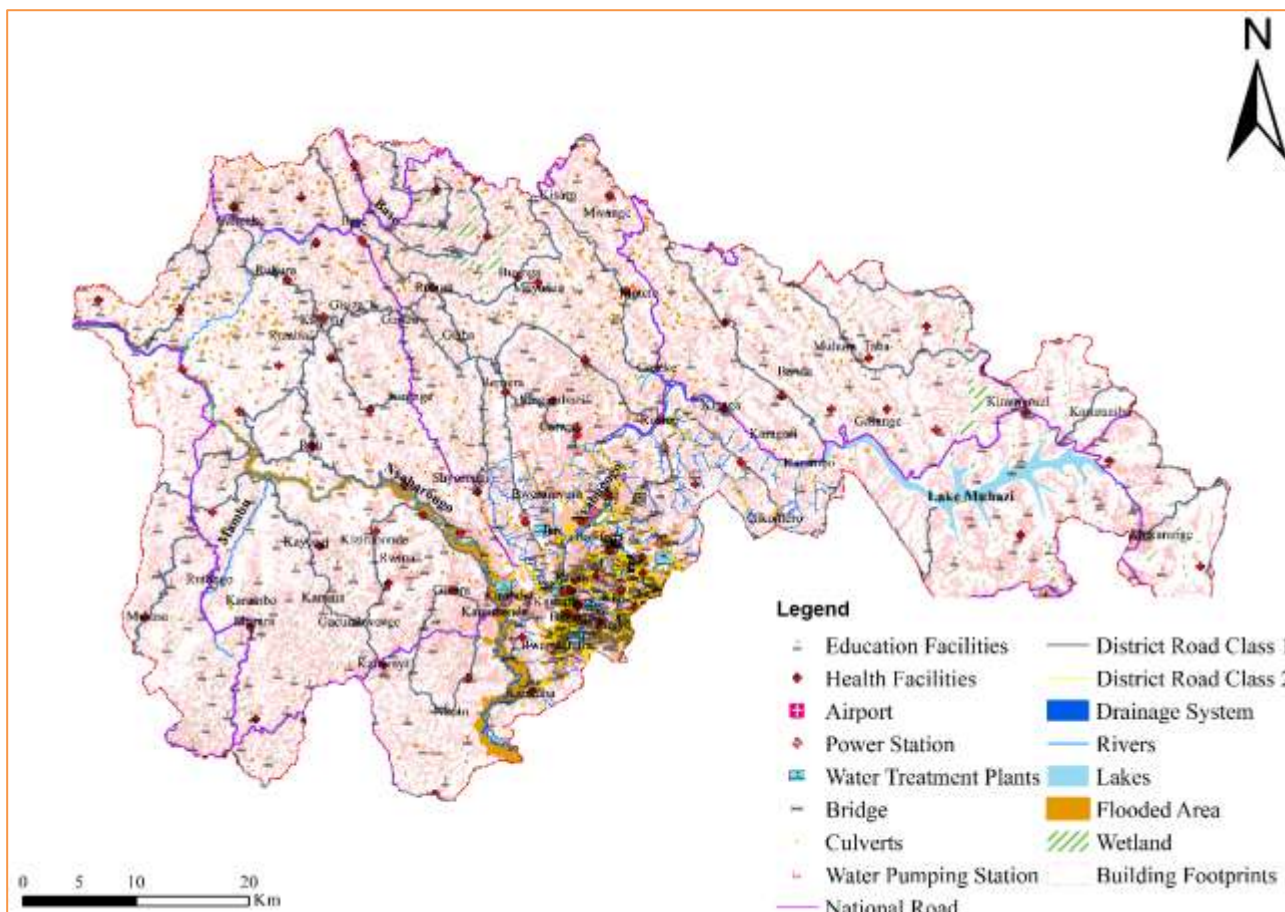


Figure 20: Element at risk map

The following table presents the magnitude of impact on key elements at risk during the flood event of May 3, 2023. It summarizes the total number or area of each element within the study area, the portion affected by the flood, and the corresponding percentage. This assessment helps quantify the severity of flood exposure across infrastructure, ecological, and socio-economic assets.

Table 10: Elements at risk magnitude

Element at Risk	Total in Study Area	Affected by Flood	% Affected
Buildings	1,047,367	380	0.04%
Roads (km)	475	393	83%
Bridges	305	6	2%
Culverts	2906	5	0.2%
Wetlands (ha)	16,221	1,898	12%
Schools	708	0	0%

Element at Risk	Total in Study Area	Affected by Flood	% Affected
Health Facilities	87	0	0%
Water Treatment Plants	6	1	17%
Power Stations	15	0	0%

The flood event in the Nile Nyabarongo Lower Level I Catchment had varying impacts on different elements at risk. Although only 380 out of over one million buildings (0.04%) were affected, indicating limited damage to built-up areas, a significant 83% of the road network experienced flooding, highlighting the vulnerability of transport infrastructure. A small number of bridges and culverts were affected, but their damage could still cause major disruptions. About 12% of wetlands were inundated, raising concerns over ecosystem stress, especially in agriculturally encroached areas. Social infrastructure such as schools, health centres, and power stations remained largely unaffected, suggesting effective planning in less flood-prone areas. However, one of the six water treatment plants was impacted, posing risks to public health.

## 4.2. Results Discussions

### 4.2.1. RS based Flood map and its Accuracy

The overall accuracy of the flood map, as indicated by the accuracy assessment, demonstrates that the results are reliable for estimating the extent of flooding. However, the exceptionally high accuracy values warrant careful interpretation, as they may overstate the method's performance within Google Earth Engine.

It is important to consider the context in which the UNOSAT reference flood maps were produced in order to understand potential differences in data processing methods. UNOSAT released the flood analysis for May 3 on May 5, 2023, and a combined analysis for May 3 and May 5 on May 9, 2023, using Sentinel-1 SAR data (ReliefWeb, 2023). The same satellite system was also used in this study, meaning that the flood maps compared in the accuracy assessment were derived from identical datasets. As such, the comparison reflects methodological differences rather than differences in data sources. The strong similarity in the results suggests that the agreement observed is more a measure of consistency than an independent validation of accuracy (UNITAR, 2021). The high level of agreement between the flood maps produced in this study and those generated by UNOSAT confirms the methodological reliability of the approach applied here (Nhangumbe et al., 2023).

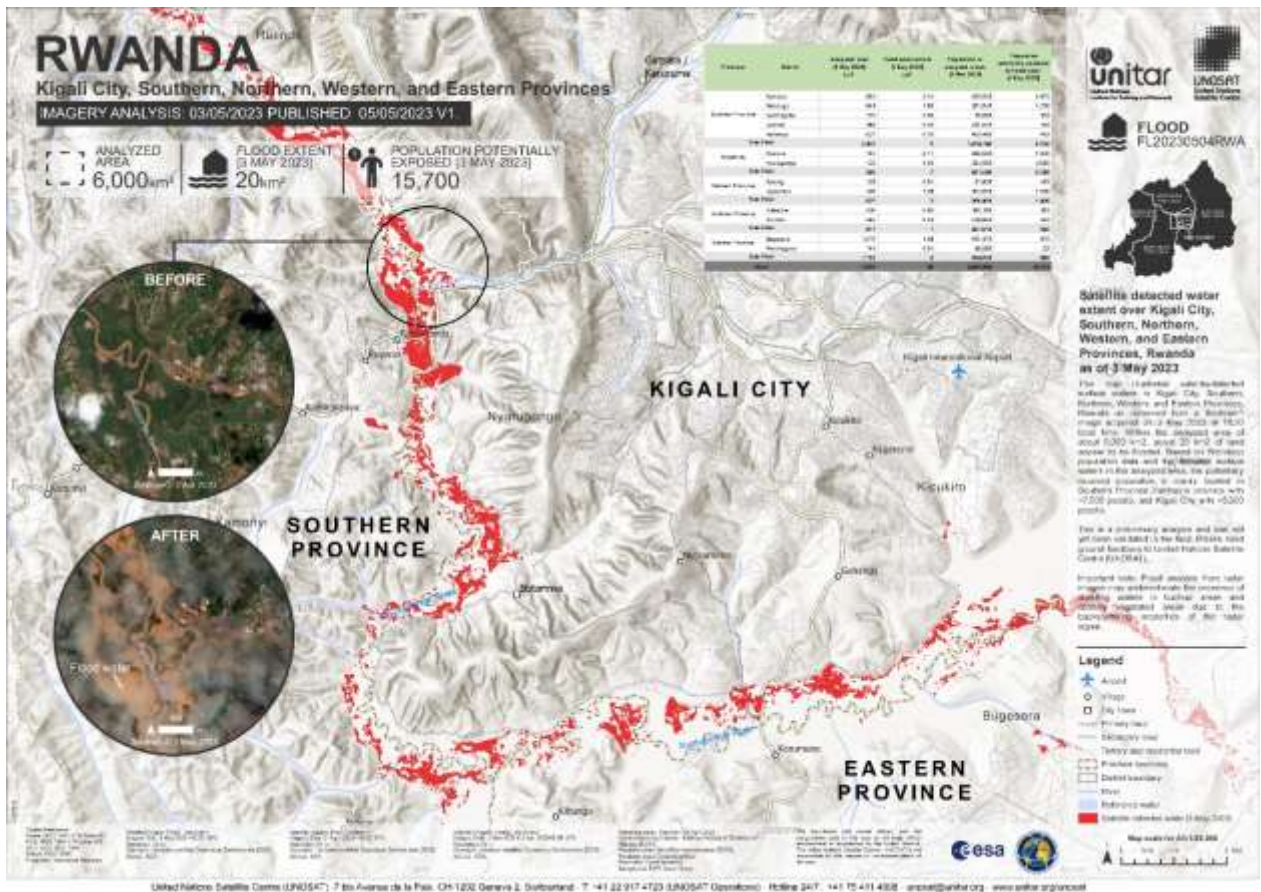


Figure 21: UNOSAT's flood map of the 3 May 2023 event in Rwanda, published on the 05th of May 2023

Source: ReliefWeb (2023)

However, the specific details of the data processing and flood calculation procedures such as thresholding techniques, methodological approaches, and analysis parameters are not explicitly documented (Nhangumbe et al., 2023). This lack of transparency introduces uncertainty regarding the production of the reference dataset and poses a significant challenge in accurately validating the results of the accuracy assessment. Since 2021, UNITAR has begun integrating artificial intelligence (AI) into UNOSAT's flood mapping workflows. With an average of 17 flood events processed annually, UNOSAT has developed a substantial archive of flood data that can be leveraged for AI-based model training and analysis also their stated accuracy of flood events are at above 0.97 (UNITAR, 2021).

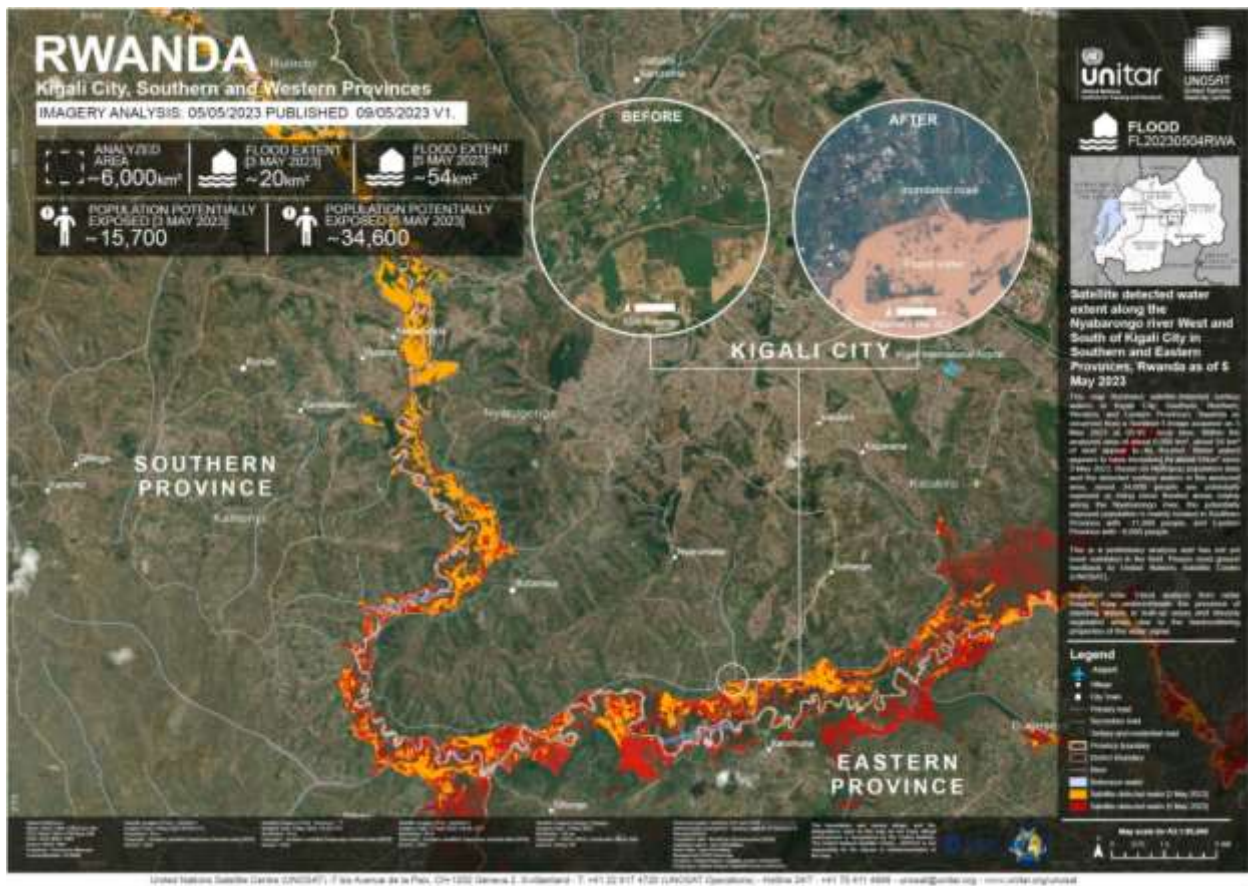


Figure 22: UNOSATs flood map of the 3 & 5 May 2023 event in Rwanda, published on the 10th of May 2023

Source: ReliefWeb (2023)

The general method for using neural networks for flood segmentation however is known and does use CNN to produce the results (Potin et al., 2022). The convolutional neural network (CNN) method represents a more advanced and computationally intensive approach, which is expected to yield improved results. Although the same statistical formulas were used for accuracy assessment, reporting an overall accuracy of 0.97, such high performance may be overly optimistic in a general context. In this specific case, however, the assessment is based on a single dataset applied to a well-defined region, using the same satellite source and similar analytical methods. As a result, the high level of agreement is likely due to the lack of variability in the input data and the methodological overlap, rather than a true reflection of generalizable accuracy (Nhangumbe et al., 2023).

The calculated flooded area for the May 3rd event closely aligns with the flood extent estimated by UNOSAT when using the same analysis boundary as the area of interest. This consistency further supports the relative accuracy of the flood maps produced in this study. According to UNOSAT, the estimated flooded area for the event was approximately 20 square kilometers (ReliefWeb, 2023).

One of the key objectives in developing the code used for flooded area calculations and SAR image processing was to ensure flexibility and portability, allowing the methodology to be applied to other regions with minimal user modification. In theory, this is achievable since the approach relies entirely on open-source software and globally accessible open data(Bergsma & Almar, 2020). However, further experimentation is needed to evaluate the method's transferability across different geographic contexts. The functions designed for generating pre- and post-flood images are robust and user-friendly, with easily adjustable parameters(Page-Tan, 2021). Orbit numbers are automatically calculated and displayed, simplifying the input process. Nonetheless, the accuracy assessment function is less streamlined; it involves redundant code, as the process is duplicated for each polarization once for VH and once for VV(Earth Engine, 2025).

#### **4.2.2. Contribution of mixed RS and crowdsourced/Social sensing data**

The use of the term 'crowdsourced' or 'social sensing' in this study refers to the methodology of utilizing social media and newspaper imagery for flood mapping(Arthur et al., 2018). This approach involves analyzing the images to geolocate the position where they were taken, determining the time and date of capture, and interpreting the visual content to assess whether the depicted area was affected by flooding(Akhtar et al., 2024).

The term crowdsourced refers to the practice of collecting and analyzing information from open sources with the goal of generating actionable intelligence(Page-Tan, 2021). In this study, we use crowdsourced as an umbrella term encompassing the methods employed to geolocate imagery through geolocating using embedded geotags and feature-matching techniques. This involves identifying distinct features within an image such as buildings, roads, or vegetation and using them to determine the image's geographic location (Rosser et al., 2017). All imagery used in this analysis was obtained from publicly available open-source platforms. Once geolocated, the visual content was analyzed to assess whether the specific location was flooded. This information was then used to evaluate the level of agreement between the crowdsourced observations and the flood map produced using SAR data. Based on the results from the field visit and the analysis of social media imagery, the ground truth points that were successfully geolocated and cross-referenced with the flood model produced for May 3, 2023, confirmed flooded conditions at those locations. With 16 verified points distributed across a large study area, the sample size is statistically significant and sufficient to support a reliable assessment of the overall accuracy of the flood map.

Despite certain limitations, this study has demonstrated the potential of using this method as a viable approach for assessing flooded areas and conducting ground-truthing through crowdsourced

resources. With the world's growing digital presence and the massive volume of data generated daily, the development of new methodologies to repurpose such data for applications beyond their original intent presents an important and promising area of research (Akhtar et al., 2024). Leveraging existing data streams or sensors to produce new actionable insights is particularly valuable in data-scarce regions, where such methods can serve as supplementary validation tools. Conversely, in data-rich environments, crowdsourced may evolve into the primary data source, with traditionally specific datasets serving as secondary confirmation (Page-Tan, 2021). In the near future, it is conceivable that urban camera networks may surpass conventional water-level monitoring systems in coverage and frequency, potentially positioning video feeds as the primary source for flood detection, with water-level sensors used as supplementary reference data (Rosser et al., 2017).

#### **4.2.3. Improved discrimination of elements at risk for efficient emergency response.**

The ability to effectively discriminate between various elements at risk is central to improving emergency response strategies. In this study, the integration of Sentinel-1 SAR data with GIS-based spatial overlays allowed for the identification and quantification of flood-impacted infrastructure, agricultural land, and ecological zones. This approach aligns with findings by Pierdicca et al. (2017) who emphasized the utility of SAR imagery in accurately detecting flood extents, especially in cloud-covered or night-time conditions. The results revealed a high impact on roads (83% of the road network), despite a relatively low impact on buildings (0.04%). This disparity mirrors patterns observed in previous studies, where linear infrastructure such as roads tends to follow natural drainage or flood-prone corridors, making them more vulnerable (Rindsfuser et al., 2024).

The inundation of 12% of the wetland area highlights the role of natural landscapes in flood storage, as previously discussed by Bates et al. (2020). However, agricultural encroachment into these buffer zones, such as sugarcane and rice cultivation observed in this study, could reduce their flood mitigation capacity, echoing concerns raised by Manizabayo et al. (2024) regarding wetland degradation in the catchment, the results demonstrate that the combination of SAR data and crowdsourced field validation can enhance the precision of emergence response .

## CHAPTER V: CONCLUSION & RECOMMENDATIONS

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### 5.1. Conclusion

The study successfully mapped the flood event and extent in the Nile Nyabarongo Lower Level I Catchment. The flood event of May 3, 2023, was effectively mapped using Sentinel-1 SAR data, revealing that approximately 21.34 km<sup>2</sup> (2,134 hectares) of land were inundated during the event. The incorporation of socio-sensing data specifically geotagged images from platforms such as X (formerly Twitter) and Flickr proved to be a valuable complement to satellite-based flood detection. Despite a high rate of image duplication, 12 unique images and four manually geolocated images provided additional spatial confirmation of flooded areas. Field verification further validated the locations and confirmed the reliability of the SAR-derived flood extent.

The study illustrates the potential of combining freely available satellite imagery with crowdsourced social media data to enhance flood mapping. It also showed the capabilities of socio sensing platforms in real time flood mapping, particularly in data-scarce regions for emergency response and post-disaster assessment.

### 5.2. Recommendations

This study demonstrates that integrating satellite remote sensing with crowdsourced social media data can significantly enhance flood mapping and disaster response in Rwanda. It is therefore recommended that disaster management agencies, such as the Ministry in charge of Emergency Management and the Rwanda Space Agency, formally incorporate social sensing into their monitoring and decision-making processes. This integration can provide real-time situational awareness and complement traditional sources of flood information.

Furthermore, awareness campaigns should be conducted to encourage the public to responsibly share geotagged information during disaster events. Training communities on how to capture and share accurate data could improve the reliability and coverage of socio-sensed information. In addition, partnerships with social media companies could help streamline the collection and verification of relevant flood-related content.

Future research should expand this approach to cover multiple flood events across different catchments to test transferability and robustness. Combining social sensing with other data sources, such as IoT water-level sensors and UAV imagery, would also help reduce uncertainty and improve

the accuracy of flood models. Finally, policy frameworks regulating data use in Rwanda should adapt to ensure ethical and responsible use of crowdsourced information while protecting privacy.

## CHAPTER VI: REFERENCES

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1. Akhtar, Z., Qazi, U., El-Sakka, A., Sadiq, R., Ofli, F., & Imran, M. (2024). Fusing remote and social sensing data for flood impact mapping. *AI Magazine*, 45(4), 486-501.
2. Arthur, R., Boulton, C. A., Shotton, H., & Williams, H. T. (2018). Social sensing of floods in the UK. *PloS one*, 13(1), e0189327.
3. Bates, B., Kundzewicz, Z., & Wu, S. (2020). *Climate change and water*. Intergovernmental Panel on Climate Change Secretariat.
4. Bergsma, E. W., & Almar, R. (2020). Coastal coverage of ESA'Sentinel 2 mission. *Advances in Space Research*, 65(11), 2636-2644.
5. Bizimana, J., & Ndahigwa, E. (2020). Cadastral information and erosion modeling for monitoring gullies in mpazi catchment area, Kigali city. *Rwanda Journal of Engineering, Science, Technology and Environment*, 3(1).
6. Bonde, B. N., Uwimana, J.-P., Sowa, F., & O'Neil, G. (2015). The state of media freedom in Rwanda. *Rwanda Media Commission*.
7. Earth Engine. (2025). Earth Engine Data Catalog, S-2 Cloud. . In.
8. El-Bestawi, I. K. (2021). *THE ASSESSMENT OF THE IMPACT OF CLIMATE CHANGES ON THE CULTURAL HERITAGE IN EGYPT USING REMOTE SENSING AND GIS TECHNIQUES* University of Sadat City].
9. eoPortal. (2023). *Copernicus: Sentinel-1*. Retrieved from [eoportal.org](https://www.eoportal.org). <https://www.eoportal.org/satellite-missions/copernicus-sentinel-1#mission-capabilitie>
10. eoPortal. (2025). *Copernicus: Sentinel-1*. Retrieved from [eoportal.org](https://www.eoportal.org). Retrieved 05/07/2025 from <https://www.eoportal.org/satellite-missions/copernicus-sentinel-1#mission-capabilities>
11. European Space Agency. (2025). *Mission ends for Copernicus Sentinel-1B satellite*. [www.esa.int/Applications/Observing\\_the\\_Earth/Copernicus/Sentinel-1/Mission\\_ends\\_for\\_Copernicus\\_Sentinel-1B\\_satellite](http://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-1/Mission_ends_for_Copernicus_Sentinel-1B_satellite)
12. Huang, X. (2020). *Remote Sensing and Social Sensing for Improved Flood Awareness and Exposure Analysis in the Big Data Era* University of South Carolina].
13. Icyimpaye, G., & Abdelbaki, C. (2022). GIS-based hydrological and hydraulic models to forecast river flood risks and proposition of management measures. In *Spatial Modelling of Flood Risk and Flood Hazards: Societal Implications* (pp. 143-159). Springer.
14. IFRC. (2018). *World disasters report: Focus on local actors, the key to humanitarian effectiveness*. [media.ifrc.org/ifrc/wp-content/uploads/sites/5/2020/12/World-Disasters-Report-2020\\_en.pdf](https://media.ifrc.org/ifrc/wp-content/uploads/sites/5/2020/12/World-Disasters-Report-2020_en.pdf)

15. Kuntla, S. K. (2021). An era of Sentinels in flood management: Potential of Sentinel-1,-2, and-3 satellites for effective flood management. *Open Geosciences*, 13(1), 1616-1642.
16. Li, J., He, Z., Plaza, J., Li, S., Chen, J., Wu, H., Wang, Y., & Liu, Y. (2017). Social media: New perspectives to improve remote sensing for emergency response. *Proceedings of the IEEE*, 105(10), 1900-1912.
17. Manizabayo, P., Ngwijabagabo, H., Nzayisenga, I., Nzamwita, S., Amani, L., Uwitonze, E., & Gilbert, K. M. (2024). Assessment of flood susceptibility utilizing remote sensing and geographic information systems: A case study of Mpazi sub-catchment in the city of Kigali. *Advanced GIS*, 4(1), 31-41.
18. Mohr, S., Ehret, U., Kunz, M., Ludwig, P., Caldas-Alvarez, A., Daniell, J. E., Ehmele, F., Feldmann, H., Franca, M. J., & Gattke, C. (2022). A multi-disciplinary analysis of the exceptional flood event of July 2021 in central Europe. Part 1: Event description and analysis. *Natural Hazards and Earth System Sciences Discussions*, 2022, 1-44.
19. Mourato, S., Fernandez, P., Marques, F., Rocha, A., & Pereira, L. (2021). An interactive Web-GIS fluvial flood forecast and alert system in operation in Portugal. *International Journal of Disaster Risk Reduction*, 58, 102201.
20. Mugiraneza, T. (2021). *Earth Observation based Monitoring of Urbanization and Environmental Impact in Kigali, Rwanda* [KTH Royal Institute of Technology].
21. Mutimukwe, C., Kolkowska, E., & Grönlund, Å. (2019). Information privacy practices in e-government in an African least developing country, Rwanda. *The Electronic Journal of Information Systems in Developing Countries*, 85(2), e12074.
22. Nhangumbe, M., Nascetti, A., & Ban, Y. (2023). Multi-temporal Sentinel-1 SAR and Sentinel-2 MSI data for flood mapping and damage assessment in Mozambique. *ISPRS International Journal of Geo-Information*, 12(2), 53.
23. Nkurunziza, M. (2024). Rwanda to benefit from ‘flash flood early warning’ initiative for Central African region. *The New Times*.
24. Page-Tan, C. (2021). The Role of Social Media in Disaster Recovery Following Hurricane Harvey. *Journal of Homeland Security and Emergency Management*, 18(1), 93-123. <https://doi.org/doi:10.1515/jhsem-2018-0054>
25. Pierdicca, N., Pulvirenti, L., & Chini, M. (2017). Flood mapping in vegetated and urban areas and other challenges: models and methods. In *Flood monitoring through remote sensing* (pp. 135-179). Springer.

26. Potin, P., Colin, O., Pinheiro, M., Rosich, B., O'Connell, A., Ormston, T., Gratadour, J.-B., & Torres, R. (2022). Status and Evolution of the Sentinel-1 mission. IGARSS 2022-2022 IEEE International Geoscience and Remote Sensing Symposium,
27. Reed, C., Anderson, W., Kruczkiewicz, A., Nakamura, J., Gallo, D., Seager, R., & McDermid, S. S. (2022). The impact of flooding on food security across Africa. *Proceedings of the National Academy of Sciences*, 119(43), e2119399119.
28. ReliefWeb. (2023). Rwanda: Floods and Landslides - Operational Update (MDRRW022). *ReliefWeb*.
29. REMA. (2020). *Technical Assistance in Environment and Natural Resources Management; Nile Nyabarongo Lower Catchment Integrated Pollution Management Plan*.
30. Rindsfuser, N., Zischg, A. P., & Keiler, M. (2024). Monitoring flood risk evolution: A systematic review. *iScience*, 27(9).
31. Robinson, M., & Ward, R. C. (2017). *Hydrology: principles and processes*. Iwa Publishing.
32. Rosser, J. F., Leibovici, D. G., & Jackson, M. J. (2017). Rapid flood inundation mapping using social media, remote sensing and topographic data. *Natural Hazards*, 87, 103-120.
33. Rwanda Water Board. (2025). *Lower Nyabarongo (NNYL)*. Rwanda Water Portal.
34. Sadiq, R., Akhtar, Z., Imran, M., & Ofli, F. (2022). Integrating remote sensing and social sensing for flood mapping. *Remote Sensing Applications: Society and Environment*, 25, 100697.
35. Smith, P., Pappenberger, F., Wetterhall, F., Del Pozo, J. T., Krzeminski, B., Salamon, P., Muraro, D., Kalas, M., & Baugh, C. (2021). On the operational implementation of the European Flood Awareness System (EFAS). In *Flood forecasting* (pp. 313-348). Elsevier.
36. The World Bank Group. (2021). *Climate Risk Profile Rwanda*.
37. UNITAR. (2021). *FUSING AI INTO SATELLITE IMAGE ANALYSIS TO INFORM RAPID RESPONSE TO FLOODS*. [unitar.org/about/news-stories/news/fusing-ai-satellite-image-analysis-inform-rapid-response-floods](https://unitar.org/about/news-stories/news/fusing-ai-satellite-image-analysis-inform-rapid-response-floods)
38. University of Twente. (2025). *SENTINEL-1C*. <https://webapps.itc.utwente.nl/sensor/getsat.aspx?name=Sentinel-1C>
39. USGS. (2025). *EWX Lite Next Generation Viewer*. Retrieved 07/05/2025 from [https://earlywarning.usgs.gov/fews/ewx\\_lite/index.html?region=af](https://earlywarning.usgs.gov/fews/ewx_lite/index.html?region=af)
40. Uwineza, A., & Irie, M. (2022). Flood analysis for estimating the impact of rainwater harvesting system installation using hydrological models. Case study: Nyabugogo valley, Kigali. *Journal of Arid Land Studies*, 32(S), 145-149.

41. Uwizeye, D., Irambeshya, A., Wiehler, S., & Niragire, F. (2022). Poverty profile and efforts to access basic household needs in an emerging city: a mixed-method study in Kigali's informal urban settlements, Rwanda. *Cities & Health*, 6(1), 98-112.
42. van Vliet, J., Bregt, A. K., & Hagen-Zanker, A. (2011). Revisiting Kappa to account for change in the accuracy assessment of land-use change models. *Ecological modelling*, 222(8), 1367-1375.
43. Wulder, M. A., Roy, D. P., Radloff, V. C., Loveland, T. R., Anderson, M. C., Johnson, D. M., Healey, S., Zhu, Z., Scambos, T. A., & Pahlevan, N. (2022). Fifty years of Landsat science and impacts. *Remote Sensing of Environment*, 280, 113195.
44. Yang, L., Driscoll, J., Sarigai, S., Wu, Q., Chen, H., & Lippitt, C. D. (2022). Google Earth Engine and artificial intelligence (AI): a comprehensive review. *Remote Sensing*, 14(14), 3253.
45. Zakaria, S., Mahadi, M. R., Abdullah, A. F., & Abdan, K. (2019). Aerial platform reliability for flood monitoring under various weather conditions: A review. *Intelligent Systems for Crisis Management: Gi4DM 2018 11*, 295-314.
46. Zhan, Y., & Zhang, G. (2019). An improved OTSU algorithm using histogram accumulation moment for ore segmentation. *Symmetry*, 11(3), 431.
47. Zvolenský, M., Mikuličková, M., Randusová, B., Halaj, M., Lemke, C.-D., Schirmeister, Z., Walawender, J., Ziese, M., GARCIA, P. M., & Grimaldi, S. (2023). European Flood Awareness System—A technical assessment of CEMS EFAS performance during the floods in Southern Italy in September and November 2022.

## CHAPTER VII: APPENDICES

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### Appendix 1. Google Earth Engine Scripts

#### SAR Flood mapping Code:

<https://code.earthengine.google.com/fa48f2ec68b110cf7878dd6836d6d843>

### Appendix 2. Social Media Imagery

#### Instagram

<https://www.instagram.com/reel/Cry6v-EAALm/?igsh=b3d4YWY5bDE4emNp>

<https://www.instagram.com/reel/CryzJhkghUV/?igsh=dnFsc3N6YmlzYTE0>

#### Flickr

<https://www.flickr.com/>

#### Twitter

<https://x.com/home>

### Appendix 3. CHIPRS satellite Five-day precipitation in mm from CHIPRS satellite

[https://docs.google.com/spreadsheets/d/1eAv0g9IPnpuzvYr88vLpm1fnE\\_Vi8bO8/edit?usp=drive\\_1ink&oid=108196834122853708507&rtpof=true&sd=true](https://docs.google.com/spreadsheets/d/1eAv0g9IPnpuzvYr88vLpm1fnE_Vi8bO8/edit?usp=drive_1ink&oid=108196834122853708507&rtpof=true&sd=true)