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Department of Geography and Environmental Science

A model for impact-based flood early warning and anticipatory actions in Uganda

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Declaration

I confirm that this is my work, and the use of all the materials from other sources has been appropriately and fully acknowledged.

Faith Kinya Mitheu

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Acronyms and Abbreviations

AU- African Union

AUC- African Union Commission

ARSDRR- Africa Regional Strategy for Disaster Risk Reduction

ActLT- Action Lifetime

CAO-Chief Administrative Office

CRA- Community Risk Assessment

CN-Correct Negative

CRED- Centre for Research on the Epidemiology of Disasters

DRR- Disaster Risk Reduction

DFO-Dartmouth Flood Observatory

DWRM-Department of Water Resources Management

DM-Disaster Management

DR-Disaster Respondent

DI- DesInventar

DREF- Disaster Relief Emergency Fund

ECMWF- European Centre for Medium Range Weather Forecasts

EWI-Early Warning Information

EWSs- Early Warning Systems

EAP-Early Action Protocol

Eco-Trust- Environmental Conservation Trust

EMS-Emergency Management Service

EMDAT- Emergency Event Database

FbA- Forecast-based Action

FbF- Forecast-based Financing

FAO- Food and Agriculture Organisation

FEWSNET- Famine Early Warning Systems NETwork

FAMVACs- Farmers Agri-Met Village Advisory Clinics

FAR-False Alarm Ratio

FEWI- Flood Early Warning Information

FATHUM- Forecast for Anticipatory Humanitarian Action

FP-Forecast Probability

FVR- Farmer Voice Radio

GloFAS- Global Flood Awareness System

GHB-Global Hazard weekly Bulletin

HEA- Household Economy Assessment

HbFEWtS- Hazard-based Flood Early Warning trigger System

IbF- Impact-based Forecasting

IFRC- International Federation for Red Cross Crescent Centre

IBFWS- Impact-based Forecasting and Warning System

IARP-Innovative Approaches for Response Preparedness

IbFEWtS-Impact-based Flood Early Warning trigger System

JWGFVR-Joint Working Group on Forecast Verification Research

KRCS- Kenya Red Cross Society

KDLG-Katakwi District Local Government

LIMB-Livelihood Impact-Based Flood Forecasting framework

LG-Listening Group

LT-Lead Time

NPDPM-National Policy on Disaster Preparedness and Management

NECOC- National Emergency Coordination and Operation Centre

NIMFRU- National scale Impact-based Forecasting of Flood Risks in Uganda

NGOs- Non-Governmental Organisations

NLRC-Netherlands Red Cross

OPM-Office of the Prime Minister

POD-Probability of Detection

P(S1)- Planting season 1

P(S2)- Planting season 2

RP-Return Period

RCMRD-Regional Centre for Mapping of resources for Development

SHEAR- Science for Humanitarian Emergencies and Resilience

TI- Type I error

TII- Type II error

UN-United Nations

UNISDR-United Nations International Strategy for Disaster Reduction

UNEP-United Nations Environmental Programme

URCS-Uganda Red Cross Society

UNDP-United Nations Development Programme

UNMA-Uganda National Meteorological Authority

UBOS-Uganda Bureau of Statistics

WRA-Water Resources Authority

WMO-World Meteorological Organisation

WFP-World Food Programme

WCI-Weather and Climate Information

Yr.-Year

Operational Definitions

Early Action Protocol- pre-agreed set of procedures and mechanisms that allow humanitarian organizations, governments, and other stakeholders to respond to disasters quickly and effectively to reduce the impacts.

Forecast-based Financing is an approach to humanitarian and development that seeks to improve the speed and effectiveness of disaster response by using scientific forecast to trigger pre-arranged funding before the hazard materialises.

Forecast based Action is a proactive approach to disaster management that uses scientific forecasts to trigger predetermined actions to mitigate the potential impacts of a disaster.

Forecast Probability-is a value between 0-100 defined as a percent that is used to indicate the likelihood of the forecasted event occurring. Higher numbers indicate greater likelihood of occurrence.

Abstract

Among the many disasters, floods are the most common disaster worldwide. The number of flood events worldwide has increased by 23% between 2000 and 2019. The trend is expected to increase due to climate variability and other environmental factors. Efforts to reduce the impacts of extreme events such as floods have been emphasised through various multilateral frameworks, resulting in the development of early warning systems. Technological advancement has also contributed to significant improvement in forecasting science leading to more accurate predictions and improved forecast skills. Despite these improvements, more focus has been on early warning of physical risks and less on incorporating the needs of the most at-risk populations and early action disaster responders. Thus, early warning systems (EWS) should be people-centred to ensure that at-risk populations can access tailored early warning information to inform their preparedness actions and protect their lives and livelihoods.

The potential for early warning information (EWI) can be achieved if all the components of a people-centred early warning system are implemented through an integrated approach that involves the at-risk population. Therefore, there is a need to redefine the development of EWS by shifting from top-down to more bottom-up community-driven approaches. To address this gap, the research developed an impact-based flood early warning trigger system for anticipatory action through a community-led process. As shown through community and disaster management practitioners' engagements, a more coordinated institutional response is needed to understand the gaps in the provision and use of EWI at the local level. Local context-specific information can also be used to verify forecast information to make them more acceptable in informing early and anticipatory actions in data-scarce regions. Further, such information could enhance the existing hazard-based systems by redefining the design of trigger thresholds and early actions.

Overall, this thesis has shown that community-led approaches based on holistic engagements can effectively ensure EWSs are locally targeted to inform local anticipatory actions.

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Chapter 1

1 Introduction

1.1 Wider context and motivation

The global population faces severe impacts from disasters. According to the Centre for Research on the Epidemiology of Disasters (CRED), in 2020, disasters affected approximately 98 million people and resulted in economic losses of over USD 171 billion (CRED, 2021). Floods were the most common disaster worldwide, with a 23% increase in events between 2000 and 2019. These impacts are increasing due to climate variability and population growth (Morton, 2007; Cools, Innocenti, and O'Brien, 2016), especially in countries in the Global South (Bunce, Rosendo, and Brown, 2010). For example, over 7 million people in Africa were affected by floods in 2020, the highest since 2006 (CRED, 2021). Many rural communities are among the most at-risk as they exhibit low coping capacity and lack localised tailor-made early warning information (EWI) to inform coping practices (Amegnaglo *et al.*, 2017; Naab, Abubakari and Ahmed, 2019).

Efforts to reduce the impacts of natural disasters on the population have been emphasised in various multilateral frameworks for the last three decades, namely: the Yokohama Strategy for a safer world (UN, 1994), the Hyogo Framework for Action (UNISDR, 2005), and the Sendai Framework for Disaster Risk Reduction (UN, 2015). These frameworks reinforce the need to promote disaster risk reduction efforts at national and local levels while calling for regions and nations to take primary responsibility for preventing the adverse effects of hazards. In Africa, efforts toward disaster management have resulted in the development of the Africa Regional Strategy for Disaster Risk Reduction (ARSDRR), which aims to strengthen the integration of Disaster Risk Reduction (DRR) into development processes (AU, 2004). Consequently, the African Union Agenda 2063 underpins the implementation of such a strategy by setting goals and targets to be attained (AUC, 2012). The recognition of the need for EWI for DRR is apparent in multilateral frameworks and regional strategies. However, more focus is needed to improve the access and availability of EWI to all people to reduce the effects of disasters.

Early warning systems (EWSs) play a critical role in DRR (Thiemig, de Roo, and Gadain, 2011; Okonya and Kroschel, 2013). These systems should be people-centred to ensure that communities and individuals are supported to take the necessary preparedness actions to reduce the impacts on their lives and livelihoods (Baudoin *et al.*, 2016; Cools, Innocenti and O'Brien, 2016). According to United Nations International Strategy for Disaster Reduction (UNISDR), an effective people-centred EWS should have four interrelated components (see Figure 1), which include; 1) knowledge of risks and vulnerability of the at-risk populations, 2) monitoring and forecasting of the hazard and its consequences, 3) communication and dissemination of useful early warning information using appropriate channels to at-risk population, and 4) preparedness and response capability at all levels. A failure in any component can fail the entire system (UNISDR, 2016).

Technological advancements have significantly improved forecasting and monitoring science over the last decade (Hallegatte, 2012; UNEP, 2012), resulting in improved forecast skills and, consequently, more accurate predictions (Cloke and Pappenberger, 2009; Mittermaier, Roberts and Thompson, 2011). However, such progress has been seen more in the Global North than in the Global South countries (Perera *et al.*, 2019). In addition, despite such improvements in forecasting science, other components of an EWS have not advanced in parallel, which often results in the warning information being perceived as unclear in informing the target user's needs (Basher *et al.*, 2006; Demeritt and Nobert, 2014). Several recent studies have focused on approaches for communicating to users complex forecasts information to improve decision-making (Taylor, Kox and Johnston, 2018; Budimir *et al.*, 2020) as well as the influence of the EWI on risk perception and early actions (Weyrich, Scolobig and Patt, 2019; Weyrich *et al.*, 2020).

The potential for effective EWI can be achieved if all the components of a people centred EWS are implemented through an integrated approach. The approach would ensure that the EWI is understandable, communicated promptly using appropriate channels, meets the intended user's needs, and is used to trigger preparedness actions (UN, 2015; Baudoin *et al.*, 2016). Robust EWSs for monitoring and forecasting extreme events are now common worldwide. However, developing robust EWSs based solely on the physical characteristics of an event only conveys information on weather and environmental conditions (e.g., 'what the weather will be') rather than what the impacts will be (e.g.

'What the weather will do'). Therefore, hazard-based systems may not be fully adequate to trigger the required anticipatory actions if people are not guided on the appropriate measures to safeguard their lives and livelihoods (WMO, 2021b).

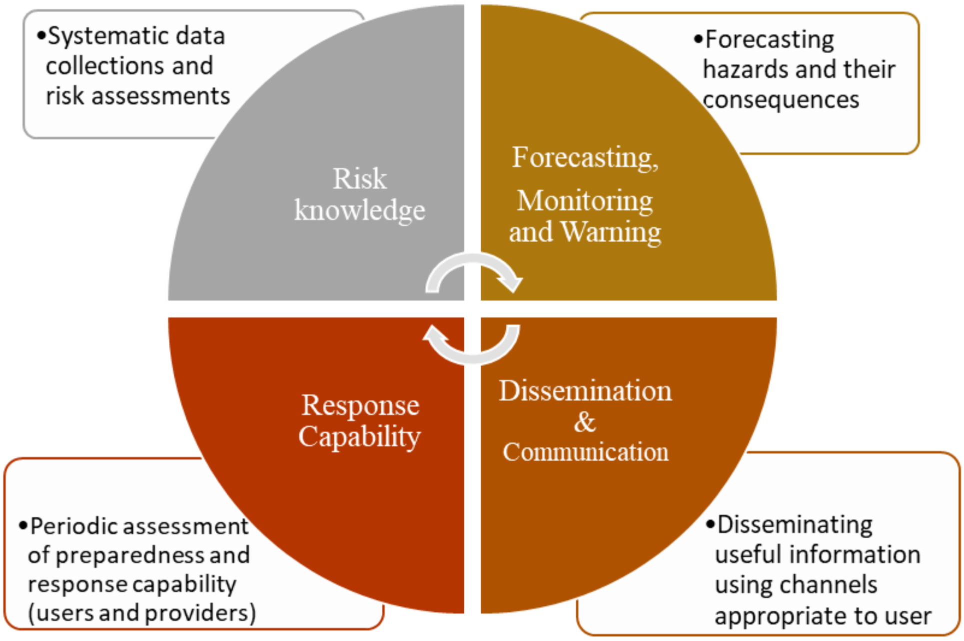

Figure 1: The components of an end-to-end people-centred EWSs: Source-(UNISDR, 2016)

In 2015 under the recommendations of the World Meteorological Organization (WMO), the development of EWSs shifted towards impact-based forecasting to address some of the challenges of the hazard-based systems (WMO, 2021b). Impact-based EWSs ensure that hazard warnings are integrated with information about the risk and vulnerability of the population and translated into possible socio-economic consequences to understand when, where, and what actions are required to reduce the impacts (Merz *et al.*, 2020). Impact-based forecasting approaches can be either quantitative or qualitative, depending on the context (Hemingway and Robbins, 2020; Kaltenberger, Schaffhauser and Staudinger, 2020). The information from impact-based forecasting and warning systems (IBFWs) can influence risk perception and preparedness actions if the users understand the magnitude of impacts that is likely to occur (Potter *et al.*, 2018; Weyrich *et al.*, 2018). Best practices of impact-based systems can already be found in several National Meteorological Services such as the United Kingdom Met Office (UK Met Office, 2019) and the National Weather Service of the USA (US National Weather Service, 2019). However, implementing IBFWs presents benefits and challenges (see Hemingway and Robbins, 2020; Merz *et al.*, 2020; Potter, Harrison and Kreft, 2021), which needs to be understood and solutions provided to ensure more countries can implement and benefit from IBFWs.

More recently, the need to consider financial resources to ensure early warning information translates to early and anticipatory actions is becoming common globally. For example, Forecast-based Actions (FbA) and Forecast-based Financing (FbF) initiatives by the International Federation of Red Cross and Red Crescent (IFRC) ensure that dedicated funding is released within the window of opportunity between the issuance of the forecast warning and the occurrence of an extreme event. The available funds can then support the implementation of pre-agreed anticipatory actions (Coughlan De Perez *et al.*, 2015, 2016; Costella *et al.*, 2017). So far, several such initiatives have been designed and implemented worldwide and have helped reduce the impacts of extreme weather events (see Wilkinson *et al.*, 2018; FAO, 2021; WFP, 2021). But are we 'out of the woods yet' in ensuring reduced risks and enhanced resilience for the most vulnerable communities?

1.2 Technical approaches for disaster risk reduction in Uganda

The integration of EWSs into institutional development and planning processes is required to improve risk reduction and preparedness (De Haen and Hemrich, 2007; UNISDR, 2015). In Uganda, all disaster management activities are guided by the National Policy on Disaster Preparedness and Management (NPDPM) (hereby after referred to as "the disaster policy"), published in 2010 (OPM, 2011). The policy provides a framework to ensure all disaster management activities are integrated into the relevant government development processes (OPM, 2011:2) and stipulates the key actors and their roles in disaster management (UNDP, 2015). The responsibility of coordinating all disaster preparedness and response activities lies with the Office of the Prime Minister (OPM), Department of Relief, Disaster Preparedness, and Management. In addition, the office coordinates all other relevant line ministries, humanitarian organisations, development partners, and the local communities on data, information, and activities for disaster risk management (UNDP, 2015). Figure 2 shows the institutional structure for the management of disasters in Uganda.

Integration of all disaster risk reduction and preparedness efforts requires a multi-sectoral and multi-skilled system of approach. Towards such advancements, the Department of Relief, Disaster Preparedness and Management with support from United Nations Development Programme (UNDP) established the National Emergency Coordination and Operations Centre (NECOC) in 2014 (Atyang, 2014). NECOC was established to oversee the implementation of the disaster policy primarily through coordinating the various emergency response institutions on response, early warning analysis, dissemination, capacity building and community resilience (OPM, 2011)(Figure 2).

The implementation of the policy has not been effective because of the disconnect between the disaster policy anticipation and the reality on the ground. Thus, the process is hindered by various challenges. To begin with, the exclusion of especially the local communities in the policy implementation even though they are included in the institutional structure leads to lack of awareness and non-compliance at the local level (Ampaire *et al.*, 2017). For example Ampaire *et al.*, (2015) in their study on policy and adaptation in Rakai district, Uganda found out that local communities were not aware of who to report to in-case of the deteriorating water quality due to tree felling. Secondly, the financial allocations at all levels are not commensurate with the actual activities to be undertaken (Clar, Prutsch and Steurer, 2013; Winthrop, Kajumba and McIvor, 2018). Thirdly, the involved institutions have limited technical capacity on disaster risks and adaptations which inhibits the process of practical implementation (Bauer, Feichtinger and Steurer, 2012). And finally, weak research-policy linkages resulting to limited research evidence on the expected future trends of disaster impacts (Winthrop, Kajumba and McIvor, 2018). Other challenges noted in literature include uncoordinated roles in disaster response (Ampaire *et al.*, 2017), communication barriers and weak legal framework to guide the in disaster risk reduction (Winthrop, Kajumba and McIvor, 2018). These policy implementation gaps can result to increase in vulnerability to disaster risks especially to the most at-risk communities.

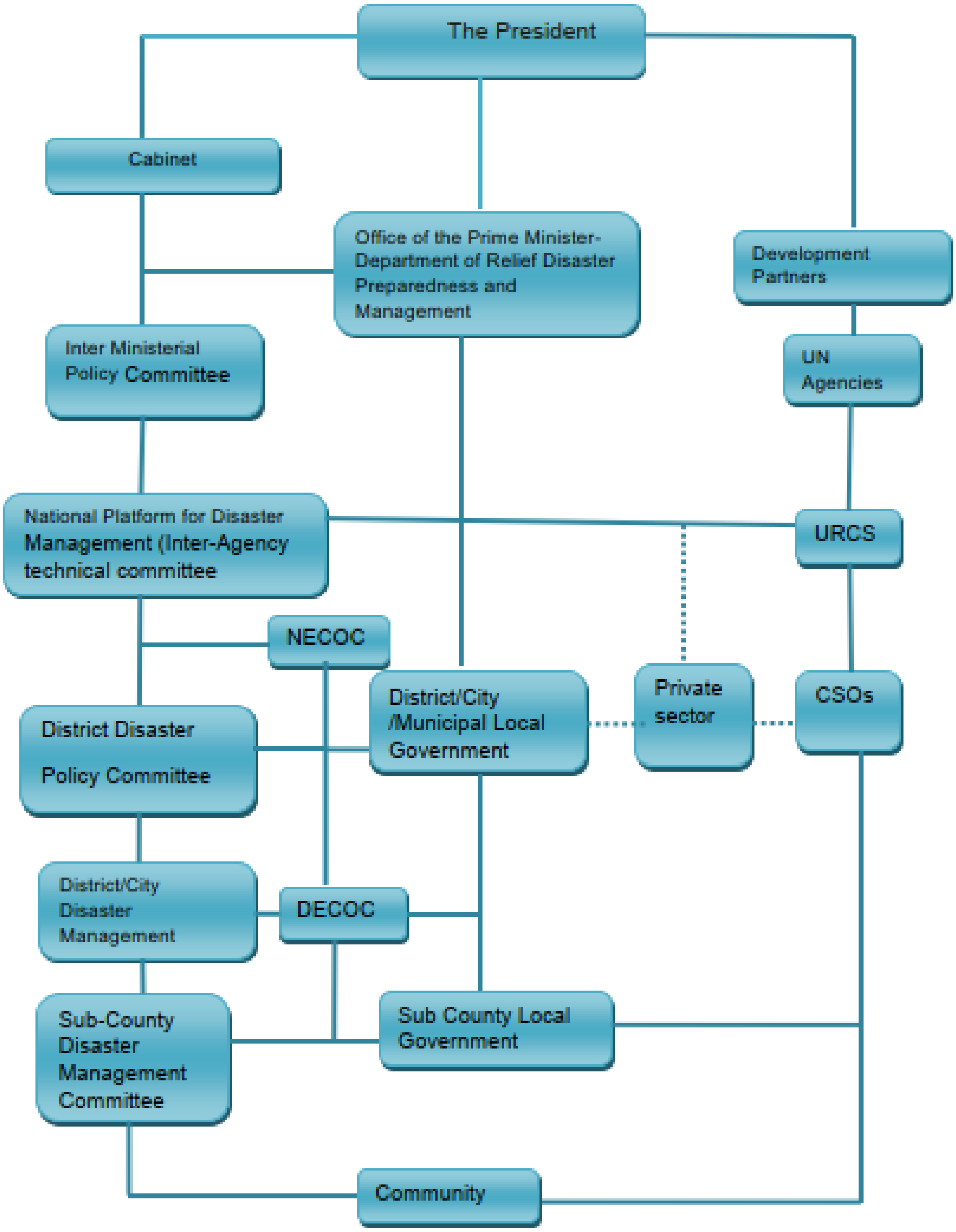

Figure 2: National Disaster Preparedness and Management institutional structure; Source: Disaster policy for Uganda (OPM, 2011)

On the other hand, the disaster policy also advocates for producing and disseminating EWI to the public to enable undertaking preparedness actions to reduce the risk of disasters. However, Uganda does not have a national forecasting system for any hazard (Atyang, 2014). The lack of a forecasting and warning system means that, for example, in the context of floods, one of the frequent natural disasters in Uganda (Hebden, 2017) and the focus of this research, localised flood early warning information required to inform preparedness, is often unavailable. Flood monitoring is therefore based on meteorological forecasts conducted by Uganda National Meteorological Authority (UNMA) (Aber and Amuron, 2020) or situation analysis at river gauging stations (for rivers that have them). There is, however, limited evidence on how at-risk communities interpret and use such information for decision-making. Moreover, implementing an effective early warning system in Uganda is further hindered by several other barriers Lumbroso, (2018). More specifically, even the existing EWSs are fragmented (see Table 1) and do not entirely address the needs of at-risk communities (Jennifer, 2018) or provide contextualised guidance on the required preparedness actions.

Several challenges are noted. First, albeit informed by local and regional analysis and joint initiatives with local organisations in some cases, the World Food Program (WFP) rainfall monitoring system and the Famine Early Warning Systems NETwork (FEWSNET) food security early warning systems are developed from a global perspective, which could limit their applicability to preparedness and anticipatory actions at a local or sub-national level. Second, most of the existing systems, for instance, the Butaleja flood early warning and the Regional Centre for Mapping of Resources for Development (RCMRD) flood simulator, are based on a situational analysis of the water levels, which limits their applicability for informing preparedness actions. Third, the pilot FbA initiative in Eastern Uganda used the GloFAS (Global Flood Awareness System) flood forecast information to trigger early actions (Coughlan De Perez *et al.*, 2016; Jjemba *et al.*, 2018) but was faced with challenges in identifying the most vulnerable communities to help in prioritising the anticipatory actions (Stephens *et al.*, 2016). Lastly, the current hazard-based systems being used to upscale the FbA initiative in the 15 flood-prone districts in Uganda have not considered context-specific socio-economic characteristics at the community level, which may affect the design of targeted interventions (Aber and Amuron, 2020; URCS, 2021).

Table 1: Findings on the status of early warning systems in Uganda

Name of EWS	Description	Scale	Source
Famine Early Warning Systems NETwork (FEWS NET)	A robust system of analysis based on livelihood approach that looks at the food security indicators such as markets and prices. Issues the information through bulletins with warning lead time of 6 months and monthly updates. Sent to various organizations (govt, NGO, Donors, Humanitarian, local)	Global	https://fews.net/east-africa/uganda-retrieved on 30th Sept 2019
World Food Program (WFP)	Monitoring of food security and nutrition based on rainfall. Developed to monitor how rainfall variability affects food availability. Information on markets issued quarterly through bulletins which are shared up to local level.	Global	(Atyang, 2014) https://dataviz.vam.wfp.org/seasonal explorer/
Flood early warning system (2014)	A situational analysis project that was commissioned in 2014 to monitor flood water levels using sensors through collaborative efforts involving the local communities. The system however broke in 2016 and its therefore not functional.	Butaleja district	(Atyang, 2014) https://ugandaradionetwork.net/story/butaleja-flood-warning-system-breaks-down-recorded on 9th June 2019, retrieved 30th Sept 2019
Flood Simulator	A flood map simulator based on gauged water levels developed by Regional Centre for Mapping of Resources for Development (RCMRD) as a web-based tool. The system has been dormant.	Manafwa and Malaba river basins	http://crest.rcmrd.org/simulator/
Forecast-based Financing (FbF) pilot in Eastern Uganda	Forecasts from GloFAS was used to trigger early actions before floods in Teso region. The Forecast-based Action (FbA) initiative was led by Red Cross Climate Centre and Joint Research Commission (JRC). Various actions were taken before floods of November 2015.	Piloted in Amuria and Katakwi districts	(Coughlan De Perez *et al.*, 2016; Jjemba *et al.*, 2018)
Up-scaling FbA mechanisms	Initiative on FbA have been pioneered by IFRC where forecasts information from GloFAS is used to trigger the release of pre-arranged funding to support the pre-agreed early actions. Early Action Protocol (EAP) developed by Uganda Red-Cross Society to guide the implementation.	15 flood prone districts in Uganda	

Among the recommendations from the study by United Nations Development Programme (UNDP) (Atyang, 2014) was the development of a roadmap to foster collaborations across the board, from the national to the district level to ensure coordination in disaster data collection and analysis. The second recommendation was on the development of a multi-hazard early warning system. A plan to actualise the development of the multi-hazard system was developed by NECOC which stipulates the key actors and relevant legislation for EWSs in Uganda (Lumbroso, 2016). Based on our interviews with disaster management institutions in October 2020, the actual development is yet to commence.

Studies in Africa shows that the implementation of EWSs is hindered by factors similar to Uganda. For example, in Namibia, the implementation of flood early warning system is hindered by various factors including undefined roles amongst institutions, unavailability of response plans at the local level and low forecasting capabilities among others (Moisès and Kunguma, 2023). Overall many countries in Sub-Saharan Africa are facing technical, financial, institutional and social challenges in the development of robust early warning systems (Perera *et al.*, 2019). However, there are many opportunities that can be explored to improve the development of EWSs such as improving data availability and quality, taking advantage of technological advances in communication and dissemination and improving access to global forecasting system among others (Perera *et al.*, 2019).

Ultimately, each country should have an effective EWSs for major hazards in place to reduce the overall impacts of these hazards on the population. Such a system should issue credible hazard forecasts and warnings accompanied by targeted advisories on the likely impacts and the appropriate early actions to avert the significant effects (Cools, Innocenti and O'Brien, 2016). This information should also be disseminated using suitable channels to enable access by all. Therefore, the system should inform the early action mechanisms and operational decisions among humanitarian organisations and communities while reducing the possibility of 'actions in vain' (Lopez *et al.*, 2020; Nidumolu *et al.*, 2020).

Climate variability is envisioned to result in more frequent and severe hydrometeorological events, with the highest impacts mainly directed to vulnerable households who depend on nature-based resources (CRED, 2021). In this context, it is essential to redefine the development of EWSs, shifting from top-down to more community-driven approaches that would ensure the development of more sustainable and locally targeted EWSs. Community-led approaches are based on holistic engagements with at-risk communities and decision-makers. Therefore, they can be an effective way of ensuring that 1) barriers that hinder effective production, and use of EWI are identified across the user-provider landscapes and integrated within the development processes, and 2) data and information collected from the at-risk communities are used to develop local context information that can be integrated into EWSs to make them more locally targeted which then informs the design of tailored anticipatory actions.

Throughout this thesis, the spotlight is on the local at-risk communities. These communities are recognised as key actors in disaster risk reduction under the Sendai Framework for DRR. Their needs and capabilities in dealing with disaster risks is therefore important. Scholarly literature shows that effects of climate variability such as extreme events (floods, drought, etc), high temperatures and rainfall variability are resulting to negative impacts on the lives and livelihoods of these communities (Apuuli et al., 2000; Hepworth and Goulden, 2008; Magrath, 2008; Hussein, 2011; Sikhu and Jurgen, 2014; Berman, Quinn and Paavola, 2015 Cooper and Wheeler, 2017). For example, Kansiime, (2012) in a study on climate change adaptation in Eastern Uganda found that extreme events such as floods affect both crops and livestock yields. The resulting impacts from such events will, however, vary across communities and households due to the underlying social and economic factors that drive households to risks (Misselhorn, 2005; Thornton *et al.*, 2009; Frelat *et al.*, 2016).

These communities have their own ways of coping with such impacts. For example, communities may engage in various coping and adaptation strategies such as land and crop management (Mondal *et al.*, 2015), off-farm activities (Shah and Dulal, 2015; Hussain *et al.*, 2016), improved access to information (John et al 2013) and improved extension services (Shisanya and Mafongoya, 2016; Wichern, van Wijk, *et al.*, 2017) among others. These strategies are geared towards improving the resilience of the communities in dealing with the impacts of extreme events. In the next sub-section, the thesis sheds light on the communities in Katakwi District. These communities are the focus of this thesis; hence it is important to unpack their lived realities and how they deal with flood risks.

1.2.1 Local Communities in Katakwi District

Katakwi district is in the North-eastern region of Uganda. The district covers an area of approximately 2500km^2. The district landscape is generally a plateau with undulating slopes in specific areas. The population in Katakwi district based on the 2014 census was 165,928 out of which 57,401 (48.3%) are male and 61,527 (51.7%) are female (KDLG, 2017). Of the total district population, 2.38% are urban while 97.62% are rural dwellers. The main economic activities in Katakwi district are pastoralism, crop production and petty trade (KDLG, 2017). The highest percent of population (81.6%) in the district engage in subsistence farming.

The district is prone to several hazards such as floods, drought, pest infestation, environmental degradation and cattle rustling among others (KDLG, 2014). Among these, floods are ranked number one based on its severity and areas affected. Seasonal floods and flash floods result to waterlogging across several sub-counties in the district (KDLG, 2014). According to the Katakwi District plan of 2017-2022, floods and waterlogging affects almost all sub-counties with the main ones being Ngariam, Ongongoja, Magoro, Usuk and Palam sub-counties. Some of the known effects of floods include school drop-out, food insecurity, health issues (outbreak of waterborne diseases), low income, loss of livestock, displacements of people and animals, damage to infrastructure among others (KDLG, 2017). Based on the 2014 population census, floods affect approximately 78% of the population.

The communities in Katakwi district employ general coping mechanisms to deal with the effects of floods. Some of these strategies include laying logs to ensure access to flooded areas, digging ditches around their houses to prevent water getting inside, temporary relocation to upper areas and having improvised raised beds to store their harvests (KDLG, 2017). These strategies have been nurtured and passed on for generations, considering that the region has rich indigenous knowledge useful to guide appropriate coping strategies (Orlove *et al.*, 2010; Egeru, 2012, 2016).

The research study in Katakwi district included respondents from the villages of Anyangabella, Kaikamosing and Agule across 3 sub-counties. The farmers discussions at the village sites were carried out using the Farmers Agri-Met Advisory Clinics (FAMVACs) approach, which was initially developed by UNMA to gather information from the communities on the use of weather information (Ciampi *et al.*, 2019). These discussions attracted community members with ages ranging from 18 to 60 years. The community members in the three villages have rich indigenous knowledge which helps them understand the changes in the weather patterns. During the study, various indicators of indigenous knowledge and their interpretation were noted (Table 2). An example use of indigenous knowledge to predict the weather and inform the coping activities is when the farmers know the rain is near when they site local birds' species such as hornbill or if they site a greening local tree known as 'ebule' in Ateso language. The indigenous knowledge needs to be integrated with science to ensure informed decisions(Nkabane and Nzimakwe, 2017). For example, although the farmers could be aware of the likelihood of rains, the exact start and end of the season as well as the expected amounts cannot be estimated using indigenous knowledge. Integration of indigenous and science can be achieved by ensuring communities are involved in the development of weather information and that feedback mechanisms are in place.

Table 2: Indicators for Indigenous knowledge used by communities in Katakwi District: Source: Farmers discussions during the study.

Indicators for Indigenous knowledge	**Interpretation**
Fogginess	Dry season
Concentration of clouds	Rain season expected
Drying of grass	Arrival of dry season
Winds blowing to West	Dry season expected
Winds blowing to East	Arrival of rain season
Tree leaves sprouting	Rain season expected
Appearance of birds locally known as arapaitelai/achobin birds flying in large numbers	Rains are almost
Hornbill bird (*Esukusuk*) making noise at dawn	Rains have come
Appearance of mushroom locally known as *(Odilitaa*) in bushes	Rains are expected

1.3 Thesis objectives and structure

The research is conducted in the context and as part of the NIMFRU (National scale IMpact-based Forecasting of flood Risk in Uganda) project. It aligns with the project's main aim of improving the targeting and communication of flood early warning information and response to support decision-making and enhance national resilience.

The thesis guides the reader through the steps that would ensure the development of a locally targeted impact-based flood early warning system for Uganda. It presents some of the challenges experienced in Uganda in the provision and use of existing flood early warning information and opportunities for improving existing systems to address the needs of at-risk rural communities. Based on a case study in Eastern Uganda, the thesis employs a multi-disciplinary approach to improve the different components of a people-centred EWS to ensure the most at-risk population is protected. First, information from the community and disaster management levels is used to understand the social science aspects of early warning information production and use. Second, non-traditional approaches for forecast verification using impact data show how data-scarce regions (regions that lack national flood forecasting systems and river gauge observations) can still enhance their early warning activities based on a skilful forecast from global systems. Lastly, livelihood information based on crop calendars and flood impacts is integrated within the existing EWS to make them more locally focused and ensure the design of variable trigger thresholds and targeted anticipatory actions. This thesis combines these perspectives to address the following research objectives:

1. Identify the barriers and opportunities in the production/provision and use of flood early warning information for flood risk preparedness.
2. Assess the usefulness of flood impact data relative to river gauge observations in verifying flood forecasts in data-scarce regions.
3. Develop an impact-based flood early warning system for rural livelihoods using an impact-oriented approach.

This thesis employs various methods to address the above objectives, including community engagements through a bottom-up approach initially developed by UNMA, interviews with disaster management practitioners, forecast verification, and information integration through an impact-oriented method. An end-to-end process is used to investigate how flood early warning mechanisms being developed in Uganda can be improved to reduce the impacts on at-risk communities. The thesis is structured around three results chapters.

Chapter 2 addresses the first objective of this research through a series of interviews and farmers' discussions. The chapter proposes a more coordinated institutional response and flow of information that can identify barriers and opportunities in the production, provision, and use of flood early warning information (FEWI)[1] across the provider-user landscapes. Using a bottom-up approach designed as Farmers Agri-Met village Advisory clinics (FAMVACs) (Ciampi *et al.*, 2019), two use cases at the local smallholder community and the disaster management level were designed to identify these barriers, opportunities and solutions to ensure improved use of EWI to inform anticipatory actions. Further, a broader perspective of disaster management in Uganda is presented by looking at the actors (disaster data providers) and processes (DRR activities, data and information required, and data sharing modes).

Chapter 3 addresses the second objective of this research. The chapter addresses the need to provide reliable forecasts to inform the development of early warning systems and support locally targeted anticipatory actions even in data-scarce regions. Building on findings from Chapter 2 (lack of a flood forecasting system and limited river gauge observations), the chapter investigates if flood impact data can be used in verifying global flood forecasts from GloFAS (Global Flood Awareness System) to build trust in their use in ensuring robust flood early warning mechanisms. The chapter also notes recommendations on how best these impact data can be improved and used to verify forecasts effectively across data-scarce regions and inform sector-specific anticipatory actions.

Chapter 4 addresses the third objective through an impact-oriented approach. An impact-based trigger framework that integrates flood forecast information (usually used in hazard-based trigger systems) with local livelihood data is developed to improve the design of locally targeted early and anticipatory action mechanisms. Building on Chapters 2 and 3, the chapter demonstrates the framework's usefulness from a humanitarian perspective using the information on the crop calendar and historical flood timelines from Katakwi District to

[1] While we refer specifically to FEWI in this chapter, FEWI is a subset of weather and climate information (WCI) which would be required to inform flood risk management. In Chapter 2, we will however use WCI in the place of FEWI to help situate the work within the broader context of climate services.

improve the way flood danger thresholds and early actions are defined and targeted. Further, the broader applicability of the trigger system is explored by subjectively tweaking the trigger thresholds to inform various interventions from a livelihood perspective.

Chapter 5 summarises the findings and the wider contribution of this research to existing literature in disaster management and flood impact-based early warning and highlights the scope for further work, including in the context of anticipatory action.

The outputs presented in this thesis provide a holistic approach relevant to developing people centred EWSs. Figure 3 shows how the thesis results chapters contribute to the various components of an end-to-end EWS. First, the study contributes to the field of climate services by identifying the barriers in the provision and use of climate information using a more coordinated approach across the provider-user landscapes and providing solutions on how such barriers can be overcome to ensure effectiveness. Second, the study enhances hazard-based systems by defining an impact-based system that integrates forecasts with local information to provide locally targeted EWSs useful in prioritising early actions to protect lives and the livelihood sources of rural communities. Third, the study contributes to the forecast verification methods by introducing a new metric in the use of non-traditional approaches and less conventional verification data to verify flood forecasts which aligns with the current research by the WMO-Joint Working Group on Forecast Verification Research (JWGFVR).

The work presented in Chapter 3 won the WMO award for the best new verification metric using non-traditional approaches (WMO, 2021a). The call for award was made by WMO through the JWGFVR. The author led the conceptualisation of the idea, data analysis and the development of the submission. Co-authors in the submission Andrea Ficchi and Elena Tarnavsky provided inputs for the submission. The first-place award was a fully paid trip for the author to attend the next forecast verification conference to present the work. The conference is yet to take place with delays attributed to Covid-19 travel restrictions. In addition, a blog post emanating from this work has also been produced and shared with a wide audience (see Mitheu, Tarnavsky and Ficchì, 2021).

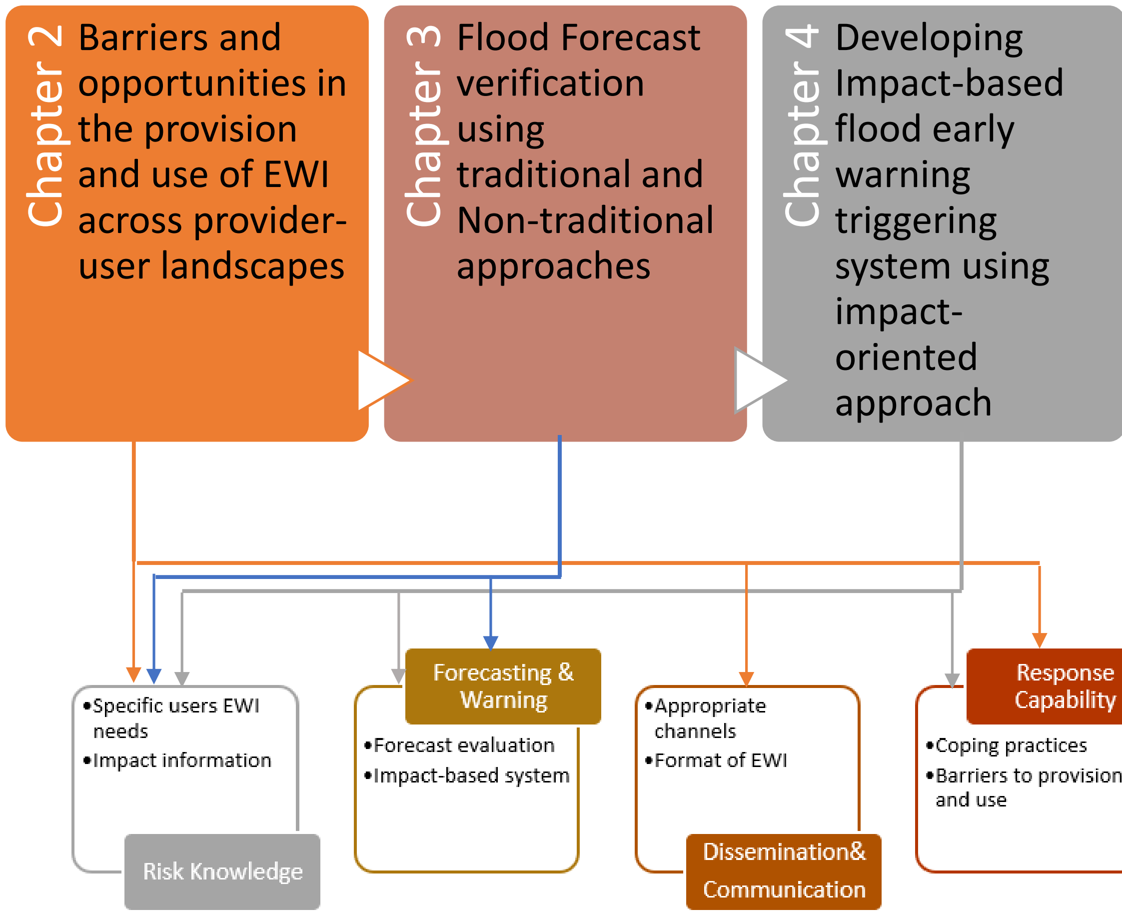

Figure 3: Flow diagram showing how the three result chapters contribute to the various components of an end-to-end EWS.

Chapter 2

2 Barriers and opportunities in the production, provision, and use of Early Warning Information for Disaster Management across the provider-user landscapes

In this chapter, data collected by other researchers has been used to inform the objective. Notably, the collection of qualitative data from the local communities was led by researchers from ECO-TRUST and UNMA. The author of the thesis contributions is on partial collection of data from local communities, design of the research at the national level, data collection at the national level, data analysis and writing.

2.1 Background

Disaster risk management is a sequence of actions undertaken to prevent or reduce the damages, loss of lives, and assets during a disaster and enable recovery after the disaster (Rawls and Turnquist, 2012). This process comprises four phases: mitigation, preparedness, response, and recovery (Khan, 2008). The heightened need to reduce the impacts of natural hazards on vulnerable communities has shifted more focus to pre-disaster actions such as mitigation and preparedness(WMO, 2021b). Mitigation actions are meant to reduce the long-term impacts of hazards and may include improving buildings and infrastructure and land-use planning. Preparedness activities are primarily short-term and may consist of prepositioning supplies (Rawls and Turnquist, 2012), training communities on disaster risk reduction, awareness, and early warning so that people can take the necessary actions to save lives and protect assets. In addition, initial response activities have also become frequent, especially when there is no time to prepare before a disaster, including evacuation and relief services.

Three main disaster actors are noted in the disaster risk management processes (Homberg and Neef, 2015). First, the professional responders are part of the professional community trained in disaster management. They include national and local government institutions, Non-Governmental Organizations (NGOs), and national coordination and emergency centres. Second, the responding community consists of the local or an outside community who may participate in the response though not trained to do so. Third, the affected communities are the people, households, or businesses who, in case of a disaster, may directly or indirectly be affected and would require immediate humanitarian assistance. These actors have a role to play in disaster management, and their holistic coordination is necessary to reduce the impacts of disasters on the population (UN, 2015).

In this chapter, we present two use cases developed at the community and national disaster management institutions, respectively, as part of this PhD. The use cases apply a coordinated bottom-up approach to identify the barriers that hinder effective production, provision, and use of early warning information for effective disaster management and the opportunities to improve EWI provision and use across the provider-user landscapes. The first section (2.2) of this chapter presents findings from the community-level use case and part of the disaster management (DM) practitioners' use case (focusing on data and information preparedness) and forms our first paper. The second section (2.3) presents additional findings from the second use case, broadly focusing on the DM activities, data providers, data sharing methods, and challenges that hinder the effective implementation of the required disaster management activities. The main aim of this chapter is to identify the barriers that impede adequate provision and use of EWI and opportunities that can be explored to ensure useful EWI is available and accessible by the intended user.

2.2 Identifying the barriers and opportunities in the provision and use of weather and climate information for flood risk preparedness: the case of Katakwi District, Uganda

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The contributions of the authors of this paper are as follows; FM designed the research and collected the qualitative data at the national level, carried out the data analysis, and led the writing of the manuscript. CP led the community-level study and qualitative data collection design and assisted in writing the manuscript. RC, ES, and ET supported the research design and assisted in writing the manuscript. LC assisted in designing the qualitative research at the community level. JB assisted in collecting the qualitative data at the community level. All authors contributed to the article and approved the submitted version.

The published article can be found in the thesis under Appendix A2.1.

Abstract: The provision of weather and climate information (WCI) can help the most at-risk communities cope and adapt to the impacts of extreme events. While significant progress has been made in ensuring improved availability of WCI, obstacles hinder the accessibility and use of this information for adaptation planning. Attention has now focused on the 'usability gap' to ensure useful, and usable WCI informs practice. Less attention has, however, been directed to barriers to the active production and use of WCI. In this study, we combine two frameworks through a bottom-up approach to present a more coordinated institutional response that would be required to ensure a better flow of information from information providers to users at the community level and vice versa. The bottom-up approach was designed in the form of Farmers Agri-Met Village Advisory Clinics (FAMVACs) and Listening Groups (LG). Uganda Meteorological Authority (UNMA) initiated it to ensure connections between the information providers, the disseminators, and the communities. This approach is used to identify the barriers and opportunities in the production/provision and use of WCI for flood risk preparedness for a case study in Eastern Uganda. First, a use-case is developed for Katakwi District, where smallholder farming communities have recorded their coping practices and barriers to using WCI in practice. Second, online interviews with practitioners from disaster management institutions are used to identify barriers to the production and provision of WCI to local farming communities. Findings show that for providers, barriers such as accessibility and completeness of data hinder the production of useful WCI. In situations where useful information is available, the technical language used in the format and timeliness in dissemination hinder usability by

local farmers. Useful and usable WCI may not be acted on in practice due to costs or market availability, e.g., lack of access to improved seeds.

Further, the study highlights possible solutions to bridge the identified gaps, including capacity building, fostering data collaborations across sectors, and data translation to simple advisories, among others. The study also presents the FAMVACs approach, which shows the importance of a more coordinated response with a shift of focus from the users of information only to a more inclusive understanding of the data and information gaps across the provider-user landscapes. We argue that this would contribute to more effective disaster management at both the national and local levels.

2.2.1 Introduction

Weather-driven shocks such as floods are becoming more extreme and frequent in many regions worldwide (IPCC, 2012). Rural at-risk communities suffer the worst impacts from these extreme events because of their dependence on natural-based livelihoods (Pricope *et al.*, 2013). The provision of Weather and Climate Information (WCI) can help these communities cope and adapt to the impacts of these extreme events (Roudier *et al.*, 2016; Amegnaglo *et al.*, 2017; Hansen *et al.*, 2019). This is because WCI can inform appropriate actions to improve preparedness and reduce impacts (Jones *et al.*, 2015). For example, scholarly literature notes that farmers with access to timely WCI can plan their livelihoods activities, such as when and what to plant, and appropriate farm management activities that may result in reduced impacts(Coulibaly *et al.*, 2015; Naab, Abubakari and Ahmed, 2019).

Significant technological advancements have resulted in increased availability of WCI (Dinku *et al.*, 2014; Hewitt *et al.*, 2020). However, this has not translated to improved accessibility, especially across user groups (practitioners and communities) in Africa, where varied access to WCI is noted (Dinku, 2019; Vaughan *et al.*, 2019). In addition, even if WCI is available and accessible, this does not necessarily mean the information is used to inform local decisions, as it may not address the information needs of specific users (Vaughan and Dessai, 2014; Naab, Abubakari and Ahmed, 2019). These obstacles, commonly termed as information 'usability gap' (Lemos, Kirchhoff and Ramprasad, 2012), have been identified as significant impediments to the use of WCI to inform climate-related decisions at all levels (Flagg and Kirchhoff, 2018; Ouedraogo *et al.*, 2018).

In their study, Vincent *et al.* (2020) developed a framework that highlights three components that would close the information usability gap and promote the use of WCI for climate risk management. These components have been broadly categorized as 'useful' information, which requires an understanding of the specific users' needs and their decision-making contexts to guide in identifying what information is useful (Carr *et al.*, 2019), 'usable' information if it's understandable by the intended user and is disseminated on time (Vincent *et al.*, 2021) using appropriate communication channels (Barihaihi and Mwanzia, 2017) and an 'enabling environment' such as supportive institutions (Vaughan *et al.*, 2017) to ensure that useful and usable information gets used in practice.

The Vincent *et al.*, (2020) framework builds on the climate services literature, including Lemos et al. (2012) framework on bridging the information usability gap. In addition, it builds on the understanding that climate information use broadly links the user and the producers by knowledge sharing and collaborations through avenues such as co-production (Vincent *et al.*, 2021). The three components, therefore, reflect both the supply and demand side of climate services towards ensuring more informed use of WCI for adaptation planning (Jones *et al.*, 2015).

We, however note that to ensure more coordinated institutional responses (such as that which would be required pre- and post-disaster) (UN, 2015) and a better flow of information (i.e., from practitioner to community and vice versa), additional components are required. First, further, to having an enabling environment, additional support based on other underlying socio-economic factors that influence how these communities cope may be necessary to ensure that the at-risk communities ('users' henceforth) actively use the information provided. For example, in a rural smallholder setting, having access to usable information may not necessarily translate to use in practice due to other individual or household social-economic factors such as income, education, and age (Mittal and Hariharan, 2018; Shah *et al.*, 2018, 2020; Petty *et al.*, 2022). Similarly, a bottom-up approach that links the information providers, the disseminators, and the communities would be required to ensure that the communities have a voice to interact and provide feedback on weather information use and their coping practices.

Second, the production of useful information goes beyond data availability (Goddard, 2016). Other obstacles remain that could hinder the potential to produce and provide useful WCI, especially in the least developed countries. Essentially, decision-makers and information producers/providers ('providers' henceforth) require access to quality and credible 'scientific' data and information to fulfil the users' information needs and manage the potential risks (Hewitt *et al.*, 2020). But the required data and information is often limited(Van Den Homberg, Visser and Van Der Veen, 2017) or inaccessible (Susha, Janssen and Verhulst, 2017; Dinku, 2019). In their framework, Van Den Homberg, *et al.*, (2017) notes that being data-prepared can help reduce the impacts associated with extreme events if high-quality data that meets the providers' information needs are accessible before the disaster hits. The Van Den Homberg *et al.*, (2017) framework focuses on five main components, which include; 'datasets' regarding data availability and accessibility, 'data services' regarding services offered and software/hardware required, 'data literacy' concerning the capability to transform the data to required information, 'governance' looking at legal and regulatory rules on data sharing and 'networking' which involves having long-term data collaborations. These components collectively would ensure that the lead institution, for example, in disaster management, has all the required data and information to guide disaster-related decisions.

In this study, we combine the two frameworks (Van Den Homberg, Visser and Van Der Veen, 2017; Vincent *et al.*, 2020) through a bottom-up approach to present a more coordinated institutional response and flow of information. The bottom-up approach was designed as Farmers Agri-Met Village Advisory Clinics (FAMVACS) and Listening Groups (LG) and was initiated by UNMA. The approach ensures communities have a voice in contrast to the top-down approach (see Ciampi *et al.*, 2019). This would allow better characterization of the barriers that hinder adequate provision and use of WCI across the provider-user landscapes and opportunities for improving the WCI use and uptake. In the context of this paper, we use WCI to refer to all information that would be required to prepare and respond to flood risks (including but not limited to information on flood impacts, flood risks, hydrometeorology, socioeconomic, etc.). We have structured the study around three questions:

1) What barriers hinder the production/provision of useful WCI in the context of the providers? How can we improve provision?

2) What opportunities/barriers support/hinder the move from useful to usable information in the context of smallholder farmers?

3) What barriers deter smallholder farmers from using useful and usable information in practice? What can be done to improve uptake?

The study uses a bottom-up approach. Here, the bottom-up approach lets communities be involved from the beginning in all activities that support improved preparedness. In contrast to the traditional top-down approach in disaster management, this study allowed the flood-affected communities to record their accounts of how floods have affected them and their coping practices. Further, disaster management practitioners were also allowed to provide information on how they help at-risk communities prepare for disasters. At the local level, a case study in Katakwi district, Uganda, is used to give voice to the smallholder farming communities to record their coping practices, information needs, and the factors that hinder them from using the WCI to inform these coping practices. At the national level, online interviews with practitioners at disaster management agencies are used to understand how these agencies respond to the users' information needs and barriers to effectively providing the required WCI.

2.2.2 Materials and Methods

In this paper, we combine the two frameworks (Van Den Homberg, Visser, and Van Der Veen, 2017; Vincent *et al.*, 2020) (

Figure 4) and use them to identify the barriers and opportunities in the production/provision and use of WCI through a case study in Uganda. Two use cases (more detailed below) are developed to help answer the research questions. As noted in the literature, we recognize that one barrier to using WCI is a lack of an enabling environment (Vaughan *et al.*, 2017). However, this paper's detailed investigation of the institutional structures and disaster/climate policies that govern how disaster management activities are undertaken in Uganda was out of scope. This section provides an overview of the study area, the use cases, and data analysis methods.

2.2.2.1 Study sites

Katakwi District, the focus of this study, is in the Eastern region of Uganda and lies between longitudes 33° 48' E - 34° 18' E and latitudes 1° 38' N – 2° 20' N. Katakwi borders Napak District in the north, Nakapiripirit in the east, Amuria in the west and northwest, Soroti in the southwest, and Kumi and Ngora in the south (Figure 5). The landscape is a plateau with undulating slopes in specific areas and lies approximately between 1,036 and 1,127 m above sea level (KDLG, 2014). The district is characterized by two livelihood zones, i.e., crop-livestock and fishing livestock. Agriculture is predominantly rain-fed, with two distinct rainfall seasons from March to May and September to November. The district experiences frequent heavy rains resulting in flooding, affecting crop yields (KDLG, 2014). Common crops in Katakwi include sweet potatoes, cassava, maize, peas, rice, groundnuts, and local vegetables.

The district was selected in discussion with NIMFRU (National scale impact-based forecasting of Flood Risks in Uganda). NIMFRU is a project in Uganda to improve flood resilience through comprehensive flood impact assessments. The project is funded under the Science for Humanitarian Emergencies and Resilience (SHEAR, 2018) program. It complements the previous SHEAR project (Forecast for Anticipatory Humanitarian Action-FATHUM) by providing a new approach that incorporates various information required to deal with flooding effectively. The project aims to strengthen the capacity to interpret and use weather and climate information, livelihood and socio-economic information among others to inform flood preparedness at all levels, ensuring improved resilience to floods(https://walker.ac.uk/research/projects/nimfru-national-scale-impact-based-forecasting-of-flood-risk-in-uganda/).

The district suffers severe impacts from floods every rainy season. The vast majority (81%) of the population in the district earns their livelihoods through subsistence farming (KDLG, 2014). As a result, poverty levels are high, with 88% of the population living below the poverty line

(Kagugube *et al.*, 2017). Project stakeholders include the Red Cross Climate Centre (RCCC), National Emergency Coordination and Operation Centre (NECOC), members of Parliament, local academic institutions, and civil organisations.

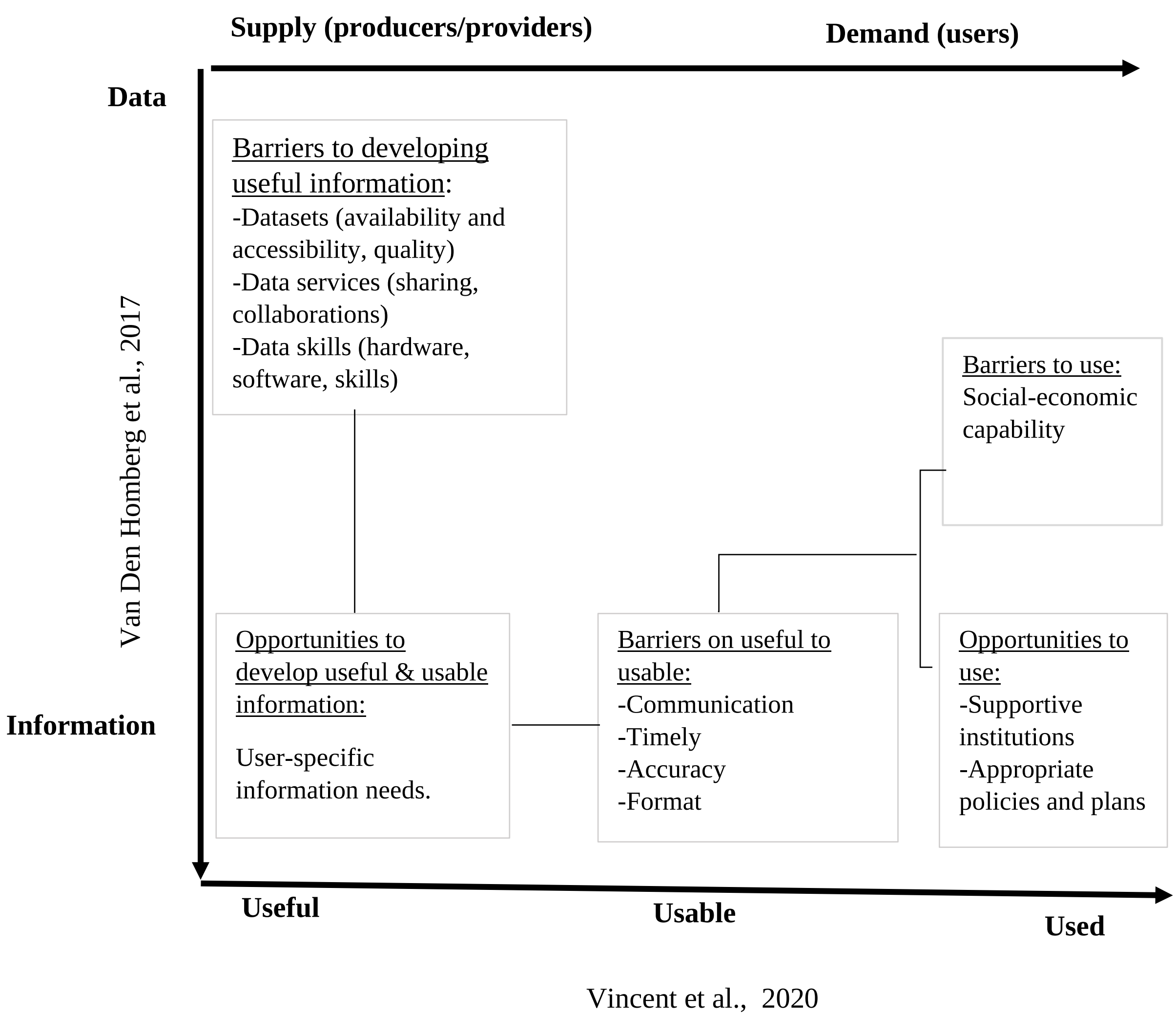

Figure 4: Conceptual framework used to identify the barriers and opportunities in the production/provision and use of WCI across the provider-user landscapes. Source: adapted from Vincent et al. (2020) and Van Den Homberg, Visser and Van Der Veen (2017) and modified by authors.

2.2.2.2 Developing the Use-Cases

This study was undertaken as part of the community preparedness to flood risks initiative within the NIMFRU project (NIMFRU, 2018). As part of the Science for Humanitarian Emergencies and Resilience (SHEAR, 2018) program, the NIMFRU project set out to improve the targeting and communication of flood warnings and response to communities in the Katakwi District. The project team developed the first use case targeting the flood-affected communities in three villages (Anyangabella, Agule, and Kaikamosing) in the Katakwi district (Figure 5). The use case was used to conduct field research to gain a deeper understanding of the livelihoods, coping capacities, and practices of groups within the study communities, barriers to coping, and their responses to flood hazards (a combination of quantitative and qualitative methodologies was used to inform this work, including quantitative livelihoods assessments, using the Household Economy Approach (HEA) (Seaman *et al.*, 2014).

Fieldwork was carried out between February 2019 to February 2020. Initial work (data collected from February 2019 to August 2019) informed the creation and the representation of two interrelated communication platforms: The Farmer Voice Radio (FVR) Listening Groups and the Farmer Agri-Met Village Advisory Clinics (FAMVACs) (Ciampi *et al.*, 2019). The well-established FVR approach complemented the new Uganda National Meteorological Authority (UNMA) led FAMVAC initiatives and led to the design of a novel methodology to ensure that both communication platforms provided a space for information needs and priorities to be identified locally. The platforms also facilitated open dialogues between community members and relevant district officials, providing a ‘vertical’ channel through which communities could feed their concerns and priorities directly into the Ugandan disaster response system. In addition, the methodology carefully ensured that there was relevant representation from both district and national authorities and that these initiatives were approved by NECOC and led by UNMA and the local non-governmental Organisation (NGO) Eco-Trust, to establish contextual validity, national ownership, and future sustainability. By the end of the fieldwork (February 2020), a total of 18 FAMVACs had taken place (6 in each target community) with an average participation of 200 local community members, and 20 individual episodes of the FVR programme were aired, reaching an estimated 67,000 people across rural Katakwi. Qualitative Field data collected from September 2019 to February 2020 using the developed

FAMVACs methodology have been used in this paper and are explained further in the following subsection.

The second use case involved the DM agencies at the national level. The focus was to understand how these agencies respond to the users' information needs, as well as to identify any gaps that hinder the effective production and provision of useful WCI. The sampling of the respondents was done through Purposive sampling techniques (Mohsin, 2016), which allowed us to choose the respondents based on predefined criteria and intended purpose. For this case, we considered national institutions and NGOs participating in Uganda's preparedness and response to natural disasters[2]. A stakeholder mapping exercise allowed us to understand organisational roles and mandates before selecting them for interviews. This exercise showed that over 25 organisations (Appendix A2.2) are involved in disaster management in Uganda. However, due to Covid 19 restrictions and response responsibilities, only 14 of these organisations were available to participate in the interviews.

[2] Here, we refer to all national-level institutions who fall into any or all these recognized stakeholders' categories (data collectors, data analysers, intermediaries, decision-makers) and are responsible one way or another in collection, analysis and production of disaster information.

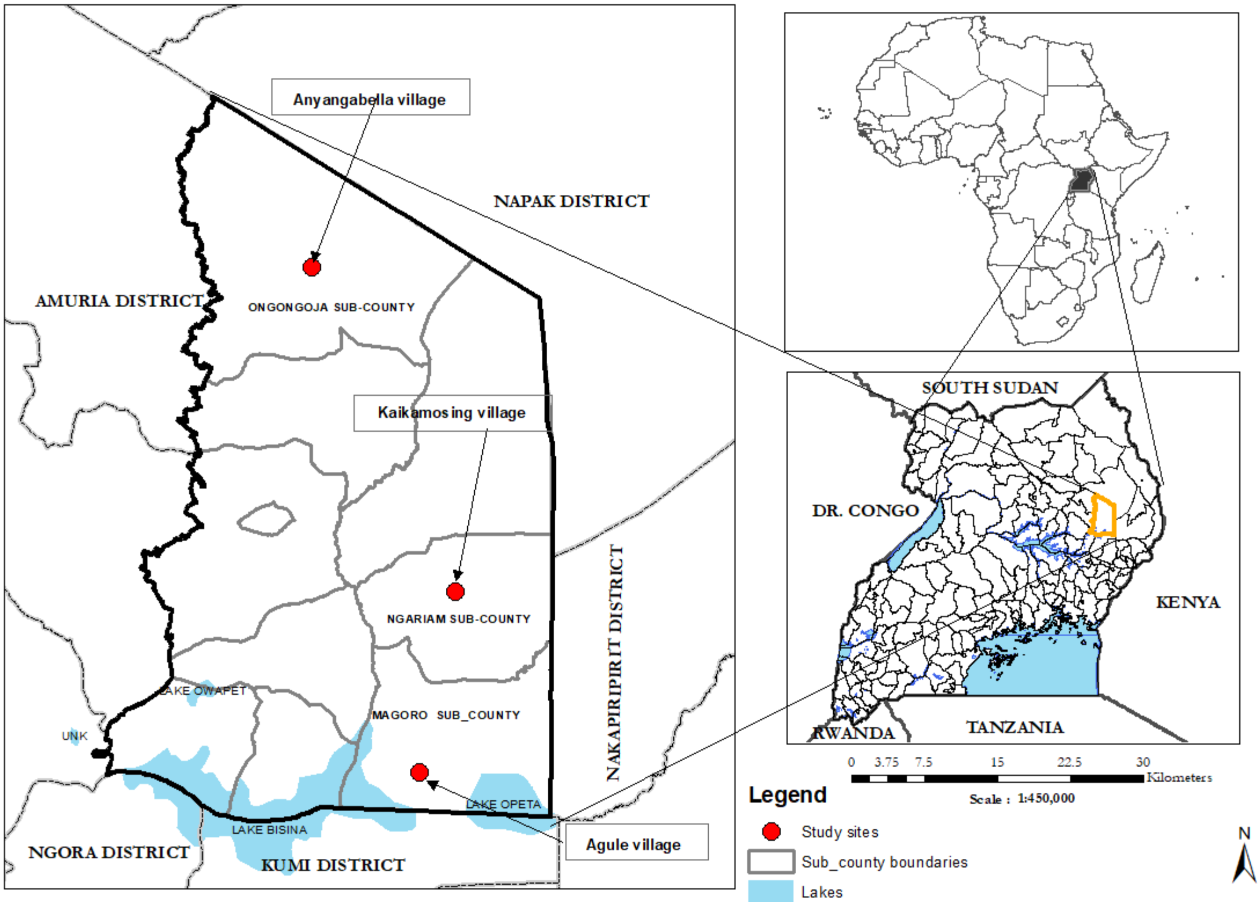

Figure 5: Location of the study sites in Katakwi District, Uganda

2.2.2.3 Data collection

Data collection was undertaken separately for the affected communities and the DM agencies. At the community level, fieldwork, led by Eco-trust Uganda using the FAMVAC toolkit, took place over six months between September 2019 and February 2020. The fieldwork exercise gathered information from the flood-affected communities through farmer's discussions and semi-structured interviews (see Appendix A2.3 for sample interview questions). The data collection exercise occurred in three villages identified during the initial NIMFRU project fieldwork. In addition, we conducted 26 oral 1-on-1 semi-structured interviews with farmers in the three villages.

Additionally, we held 18 farmers' discussions (6 from each village) involving a large group of farmers (each farmers' group consisted of approximately 70 farmers). The interviews and discussions were done during the main rainy season. All interviews and discussions were carried out in the local language, 'Ateso', with an interpreter and were subsequently transcribed.

At the DM level, data collection took place from October 2020 to December 2020 through online semi-structured interviews. A staged process was used where the first stakeholders mapping exercise was conducted based on the predefined criteria (see section 2.2.2.2). The second step involved sorting and identifying how many informants would be required from these institutions based on the number of departments and their roles. For example, an institution like Uganda National Meteorological Authority has both a forecasting and data centre; hence more than one informant would be ideal. The third step involved contacting the institutions to provide the key informants to participate in the interviews. In total, 14 institutions (see Table 3) took part in the interviews. Interview questions were framed around key themes such as their disaster management activities, information required, and the barriers to fulfilling users' information needs (see Appendix A2.4 for sample interview questions). For anonymity, direct quotes from disaster management practitioners have been denoted with the pseudonym Disaster Respondent (DR).

Table 3: Institutions that took part in the online semi-structured interviews.

Name of the Institution/department	Type
1. Ministry of Water and Environment (MWE)	Government
2. UNMA- forecasting unit	Government
3. Katakwi District office	Government
4. Office of the Prime Minister (OPM)-Climate Change Department	Government
5. OPM-Disaster Risk Reduction	Government
6. MWE-Water Resources Department	Government
7. NECOC	Government
8. UNMA-Data Centre	Government
9. Uganda Red Cross Society	NGO
10. Humanitarian Open-Street Mapping Team (HOT)	NGO
11. World Vision _Uganda	NGO
12. RCCC	NGO
13. Makerere University	Research
14. Africa Disaster Reduction Research and Emergency Missions (ADRREM)	Humanitarian indigenous NGO

2.2.2.4 *Data Analysis*

The software package Nvivo 12 for MS Windows (QSRInternational, 2018) was used to analyse the data from the local communities and disaster management practitioners. The Nvivo programme, unlike manual methods of qualitative data analysis, offers the user an intricate, methodical, and iterative data interrogation process (Jackson and Bazeley, 2019). Data analysis in Nvivo is done through a content analysis approach where the mode of analysis can be either inductive or deductive (Elo and Kyngäs, 2008; Mayring, 2014). The inductive approach is used when the researcher has limited or no theory on the research outcome (Mayring, 2014) and entails letting the themes emerge from the raw data directed by existing study components (Harding, 2018). The deductive approach is based on a predetermined structure guided by previous findings, literature review, or an existing conceptual framework (Hsieh and Shannon, 2005; Mayring, 2014). In this study, we base our analysis on a combination of existing literature and frameworks on climate services and data preparedness (Van Den Homberg, Visser and Van Der Veen, 2017; Vincent *et al.*, 2020) (Figure 4) in a case study context hence the deductive content analysis approach is used to analyse our research data.

Deductively, the following steps were followed. First, the categorization matrix based on themes from the framework presented in

Figure 4 was developed. For this case, an unconstrained matrix was used to allow any other emerging concepts to be captured (Elo and Kyngäs, 2008). Table 4 shows the themes used in the categorization matrix based on our research aim. Second, the familiarisation phase was conducted. This involved reading through the transcripts to become aware of the ideas and words used by the respondents before coding. We then reviewed all the transcripts and coded them into the corresponding themes while allowing the inclusion of any other emerging categories (Elo and Kyngäs, 2008). For information that did not fall into any existing themes, coding was done using words and phrases that the respondents used in their transcripts, ensuring minimal misinterpretation. Coding was done separately for the community interviews and the disaster management interviews. However, the same themes were used.

The analysis process has been explicitly explained and the themes used are supported by existing literature. The data has also been explicitly linked to the results from the analysis. In addition, to ensure the validity of the coding process, two approaches have been used; visual representation (Siccama and Penna, 2008) and data scoping (Richards, 2004). For the visual representation, visual captures of the coding process have been done to authenticate the various steps used in coding (Appendix A2.5, A2.8). Scoping approaches using text query and matrix coding tools in Nvivo have been used to check coding validity (Richards, 2004). These tools allow the identification of the commonly used words in specific themes relevant to coding. For example, through matrix coding, the word 'accessibility' was mentioned in 9 out of 14 respondents (Appendix A2.6), with the majority coming from the government and NGOs (Appendix A2.7). In addition, direct phrases/words from the respondents (such as 'improved seeds, early harvesting) were used as code sub-categories which reduces misinterpretation (Richards, 2014). Using the text query tool in Nvivo, we also verified if the phrase 'improved seeds' used as a sub-category was relevant for coding. Results show that the exact phrase was mentioned in 8 out of 9 transcripts from farmers' interviews (Appendix A2.9). Furthermore, the Phrase was mentioned more than once in five out of the nine transcripts. This shows that using the same phrase in coding is relevant to ensure validity.

Table 4: Categorization matrix showing the themes used in the coding of data in Nvivo

Themes	Barriers to producing useful information	Opportunities to produce usable information	Barriers to moving useful to usable	Barriers to use in practice
To identify the barriers and opportunities in the production/provision and use of WCI				

2.2.3 Results

In this section, we present the outputs from the research data analysis based on broad themes identified during the coding and the research questions.

2.2.3.1 What are the barriers to producing useful WCI?

The DM practitioners expressed that most of the data required to prepare for a disaster are available. These datasets include weather and climate data (rainfall, temperature, river flow) and risk data (vulnerability, exposure, hazard). The weather data is provided by UNMA, while disaster risk data comes from various institutions, including NECOC and the Uganda Bureau of Statistics (UBOS). These data support the main activities carried out during preparedness and response to flood risk. The main disaster preparedness activities are disseminating weather and climate information and identifying flood risk areas.

Although 'scientific' data is available, transforming these data into necessary and useful information is often hindered by various factors, as reported by DM practitioners. First, these data are not easily accessible since they are held by individual institutions that mandate data collection and production. Second, a memorandum of understanding is often required between these institutions to facilitate data sharing. Third, due to institutional rules and regulations, the data sharing process can take longer than expected, affecting the preparedness and response activities.

> "Data from most institutions is not readily accessible due to institutional rules and guidelines on data sharing. The institution often demands a memorandum of understanding between the two institutions before sharing, which can delay the process by up to 2 months. [DR01, DR04]"

Second, the data available lack the level of detail required for comprehensive risk assessment at the local level (most data do not cover the village level). For example, most of the risk indicators, such as those that would be required to understand the vulnerability of the communities to disasters, vary in spatial coverage; some go up to sub-county while others go up to county level, with none covering the village level. Weather data also does not fully represent the situation due to limited and scattered weather stations.

> "There are gaps in the data available for example, the risk atlas covers up to district level and doesn't cover parishes and villages" [DR03].

> "Weather Information is generalised to a vast area, but the farmers need localised information." [DR014].

Third, not all the available data, especially on hazards and vulnerability, are complete. In addition, some of the risk indicators, such as the data on poverty levels, population density, and literacy levels, are not up to date, mainly if they depend on national census data. This affects the development of up-to-date risk layers. The lack of a national flood forecasting system also affects the quality of information produced for flood risk management. If global flood forecast information is to be used to inform preparedness, it should be verified[3] first for reliability. Although the development of the community Risk Assessment (CRA) framework is underway with support from the 510 group of the Netherlands Red Cross (NLRC))(NLRC, 2022), it is still hampered by the limited data available. The DM practitioners reported that this is based on secondary data and does not include any data collected from the grassroots level.

> "Verified flood information is required to inform disaster management. Many global sources are available, but they need to be verified by the Ministry of Water and Environment before use" [DR02].

> "Flood forecasting capacity is low in the country. Therefore, they forecast rain and not floods" [DR012].

Lastly, institutions that have a role in transforming data into the required information noted that they have the required skills to do that. However, frequent capacity building to keep up with evolving technology in climate science, such as forecasting and forecast evaluation skills, is required. Figure 6 shows the most common barriers to developing useful WCI.

[3] Verification here means that the flood forecasts information from global sources should be compared with ground-based river gauge observations or historical flood timelines to ensure that they capture the flood situation of the location

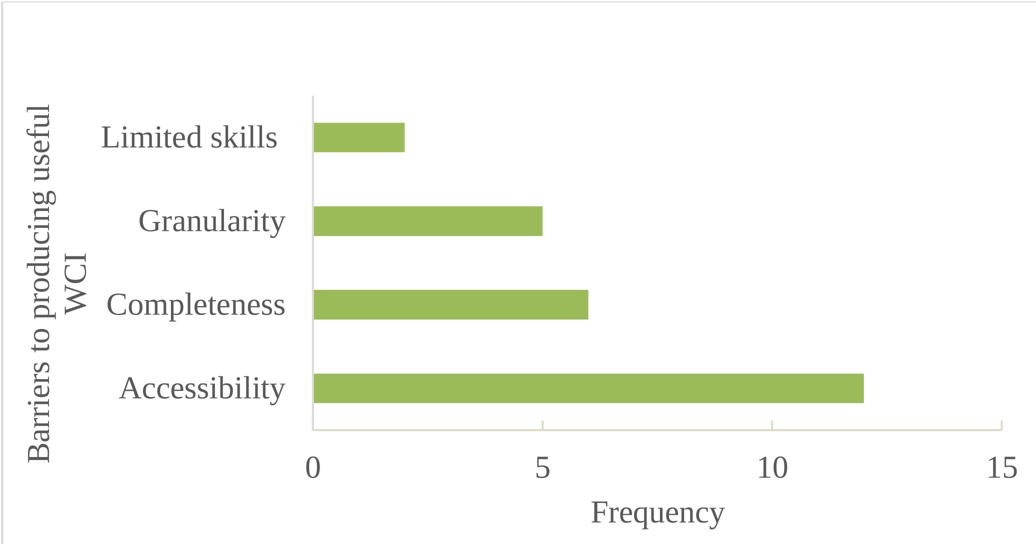

Figure 6: Barriers that hinder the production of useful WCI.

2.2.3.2 What are the opportunities and barriers to ensuring useful information is usable?

Understanding the users' information needs presents an opportunity to develop usable information. From our study, various information needs for the smallholder farmers have been identified based on the coping practices that the farmers undertake during flood preparedness. These information needs have been grouped into weather and climate, agricultural practices, and physical access to safe locations (Table 5). The information needs have also been grouped according to when it would be required. For example, the dynamic category includes information that would require an update every season. The second category captures situations where the dynamism of information would depend on the season. For instance, the location of safe areas may change depending on the magnitude of flooding experienced. What to plant and when to harvest will also depend on the rainfall factors such as duration, onset, etc.

Useful information such as weather information is available and accessible to local farmers. However, the information does not meet farmers' needs due to various factors. First, the weather information is packaged in a technical format and disseminated in English, making it hard for farmers to understand and use. For example, though the weather bulletins produced by UNMA are available through the district office, farmers cannot utilise them, especially if they do not have any advisories or are not interpreted in their local language.

Second, the timing of information dissemination is often unfavourable to local farmers. For example, the farmers and DM practitioners reported that information should reach the farmers 1-2 months before the start of the season to help them prepare. In addition, since the information is issued quarterly, with frequent updates, sometimes the local farmers do not receive these updates to help them keep up to date with the changes in the weather patterns.

Third, the DM practitioners working at the local level reported that communication and dissemination of WCI are often exclusively top-down. Therefore, communities cannot share any feedback with the producers and the decision-makers. Table 6 lists these challenges and quotes from farmers and DM practitioners.

Table 5: Categorization of farmers' information needs based on when they are required.

Dynamic Information (seasonally)	Dynamic (depends on the season)
Weather and climate ● Rainfall magnitude, intensity, timing ● Rainfall predictions ● Flood duration ● Flood timing ● Inundated areas ● Risk areas	Agricultural practices ● When to harvest ● Types of seeds (improved, early maturing, water-tolerant, etc.) ● Post-harvest handling methods ● Land management practices ● Livelihood diversity methods Safe locations & their accessibility ● Shelter for animals ● Shelter for people ● Agrovet locations ● Drinking water locations ● Location of health facilities ● Road's accessibility ● Market information ● Market accessibility

Table 6: Barriers that hinder useful information from becoming usable in the context of smallholder farmers.

Theme	Frequency	Meaning	Evidence (DM practitioners)	Evidence(farmers)
Technical language	6	The language used to produce and disseminate the weather information	"The weather information is technical, and they don't understand what normal and above normal means" [DR014]. "We produce weather information but to help the communities understand, we need to translate the information into local languages" [DR08].	"Climate and weather bulletins are available at sub-county offices; however, these are not easily interpretable by the farmers" [Farmers: 3 villages].
Lead time(timely)	5	The time between when the information is produced and when it's required	"Farmers require weather information two months before the start of the season to help them plan the activities" [DR06]	"We need weather information on time for proper planning and to help choose which crops to grow" [Farmer: Kaikamosing village]
Top-down approach	4	Communication and dissemination of information is from the producers to the users only	"Communication is top-down, and communities do not share their information" [DR06].	

2.2.3.3 *What are the barriers to the use of WCI to inform coping practices?*

Smallholder farmers know the recommended coping practices for preparedness for floods. The most common is how to protect their crops before flooding, including early harvesting, post-harvest handling, and planting improved seeds. This is followed by ensuring their safety through activities such as clearing bushes and draining water from their compound. Activities to protect livestock before floods include vaccination, improving animal shelters, and buying improved breeds. On the other hand, farmers in the study villages did not engage in many activities to enhance financial security, such as belonging to saving societies. Figure 7 highlights all the coping practices the farmers in Katakwi identified, while Table 7 shows the most common coping practices based on the frequency.

Although the farmers were aware of the recommended coping practices, the actual implementation of these practices was hindered by various factors. These include agricultural-related challenges such as the lack of improved seeds and other farm inputs. In addition, farmers in Katakwi do not have access to proper post-harvest handling kits to store their crops. Most of these challenges are associated with the social-economic capabilities of these communities, which we were unable to analyse further within the scope of this study.

Second, environmental factors such as the invasion of desert locusts and strong winds were identified as challenges to implementing coping practices. Third, farmers noted that age and disease outbreaks also derail the necessary coping practices. Figure 8 shows the common challenges affecting the implementation of the coping practices.

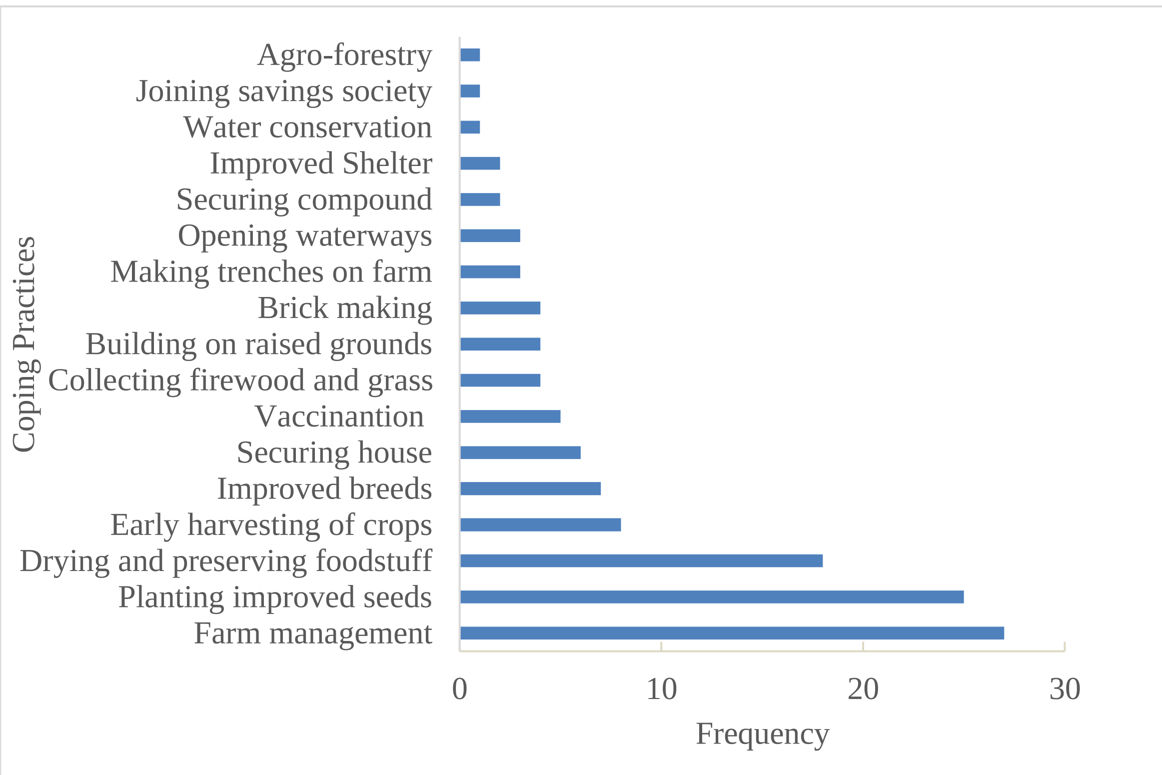

Figure 7: Coping practices used by flood-affected communities in the three villages (Anyangabella, Kaikamosing, and Agule) in Katakwi District, Uganda

Table 7: Common coping practices that farmers undertake and their meaning.

Activity	Frequency	Meaning	Evidence
Farm management practices	27	Practices such as contour ploughing, mulching pest control, crop rotation and making manure	"My garden supported increased yields because I learned how to make manure" [Farmer: Kaikamosing village].
Planting improved seeds	25	Planting crops that can survive forecasted rainfall, e.g., early maturing, water tolerant crops	"I was able to decide which crops to plant based on the rainfall information provided" [Farmer: Anyangabella Village]
Securing houses	6	Building strong houses using materials such as bricks, damp proof course (DPC).	"I used DPC for the foundation of the house to make it strong" [Farmer: Agule Village]

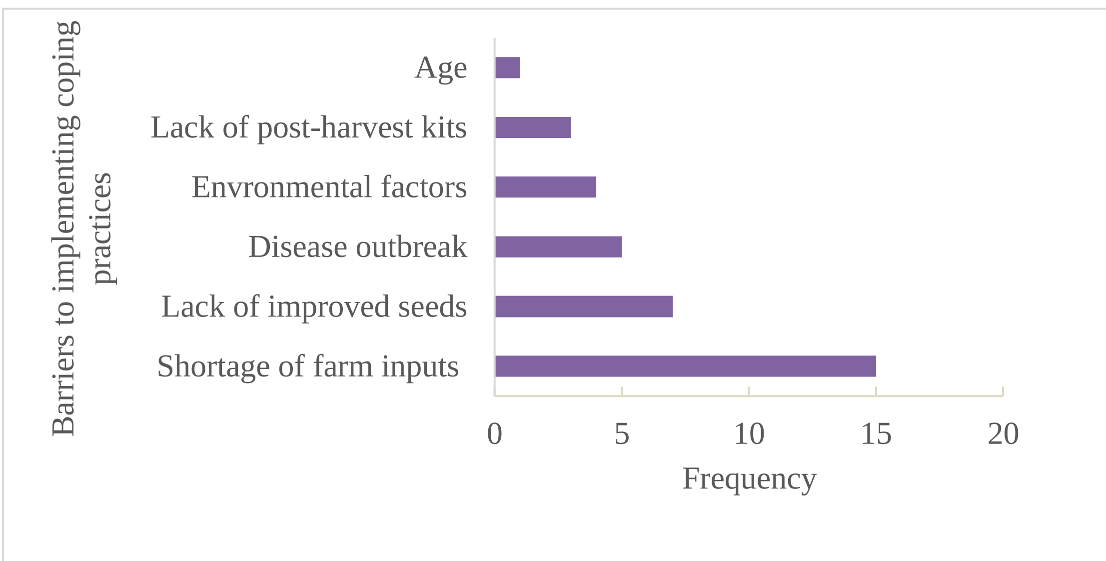

Figure 8: Barriers to implementing coping practices across the three villages (Anyangabella, Kaikamosing, and Agule) in Katakwi District, Uganda.

2.2.4 Discussion

While the role of WCI in smallholder farmers' decision-making is now common knowledge (Roudier *et al.*, 2014; Coulibaly *et al.*, 2015), the understanding and use of WCI by farmers have not been very effective, especially where it does not meet their specific information needs (Carr *et al.*, 2019). In addition, developing useful information is not only contingent on data availability (Goddard, 2016) but can also be hindered by various factors from the providers' side. Therefore, developing useful and usable WCI requires a more coordinated flow of information from the providers to the users and vice versa to understand the barriers that hinder the provision and use of WCI. In this research, we have combined two frameworks through a bottom-up approach (FAMVACs method) to identify the barriers and opportunities across the provider-user landscapes in the production and use of WCI for a case study in Uganda. The approach used in this study to identify the barriers has broader applicability across most natural disasters, where a more coordinated response and flow of information would be required to understand the gaps in the provision and use of WCI for disaster management. Here, we first discuss the common barriers that hinder the production/provision and use of useful and usable WCI at the local level and the potential ways to address these barriers. We then highlight any future work that would be required to improve the use of WCI at the rural level. Figure 9 shows the various components for a coordinated institutional response and flow of information towards ensuring; that 1) useful information is produced, 2) useful becomes usable, and 3) usable is used in practice based on the findings from Uganda.

2.2.4.1 Ensuring the production/provision of useful WCI

The development of useful information spans beyond the data available to include other factors. Our findings show that barriers such as accessibility, completeness, and granularity of the data may hinder the development of useful information from the providers' side (see Figure 6). These dimensions are commonly used to check the quality of the available data. For example, they have been used to develop the data preparedness index (Van Den Homberg, Visser and Van Der Veen, 2017) and by other international organisations in data quality assessments to understand how prepared a country or an institution is in disaster management activities (WorldBank, 2012). These factors will, however, vary according to the context. For example, a study by Dinku (2019) found that the availability and completeness of climate data vary across Africa due to the scarcity of weather stations. In addition, the limited accessibility of available data has been attributed to the legal regulations governing how institutions share data, and the high costs levied to access the data.

Therefore, there is a need to understand the existing data gaps and how they can be addressed to ensure development of useful information. The data quality dimensions noted above, including recency and reliability, can be used to assess these gaps (Van Den Homberg, Visser and Van Der Veen, 2017). In Uganda, most of the required data to inform disaster preparedness is available. However, the accessibility of these data is hindered by a lack of coordination between the various institutions involved in disaster management, which means data is developed and managed by individual institutions (Atyang, 2014; Lumbroso, 2018).

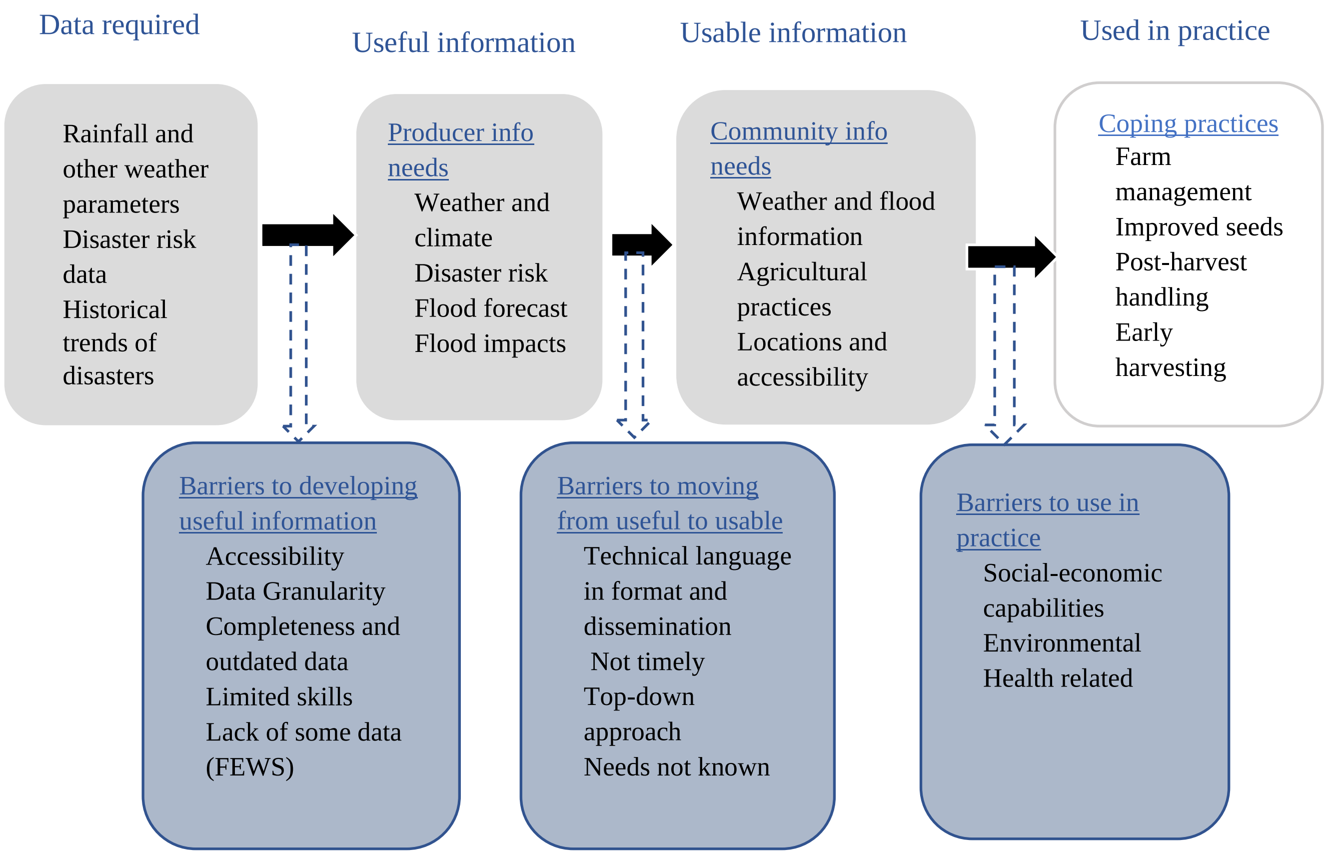

Figure 9: Components that would be required to achieve a more coordinated institutional response and flow of information to ensure useful and usable information is produced/provided and used in practice: the component headings have been adopted from Vincent et al. (2020) and Van Den Homberg, Visser and Van Der Veen, (2017)while their contents are based on findings from Uganda

Access to data that meets the required quality dimensions can help bridge the providers' information gap (Homberg, Monné and Spruit, 2018) and ensure that useful information is developed and made available for timely disaster preparedness and response. One way to ease data accessibility would be by embracing technology in data sharing, for example, through multi-sector platforms such as the one developed by Cornforth et al. (2018). Fostering data collaborations across sectors can also help ensure that the required data is easily accessible (Susha, Janssen and Verhulst, 2017).

2.2.4.2 Ensuring useful WCI is usable.

Useful WCI becomes usable if it meets the information needs of the users. User needs are context-specific and evolving and will vary depending on livelihood type (Carr and Owusu-Daaku, 2016), geographical location, and gender, among others (Barihaihi and Mwanzia, 2017; Carr and Onzere, 2018). This means that although useful climate information is becoming increasingly available (Hewitt *et al.*, 2020), its usability will require a constant context-specific understanding of the climate information needs of the users to ensure that the information is tailored to their needs. For example, in the Katakwi district, farmers require information on weather, climate, and appropriate agricultural practices (see Table 5) to inform their coping practices. This is also consistent with findings across Sub-Saharan Africa on the use of WCI to inform agricultural practices (Amegnaglo *et al.*, 2017; Nyadzi *et al.*, 2019). Farmers with access to WCI tailored to their needs can benefit from the required coping and adaptation strategies (Singh *et al.*, 2018; Vaughan *et al.*, 2019).

The WCI available and accessible by farmers in the Katakwi district are not timely (Vincent *et al.*, 2021) and are too technical for them to understand and use(Barihaihi and Mwanzia, 2017; Nkiaka *et al.*, 2019). For example, farmers would require weather information with a lead time of 1 to 2 months before the season's onset to inform practices such as acquiring the required seed variety (Amegnaglo *et al.*, 2017). In addition, the weather bulletins issued by UNMA come in English, and the farmers would need translation to make them usable. Efforts to help translate the weather information are already seen under the collaboration between UNMA and local NGOs which can have a positive impact (Ouedraogo *et al.*, 2018). Furthermore, fostering communication between the users and providers can help understand the WCI needs of the users and barriers that make useful information unusable. Ways to make the information usable, including capacity building (Conway *et al.*, 2017), interpretation of the information into simple advisories (Harvey *et al.*, 2019), and co-production (Vincent *et al.*, 2021) can then be explored based on the target user. Overall, engaging the users from the start in the production of WCI can help ensure the information is usable and trusted, boosting uptake (Nkiaka *et al.*, 2019). However, the extent to which these solutions can be implemented will depend on other factors. Scholarly studies have shown that limited financial and human resources can limit the local institutions' preparedness. These factors should therefore be considered on top of the data preparedness factors to ensure that useful information is translated into usable information.

2.2.4.3 Ensuring usable WCI is used in practice.

Availability and accessibility of useful and usable WCI by the target user do not necessarily translate to the actual use to inform coping practices. Although smallholder farmers may be aware of the coping practices to undertake (Berman, Quinn and Paavola, 2015; Shah *et al.*, 2017; Wichern, Wijk, *et al.*, 2017), studies have shown that one of the barriers to the use of WCI in practice is the lack of an enabling environment such as supportive institutions (Vaughan *et al.*, 2017) to support adaptation planning. Other barriers, such as the users' social-economic capabilities (age, income, health, etc.), can also hinder use(Mittal and Hariharan, 2018; Shah *et al.*, 2020). This means that even though useful and usable information that meets users' needs is provided, the actual uptake of this information to inform coping practices will be context specific. For example, in this study, farmers in the Katakwi district cannot afford the agricultural farm inputs required, such as improved seeds (Fisher *et al.*, 2015), to enable them to undertake the recommended coping practices. Other factors noted include limited land and inadequate farm tools (Tall *et al.*, 2014). These factors have also been linked to financial resources to enable the farmers to undertake these coping activities (Shah *et al.*, 2017).

Farmers can derive many benefits from using WCI (Tarchiani *et al.*, 2017; McKune *et al.*, 2018; Ouedraogo *et al.*, 2018). Hence, the barriers related to the socio-economic capabilities of the users and how they affect coping and adaptation should be identified so that the necessary support is provided (Petty *et al.*, 2022). This could be done through existing institutions where interventions such as giving cash or subsidised farm inputs can be introduced (Assan *et al.*, 2018). In addition, encouraging farmers to be part of farm-based organisations can help boost the uptake and use of WCI. These facilitate access to the required capital to support coping practices (Amegnaglo *et al.*, 2017; Tarchiani *et al.*, 2017).

2.2.4.4 Improving the uptake of WCI among local farmers

Overall, the disconnect between the users and providers of WCI can result in ineffective use of WCI to inform local-level decision-making (Lemos, Kirchhoff and Ramprasad, 2012; Singh, Dorward and Osbahr, 2016). A first step towards ensuring effective use would be identifying barriers that hinder effective production/provision and use of WCI across the provider-user landscapes. By combining two frameworks (Van Den Homberg, Visser and Van Der Veen, 2017; Vincent *et al.*, 2020), through a bottom-up FAMVAC approach, this study provides a more coordinated institutional response that would ensure a shift of focus from only the users to a more inclusive approach where even the data and information needs of the providers are identified. This would make it easy to characterize the gaps from both levels more dynamically and ensure that the necessary support is provided. For example, findings from practitioners in Uganda indicate that the skills to work on 'scientific' data are available, but as technology in the production of WCI changes, continuously institutional capacity building will be necessary (Dinku, 2019; Mataya, Vincent and Dougill, 2020) to ensure that they can keep up with the demand for useful WCI.

The field of disaster risk management is shifting towards impact-based forecasting and forecast-based actions (Coughlan De Perez *et al.*, 2016; WMO, 2021b). Interventions that target the at-risk communities should therefore consider their information needs, coping practices, and social-economic capabilities to ensure the design of more tailored interventions. In addition, understanding the capabilities of the information providers and the gaps that may hinder effectiveness in producing the required useful information will be essential to ensure a more coordinated response to the user needs. As the impacts of weather-driven shocks on rural smallholder communities increase, they will continue to demand relevant and timely information to support their coping practices (Hansen *et al.*, 2019). The providers will also need to be supported to meet these information needs. The potential benefits of WCI can be realised by understanding the barriers to production and use of WCI at different levels and promoting required interventions to improve disaster preparedness and response activities. For example, through promoting coordination and collaborations among multiple providers to ease data accessibility (Susha, Janssen and Verhulst, 2017) as well as ensuring that the needs of the users and barriers that affect effective utilisation of WCI are understood and streamlined into the disaster management plans to support community preparedness (Nurye, 2016).

2.2.4.5 Future work

Identifying barriers that hinder effective provision and use of WCI can inform the design of the required interventions. For example, a barrier such as data granularity (lack of data at the local level) can trigger support for frequent data collection at the local household level. Methods that are applicable based on context can then be assessed using criteria such as the one developed by Alkire & Samman (2014). In addition, calculating the data preparedness index (Van Den Homberg, Visser and Van Der Veen, 2017) based on the quantifiable data quality dimensions can also help shed light on the improvement required to ensure that a country is prepared to undertake timely preparedness and response activities.

Barriers because of the social-economic capability of the users would also call for more in-depth methods to quantify the capability of these communities to undertake the coping practices and understand the type of support that would be required. For example, further research could look at an in-depth quantitative analysis of the household social-economic characteristics (sources of income, expenditures, health, age, etc.) such as that provided by HEA assessments (Seaman *et al.*, 2014; Petty *et al.*, 2022) and individual household surveys (Shah *et al.*, 2020). Such an analysis can shed light on the household's capacity to undertake the various coping practices, the level to which these households may require external support, and the type of support needed. In addition, categorising the different coping practices stratified by wealth groups would also be essential to safeguard poor households against high-cost practices that may compromise their ability to cope in the future (Heltberg, Jorgensen and Siegel, 2009; Gautam and Andersen, 2016).

We did not get a chance to look at the disaster management structures and policies that govern how disaster-related activities are undertaken in Uganda. A thorough desktop study would therefore form part of future work to understand Uganda's plans for disaster risk reduction (DRR), including how various institutions coordinate to ensure emerging issues on disaster management are streamlined into the development process. Uganda has a DRR policy approved in 2011(OPM, 2011) which stipulates the roles of various local and national institutions in addressing disasters. However, a study by Ampaire et al., (2017) notes that the district and local level actors are often not included in implementing various policies. With climate variability expected to result in more extreme events, ensuring that the existing policies can still inform the required interventions is important. In addition, as we shift towards more locally targeted interventions, coordination between local and national institutions would be required to ensure that the needs of the most at-risk communities are centre in designing and implementing the DRR policies.

2.2.5 Conclusion

The study findings have shown that the provision of useful and usable WCI spans beyond understanding the users' needs -- for this case, the farmers -- to include the providers' data and information needs and the users' capabilities to use the information to inform practice. Ensuring that useful information is available, usable, and used in practice by the intended users is, therefore, an integral part of an effective disaster management plan. The barriers and opportunities to achieve positive impacts in using WCI should consequently be continuously assessed to ensure that developed WCI meets the needs of the potential users.

This study has provided a more coordinated institutional response approach that integrates two frameworks (Van Den Homberg, Visser and Van Der Veen, 2017; Vincent *et al.*, 2020) and applies a bottom-up approach through the FAMVACs method to help identify the barriers and opportunities in the provision and use of WCI across user/user groups. Such an approach would ensure these barriers are identified across the user-provider landscape and provide solutions to bridge the specific gaps. Our findings on the barriers to the provision and use of WCI are consistent with other scholarly findings in the literature and are evidence of the various gaps that broadly affect the provision of climate services. However, specific solutions would be required depending on the context (user, location, etc.). For example, the lead time at which WCI should be provided to the local farmer will depend on the seasonal timing, which varies across locations. In addition, designing solutions to improve data preparedness will require specific information on the gaps in the various data dimensions (access, availability, granularity, recency, etc.), which might also vary across contexts. The combined frameworks can therefore provide a coordinated way of ensuring that prior information required to inform the development of specific solutions for improving the provision of climate services are identified across the users and providers. This will also ensure that co-production takes centre stage in the design and dissemination of WCI.

Increased availability of weather and climate data and information provides an opportunity to improve climate adaptation planning. However, actionable programmes are needed to ensure that this information is translated and disseminated appropriately according to the users' information needs. Weather information is fundamental in informing the coping and adaptation among, for example, farming communities. There is, therefore, an urgent need to invest in strengthening the production, dissemination, and uptake of weather information for effective disaster management. This can be achieved by understanding the specific information gaps at the national and local levels, ensuring an improved dialogue between disaster management institutions and at-risk communities for resilience building. Such information can then be used to improve disaster management plans and activities, ensuring timely preparedness for floods.

Data Availability: The original contributions presented in the study are included in the article/supplementary material. Further inquiry can be directed to the corresponding author.

Ethical Statement: The study involving human participants was reviewed and approved by the SAGES (School of Archaeology, Geography, and Environmental Science) and the Ethics Committee University of Reading. Conflict of Interest

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2.3 Coordination and disaster management: Insights from disaster management practitioners in Uganda

In Uganda, Disaster Management (DM) institutions work toward delivering credible information to the local communities to enable them to prepare for a hazard. To ensure coordination in preparedness and response (see section 2.2.4), information and data are required, and the capacity to ensure the information is disseminated on time.

This section presents additional findings from disaster management partitioners on the processes, data, and information required to ensure a more coordinated approach to disaster management. In this section, we highlight various aspects of disaster management in the Ugandan context based on findings from interviews with disaster practitioners in Uganda. Notably, we highlight the disaster information required, data available to fulfil the information needs, the standard data providers, and challenges that affect preparedness and response activities. These insights can ensure a better understanding of what would be required to provide adequate preparedness and response to disasters in Uganda.

2.3.1 Disaster management activities and gaps that hinder the implementation.

Discussions with the DM practitioners indicated several common activities undertaken during disaster preparedness and response. Preparedness activities include the production of weather forecasts information (includes updating weather systems, downscaling weather data, developing dissemination packages, monitoring, and getting feedback from the community on information use), dissemination of the required information to communities, capacity building of the district disaster committees and the communities on disaster risk reduction (DRR) and identification of disaster risks (safe areas, monitoring, and mapping). During initial response, activities include rapid risk assessments, search and rescue, and distribution of relief items. Most of these activities are undertaken through a process that often does not involve the local communities due to insufficient links between the local and national governments (Ampaire *et al.*, 2015). This could be attributed to the fact that at-risk communities are often viewed as recipients of information rather than actors in disaster management. Table 8 below shows the activities during preparedness and response to flood risk.

Table 8: Common activities during disaster preparedness and initial response

Preparedness	**Source**	**References**
Production of weather forecasts	5	10
Information dissemination to the communities	7	8
Identifying disaster risks in the communities	6	7
Capacity building DMC and communities on DRR	5	5
Initial Response		
Rapid assessments	8	8
Search and rescue	5	5
Distribution of relief goods	4	4

The implementation of these activities presents various challenges. The practitioners indicated several challenges affecting their day-to-day work from the discussions. For example, 45% of the respondents noted limited financial resources as one of the significant obstacles to implementation (Shah *et al.*, 2019). Challenges in disseminating the information were also highlighted, including lack of community trust, poor transmission networks, and uneven dissemination (which does not often reach all the communities depending on the means used). Lack of coordination also derails implementing the preparedness and response activities.

> "Getting all the stakeholders together is a problem. Some stakeholders go to the disaster sites before even informing the Office of the Prime Minister" [DR08]

During the response, significant challenges include limited financial resources, inaccessibility of the affected areas, and limited information to inform the response activities (e.g., how many people are affected, roads to use, etc.). Figure 10 shows the significant challenges during preparedness and initial response.

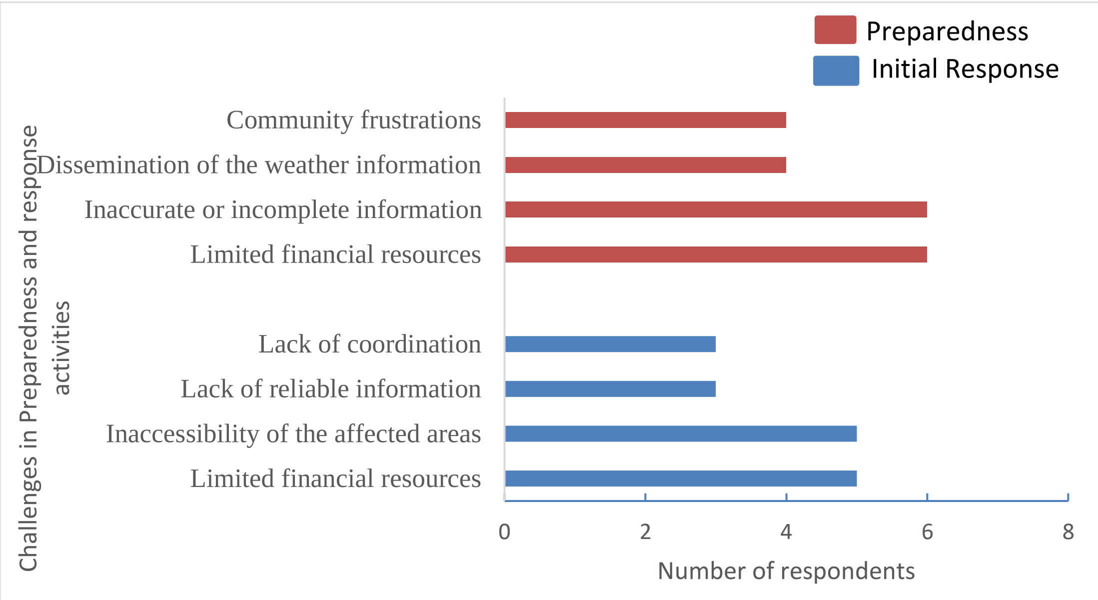

Figure 10: The most common challenges to implementing preparedness and response activities.

The analysis also shows that most of the respondents who had indicated the three initial response activities (Table 8) also indicated limited resources as the main challenge to their implementation, followed by the inaccessibility of the affected areas. This means that even though the disaster management practitioners know the activities to be implemented, the actual performance can be hindered by various factors, as shown in

Table 9.

Table 9:Matrix coding showing how the various response activities relate to the challenges noted by the respondents.

Activities/Challenges	Scarce resources	Inaccessibility of the affected areas	Lack of coordination	Lack of reliable information
Rapid assessments	4	3	2	3
Search and rescue	4	3	2	0
Distribution of relief goods	4	2	2	0

2.3.2 Data and information required to support disaster preparedness and response activities.

The most common data and information required for disaster management vary depending on the disaster management stage. During preparedness, data required include the weather data (rainfall, temperature), disaster risk information (areas to be affected, vulnerability profiles, hazard maps,) information on the lead agency, and flood forecast information. The DM practitioners could not differentiate between data and information; the same were used interchangeably while answering questions on data and information. During the response, data, and information on the impacts of the hazard and the needs of the affected communities are required. Figure 11 shows the most common data/information needed during preparedness and response to flood risks.

Despite being required, the practitioners noted that most of this data/information is not readily available, which has been attributed to how individual institutions produce and manage their data and information (Atyang, 2014; Lumbroso, 2018). For example, 5 out of 14 respondents noted that comprehensive and quantifiable impact information is not available, while 4 of the respondents pointed out that flood forecast information is unavailable. The lack of flood forecast information has been attributed to the absence of a national flood forecasting system (Atyang, 2014).

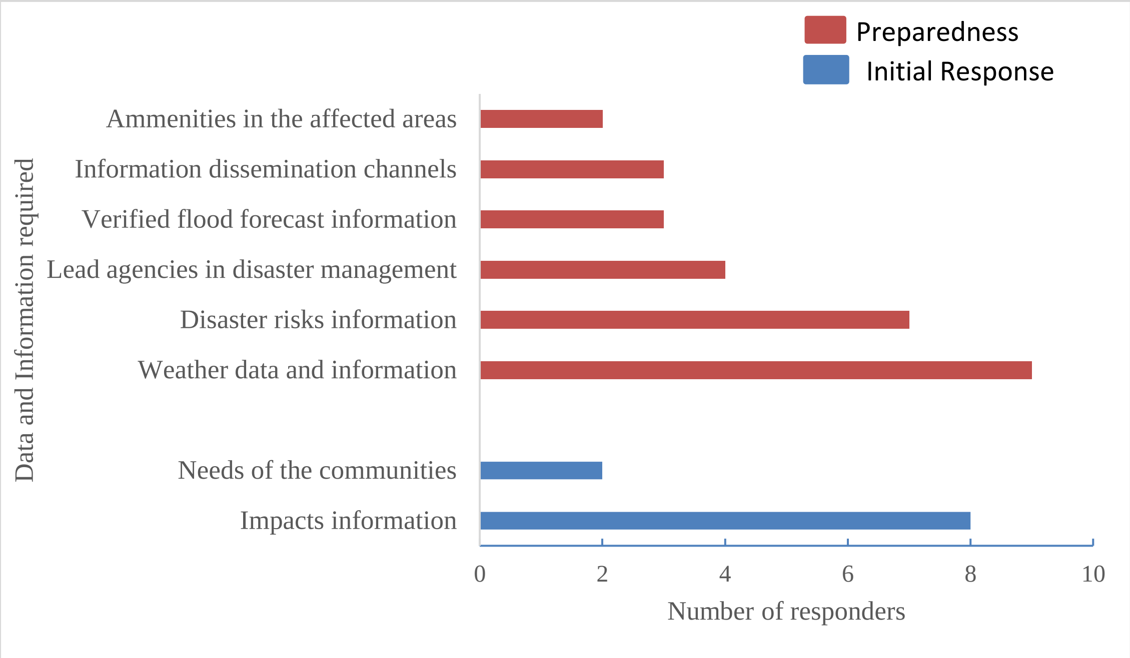

Figure 11: Data and information required by the DM practitioners.

2.3.3 Data and information providers and data sharing methods

Various institutions, including UNMA, Uganda Bureau of Statistics (UBOS) and other Ministries, provide the data and information required during preparedness and response to disasters. The respondents indicated that 57% of the data and information needed for disaster management is provided by UNMA, followed by URCS at 43%. This is because the most common data and information required, as indicated by the respondents, is weather information followed by disaster risk information (see Figure 11). The data available is also heterogenous since it comes from different institutions that regulate data production and formats (Hristidis *et al.*, 2010). Therefore, such information should be tailored to the needs of the at-risk communities for effective use(Winthrop, Kajumba and McIvor, 2018). Some local NGOs are, however, helping tailor the information to local needs. Table 10 shows the primary data providers during preparedness and response.

> "We started translating weather information to four local languages in 2009 and then increased to ten and thirty-five in 2019 through funded projects. We are, however, continuing with the translation to the major ten languages" [DR06].

Table 10: The primary disaster data and information providers in Uganda. The reference shows the number of times the data provider was mentioned during the interviews.

Data providers	Reference
Uganda Red Cross Society	6
Uganda National Meteorological Authority	8
Uganda Bureau of Statistics (UBOS)	4
NECOC	4
Ministry of Water and Environment	4
Ministry of Agriculture	4
Global systems (ECMWF _GloFAS)	3

The data and information that is available are shared using various means. For example, emails were highlighted as the most common mode of sharing disaster data between institutions by 11 out of 14 respondents (Table 11). Other means of sharing data and information include physical delivery, online platform, and bulletins.

However, data sharing is not guaranteed, especially if the data is not freely accessible. The institution that requires the data must make a formal request before the information is shared. Other institutions require a memorandum of understanding between institutions to facilitate data sharing.

Table 11: Common data sharing methods in Uganda. Reference refers to the number of respondents who mentioned the data sharing method.

Data sharing modes	**Reference**
Emails	11
Physical means	7
online platforms	4
Bulletins	4
Media (Radio, TV)	2
Institution websites	1

2.3.4 Discussion

Communities at risk of disasters are among the critical actors in disaster risk reduction. Therefore, these communities need access to the required information and are sensitised on how to use it to inform their coping practices. Ensuring communities have the required information and can use it is the mandate of disaster management practitioners. However, these disaster management practitioners face challenges that may derail the provision of the necessary information for timely preparedness. Our findings from Uganda indicate that the disaster management institutions are aware of the activities to implement during preparedness and response to disasters. Still, sometimes they may not have the financial resources to do them (Shah *et al.,* 2019). Scarce or incomplete information is also a significant barrier to implementing the required activities at the community level (Šakić Trogrlić *et al.*, 2022).

The common data and information to inform disaster management activities is weather information which UNMA provides. However, the state of hydrometeorological networks in Uganda is limited (Dinku, 2019). The capacity of UNMA to install, collect and produce this information should therefore be strengthened through continuous capacity building (Mataya, Vincent and Dougill, 2020). Data collaborations between institutions should also be maintained to ensure accessibility (Susha, Janssen and Verhulst, 2017). This can promote the development of open access multi-sector platforms to ease data sharing and reduce data heterogeneity which might delay preparedness actions.

In chapter 2, the barriers and opportunities in the production, provision, and use of EWI across the provider-user landscapes have been assessed using two use cases developed at the community and national institutional levels.

Chapter 3 addresses forecasts verification in data-scarce regions. More specifically, building on Chapter 2 on the lack of a national flood forecasting system in Uganda, the chapter assesses how global flood forecast can be used with confidence to inform preparedness actions at the community level.

Chapter 3

3 Flood Forecast verification using traditional and non-traditional approaches.

This chapter was entirely conceptualised and written by the author. The author collected the data, undertook the analysis, and wrote the chapter. Section 3.3 which is published in the Journal of Flood Risk Management had contributions as follows. FM developed the concept, collected the data, undertook the analysis, and led the writing of the manuscript. AF & LS developed the r-script that was used for forecasting verification and provided inputs in writing the manuscript. ET, RC, and CP provided inputs in the writing of the manuscript.

3.1 Background

Forecast information plays a crucial role in supporting local decisions. These forecasts should be verified using local observations to provide the required evidence. Forecast verification has evolved beyond conventional observations to include other less conventional data sources such as social media (de Bruijn *et al.*, 2019), crowdsourcing, crop yield, and societal impact data, among others. Their use would ensure that there is greater confidence in the use of these forecasts for decision-making.

Conventional observations from river gauge locations are commonly used to verify flood forecasts from global systems. However, these observations are usually sparse and insufficient for verifying spatial patterns of flood occurrence, magnitude, and severity across lower administrative levels. Further, the observations hinder impact-based modelling since they do not provide meaningful information on how the floods will affect the lives and livelihoods of at-risk communities. Therefore, non-traditional verification approaches that take into consideration less conventional observations (observations that are often not used in verification) have been encouraged to enable more direct verification of the physical event (Marsigli *et al.*, 2021). Efforts to use non-traditional approaches in forecast verification are already seen through the WMO joint working Group on forecast Verification research(WMO, 2021c).

In this chapter, we present findings from flood forecast verification using non-traditional approaches and impact data in Kenya and Uganda. In addition, the chapter addresses the need for reliable forecasts by investigating if impact data can be used to evaluate forecasts, provide the evidence required to inform local sector-specific decisions, and further build confidence in flood forecasts. Section 3.2 presents the hydrological characteristics of the catchments considered in the study including their spatial location, hydrographs, and the bar-graphs for the available data. Section 3.3 presents findings from forecasts verification comparative analysis using river-gauge observations from 6 locations in Kenya and Uganda and impact data from districts/counties affected by flooding from the gauge locations and forms our second paper. We further present a summary (section 3.4) on how varying the forecast verification features can influence the use of flood forecasts to inform sector-specific early actions in data-scarce regions.

The work presented in section 3.3 won the WMO award for the best new verification metric using non-traditional approaches (WMO, 2021a). In addition, a blog post emanating from this work has also been produced and shared with a wide audience (see Mitheu, Tarnavsky and Ficchì, 2021).

3.2 Hydrological Characteristics of the Study Catchments

Flooding characteristics are governed by various factors such as the amount of precipitation, topography, geology, catchment area, and land use activities. These factors define the amount of water that is measured at the river-gauging stations. Understanding these context- specific factors for each catchment is therefore important to ensure a prior understanding of the type of flooding. This chapter covers 6 catchments, three each in Kenya and Uganda. River flow data from these catchments is used in the comparative analysis and forecast verification. The catchments were selected due to the frequency of flood events and the resulting impacts. The catchments have varying characteristics (Table 12) which defines the magnitude of the measured quantities of streamflow at the outlet. Uganda mainly experiences a bimodal rainfall pattern in most areas expect the north where only one rain season is experienced. These seasons occur during the March to May period and the September to December. Similarly, Kenya has two rain seasons during the months of March to May and October to December.

Both riverine and flash floods are experienced in all the catchments. For example, in Manafwa, the topography of the catchment influences flood occurrence where surface water from the upstream areas results to abrupt flooding in the lower regions of Butaleja and Manafwa (Cecinati, 2013). Table 12 shows the various characteristics of the study catchments while Figure 12 and Figure 13 shows the spatial location of the catchments in Kenya and Uganda respectively.

Table 12: Characteristics of the catchments considered. Annual discharge value was computed by the author based on the data available. Sources of other information (Onyutha *et al.*, 2021; Erima *et al.*, 2022; Tumusiime *et al.*, 2022; Wanzala *et al.*, 2022)

River name	Outlet name	Lon	Lat	Drainage area (km2)	Mean elevation (m.a.s.l)	Mean annual rainfall (mm)	Annual discharge (m3/s)	Physical characteristics	Length of records considered
Tana	Garissa	39.7	-0.45	32,695	870	868	182.24	Forests on highlands, semi-arid plains on lowlands	1999-2018
Nzoia	Ruambwa	34.09	0.12	12,643	1740	1488	160.68	Continuous vegetation on highlands, flat lowlands	1999-2018
Athi	Kibwezi	38.05	-2.25	5860	1300	810	144.22	Forests on highlands, semi-arid lowlands	1999-2018
Akokorio	Akokorio	33.85	1.75	13,356	914	1466	4.32	Semi-arid and flat lowlands	1999-2018
Manafwa	Butaleja	33.95	0.95	2280	1083	1500	6.93	Mountains, steep slopes towards the outlet	1999-2018
Mayanja	Mayanja	32.15	0.65	2473	1200	1181	9.42	Swampy and slow-moving rivers in a gentle terrain	1999-2018

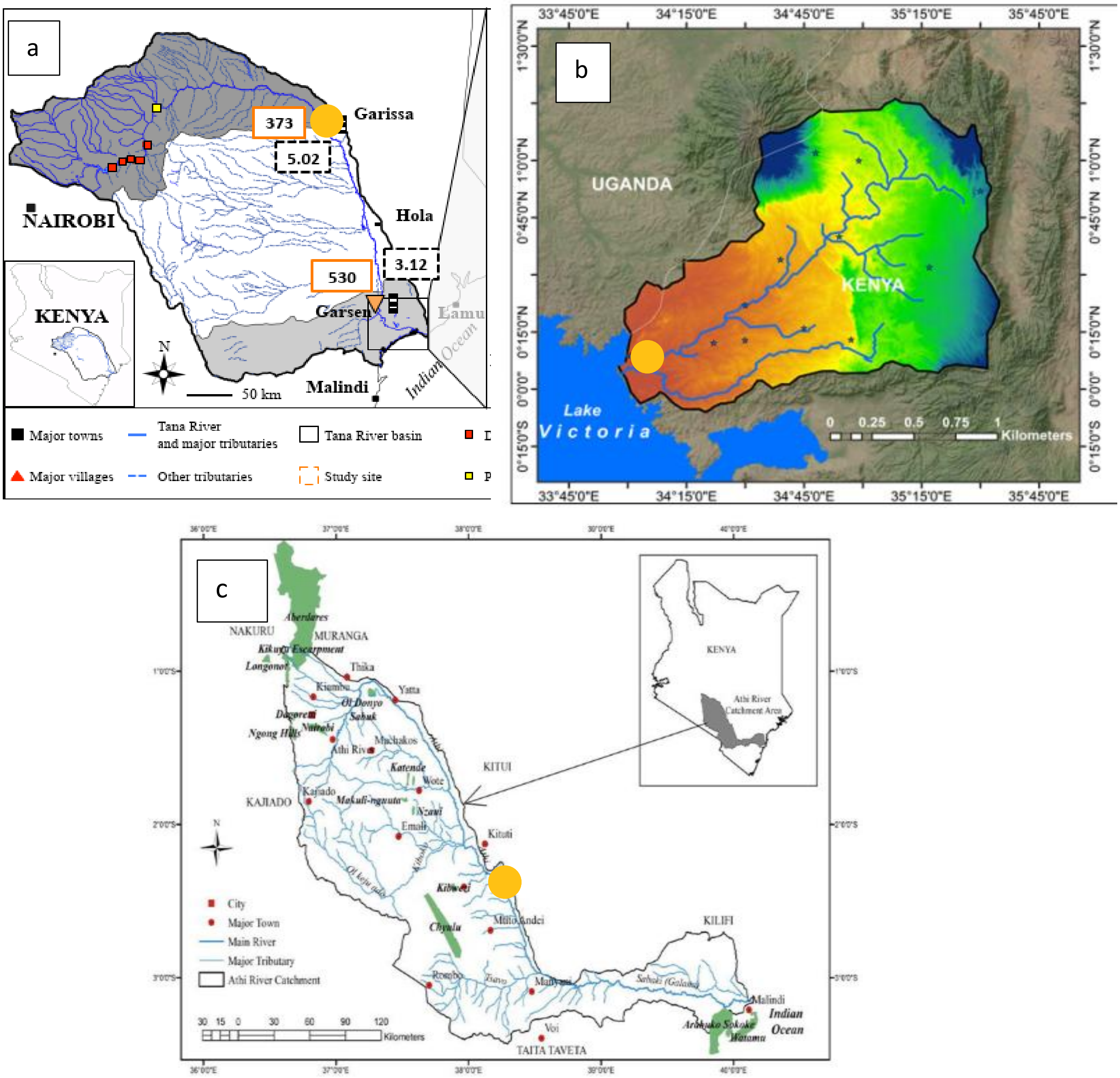

Figure 12: Study catchments in Kenya; a) Tana, b) Nzoia and c) Athi. Source (Adhikari and Hong, 2013; Leauthaud *et al.*, 2013; Kithiia, 2022). Daily river discharge data from the gauging stations (marked in yellow circle) were used in this study.

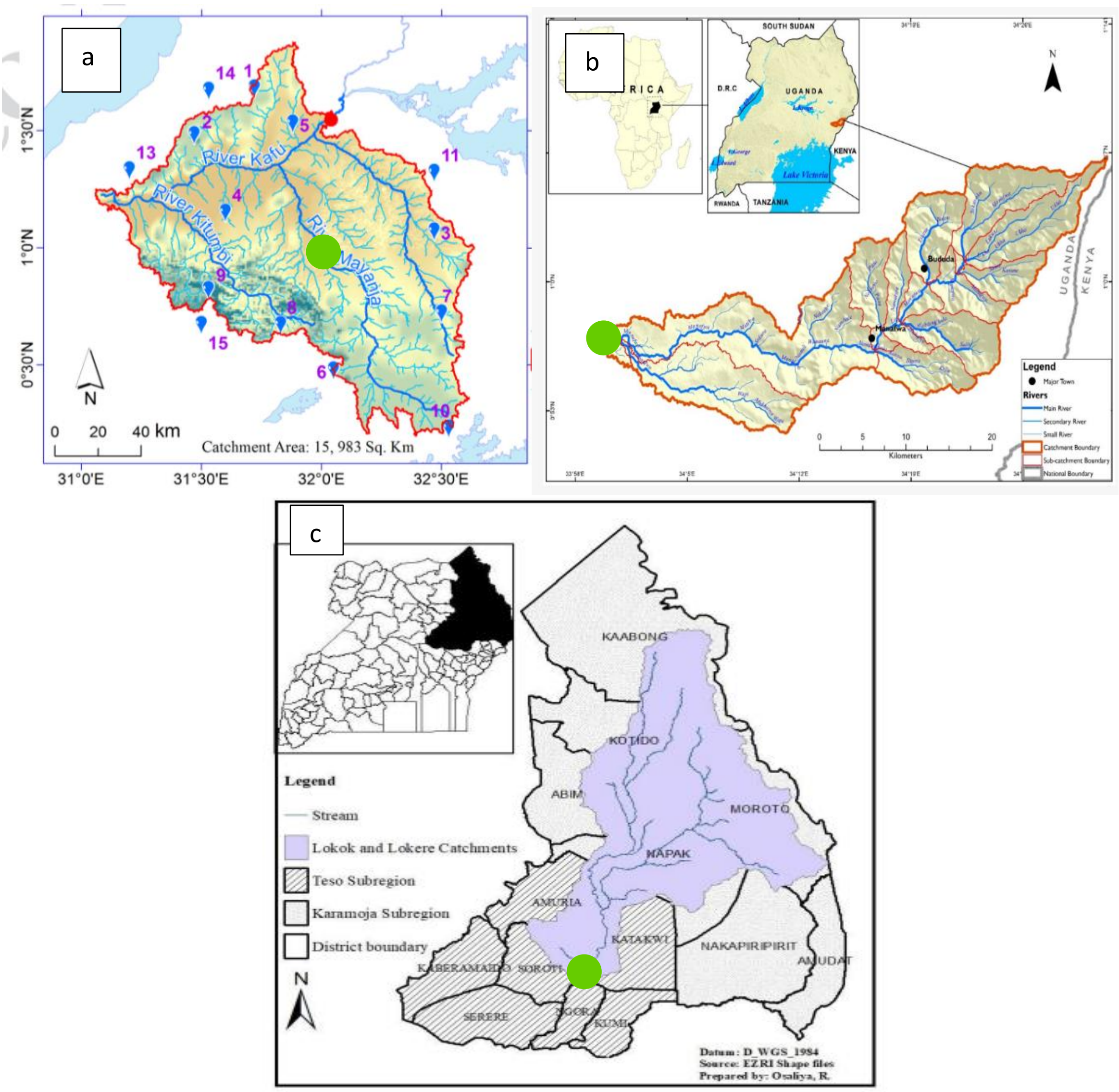

Figure 13: Study catchments in Uganda; a) Mayanja, b) Manafwa and c) Akokorio. Source (Onyutha *et al.*, 2021; Osaliya, 2021; Erima *et al.*, 2022). Daily river discharge data from the gauging stations (marked in green circle) was used in this study.

In forecast verification, the amount of available reference data such as the river-gauge data can influence the resulting output. In this chapter, we used both river-gauge data and impact data as references to the verification of forecast. The daily data for the gauging stations was provided by Water Resource Authority for Kenya and Department of Water Resources Management for Uganda. The data was transformed into hydrographs to understand the availability of the data for the subsequent analysis. Corresponding bar-graphs showing the percent of available data each year were developed. Figure 14 to 19 shows the hydrographs of river discharge data for each of the gauging station considered and the corresponding percent data available for each year. The graphs shows that many of the years when records were obtained have missing data. for example, in the Tana River catchment, river-gauge data for 2017 and 2018 were not available. For the analysis in this chapter, continuous data series from 2007 to 2018 was used. The entire row with no data was therefore deleted across all the data columns used (i.e., impact data, forecast data and observed gauge data) for uniformity in the analysis. This means that for locations with a higher percent of missing data, only few records of available data were used in the analysis which may affect the resulting output.

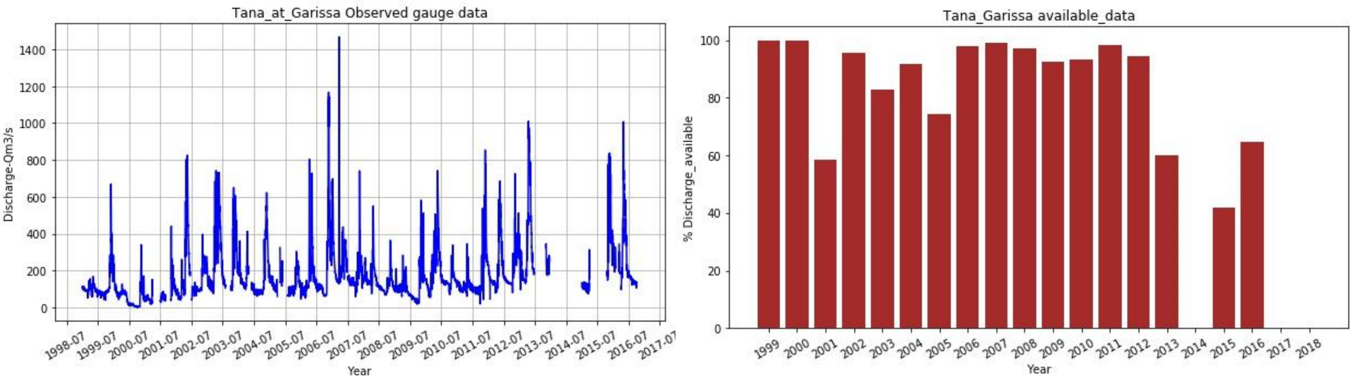

Figure 14: Hydrograph for the daily discharge data at Tana River at Garissa station and the percent available.

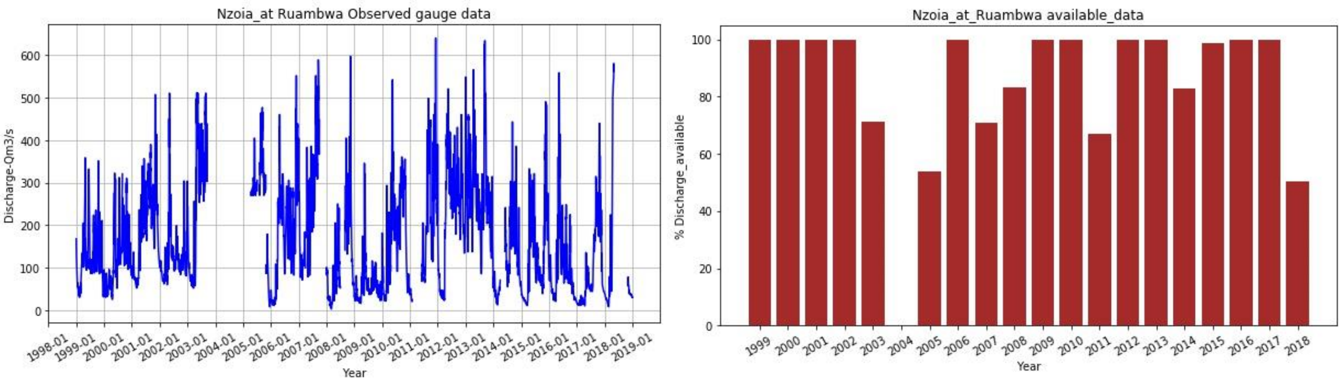

Figure 15: Hydrograph for the daily discharge data at Nzoia River at Ruambwa station and the percent available.

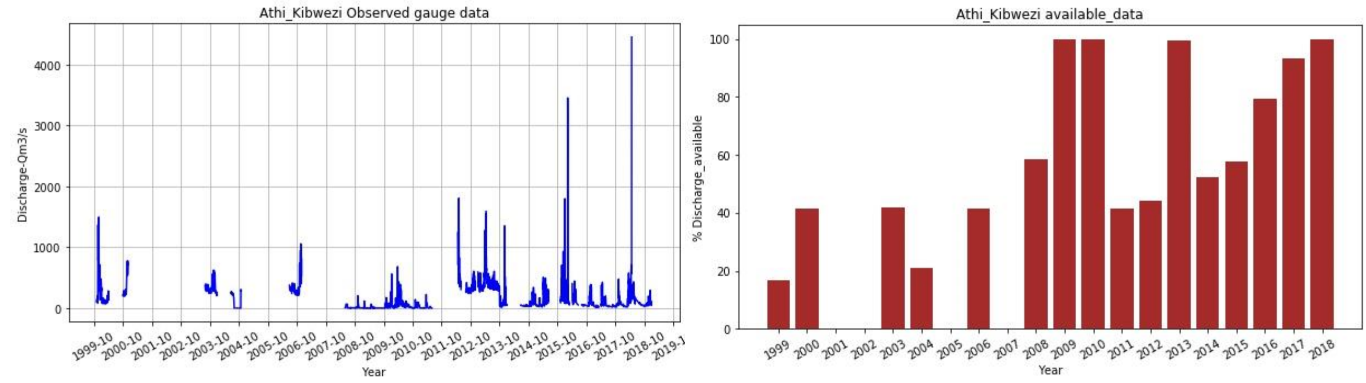

Figure 16: Hydrograph for the daily discharge data at Athi River at Kibwezi station and the percent available.

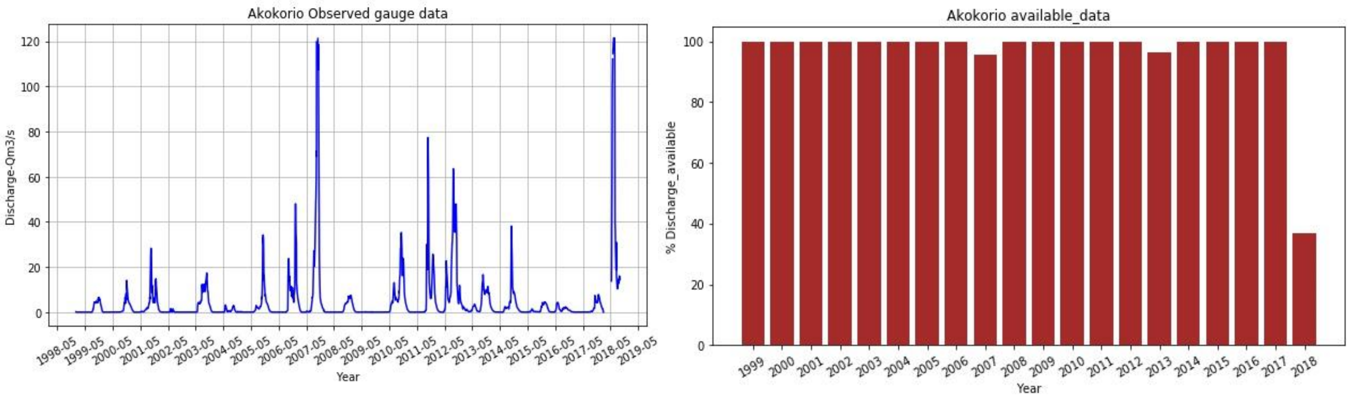

Figure 17: Hydrograph for the daily discharge data at Akokorio River at Akokorio station and the percent available.

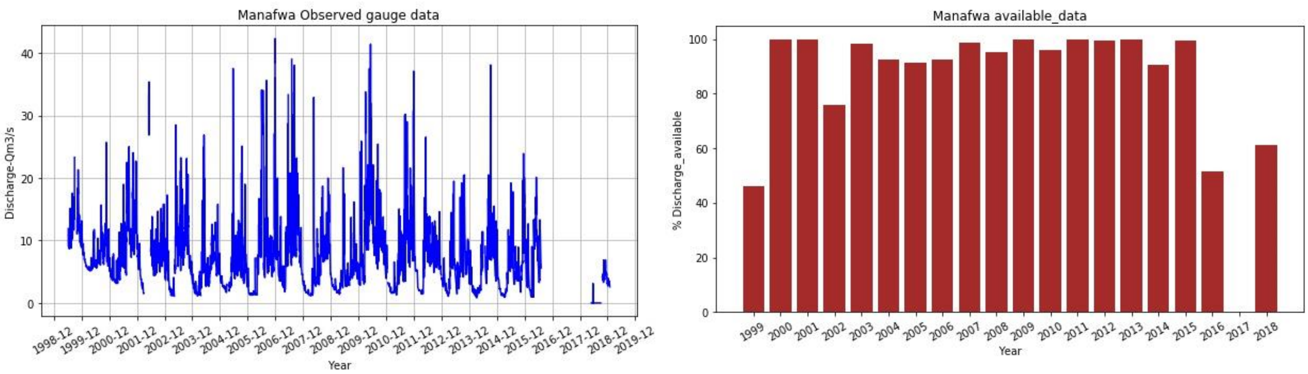

Figure 18: Hydrograph for the daily discharge data at Manafwa River at Butaleja station and the percent available.

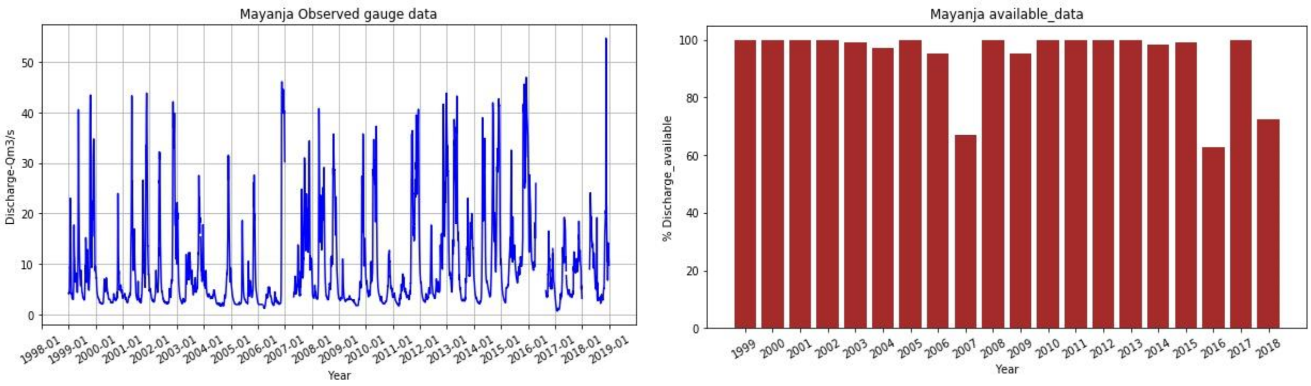

Figure 19: Hydrograph for the daily discharge data at Mayanja River at Mayanja station and the percent available.

3.3 The utility of impact data in flood forecast verification for anticipatory actions: Case studies from Uganda and Kenya.

This section has been published in the Journal of Flood Risk Management- Wiley with the following reference:

Mitheu F, Tarnavsky E, Ficchi A, Stephens E, Cornforth R, and Petty C: The utility of impact data in flood forecast verification for anticipatory actions; Case studies from Uganda and Kenya. Journal of Flood Risk Management, e12911. https://doi.org/10.1111/ jfr3.

The published article can be found in the thesis under Appendix A3.0.

Abstract: Skilful flood forecasts have the potential to inform anticipatory actions across scales, from smallholder farmers through to humanitarian actors, but require verification first to ensure such early warning information is robust. However, verification efforts in data-scarce regions are limited to only a few sparse locations at pre-existing river gauges. Hence, alternative data sources are urgently needed to enhance flood forecast verification and guide preparedness actions. In this study, we assess the usefulness of less conventional data, such as flood impact data, for verifying flood forecasts compared to river gauge observations in Uganda and Kenya. The flood impact data contains semi-quantitative and qualitative information on the location

and number of reported flood events derived from five different data repositories (EM-DAT, DesInventar, Dartmouth Flood Observatory, GHB, local) over the 2007-2018 period. In addition, river gauge observations from stations located within the affected districts and counties are used as a reference for verification of flood forecasts from the Global Flood Awareness System (GloFAS). Our results reveal both the potential and the challenges of using impact data to improve flood forecast verification in data-scarce regions. From these, we provide strategic recommendations for using impact data to support anticipatory action planning.

3.3.1 Introduction

Climate change, variability, and environmental changes are affecting Africa's agricultural and humanitarian sectors. In the agricultural sector, these changes could force smallholder farmers who depend on rain-fed crops or flood recession agriculture to significantly adjust their farm activities (Salack *et al.*, 2015; Ochieng, Kirimi and Mathenge, 2016; Ficchì and Stephens, 2019). For example, in Uganda, farmers need reliable and skilful information on the rainy season onset and amount of rainfall, as well as flood occurrence, duration, magnitude, and severity approximately 1-2 months before the season onset to inform their coping strategies(Mitheu *et al.*, 2022). In addition, decision-makers and humanitarian actors aiming to reduce risks and protect livelihoods are also increasingly considering forecast information to inform the early action mechanisms and operational decisions (Coughlan De Perez *et al.*, 2016; Hansen *et al.*, 2019; Emerton *et al.*, 2020; Lopez *et al.*, 2020; Nidumolu *et al.*, 2020). Given this, the skill of any forecast information provided needs to be transparent and well understood to inform preparedness actions appropriately.

In the context of users' needs, forecasts should be evaluated with regard to their potential to trigger early actions, which can, in turn, reduce expected losses if an extreme event occurs (Lopez *et al.*, 2020) but also considering the consequences of 'acting in vain', which are particularly important in the context of disaster risk reduction and humanitarian actions (Coughlan De Perez *et al.*, 2015). Indeed, several studies have shown that verified and skilful forecasts have the potential to improve preparedness actions for both the agricultural and humanitarian sectors (MacLeod et al., 2021; Nidumolu et al., 2020; Nyadzi et al., 2019; Paparrizos et al., 2020; Coughlan de Perez et al. 2016). But this verification is carried out only for regions that have long-term historical hydrometeorological observations typically from in-situ stations such as river gauges. In forecast verification, these observations are commonly known as conventional observations (Marsigli *et al.*, 2021).

In data-scarce regions, where conventional observations are limited (Coughlan de Perez et al., 2016; Ogutu et al., 2017), less conventional verification data can be derived from, e.g., social media reports, citizen volunteered information, impact/damage reports, and insurance data. The resulting information can be used to bridge the forecast verification gap through non-traditional approaches as they provide a more direct representation of the event (Marsigli *et al.*, 2021). For example, information from insurance databases (Bernet, Prasuhn and Weingartner, 2017; Cortès *et al.*, 2018), as well as online tools such as Google Trends and Twitter feeds (de Bruijn *et al.*, 2019; Thompson *et al.*, 2021) have been used as reference information to evaluate the occurrence of floods. Impact data have also been used with river-gauge observations to identify the magnitude of discharge associated with flooding (Coughlan De Perez *et al.*, 2016). Notably, impact data offer an advantage in verifying forecast information because they can be derived from openly accessible data repositories containing quantitative and qualitative information across large spatial areas that enable a better and direct representation of the impacts of the extreme event. However, the use of impact data in forecast verification can be only possible in areas with exposure and vulnerability for the impact to be reported.

Global data repositories such as the Emergency Events Database (EM-DAT) (EM-DAT, 2020) and the United Nations' Disaster Inventory System (DesInventar) (UNISDR, 2018) are prone to biases due to known limitations (Gall, Borden and Cutter, 2009). These limitations include the under/over-reporting of the hazards, aggregated spatial coverage, over-representation of certain locations, and/or focus on the specific type(s) of impacts. Furthermore, differences in the criteria for inclusion of events in the repositories may result in non-uniformity in the estimates of the impacts reported in each repository. In addition, if unverified, impact data collection methods (e.g. from governments and media) may lead to errors in the resulting information (Guha-Sapir and Below, 2002). Despite these biases, the EM-DAT and DesInventar represent a potentially valuable source of less conventional data for monitoring and verification of hazards. For example, a study by Kruczkiewicz et al., (2021) shows that impact data can be integrated with other geophysical parameters to sub-categorize flash floods from the primary corresponding disaster type. Therefore, if their limitations are adequately understood, guidance provided on the interpretation of their outputs and recommendations provided, impact data can be improved and applied in supporting anticipatory actions.

In this study, we assess the usefulness of flood impact data to verify flood forecast information across Uganda and Kenya compared to river-gauge observations. We verify river flood forecasts from the Global Flood Awareness System (GloFAS) of the Copernicus Emergency Management Service (EMS) (Harrigan *et al.*, 2020) using two reference observations. The river-gauge observations and flood impact data were derived from several global and national data repositories.

The study addresses two research questions:

1. How adequate are the impact data for verifying flood forecasts compared to river gauge observations?
2. Where river-gauge observations are limited or unavailable, how best can the impact data be used to verify flood forecasts and ensure anticipatory actions are informed?

Through focussed case studies in two East African countries, we investigate the non-traditional approach of forecast verification using impact data relative to the traditional way of verification using river gauge observations. Consequently, we provide recommendations on how best impact data can be used in areas with no or limited river-gauge observations to increase confidence in using forecast products in data-scarce regions.

3.3.2 Context

In this section, we describe the case study regions and the datasets used for the analysis, i.e., the GloFAS re-forecast discharge data, river gauge observations, and the impact data from several data repositories, including EM-DAT and DesInventar.

3.3.2.1 Case Study Regions

The Netherlands-based IKEA Foundation is supporting the Uganda and Kenya Red Cross Societies (URCS and KRCS, respectively) to develop early warning mechanisms to prepare for floods through the Innovative Approaches for Response Preparedness (IARP) project. In Uganda, several high-risk areas were identified using vulnerability and risk layers developed by the National Emergency Operations and Coordination Centre (NECOC), including 15 districts, for the development of early action protocol (EAP). These regions are prone to flooding and waterlogging across the two rainy seasons between May and November (April-May, Long Rains; September-November, Short Rains). In Kenya, flood-prone river basins, including Tana, Nzoia, and Athi, are considered for the implementation of early flood actions.

Examples of early actions include community awareness, distribution of cash and shelter kits, dissemination of early warning information among others (see KRCS, 2021; URCS, 2021) for all the early actions considered in the Kenya and Uganda EAPs.

The case study regions in Uganda and Kenya were selected based on locations with available river gauge observations. In Uganda, the districts of Katakwi and Amuria on the Akokorio river (hereafter 'Katakwi'), Tororo (Butaleja) and Mbale (Bududa and Manafwa) on Manafwa River (hereafter 'Manafwa'), and Kiboga, Mubende, and Hoima on the Mayanja River (hereafter 'Mayanja') are considered. In Kenya, the county of Tana-river and Garissa on Tana River (hereafter 'Tana'), Busia and Siaya on Nzoia river (hereafter 'Nzoia'), and Taita-taveta and Kilifi on Athi river (hereafter 'Athi') have been considered. Figure 20 shows the locations of the gauge stations and the affected counties/districts in Kenya and Uganda, respectively.

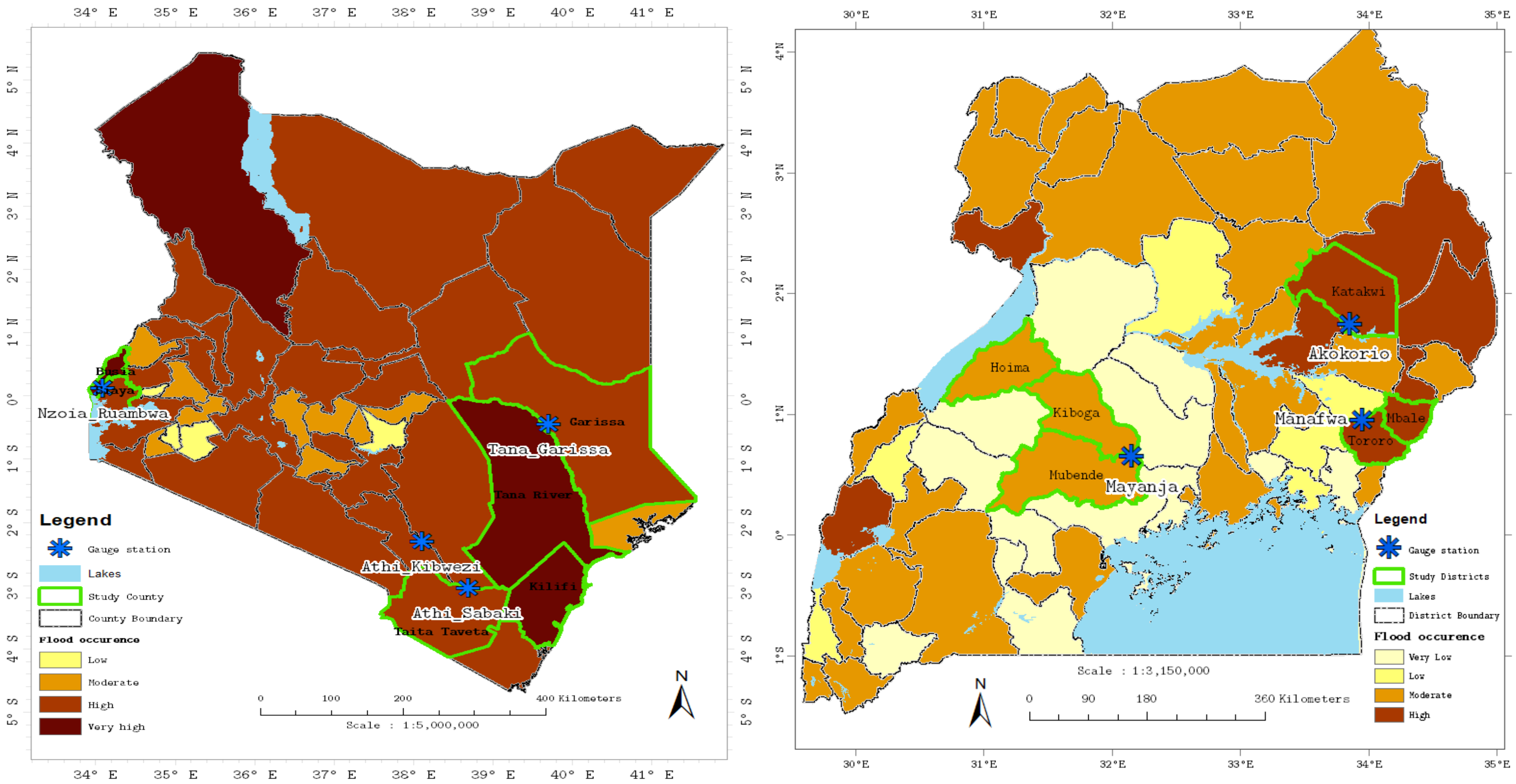

Figure 20: Flood occurrence maps for Kenya and Uganda show the study counties/districts and the river gauge locations. The map was created using impact data collated from four different data repositories from 2007 to 2018. The colour scheme represents the number of years out of the 12 years considered when floods occurred, ranging from low (1-3 years), moderate (4-6 years), high (7-9 years), and very high (10-12 years)

3.3.2.2 GloFAS Flood Forecasts

GloFAS is an operational global ensemble flood forecasting system developed jointly between the European Commission's Joint Research Centre (JRC), the European Centre for Medium-Range Weather Forecasts (ECMWF), and the University of Reading researchers (Alfieri *et al.*, 2013). The system provides probabilistic extended range discharge forecasts for up to 30-days and seasonal outlooks up to 4 months lead time (Emerton *et al.*, 2018) over the entire globe at a resolution of 0.1^{o}. From GloFAS v3.1 (current operational version), the LISFLOOD hydrological model (van der Knijff, Younis and de Roo, 2010) is forced by an ensemble of medium to extended range meteorological forecasts from the ECMWF Integrated Forecast System to produce 51 ensemble members of daily streamflow at various lead times up to 45 days; LISFLOOD has been calibrated using daily streamflow data at over 1200 river basins worldwide (Hirpa *et al.*, 2018).

GloFAS v3.1 hydrological performance was evaluated for the period 1979-2019 for over 1500 verification stations across the world using various verification metrics (Kling Gupta Efficiency, Bias, variance etc). Prudhomme and Zsoter (2021) provide details on the hydrological assessment methodology and further discussion on GloFAS performance evaluation. GloFAS provides daily discharge amounts [m3/s] from which probabilities of flood threshold exceedance can be derived. For flood detection, these forecasts time series are compared against a set of flood thresholds that are derived from the same model climatology (Zsoter *et al.*, 2020) to avoid the impact of systematic biases in the GloFAS climatology on flood forecast probabilities. In this study, we use daily GloFAS v3.1 reforecast discharge data from 2007 to 2018 extracted for the gauge locations in Kenya and Uganda, respectively (Figure 20).

3.3.2.3 Flood Thresholds

In the 30-day operational GloFAS forecast interface (https://www.globalfloods.eu/), four different flood return periods (2-, 5-, 10-, and 20-years) are provided and can be used as the thresholds for severe flood events. Zsoter et al. (2020) provide a detailed explanation of how these return periods are computed using GloFAS ensemble reforecasts. Furthermore, thresholds computed as percentiles of the daily river flow time series can also be used to define various hydrological conditions (e.g. high/low river flows) and have been used by several authors to evaluate forecasts from GloFAS or similar forecasting systems (see Alfieri *et al.*, 2013; Arnal *et al.*, 2018; Emerton *et al.*, 2018; MacLeod *et al.*, 2021). For example, high percentiles (90th percentile or greater) have been used to show a high likelihood of floods when the river flow at a gauging station is above that percentile (MacLeod *et al.*, 2021). In the broad hydrological literature, the notation for flow percentiles is not always consistent or clear, so when percentiles are used, the definition needs to be specified clearly.

In this study, we adopt the traditional definition of percentiles used in statistics where a *k-th percentile* (with *k* in the range of 1-100) for a time series is the level below which (or at which) a *k percentage* of values in its distribution falls (the inclusive definition of percentile is adopted). For example, a 90th percentile is equal to or greater than 90% of the river discharge recorded during the specified period. In flood related studies, a percentile flow can also be referred to in terms of 'percent exceedance' to indicate the percentage of time that the discharge value is likely to be equalled or exceeded (see *Derived Flow Statistics | National River Flow Archive*, no date; *Flow, Excedance and Percentiles*, no date). Thus, in this study we use the 90th, 95th and 99th percentile calculated from the re-forecast (all ensemble members) or observed time series of daily discharge, corresponding to high-flow levels exceeded only by a minor portion of the days in the data, i.e.,10%, 5% and 1% respectively.

Due to data availability, we followed a percentile-based method to compute flood thresholds for forecast verification similar to previous authors (e.g. Alfieri *et al.*, 2013; Arnal *et al.*, 2018; Emerton *et al.*, 2018; MacLeod *et al.*, 2021). The choice of using these thresholds and not higher Return Periods (e.g., 5- or 20-year return periods computed from annual maxima) is motivated by the need for robust statistics, given the short data periods available (2007-2018). For the forecasts, these thresholds are lead-time dependent (Zsoter *et al.*, 2020), i.e. calculated from the reforecast time series at each given lead time available.

3.3.2.4 River Gauge Observations

Observed point-based discharge time series for the river gauges considered here were provided by the Department of Water Resources Management (DWRM) in Uganda and by the Kenya Water Authority (WRA) for Kenya. The time series consists of daily river flow values over long periods, with all stations having at least five years of daily data over the study period. The observed gauge data corresponding to the period of the impact data (2007-2018) has been used for the subsequent analysis.

3.3.2.5 Flood impacts data

Flood impact data has been used to extend our capability to verify GloFAS flood forecasts beyond conventional observations from sparse river gauge networks. The flood impact data contains semi-quantitative and qualitative information on the location and number of reported flood events derived from five different data repositories: (1) EM-DAT (EM-DAT, 2020), (2) DesInventar (DI; UNISDR, 2018), (3) Dartmouth Flood Observatory (DFO) Archive (Brakenridge, 2015), (4) the Global Hazard Weekly Bulletin (GHWB; (PHE, no date), and (5) local sources (URCS, KRCS, media, etc.) for the 2007-2018 period. These data were collated for Kenya and Uganda for the study regions(counties/districts) for further analysis. The characteristics of these repositories are summarised in Table 13.

In an ideal situation, an impact would be defined as a combination of the number of people affected and the quantitative estimate of any loss of property and livelihoods. However, the used repositories do not have enough quantitative loss and damage information disaggregated to sub-national administrative units to enable the quantification of impacts. We, therefore, consider the number of flood events reported as a proxy to the impact with an assumption that flood events that result in considerable impacts would be reflected in the data repositories used. The flood events are then classified as either 1 or 0 if the event was reported or not, respectively. The assessment of the number of flood events from the various sources, as well as the overlap (events that are common across the repositories used here), would help understand which data repository is used to identify the highest number of flood events for each study location.

Table 13: Characteristics of the data repositories that were used to derive impact data used for the study.

Database name (Reference)	Temporal Coverage	Criteria for inclusion	Actors/collection methods	Accessibility	Spatial coverage	Parameters
DesInventar (DI) (UNISDR, 2018)	1994-present	• One or more human loss and/or Loss of 1 or more US dollars	National governments and sectoral ministries	Publicly available at www.desinventar.net	Zoning level entry (country, districts, etc.)	Reports as a flood. Reports various categories of loss and damage (see Appendix A3.1). Includes qualitative information
Dartmouth Flood Observatory (DFO) (Brakenridge, 2015)	1993- present	• Large and extreme flood events.	News reports, Governments, Flood lists, remote sensing sources	Available upon request at https://floodobservatory.colorado.edu/	Country-level but provides the centroids for locations affected	Reports the main cause of impacts and categories of loss (see Appendix A3.1)
EM-DAT (EM-DAT, 2020)	1995- present	• Ten (10) or more people killed. • Hundred (100) or more people affected. • Declaration of a state of emergency	UN agencies, National Governments, International Federation of Red Cross and Red Crescent Societies (IFRC) and NGOs	Publicly available at https://public.emdat.be/	National and sub-national level	Subtypes of floods and origin, several categories of loss and damage (Appendix A3.1)
Global hazards weekly bulletin (GHWB) (PHE, no date)	2013- present	• Selected news on floods	Media reports (Flood list)	Publicly available via email bulletins to subscribers and archived independently at http://www.met.reading.ac.uk/~sgs02rpa/extreme.html	Provides information specific to the location affected	Reports the location and categories depending on impacts (deaths or displaced)
Local sources (URCS, KRCS)	2000-2018	Depending on the main source	Disaster Relief Emergency Fund (DREF) reports, relief web, flood list, districts offices	Request sent to National societies to support this research	Disaster prone areas	All the above

3.3.3 Methodology

Here, we outline the comparative analysis of river gauge observations and impact data and the verification of GloFAS flood forecasts using these two reference datasets using a set of skill scores. To assess the usefulness of flood impact data in verifying flood forecasts, firstly, the adequacy of the impact data in supplementing the river gauge is evaluated using Type I and Type II error indices. Secondly, the flood forecast data is verified using river discharge and impact data as a reference, and the verification outcomes are compared.

3.3.3.1 Comparison of River Gauge Observations and Impact data

In this part of the analysis, we compare the river gauge observations and impact data. River-discharge value (Q) that has the potential to cause flooding is defined by using the 90th and 95th percentile as the threshold, i.e., a flood event (binary) occurs when Q is above the threshold, and it does not occur if Q is below the threshold. The total flood events from impact data consider the overlaps using the timestamp to avoid duplication in the total events. This means that an event occurring across all the data repositories for the same timestamp is considered one event. The total flood events from impact data (binary) are then compared with river gauge observations (binary). Here, we assess the consistency of impact data false positive and false negative outcomes using a window of 7 days (from the day of the observed event up to 7 days ahead) against the flood events picked from the river gauge observations. Using a 2 x 2 contingency table, the false-positive outcome (hereafter 'Type I error') is when the gauge observation signals flooding, but no impacts are captured within the specified window. While false negative outcome (hereafter 'Type II error') is when the gauge observations did not report any flooding, but impacts are reported. We first compare the river gauge data (binary) with the impact data (binary) from the various sources across the locations. Next, we compare the river gauge observations against impact data from a single data repository to assess if some repositories are better than others in detecting flood events. Type I and II errors are calculated according to the equations in Table 14.

Table 14: Type I and Type II error equations for the comparative analysis

Index name	Equation	Score range	Perfect score
Type I error (TI)	$\frac{Number\ of\ observed\ flood\ events\ with\ no\ impacts\ reported}{Total\ number\ of\ observed\ flood\ events}$	0 to 1	0
Type II error (TII)	$\frac{Number\ of\ impacts\ events\ with\ no\ observations}{Total\ number\ of\ impact\ events}$	0 to 1	0

3.3.3.2 Flood Forecast Verification using River Gauge Observations and Impact data

A set of skill scores were used to evaluate the occurrence of forecasted floods from the GloFAS system against river gauge observations and flood impact data. The ability of the forecast to discriminate between events and non-events is commonly measured using skill metrics calculated from a 2 x 2 contingency table. Two skill scores were used to quantify the occurrence of flood events (Wilks, 2006): (1) the Probability Of Detection (POD), or hit rate, which measures the fraction of observed events that were correctly predicted (perfect score of 1); and (2) the False Alarm Ratio (FAR), which indicates the fraction of the predicted events that did not occur (perfect score of 0). Table 15 shows the equations used to calculate the skill scores.

Table 15: Skill scores used for forecast verification.

Skill Score	Equation	Values range	Perfect score
Probability Of Detection (POD)	$POD = \frac{H}{H + M}$	0 to 1	1
False Alarm Ratio (FAR)	$FAR = \frac{FA}{H + FA}$	0 to 1	0

Notes: H = Hits, M = Misses, FA = False Alarms

In this study, the verification of flood forecast events is based on the need to provide reliable flood forecast information to inform anticipatory actions taken by the communities and humanitarian actors. The preferred verification outcome will depend on the decision-making strategies the actors are willing to take. For example, humanitarian actors might need to decide if actions should be taken based on any forecast probability, which might be costly due to the number of events but would ensure reduced losses if the events materialise. The alternative would be if actions should be taken based on a forecast that shows a high likelihood of event occurrence to minimise the expenses incurred if the actions are in vain (see Lopez *et al.*, 2020).

Various factors identified from the EAPs developed by URCS and KRCS have been adopted in this study. Firstly, a flood forecast with a 60% chance of happening triggers early actions. Hence, we consider forecasts that indicate a forecast probability of 60% and above to correspond to a flood forecast event and below 60% to a 'no-flood' event. Secondly, in the calculations of events correctly forecasted, an action lifetime of 7 days is considered. 'Action lifetime' is defined as the length of time during which action will remain effective in reducing impacts(Coughlan De Perez et al., 2016). In forecast verification, the action lifetime is commonly known as the 'margin of error', and it's used to give more tolerance to the forecasts such that even if the forecast is late but materialises within the duration of the action lifetime, the actions will still be considered successful. For example, if an action is taken and a flood occurs up to 7 days after the forecasted date, this will still be considered a 'hit' if the action lifetime is greater than 7-days (see Figure 21 for a visual description of the action lifetime and margin of error). Depending on the type of action, the action lifetime can range from 7 to 90 days. This can also vary depending on the specific country's flexibility on the actions to take and the acceptable number of times the stakeholders are willing to 'act in vain'. For Uganda and Kenya, the stakeholders set the probability of 'action in vain' to 50%, indicated using the FAR. From Figure 21, the margin of error can vary between 1-day to 10 days depending on the type of action.

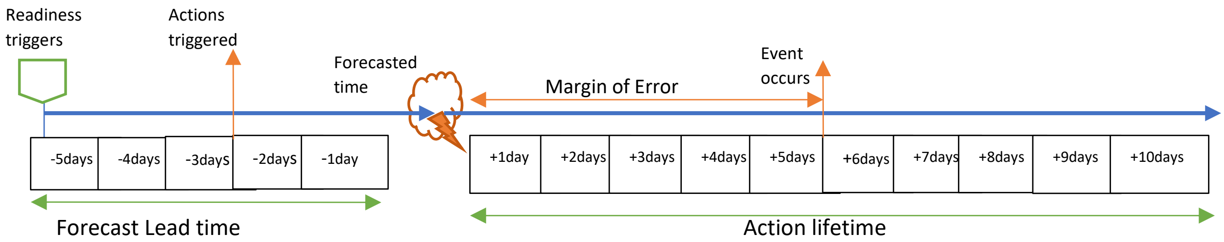

Figure 21: Visual representation of the action lifetime and margin of error based on early warning and action triggers.

Using distinct flood thresholds (i.e., 90th and 95th percentile) calculated from the GloFAS reforecast data and river-gauge observations, we verify flood forecasts using river-gauge observations and impacts data as a reference. This was done to assess the usefulness of impact data in verifying forecast information, especially in regions that may lack conventional observations, such as river-gauge data. This study was, therefore, not meant to evaluate the hydrological performance of GloFAS (calibration and validation of GloFAS time series). Using a seven days-action lifetime and a 60% probability of flooding, we compute the differences in the skill scores (POD and FAR) for forecast-gauged and forecast-impact data pairs, respectively. Here, if the difference between the 'POD observed' and 'POD impact' is negative and the FAR difference is positive, impact data are more favourable in skill assessment than river gauge observations and vice versa. This analysis assumes that if either the river gauge observations or impact data (or both) report a flood event for the same days as in the GloFAS flood forecast (within the action lifetime of 7 days from the warning), the reference data (observed or impact) are favourable in skill assessments.

3.3.4 Results

3.3.4.1 Impact data from the data repositories

In Uganda, in two districts (Katakwi and Manafwa), the reported impacts from the data repositories show a high number of flood events reported in 2007, 2010, 2011, 2012, and 2018 from DI and DFO as compared to the other years. However, the flood events for Mayanja from all the data repositories across the years are low. Table 16 shows the events spread across Uganda and the 3 locations from 2007 to 2018. The number of flood events from each repository is independent (does not consider any overlap across the repositories).

The analysis of the number of flood events from multiple and single data repositories shows that in Katakwi, there are 434 flood events where DI recorded the highest number of events at 36%, followed by DFO at 19% (Table 17). Data collected across Katakwi by URCS also contribute substantially (14%) to the flood events in the area. The overlap from multiple data repositories (EM-DAT, DI, and DFO) contributes to 11% of the total flood events. In Manafwa, from a total of 304 events, the highest number of events are from single source DI and overlap between EM-DAT and DFO, at 33% and 28%, respectively. EM-DAT alone contributes 14% of the total events. In Mayanja, only 2 data repositories contribute to the flood events. These are the DI at 23% and EM-DAT at 77%, totalling 102 events.

In Kenya, many flood events were reported in 2007, 2010, 2011, 2013, 2015, and 2018 across the country and the 3 study locations (see Table 16). EMDAT also records the highest number of flood events across the 3 locations, which contrasts with findings in Uganda, while DI reported the lowest. For example, in Nzoia, EM-DAT represents 69% of the total flood events, local sources contribute 12%, while DI covers 6%. The overlaps between the various sources contribute marginally across the locations. For example, EM-DAT and DI contribute less than 1% in Tana, 3% in Nzoia, and 1% in Athi (Table 17).

Table 16: Number of flood events from 2007 to 2018 for Uganda and Kenya locations derived from various data repositories.

Year	Kenya EMDAT	Tana EMDAT	Nzoia EMDAT	Athi EMDAT	Kenya DI	Tana DI	Nzoia DI	Athi DI	Kenya Local	Tana Local	Nzoia Local	Athi Local
2007	110	0	82	32	0	0	0	0	3	0	1	1
2008	57	8	16	20	6	2	15	2	15	3	4	2
2009	15	15	0	15	11	1	2	0	13	1	3	3
2010	97	87	17	87	35	3	1	4	53	8	7	3
2011	50	25	24	0	5	0	1	2	12	1	4	2
2012	27	27	27	27	13	2	3	1	39	5	3	4
2013	60	0	52	1	30	4	9	1	39	4	7	3
2014	0	0	0	0	0	0	0	0	20	1	3	0
2015	45	20	20	0	26	4	5	4	72	6	9	10
2016	11	6	6	0	2	0	0	0	29	2	3	6
2017	9	9	9	9	0	0	0	0	26	4	1	4
2018	79	79	0	0	0	0	0	0	144	61	17	28
Year	Uganda EMDAT	Katakwi EMDAT	Manafwa EMDAT	Mayanja EMDAT	Uganda DI	Katakwi DI	Manafwa DI	Mayanja DI	Uganda DFO	Katakwi DFO	Manafwa DFO	Mayanja DFO
2007	82	78	78	77	91	62	41	0	82	78	78	0
2008	1	1	0	1	12	1	1	0	0	0	0	0
2009	0	0	0	0	16	0	3	2	0	5	5	0
2010	5	5	5	0	109	48	40	2	11	5	5	0
2011	21	0	20	0	83	45	47	2	41	30	29	0
2012	1	0	1	0	49	37	3	1	29	2	0	0
2013	5	0	0	0	50	28	4	8	2	0	0	0
2014	0	0	0	0	33	1	2	1	5	0	0	0
2015	0	0	0	0	25	0	1	1	0	0	0	0
2016	7	0	0	0	16	0	2	3	7	0	0	0
2017	8	0	0	0	32	1	11	1	8	3	3	0
2018	1	0	1	0	32	28	10	2	17	8	8	0

Table 17: Percent of the total number of flood events from multiple (overlaps) and single source data repositories for the study locations in Uganda and Kenya. The first two sources that represent the highest percentage over each district/county are highlighted in bold.

Uganda	**Katakwi**	**Manafwa**	**Mayanja**
Number of events	434	304	102
Sources	Percent from the total events in each location		
Single source contribution			
DI	**36.41**	**32.57**	**22.55**
EM-DAT	1.38	13.82	**77.45**
DFO	**18.89**	12.5	0
Local sources (URCS)	13.59	0	0
GWHB	0.00	2.30	0
Multiple (with overlaps)			
EM-DAT, DI, DFO	11.06	4.28	0
EM-DAT, DFO	6.91	**28.29**	0
DI, DFO	8.29	5.59	0
URCS, DI	3.46	0.00	0
EM-DAT, GWHB	0.00	0.66	0

Kenya	**Nzoia**	**Tana**	**Athi**
Number of events	316	359	251
Sources			
Single source contribution			
EM-DAT	**69.94**	**70.75**	**72.11**
DI	6.33	3.34	3.19
Local sources	**12.03**	**19.22**	**19.92**
Multiple (with overlaps)			
EM-DAT, DI	3.48	0.56	1.20
EM-DAT, Local	6.01	5.85	3.19
EM-DAT, DI, local	2.22	0.28	0.40

3.3.4.2 How adequate are the impacts data in supplementing river-gauge observations in identifying flood events?

The comparative analysis in the three locations in Uganda using combined impact data from the various data repositories and observed gauge data shows varied results across locations and gauged data thresholds. For example, in Katakwi (Figure 22a), using the 90th percentile from the gauged observations, the impact data captures 60% of all gauged flood events, but 42% of the reported flood events from the impact data do not correspond to flows above the 90th percentile threshold.

This could mean either the threshold is too high, with lower flows still causing impacts, or the impacts reported resulted from another form of flooding like flash floods or waterlogging from heavy rainfall. In Manafwa and Mayanja (Figure 22b and Figure 22c), Type I and Type II errors across the thresholds are high (above 0.5), which could mean that the quality and quantity of available impacts data for these locations were not adequate (Type I) and the impacts reported were not as a result of riverine flooding (Type II).

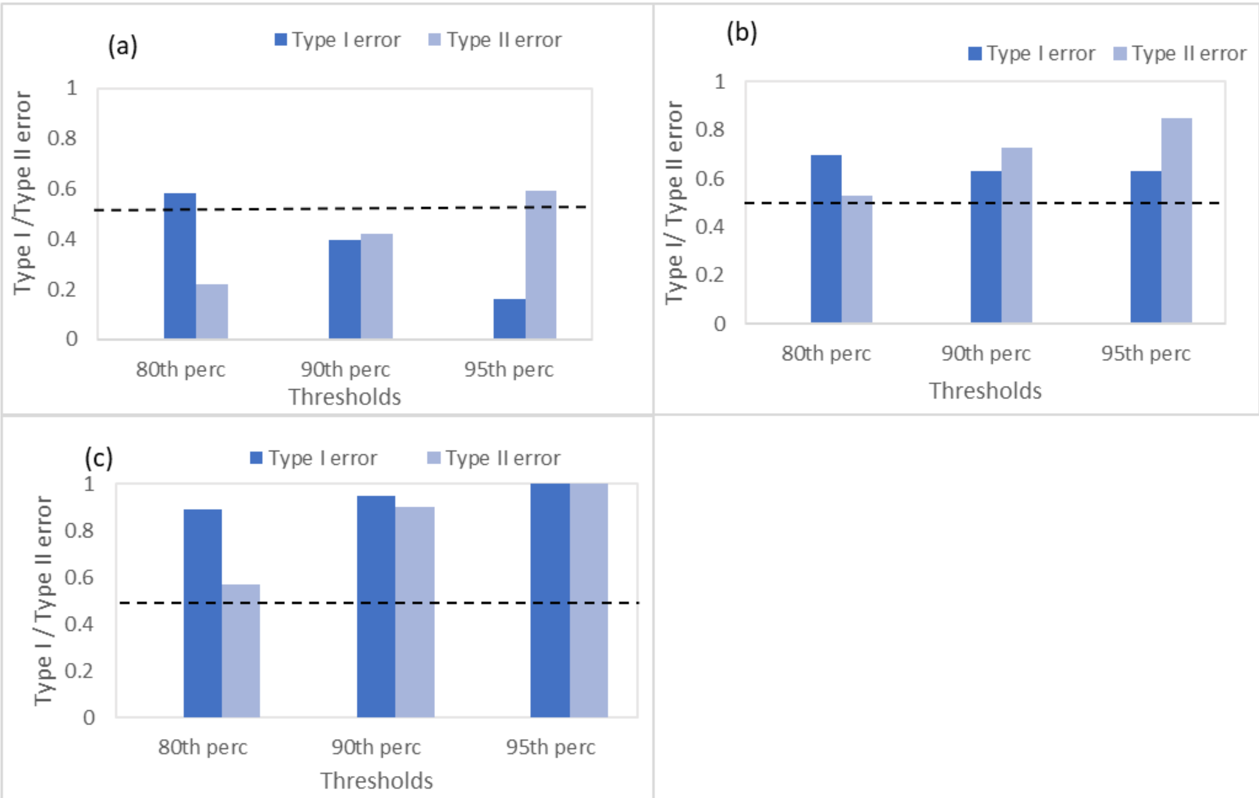

Figure 22: Comparative analysis of the impacts (all sources) and observed data at three percentile thresholds (80^{th}, $90^{th,}$ and 95^{th}) of daily river flows from the gauged stations in Uganda for a) Katakwi, b) Manafwa, and c) Mayanja.

The comparative analysis shows a high Type I error across the 90th and 95th percentile in the Kenyan locations. This means that though the observations indicate flood events, no impact data corresponded to these events, or the quality of the available impacts data was not good enough. On the other hand, the Type II error is also high across the locations, suggesting that impacts reported resulted from different forms of flooding, such as flash floods. For example, in Tana, at the 90^{th} percentile, impact data captures only 40% of all gauged flood events, but half of the reported flood events do not correspond to flows above the 90^{th} percentile. Figure 23a-c shows the comparative analysis across the thresholds for Tana, Nzoia, and Athi, respectively.

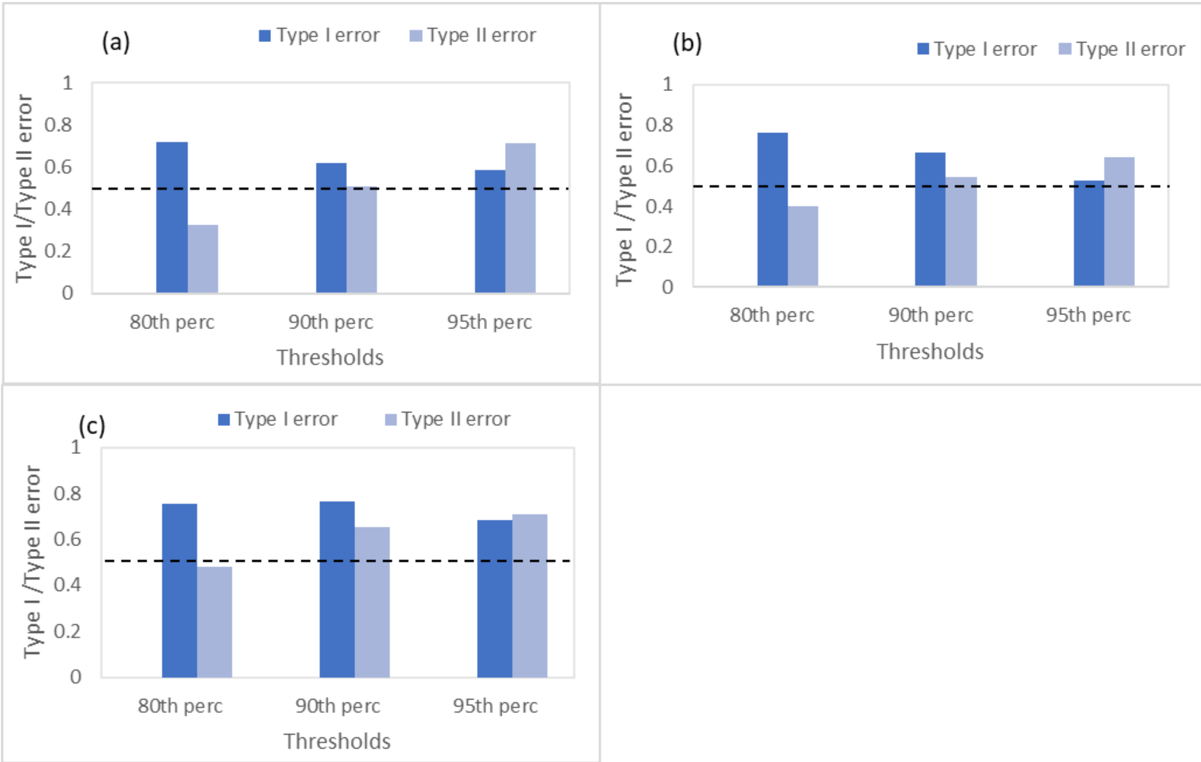

Figure 23: Comparative analysis of the impacts and observed data at three percentile thresholds (80^{th}, $90^{th,}$ and 95^{th}) of daily river flows from the gauged station in Kenya for a) Tana, b) Nzoia, and c) Athi.

The analysis using a single data repository shows an increase in Type I error in all the locations in Kenya and Uganda (Figure 24a-b). For example, in Katakwi, using DI alone results in a Type I error (TI) of 0.59 compared to a TI of 0.39 while using four data repositories (DI, EM-DAT, local, DFO). In Tana, EM-DAT results in a TI of 0.79 compared to 0.61 while using data from all the repositories. Type II error fluctuates across the locations (Figure 24c-d). For example, at the 90^{th} percentile, despite Nzoia having almost the same number of flood events from EM-DAT and local sources, Type II error is higher when using local sources than EM-DAT (Figure 24d). This shows that at the same (higher) threshold for example at the (90^{th} percentile) more events are likely to be missed out (events falling below the threshold) from the local source which takes into consideration more localised events compared to high-impact data repository like EM-DAT In other words, a data repository that considers a low threshold for inclusion of the event in their database may require a low threshold based on gauge observation to correctly identify the flood events as compared to a data repository that considers high threshold for inclusion.

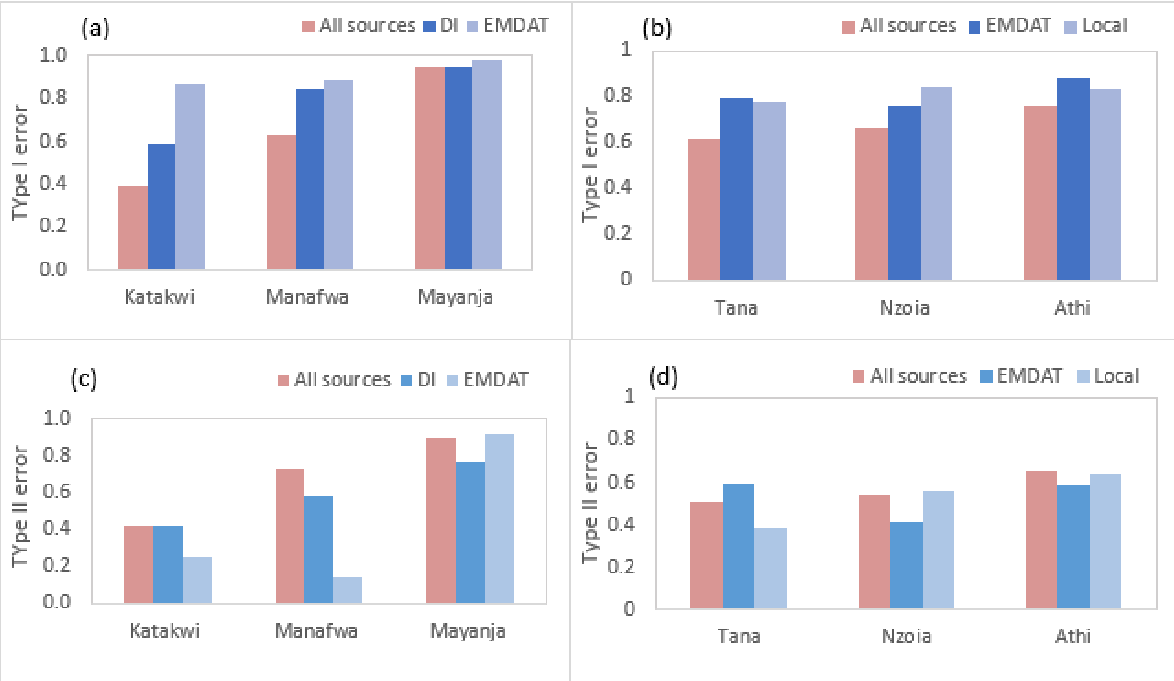

Figure 24: Type I and Type II error at 90th percentile resulting from using all impact sources (including overlaps) and single-source contributions for a) Type I in Uganda locations, b) Type I in Kenya locations, c) Type II Uganda locations, and d) Type II Kenya locations.

3.3.4.3 *Where river-gauge observations are limited or unavailable, how best can the impact data be used to verify flood forecasts and ensure anticipatory actions are informed?*

We plotted the difference between the forecast skill scores (POD and FAR) obtained using the river-gauge observations and impact data (i.e., $POD_{observed} - POD_{impact}$ and $FAR_{observed} - FAR_{impact}$) as a reference for verifying flood forecasts across all the locations and two percentile thresholds to assess their potential in forecast verification (Figure 25). The results show that impact data gives a more favourable assessment of skill as compared to the observed data at the 90th and 95th percentile across lead times in Katakwi (i.e., $POD_{impact} > POD_{observed}$ and $FAR_{impact} < FAR_{observed}$). For other locations at a lead time of up to 15 days, the impact data underestimates the GloFAS skill both in terms of POD and FAR. At longer lead times (>15 days), Nzoia shows a good assessment of skill in terms of POD. These outcomes can be associated with the quantity, and quality of the impact reports available for most locations (except Katakwi and partly Nzoia) which also corresponds to the findings in Section 2.2.4.2. The highest difference in the POD of up to 0.4 is seen in Mayanja at the 90th percentile, while other locations show a difference of below 0.2. The FAR is, however, spread out across locations with a change of about 0.5 in Mayanja and Athi. POD and FAR graphs for the study locations at 90th and 95th percentile using gauged and impacts reports are provided in Appendix A3.2.

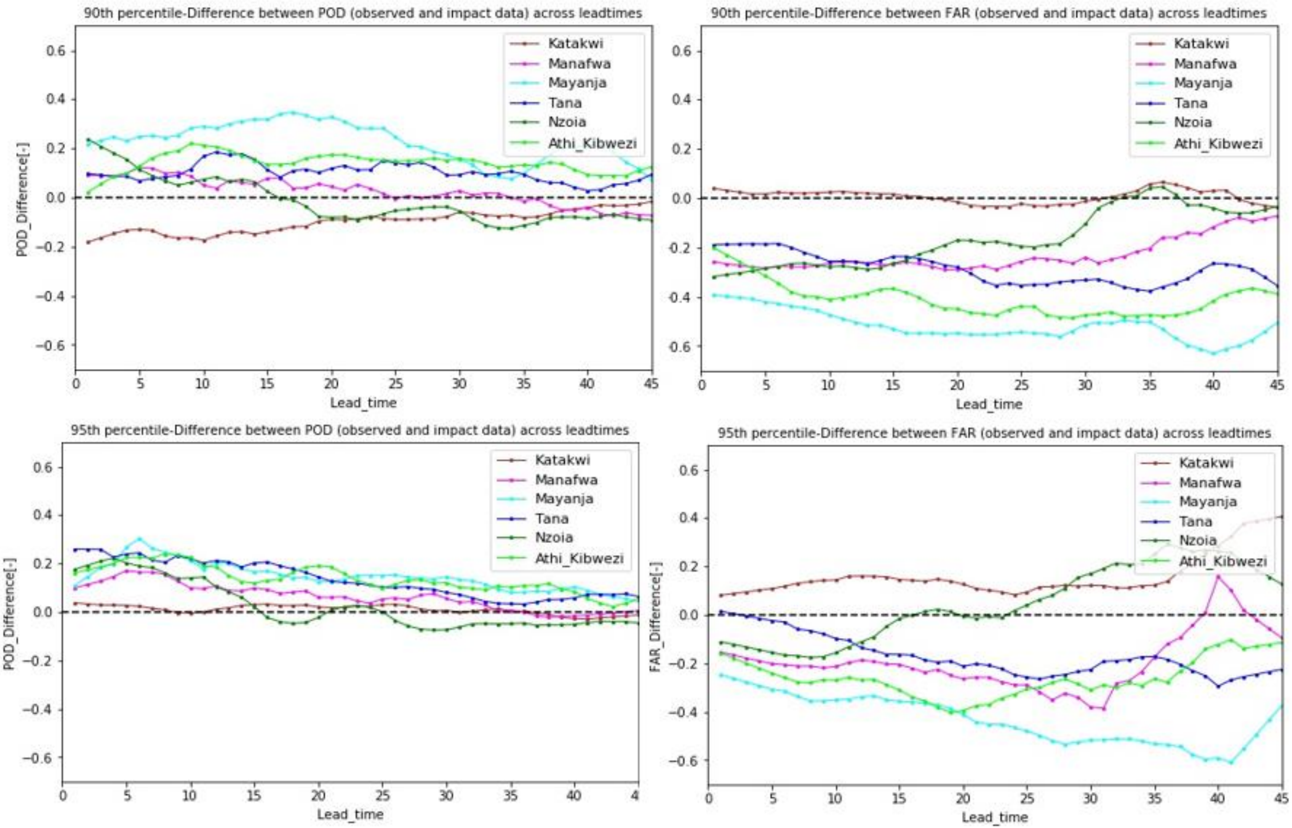

Figure 25: Differences in POD and FAR for locations in Uganda (Katakwi, Manafwa, Mayanja) and Kenya (Tana, Nzoia, Athi-Kibwezi) across lead times at the 90th and 95th percentiles.

3.3.5 Discussion

Using less conventional data such as impact data in forecast verification is gaining interest among researchers and practitioners. However, these data, like hydro-meteorological data, are subject to errors and biases (Wilby *et al.*, 2017). Despite these shortcomings, the impact data have the potential to be used to ensure early warning systems are robust. In this section, we discuss the findings and implications of using impact data to verify flood forecasts and the assumptions that have been considered. Firstly, we discuss the available impact data from the various data repositories in the East African countries (Uganda and Kenya). Secondly, we highlight the adequacy of the impact data compared to river gauge observations and how that may influence the verification of forecasts. Lastly, we highlight the potential and challenges of using impact data to verify forecast information in data-scarce regions and provide recommendations that can be useful in improving the impact data to ensure effective early actions.

3.3.5.1 What does the available impact data from Uganda and Kenya tell us?

Among the four main data repositories used in this study, DI had the highest number of flood events in Uganda (Katakwi and Manafwa districts) (Table 16). Across Kenya and the three counties, EM-DAT reports the highest number of flood events (Table 16). The differences can be associated with the criteria used to include impact data in these repositories and the country-specific regulations on the collection and systematic reporting of impact data (Osuteye, Johnson and Brown, 2017). Due to such differences, using only one repository can lead to a bias in the outputs generated (e.g., underestimation of event frequency).

Although we disaggregated the impact data up to the district and county levels in Uganda and Kenya respectively, we only used the qualitative information classified as impact/no impact to guide the analysis. This is because there are no direct quantitative loss estimates available for these administrative levels useful in understanding the severity of each flood event. Quantitative estimates are usually reported as aggregated quantities across a region rather than disaggregated quantities for smaller geographical areas within the region (Gall, 2015). For example, from EM-DAT, the 2007 flooding between August and October that impacted different parts of Uganda are combined as one record (Disaster number 2007-0408 (EM-DAT, 2020) with the quantified impact on, for example, the ‘number of people affected’, also aggregated. The insufficient reporting of quantitative estimates in areas of small spatial coverage can limit the analysis and affect the robustness of any conclusion, especially from a livelihood perspective (Osuteye, Johnson and Brown, 2017). In addition, these repositories have differences in the parameters used for reporting. For example, EM-DAT reports only one parameter of 'number of people affected' while DI reports two parameters; 'directly affected and indirectly affected'. Below et al. (2010) also noted that this hinders the direct quantitative comparison between the two data repositories.

3.3.5.2 How adequate are the impact data in identifying thresholds for impactful river flooding and in verifying flood forecasts?

Setting up early warning mechanisms for floods often depends on the thresholds derived from river gauge data to identify the level at which the river discharge may result in impactful flooding. In data-scarce regions, impact data can help to determine such thresholds (Coughlan De Perez *et al.*, 2016), but this requires a large number of good quality impact data to reduce the chances of over/under-representation of impacts(Ranger *et al.*, 2011). We have found that even within the same country, impact data are not consistently available across all locations, as noted (Barabadi and Ayele, 2018), which may lead to bias in the outputs. Our analysis shows that using more than one source of impact data reduces the chances of a Type I error or situation where flooding occurs, but impact data are unavailable. For example, although EM-DAT contributes to over 69% of all impact reported in Tana, Nzoia, and Athi, respectively, using this repository alone results in an increase in Type I error (flood observed in gauged data but not reported) compared with using all three databases (EM-DAT, DI, Local) (Figure 24b). This can be associated the inclusion criteria for the various data repositories. For example, for a repository like EM-DAT, only high impacts flood events are represented leaving out low impact flood events.

We have found that the consistency between impact data and river-gauge data varies markedly across the thresholds, but the variability is location-dependent. For example, in Katakwi, there is good correspondence between the river-gauge observations and impact data at the 90th percentile. This suggests impact data can be used to identify river discharge critical thresholds at which impactful flooding occurs. These findings are consistent with scientific literature where impact data has been successfully used to define flood thresholds. For example, Young et al. (2021) used impact reports to determine the rainfall thresholds that resulted in flooding in the urban city of Alexandria, Egypt.

Although we used the percentile-based method to identify flood events, we acknowledge that high impact events are generally higher than the 99th percentile (MacLeod *et al.*, 2021), but to ensure robustness of the statistical analysis, we adopted the 90th and 95th percentile thresholds as several previous authors did (e.g. Arnal *et al.*, 2018; MacLeod *et al.*, 2021) .These percentiles may include low impact flood events that are likely to affect local limited areas (with relatively high frequency, e.g., 5% of days over a year for the 95th percentile) but are useful in cases where impact data is used in the verification due to the differences in the inclusion criteria of flood events in the various data repositories (see Table 1). In some previous studies, even lower thresholds are used because of data availability limitations, to ensure robustness in the verification. For example, Arnal *et al.* (2018) used terciles (33rd, 66th percentiles) of the simulated streamflow for the verification of seasonal streamflow forecasts and discussed the need to consider high thresholds such as the 95th percentile if more data were available. We therefore recommend that further studies with possible longer data periods available, should look at the representativeness of results across flood thresholds, also higher than 99-th percentile.

Other locations in Uganda and Kenya show an increase in Type I (and Type II) error as the river flow threshold decreases (increases). The increase in Type I error can be related to the inadequacy or the low quality of impact data used in this analysis, i.e., for both inadequate impact data (if the repository did not include an observed event) and low-quality data (if the timestamp of the impact data is incorrect) a false positive is produced. Type II error could have resulted if impacts reported were not because of riverine flooding but other subtypes of flooding, and this can also be influenced by the inclusion criteria which are specific to each data repository. Although a repository like EM-DAT differentiates floods using subtypes such as riverine and flash flooding, DI does not include such subtypes. These subtypes would help ensure that flood events are further categorised before analysis to reduce the Type II error. In addition, such differentiation can help in designing appropriate preparedness and response interventions which vary based on the sub-type of flooding (Nauman *et al.*, 2021; Paprotny, Kreibich and Morales, 2021). To further confirm the source of increase in Type II error, data derived from satellite imagery (e.g., Sentinel-1 and -2) could be used to identify if floods occurred as well as their spatial location (with respect to rivers), which can help discriminate riverine floods (Tarpanelli, Mondini and Camici, 2022).

The differences in POD and FAR vary across the study locations considered here. Except in Katakwi and partly in Nzoia (> 15 days lead time), where we get a more favourable assessment of skill while using impact data, other locations show that using impact data underestimates the GloFAS skill both in terms of POD and FAR. Though the differences are minimal in the majority of the locations, it still means that impact data cannot be adequately used to verify flood forecasts in most locations, as highlighted previously by Gall (2015). However, the available river-gauge observations and impact data could be used to train the hydrological model used in the GloFAS system through calibration and validation in specific locations that show poor detection of flood events. In other words, the available historical impact data and gauge observations can be used to assess the hydrological skill of the GloFAS using scores such as Nash-Sutcliffe efficiency which assesses temporal variability and agreement between the modelled and observed data (see Teule *et al.*, 2020). Overall, being aware of uncertainties that can result in using the available impact data can help ensure the outputs are used appropriately in supporting anticipatory actions.

3.3.5.3 How best can the impact data be used to verify flood forecasts in data-scarce regions?

Our exploratory analysis has highlighted several factors that are affecting the efficacy of impact data for verifying flood forecasts in most of the study locations in Uganda and Kenya. These are inadequacy of events records, poor quality and spatial resolution/ granularity among others. Therefore, using impact data may result in underestimation of forecast skill, leading to reduced confidence in using the forecast to support anticipatory actions. In other words, if we use impact data to verify and it turns out to be unwittingly underestimating the forecast skill, we might discard a forecast that is good enough to support preparedness actions for vulnerable people. Nevertheless, positive results obtained for Katakwi in Uganda and Nzoia in Kenya show that with some improvements, the impact data could be used to determine critical thresholds for flooding and inform the design of early warning mechanisms in data-scarce regions. For such regions, the following improvements would increase the usability of impacts data.

a) **Characterising the gaps/uncertainties**

The uncertainties in the impact data should be explicitly stated, as well as the implications for the outputs, especially if the outputs are intended to inform actions. The uncertainty around the estimate can be denoted using standard error, which indicates how far the estimate is from the mean. For example, from our analysis, the standard error in the FAR calculation varies between 0.02 to 0.05. Therefore, if the recommended forecast FAR to trigger humanitarian action is less than 0.5, using impact data will require a FAR of less than 0.4 to minimize actions taken in vain.

b) **Combining databases**

A combination of impact data from multiple data repositories should be explored, especially if the data is scarce (Barabadi and Ayele, 2018). This can help reduce the biases and possibility of missed events in the reference datasets for forecast verification because of the differences in the methods and criteria used to compile the various data repositories. For example, comparing river gauge observations with impact data from all repositories against EM-DAT in Tana improved the Type I error from 0.8 to 0.6 (Figure 24b). However, the combination should be carefully explored to avoid duplicate entries, especially from repositories fed from the same primary source or if there is a slight difference in the timestamp for the same event. Some of these replication challenges can be handled using a tolerance interval such that entries within a specific interval are considered one event. In this study, an interval of seven days was used.

The combination should also consider the differences in the indicators used in each repository. For example, EM-DAT reports the ‘number of people affected’ as one indicator while DI reports in two separate indicators (i.e., ‘directly and indirectly affected’). In addition, EM-DAT makes clear differentiations of the disaster type and subtypes, such as riverine flood and flash flooding, while DI does not have such differentiation. Such differences make it challenging to combine and compare the data and disaggregate further, for instance, if you want to monitor only a subtype of the disaster. For example, in our analysis, most Type II errors could have resulted from impact data that were not necessarily from riverine flooding. Harmonising and differentiating these parameters and clarifying their meanings would help minimise these difficulties (Below, Vos and Guha-sapir, 2010). This can be done by ensuring that these subtypes are indicated during the data collection process or by applying index-based approaches to differentiate between the various disaster sub-types (see Kruczkiewicz et al., 2021).

In addition, satellite data (e.g., from Sentinel-1 and -2) can be used alongside the impacts reports to identify the nature and extent of flooding as well as the spatial location which can help in complementing the impact reports for future applications in forecast verification. The usefulness of satellite images in assessing flood event types and extent has already been demonstrated in several recent studies, although also these datasets have their own current limitations that should be taken into account (see Notti *et al.*, 2018; Landuyt *et al.*, 2019; Tarpanelli, Mondini and Camici, 2022).

c) **Harmonising of the primary data collection and Information Management process**:

Primary data collection process: primary data collection in most countries is done through normal government procedures. This is mainly done using the damage and needs assessment (DNAs) approach (Roberto and Mohinder, 2010) at the local level and the collected data analysed at the national level. If the collected information shows that impacts are considerable, the country may decide to seek external support. In this case, the United Nations Office for Coordination of Humanitarian Affairs (UN-OCHA) may coordinate more rapid needs assessments to collect more information using approaches such as the Multi-sector Initial Rapid Assessment Framework (MIRA) (Inter-Agency Standing Committee, 2015). Countries can, however, use their guidelines for collecting the data. In Uganda, the Office of the Prime Minister is tasked with collecting and uploading impact data to the DesInventar repository. However, recent interviews in Uganda noted that rapid response assessments and collection of impact data are carried out by various institutions, including the Office of the Prime Minister, the Uganda Red Cross Society, the Humanitarian Open Street mapping team, local NGOs, and the district office, among others (personal communication, October 2020). There is a need to harmonise the data collection process through clear guidelines and dedicated institutions to avoid the probability of competing reports of unknown credibility (Guha-Sapir and Below, 2006).

Furthermore, impact reporting can benefit from improved weather and river gauge networks. Improving gauge networks can be strategized such that it is done alongside the improvement on impact data collection (Baddour and Douris, 2018). This can ensure improvement in the flood forecasting systems by providing key inputs for hydrological model calibration and forecast verification, as well as for further impact reports verification.

Information management process: impact data collected through primary sources such as in-country institutions are often uploaded to data repositories such as DI. Due to a lack of resources, most countries might not be able to upload the collected information regularly. Therefore, the impact data collected is held in internal disaster management systems and managed by the primary institutions. National data repositories could be explored to ensure that all impact data collected in-country is stored in a central in-country repository for ease of accessibility.

d) **Impact data outside the official public sources**

A broader and more accurate collection of temporal and geospatial data on disaster occurrence would ensure improved risk estimations (Bakkensen, Shi and Zurita, 2018). An extended search of impact data available at the in-country archives, e.g., in private institutions and insurance companies, but not yet available in the open repositories, would help improve the quantity and detail level (spatial-temporal data) of the available impact data. For example, a study by Smith and Katz, (2013) shows that a significant under-reporting of disaster loss estimates can occur due to reliance on only public sources because of their ease of accessibility.

e) **Use of new technologies**

New technologies such as artificial intelligence can expand the impact data (Homberg, Monné and Spruit, 2018). Initiatives to expand the impact data, for example, through web scraping, text mining (Margutti and Homberg, 2020), and application of earth observation data (Kruczkiewicz, McClain, *et al.*, 2021; Nauman *et al.*, 2021) and social media platforms should therefore be explored. For example, social media platforms like Google Trends and Twitter have shown promising results in detecting and reporting flood events (Rossi *et al.*, 2018; de Bruijn *et al.*, 2019; Thompson *et al.*, 2021). In addition, an ongoing study by Homberg and Margutti (2021) has shown that flood impact data generated from news articles can complement other known data repositories such as DI, both geographically and temporally, improving the usefulness of the data. However, ensuring that any new data is interoperable with data from these repositories will require clear technical guidelines and protocols (Wirtz *et al.*, 2014), such as the WMO data standardisation initiative (see Baddour and Douris, 2018).

Overall, impact data represent an essential source of less conventional data for monitoring and improving early warning and preparedness actions. There is also great potential for improving these data quantity and quality through strengthening in-country disaster monitoring capabilities and ensuring standardized process of data collection that captures all the relevant data features such as flood extent, gauge level, contact information among others(Integrated Research on disaster risk, 2014).

3.3.6 Conclusion

As the world faces an uncertain future due to climate variability, environmental and climate change, and an increase in extreme hydrometeorological events, investing in early warning early action mechanisms can be an effective way to prepare and adapt to these extreme events. However, such an investment will require understanding how forecast information performs in detecting these extreme events to ensure that anticipatory actions are not taken in vain. While forecast verification has been successful in regions where long-term hydro-meteorological observations are available, this is very challenging in data-scarce regions.

Verification of forecasts using non-traditional approaches that use less conventional data would ensure the development of these mechanisms even in locations with scarce/no conventional observations. In this study, we investigated the usefulness of flood impact data to verify flood forecasts. Our findings show that although existing impact data have shortcomings, they also have the potential for flood event analysis and forecast verification and can be used in regions with no long-term hydro-meteorological observations. These impact data may, however, require improvement to enhance their utility and make the forecast verification more acceptable and reliable.

Among the recommendations outlined above, supporting the national institutions to streamline impact data collection, and expanding impact data using new technologies is of critical importance. Addressing these issues will, however, require a recognition of the role that impact data can play in verifying hydrometeorological forecasts and identifying trends in extreme events to inform risk management. In addition, a collaborative effort among international humanitarian actors, disaster management institutions, the private sector, and local communities is needed to ensure that quality impact data are collected consistently and made available in near real-time.

Data availability statement: The GloFAS v3.1 reforecast are available from Copernicus Climate Change Service- Climate Data Store (https://cds.climate.copernicus.eu/). Impact reports from DesInventar and EM-DAT are freely available from their respective web pages (https://www.desinventar.net/ and https://www.emdat.be/database). DFO reports are available upon request from the University of Colorado. The R-scripts used in forecast verification are available upon request from the Authors.

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3.4 Considering varying forecast features in forecast verification to inform sector-specific anticipatory actions.

In section 3.3, we have used forecast evaluation features as per the EAPs (forecast probability, lead time and margin of error/action lifetime) based on the stakeholders' preferences to verify flood forecast information for several sites in Kenya and Uganda. These features were informed through stakeholders' consultation during the development of the EAPs. The EAPs were developed within humanitarian actions targeting high-magnitude flood events. However, some of these features will vary depending on the specificity of the early actions (Bischiniotis *et al.*, 2019). For example, the acceptable margin of error (time allowed between the forecast date and actual event occurrence) might vary based on the time it takes to implement the action as well as the action lifetime. Actions such as evacuation might therefore require forecasts with an acceptable lead time that does not compromise the forecast skill, high probability, and low margin of error. In addition, actions that have a high implementation cost require a higher forecast probability and low margin of error to reduce the risk of acting in vain (Bazo *et al.*, 2018) as well as to reduce the anxiety among the humanitarian actors as they wait for the event to occur (Tanner *et al.*, 2019).

However, various actions can remain effective for more extended periods exceeding the duration of the flood event. For example, actions such as dissemination of EWI, training and awareness, distribution of flood-proof kits, and livestock vaccination can ensure that communities are prepared even if the flood event does not materialise. Some of these actions can contribute to improved resilience of the communities. Most of these actions reflect the priority actions selected across case studies in Africa, Southeast Asia, and South America (Bazo *et al.*, 2018; KRCS, 2021; URCS, 2021). Forecast evaluation should therefore be based on a decision-led criterion where specific actions may require a particular set of features which can be decided upon through stakeholders' consultations. The evaluation of the forecasts should also consider these variations to ensure that skilful forecasts that would be useful in informing some specific early actions are not discarded.

In Kenya and Uganda, forecasts with a forecast probability between 60-85% lead time of 5-7 days at five years return period have been used to define the flood EAPs. In section 3.2, these variables, and a margin of error of 7 days have been used to verify forecast information and assess flood impact data's usefulness. However, it is worth noting that the selection of early actions by the KRCS and URCS considered actions that will still have long-term benefits to the communities even if the flood event does not materialise. For example, the URCS suggested a 30days action lifetime for many of the selected early actions. At the same time, KRCS considered actions that, if implemented, will contribute to disaster risk reduction and resilient communities (Table 18). Notably, most of the early actions within the URCS and KRCS EAPs can benefit the communities up to the next rain season (up to 3 months ahead). For example, dug and desilted drainage systems/ trenches can last up to 90 days before degrading (Coughlan De Perez *et al.*, 2016). Therefore, using a fixed value of the margin of error, like in section 3.3, may limit the assessment of forecasts skill.

In this section, we vary the action lifetime to 10 and 30 days (corresponding to the stakeholders' preferences in the EAPs) in all six sites in Kenya and Uganda to assess how these can inform different early actions. We then evaluate flood forecasts from GloFAS using river gauge observations and impact data to answer the following question.

1. Does varying the action lifetime give more confidence in using forecasts to inform specific anticipatory actions in data-scarce regions?

The terms action lifetime and margin of error have been differentiated in section 3.2. These terms can, however, be used interchangeably in forecast evaluation in the context of early actions. In this section, we use the term action lifetime to correspond to the EAPs.

Although we only vary the action lifetime, forecast evaluation offers limitless ways of modifying the many features based on sector-specific decisions (including lead time and forecast probabilities) to optimize decisions, actions and costs (see Bischiniotis et al., 2019; Lala et al., 2021; Lopez et al., 2020). Here, the forecast probability and the forecast lead time preferences from stakeholders remain the same.

Table 18: Early actions for floods showing the margin of error and the acceptable false alarm ratio (FAR). It is extracted from the EAPs for Kenya and Uganda.

Uganda	**Early actions**	Action Lifetime (ActLT)	Acceptable FAR
	Community awareness of anticipated risks and selected early actions	30	0.5
	Distribution of water purification chemicals, water storage vessels and soap	30	0.5
	Distribution of Cash and Voucher Assistance to facilitate evacuation and meet other basic needs	30	0.5
	Distribution of customized shelter kits	30	0.5
	Cleaning water sources/desilting drainage channels/dredging in Urban and rural areas	30	0.5
	Community mapping - (map out designated centres, evacuation roots and holding stores)	30	0.5
Kenya			
	Placement of flood markers	30	0.5
	Dissemination of early warning messages for EA	30	0.5
	Physical evacuation		0.5
	Vaccination /treatment of livestock	30	0.5
	Prepositioning supplies	30	0.5

3.4.1 Does varying the action lifetime provide more confidence in using forecast to inform sector-specific anticipatory actions?

The evaluation results while using impacts data show that varying the action lifetime to 10 days results in a slight decrease in the POD in Mayanja at five days lead time and an increase in POD for Tana, Nzoia and Athi. However, varying the ActLT to 30 days resulted in an increase in POD across all the locations, with the highest increase noted in Tana and Athi (Table 19). This shows that increasing the ActLT to 30 days presents more locations with a more favourable assessment of skill as compared to our previous findings (see section 3.3), where only Katakwi showed a favourable evaluation of skill.

A comparative analysis shows that in Tana and Athi, a more favourable assessment of skill is achieved using impact data compared to the river gauge observations.

Table 19: POD while using impact and river gauge data at 90th percentile across varying action lifetime (ActLT) in the 6 locations.

	Katakwi			Manafwa			Mayanja			Tana			Nzoia			Athi_K		
Impact data	Action lifetime/Margin of error																	
Lead time	7	10	30	7	10	30	7	10	30	7	10	30	7	10	30	7	10	30
5	0.51	0.51	0.73	0.26	0.30	0.45	0.25	0.21	0.50	0.53	0.56	0.68	0.43	0.46	0.52	0.32	0.43	0.74
7	0.55	0.52	0.76	0.19	0.30	0.45	0.23	0.27	0.38	0.53	0.61	0.64	0.49	0.47	0.62	0.32	0.40	0.58
Observed data																		
5	0.39	0.43	0.56	0.33	0.34	0.45	0.49	0.56	0.67	0.63	0.60	0.66	0.51	0.6	0.6	0.50	0.38	0.52
7	0.43	0.44	0.61	0.38	0.41	0.51	0.46	0.50	0.59	0.54	0.56	0.6	0.53	0.62	0.63	0.53	0.5	0.56

There is an improvement in the False alarm ratio (FAR) at 30 days of ActLT across several locations. For example, Katakwi, Tana, and Athi locations show an improvement in FAR where the FAR is below the acceptable threshold (0.5) at 0.43, 0.42 and 0.48, respectively, at the five days lead time (Table 20). Although the FAR using river gauge observations as reference are more favourable in Tana and Athi, using impacts data provides an opportunity to validate the outputs, while using river gauge observations which increases the confidence in using the forecast.

Table 20: FAR while using impacts and gauge observations across ActLT at the 6 locations.

	Katakwi			Manafwa			Mayanja			Tana			Nzoia			Athi_K		
Impact data	Action lifetime/Margin of error																	
Lead time	7	10	30	7	10	30	7	10	30	7	10	30	7	10	30	7	10	30
5	0.59	0.60	0.43	0.81	0.79	0.64	0.90	0.92	0.77	0.52	0.51	0.42	0.67	0.65	0.54	0.78	0.73	0.48
7	0.53	0.55	0.39	0.85	0.75	0.58	0.91	0.90	0.82	0.50	0.45	0.42	0.63	0.65	0.54	0.76	0.69	0.52
Observed data																		
5	0.59	0.56	0.53	0.53	0.50	0.36	0.49	0.44	0.35	0.37	0.39	0.32	0.42	0.33	0.28	0.45	0.50	0.33
7	0.54	0.54	0.49	0.55	0.48	0.29	0.49	0.43	0.36	0.30	0.28	0.25	0.36	0.27	0.24	0.38	0.38	0.25

Overall, using impacts data in forecast evaluations presents a favourable assessment of skill based on acceptable FAR and short lead times in 3 out of the 6 locations at longer ActLT.

3.4.2 Discussion

The developed EAPs consider various early actions that can be taken to reduce the risks of the impending event. These actions will vary based on multiple features such as the time required to implement, the cost, as well as the duration up to which the action will be effective (Bischiniotis *et al.*, 2019). The choice of the forecasts to inform the early actions should therefore also take into consideration these features. In practical situations, the variables used in forecast evaluations are mostly decided upon through stakeholders' consultations. The most common agreed-upon variables are the flood danger level at which action will be taken, the forecast probability and the forecast lead time, with little attention paid to the margin of error or the action lifetime.

Our analysis shows that the assessment of forecast skills will vary across these factors. Therefore, there is a need to identify the optimal forecast features at which specific early actions can be effectively implemented while reducing the chances of acting in vain (Bischiniotis *et al.*, 2019; Lopez *et al.*, 2020). Using impact data does not result in a favourable skill assessment across all locations. However, the assessment provides a possible way to validate the forecast evaluations (using gauge observations as the reference) in these locations, which can help build confidence in using verified forecasts to inform early actions. For example, forecast evaluation in Katakwi using gauge observations as reference results in POD less than 0.5 and a FAR greater than 0.5. This means that the forecasts have less skill in this location.

In contrast, using impact data on the exact location results in more favourable skills. In addition, using a longer action lifetime ensures that more locations are within the acceptable range of forecast features. Further work could focus on updating the early actions (Table 18) through stakeholders' consultations to develop decision-led criteria that identify the preferred forecast variables (lead time, ActLT, and forecast probability, among others) for sector-specific decisions to support flood forecast verification in Uganda and Kenya.

Chapter 3 highlights the usefulness of flood impact data for forecast verification across several locations in Uganda and Kenya. More specifically, the variability in quantity and quality of the impact data and how that can affect forecast verification is noted, and recommendations for improving the data. Overall, the use of impact data for forecast verification has potential, especially in data-scarce regions, which provides an opportunity to enhance early warning mechanisms.

In chapter 4, the local information on coping practices and flood impacts presented in chapters 2 and 3 are used to redefine the development of flood EWS to make them effective in informing local decisions. Notably, the chapter presents the development of an impact-based trigger system that integrates flood forecasts with livelihood information to ensure more variable trigger thresholds and targeted anticipatory actions to ensure that smallholder farmers can protect their livelihoods during critical times when extreme events are expected.

Chapter 4

4 Developing an impact-based flood early warning triggering system through an impact-oriented approach

This chapter was entirely conceptualised and written by the author. The author collected the data, undertook the analysis, and wrote the chapter. Section 4.2 which has been accepted for scientific publication had contributions as follows. FM developed the concept, collected the data, undertook the analysis, and led the writing of the manuscript. LS, AF, ET, RC, and CP provided inputs in the writing of the manuscript.

4.1 Background

Early warning systems have the potential to inform early actions and reduce the risks of extreme events. The potential for early warning systems can be achieved if the EWI is understandable, timely, and informs the users' needs (Baudoin *et al.*, 2016). Technological advancement has ensured that skilful forecasts at longer lead times are available (Hallegatte, 2012). However, the forecast information may not necessarily inform the required early actions, especially at the community level, due to their context-specific needs and priorities.

The shift towards impact-based forecasts would ensure that hazard forecasts are integrated with the risks and vulnerabilities of the population to understand the locations and the likely impacts (Merz *et al.*, 2020). Moreover, in data-scarce regions where impact-based modelling of risks is not possible, local contextual information collected through community engagements can be used to inform on the potential risks of extreme events to the at-risk communities. Such information can then be integrated into the EWS to redefine the development and implementation of locally targeted early warning mechanisms that contain clear information on the likely impacts and advisories on the actions to protect lives and livelihoods.

This chapter presents an impact-based early warning triggering system for floods developed by integrating livelihood information with flood forecasts through an impact-oriented approach. In addition, the chapter addresses the value of local information in refining hazard-based trigger systems through variable thresholds and targeted anticipatory actions to ensure that the local at-risk communities are protected. The first section (4.2) presents findings from a case study in the Katakwi district, where the impact-based flood early warning trigger system is refined for humanitarian actions using local information on crop cycles and flood impacts collected from three village sites in the district. Section 4.3 further presents a summary of the broad applicability of the impact-based trigger system and the need to consider sector-specific decisions in their design to influence the choice of the trigger thresholds based on early actions.

4.2 Impact-based Flood Early Warning for Rural Livelihoods in Uganda

This section has been accepted for publication in the Journal of Weather, Climate and Society- American Meteorological Society with the following reference:

FAITH Kinya MITHEU; Elisabeth Stephens; Celia Petty; Andrea Ficchi; Elena Tarnavsky; Rosalind Cornforth:
Impact-based Flood Early Warning for Rural Livelihoods in Uganda-In production with DOI: 10.1175/WCAS-D-22-0089.1.

Abstract: Anticipatory actions are increasingly being taken before an extreme flood event to reduce the impacts on lives and livelihoods. Local contextualised information is required to support real-time local decisions on where and when to act and what anticipatory actions to take. This study defines an impact-based early warning trigger system that integrates flood forecasts with contextual livelihood information, such as crop calendars, to target anticipatory actions better. We demonstrate the application of this trigger system using a flood case study from the Katakwi District in Uganda. First, we integrate information on the local crop cycles with the flood forecasts to define the impact-based trigger system. Second, we verify the impact-based system using historical flood impact information and then compare it with the existing hazard-based system in the context of humanitarian decisions. Study findings show that the impact-based trigger system has a slightly improved probability of flood detection compared to the hazard-based system. The trigger dates are similar, but the hazard-based system has more missed events than the impact-based system. In a humanitarian context, the two systems trigger anticipatory actions at the same time.

However, the impact-based trigger system can be further investigated in a different context (e.g., for livelihood protection) to assess the value of this contextual information. The impact-based system could also provide a valuable tool to validate the existing hazard-based system, which builds more confidence in its use in informing anticipatory actions. The study findings should therefore open avenues for further dialogue on what the impact-based trigger system could mean within the broader Forecast-based Action landscape towards building the resilience of at-risk communities.

4.2.1 Introduction

Disasters associated with weather extremes are affecting the lives and livelihoods of millions of people across the world. In 2020 floods were the most common type of disaster, with a 23% increase in events from 2000 to 2019. In 2020 in Africa, floods affected over 7 million people – the highest since 2006 (CRED, 2021). In Uganda, floods affected approximately 800,000 people across 64 districts in 2020 (ECHO, 2020). Rural vulnerable communities are most at risk due to low coping capacity and lack of localised tailor-made early warning information Timely and actionable information should be available to rural at-risk communities and dialogue involving these communities around appropriate coping strategies improved. To support this, humanitarian actors and disaster management agencies require local, contextualized information about the hazard and likely impacts on at-risk communities to guide more targeted interventions.

Early warning information (EWI) can therefore play a key role in risk reduction and management of flood risks (Thiemig, de Roo, and Gadain, 2011; Okonya and Kroschel, 2013). Notably, frameworks such as the Sendai Framework for Disaster Risk Reduction highlight the need to disseminate EWI to support the shift from response to anticipatory actions and to mitigate the risks of extreme events for at-risk communities (UN, 2015). The development of flood early warning systems has advanced significantly over the last decade (Pappenberger *et al.*, 2008; Cloke and Pappenberger, 2009; Hallegatte, 2012; Dale *et al.*, 2014). However, a gap still exists in ensuring that EWIs are used effectively to activate early flood interventions, especially at the local level (Baudoin *et al.*, 2016; Cools, Innocenti and O'Brien, 2016). This is because most hazard-based EWIs describe the physical features of the hazard with little or no information on the likely impacts of the expected extreme event, which can limit the design of the required interventions. if an hazard/damage curve is not previously established. For example, in Uganda, there were difficulties in using the forecast information to define the magnitude/danger thresholds that would result in significant impacts (Coughlan De Perez *et al.*, 2016).

Impact-based Forecasting (IbF) ensures that EWI is linked to the expected consequences (impacts) on the population and their livelihoods to understand where, when, and what specific anticipatory actions are needed(WMO, 2021b). In addition, the provision of impact-based information can significantly influence risk perception among the users and decision makers (Potter *et al.*, 2018; Weyrich *et al.*, 2018; Potter, Harrison and Kreft, 2021). However, the development of impact-based forecast information requires a people-centred approach supported by multi-stakeholder collaborations and driven by at-risk communities (Baudoin *et al.*, 2016; Sai *et al.*, 2018; Klassen and Oxley, 2021).

Several approaches can be used for impact-based forecasting (Wilkinson *et al.*, 2018), with the common ones being impact-based modelling (Hemingway and Robbins, 2020) and impact-oriented approach (Kaltenberger, Schaffhauser and Staudinger, 2020). While impact-based modelling includes complex quantitative impact models overlaying hazard, vulnerability, and exposure, the impact-oriented approach can be based on qualitative, either subjective or objective criteria, e.g., by subjectively discussing the likely impacts of a flood event with stakeholders (Kaltenberger, Schaffhauser and Staudinger, 2020) or setting variable trigger thresholds and targeted early actions through stakeholders consultations. The method adopted will depend on the hazard context, available data, information to build the hazard risk knowledge (Potter et al., 2021; Wagenaar et al., 2017), and available historical impact information to set up danger thresholds (Harrison *et al.*, 2022), and the validation of the impact models (Dottori *et al.*, 2017), as well as the intended user or user-groups of the impact-based information (WMO, 2021b).

In the least developed countries, IbF based on a quantitative impact-based modelling approach has been hindered by scarce risk and impact information. Such information is required to build a link between hazard, vulnerability, exposure, and impacts (Wilkinson *et al.*, 2018) and to validate the impacts of different levels of forecast (Mitheu *et al.*, 2023). Nevertheless, each situation would require a specific approach that meets the remits of the users. For example, at-risk communities could benefit more from an impact-oriented approach (Kaltenberger, Schaffhauser and Staudinger, 2020), which uses available historical flood impact information to define the danger levels at which flooding occurs. For example, available impact information from data infrastructures such as DesInventar (UNISDR, 2018) and EM-DAT (EM-DAT, 2020) can be integrated with local information gathered from community engagement (Tarchiani *et al.*, 2020) to provide more localized risk information. The local information is useful in ensuring IbF systems are more dynamic regarding the danger levels and valuable to trigger targeted anticipatory actions. Depending on the context, local information in addition to information about built-up area, infrastructure and inhabitants could include the seasonal crop calendar, livestock sale schedules, market functionalities, and household economy analysis (Seaman et al., 2014). For example, during the 2020 monsoon floods in Bangladesh, the seasonal rice calendar helped the UN Food and Agriculture Organisation (FAO) intervene just before the sowing season to protect rice seeds for the most vulnerable communities by providing watertight storage kits (FAO, 2021).

'Livelihood' is defined as how people make a living, which comprises capabilities, assets, and activities required to secure life necessities, including food and non-food items (Chambers, 1995; Scoones, 1999; Boudreau *et al.*, 2008). In East Africa, anticipatory actions toward livelihood protection and food insecurity crises, such as reduced crop yields and livestock losses, are often focused on slow-onset disasters such as drought (WFP, 2021). However, floods due to heavy rainfall and waterlogging also lead to devastating losses of crops and livestock. For example, in the Katakwi district of Uganda, over 65,000 acres of significant crops (beans, groundnuts, green grams, potatoes) were destroyed during the April to June 2018 rainy season (UNISDR, 2018). These agriculture-based livelihoods are mainly rain-fed and support approximately 80% of Uganda's rural population. Therefore, there is a need to consider people's livelihood sources and coping strategies in developing IbF systems so that at-risk rural communities can better protect their livelihoods and develop coping practices better adapted to changing weather patterns.

In Uganda, due to the current lack of a local flood forecasting system (Atyang, 2014), forecast information from the Global Flood Awareness System (GloFAS) has been used to inform early warnings and anticipatory actions through the development of a hazard-based flood early warning trigger system (HbFEWtS) (URCS, 2021). GloFAS provides freely available flood hazard forecasts under the funding from European Commission's Copernicus Emergency Management Service(Alfieri *et al.*, 2013). Our study aims to refine the existing HbFEWtS by integrating crop cycles and flood impact information to explore variable triggering thresholds and targeted anticipatory actions. The objectives of the study are to (1) gather the livelihood data from the local communities, (2) develop the impact-based component and integrate it with the forecasts to define an impact-based flood early warning trigger system (IbFEWtS) using the impact-oriented approach proposed by (Kaltenberger, Schaffhauser and Staudinger, 2020), and (3) evaluate the two systems using historical flood impacts information in the context of humanitarian actions (actions that are triggered based on the likelihood of high magnitude floods and the available resources) by the Uganda Red Cross Society (URCS). In this study, we use the term 'impact data/information' to refer to quantitative and qualitative information reported on the type of impacts on lives, livelihoods, and infrastructure derived from global data repositories (DesInventar and EMDAT).

In the following sub-sections, we describe the HbFEWtS already in use by URCS, highlight the data collection method at the local level, and define the IbFEWtS that integrates forecasts and crop impact information based on the Livelihoods Impact-Based Flood Forecasting (LIMB) framework (see Ciampi *et al.*, 2021) developed under the SHEAR *[4]NIMFRU project. The IbFEWtS and the HbFEWtS are then compared through a case study based in the Katakwi district, and the following research questions are addressed:

1. How do the skill (as measured by statistical skill scores) and the thresholds of the two trigger systems compare for humanitarian actions?
2. Does the impact-based flood early warning trigger system change how anticipatory actions are targeted?

4.2.2 Materials and Methods

4.2.2.1 Case Study

The Uganda Red Cross Society (URCS) is currently implementing the Early Action Protocol (EAP) for floods in flood-prone districts under the IKEA Innovative Approaches for Response Preparedness (IARP) project. An EAP refers to a pre-agreed set of procedures and mechanisms that allow humanitarian organizations, governments, and other stakeholders to respond to disasters quickly and effectively to reduce the impact of the disaster and save lives. One of the floods prone districts include Katakwi, which the NIMFRU stakeholders

[4] NIMFRU: National-Scale Impact-Based Forecasting of Flood Risk in Uganda project, co-funded by the UK Foreign, Commonwealth, and Development Office (FCDO) and the UK Natural Research and Environment Council (NERC). See https://walker.ac.uk/research/projects/nimfru-national-scale-impact-based-forecasting-of-flood-risk-in-uganda/.

also selected. Katakwi suffers from waterlogging and seasonal flooding and is among the districts that have experienced the highest flood events from 2007 to 2018 (see Figure 26A). The district comprises two livelihood zones: crop and livestock and fishing and livestock. The crop and livestock zone covers Ongongoja, Ngariam, and parts of Magoro sub-counties, while the fishing and livestock zone covers areas around lake Opeta and Bisina in Opeta parish (Figure 26B). The Katakwi district is selected to develop the IbFEWtS as a proof-of-concept by adding crop impact information collected from three purposively selected villages to flood forecast information from GloFAS.

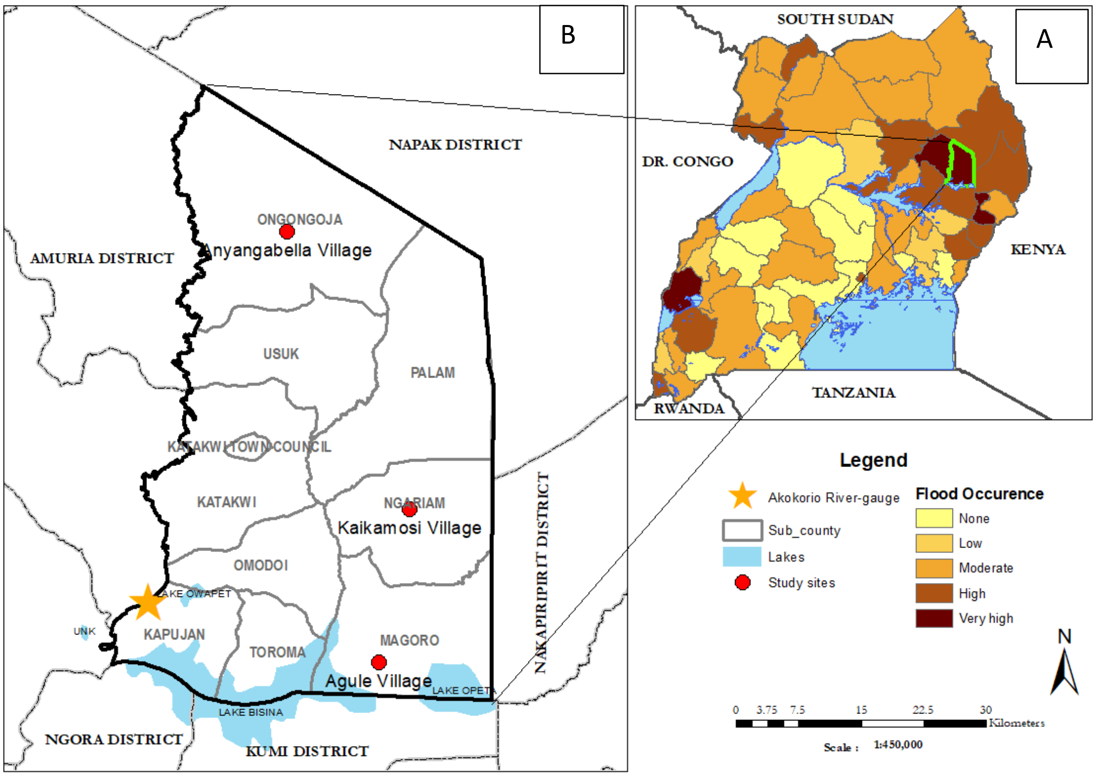

Figure 26: A) Map of Uganda showing flood occurrence where Katakwi is ranked among the priority district due to the high occurrence of floods. B) The zoomed inset shows the Akokorio river-gauge location and the study villages within the Katakwi district where local information on flood impacts and crop calendars were collected.

4.2.2.2 *The current hazard-based flood early warning trigger system for Uganda*

The current HbFEWtS uses a pre-defined trigger threshold derived from discharge probability to define the danger threshold when anticipatory action(s) should be taken (Coughlan De Perez *et al.*, 2016; Wilkinson *et al.*, 2018). These systems ensure that decisions on triggers, actions, and targeting are made well in advance and implemented through an EAP whenever the set criteria are met(IFRC, 2020a). Anticipatory actions can be triggered if a pre-defined threshold representing an impactful flood is reached. This threshold is obtained from observational data, historical river flow forecasts or rainfall observations.

Setting up a hazard-based early warning system for a particular hazard begins by identifying the areas at risk and the priority impacts that would require anticipatory actions. Forecast information that meets the preferences of the stakeholders is then chosen based on availability. A wide range of forecast information can be used. The forecast information should be evaluated before being used in the hazard-based system to minimize the chances of taking actions that are not followed by an extreme event. Forecast skill assessment is therefore important in designing these robust systems. Based on stakeholders' preferences, the current HbFEWtS for Uganda uses forecast information from GloFAS v3.1. For example, when GloFAS indicates a 60-70% chance of a 5-year return period flood at a 5-day lead time (LT), pre-agreed actions will be triggered through the EAP (URCS, 2021). This forecast information has been evaluated as skilful using river-gauge observations collected across Uganda (Ficchi *et al.*, 2021; Mitheu *et al.*, 2023). Mitheu *et al.* (2023) provides a full description of GloFAS v3.1.

4.2.2.3 Data collection

Data collection was organised as part of NIMFRU project and included researchers from both Uganda and international institutions. Data collection fieldwork took place from February 2019 to February 2020 where both qualitative and quantitative data was collected from three village sites in Katakwi District. The initial process started with the development of use cases targeting at-risk communities in the selected sites. Mitheu *et al.* (2022) provide a comprehensive description of the use cases. Quantitative data was collected using the Household Economic Assessment methods (Seaman *et al.*, 2014) and included assessing the various livelihood components (e.g., livelihood type, source of income, assets owned, expenditure, off-farm activities among others) at household level. Qualitative data which included coping practices, barriers to coping, response to flood hazards as well as impacts on crops were collected through the Farmers' Agri-Met Village Advisory Clinics (FAMVACs), co-designed during the NIMFRU project with the Uganda National

Meteorological Authority (UNMA). The FAMVAC method was complemented by semi-structured one- on- one interviews. Ciampi *et al.* (2019) and Mitheu *et al.* (2022) provide a comprehensive description of the FAMVACs approach and the qualitative data collection methods respectively.

Among the qualitative data collected from village sites, data on the crop types and dates/months when various crops were affected by floods were used to inform this study. These data were integrated with crop calendars for Uganda retrieved from the Famine Early Warning System NETwork(FEWS NET, 2013) and combined with the NIMFRU crop calendars drawn up by the Household Economy Assessment (HEA) researchers as part of the NIMFRU baseline study (Petty C.;Acidri, 2021). This calendar reflects the timing for the different crop cycles in an agricultural year. The combined crops calendars and the timing of the impacts on the various crops were used to develop crop-impact matrices for the three villages to inform the impact-based trigger system. The historical flood impact information for Katakwi derived from DesInventar and EM-DAT from 2007 to 2018 was then used to evaluate the two systems using the Probability of Detection (POD) and false alarm ratio (FAR) skill scores (Wilks, 2006). Mitheu *et al.* (2023) provides a detailed description of these global data repositories for Uganda. Table 21 shows the type of flood impacts reported, their timing, and the magnitude of the flooding during that period. The flood magnitudes were extracted from the GloFAS v3.1 for the Akokorio river gauge station. All other data as described above that was not used in this paper will be published separately to inform the aim of the NIMFRU project.

Table 21: Flood timelines for Katakwi based on historical flood impact information from DesInventar and EM-DAT repositories. For the years between 2007 to 2018 that are omitted in this table, no impacts information was available.

Flood timelines based on historical impact information (from DesInventar and EMDAT data repositories				**GloFAS v3.1 (5-days LT)**	
Flood year	**Flood month/s**	**Flood impacts**	**Data collectors/provider**	**Highest flood magnitude**	**Description**
2007	July-October	Thousands of people were affected, homes were damaged, and crops were destroyed. A total of 29,000 households were affected in the six districts	URCS, Office of Prime Minister (OPM)	10yrs Return Period (RP)	The highest magnitude of above 10yrs RP was reached in July, August (3yrs), and September(5yrs)
2008	November	About 6000 people were affected by floods	News-Vision	95^{th} percentile	Flows were above the 95^{th} percentile on 12^{th} November
2010	April, May, September	In April, flooding -7000 People were affected in 4 sub-counties, and roads were affected. In May, water logging resulted in the rotting of crops like cassava, with about 240 gardens destroyed in various villages. In September, water from neighbouring districts affected infrastructure, crops, and grazing lands. Over 3500ha of crops lost	Chief administrative office (CAO)-Katakwi, OPM News-vision	1.5yrs RP	The peak flow of above 1.5yrs RP in mid-May. In September, flows were above the 90th percentile
2011	September-October-November	Thousands of people were affected, and crops were destroyed in Aketa and Obulengorok in Ongongoja	URCS, New vision	3yrs RP	The peak flow of 3yrs in September
2012	August-September	Crops such as cassava and sorghum were destroyed, roads unpassable, houses and latrines damaged, and crops rotting. Water sources were contaminated. Over 10,000 acres of crops submerged	CAO, OPM	10yrs RP	Flows were above the 95th percentile, with a peak of above 10yrs at the end of July and 3yrs in August
2013	October	Crops planted started rotting in several villages of Acuru, Abwokodia, Otujai, and Adurukai.	OPM	3yrs RP	Flows with a peak of above 3 yrs. RP in August
2014	October	Crops in the sub-counties of Omodoi, Usuk, and Ongongoja were destroyed	CAO-Katakwi	2yrs RP	Flows above 2 yrs. RP in September
2017	September	Crops were destroyed, including 210 acres of millet	District files, CAO	2yrs RP	Flows peaked at a 2yrs RP in mid-August
2018	April-June	Major crops (beans, groundnuts, potatoes, green grams) were destroyed, 65403 acres of crops were destroyed, and houses, schools, and latrines were damaged.	District files, News vision, interviews	10yrs RP	Flows were above 95th from April with a peak of above 10yrs in May. Late June 2yrs flows

4.2.2.4 The Impact-based flood early warning trigger system

For wider applicability in informing sectoral-based decisions (i.e., in agriculture, livestock, health, etc.), we define an impact-based trigger system that integrates forecasts with local information through an impact-oriented approach (Kaltenberger, Schaffhauser and Staudinger, 2020). We then refined the system with information on crop cycles and flood impacts from the Katakwi district. Here, we assess how the crop cycles help identify critical times when floods affect crops and how targeted interventions can be designed to ensure reduced risks. The components of the IbFEWtS are elaborated further below.

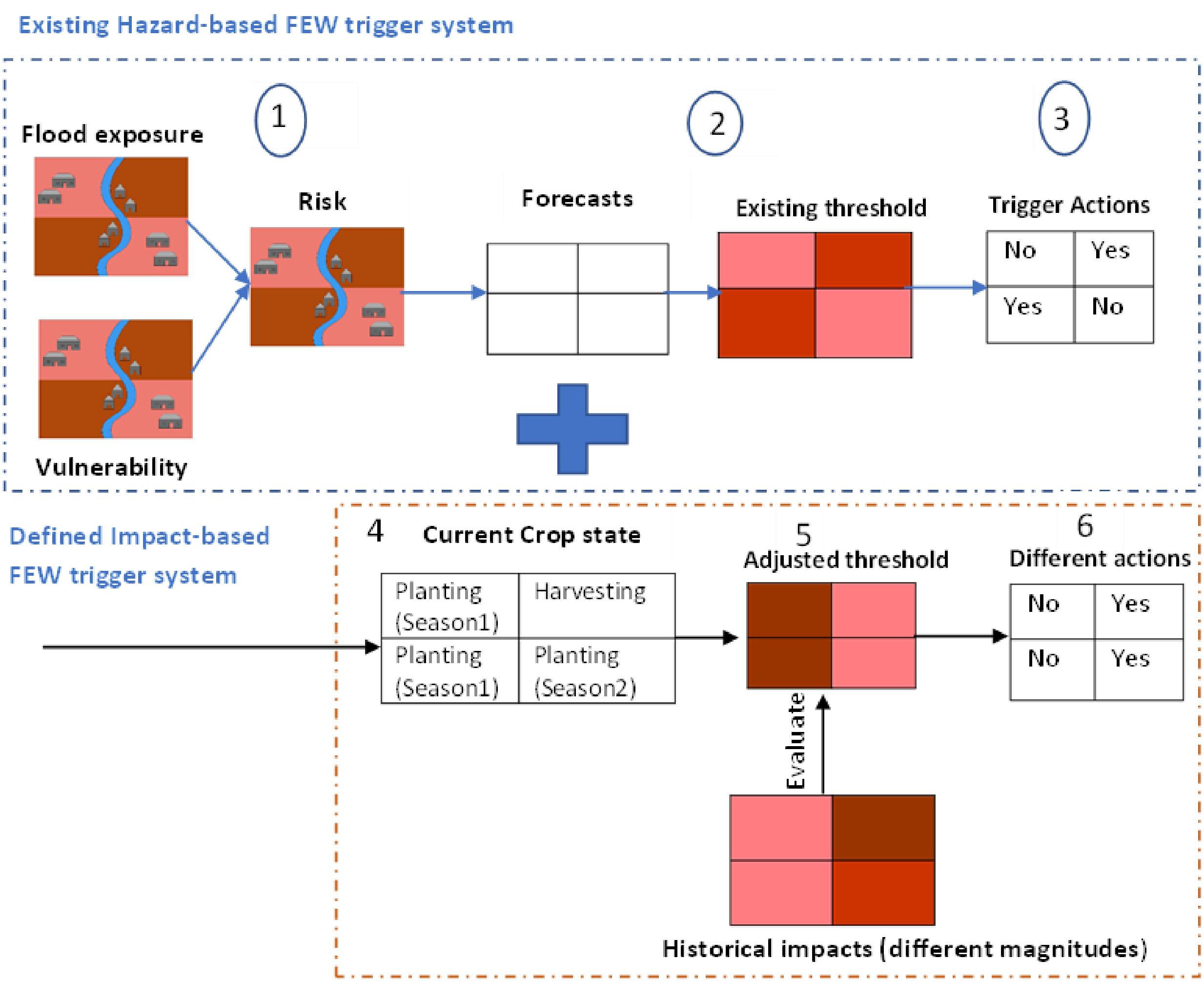

Figure 27: The IbFEWtS that integrates local information developed based on concepts from Boult et al. (2022). Number 1 to 3: represents the existing components of the HbFEWtS. Number 4 to 6: new local dynamic IbF components. Grid boxes (matrices) represent spatially varying values (from dark brown: high values to light brown: low values) of vulnerability, exposure, risk, and impacts. Colours in component 2 represent varying trigger threshold values (dark brown: pre-defined trigger reached, light brown: not reached). Component 5 represents adjusted thresholds based on local information (dark brown: threshold adjusted upwards- no triggering, light brown: adjusted downwards to ensure triggering).

The components of the IbFEWtS are summarized in Figure 27. The principal components of existing HbFEWtS (e.g., the one followed for the Uganda EAP for floods) are retained (components 1-3). Within each component, the grid box represents spatial variability (e.g., different districts/counties in Uganda at a given time). The retained components are summarized below:

1. A risk analysis combines flood hazard, exposure, and vulnerability layers to delineate areas at risk of flooding. Depending on the location and context, this component can also represent the risks and vulnerability of any other hazard such as drought and tropical cyclone.

2. Hydrometeorological forecasts (considering forecast skill) derive trigger thresholds based on stakeholders' preferences and consider the risk profiles. The distribution of threshold exceedances shows areas likely to report a high risk of impacts (i.e., for this case, a high probability of flooding with significant exposure and vulnerability).

3. The threshold exceedances show areas that will require triggering early actions. Conversely, no actions will be triggered if the forecast threshold is below the pre-defined threshold.

The additional components needed for the IbFEWtS include:

4. The integration of crop cycles with forecasts for each administrative area. Based on the context, this component can consist of other local information (livestock sale schedules, social-economic variables etc.).

5. A variable trigger threshold can be adapted to ensure differential triggering that better reflects more critical times of the cropping year. For example, the trigger threshold is lowered (right-hand side squares) during the harvesting and the start of the second planting season. Historical flood impact information is used to evaluate the trigger systems (both hazard and impact-based) based on the set criteria and selected skill scores.

6. A range of anticipatory actions is derived through stakeholders' consultations reflecting agricultural management practice at specific times of the year. For example, actions during the harvesting season are likely to be different from those during the planting season.

4.2.3 Results

In this section, we describe the crop impact information collected from the local communities in Katakwi and demonstrate how the IbFEWtS could be deployed in a local context based on flood forecasts and this local information.

4.2.3.1 Local impact data from village sites in the Katakwi district

The crop calendar developed by NIMFRU project (Petty C.;Acidri, 2021) in combination with the crop calendar developed be FEWSNET and flood impact on crops information collected from village sites in Katakwi was used to develop crop-impact matrices for each(Figure 28). These matrices show that most major crops are negatively affected by floods and waterlogging from July to November, with slight variations across the villages. For example, significant adverse impacts occurred from July-October in Anyangabella village, August-November in Kaikamosing, and August-October in Agule village. Major crops affected include cassava, sweet potatoes, groundnuts, sorghum, green grams, cowpeas, millet, and maize. On the other hand, positive impacts are noted during the same period, especially for fruit trees such as lemon, orange, mango, and jackfruit across all village sites (Appendix 4.1) and for bananas and rice in Kaikamosing and Agule villages, but not in Anyangabella in the north. Livestock is also negatively affected by floods across the three villages during the two rainy seasons. The negative impacts on crops are mostly experienced during the harvesting (June-August) and second planting season (September-November), as seen from the crop (Figure 28). For this study, we have indicated distinct periods for the harvesting and planting seasons based on the generic calendar that combines all crops that was derived from FEWSNET. We however note that specific major crops may have overlaps between the harvesting and second planting season where for most crops the harvesting season may be extended up to December (FAO, no date). The information on crop impacts has been integrated with GloFAS v3.1 flood forecasts to define the IbFEWtS for Katakwi, as elaborated further in section 4.2.3.2.

Figure 28: Crops, crop calendar, and flood/waterlogging impacts matrices for the three village sites in the Katakwi district. Source: NIMFRU Household Economy Assessment (HEA) study, SHEAR NIMFRU project.

4.2.3.2 The impact-based flood early warning trigger system applied to Katakwi.

Forecast information from GloFAS v3.1 at the Akokorio gauging station is integrated with the crop cycles for Katakwi within the defined IbFEWtS (Figure 27) to develop the IbFEWtS for the Katakwi district. This system considers floods at five days LT at 60-70% forecast probability (FP) and a varied threshold based on the crop cycles. For this case, we have adopted different thresholds for the first planting season (March-May), second planting season (September-November), and the harvesting season (June-August), respectively, based on initial reports on flood impacts on crops collected from the communities (Figure 28) and the need to minimise the trigger frequency. Based on this information, a threshold of 10-year RP has been adopted for the first planting season, which is noted at a non-critical period when minimal impacts are likely to occur. On the other hand, the harvesting period has been noted as most critical where high impacts are likely to occur; hence a threshold of 3-year RP has been assigned. While the second planting season has been noted as moderately critical since it overlaps with the harvesting period for most crops; hence, a threshold of 5-year RP has been assigned. The choice of the varied thresholds used here is based on one-year impact data from farmers (Figure 28); hence they can be subjective. In addition, actions cannot be re-triggered within a period equivalent to the action's lifetime. Here, the action lifetime is defined as the period up to which anticipatory action will still have positive impacts (see Coughlan De Perez *et al.*, 2016). For this study, which is based on a crop calendar, we have considered an action lifetime of 30 days.

The historical flood impacts information (Table 21) is then used to evaluate both the hazard-based and the impact-based systems. The two systems are presented in Figure 29. Due to the lack of complete flood impact information for the Katakwi district before 2007, only 12 years have been considered in this study. The exact dates when anticipatory actions could have been triggered for the two systems are shown in Table 22. The outputs from these systems have been used to address several important questions in the following sub-sections.

	Months / Years	March	April	May	June	July	August	September	October	November
Hazard-based trigger model	GloFAS reforecasts ENS v3.1 at 90th percentile-ref observed Q (60-70% probability, 5days LT). Predfined threshold-5 Years RP									
A	2007					Yes		Yes		
	2008									
	2009									
	2010									
	2011									
	2012					Yes				
	2013									
	2014									
	2015									
	2016									
	2017									
	2018			Yes						

Year-yr
Harvesting [H]
Planting season 1-P(S1)
Planting season 2-P(S2)
Triggers

		March	April	May	June	July	August	September	October	November
Impact-based trigger model	GloFAS reforecasts ENS v3.1 integrated with crop cycles. Magnitudes derived from GloFAS(60-70% FP),5days LT									
	Crop cycle	P(S1)			Harvesting			P(S2)		
	Threshold	**10years**			**3years**			**5years**		
B	2007	<1yr			<1yr	10yr	3yr	5yr	<1yr	
	2008	<1yr			<1yr			<1yr		
	2009	<1yr			<1yr			<1yr		
	2010	<1yr		1.5yr	<1yr			<1yr		
	2011	<1yr			<1yr	1.5yr		3yr	<1yr	
	2012	<1yr			1.5yr	10yr	3yr	<1yr		
	2013	<1yr		2yr	<1yr		3yr/<60FP	<1yr		
	2014	<1yr			<1yr			2yr	<1yr	
	2015	<1yr			1.5yr	<1yr		<1yr		
	2016	<1yr								
	2017	<1yr					2yr	<1yr		
	2018	<1yr	2yr	10yr	2yr	<1yr	<1yr			

Figure 29: A) The existing HbFEWtS. B) the IbFEWtS for the Katakwi District. The impact-based trigger system integrates local information on crop cycles with forecasts. Flood return periods (RP) have been extracted from GloFAS v3.1. The crop cycle reflects the actual stage of crops when floods occur. The triggers represent the time/month when actions are triggered.

Table 22: Trigger dates for the Hazard-based and Impact-based systems

Trigger dates for the hazard-based system, 60-70% Forecast Probability, 5yr RP, five days Lead time		
	Year	**Trigger dates**
Hazard-based system	2007	4th July
	2007	12th September
	2012	18th July
	2018	20th May
Trigger dates for the impact-based system, 60-70% Forecast Probability, varied thresholds, five days Lead time		
Impact-based system	2007	4th July
	2007	5th August
	2007	12th September
	2012	18th July
	2018	23rd May

4.2.3.3 How do the skill and the trigger thresholds of the two systems compare?

From Figure 29, we can assess the skill of the two trigger systems in detecting flood events using historical flood impact information (Table 21). A contingency table is developed for each system, as shown in Figure 30 below and is used to compute the POD and FAR for each system.

Hazard-based model			**Impact-based model**		
	Impacts	No impacts		Impacts	No impacts
Forecast	Hits (4)	False alarm (0)	Forecast	Hits (5)	False alarm (0)
No forecast	Miss (8)	CN(3)	No forecast	Miss (7)	CN(3)
POD (0.33)	hits/(hits+misses)		**POD (0.42)**	hits/(hits+misses)	
FAR (0)	False alarm/(hits+ false alarm)		**FAR (0)**	False alarm/(hits+ false alarm)	

Triggered, with impacts
Triggered, no impacts
Not triggered, with impacts
Not triggered, no impacts

Figure 30: Contingency tables for the two trigger systems and their computed POD and FAR

The POD for the hazard-based trigger system using a predefined threshold was 0.33, while the impact-based trigger system using a varied threshold showed an improved POD of 0.42. Neither system had false alarms. The hazard-based system had 8 missed events that occurred in 2007 (1), 2008, 2010(2), 2011, 2013, 2014, and 2017 while the impact-based system had 7 missed events during 2008, 2010(2), 2011, 2013, 2014 and 2017. This shows that the two trigger systems are comparable in detecting flood events and minimising 'actions in vain'. Regarding the trigger dates, both systems trigger actions simultaneously for the common triggers (see Table 22). However, an additional trigger occurred for the impact-based system on 5th August 2007. Severe impacts were reported for some of the years that the forecast did not reach the required threshold in both systems (missed events). For example, in 2010, flooding affected over 7000 people in April across several sub-counties in Katakwi. In May and September, waterlogging resulted in crops rotting, with over 240 gardens destroyed (UNISDR, 2018). The highest flow magnitude reported in 2010 at five days LT was in May at 1.5-year RP. The impacts could therefore be because of flash floods and not riverine flooding. Similarly, 2008, 2011, 2013, 2014, and 2017 reported impacts across several locations in Katakwi.

Investigating the missed events further shows that, in 2010, the flow magnitude was at 3-year RP in May at ten days LT, but it was still below the set threshold; hence no triggering was required. In September 2011, though the magnitude was at 3-year RP at five days LT, a magnitude of 10-year RP was reached at ten days LT, which could have resulted in the reported impacts (Table 21). In 2013, the magnitude was 3-year RP in August but resulted in a missed event since the forecast probability was below 60%. Finally, in 2014 and 2017, the magnitudes were at 2-year RP at longer LT; hence no actions were triggered.

For the case study in Katakwi, we note slight differences between the hazard-based and the impact-based trigger systems on the thresholds. For example, lowering the trigger threshold during the harvesting period to 3-year only results in one additional trigger. This can be associated with other variables, such as the forecast probability and the action lifetime, which also play a key role in trigger selection.

4.2.3.4 Does the impact-based trigger system change how anticipatory actions are targeted?

According to the EAP for Uganda, pre-agreed actions would be triggered through the Disaster Relief Emergency Fund (DREF) if high magnitude flooding (above 5-yr RP) is expected (IFRC, 2020b). Based on these attributes, the trigger thresholds would have been reached within the hazard-based system in 2007, 2012, and 2018, and the pre-agreed actions according to the EAP guidelines would be implemented.

The defined IbFEWtS, which includes the crop cycles from the cropping calendar, shows that actions can be more targeted to correspond to the time of the agricultural season. For example, in 2007, the trigger dates would have occurred during harvesting (July, August) and the start of the second planting season (September), resulting in different actions each time. Actions during the harvesting season could include recommending early harvesting and provision of storage kits, while planting season actions would call for late planting, draining water from farms, and other farm management activities (Appendix A4.2). These actions have been derived from farmers' coping practices during the field interviews (see Mitheu et al., 2022). The crop cycles can therefore be used to tailor interventions with an improved chance of protecting livelihoods at the community level.

4.2.4 Discussion

Anticipatory actions are increasingly being taken before an extreme weather event (see Wilkinson et al., 2018), with humanitarian organizations using forecasts to inform interventions (FAO, 2021; WFP, 2021). Evidence suggests that taking preparedness actions before a hazard can result in significant benefits (Gros et al., 2019). However, hazard-based early warning systems based on predefined trigger thresholds and pre-agreed actions could result in the exclusion of low-magnitude flood events, which can still result in significant livelihood impacts to the most vulnerable communities at critical times of the agricultural year. The FbA approach focuses on extreme events that are not likely to occur every year (RCCC, 2022), and most humanitarian organizations prefer pre-defined hazard-based systems due to various beneficial reasons such as avoiding delays associated with real-time decision-making (see Boult et al., 2022). However, decisions on where and when to act and what preparedness actions to take call for local information from at-risk communities (Klassen and Oxley, 2021).

Drawing from the Katakwi case study, we discuss the overall benefit of an impact-based trigger system. More specifically, we discuss the value of local information in developing a trigger system and the need for more targeted anticipatory actions. Lastly, we provide insights into whether the existing hazard-based trigger system should be changed entirely based on local information or just the targeting of the interventions to ensure local at-risk communities are protected.

4.2.4.1 Would integrating local information into a trigger system improve the skill?

A pre-defined trigger threshold ensures that actions can only be triggered if that threshold is reached. Such a criterion has known benefits (see Boult *et al.*, 2022). For example, pre-defined thresholds reduce subjectivity which can result from varying the thresholds depending on the situation. However, with the level of impacts changing across specific users/user groups (Stephens *et al.*, 2016), a general pre-defined trigger based on a danger threshold could result in not enough warnings, leaving out events that could result in major local impacts (Potter, Harrison and Kreft, 2021). An alternative is using variable thresholds to define triggers at which actions should be taken—for example, designing flexible thresholds based on real-time expert judgement (Boult *et al.*, 2022) or operationally integrating forecasts with local information to define the trigger thresholds as applied here.

The choice of the trigger threshold at which actions should be taken can determine the system's skill. While the aim would be to have a trigger system that minimises false alarms and trigger frequency, decision-makers and humanitarian actors often face the dilemma of when early actions should be triggered. For example, if they should act based on any forecasts to prevent any damages/losses or only based on forecasts that show a high likelihood of event occurrence to minimise expenses. Lopez et al., (2020) provides a detailed explanation of the two decision criteria. The choice of the trigger threshold can therefore be subjective and will depend on the sector-specific decisions.

Trigger thresholds can be determined using several methods, as noted in the scholarly literature (Coughlan De Perez *et al.*, 2016; Lopez *et al.*, 2020). This study has shown that these thresholds can be further varied based on context-specific information such as crop calendars and livestock sale schedules to improve the targeting of anticipatory actions. For example, adjusting the threshold so that alerts for low-magnitude floods are triggered only during critical times of the years when low-cost interventions can be initiated through existing disaster management structures (MacLeod *et al.*, 2020).

In the Katakwi district, integrating the crop cycles with flood forecast information allowed us to subjectively vary the trigger threshold across the crop cycles to define an Impact-based trigger system. Evaluating the POD using historical flood impacts information showed an improvement in flood detection from the existing hazard-based trigger system (

Figure 30). However, the number of missed events remained high, even for the IbFEWtS, which affects the overall skill. For example, in 2010, though severe impacts were reported in April, May, and September (see Table 21), the flow magnitude was at 3-year RP, even at longer lead times. Therefore, the flood impacts could have resulted from flash floods and not necessarily riverine flooding. In contrast, 2011 was reported as a missed event at 5-days LT since the flow magnitude was below 5-year RP, but the flow magnitude reached a 10-year RP at ten days LT. This means that the flood event may have occurred although not at the forecasted date which explains the impacts that were reported during that period (Table 21).

Our findings show that other forecast features, such as the forecast probability and the forecast lead time, also play a crucial role in developing a trigger system. Therefore, forecasts should be monitored beyond the set criteria and actions triggered if necessary. For Katakwi, floods that are likely to reach the 3-year RP during harvesting and 5-year RP during the second planting season can be monitored at longer lead times, and actions taken if they show a high probability of occurring. For example, in September 2011, high magnitude floods (10-year RP) were correctly forecasted at ten days LT, which can be used to trigger early actions.

Overall, local information can be used to adjust trigger thresholds at which different actions should be taken (Stephens *et al.*, 2016; Ciampi *et al.*, 2021). However, the cost/benefits associated with varying the thresholds to trigger anticipatory actions should be investigated (Lala *et al.*, 2021). In addition, the quality and quantity of impact information that varies across contexts and locations (Mitheu *et al.*, 2023) and the relevant forecast features (lead time, probability) will determine the overall skill of the resulting triggers. A combination of these variables should be co-designed with the stakeholders to ensure an optimal trigger system is developed.

4.2.4.2 The need for more targeted early actions

The existing hazard-based system triggers pre-agreed actions (Appendix A4.2) based on the set criteria within the EAP. However, these pre-agreed actions might not fully benefit at-risk communities due to the context-specific nature of their needs and coping practices. For example, interventions such as cash transfers may not be appropriate in all locations if the market's functionalities (accessibility and availability of a required commodity) are likely to be affected (Bailey and Harvey, 2015; Wilkinson *et al.*, 2018). In contrast, targeted anticipatory actions can ensure that communities effectively implement the right coping practices during a specific time in the agricultural season. Anticipatory actions should therefore be designed based on user-specific needs and practices (WMO, 2021b), which change across users and over time.

In the case of the Katakwi district, most impacts of floods on crops occurred during the harvesting season based on the calendar that was used (Table 21, Figure 29). Therefore, information on the crop cycles can be used to design actions to help these communities protect their livelihoods during these critical times. Such local information can also ensure that interventions are better designed. For example, more frequent floods might only require no-regret actions such as raising awareness of the likelihood of impactful flooding. Local farmers can then use such information to inform their coping practices and improve their resilience to floods.

Although we have used a generic crop calendar derived from FEWSNET(FEWS NET, 2013) (see Figure 28), we note that specific major crops may have overlaps between the harvesting and second planting season where for most crops the harvesting season may be extended up to December. For example, a crop like sweet potato grown in Eastern Uganda has a harvesting period starting from July to December while a crop like groundnut has the harvesting season running from June to August (FAO, no date). The design of targeted actions for specific crops should therefore take into considerations such variations in the cropping calendar.

4.2.4.3 Should the hazard-based trigger system be changed or just the targeting of the interventions?

The appropriate danger thresholds used in the different EAPs are selected through a consultative process. The process involves disaster managers, alongside forecasters, to 1) select the hazard threshold that could lead to significant losses and 2) decide on the acceptable number of times that they may be willing to take actions ‘in vain’, i.e., actions that are not followed by an extreme event. In Uganda, this threshold was set for a flood magnitude of 5-year RP with an acceptable probability to ‘act in vain’ of 50%. In the FbA approach, this would mean targeting events that are unlikely (20% chance) to happen each year and leaving out low-magnitude events, which might result in high impacts at specific times of the year, e.g., crop fruiting phase.

Given this and based on the LIMB framework (Ciampi *et al.*, 2021), the crop cycle information has been integrated with forecasts information to develop a trigger system for Forecast-based Action (FbA) that allows variable triggers and different interventions for communities at risk. The contextual information incorporated into the impact-based system will unavoidably change depending on the hazard and the area of interest. Therefore, deciding whether to change the entire system or just a specific part (such as the selected actions or the thresholds) is not straightforward. Here we highlight two possible recommendations:

1. The existing hazard-based trigger system (Figure 29A) can be enhanced by integrating livelihood-based information, such as the crop cycles, to help better target the pre-agreed actions. For Katakwi, this would mean having four triggers (2007(2), 2012, 2018) with different interventions based on the crop cycles (Appendix A4.2). Crop calendars will vary across countries and districts and should be developed in consultation with the local communities (see NIMFRU, 2020). For example, Uganda has eleven crop calendars across different climate zones (FAO, no date). Co-designing pre-agreed actions with local stakeholders is crucial to properly reflect households' various coping strategies at different times of the year. The co-design of targeted activities should also consider the current practices per the disaster management plans to avoid replication (Stephens *et al.*, 2016). For example, in Katakwi, some priority coping practices within the agricultural livelihood sector include post-harvest handling and seeds distribution (KDLG, 2017).
2. An impact-based trigger system (Figure 29B) could be developed based on variable triggers and crop cycles. The choice of the trigger thresholds across the crop cycles must be co-designed with stakeholders based on the decision-making context (e.g., livelihood coping strategies). Historical impact information can then be used to evaluate the trigger system in comparison to the existing system to assess if it is necessary to develop a new trigger system. The evaluation using historical impact information can, however, result in uncertainty. Notably, the quality and quantity of the impact data available for each location can vary greatly(Mitheu *et al.*, 2023). In such circumstances, historical impact data should be used alongside other available and relevant data based on the location to evaluate the trigger system, for example, including rainfall for cases of flash floods (Yang *et al.*, 2015). The available impact data should also be used with caution, and where possible local knowledge from the communities should be used to enhance them. In addition, the impact data can be disaggregated to the various sub-categories and the relevant information used (Kruczkiewicz, Bucherie, *et al.*, 2021). For example, impacts because of flash floods may

not be useful in evaluating riverine flood forecasts. However, such information can ensure the design of appropriate interventions for each flood type (Paprotny, Kreibich and Morales, 2021).

For the Katakwi case study, an improved POD and reduced number of missed events is seen between the existing hazard and the defined impact-based trigger system. However, the false alarms, and the trigger dates are similar in the two systems. This could have resulted due to the length of the data records (12 years) used in the analysis and might be different if more flood events are considered. Based on these findings, the existing hazard-based trigger system could remain the same in a humanitarian context, but early actions could be further enhanced using crop cycles. The impact-based trigger system can then be further examined in a different context (e.g., for livelihood protection) to assess the value of this contextual information. Although a slight difference is noted between the two systems, the impact-based system is still relevant to show the use of local information to adapt global forecasting systems to local contexts and how anticipatory actions could be better targeted.

Overall, we have provided recommendations on how local information can contextualise and enhance hazard-based trigger systems and ensure variable trigger thresholds and more locally targeted actions. We also acknowledge that a decision on whether to change a trigger system would require clarity in understanding the benefits and consequences of implementing the new method, which will vary across communities and locations. In addition, the decision to implement might not be straightforward and will depend on background issues shaping the implementing agencies' political and institutional environment. Our findings should, however, open avenues for further dialogue on what the impact-based trigger system could mean within the broader FbA landscape towards building the resilience of at-risk communities.

4.2.5 Future work

The shift from hazard-based to impact-based forecasting would ensure that users and communities have access to the forecasts and advisories on the likely impacts of any extreme threatening event. Therefore, to implement effective preparedness measures at the community level, locally customized EWI will be required due to the context-specific needs and priorities among communities (Bailey, Hassan and Dhungel, 2019). Therefore, local contextual information plays a crucial role in improving the trigger models by ensuring that household-level anticipatory actions are designed.

In this study, data on crops and how they are affected by floods was used to redefine the trigger model. We note that local information will be context-specific and additional data collected from the communities can be used to provide the required personalization of the impact-based trigger model. Future work can therefore look at collection of additional information such as personal trigger preferences, anticipatory actions preferred by communities, flood impact perception and location specific impacts on other amenities such as roads and markets. Such data can then be used to develop impact-based trigger systems that are sector relevant.

4.2.6 Conclusion

The study findings have shown that contextualized livelihood information can be used to enhance the development of variable trigger thresholds and more targeted anticipatory actions. Hazard-based systems can therefore be adapted to the local context to ensure that even at-risk communities are protected. However, developing an impact-based trigger system requires sustained engagement with local communities to ensure their expert inputs can be included in the design and to facilitate the collection of HEA information to understand the livelihood systems of the local communities and the differential coping strategies. Further, to broaden the usefulness of the defined trigger system, future research could look at in-depth consultations with the relevant stakeholders under different sectors to develop the criteria required to tailor the impact-based trigger system to sector-specific decisions.

Integrating the local contextual information with forecast information has shown that even data-scarce regions can benefit from impact-oriented approaches based on qualitative criteria. The approach can be tailored to ensure improved preparedness for flood risks at the community level. An impact-based system can also be very useful in validating the existing hazard-based systems to build more confidence in their use in informing anticipatory actions.

Data Availability Statement: The field data collected and analysed during the study are included in this article in the form of Tables and Figures. The GloFAS v3.1 reforecast is available from Copernicus Climate Change Service- Climate Data Store (https://cds.climate.copernicus.eu/). Impacts reports from DesInventar and EM-DAT are freely available from their respective web pages (https://www.desinventar.net/ and https://www.emdat.be/database).

Ethical Statement:

The study involving human participants that the researchers led was reviewed and approved by the SAGES (School of Archaeology, Geography, and Environmental Science) and the Ethics Committee University of Reading. The NIMFRU study was also approved by University of Reading ethics committee where all survey instruments (research protocols, interview guides, participant consent forms among others) were submitted for approval. In addition, the field researchers drawn from various local institutions including UNMA, Eco-TRUST were trained on procedures for data collection.

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4.3 Wider applicability of the impact-based trigger system.

In section 4.2, we defined an impact-based trigger system and demonstrated its application for floods in the Katakwi district within the context of humanitarian decisions. Here, the choice of the trigger thresholds was therefore pegged on the need to reduce frequent triggers; hence high, magnitude flood events were considered. The trigger threshold choice is context-specific and will depend on sector-specific decisions (Bazo *et al.*, 2018). Impact-based information is therefore useful in designing trigger thresholds that are sector relevant to ensure the design of tailored early actions. From a livelihood perspective, this would mean focusing on improving the resilience of the communities by ensuring that they are aware of the likely impacts and the appropriate coping practices to undertake (Mitheu *et al.*, 2022).

In this section, we demonstrate the wider applicability of the proposed impact-based trigger system by presenting three additional trigger models for Katakwi developed by varying the trigger thresholds at which actions should be taken. Historical flood impact data show that even floods of magnitude above a 2-year return period can also severely impact lives and livelihoods (URCS, 2021). Our models, therefore, consider floods with a magnitude of above two years. The four models have been evaluated using flood impact data described in section 4.2.

We have considered a varying threshold of between 2-3yrs for the harvesting period, 3-5yrs for the second planting season, and 10yrs the return period for the first planting season. Model 3, which results in fewer triggers, has been adopted for the humanitarian decisions and further described in section 4.2 above. The other three models are presented in Figure 31 below and have been used to answer the below question:

1. Should sector-specific decisions influence the design of trigger systems?

4.3.1 Should sector-specific decisions influence the design of trigger systems?

The three systems show that varying the magnitude can define the resulting number of triggers. From a livelihood perspective, a model that minimises the number of false alarms and missed flood events would be ideal. In this case, model 1 or 2 could be adopted since missed events (type 2 error) are minimal at 0.25 and 0.33, respectively (Figure 32) .Here we note that even floods that may not reach the predefined threshold but are likely to result in loss of crops or livestock should be considered and low-cost actions designed. Notably, scholarly studies show that taking action during a low threshold flood event can result in high benefits of the early action as compared to waiting for high magnitude flood events to occur (Bischiniotis *et al.*, 2019; Lala *et al.,* 2021).

However, adapting the two impact-based models (model 1 or 2) would mean having frequent triggers at a trigger frequency of 0.75 and 0.67 times in a year, respectively (Table 23). Therefore, the influence of sector-specific variable triggers on the cost/benefits of taking early actions should be further investigated to understand the associated benefits of lowering the trigger thresholds and the avoided loss if the actions are taken (Bischiniotis *et al.*, 2019; Lala *et al.,* 2021). In addition, optimal trigger thresholds can be developed for specific actions at specific times of the year. The choice of the model is also highly subjective, and the choice should be discussed with the stakeholders depending on the decisions to be made. In-depth consultations with the stakeholders ensure that the required sector-specific criteria are developed and used to tailor the impact-based trigger systems (Bailey, Hassan and Dhungel, 2019).

Impact-based trigger model	GloFAS reforecasts ENS v3.1 integrated with crop cycles. Magnitudes derived from GloFAS(60-70% FP),5days LT							
	Crop cycles	P(S1)			Harvesting			P(S2)	
Model 1	Threshold	10yrs			2yrs			3yrs	
	2007	<1yr			<1yr	10yr	3yr	5yr	<1yr
	2008	<1yr			<1yr			<1yr	
	2009	<1yr			<1yr			<1yr	
	2010	<1yr		1.5yr	<1yr			<1yr	
	2011	<1yr			<1yr	1.5yr		3yr	<1yr
	2012	<1yr			1.5yr	10yr	3yr	<1yr	
	2013	<1yr		2yr	<1yr		3yr	<1yr	
	2014	<1yr			<1yr			2yr	<1yr
	2015	<1yr			1.5yr	<1yr		<1yr	
	2016	<1yr							
	2017	<1yr					2yr	<1yr	
	2018	<1yr	2yr	10yr	10yr	<1yr	<1yr		

Impact-based trigger model	GloFAS reforecasts ENS v3.1 integrated with crop cycles. Magnitudes derived from GloFAS(60-70% FP),5days LT							
	Crop cycles	P(S1)			Harvesting			P(S2)	
Model 2	Threshold	10yrs			2yrs			5yr	
	2007	<1yr			<1yr	10yr	3yr	5yr	<1yr
	2008	<1yr			<1yr			<1yr	
	2009	<1yr			<1yr			<1yr	
	2010	<1yr		1.5yr	<1yr			<1yr	
	2011	<1yr			<1yr	1.5yr		3yr	<1yr
	2012	<1yr			1.5yr	10yr	3yr	<1yr	
	2013	<1yr		2yr	<1yr		3yr	<1yr	
	2014	<1yr			<1yr			2yr	<1yr
	2015	<1yr			1.5yr	<1yr		<1yr	
	2016	<1yr							
	2017	<1yr					2yr	<1yr	
	2018	<1yr	2yr	10yr	10yr	<1yr	<1yr		

Impact-based trigger model	GloFAS reforecasts ENS v3.1 integrated with crop cycles. Magnitudes derived from GloFAS(60-70% FP),5days LT							
	Crop cycles	P(S1)			Harvesting			P(S2)	
Model 3	Threshold	10yrs			3yr			5yr	
	2007	<1yr			<1yr	10yr	3yr	5yr	<1yr
	2008	<1yr			<1yr			<1yr	
	2009	<1yr			<1yr			<1yr	
	2010	<1yr		1.5yr	<1yr			<1yr	
	2011	<1yr			<1yr	1.5yr		3yr	<1yr
	2012	<1yr			1.5yr	10yr	3yr	<1yr	
	2013	<1yr		2yr	<1yr		3yr	<1yr	
	2014	<1yr			<1yr			2yr	<1yr
	2015	<1yr			1.5yr	<1yr		<1yr	
	2016	<1yr							
	2017	<1yr					2yr	<1yr	
	2018	<1yr	2yr	10yr	10yr	<1yr	<1yr		

Impact-based trigger model	GloFAS reforecasts ENS v3.1 integrated with crop cycles. Magnitudes derived from GloFAS(60-70% FP),5days LT							
	Crop cycles	P(S1)			Harvesting			P(S2)	
Model 4	Threshold	10yrs			3yr			3yr	
	2007	<1yr			<1yr	10yr	3yr	5yr	<1yr
	2008	<1yr			<1yr			<1yr	
	2009	<1yr			<1yr			<1yr	
	2010	<1yr		1.5yr	<1yr			<1yr	
	2011	<1yr			<1yr	1.5yr		3yr	<1yr
	2012	<1yr			1.5yr	10yr	3yr	<1yr	
	2013	<1yr		2yr	<1yr		3yr	<1yr	
	2014	<1yr			<1yr			2yr	<1yr
	2015	<1yr			1.5yr	<1yr		<1yr	
	2016	<1yr							
	2017	<1yr					2yr	<1yr	
	2018	<1yr	2yr	10yr	10yr	<1yr	<1yr		

Figure 31: Impact-based trigger systems for Katakwi that could be applicable for sector-specific decisions

	Model 1	
Impact-based model		
	Impacts	No impacts
Forecast	Hits (9)	False alarm (0)
No forecast	Miss (3)	CN(3)
POD (0.75)	hits/(hits+misses)	
FAR (0)	False alarm/(hits+ false alarm)	

	Model 2	
Impact-based model		
	Impacts	No impacts
Forecast	Hits (8)	False alarm (0)
No forecast	Miss (4)	CN(3)
POD (0.67)	hits/(hits+misses)	
FAR (0)	False alarm/(hits+ false alarm)	

	Model 4	
Impact-based model		
	Impacts	No impacts
Forecast	Hits (6)	False alarm (0)
No forecast	Miss (5)	CN(3)
POD (0.54)	hits/(hits+misses)	
FAR (0)	False alarm/(hits+ false alarm)	

Figure 32: Evaluation results for the three impact-based trigger systems

Table 23: Trigger dates for the various impact-based models

Trigger dates for the impact-based model, 60-70% FP, varied thresholds, 5 days LT							
Model 1	Trigger dates	Model 2	Trigger dates	Model 3	Trigger dates	Model 4	Trigger dates
2007	4th July	2007	4th July	2007	4th July	2007	4th July
2007	5th August	2007	5th August	2007	5th August	2007	5th August
2007	9th September	2007	12th September	2007	12th September	2007	9th September
2011	5th September	2012	1st July	2012	18th July	2011	5th September
2012	1st July	2012	1st August	2018	23rd May	2012	18th July
2012	1st August	2013	22nd August			2018	23rd May
2013	22nd August	2017	12th August				
2017	12th August	2018	23rd May				
2018	23rd May						

4.3.2 Discussion

The new paradigm shift from hazard-based to impact-based forecasting would ensure that users and communities have access to the forecasts and advisories on the likely impacts of any extreme threatening event. Although the objective is to implement effective preparedness measures at the community level, locally customised EWI will be required due to the context-specific needs and priorities among communities (Bailey, Hassan and Dhungel, 2019). Therefore, local contextual information plays a crucial role in improving the trigger models by ensuring that household-level anticipatory actions are designed. In the three systems in Figure 31, we note that the POD improves when the trigger thresholds are lowest during the harvesting period. In addition, all the models have no false alarms, which means the forecast data has the skill of detecting flood events.

Most countries, including Uganda, are already implementing the EAPs for floods. Therefore, to ensure that the existing FbA approach is maintained, the system could be implemented in a phased process within the current FbA initiatives. First, the traditional trigger development framework could be followed by humanitarian agencies to develop the EAPs; next, adjusted thresholds and low-regret actions proposed based on the additional local information could be embedded into the developed EAPs. For example, lowered flood thresholds could be considered in a particular area and season to ensure minimised impacts even during periods when the pre-defined thresholds are not reached but impacts and vulnerabilities are high. For example, in Katakwi, forecasts that show a high likelihood of a 2-year flood can be used to trigger low-cost anticipatory actions by local disaster managers in consultation with the Red Cross and other humanitarian organisations through institutional disaster management plans. The DREF funding can then be activated if there is a likelihood of the 5-year return period flood per the EAP guidelines. The system can also be applied across other disasters to test its applicability in informing the design of local actions.

Chapter 5

5 Conclusions

The aim of the research in the context and as part of the NIMFRU project was to improve the targeting and communication of flood early warning information and response to support decision-making and enhance national resilience. The advancement in science and technology has contributed to more improved forecasts information. The forecast information has, however, not been effective in informing local decisions, especially in the Global South countries. As the frequency and severity of hydrometeorological events increase, early warning systems that integrate local information are required to protect the most at-risk communities.

This thesis has enhanced research and practice in redefining EWSs through community-led approaches that allow more sustainable and locally targeted EWSs. More specifically, the thesis employs a multi-disciplinary approach that focuses on improving the main components of a people-centred EWS through three main objectives:

1. Identify the barriers and opportunities in the production/provision and use of flood early warning information for flood risk preparedness.
2. Assess the usefulness of impact data relative to river gauge observations in verifying flood forecasts in data-scarce regions.
3. Develop an impact-based flood early warning system for rural livelihoods using an impact-oriented approach.

This thesis was structured around these objectives and explored through various methods, including community and disaster practitioners' engagements, forecast evaluations, and an impact-oriented approach. The thesis presents three first-author papers, two are published, and the third one is accepted for publication and its under production, and a summary connecting sub-sections within each result chapter.

This chapter outline the key conclusions from each objective, the wider contribution of the research in scholarly literature, sources of uncertainty and scope for the next steps.

5.1 Key conclusions

5.1.1 Objective 1: Identify the barriers and opportunities in the production/provision and use of flood early warning information for flood risk preparedness.

The first objective of this thesis was addressed in Chapter 2. The use of EWI among local communities has not been effective. Scholarly literature notes that this has been because of the information usability gap that affects the provision of useful and usable information. Developing useful and usable information depends on context-specific factors such as the information needs, coping practices, and the capability of both the information providers and the users. The first objective of this thesis was to identify such barriers that hinder the effective provision of EWI and the actual use of the provided information to inform coping at the community level as well as opportunities to improve usage. The objective is addressed through **a bottom-up approach that ensures connections between the information providers and the communities** for a better flow of information.

Chapter 2 presents **a more coordinated institutional response approach useful in identifying these barriers and opportunities in a context-specific setting across the provider-user landscapes.** The barriers in the provision and use of EWI identified in the context of Uganda are consistent with other similar scholarly literature. However, context-specific solutions will be required to bridge the gap. Our findings identified unique opportunities to improve EWI provision and use. These include the need to understand the **data gaps by assessment of the various data dimensions,** fostering **data collaborations across institutions**, **assessing the information needs and use capability at the user level**, and **tailoring EWI to the local needs and coping strategies** of the users.

Increased availability of EWI does not necessarily translate to increased use. Improving the uptake of EWI, especially among local farmers, will require the **development of actionable programmes that integrate information from these communities** and are embedded in disaster management plans and processes. The local information can also be useful in improving three components of a people centred EWS. First, the information needs, and the coping practices identified provide knowledge on the farmers' risks **due to flooding and what activities they undertake to avert the threats**. Secondly, findings on the current format of weather information, dissemination language, and timing provide information that can be used to **improve EWI format, targeting, and communication channels**. Thirdly, factors that affect the actual use of EWI by local farmers, such as lack of required farm inputs, financial difficulties, and the data gaps from the providers' context, provide information that is **useful in informing the current disaster preparedness and response capabilities across the provider-user landscapes.** In addition**,** ways to improve preparedness, such as providing subsidised farm inputs and pre-staging data required during the preparedness, are noted.

5.1.2 Objective 2: Assess the usefulness of flood impact data relative to river gauge observations in verifying flood forecasts in data-scarce regions.

The first objective (Chapter 2) shows that barriers to providing useful EWI are context specific. One of the barriers identified in the Ugandan context is the lack of a national flood forecasting and warning system. This means that the required EWI to inform local decisions is often not available. However, like many other data-scarce countries, Uganda still requires reliable forecasts to inform early actions and reduce the impacts of extreme events. Therefore, the second objective of this thesis was to assess if impact data can be used to verify flood forecasts from global systems to build confidence in their use in informing practical anticipatory actions. The objective is addressed through a **forecast verification comparative analysis using flood impact data and river-gauge observations.**

The **adequacy of flood impact data varies across locations**. This chapter has provided **information on the adequacy of flood impact data** across several districts and counties in Uganda and Kenya. Findings show that the impact data (quantity and quality) are insufficient **to verify flood forecasts in most locations** where verification was done. Nevertheless, the data can be **useful in defining the danger thresholds** at which flooding might occur. However, there is the need to state the **uncertainties while using the impact data** to ensure that stakeholders know the likely implications of using the outputs to inform decisions.

The role of less conventional data, such as impact data, in forecast verification has already been recognised through the WMO Joint Working Group on Forecast Verification Research program. Therefore, these data can potentially **improve early warning mechanisms, especially in data-scarce regions**. Based on our findings, various recommendations have been made to improve the usefulness of impact data. For example, **strengthening the collection of quality impact data at the country level, using new technology, and harmonising the existing impact data** can ensure that the forecast verification outputs are more acceptable. In addition, these impact data **provide local context information, which can be used as a baseline in impact-based forecasting**.

Forecast verification should take into consideration sector-specific early actions. Stakeholders in disaster management should therefore be allowed to develop a criterion that identifies the preferred forecast features across each early action. This will ensure that **optimal forecast features** (lead time, the margin of error, forecast probability, etc.) at which specific actions are effective are used in the verification to improve the skill of the forecasts. Although the outcome of the forecast verification using impact data is not favourable across all the locations, **the assessment provides a possible way to validate forecast verification using river-gauge observations, especially in data-scarce regions.** The findings contribute to two components of a people-centred EWS through the provision of flood impact data collected at the local level, which adds to risk knowledge, and through verification of forecasts from global systems, which builds on the forecasting and warning component.

5.1.3 Objective 3: Develop an impact-based flood early warning system for rural livelihoods using an impact-oriented approach.

The first objective of this thesis has shown that the information needs of local at-risk communities are context-specific, which would require tailored EWI to ensure adequate preparedness to flood risks. We have also gained perspectives from the second objective on the usefulness of local flood impact data to verify forecasts and inform the development of early warning and action mechanisms. Objective 2 also shows that local impact data, though insufficient on their own, can be used to validate impact-based early warning systems. The need to provide EWSs tailored to the local context has motivated the third objective to develop a flood impact-based system for rural livelihoods. The objective is addressed **by integrating flood forecasts with local information through an impact-oriented approach.**

Local context information can enhance hazard-based systems by providing information on the likely impacts of any upcoming event. Integrating the information with forecasts would allow a variable threshold across the different early actions and the **design of**

household-level anticipatory actions. The development of an impact-based early warning trigger system should consider sector-specific decisions as this will inform the choice of the thresholds. For example, from a humanitarian perspective, a system that reduces the number of actions triggered by only focusing on high-impact events is desired. In contrast, a livelihood perspective would require an impact-based system that **reduces the number of missed events while considering the need to build resilient communities**.

The impact-oriented approach allows **impact-based early warning systems to be developed through stakeholder consultations**. Therefore, the approach **benefits data-scarce regions through robust early warning mechanisms.** However, validation of an impact-based early warning system using impact data should be done with caution since the **quality of these data varies greatly across locations, as found in Chapter 3**. The findings should also **open dialogues on how the outputs can be used effectively to inform actions at the local level**. From our results, we further provide recommendations on if the local information should be integrated into the existing hazard-based system for Uganda. The findings also contribute to three components of the end-to-end EWS. First, the use of local impact information contributes to risk knowledge. Second, the developed impact-based system contributes to the forecasting and monitoring component, and last, the design of targeted anticipatory actions contributes to the response capability component.

5.2 Contributions to Scientific Literature

The recent recommendation from WMO to shift to impact-based forecasting calls for more focus on the consequences of extreme hydrometeorological events to the most at-risk communities. This means focusing on all four components of a people-centred EWS while considering context-specific needs and priorities (Figure 1). In undertaking this research, the three results chapters addresses various gaps in the development/ utilisation of EWS/EWI to inform local context decisions. Figure 33 provides a summary of how the three chapters are connected to each other into a more cohesive thesis and the key contributions both at the case study level and with relation to scientific literature. Notably, the thesis contributes to literature in three main areas; climate services, forecast verification and impact-based forecasting. These contributions are described below.

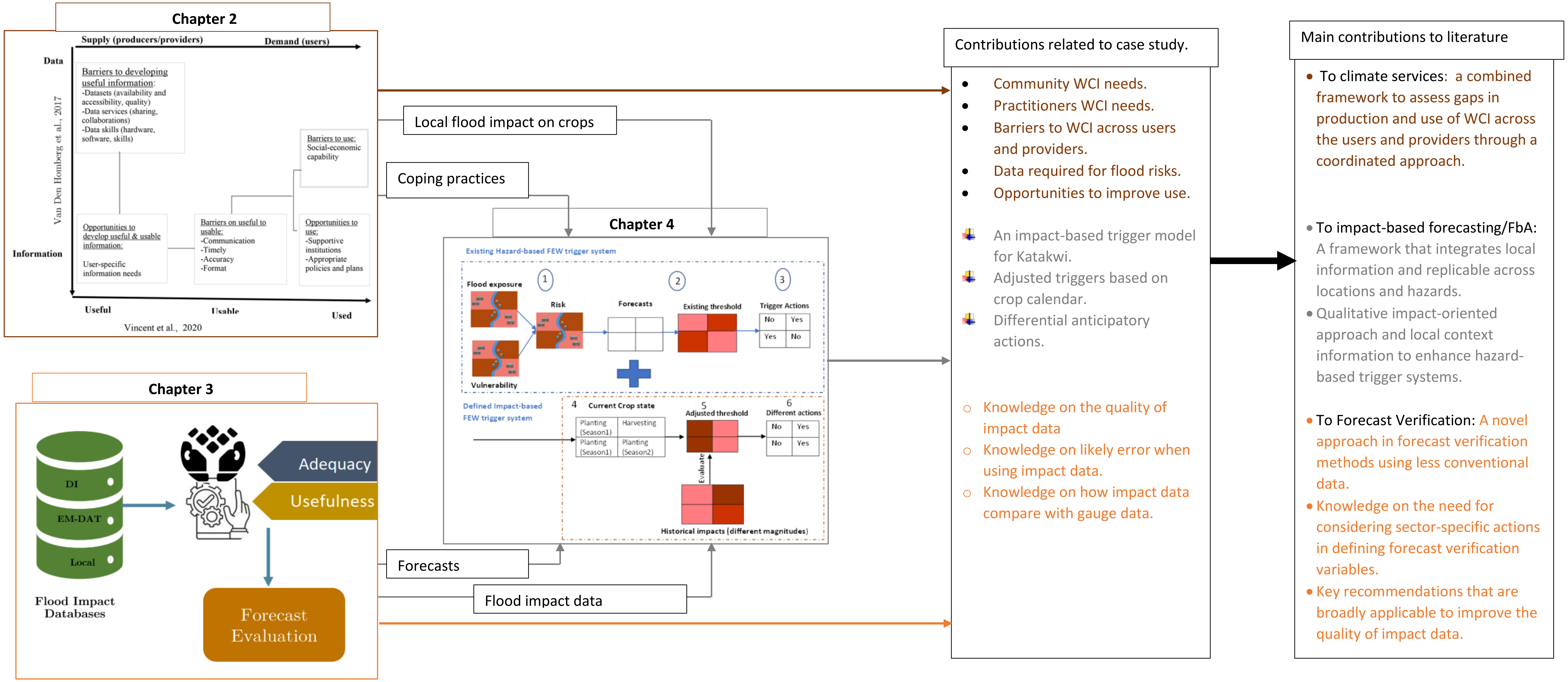

Figure 33: Diagram to illustrate the connection between the results chapters and key contributions to the case study and to the scientific literature. Source: developed by the author

5.2.1 Contributions to Climate Services (CS)

In the last decade, a lot of advancement has been seen in the field of climate services where scholarly literature has focused on addressing various components of climate services such as benefits of CS (Amegnaglo *et al.*, 2017; Hansen *et al.*, 2019; Naab, Abubakari and Ahmed, 2019), the need to identify user needs(Coulibaly *et al.*, 2015; Carr *et al.*, 2019) , barriers to use (Flagg and Kirchhoff, 2018; Ouedraogo *et al.*, 2018), the CS information usability gaps (Lemos, Kirchhoff and Ramprasad, 2012; Vincent *et al.*, 2020) and co-production (Lemos *et al.*, 2018; Vincent *et al.*, 2021). Despite such progress, effective use of climate services has not been realised. This has been attributed to various factors including the perceived needs of the users when developing such services as well as the nature of the information disseminated (technical formats and languages).

The framework by Vincent *et al.* (2020) describes the various gaps that affect the use of climate services. This framework builds on the work by (Lemos, Kirchhoff and Ramprasad, 2012) on the information usability gaps and provides guidelines for consideration to closing the gap. This thesis (Chapter 2) further builds on the work by Vincent *et al.* (2020) by combining their framework with the framework by Van Den Homberg, *et al.*, (2017) to provide a holistic and coordinated approach applicable in ensuring gaps in CS are identified across not only the users (as seen in various literature) but also the providers of such information. By extending the framework to providers, the thesis shows that effective CS information use will also depend on the capabilities of the providers to develop useful information and tailor it to usable information based on the user-needs.

The thesis also contributes to the literature on identifying specific users' needs by giving voice to the local at-risk communities. Notably, the thesis findings on barriers to developing useful flood risk information are similar to Lumbroso. (2018) who found out that factors around limited financing, lack of coordination among institutions and limited accessibility of data and information among others affects the provision and use of flood early warning information. The study by Jennifer. (2018) however contradicts our fundings especially on the timeliness of early warning information disseminated to the local communities where in her study, the timeliness of information was rated as good while this study found out that information delivery is not timely which affects the undertaking of the coping practices.

5.2.2 Contributions to Forecast Verification.

Traditionally, forecast verification is often based on conventional observations such as river-gauge and rain-gauge data (for the case of floods) among others. This means that in data scarce areas, forecast verification efforts are limited. Scholarly literature on forecast verification has focused on the traditional verification methods and the benefits of forecast verification (Nidumolu *et al.*, 2020; Paparrizos *et al.*, 2020; MacLeod *et al.*, 2021). By the time of writing this thesis, there was no scholarly literature that had been published on the application of non-traditional approaches in flood forecast verification.

Efforts to use less conventional observations are being supported through the WMO joint working group on forecast verification. The working group supports research geared towards development of new verification metrics through the application of non-traditional approaches. This Thesis contributes to the scholarly literature on forecast verification by providing a novel approach in the verification of flood forecasts using impact data (Chapter 3). The methodology developed would ensure that flood forecasts for any data scarce location can be verified and the outputs used to inform local decisions. In addition, the work won the WMO award on the best new metric for forecast verification which builds confidence in the replication of the methodology to support anticipatory actions.

The thesis (Chapter 3) also contributes to the general knowledge on the factors that need to be considered in forecast verification to address sector specific decisions. The findings therefore contribute to the scholarly literature on the optimisation and sensitivity analysis of early action protocols (cost, time, quality of forecasts) on the forecast-based actions (Bischiniotis *et al.*, 2019; Lala *et al.*, 2021) by assessing the implication of varying the action lifetime in forecast verification to inform specific action.

Consequently, the thesis provides broad recommendations to improve impact data that are applicable across context. The thesis collated impact data from various global repositories and analysed them to identify the gaps that affects the use of the data hence building on existing literature (Gall, 2015; Harrison *et al.*, 2022). Therefore, although the analysis only focused on two countries, the recommendations provided are broadly useful in informing the improvement of impact data for subsequent verification or for impact-based modelling.

On a practical perspective, based on the Conference of Parties (COP) 27 outcome, credible impact data will be required to inform the allocation or compensation based on the damage and loss funds. These recommendations can therefore be used as a steppingstone towards ensuring countries are able to collect and manage impact data of required quality (Guha-Sapir and Below, 2002).

5.2.3 Contribution to Impact-based Forecasting and Forecast-based Action.

Impact-based forecasting is often conceptualised and undertaken through quantitative approaches. Such approaches require quantified information on vulnerability, exposure and impacts to develop impact-based models. This means that data scarce regions are disadvantaged in the development and implementation of such systems.

Scholarly literature on impact-based forecasting has advance in the recent past following the 2015 declaration by WMO on the need to provide impact-based warnings. However, most of the impact-based systems are being researched and implemented in the Global North countries (Dottori *et al.*, 2017; UKMet Office, 2019; Hemingway and Robbins, 2020; Ritter *et al.*, 2020). The development of IbF in the Global South countries has been hindered by data scarcity (risk and impact information). This thesis (Chapter 4) shows that these countries can still benefit from IbF systems developed through qualitative approaches. Scholarly literature has assessed the practical implementation of the IbF (Kaltenberger, Schaffhauser and Staudinger, 2020), gaps in data use for IbF (Harrison *et al.*, 2022), as well as the perception of IbF among users and decision makers (Weyrich *et al.*, 2018; Potter, Harrison and Kreft, 2021). Recently, a framework for drought that uses real time expert judgement to decide on triggers was developed (Boult *et al.*, 2022). This thesis builds on the existing literature of IbF by developing a novel framework that qualitatively integrates flood forecasts with local risk information for operational triggering of anticipatory actions. Furthermore, the system can be replicated for any rapid onset hazard at any location.

The development of trigger systems has been focused on predefined trigger threshold derived from forecasts and pre-agreed anticipatory actions (Coughlan De Perez *et al.*, 2016; Wilkinson *et al.*, 2018). This means that low magnitude flood events which can still result to significant impacts may be excluded (Potter, Harrison and Kreft, 2021). The thesis (Chapter 4) contributes to the existing literature on forecast-based actions in the development of tailored impact-based trigger systems. The findings show the relevance of local information and how they can be integrated to adapt global hazard-based forecasts to local context to ensure that thresholds are flexible and anticipatory actions are better targeted. Ensuring that we move from ‘one size fits all’ warnings to impact-based warnings. In addition, the findings contribute to general knowledge on forecasts features and the importance of considering sector-specific actions and decisions in identifying optimal forecast features that can affect the design of a trigger system- building on anticipatory actions optimisation literature (Lopez *et al.*, 2020; Lala *et al.*, 2021).

From a practical perspective, the findings in Chapter 4 are useful in informing the current development of the flood trigger system in Uganda. Notably, the findings can be embedded in the existing trigger system to ensure that floods that are at a lower magnitude are monitored, and low cost/ no regrets actions triggered only during critical time to reduce impacts on the crops.

5.3 Sources of Uncertainty that may have affected the findings in the thesis.

Uncertainty in research may arise because of limited accuracy in the data, observations, and methods in the research process. Acknowledging any uncertainty that may have affected the outputs is therefore important. Some of the known sources of uncertainty include, measurement errors, sampling error, bias, model error and external factors. Errors resulting from measurement of data can further be classified as missing information/data, conflicting information, unreliable information, or noisy information.

This thesis acknowledges the various sources of uncertainty that may have resulted to the findings. In Chapter 2, the data collection process targeting the disaster management practitioners included only 14 institutions. The generalizability of the outputs based on only 14 institutions could therefore be biased. More interviews with other players in disaster management could be undertaken to ensure that the findings can be further validated. Qualitative approaches of data analysis are subjective which can lead to biased outputs. To ensure reliability, the thesis employs various methods used in minimising bias such as visual representations and text query (section 2.2.2.3). In addition, the thesis in Chapter 2 used direct phrases/words from the respondents in the coding process to avoid misinterpretation.

In Chapter 3, data from various sources was used. First the river-gauge observations could have been subject to measurement error especially if the methods used by the data collectors was flawed. There was also a lot of missing information in the river-gauge data which could have introduced uncertainty in the analysis (comparative and verification). Although the research only used the available gauge data, the length of the time-series was short for most of the locations which could have affected the outputs. A way around this problem is the use of longer time-series of river-gauge observations in the comparative analysis and in forecast verification.

Second, the impact data collated from various data repositories could have been subject to uncertainty due to the criteria used in the collection and management of these data. For example, DI data is collected and uploaded by national institutions. However, it was apparent that there are no clear in-country procedures or guidelines to guide the data collection process. The process could therefore result to poor quality data getting into the repositories and its use resulting to uncertainty in the findings. The variations in the criteria used can also result to uncertainty. For example, data from most of the repositories was aggregated and it was not possible to differentiate impacts from the various types of floods. Most of the study catchment experience both flash floods and riverine floods (section 3.2), the lack of differentiation in the impact data could therefore have resulted to high type II errors in the analysis (section 3.3.4.2). This thesis in Chapter 3 provides recommendations that can be adopted to improve the quantity and quality of the impact data and make them more reliable.

Third, the flood forecasts data used in the verification could have been subject to model and measurement errors emanating from the hydrological and forecasting models used as well as the weather data used in the analysis. This means that, it is not possible to know how accurate the forecast was before using appropriate methods to assess the accuracy. Although this thesis did not assess the forecast accuracy, it would have been important to consider the accuracy of the forecasts before assessing the usefulness of the two reference datasets in forecast verification. That way, it would have been easy to ascertain the sources of error in the findings.

In Chapter 4, uncertainty could have resulted from the qualitative approach used in developing the trigger system. The approach was subjective in the selection of varying trigger thresholds and probably could have resulted to a different set of findings if it was done by a different researcher. The author however has acknowledged the subjectivity of the approach and recommended that the use of the findings should be subject to consultations with the relevant stakeholders.

Uncertainty can also occur because of external factors. for example, climate variability can introduce changes in the various variables especially the hydrometeorological parameters used in forecasting. This means that there is need for continuous monitoring and verification of forecasts to ensure that the changes do not result to a major variation in the overall outputs being used for decision making. For example, in Chapter 3, the thesis looks at the usefulness of impact data in forecast verification. Climate variability may result to changes in the forecasts and the resulting impacts (e.g., same magnitude, more impacts due to climate variability). Continuous verification would therefore be required. Consequently, in Chapter 4, the developed trigger model will require continuous monitoring and validation with in-situ information to ensure that the model reflects the realities (impacts of the events based on changes in social vulnerability) and it's still useful in informing local decisions.

5.4 Next Steps

The research findings in this thesis contribute toward developing an impact-based flood early warning system for Uganda based on local context-specific information. While significant progress has been made, including identifying the local WCI needs, verifying forecasts, and developing an impact-based system for Katakwi, the research also identified gaps that motivate further work to enhance the development of locally targeted flood EWSs. In addition, the identified gaps would ensure that the research can be replicated or extended across contexts. The following research gaps have been identified.

- In the Katakwi district, our findings show that the extent to which FEWI is used to inform coping practices is further hindered by the socio-economic capabilities of at-risk communities. Future work could undertake a comprehensive analysis of these capabilities to provide information that can be used to prioritise support among the most vulnerable communities. The NIMFRU project has already developed methodologies that can be used to map out these social-economic capabilities across contexts (see Petty et al., 2022).

- The community information needs and gaps identified can only make a difference if they are mainstreamed in the development of disaster management plans. This is because disaster managers at all levels need to be aware of the current gaps and solutions to improve coping among the local communities. The next step could be a study of the existing disaster management plans at the national and district level and how findings from this thesis can be useful in shaping local interventions.
- Forecast verification using impact data has been used for the first time in this thesis. Therefore, being a novel approach, it would be of interest to extend this method to other data-scarce regions in Africa to assess the applicability of these non-traditional approaches and less conventional data in forecast verification.
- Some of the recommendations for improving flood impact data, such as strengthening in-country data collection, creating awareness, and capacity building, can be further pursued by identifying gaps in data collection. For example, the institutions that collect and populate the DesInventar database could be trained on the approved guidelines and methods. The UNDRR office has already developed methods to help national institutions improve the collection, access, and use of disaster loss and damage data (see Fernando *et al.*, 2020).

- The use of new technology to expand impact data, including text mining (Margutti and Homberg, 2020) and social media(Thompson *et al.*, 2021), could be explored and considered for the data-scarce regions in Africa to improve the quantity and quality of the existing impacts data.
- The choice of the forecast features to inform forecast verification and development of impact-based trigger systems are context-specific and will vary depending on various factors (early actions, type of sector, etc.). Future developments to improve the verification and development of these systems could include the prior development of a sector-specific decision-led criterion which can be undertaken through stakeholders' consultations.
- Investigation of the associated benefits of lowering the trigger thresholds and the losses avoided if the actions materialise could be undertaken to ascertain if it makes any economic sense to tailor EWS and anticipatory actions to the local context.
- The impact-based flood early warning trigger system was developed using local information from Katakwi as a proof of concept. However, the system could be extended

to other locations/contexts to assess the value of contextual information in redefining the development of EWSs for more tailored anticipatory actions.

- The development of such a trigger system for operational purposes can be explored through the existing FbA initiatives. For example, many countries in Africa and Southeast Asia are implementing EAP for different disasters such as cyclones, flood and drought. Local information collected from the at-risk communities can therefore be integrated into the EAPs such that every time there is a new forecasts, the necessity to trigger using the forecast is further checked by incorporating the available local information (such as the time of the year, livelihood activities, etc). The resulting information can then be used to inform decisions on varying the trigger threshold and the anticipatory actions.

5.5 Closing Remarks

This thesis presents research that has provided information on how to holistically improve the use of EWI at the local level and how context-specific information can be used to redefine the development of locally targeted EWSs. Significant improvements have been made in forecasting science. Still, effective use of EWI to inform early actions will require more information on how at-risk communities cope and respond to extreme events. As the field of disaster risk management moves toward impact-based forecasting, the need for more tailored EWI will increase as at-risk communities demand this to inform their coping practices. Due to the lack of comprehensive risk information, more challenges are also likely to be experienced in data-scarce regions. Approaches that can still benefit the at-risk communities by ensuring early warning mechanisms are in place are essential. Although these research findings provide the potential to inform decision-making in a range of sectors, including disaster management and agriculture, more work is still needed to make these outputs actionable in practice. Notably, effective communication and advocacy would be required to ensure decision-makers in these sectors can interpret and use the information to bridge the gap between science and practice. For operational purposes, more collaborations with at-risk communities will be required to ensure that the required local information is collected and integrated with forecast to inform context-specific anticipatory actions. The Disaster Management practitioners also need to see the value of such local information and how they can be used to redefine the development of EWSs to ensure all are protected.

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Appendix

This appendix contains the typeset version of the published section (Chapter 2, section 2.2, Chapter 3, section 3.3) and other supplementary materials supporting Chapters 2, 3, and 4.

Appendix A2: Published article on section 2.2 and supplementary materials for Chapter 2

Appendix A2.1- Published article (section 2.2)

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Identifying the Barriers and Opportunities in the Provision and Use of Weather and Climate Information for Flood Risk Preparedness: The Case of Katakwi District, Uganda

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The provision of weather and climate information (WCI) can help the most at-risk communities cope and adapt to the impacts of extreme events. While significant progress has been made in ensuring improved availability of WCI, there remain obstacles that hinder the accessibility and use of this information for adaptation planning. Attention has now focused on the "usability gap" to ensure useful and usable WCI informs practise. Less attention has however been directed on barriers to the active production and use of WCI. In this study, we combine two frameworks through a bottom-up approach to present a more coordinated institutional response that would be required to ensure a better flow of information from information providers to users at community level and vice versa. The bottom-up approach was designed in form of Farmers Agri-Met Village Advisory Clinics (FAMVACs) and Listening Groups (LG) and was initiated by Uganda Meteorological Authority (UNMA) as a way of ensuring connections between the information providers, the disseminators, and the communities to specifically give voice to the communities to provide feedback on the use of WCI in coping with flood risks. This approach is used to identify the barriers and opportunities in the production/provision and use of WCI for flood risk preparedness for a case study in Eastern Uganda. First, a use-case is developed for Katakwi District where smallholder farming communities have recorded their coping practises and barriers to the use of WCI in practise. Second, online interviews with practitioners from disaster management institutions are used to identify barriers to the production and provision of WCI to local farming communities. Findings show that for providers, barriers such as accessibility and completeness of data hinder the production of useful WCI. In situations where useful information is available, technical language used in the format and timeliness in dissemination hinder usability by local farmers. Useful and usable WCI may not be acted on in practise due to factors such as costs or market availability e.g., lack of access to improved seeds.

Further, the study highlights possible solutions to bridge the identified gaps and they include capacity building, fostering data collaborations across sectors, data translation to simple advisories, among others. The study also presents the FAMVACs approach which shows the importance of a more coordinated response with a shift of focus from the users of information only, to a more inclusive understanding of the data and information gaps across the wider provider-user landscapes. We argue that this would contribute to more effective disaster management at both the national and local levels.

Keywords: community information needs, weather and climate information, smallholder farmers, information providers, flood risk management

INTRODUCTION

Weather-driven shocks such as floods are becoming more extreme and frequent in many regions across the world (IPCC, 2012). Rural at-risk communities suffer the worst impacts from these extreme events because of their dependence on natural-based livelihoods (Pricope et al., 2013). Provision of Weather and Climate Information (WCI) can help these communities cope and adapt to the impacts of these extreme events (Roudier et al., 2016; Amegnaglo et al., 2017; Hansen et al., 2019). This is because WCI can inform appropriate actions to improve preparedness and reduce impacts (Jones et al., 2015). For example, scholarly literature notes that farmers who have access to timely WCI can plan their livelihoods activities for example when and what to plant, and appropriate farm management activities that may result in reduced impacts (Coulibaly et al., 2015; Naab et al., 2019).

Significant efforts and advancements in technology have resulted in increased availability of WCI (Dinku et al., 2014; Hewitt et al., 2020). However, this has not translated to improved accessibility, especially across user groups (practitioners and communities) in Africa where varied access to WCI is noted (Dinku, 2019; Vaughan et al., 2019). In addition, even if WCI is available and accessible, this does not necessarily mean the information is used to inform local decisions as it may not address the information needs of specific users (Vaughan and Dessai, 2014; Naab et al., 2019). These obstacles, commonly termed as information “usability gap” (Lemos et al., 2012) have been identified as major impediments to the use of WCI to inform climate-related decisions at all levels (Flagg and Kirchhoff, 2018; Ouedraogo et al., 2018).

In their study, Vincent et al. (2020) developed a framework that highlights three components that would enable closing the information usability gap and promote the use of WCI for climate risk management. These components have been broadly categorised as “useful” information which requires an understanding of the specific users’ needs and their decision-making contexts to guide in identifying what information is useful (Carr et al., 2019), “usable” information if it’s understandable by the intended user and is disseminated on time (Tembo-Nhlema et al., 2021) using appropriate communication channels (Barihaihi and Mwanzia, 2017) and an “enabling environment” such as supportive institutions (Vaughan et al., 2017) to ensure that useful and usable information gets used in practise.

The Vincent et al. (2020) framework builds on the climate services literature including Lemos et al. (2012) framework on bridging the information usability gap. In addition, it builds on the understanding that climate information use broadly links the user and the producers by knowledge sharing and collaborations through avenues such as co-production (Vincent et al., 2021). The three components, therefore, reflect both the supply and demand side of climate services towards ensuring more informed use of WCI for adaptation planning (Jones et al., 2015).

We however note that to ensure more coordinated institutional responses (such as that which would be required pre- and post-disaster) (UN, 2015) and a better flow of information (i.e., from practitioner to community and vice versa), additional components are required. First, further, to having an enabling environment, additional support based on other underlying socio-economic factors that influence how these communities cope may be required to ensure that the at-risk communities (“users” henceforth) actively use the information provided. For example, in a rural smallholder setting, having access to usable information may not necessarily translate to use in practise due to other individual or household social-economic factors such as income, education and age (Mittal and Hariharan, 2018; Shah et al., 2018, 2020; Petty et al., 2022). Similarly, a bottom-up approach that links the information providers, the disseminators and the communities would be required to ensure that the communities have a voice to interact and provide feedback on weather information use and their coping practises.

Second, the production of useful information goes beyond data availability (Goddard, 2016) and there remain other obstacles that could hinder the potential to produce and provide useful WCI, especially in the least developed countries. Essentially, decision-makers and information producers/providers (“providers” henceforth) require access to quality and credible “scientific” data and information to be able to fulfil the information needs of the users and manage the potential risks (Hewitt et al., 2020). But the required data and information is often limited (Van Den Homberg et al., 2017) or inaccessible (Susha et al., 2017; Dinku, 2019). In their framework, Van Den Homberg et al. (2017) notes that being data-prepared can help reduce the impacts associated with extreme events if high-quality data that meets the information needs of the providers are accessible before the disaster hits. The Van Den Homberg et al. (2017) framework focuses on five main components which include; "datasets" regarding data availability and accessibility, "data services" regarding services offered and software/hardware required, "data literacy" concerning the capability to transform the data to required information, "governance" looking at legal and regulatory rules on data sharing and "networking" which involves having long-term data collaborations. These components collectively would ensure that the lead institution for example, in disaster management has all the required data and information beforehand to guide disaster-related decisions.

In this study, we combine the two frameworks (Van Den Homberg et al., 2017; Vincent et al., 2020) through a bottom-up approach to present a more coordinated institutional response and flow of information. The bottom-up approach was designed in form of Farmers Agri-Met Village Advisory Clinics (FAMVACS) and Listening Groups (LG) and was initiated by UNMA as a way of ensuring connections between the information providers, and the communities to specifically give voice to the communities in contrast to the top-down approach (see Ciampi et al., 2019). This would allow better characterisation of the barriers that hinder effective provision and use of WCI across the provider-user landscapes as well as opportunities for improving the WCI use and uptake. In the context of this paper, we use WCI to refer to all information that would be required to prepare and respond to flood risks (and they include but are not limited to information on flood impacts, flood risks, hydrometeorology, socioeconomic, etc.). We have structured the study around three questions:

1) What barriers hinder the production/provision of useful WCI in the context of the providers? How can we improve provision?
2) What opportunities/barriers support/hinder the move from useful to usable information in the context of smallholder farmers?
3) What barriers deter useful and usable information from being used in practise by smallholder farmers? What can be done to improve uptake?

The study uses a bottom-up approach. Here, the bottom-up approach allows communities to be involved from the beginning in all activities that support improved preparedness. In contrast to the traditional top-down approach in disaster management, this study allowed the flood affected communities to record their own accounts of how floods have affected them and their coping practises. Further, disaster management practitioners were also given an opportunity to provide information on how they help the at-risk communities prepare for disasters. At the local level, a case study in Katakwi district, Uganda in the context of flood risks to livelihoods is used to give voice to the smallholder farming communities to record their coping practises, information needs, and the factors that hinder them from using the WCI to inform these coping practises. At the national level, online interviews with practitioners at disaster management agencies are used to understand how these agencies respond to the information needs of the users and barriers to effective provision of the required WCI.

MATERIALS AND METHODS

In this paper, we combine the two frameworks (Van Den Homberg et al., 2017; Vincent et al., 2020) (**Figure 1**) and use them to identify the barriers and opportunities in the production/provision and use of WCI through a case study in Uganda. Two use-cases (more detailed below) are developed to help answer the research questions. We recognize that one of the barriers to the use of WCI as noted in literature is a lack of an enabling environment (Vaughan et al., 2017). However, a detailed investigation of the institutional structures and disaster/climate policies that governs how disaster management activities are undertaken in Uganda was out of scope in this paper. This section provides an overview of the study area, the use-cases, and data analysis methods.

Study Sites

Katakwi District, the focus of this study, is in the Eastern region of Uganda and lies between longitudes $33°48'E–34°18'E$ and latitudes $1°38'N–2°20'N$. Katakwi borders Napak District in the north, Nakapiripirit in the east, Amuria in the west and northwest, Soroti in the southwest, and Kumi and Ngora in the south (**Figure 2**). The landscape is a plateau with undulating slopes in specific areas and lies approximately between 1,036 and 1,127 m above sea level (KDLG, 2014). The district is characterised by two livelihood zones, i.e., crop-livestock and fishing-livestock zones. Agriculture is predominantly rain-fed with two distinct rainfall seasons from March to May and September to November. The district experiences frequent heavy rains leading to flooding, which affects crop yields (KDLG, 2014). Common crops grown in Katakwi include sweet potatoes, cassava, maize, peas, rice, groundnuts, and a variety of local vegetables.

The district was selected in discussion with NIMFRU (National scale Impact-based forecasting of Flood Risks in Uganda). NIMFRU is a project in Uganda to improve flood resilience through comprehensive flood impact assessments. The project is funded under Science for Humanitarian Emergencies and Resilience (SHEAR, 2018) program and it complements the previous SHEAR project (Forecast for Anticipatory Humanitarian Action-FATHUM) by providing a new approach that incorporates various types of information required to effectively deal with flooding. The project aim is to strengthen the capacity in interpreting and using weather and climate information, livelihood and socio-economic information among others to inform flood preparedness at all levels which would ensure improved resilience to floods (https://walker.ac.uk/research/projects/nimfru-national-scale-impact-based-forecasting-of-flood-risk-in-uganda/).

The district suffers severe impacts from floods every rainy season. The vast majority (81%) of the population in the district earn their livelihoods through subsistence

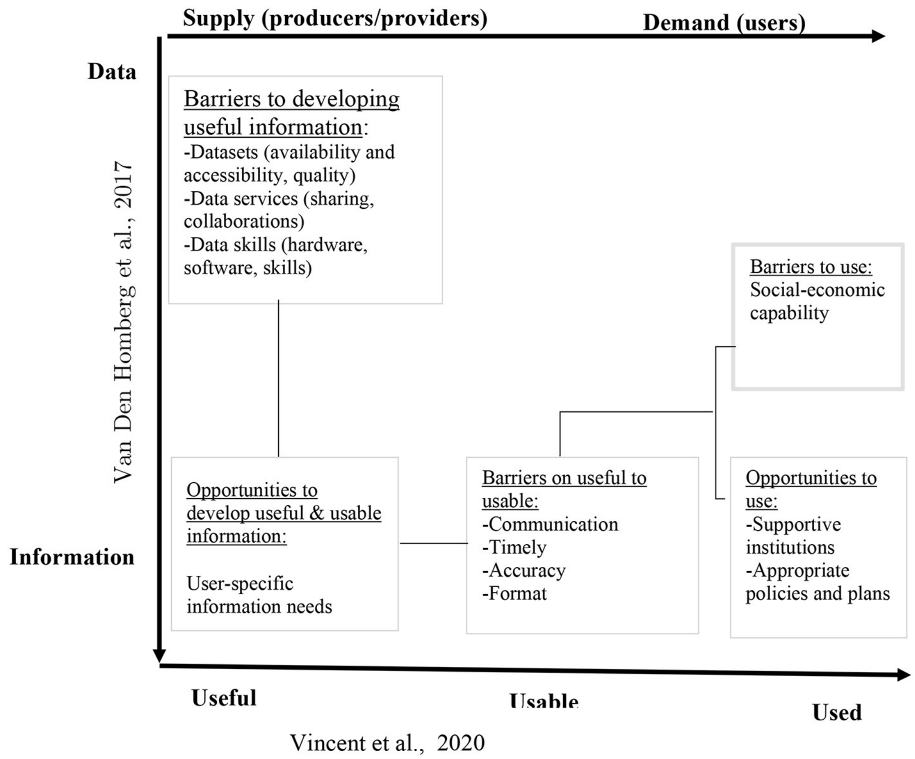

FIGURE 1 | Conceptual framework used to identify the barriers and opportunities in the production/provision and use of WCI across the provider-user landscapes. Source: adapted from Vincent et al. (2020) and Van Den Homberg et al. (2017) and modified by authors.

farming (KDLG, 2014). Poverty levels are high with 88% of the population living below the poverty line (Kagugube et al., 2017). Project stakeholders include the Red Cross Climate Centre (RCCC), National Emergency Coordination and Operation Centre (NECOC), members of Parliament, local academic institutions, and civil organisations.

Developing the Use-Cases

This study was undertaken as part of the community preparedness to flood risks initiative within the NIMFRU project (NIMFRU, 2018). As part of the Science for Humanitarian Emergencies and Resilience (SHEAR, 2018) program, the NIMFRU project set out to improve the targeting and communication of flood warnings and response to communities in the Katakwi District. To do this, the first use case targeting the flood-affected communities in three villages (Anyangabella, Agule, and Kaikamosing) in Katakwi district (**Figure 2**) was developed by the project team and used to conduct field research to gain a deeper understanding of the livelihoods, coping capacities, and practises of groups within the study communities, barriers to coping as well as their responses to flood hazards. A combination of quantitative and qualitative methodologies was used to inform this work, including quantitative livelihoods assessments, using the Household Economy Approach (HEA) (Seaman et al., 2014).

Fieldwork was carried out during the period February 2019 to February 2020. Initial work (data collected from February 2019 to August 2019) informed the creation and the representation of two interrelated communication platforms: The Farmer Voice Radio (FVR) Listening Groups, and the Farmer Agri-Met Village Advisory Clinics (FAMVACs) (Ciampi et al., 2019). The well-established FVR approach complemented the new Uganda National Meteorological Authority (UNMA) led FAMVAC initiatives, and a novel methodology was designed to ensure that both communication platforms provided a space for information needs and priorities to be identified locally. The platforms also facilitated open dialogues between community members and relevant district officials providing a "vertical" channel through which communities were able to feed their concerns and priorities directly into the Ugandan disaster response system. The methodology carefully ensured that there was relevant representation from both district and national authorities and that these initiatives were approved by NECOC and led by UNMA and the local non-governmental Organisation (NGO) Eco-Trust, to establish contextual validity, national ownership, and future sustainability. By the end of the fieldwork (February 2020), a total of 18 FAMVACs had taken place (six in each target community) with an average participation of 200 local community members, and 20 individual episodes of the FVR programme were aired reaching an estimated 67,000 people across rural Katakwi. Qualitative Field data collected from

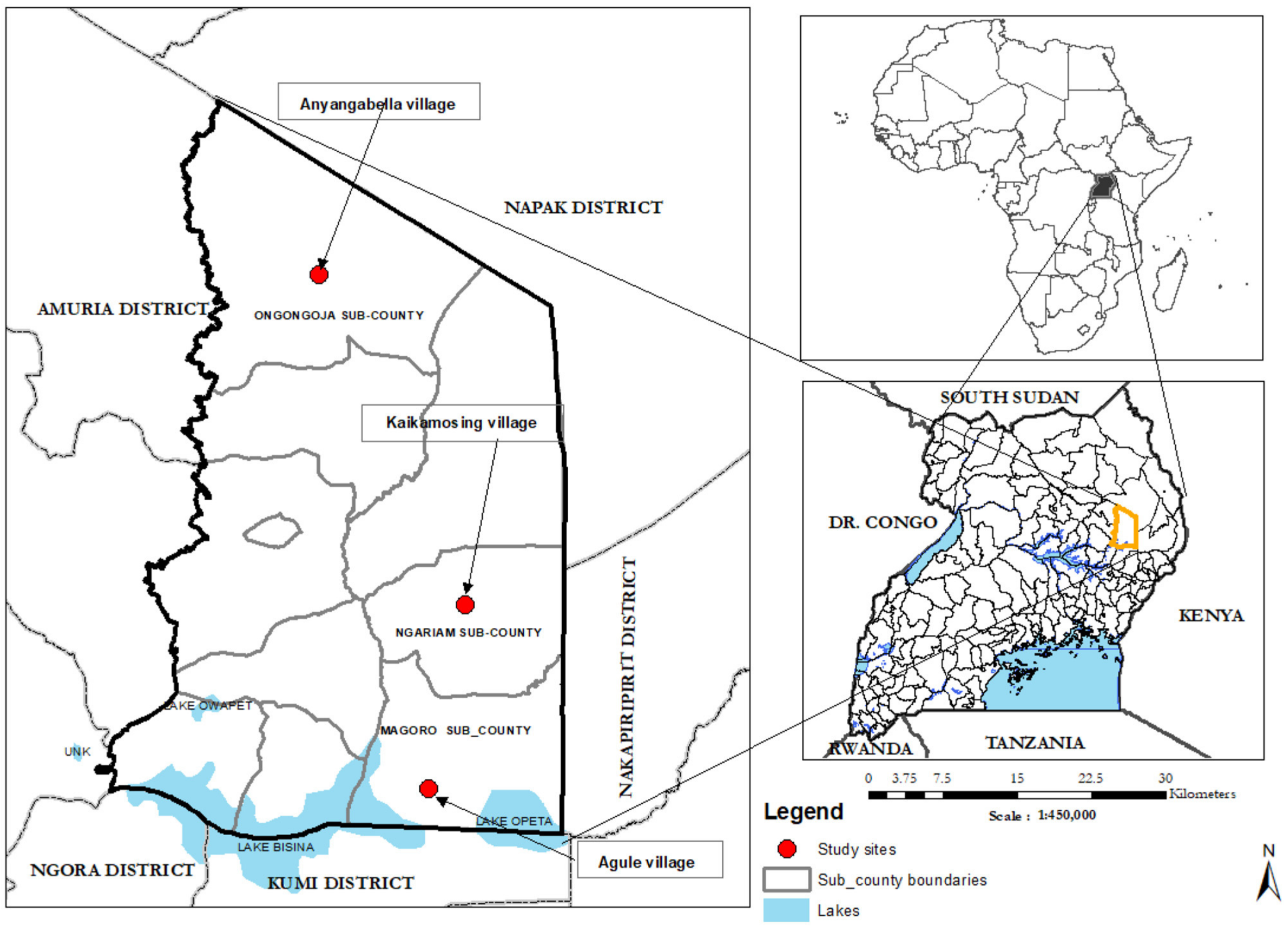

FIGURE 2 | Location of the study sites in Katakwi District, Uganda.

September 2019 to February 2020 using the developed FAMVACs methodology have been used in this paper and are explained further in the next subsection.

The second use case involved the disaster management (DM) agencies at the national level. The focus was to understand how these agencies respond to the information needs of the users, as well as to identify any gaps that hinder the effective production and provision of useful WCI. The sampling of the respondents was done through Purposive sampling techniques (Mohsin, 2016) which allowed us to choose the respondents based on predefined criteria and intended purpose. For this case, we considered national institutions and NGOs that take part in preparedness and response to natural disasters in Uganda[1]. A stakeholder mapping exercise allowed us to understand organisational roles and mandates before selecting them for interview. This exercise showed that more than 25 organisations (**Supplementary Table 1**) are involved in disaster management in Uganda. Due to Covid 19 restrictions and response responsibilities, only 14 of these organisations were available to take part in the interviews.

[1]Here, we refer to all national-level institutions who fall into any or all of these recognized stakeholders' categories (data collectors, data analysers, intermediaries, decision-makers) and are responsible one way or another in collection, analysis and production of disaster information.

Data Collection

Data collection was undertaken separately for the affected communities and the DM agencies. At the community level, fieldwork, led by Eco-trust Uganda using the FAMVAC toolkit, took place over 6 months between September 2019 and February 2020 to gather information from the flood-affected communities through farmer's discussions and semi-structured interviews (see **Supplementary Table 2** for sample interview questions). The data collection exercise took place in three villages which had been identified during the initial NIFMRU project fieldwork. We conducted 26 oral 1-on-1 semi-structured interviews with farmers in the three villages. Additionally, we held 18 farmers' discussions (six from each village) involving a large group of farmers (each farmers' group discussion consisted of ≈70 farmers). The interviews and discussions were done during the main rainy season. All interviews and discussions were carried out in the local language "Ateso" with an interpreter and were subsequently transcribed.

TABLE 1 | Institutions that took part in the online semi-structured interviews.

Name of the Institution/department	Type
1. Ministry of Water and Environment (MWE)	Government
2. UNMA-forecasting unit	Government
3. Katakwi District office	Government
4. Office of the Prime Minister (OPM)-Climate Change Department	Government
5. OPM-Disaster Risk Reduction	Government
6. MWE-Water Resources Department	Government
7. NECOC	Government
8. UNMA-Data Centre	Government
9. Uganda Red Cross Society	NGO
10. Humanitarian Open-Street Mapping Team (HOT)	NGO
11. World Vision _Uganda	NGO
12. RCCC	NGO
13. Makerere University	Research
14. Africa Disaster Reduction Research and Emergency Missions (ADRREM)	Humanitarian indigenous NGO

At the DM level, data collection took place from October 2020 to December 2020 through online semi-structured interviews. A staged process was used where first stakeholders mapping exercise was conducted based on the predefined criteria (see Section Developing the Use-cases). The second step involved sorting and identifying how many informants would be required from these institutions based on the number of departments and their roles. For example, an institution like Uganda National Meteorological Authority has both a forecasting and data centre hence more than one informant would be ideal. The third step involved contacting the institutions to provide the key informants to take part in the interviews. In total 14 institutions (see **Table 1**) took part in the interviews. Interview questions were framed around key themes such as their disaster management activities, information required, and the barriers to fulfilling the information needs of users (see **Supplementary Table 3** for sample interview questions). For anonymity, the direct quotes from disaster management practitioners have been denoted with the pseudonym Disaster Respondent (DR).

Data Analysis

The software package Nvivo 12 for MS Windows (QSRInternational, 2018) was used for the analysis of the data from the local communities and the disaster management practitioners. The Nvivo programme, unlike manual methods of qualitative data analysis, offers the user an intricate, methodical, and iterative data interrogation process (Jackson and Bazeley, 2019). Data analysis in Nvivo is done through a content analysis approach where the mode of analysis can be either inductive or deductive (Elo and Kyngäs, 2008; Mayring, 2014). The inductive approach is used when the researcher has limited or no theory on the research outcome (Mayring, 2014) and entails letting the themes emerge from the raw data, while directed by existing components of the study (Harding, 2018). The deductive approach is based on a predetermined structure guided by previous findings, literature review, or an existing conceptual framework (Hsieh and Shannon, 2005; Mayring, 2014). In this study, we base our analysis on a combination of existing literature and frameworks on climate services and data preparedness (Van Den Homberg et al., 2017; Vincent et al., 2020) (see **Figure 1**) in a case study context hence the deductive content analysis approach is used to analyse our research data.

Deductively, the following steps were followed. First, the categorisation matrix based on themes from the framework presented in **Figure 1** was developed. For this case, an unconstrained matrix was used to allow any other emerging concepts to be captured (Elo and Kyngäs, 2008). **Table 2** shows the themes used in the categorisation matrix based on our research aim. Second the familiarisation phase was conducted. This involved reading through the transcripts to become aware of the ideas and words used by the respondents before coding. We then reviewed all the transcripts and coded them into the corresponding themes while also allowing the inclusion of any other emerging categories (Elo and Kyngäs, 2008). For information that did not fall into any of the existing themes, coding was done using words and phrases that the respondents used in their transcripts which ensured minimal misinterpretation. Coding was done separately for the community interviews and the disaster management interviews. However, the same themes were used.

To ensure trustworthiness, the analysis process has been explicitly explained and the themes used are supported by existing literature. The data has also been explicitly linked to the results from the analysis. In addition, to ensure validity of the coding process, two approaches have been used; visual representation (Siccama and Penna, 2008) and data scoping (Richards, 2004). For the visual representation, visual captures of the coding process have been done to authenticate the various steps used in coding (**Supplementary Figures S1**, **S4**). Scoping approaches using text query and matrix coding tools in Nvivo have been used to check the validity of coding (Richards, 2004). These tools allow identification of the commonly used words in specific themes and that were relevant in coding. For example, through matrix coding, the word "accessibility" was mentioned in nine out of 14 respondents (**Supplementary Figure S2**), with the majority coming from government and NGOs (**Supplementary Figure S3**). In addition, direct phrases/words from the respondents (such as "improved seeds, early harvesting") were used as code sub-categories which reduces misinterpretation (Richards, 2014). Using the text query tool in Nvivo, we also verified if the phrase "improved seeds" used as a sub-category was relevant for coding. Results show that the same phrase was mentioned in eight out of nine transcripts from farmers' interviews (**Supplementary Figure 5**). The Phrase was mentioned more than once in five of the nine transcripts. This shows that it is relevant to use the same phrase in coding to ensure validity.

TABLE 2 | Categorisation matrix showing the themes used in the coding of data in Nvivo.

Themes	Barriers to producing useful information	Opportunities to produce usable information	Barriers to moving useful to usable	Barriers to use in practise
To identify the barriers and opportunities in the production/provision and use of WCI				

RESULTS

In this section, we present the outputs from the analysis of the research data based on broad themes identified during the coding and the research questions.

What Are the Barriers to Producing Useful WCI?

The DM practitioners expressed that most of the data that would be required to prepare for a disaster are available. These datasets include weather and climate data (rainfall, temperature, and river flow) and risk data (vulnerability, exposure, and hazard). The weather data is provided by UNMA, while disaster risk data comes from various institutions with the main ones being NECOC and the Uganda Bureau of Statistics (UBOS). These data support the main activities carried out during preparedness and response to flood risk. The main disaster preparedness activities are the dissemination of weather and climate information and the identification of flood risk areas.

Although "scientific" data is available, transforming these data into necessary and useful information is often hindered by various factors, as reported by the DM practitioners. First, these data are not easily accessible since they are held by individual institutions that have a mandate in data collection and production. A memorandum of understanding is often required between these institutions to facilitate data sharing. Due to institutional rules and regulations, the process of data sharing can however take longer than expected which affects the preparedness and response activities.

> "Data from most of the institutions is not readily accessible due to institutional rules and guidelines on data sharing. The institution often demands a memorandum of understanding between the 2 institutions before sharing which can delay the process by up to 2 months. [DR01, DR04]"

Second, the data available lack the level of detail that would be required for comprehensive risk assessment at the local level (most data do not cover the village level). For example, most of the risk indicators such as those that would be required to understand the vulnerability of the communities to disasters vary in spatial coverage where some go up to sub-county while others up to county level, with none covering the village level. Weather data also does not give a full representation of the situation due to limited and scattered weather stations.

> "There are gaps in the data available for example, the risk atlas covers up to district level and doesn't cover parishes and villages" [DR03].
>
> "Weather Information is generalised to a very big area, but the farmers need localised information." [DR014].

Third, not all the available data, especially the data on hazards and vulnerability are complete. In addition, some of the risk indicators such as the data on poverty levels, population density, and literacy levels are not up to date especially if they depend on national census data. This affects the development of up-to-date risk layers. The lack of a national flood forecasting system also affects the quality of information that is produced for flood risk management. If global flood forecast information is to be used to inform preparedness, it should be verified[2] first for reliability. Although the development of the community Risk Assessment (CRA) framework is underway with support from the 510 group of the Netherlands Red Cross (NLRC) (NLRC, 2022), it is still hampered by the limited data available. The DM practitioners reported that this is based on secondary data and does not include any data collected from the grassroots level.

> "Verified flood information is required to inform disaster management. Many global sources are available, but they need to be verified by the Ministry of Water and Environment before use" [DR02].
>
> "Flood forecasting capacity is low in the country. They forecast rain and not floods" [DR012].

Last of all, institutions that have a role to transform data into the required information noted that they do have the required skills to do that. Frequent capacity building to keep up with evolving technology in climate science such as skills in forecasting and forecast evaluation is however required. **Figure 3** shows the most common barriers to developing useful WCI.

What Are the Opportunities and Barriers to Ensuring Useful Information Is Usable?

Understanding the information needs of the users presents an opportunity to develop usable information. From our study, various information needs for the smallholder farmers have been identified based on the coping practises that the farmers undertake during flood preparedness. These information needs have been grouped into three themes: weather and climate,

[2]Verification here means that the flood forecasts information from global sources should be compared with ground-based river gauge observations or historical flood timelines to ensure that they capture the flood situation of the location.

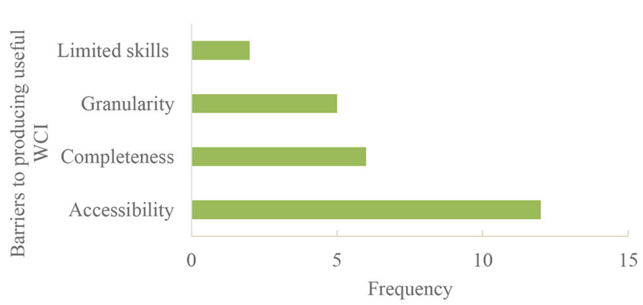

FIGURE 3 | Barriers that hinder production of useful WCI.

TABLE 3 | Categorisation of farmers' information needs based on when they are required.

Dynamic Information (seasonally)	Dynamic (depends on the season)
Weather and climate • Rainfall magnitude, intensity, timing • Rainfall predictions • Flood duration • Flood timing • Inundated areas • Risk areas	Agricultural practises • When to harvest • Types of seeds (improved, early maturing, water-tolerant, etc.) • Post-harvest handling methods • Land management practises • Livelihood diversity methods Safe locations and their accessibility • Shelter for animals • Shelter for people • Agrovet locations • Drinking water locations • Location of health facilities • Road's accessibility • Market information • Market accessibility

agricultural practises, and physical access to safe locations (**Table 3**). The information needs have also been grouped according to when it would be required. For example, the dynamic category includes information that would require an update every season. The second category captures situations where the dynamism of information would depend on the season. For instance, the location of safe areas may change depending on the magnitude of flooding experienced. What to plant and when to harvest will also depend on the rainfall factors such as duration, onset, etc.

Useful information such as weather information is available and accessible to local farmers. However, the information does not meet farmers' needs due to various factors. First, the weather information is packaged in a technical format and disseminated in English which makes it hard for farmers to understand and use. For example, though the weather bulletins produced by UNMA are available through the district office, farmers are not able to utilise them especially if they do not have any advisories or if they are not interpreted in their local language.

Second, the timing of information dissemination is often unfavourable to local farmers. For example, both the farmers and DM practitioners reported that information should reach the farmers 1–2 months before the start of the season to help them prepare. In addition, since the information is issued quarterly, with frequent updates, sometimes the local farmers do not receive these updates to help them keep up to date with the changes in the weather patterns.

Third, the DM practitioners working at the local level reported that communication and dissemination of WCI is often exclusively top-down. Communities are therefore not able to share any feedback with the producers and the decision-makers. **Table 4** lists these challenges together with quotes from both farmers and DM practitioners.

What Are the Barriers to the Use of WCI to Inform Coping Practises?

Smallholder farmers are aware of the recommended coping practises to be undertaken in preparedness for floods. The most common are on how to protect their crops before flooding, which includes early harvesting, post-harvest handling, and planting improved seeds. This is followed by ensuring their safety through activities such as clearing bushes and draining water from their compound. To protect livestock before floods, activities include vaccination, improving animal shelters, and buying improved breeds. Farmers in the study villages did not engage in many activities to enhance financial security, such as belonging to saving societies. **Figure 4** highlights all the coping practises that were identified by farmers in Katakwi while **Table 5** shows the most common coping practises based on the frequency.

Although the farmers were aware of the recommended coping practises, the actual implementation of these practises was hindered by various factors. These include agricultural-related challenges such as lack of improved seeds and other farm inputs. In addition, farmers in Katakwi do not have access to proper post-harvest handling kits to store their crops. Most of these challenges are associated with the social-economic capabilities of these communities, which we were not able to analyse further within the scope of this study.

Second, environmental factors such as invasion of desert locusts and the presence of strong winds were identified as challenges to implementing coping practises. Third, farmers noted that age and outbreaks of disease also derail the necessary coping practises. **Figure 5** shows the common challenges that affect the actual implementation of the coping practises.

DISCUSSION

While the role of WCI in smallholder farmers' decision-making is now common knowledge (Roudier et al., 2014; Coulibaly et al., 2015), the understanding and use of WCI by farmers has not been very effective, especially where it does not meet their specific information needs (Carr et al., 2019). In addition, developing useful information is not only contingent on the availability of data (Goddard, 2016) but can also be hindered by various factors from the providers' side. The development of useful and usable WCI, therefore, requires a more coordinated flow of information from the providers to the users and vice versa to understand the barriers that hinder the provision and use of WCI. In this research, we have combined two frameworks through a

TABLE 4 | Barriers that hinder useful information becoming usable in the context of smallholder farmers.

Theme	Frequency	Meaning	Evidence (DM practitioners)	Evidence (farmers)
Technical language	6	The language used to produce and disseminate the weather information	"The weather information is technical, and they don't understand what normal and above normal means" [DR014]. "We produce weather information but to help the communities understand we need to translate the information into local languages" [DR08].	"Climate and weather bulletins are available at sub-county offices; however, these are not easily interpretable by the farmers" [Farmers: 3 villages].
Lead time (timely)	5	The time between when the information is produced and when its required	"Farmers require weather information 2 months prior to the start of the season to help them plan the activities" [DR06]	"We need weather information on time for proper planning and to help choose which crops to grow" [Farmer: Kaikamosing village]
Top-down approach	4	Communication and dissemination of information is from the producers to the users only	"Communication is somehow top down and communities do not share their information" [DR06].	

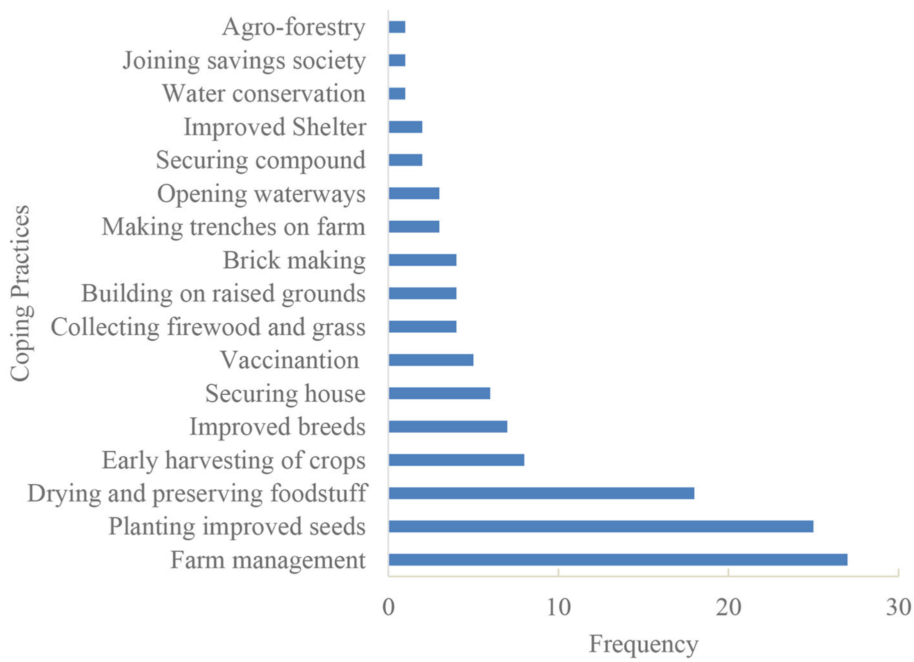

FIGURE 4 | Coping practises used by flood-affected communities in the three villages (Anyangabella, Kaikamosing, and Agule) in Katakwi District, Uganda.

bottom-up approach (FAMVACs method) to identify the barriers and opportunities across the provider-user landscapes on the production and use of WCI for a case study in Uganda. The approach used in this study to identify the barriers has a wider applicability across most natural disasters where a more coordinated response and flow of information would be required to understand the gaps in the provision and use of WCI for disaster management. Here, we first discuss the common barriers that hinder the production/provision and use of useful and usable WCI at the local level and the potential ways to address these barriers. We then highlight any future work that would be required to improve the use of WCI at the rural level. **Figure 6** shows the various components for a coordinated institutional response and flow of information towards ensuring; (1) useful information is produced, (2) useful becomes usable, and (3) usable is used in practise based on the findings from Uganda.

Ensuring the Production/Provision of Useful WCI

Developing useful information spans beyond the available data to include other factors. Our findings show that barriers such as accessibility, completeness, and granularity of the data may hinder the development of useful information from the providers' side (see **Figure 3**). These dimensions are commonly used to

TABLE 5 | Common coping practises undertaken by the farmers and their meaning.

Activity	Frequency	Meaning	Evidence
Farm management practises	27	Practises such as contour ploughing, mulching pest control, crop rotation and making manure	"My garden supported increased yields because I learned how to make manure" [Farmer: Kaikamosing village].
Planting improved seeds	25	Planting crops that can survive forecasted rainfall, e.g., early maturing, water tolerant crops	"I was able to decide which crops to plant based on the rainfall information provided" [Farmer: Anyangabella Village]
Securing houses	6	Building strong houses using materials such as bricks, damp proof course (DPC).	"I used DPC for the foundation of the house to make it strong" [Farmer: Agule Village]

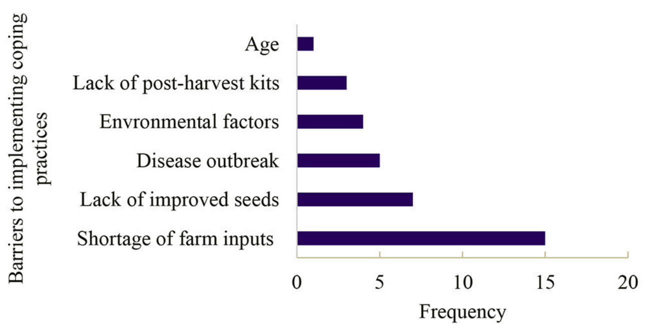

FIGURE 5 | Barriers to implementing coping practises across the three villages (Anyangabella, Kaikamosing, and Agule) in Katakwi District, Uganda.

check the quality of the available data and have been used to develop the data preparedness index (Van Den Homberg et al., 2017) as well as by other international organisations in data quality assessments to understand how prepared a country or an institution is in undertaking disaster management activities (WorldBank, 2012). These factors will however vary according to the context. For example, a study by Dinku (2019) found that the availability and completeness of climate data vary across Africa due to the scarcity of weather stations. In addition, the limited accessibility of available data has been attributed to the legal regulations that govern how institutions share data as well as the high costs levied to access the data.

In developing useful information, there is, therefore, a need to understand the data gaps that exist and how they can be addressed. The data quality dimensions noted above including others such as recency and reliability can be used to assess these gaps (Van Den Homberg et al., 2017). In Uganda, most of the required data to inform disaster preparedness is available. The accessibility of these data is however hindered by a lack of coordination between the various institutions involved in disaster management which means data is developed and managed by individual institutions (Atyang, 2014; Lumbroso, 2018). Having access to the data that meets the required quality dimensions can help bridge the providers' information gap (van den Homberg et al., 2018) and ensure that useful information is developed and made available for timely disaster preparedness and response. One way to ease data accessibility would be through embracing technology in data sharing for example through the use of multi-sector platforms such as the one developed by Cornforth et al. (2018). Fostering data collaborations across sectors can also help ensure that the required data is easily accessible (Susha et al., 2017).

Ensuring Useful WCI Is Usable

Useful WCI becomes usable if it meets the information needs of the users. User needs are context-specific and evolving and will vary depending on livelihood type (Carr and Owusu-Daaku, 2016), geographical location, and gender among others (Barihaihi and Mwanzia, 2017; Carr and Onzere, 2018). This means that although useful climate information is becoming increasingly available (Hewitt et al., 2020), its usability will require a constant context-specific understanding of the climate information needs of the users to ensure that the information is tailored to their needs. In Katakwi district, farmers require information on weather and climate and appropriate agricultural practises (see **Table 3**) to inform their coping practises. This is also consistent with findings across Sub-Saharan Africa on the use of WCI to inform agricultural practises (Amegnaglo et al., 2017; Nyadzi et al., 2019). Farmers who have access to WCI which has been tailored to their needs can therefore benefit from undertaking the required coping and adaptation strategies (Singh et al., 2018; Vaughan et al., 2019).

The WCI available and accessible by farmers in Katakwi district are not timely (Tembo-Nhlema et al., 2021), and are too technical for them to understand and use (Barihaihi and Mwanzia, 2017; Nkiaka et al., 2019). For example, farmers would require weather information with a lead time of 1–2 months before the onset of the season to inform practises such as the acquisition of the required seed variety (Amegnaglo et al., 2017). In addition, the weather bulletins issued by UNMA come in English and the farmers would require translation to make them usable. Efforts to help translate the weather information are already seen under the collaboration between UNMA and local NGOs which can have a positive impact (Ouedraogo et al., 2018). Fostering communication between the users and providers can therefore help understand the WCI needs of the users as well as barriers that make useful information unusable. Ways to make the information usable including capacity building (Conway et al., 2017), interpretation of the information into simple advisories (Harvey et al., 2019), and co-production (Vincent et al., 2021) can then be explored based on the target user. Overall, engaging the users from the start in the production of WCI can help ensure the information is usable as well and trusted which then boosts uptake (Nkiaka et al., 2019). The extent up to which these solutions can be implemented will however depend on other factors. Scholarly studies have shown

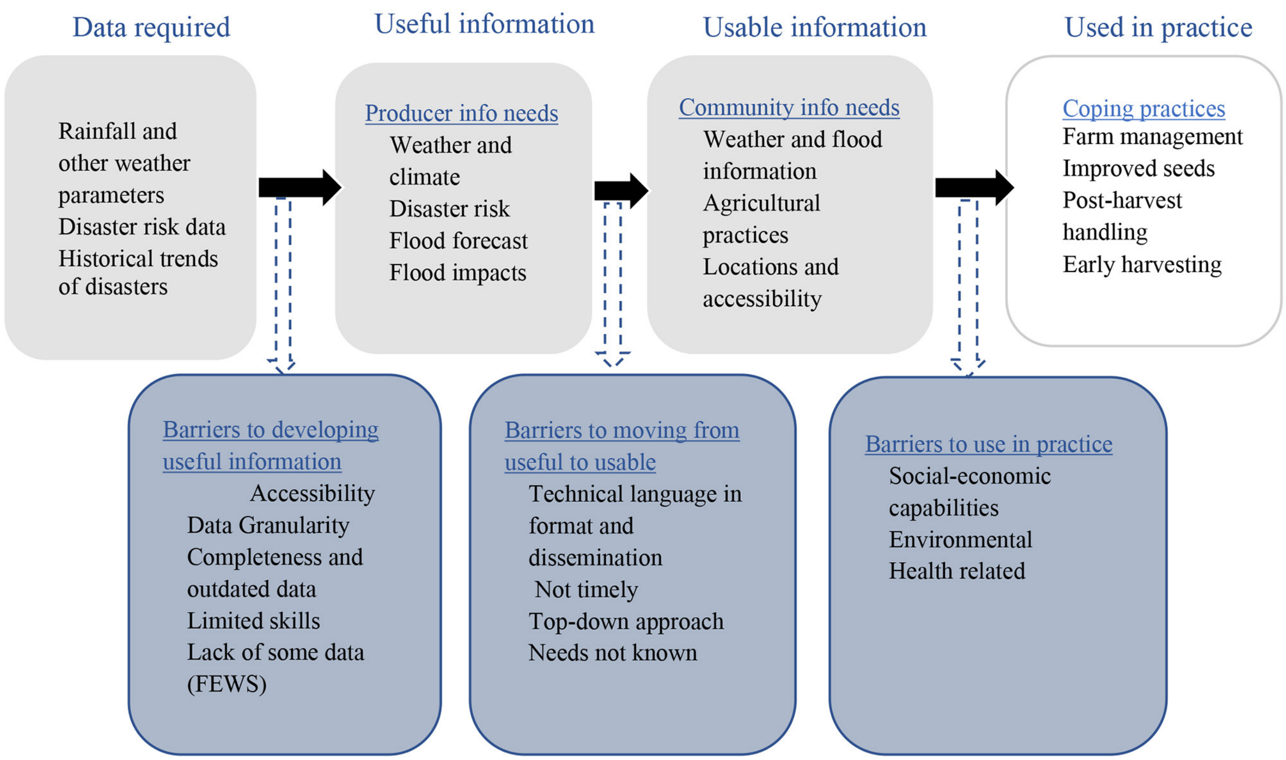

FIGURE 6 | Components that would be required to achieve a more coordinated institutional responses and flow of information to ensure useful and usable information is produced/provided and used in practise: the component headings have been adopted from Vincent et al. (2020) and Van Den Homberg et al. (2017) while their contents are based on findings from Uganda.

that limited financial and human resources can limit the level of preparedness among the local institutions (Shah et al., 2019). These factors should therefore be taken into consideration on top of the data preparedness factors to ensure that useful information is translated into usable information.

Ensuring Usable WCI Is Used in Practise

Availability and accessibility of useful and usable WCI by the target user does not necessarily translate to the actual use to inform coping practises. Although smallholder farmers may be aware of the coping practises to undertake (Berman et al., 2015; Shah et al., 2017; Wichern et al., 2017), studies have shown that one of the barriers to the use of WCI in practise is the lack of an enabling environment such as supportive institutions (Vaughan et al., 2017) to support adaptation planning. Other barriers such as the social-economic capabilities (age, income, health, etc.) of the users can also hinder use (Mittal and Hariharan, 2018; Shah et al., 2020). This means that even though useful and usable information that meets the needs of users is provided, the actual uptake of this information to inform coping practises will be context specific. For example, in this study, farmers in Katakwi district cannot afford the agricultural farm inputs required such as improved seeds (Fisher et al., 2015) to enable them to undertake the recommended coping practises. Other factors noted include limited land and inadequate farm tools (Tall et al., 2014). These factors have also been linked to financial resources to enable the farmers undertake these coping activities (Shah et al., 2017).

The benefits that farmers can derive from making use of WCI are many (Tarchiani et al., 2017; McKune et al., 2018; Ouedraogo et al., 2018). Hence, the barriers related to the socio-economic capabilities of the users and how they affect coping and adaptation should be identified so that the required support is provided (Petty et al., 2022). This could be done through existing institutions where interventions such as the provision of cash or subsidised farm inputs can be introduced (Assan et al., 2018). In addition, encouraging farmers to be part of farm-based organisations can help boost the uptake and use of WCI where these facilitate access to the required capital to support coping practises (Amegnaglo et al., 2017; Tarchiani et al., 2017).

Improving the Uptake of WCI Among Local Farmers

Overall, the disconnect between the users and providers of WCI can result in ineffective use of WCI to inform local level decision-making (Lemos et al., 2012; Singh et al., 2016). A first step towards ensuring effective use would therefore be to identify barriers that hinder effective production/provision and use of WCI across the provider-user landscapes. By combining two frameworks (Van Den Homberg et al., 2017; Vincent et al., 2020), through a bottom-up FAMVAC approach, this study provides a more coordinated institutional response that would ensure a shift of focus from only the users to a more inclusive approach where even the data and information needs of the providers are identified. This would make it easy to characterize the gaps from both levels in a more dynamic way and ensure that the required support is provided. For example, findings from practitioners in Uganda indicate that the skills to work on "scientific" data are available, but as technology in the production of WCI changes, continuously building the technical capacity of these institutions will be important (Dinku, 2019; Mataya et al., 2020) to ensure that they can keep up with the demand for useful WCI.

The field of disaster risk management is shifting towards impact-based forecasting and forecast-based actions (Coughlan De Perez et al., 2016; WMO, 2021). Interventions that target the at-risk communities, should therefore consider their information needs, coping practises, and social-economic capabilities to ensure the design of more tailored interventions. In addition, understanding the capabilities of the information providers and the gaps that may hinder effectiveness in producing the required useful information will be important to ensure a more coordinated response to the user needs. As the impacts of weather-driven shocks on rural smallholder communities increase, these communities will continue to demand relevant and timely information to support their coping practises (Hansen et al., 2019). The providers will also need to be supported to meet these information needs. The potential benefits of WCI can therefore be realised through understanding the barriers to production and use of WCI at different levels and promoting required interventions to improve disaster preparedness and response activities. For example, through promoting coordination and collaborations among multiple providers to ease data accessibility (Susha et al., 2017) as well as ensuring that the needs of the users and barriers that affect effective utilisation of WCI are understood and streamlined into the disaster management plans to support community preparedness (Nurye, 2016).

Future Work

Identifying barriers that hinder effective provision and use of WCI can inform the design of the required interventions. For example, a barrier such as data granularity (lack of data at the local level) can trigger support for frequent data collection at the local household level. Methods that are applicable based on context can then be assessed using criteria such as the one developed by Alkire and Samman (2014). Calculating the data preparedness index (Van Den Homberg et al., 2017) based on the quantifiable data quality dimensions can also help shed light on the improvement required to ensure that a country is prepared to undertake timely preparedness and response activities.

Barriers because of the social-economic capability of the users would also call for more in-depth methods to quantify the capability of these communities to undertake the coping practises and understand the type of support that would be required. Further research could look at an in-depth quantitative analysis of the household social-economic characteristics (sources of income, expenditures, health, age, etc.) such as that provided by HEA assessments (Seaman et al., 2014; Petty et al., 2022) and individual household surveys (Shah et al., 2020). Such an analysis can shed light not only on the household's capacity to undertake the various coping practises but also on the level up to which these households may require external support and the type of support required. Categorisation of the various coping practises stratified by wealth groups would also be essential to safeguard poor households against high-cost practises which may compromise their ability to cope in the future (Heltberg et al., 2009; Gautam and Andersen, 2016).

We did not get a chance to look at the disaster management structures and policies that govern how disaster-related activities are undertaken in Uganda. A thorough desktop study would therefore form part of future work to understand Uganda's plans for disaster risk reduction (DRR) including how various institutions coordinate to ensure emerging issues on disaster management are streamlined into the development process. Uganda has a DRR policy that was approved in the year 2011 (OPM, 2011) which stipulates the roles of various local and national institutions in addressing disasters. A study by Ampaire et al. (2017) however notes that the district and local level actors are often not included in the implementation of various policies. With climate variability expected to result in more extreme events, ensuring that the existing policies can still inform the required interventions is important. In addition, as we shift towards more locally targeted interventions, coordination between local and national institutions would be required to ensure that the needs of the most at-risk communities are centre in the design and implementation of the DRR policies.

CONCLUSION

The study findings have shown that the provision of useful and usable WCI spans beyond understanding the needs of the users—for this case the farmers—to include the data and information needs of the providers, and the capabilities of the users to use the information to inform practise. Ensuring that useful information is available, usable and is used in practise by the intended users is, therefore, an integral part of an effective disaster management plan. The barriers and opportunities to achieve positive impacts in the use of WCI should therefore be continuously assessed to ensure that developed WCI meets the needs of the potential users.

This study has provided a more coordinated institutional response approach that integrates two frameworks (Van Den Homberg et al., 2017; Vincent et al., 2020) and applies a bottom-up approach through the FAMVACs method to help identify the barriers and opportunities in the provision and use of WCI across user/user groups. Such an approach would ensure these barriers are identified across the user-provider landscape and solutions to bridge the specific gaps provided. Our findings on the barriers to provision and use of WCI are consistent with other scholarly findings in literature and are evidence of the various gaps that broadly affect the provision of climate services. However, specific solutions would be required depending on the context (user, location, etc.). For example, the lead time at which WCI should be provided to the local farmer will depend on the seasonal timing which varies across locations. In addition, designing solutions to improve data preparedness will require specific information on the gaps in the various data dimensions (access, availability, granularity, recency, etc.) which might also vary across contexts. The combined frameworks can therefore provide a coordinated way of ensuring that prior information required to inform development of specific solutions towards improving the provision of climate services are identified across the users and providers. This will also ensure that co-production takes centre stage in the design and dissemination of WCI.

Increased availability of weather and climate data and information provides an opportunity to improve climate adaptation planning. However, actionable programmes are needed to ensure that this information is translated and disseminated appropriately according to the information needs of the users. Weather information plays a fundamental role in informing the coping and adaptation among, for example, farming communities. There is therefore an urgent need to invest in strengthening the production, dissemination, and uptake of weather information for effective disaster management. This can be achieved by understanding the specific information gaps at the national and local levels which would also ensure that an improved dialogue is fostered between disaster management institutions and the at-risk communities for resilience building. Such information can then be used to improve disaster management plans and activities which would then ensure timely preparedness to floods.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by School of Archaeology Geography and Environmental Science (SAGES) Ethics Committee, University of Reading, UK. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

FM designed the research and collected the qualitative data at the national level, carried out the data analysis, and led the writing of the manuscript. CP led the design of the community-level research, collection of qualitative data, and assisted in writing the manuscript. RC, ES, and ET supported the research design and assisted in writing the manuscript. LC assisted in designing the qualitative research at the community level. JB assisted in collecting the qualitative data at the community level. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fclim.2022.908662/full#supplementary-material

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Appendix A3: Supplementary materials for Chapter 3

Appendix 3.0: Published article (Section 3.3)

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The utility of impact data in flood forecast verification for anticipatory actions: Case studies from Uganda and Kenya

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Abstract

Skilful flood forecasts have the potential to inform preparedness actions across scales, from smallholder farmers through to humanitarian actors, but require verification first to ensure such early warning information is robust. However, verification efforts in data-scarce regions are limited to only a few sparse locations at pre-existing river gauges. Hence, alternative data sources are urgently needed to enhance flood forecast verification to better guide preparedness actions. In this study, we assess the usefulness of less conventional data such as flood impact data for verifying flood forecasts compared with river-gauge observations in Uganda and Kenya. The flood impact data contains semi-quantitative and qualitative information on the location and number of reported flood events derived from five different data repositories (Dartmouth Flood Observatory, DesInventar, Emergency Events Database, GHB, and local) over the 2007–2018 period. In addition, river-gauge observations from stations located within the affected districts and counties are used as a reference for verification of flood forecasts from the Global Flood Awareness System. Our results reveal both the potential and the challenges of using impact data to improve flood forecast verification in data-scarce regions. From these, we provide a set of recommendations for using impact data to support anticipatory action planning.

KEYWORDS

disaster risk reduction, floods, forecast verification, humanitarian early action, impacts, non-traditional verification data

1 | INTRODUCTION

Climate change, variability, and environmental changes disproportionately affect the agricultural sector in Africa with important implications for anticipatory action as part of humanitarian response. In the agricultural sector, these changes could force smallholder farmers who depend on rain-fed crops or flood-recession agriculture to significantly adjust their farm activities (Ficchì & Stephens, 2019; Ochieng et al., 2016; Salack et al., 2015). In Uganda, farmers need reliable and skilful information on the rainy season onset and amount of rainfall, as well as flood occurrence, duration, magnitude, and severity ~1–2 months before the season onset to inform their coping strategies (Mitheu et al., 2022). Decision-makers and humanitarian actors aiming to reduce risks and protect livelihoods are also increasingly considering forecast information to inform the early action mechanisms and operational decisions (Coughlan De Perez et al., 2016; Emerton et al., 2020; Hansen et al., 2019; Lopez et al., 2020; Nidumolu et al., 2020). Given this, the skill of any forecast information provided needs to be transparent and well understood if it is to inform preparedness actions appropriately.

In the context of users' needs, forecasts should be evaluated based on their potential to trigger early actions, which can reduce expected losses if an extreme event occurs (Lopez et al., 2020). The evaluation should also consider the consequences of 'acting in vain', which are particularly important in disaster risk reduction and humanitarian actions (Coughlan De Perez et al., 2015). Indeed, several studies have shown that verified and skilful forecasts have the potential to improve preparedness actions for both the agricultural and humanitarian sectors (Coughlan De Perez et al., 2016; MacLeod et al., 2021; Nidumolu et al., 2020; Nyadzi et al., 2019; Paparrizos et al., 2020). However, this verification is carried out only for regions with long-term historical hydrometeorological observations, typically from in situ stations such as river gauges. In forecast verification, these observations are commonly known as conventional observations (Marsigli et al., 2021).

In data-scarce regions, where conventional observations are limited (Coughlan De Perez et al., 2016; Ogutu et al., 2017), less conventional verification data can be derived from, for example, social media reports, citizen volunteered information, impact/damage reports, and insurance data. The resulting information can be used to bridge the forecast verification gap through non-traditional approaches as they provide a more direct representation of the event (Marsigli et al., 2021). For example, information from insurance databases (Bernet et al., 2017; Cortès et al., 2018), as well as online tools such as Google Trends and Twitter feeds (de Bruijn et al., 2019; Thompson et al., 2022) have been used as reference information to evaluate the occurrence of floods. Impact data have also been used with river-gauge observations to identify the magnitude of discharge that is associated with flooding (Coughlan De Perez et al., 2016). Notably, impact data offer an advantage in the verification of forecast information, because they can be derived from openly accessible data repositories containing quantitative and qualitative information across large spatial areas that enable a better and direct representation of the impacts of the extreme event. The use of impact data in forecast verification can only be possible in areas with exposure and vulnerability for the impact to be reported.

It is worth noting that global data repositories such as the Emergency Events Database (EM-EM-DAT, 2020) and the United Nations Disaster Inventory System (DesInventar [DI]; UNISDR, 2018) are prone to biases due to known limitations (Gall et al., 2009). These limitations include under-reporting/over-reporting of the hazards, aggregated spatial coverage, over-representation of certain locations, and/or focus on the specific type(s) of impacts. Furthermore, differences in the criteria for the inclusion of events in the repositories may result in non-uniformity in the estimates of the impacts reported in each repository. In addition, if unverified, impact data collection methods (e.g., from governments and media) may lead to errors in the resulting information (Guha-Sapir & Below, 2002). Despite these caveats, these data repositories represent a potentially valuable source of less conventional data for monitoring and verifying hazards. For example, impact data can be integrated with other geophysical parameters to sub-categorise flash floods from the primary corresponding disaster type (Kruczkiewicz, Bucherie, et al., 2021). Therefore, if the limitations of impact data are appropriately understood, with guidance on their interpretation and relevant recommendations, impact data can be improved to effectively support anticipatory actions.

In this study, we assess the usefulness of flood impact data to verify flood forecast information across Uganda and Kenya compared with river-gauge observations. We verify the river flood forecast from the Global Flood Awareness System (GloFAS) of the Copernicus Emergency Management Service (Harrigan et al., 2023) using two reference observations. The river-gauge observations and flood impact data were derived from several global and national data repositories.

The study addresses two research questions:

1. How suitable are impact data for verifying flood forecasts compared to river-gauge observations?
2. Where river-gauge observations are limited or unavailable, how best can impact data be used to verify flood forecasts and ensure anticipatory actions are informed?

Through focussed case studies in two East African countries, we investigate the non-traditional approach of forecast verification using impact data relative to the traditional way of verification using river-gauge observations. Consequently, we provide recommendations on how best impact data can be used in areas with no or limited river-gauge observations to increase confidence in the use of forecast products in data-scarce regions.

2 | CONTEXT

In this section, we describe the case study regions and the datasets used for the analysis, that is, the GloFAS reforecast discharge data, river-gauge observations, and the impact data from several data repositories.

2.1 | Case study regions

The Netherlands-based IKEA Foundation is supporting the Uganda and Kenya Red Cross Societies (URCS and KRCS, respectively) to develop early warning mechanisms to prepare for floods through the Innovative Approaches for Response Preparedness (IARP) project. In Uganda, several high-risk areas were identified using vulnerability and risk layers developed by the National Emergency Operations and Coordination Centre (NECOC), including a total of 15 districts, for the early action protocol (EAP) development. These regions are prone to flooding and waterlogging across the two rainy seasons between May and November (April–May, Long Rains; September–November, Short Rains). In Kenya, flood-prone river basins including Tana, Nzoia, and Athi are considered for the implementation of flood early actions. Examples of early actions include community awareness, distribution of cash and shelter kits, dissemination of early warning information among others (see KRCS, 2021; URCS, 2021).

The case study regions in Uganda and Kenya were selected based on locations with available river-gauge observations. In Uganda, the districts of Katakwi and Amuria on the Akokorio river (hereafter 'Katakwi'), Tororo (Butaleja), and Mbale (Bududa and Manafwa) on Manafwa River (hereafter 'Manafwa'), and Kiboga, Mubende, and Hoima on the Mayanja River (hereafter 'Mayanja') are considered. In Kenya, the county of Tana-river and Garissa on Tana River (hereafter 'Tana'), Busia and Siaya on Nzoia river (hereafter 'Nzoia'), and Taita-taveta and Kilifi on Athi river (hereafter 'Athi') have been considered. Figure 1 shows the locations of the river-gauge stations and the affected counties/district in Kenya and Uganda, respectively.

2.2 | GloFAS flood forecasts

GloFAS is an operational global ensemble flood forecasting system developed jointly between the European Commission's Joint Research Centre (JRC), the European Centre for Medium-Range Weather Forecasts (ECMWF), and the University of Reading researchers (Alfieri et al., 2013). The system provides probabilistic extended range discharge forecasts for up to 45 days and seasonal outlooks up to 4 months lead time (Emerton et al., 2018) over the entire globe at a resolution of 0.1°. From GloFAS v3.1 (current operational version), the LISFLOOD hydrological model (van der Knijff et al., 2010) is forced by an

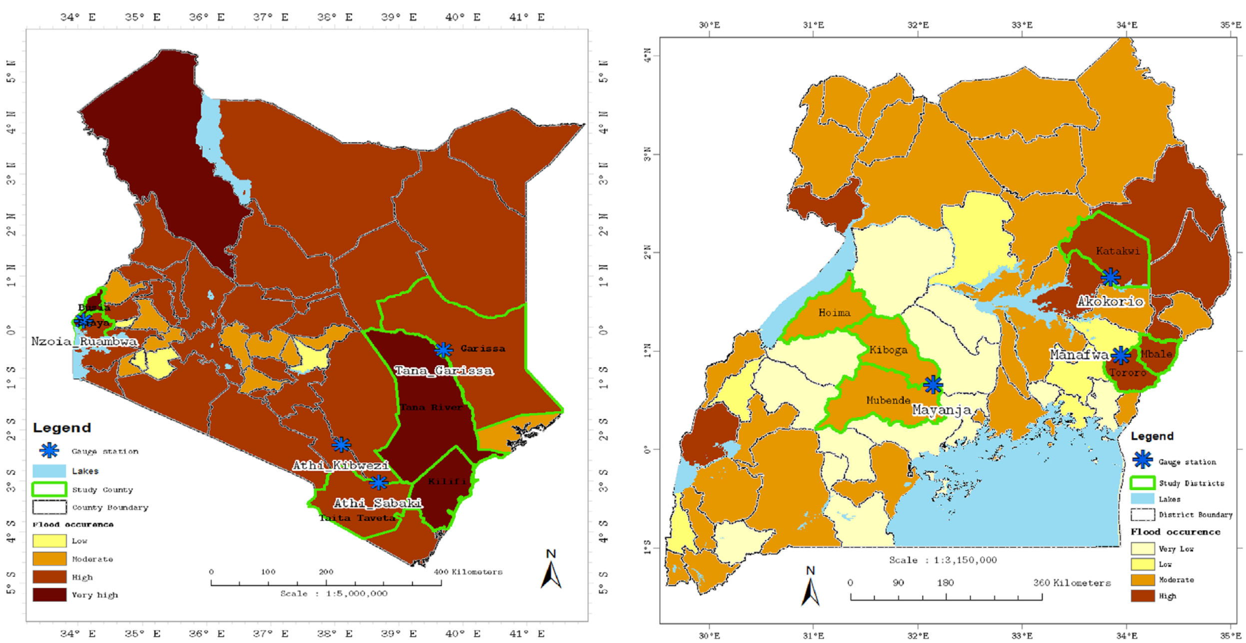

FIGURE 1 Flood occurrence maps for Kenya and Uganda show the study counties/districts and the river gauge locations. The map was created using impact data collated from four different data repositories from 2007 to 2018. The colour scheme represents the number of years out of the 12 years considered when floods occurred ranging from low (1–3 years), moderate (4–6 years), high (7–9 years), and very high (10–12 years).

ensemble of medium to extended range meteorological forecasts from the ECMWF Integrated Forecast System to produce 51 ensemble members of daily streamflow at various lead times. LISFLOOD has been calibrated using daily streamflow data at over 1200 river basins worldwide (Hirpa et al., 2018).

GloFAS v3.1 hydrological performance was evaluated for the period 1979–2019 for over 1500 verification stations across the world using various verification metrics (Kling Gupta Efficiency, Bias, variance, etc). Prudhomme and Zsoter (2021) provide details on the hydrological assessment methodology and further discussion on GloFAS performance evaluation. GloFAS provides daily discharge amounts [m^3/s] from which probabilities of flood threshold exceedance can be derived. For flood detection, these forecasts time series are compared against a set of flood thresholds that are derived from the same model climatology (Zsoter et al., 2020) to avoid the impact of systematic biases in the GloFAS climatology on flood forecast probabilities. In this study, we use daily GloFAS v3.1 reforecast discharge data from 2007 to 2018 extracted for the gauge locations in Kenya and Uganda, respectively (Figure 1).

2.3 | Flood thresholds

In the 30-day operational GloFAS forecast interface (https://www.globalfloods.eu/), four different flood return periods (2, 5, 10, and 20 years) are provided and can be used as the thresholds for severe flood events. Zsoter et al. (2020) provide a detailed explanation of how these return periods are computed using GloFAS ensemble reforecasts. Furthermore, thresholds computed as percentiles of the daily river flow time series can also be used to define various hydrological conditions (e.g., high/low river flows) and have been used by several authors to evaluate forecasts from GloFAS or similar forecasting systems (see Alfieri et al., 2013; Arnal et al., 2018; Emerton et al., 2018; MacLeod et al., 2021). For example, high percentiles (90th percentile or greater) have been used to show a high likelihood of floods when the river flow at a gauging station is above that percentile (MacLeod et al., 2021). In the broad hydrological literature, the notation for flow percentiles is not always consistent or clear, so when percentiles are used, the definition needs to be specified clearly.

In this study, we adopt the traditional definition of percentiles used in statistics where a kth *percentile* (with k in the range of 1–100) for a time series is the level below which (or at which) a k *percentage* of values in its distribution falls (the inclusive definition of percentile is adopted). For example, a 90th percentile is equal to or >90% of the river discharge recorded during the specified period. In flood-related studies, a percentile flow can also be referred to in terms of 'percent exceedance' to indicate the percentage of time that the discharge value is likely to be equalled or exceeded (see; Flow, Excedance and Percentiles, 2023; National River Flow Archive, 2023). Thus, in this study we use the 90th, 95th, and 99th percentile calculated from the re-forecast (all ensemble members) or observed time series of daily discharge, corresponding to high-flow levels exceeded only by a minor portion of the days in the data, that is,10%, 5%, and 1% respectively.

Due to data availability, we followed a percentile-based method to compute flood thresholds for forecast verification similar to previous authors (e.g., Alfieri et al., 2013; Arnal et al., 2018; Emerton et al., 2018; MacLeod et al., 2021). The choice of using these thresholds and not higher Return Periods (e.g., 5-year or 20-year return periods computed from annual maxima) is motivated by the need for robust statistics, given the short data periods available (2007–2018). For the forecasts, these thresholds are lead-time dependent (Zsoter et al., 2020), that is, calculated from the reforecast time series at each given lead time available.

2.4 | River-gauge observations

Observed point-based discharge time series for the river gauges considered here were provided by the Department of Water Resources Management (DWRM) in Uganda and by the Kenya Water Authority (WRA) for Kenya. The time series consists of daily discharge values over long periods with all stations having at least 5 years of daily discharge data over the study period. The river-gauge observations corresponding to the period of the impact data (2007–2018) have been used for the subsequent analysis.

2.5 | Flood impact data

Flood impact data have been used to extend our capability to verify GloFAS flood forecasts beyond conventional observations from sparse gauge networks. The flood impact data contain semi-quantitative and qualitative information on the location and number of reported flood events derived from five different data repositories: (1) Dartmouth Flood Observatory (DFO) Archive (Brakenridge, 2015), (2) DI (UNISDR, 2018), (3) EM-DAT (EM-DAT, 2020), (4) the Global Hazard Weekly Bulletin (PHE, 2015), and (5) local sources (URCS, KRCS, media, etc.) for the 2007–2018 period. These data were collated for Uganda and Kenya for the study regions (districts/counties) for further analysis. The characteristics of these data repositories are summarised in Table 1.

In an ideal situation, an impact would be defined as a combination of the number of people affected and the quantitative estimate of any loss of property and livelihoods. However, the used repositories do not have enough quantitative loss and damage information disaggregated to sub-national administrative units to enable the quantification of impacts and the severity of the flood events. We, therefore, consider the number of flood events reported as a proxy to the impact with an assumption that flood events that result in considerable impacts would be reflected in the data repositories used. The flood events are then classified as either 1 or 0 if the event was reported or not, respectively. The assessment of the number of flood events from the various sources, as well as the overlap (events that are common across the repositories used here), would help understand which data repository is used to identify the highest number of flood events for each study location.

3 | METHODOLOGY

Here, we outline the comparative analysis of river-gauge observations and impact data and the verification of GloFAS flood forecasts using two reference data sets through a set of skill scores. To assess the usefulness of flood impact data in verifying flood forecasts, first, the adequacy of the impact data in supplementing the river-gauge observations is evaluated using Type I and Type II error indices. Second, the flood forecast data are verified using river discharge and impact data as reference, and the verification outcomes based on the probability of detection (POD) and false alarm ratio (FAR) are compared.

3.1 | Comparison of river-gauge observations and impact data

In this part of the analysis, we compare the river-gauge observations and impact data. River-discharge value (Q) that has the potential to cause flooding is defined using the 90th and 95th percentile as the threshold, that is, a flood event (binary) occurs when Q is above the threshold, and it does not occur if Q is below the threshold. The total flood events from impact data are derived from the data repositories while considering the overlaps using the timestamp to avoid duplication in the total events. This means that an event that occurs across all the data repositories for the same timestamp is considered one event. The total flood events from impact data (binary) are then compared with river-gauge observations (binary).

Here, we assess the consistency of impact data false positive and false negative outcomes using a window of 7 days (from the day of the observed event up to 7 days ahead) against the flood events picked from the river-gauge observations. Using a 2×2 contingency table, the false-positive outcome is used to compute the 'Type I error' which represents the ratio of the flood events detected by river-gauge observations with no impacts divided by the total flood events (from gauge observations). Additionally, the false negative outcome is used to compute 'Type II error' which represents the ratio of flood events detected in the impact data and not by river-gauge observations divided by the total number of flood events (from impact data). We first compare the river-gauge data (binary) with the impact data (binary) from the various sources across the locations. Next, we compare the river-gauge observations against impact data from a single data repository to assess if impact data from some repositories are better than others in detecting flood events. Type I and II errors are calculated according to the equations in Table 2.

3.2 | Flood forecast verification using river-gauge observations and impact data

A set of skill scores were used to evaluate the occurrence of forecasted floods from the GloFAS system against river-gauge observations and impact data. The ability of the forecast to discriminate between events and non-events is commonly measured using skill metrics calculated from a 2×2 contingency table. Two skill scores were used to quantify the occurrence of flood events (Wilks, 2006): (1) POD or hit rate, which measures the fraction of observed events that were correctly predicted (perfect score of 1) and (2) FAR, which indicates the fraction of the predicted events that did not occur (perfect score of 0). Table 3 shows the equations used to calculate the skill scores.

In this study, the verification of flood forecast events is based on the need to provide reliable flood forecast information to inform anticipatory actions taken by the communities and humanitarian actors. The preferred verification outcome will therefore depend on the decision-making strategies the actors are willing to take. For example, humanitarian actors might need to decide if actions should be taken based on any forecast probability which might be costly due to the number of events but would ensure reduced losses if the events materialise.

TABLE 1 Characteristics of the data repositories that were used to derive impact data for the study.

Data repository (reference)	Temporal coverage	Criteria for inclusion	Actors/collection methods	Accessibility	Spatial coverage	Parameters
Dartmouth flood observatory (Brakenridge, 2015)	1993 to present	• Large and extreme flood events	News reports, Governments, Flood lists, and remote sensing sources	Available upon request at https://floodobservatory.colorado.edu/	Country-level but provides the centroids for locations affected	Reports the main cause of impacts and categories of loss (see Table S1)
DesInventar (Integrated Research on disaster risk, 2014; UNISDR, 2018)	1994 to present	• One or more human loss and/or • Loss of 1 or more US dollars	National governments and sectoral ministries	Publicly available at www.desinventar.net	Zoning level entry (country, districts, etc.)	Reports as a flood. Reports various categories of loss and damage (see Table S1). Includes qualitative information
Emergency Events Database (EM-DAT, 2020)	1995 to present	• Ten (10) or more people killed • Hundred (100) or more people affected • Declaration of a state of emergency	UN agencies, National Governments, International Federation of Red Cross and Red Crescent Societies (IFRC), and NGOs	Publicly available at https://public.emdat.be/	National and sub-national level	Subtypes of floods and origin, several categories of loss and damage (Table S1)
Global hazards weekly bulletin (PHE, 2015)	2013 to present	• Selected news on floods	Media reports (Flood list)	Publicly available via email bulletins to subscribers and archived independently at http://www.met.reading.ac.uk/sgs02rpa/extreme.html	Provides information specific to the location affected	Reports the location and categories depending on impacts (deaths or displaced)
Local sources (URCS and KRCS)	2000–2018	Depending on the main source	Disaster Relief Emergency Fund (DREF) reports, relief web, flood list, and districts offices	Request sent to National societies to support this research	Disaster prone areas	All the above

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TABLE 2 Type I and Type II error equations for the comparative analysis.

Index name	Equation	Score range	Perfect score
Type I error (TI)	$\frac{\text{Number of gauge observed flood events with no impacts reported}}{\text{Total number of flood events from river gauge observations}}$	0–1	0
Type II error (TII)	$\frac{\text{Number of flood events detected by impact data, with no gauge observations}}{\text{Total number of flood events from impact data}}$	0–1	0

TABLE 3 Skill scores used for the verification of forecasts.

Skill score	Equation	Values range	Perfect score
probability of detection (POD)	$\text{POD} = \frac{\text{H}}{\text{H+M}}$	0–1	1
false alarm ratio (FAR)	$\text{FAR} = \frac{\text{FA}}{\text{H+FA}}$	0–1	0

Abbreviations: FA, false alarms; H, Hits; M, Misses.

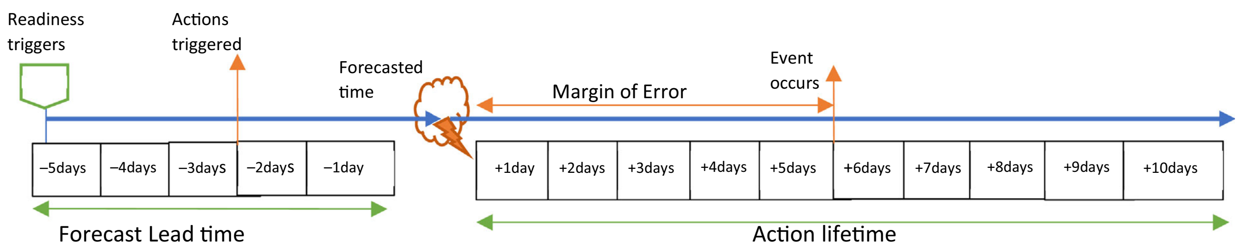

FIGURE 2 Visual representation of the action lifetime and margin of error based on early warning and action triggers.

The second alternative would be if actions should be taken based on a forecast that shows a high likelihood of event occurrence to minimise the expenses that would be incurred if the actions turn out to be in vain (see Lopez et al., 2020).

Various factors identified from the EAPs developed by URCS and KRCS have been adopted in this study. First, a flood forecast with a 60% chance of happening triggers early actions. Hence, we consider forecasts that indicate a forecast probability of 60% and above to correspond to a flood forecast event, and below 60% to correspond to a 'no-flood' event. Second, in the calculations of events correctly forecasted, an action lifetime of 7 days, is considered. 'Action lifetime' is defined as the length of time during which action will remain effective in reducing impacts (Coughlan De Perez et al., 2016). In forecast verification, the action lifetime is commonly known as the 'margin of error' and it is used to give more tolerance to the forecasts such that even if the forecast is late but materialises within the duration of the action lifetime, the actions will still be considered successful. For example, if an action is taken and a flood occurs up to 7 days after the forecasted date, this will still be considered a 'hit' if the action lifetime is >7 days (see Figure 2 for a visual description of the action lifetime and margin of error). Depending on the type of action, the action lifetime can range from 7 to 90 days. This can also vary depending on a specific country's flexibility on the actions to take and the acceptable number of times the stakeholders are willing to 'act in vain'. For Uganda and Kenya, the stakeholders set the probability of 'action in vain' to 50%, indicated using the FAR. From Figure 2, We have considered a margin of error of 5 days and action lifetime of 10 days. However, these parameters can still vary depending on the type of action.

Using distinct flood discharge thresholds (i.e., 90th and 95th percentile) calculated from the GloFAS reforecast data and river-gauge observations, we verify flood forecast using river-gauge observations and impact data as a reference. This study was therefore not meant to evaluate the hydrological performance of GloFAS (calibration and validation of GloFAS time series) but to assess the usefulness of the two reference datasets in forecasts verification. Using a 7 days-action lifetime and 60% probability of flooding, we compute the differences in the skill scores (POD and FAR) for forecast-observed data and forecast-impact data pairs, respectively. Here, if the difference between the 'POD observed' and 'POD impact' is negative and the FAR difference is positive, impact data are more favourable in skill assessment than river-gauge observations and vice versa. Additionally, if the river- gauge observations or impact data (or both) report a flood event for the same days as in the GloFAS flood forecast (within the action lifetime of 7 days from the warning), the reference data (observed or impact) are favourable in skill assessments.

4 | RESULTS

4.1 | Impact data from the data repositories

In Uganda, in two districts (Katakwi and Manafwa) the reported impacts from the data repositories show a higher number of events reported in 2007, 2010, 2011, 2012, and 2018 from DI and DFO as compared with other years. However, the flood events for Mayanja from all the data repositories across the years are low. Table 4 shows the number of events across Uganda and the three locations from 2007 to 2018. The number of flood events from each repository presented in Table 4 is independent, that is, it does not consider any overlap across the repositories.

The analysis of the number of flood events from multiple and single data repositories shows that in Katakwi there are 434 flood events where DI recorded the highest number of events at 36%, followed by DFO at 19% (Table 5). Data collected across Katakwi by URCS also provide a substantial contribution (14%) to the flood events in the area. The overlap from multiple data repositories (EM-DAT, DI, and DFO) contributes to 11% of the total flood events. In Manafwa from a total of 304 events, the highest number of events are from single source DI and overlap between EM-DAT and DFO, at 33% and 28% respectively. EM-DAT alone contributes 14% of the total events. In Mayanja, only two data repositories contribute to the flood events. These are the DI at 23% and EM-DAT at 77% totalling 102 events.

In Kenya, many flood events were reported in 2007, 2010, 2011, 2013, 2015, and 2018 across the country and the three study locations (see Table 4). EM-DAT also records the highest number of flood events across the three locations contrasting with findings in Uganda, whereas DI reported the lowest. For example, in Nzoia EM-DAT represents 69% of the total flood events, local sources contribute 12%, whereas DI covers 6%. The overlaps between the various sources contribute marginally across the locations. For example, EM-DAT and DI together contribute <1% in Tana, 3% in Nzoia, and 1% in Athi (Table 5).

4.2 | How adequate are the impact data in supplementing river-gauge observations in identifying flood events?

The comparative analysis in the three locations in Uganda using combined impact data from the various data repositories and observed gauge data show varied results across locations and thresholds. For example, in Katakwi (Figure 3a) by using the 90th percentile from the river-gauge observations, the impact data capture 60% of all gauged flood events, but 42% of the reported flood events from the impact data do not correspond to flows above the 90th percentile threshold. This could mean that either the threshold is too high, with lower flows still causing impacts or the impacts reported were a result of another form of flooding like flash floods or waterlogging from heavy rainfall. In Manafwa and Mayanja (Figure 3b,c), Type I and Type II errors across the thresholds are high (above 0.5) which could mean that the quality and quantity of available impact data for these locations were not adequate (Type I), and the impacts reported were not as a result of riverine flooding (Type II).

The comparative analysis shows a high Type I error across the 90th and 95th percentile in the Kenyan locations. This means that though the observations indicate flood events, there were no impact data to correspond to these events or the quality of the available impact data was not good enough. On the other hand, the Type II error is also high across the locations, suggesting that impacts reported resulted from different forms of flooding, such as flash floods. For example, in Tana at the 90th percentile, impact data capture only 40% of all gauged flood events, but half of the reported flood events do not correspond to flows above the 90th percentile. Figure 4a–c shows the comparative analysis across the thresholds for Tana, Nzoia, and Athi respectively.

The analysis using a single data repository shows an increase in Type I error in all the locations in Kenya and Uganda (Figure 5a,b). For example, in Katakwi using DI alone results in a Type I error of 0.59 as compared to a Type I error of 0.39 while using four data repositories (DI, EM-DAT, local, and DFO). In Tana, EM-DAT results in a Type I error of 0.79 as compared to 0.61 while using data from all the repositories. Type II error fluctuates across the locations (Figure 5c,d). For example, at the 90th percentile, despite Nzoia having almost the same number of flood events from EM-DAT and local sources, Type II error is higher while using local sources as compared to using EM-DAT (Figure 5d). This shows that at the same (higher) threshold for example at (90th percentile) more events are likely to be missed out (events falling below the threshold) from the local source which takes into consideration more localised events as compared to a high-impact data repository like EM-DAT. In

TABLE 4 Number of flood events from 2007 to 2018 for Uganda and Kenya locations derived from various data repositories.

Year	Kenya EM-DAT	Tana EM-DAT	Nzoia EM-DAT	Athi EM-DAT	Kenya DI	Tana DI	Nzoia DI	Athi DI	Kenya local	Tana local	Nzoia local	Athi local
2007	110	0	82	32	0	0	0	0	3	0	1	1
2008	57	8	16	20	6	2	15	2	15	3	4	2
2009	15	15	0	15	11	1	2	0	13	1	3	3
2010	97	87	17	87	35	3	1	4	53	8	7	3
2011	50	25	24	0	5	0	1	2	12	1	4	2
2012	27	27	27	27	13	2	3	1	39	5	3	4
2013	60	0	52	1	30	4	9	1	39	4	7	3
2014	0	0	0	0	0	0	0	0	20	1	3	0
2015	45	20	20	0	26	4	5	4	72	6	9	10
2016	11	6	6	0	2	0	0	0	29	2	3	6
2017	9	9	9	9	0	0	0	0	26	4	1	4
2018	79	79	0	0	0	0	0	0	144	61	17	28
Year	**Uganda EM-DAT**	**Katakwi EM-DAT**	**Manafwa EM-DAT**	**Mayanja EM-DAT**	**Uganda DI**	**Katakwi DI**	**Manafwa DI**	**Mayanja DI**	**Uganda DFO**	**Katakwi DFO**	**Manafwa DFO**	**Mayanja DFO**
2007	82	78	78	77	91	62	41	0	82	78	78	0
2008	1	1	0	1	12	1	1	0	0	0	0	0
2009	0	0	0	0	16	0	3	2	0	5	5	0
2010	5	5	5	0	109	48	40	2	11	5	5	0
2011	21	0	20	0	83	45	47	2	41	30	29	0
2012	1	0	1	0	49	37	3	1	29	2	0	0
2013	5	0	0	0	50	28	4	8	2	0	0	0
2014	0	0	0	0	33	1	2	1	5	0	0	0
2015	0	0	0	0	25	0	1	1	0	0	0	0
2016	7	0	0	0	16	0	2	3	7	0	0	0
2017	8	0	0	0	32	1	11	1	8	3	3	0
2018	1	0	1	0	32	28	10	2	17	8	8	0

Abbreviations: DFO, Dartmouth Flood Observatory; DI, DesInventar; EM-DAT, Emergency Events Database.

TABLE 5 Percent of the total number of flood events from multiple (overlaps) and single source data repositories for the study locations in Uganda and Kenya.

Uganda	**Katakwi**	**Manafwa**	**Mayanja**
Number of reports	**434**	**304**	**102**
Sources	**Percent of total events in each location**		
Single source contribution			
DI	**36.41**	**32.57**	**22.55**
EM-DAT	1.38	13.82	**77.45**
DFO	**18.89**	12.5	0
Local sources (URCS)	13.59	0	0
GWHB	0.00	2.30	0
Overlaps			
EM-DAT, DI, and DFO	11.06	4.28	0
EM-DAT and DFO	6.91	**28.29**	0
DI and DFO	8.29	5.59	0
URCS and DI	3.46	0.00	0
EM-DAT and GWHB	0.00	0.66	0
Kenya	**Nzoia**	**Tana**	**Athi**
Number of reports	**316**	**359**	**251**
Sources			
Single source contribution			
EM-DAT	**69.94**	**70.75**	**72.11**
DI	6.33	3.34	3.19
Local sources	**12.03**	**19.22**	**19.92**
Overlaps			
EM-DAT and DI	3.48	0.56	1.20
EM-DAT and local	6.01	5.85	3.19
EM-DAT, DI, and local	2.22	0.28	0.40

Note: The first two sources that represent the highest percentage over each district/county are highlighted in bold.
Abbreviations: DFO, Dartmouth Flood Observatory; DI, DesInventar; EM-DAT, Emergency Events Database.

other words, a data repository that considers a low threshold for inclusion of the event in their database may require a low threshold based on gauge observation to correctly identify the flood events as compared to a data repository that considers high threshold for inclusion.

4.3 | Where river-gauge observations are limited or unavailable, how best can the impact data be used to verify flood forecasts and ensure anticipatory actions are informed?

We plotted the difference between the forecast skill scores (POD and FAR) obtained using the river-gauge observations and impact data (i.e., $POD_{observed} - POD_{impact}$ and $FAR_{observed} - FAR_{impact}$) as a reference for verifying flood forecasts across all the locations and two percentile thresholds to assess their potential in forecast verification (Figure 6). The results show that impact data gives a more favourable assessment of skill as compared to the observed data at the 90th and 95th percentile across lead times in Katakwi (i.e., $POD_{impact} > POD_{observed}$ and $FAR_{impact} < FAR_{observed}$). For other locations at a lead time of up to 15 days, the impact data underestimate the GloFAS skill in terms of POD and FAR. At longer lead times (>15 days), Nzoia shows a good assessment of skill in terms of POD. These outcomes can be associated with the quantity and quality of the impact data that were available for most locations (except Katakwi and partly Nzoia) which also corresponds to the findings in Section 4.2. The highest difference in the POD of up to 0.4 is seen in Mayanja at the 90th percentile while other locations show a difference of below 0.2. The FAR is however spread out

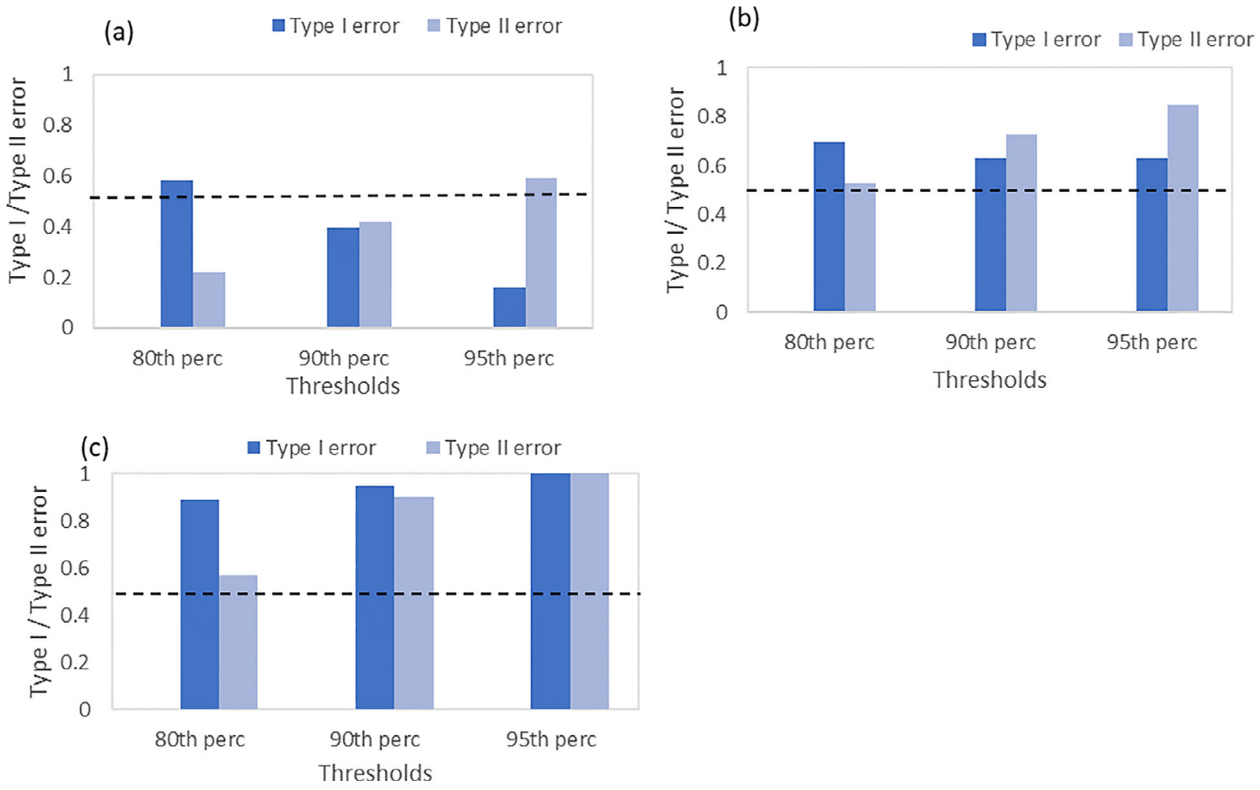

FIGURE 3 Comparative analysis of the impacts (all sources) and observed data at three percentile thresholds (80th, 90th, and 95th) of daily river flows from the gauged stations for (a) Katakwi, (b) Manafwa, and (c) Mayanja in Uganda.

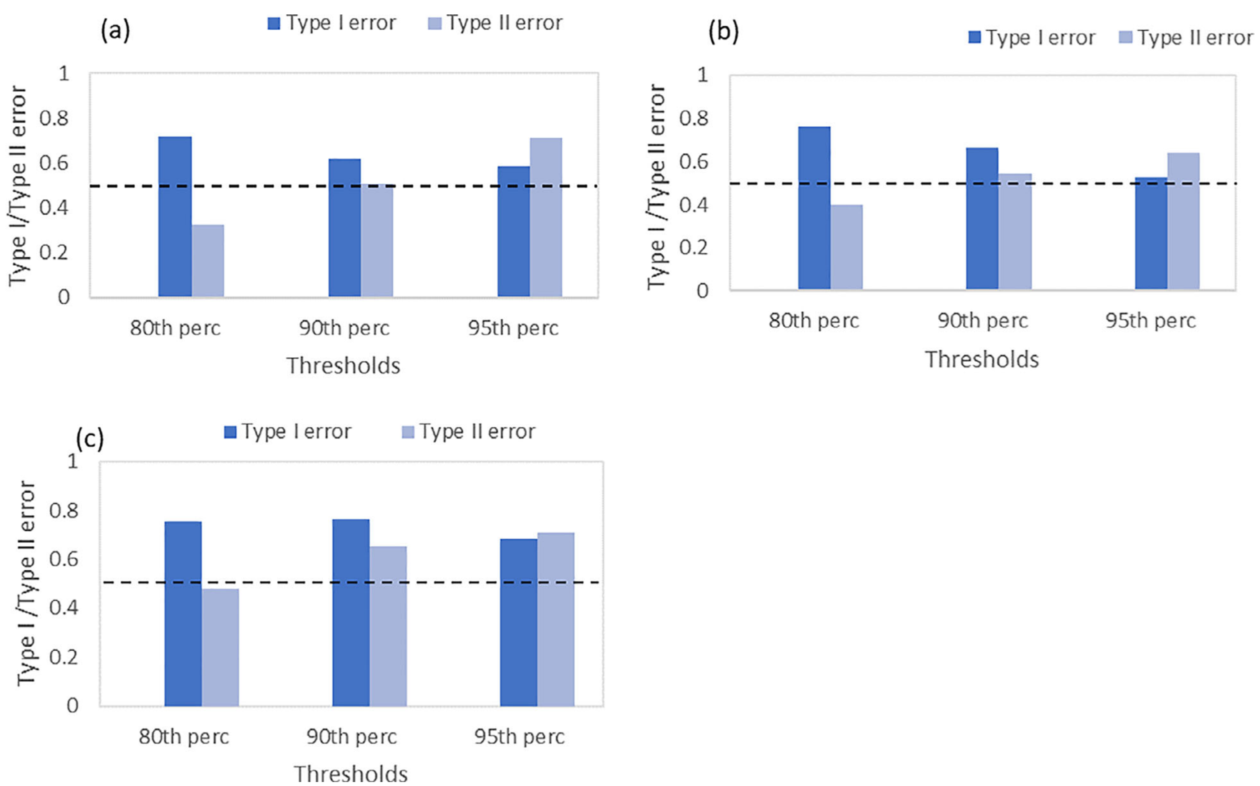

FIGURE 4 Comparative analysis of the impacts and observed data at three percentile thresholds (80th, 90th, and 95th) of daily river flows from the gauged stations for (a) Tana, (b) Nzoia, and (c) Athi in Kenya.

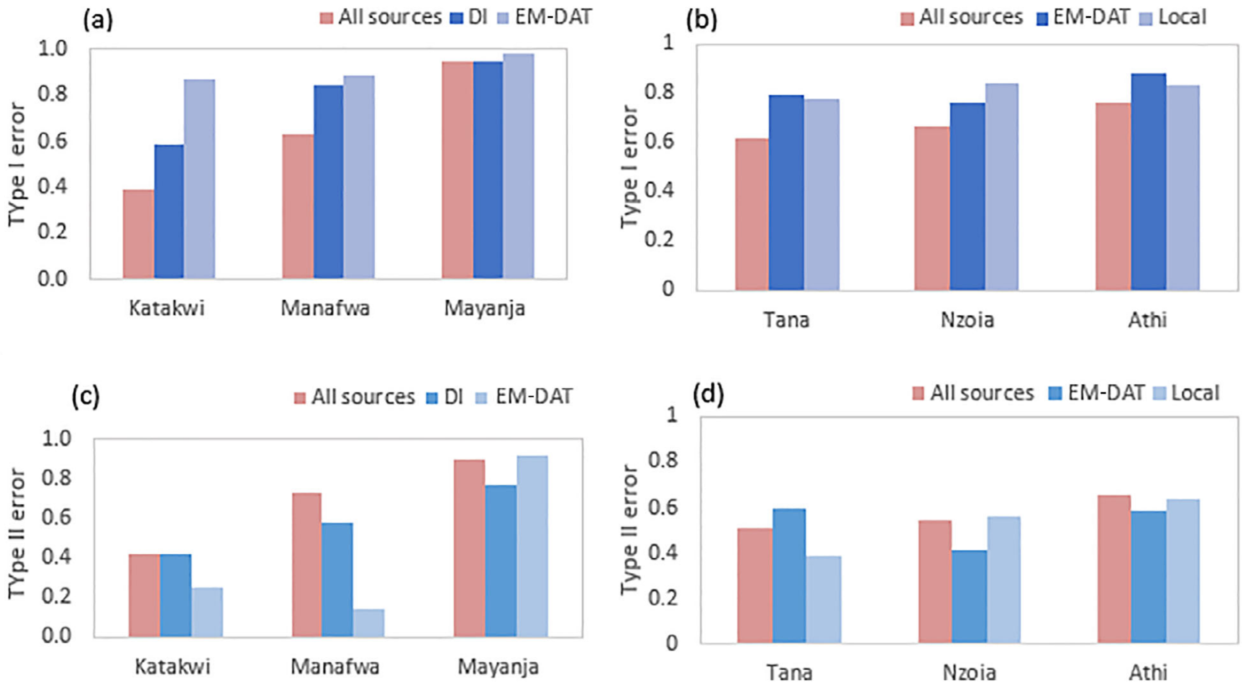

FIGURE 5 Type I and Type II error at 90th percentile for all data repositories (including overlaps) and single source data repositories for (a) Type I in Uganda locations, (b) Type I in Kenya locations, (c) Type II Uganda locations, and (d) Type II Kenya locations. DI, DesInventar; EM-DAT, Emergency Events Database.

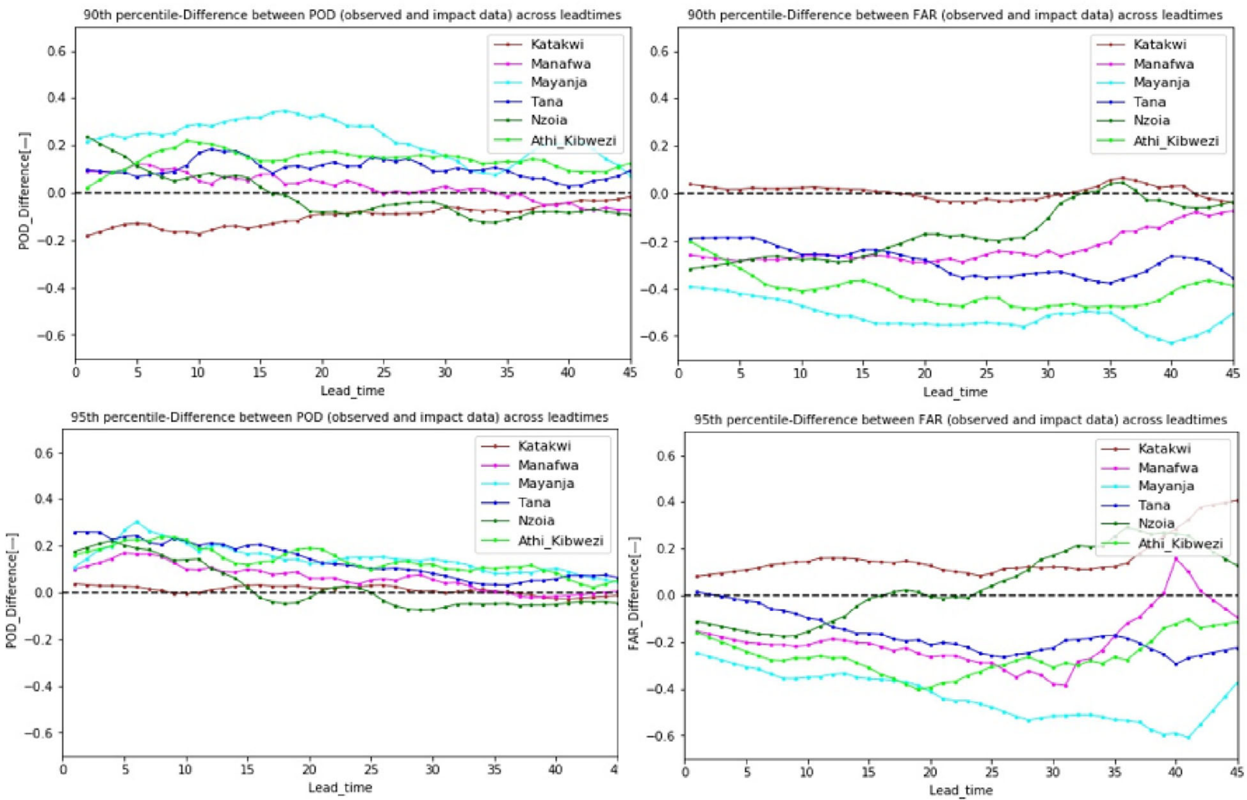

FIGURE 6 Differences in POD and FAR for locations in Uganda (Katakwi, Manafwa, and Mayanja) and Kenya (Tana, Nzoia, and Athi) across lead times at the 90th and 95th percentiles. FAR, false alarm ratio; POD, probability of detection.

across locations with a change of about 0.5 in Mayanja and Athi. POD and FAR graphs for the study locations at 90th and 95th percentile using river-gauge observations and impact data are provided in Figure S1.

5 | DISCUSSION

Using less conventional data such as impact data in forecast verification are gaining interest among researchers and practitioners. However, these data sources, just like hydro-meteorological data, are subject to errors and biases (Wilby et al., 2017). Despite these shortcomings, the impact data have the potential to ensure early warning systems are robust. In this section, we discuss the findings and implications of using impact data to verify flood forecasts and the assumptions that have been considered. First, we discuss the available impact data in the East African countries (Uganda and Kenya). Second, we highlight the adequacy of the impact data compared with river-gauge observations and how that may influence forecast verification. Last, we highlight the potential and challenges of using impact data to verify forecast information in data-scarce regions and provide recommendations that can be useful in improving the impact data to ensure effective early actions.

5.1 | What does the available impact data from Uganda and Kenya tell us?

Among the four main data repositories used in this study, DI had the highest number of flood events in Uganda (Katakwi and Manafwa districts), whereas across Kenya and the three counties, EM-DAT reports the highest number of flood events (Table 4). The differences can be associated with the criteria used for the inclusion of impact data in these repositories as well as the country-specific regulations on the collection and systematic reporting of impact data (Osuteye et al., 2017). For example, in Katakwi, if we consider a specific period from 1 August 2007 to 31 October 2007, EM-DAT reported a total of 11 flood events while DI reported 9 flood events (all considering the 7-day window, Section 3.1). Among the events, seven flood events overlap across the repositories while EM-DAT has four distinct events and DI has two distinct events. Therefore, using DI alone will result in fewer (−4) flood events while using EM-DAT alone will result in fewer (−2) flood events. This is just one example and the differences in flood events across data repositories might increase or decrease. Due to such differences, using only one repository can lead to a bias in the outputs generated (e.g., underestimation of event frequency).

Although we disaggregated the impact data into districts and counties, we only used the qualitative information classified as impact/no impact to guide the analysis. This is because there are no direct quantitative loss estimates available for these locations useful in understanding the severity of each flood event. Quantitative estimates are usually reported as aggregated quantities across a region, rather than disaggregated quantities for smaller geographical areas within the region (Gall, 2015). For example, in EM-DAT, the 2007 flooding between August and October that impacted different parts of Uganda are combined as one record (Disaster number 2007-0408; EM-DAT, 2020) with the quantified impact on, for example, the 'number of people affected', also aggregated. The insufficient reporting of quantitative estimates in areas of small spatial coverage can limit the analysis and affect the robustness of any conclusion, especially from a livelihood perspective (Osuteye et al., 2017). In addition, these repositories have differences in the parameters used for reporting. For example, EM-DAT reports only one parameter of 'number of people affected', whereas DI reports the same using two parameters; 'directly affected and indirectly affected'. As also noted in Below et al. (2010), this hinders the direct quantitative comparison between the two data repositories.

5.2 | How adequate are the impact data in identifying thresholds for impactful river flooding and in verifying flood forecasts?

Setting up early warning mechanisms for floods often depends on the thresholds derived from river-gauge data to identify the level at which the river discharge may result in impactful flooding. In data-scarce regions, impact data can help to determine such thresholds (Coughlan De Perez et al., 2016) but this requires a large number of good quality impact data to reduce the chances of over-representation/under-representation of impacts (Ranger et al., 2011). We have found that even within the same country impact data are not consistently available across all locations (Barabadi & Ayele, 2018), which may lead to bias in the outputs. Our analysis shows that using more than one source of impact data reduces the chances of a Type I error or situation where flooding occurs but impact data are not available. For example, although EM-DAT contributes to over 69% of all impact reported in Tana, Nzoia, and Athi respectively, using this repository alone results in an increase in Type I error (flood observed in gauged data but not reported) compared with using all three repositories (EM-DAT, DI, Local; Figure 5b). This can be associated with the inclusion criteria for the various data repositories. For example, for a repository like EM-DAT, only high-impact flood events are represented leaving out low-impact flood events.

We have found that the consistency between impact data and river-gauge data varies markedly across the thresholds, but the variability is location-dependent. For example, in Katakwi, there is good correspondence between the river-gauge observations and impact data at the 90th percentile. This suggests impact data can be used to identify river discharge critical thresholds at which impactful flooding occurs. These findings are consistent with scientific literature where impact data have been successfully used to define flood thresholds. For example, Young et al. (2021) used impact reports to determine the rainfall thresholds that resulted in flooding in the urban city of Alexandria, Egypt.

Although we used the percentile-based method to identify flood events, we acknowledge that high-impact events are generally higher than the 99th percentile (MacLeod et al., 2021), but to ensure robustness of the statistical analysis, we adopted the 90th and 95th percentile thresholds as several previous authors did (e.g., Arnal et al., 2018; MacLeod et al., 2021). These percentiles may include low-impact flood events that are likely to affect local limited areas (with relatively high frequency, e.g., 5% of days over a year for the 95th percentile) but are useful in cases where impact data is used in the verification due to the differences in the inclusion criteria of flood events in the various data repositories (see Table 1). In some previous studies, even lower thresholds are used because of data availability limitations, to ensure robustness in the verification. For example, Arnal et al. (2018) used terciles (33rd and 66th percentiles) of the simulated streamflow for the verification of seasonal streamflow forecasts and discussed the need to consider high thresholds such as the 95th percentile if more data were available. We therefore recommend that further studies with possible longer data periods available, should look at the representativeness of results across flood thresholds higher than the 99th percentile.

Other locations in Uganda and Kenya show an increase in Type I (and Type II) error as the river flow threshold decreases (increases). The increase in Type I error can be related to the inadequacy or the low quality of impact data used in this analysis, i.e. for both inadequate impact data (if the repository did not include an observed event) and low-quality data (if the timestamp of the impact data is incorrect) a false positive is produced. Type II error could have resulted if impacts reported were not because of riverine flooding but other subtypes of flooding, and this can also be influenced by the inclusion criteria which are specific to each data repository. Although a repository like EM-DAT differentiates floods using subtypes such as riverine and flash flooding, DI does not include such subtypes. These subtypes would help ensure that flood events are further categorised before analysis to reduce the Type II error. In addition, such differentiation can help in designing appropriate preparedness and response interventions which vary based on the sub-type of flooding (Nauman et al., 2021; Paprotny et al., 2021). To further confirm the source of increase in Type II error, data derived from satellite imagery (e.g., Sentinel-1 and Sentinel-2) could be used to identify if floods occurred as well as their spatial location (with respect to rivers), which can help discriminate riverine floods (Tarpanelli et al., 2022).

The differences in POD and FAR vary across the study locations considered here. Except in Katakwi and partly in Nzoia (>15 days lead time), where we get a more favourable assessment of skill while using impact data, other locations show that using impact data underestimate the GloFAS skill both in terms of POD and FAR. Though the differences are minimal in the majority of the locations, it still means that impact data cannot be adequately used to verify flood forecasts in most locations, as highlighted previously by Gall (2015). However, the available river-gauge observations and impact data could be used to train the hydrological model used in the GloFAS system through calibration and validation in specific locations that show poor detection of flood events. In other words, the available historical impact data and gauge observations can be used to assess the hydrological skill of the GloFAS using scores such as Nash-Sutcliffe efficiency which assesses temporal variability and agreement between the modelled and observed data (see Teule et al., 2020). Overall, being aware of uncertainties that can result in using the available impact data can help ensure the outputs are used appropriately in supporting anticipatory actions.

5.3 | How best can the impact data be used to verify flood forecasts in data-scarce regions?

Our exploratory analysis has highlighted several factors that are affecting the efficacy of impact data for verifying flood forecasts in most of the study locations in Uganda and Kenya. These are inadequacy of events records, poor quality, and spatial resolution/granularity among others. Therefore, using impact data may result in underestimation of forecast skill, leading to reduced confidence in using the forecast to support anticipatory actions. In other words, if we use impact data to verify and it turns out to be unwittingly underestimating the forecast skill, we might discard a forecast that is good enough to support preparedness actions for vulnerable people. Nevertheless, positive results obtained for Katakwi in Uganda and Nzoia in Kenya show that with some improvements, the impact data could be used to determine critical thresholds for flooding and inform the design of early warning mechanisms in data-scarce regions. For such regions, the following improvements would increase the usability of impact data.

5.3.1 | Characterising the gaps/uncertainties

The uncertainties in the impact data should be explicitly stated, as well as the implications for the outputs, especially if the outputs are intended to inform actions. The uncertainty around the estimate can be denoted using standard error, which indicates how far the estimate is from the mean. The standard error can be calculated by dividing the standard deviation by the square root of the sample size (Walker, 2018). From our analysis, the standard error in the FAR calculation varies from 0.02 to 0.05. Therefore, if the recommended forecast FAR to trigger humanitarian action is <0.5, using impact data will require a FAR of <0.4 to minimise actions taken in vain. Continuous operational evaluation of the forecasts is also required in situations where real-time reference data are available.

5.3.2 | Combining databases

A combination of impact data from multiple data repositories should be explored especially if the data is scarce (Barabadi & Ayele, 2018). This can help reduce the biases and possibility of missed events in the reference datasets for forecast verification, because of the differences in the methods and criteria used in the compilation of the various data repositories. For example, comparing river-gauge observations with impact data from all repositories against EM-DAT in Tana resulted in an improvement of the Type I error from 0.8 to 0.6 (Figure 5b). However, the combination should be carefully explored to avoid duplication of entries, especially from repositories fed from the same primary source or if there is a slight difference in the timestamp for the same event. Some of these challenges of replication can be handled by using a tolerance interval such that entries that are within a certain interval are considered one event. In this study, an interval of 7 days was used.

The combination should also consider the differences in the indicators used in each repository. For example, EM-DAT reports the 'number of people affected' as one indicator while DI reports the same in two separate indicators (i.e., 'directly and indirectly affected'). In addition, EM-DAT makes clear differentiations of the disaster type and subtypes, such as riverine flood and flash flooding, whereas DI does not have such differentiation. Such differences make it challenging to combine and compare the data and disaggregate further, for instance, if you want to monitor only a subtype of the disaster. For example, in our analysis, most Type II errors could have resulted from impact data that were not necessarily from riverine flooding.

Harmonising and differentiating these parameters and clarifying their meanings would help minimise these difficulties (Below et al., 2010). This can be done by ensuring that these subtypes are indicated during the data collection process or by applying index-based approaches to differentiate between the various disaster sub-types (see Kruczkiewicz, Bucherie, et al., 2021). In addition, satellite data (e.g., from Sentinel-1 and Sentinel-2) can be used alongside the impacts reports to identify the nature and extent of flooding as well as the spatial location which can help in complementing the impact reports for future applications in forecast verification. The usefulness of satellite images in assessing flood event types and extent has already been demonstrated in several recent studies, although also these datasets have their own current limitations that should be taken into account (see Landuyt et al., 2019; Notti et al., 2018; Tarpanelli et al., 2022).

5.3.3 | Harmonising primary data collection and information management processes

Primary data collection process
primary data collection in most countries is done through normal government procedures. This is mainly done using the damage and needs assessment approach at the local level and the collected data analysed at the national level (see The International Bank for Reconstruction and Development & The World Bank, 2010). If the collected information show that impacts are considerable, the country may decide to seek external support. In this case, the United Nations Office for Coordination of Humanitarian Affairs (UN-OCHA) may coordinate more rapid needs assessments to collect more information using approaches such as the Multi-sector Initial Rapid Assessment (MIRA) framework (Inter-Agency Standing Committee, 2015). Countries can, however, use their own guidelines for collecting the data. In Uganda, the Office of the Prime Minister is tasked with the collection and uploading of impact data in the DI. However, recent interviews in Uganda noted that rapid response assessments and collection of impact data are carried out by various institutions, including the Office of the Prime Minister, the Uganda Red Cross Society, the Humanitarian Open Street mapping team, local NGOs, and the district office, among others (personal communication, October 2020). There is a need to harmonise the data collection process through clear guidelines and dedicated institutions to avoid the probability of competing reports of unknown credibility (Guha-Sapir & Below, 2006).

Furthermore, impact reporting can benefit from improved weather and river-gauge networks. Improving gauge networks can be strategized such that it is done alongside the improvement on impact data collection (Baddour & Douris, 2018). This can ensure improvement in the flood forecasting systems by providing key inputs for hydrological model calibration and forecast verification, as well as for further impact reports verification.

Information management process

impact data collected through primary sources such as in-country institutions are often uploaded to data repositories such as DI. Due to a lack of resources, most countries might not be uploading the collected information regularly. Therefore, the impact data collected are held in internal disaster management systems and managed by the primary institutions. National data repositories could be explored to ensure that all impact data collected in-country is stored in a central in-country repository for ease of accessibility.

5.3.4 | Impact data outside the official public sources

A broader and more accurate collection of temporal and geospatial data on disaster occurrence would ensure improved risk estimations (Bakkensen et al., 2018). An extended search of impact data available at the in-country archives, for example, in private institutions, and insurance companies, but not yet available in the open repositories would therefore help improve the quantity and detail level (spatial–temporal data) of the available impact data. For example, a study by Smith and Katz (2013) shows that a significant under-reporting of disaster loss estimates can occur due to reliance on only public sources because of their ease of accessibility.

5.3.5 | Use of new technologies

New technologies such as artificial intelligence can be used to expand impact data (van den Homberg et al., 2018). Initiatives to expand the impact data, for example, through web scraping, text mining (Margutti & van den Homberg, 2020), and application of earth observation data (Kruczkiewicz, McClain, et al., 2021; Nauman et al., 2021) and social media platforms should be explored. For example, social media platforms like Google Trends and Twitter have shown promising results in the detection and reporting of flood events (de Bruijn et al., 2019; Rossi et al., 2018; Thompson et al., 2022). In addition, an ongoing study by van den Homberg et al. (2022) has shown that flood impact data generated from news articles can complement data from global repositories such as DI both geographically and temporally, improving the usefulness of the data. Ensuring that any new data are interoperable with data from these repositories will require clear technical guidelines and protocols (Wirtz et al., 2014) such as the WMO data standardisation initiative (see Baddour & Douris, 2018).

Overall, impact data represent an important source of less conventional data for monitoring and improving early warning and preparedness actions. There is also great potential for improving these data quantity and quality through strengthening in-country disaster monitoring capabilities and ensuring standardised process of data collection that captures all the relevant data features such as flood extent, gauge level, contact information among others are in place(Integrated Research on disaster risk, 2014).

6 | CONCLUSION

As the world faces an uncertain future due to climate variability, environmental, and climate change, and an increase in extreme hydrometeorological events, investing in early warning early action mechanisms can be an effective way to prepare and adapt to these extreme events. However, such an investment will require understanding how forecast information performs in detecting these extreme events to ensure that anticipatory actions are not taken in vain. While forecast verification has been successful in regions where long-term hydrometeorological observations are available, this is very challenging in data-scarce regions.

Verification of forecasts using non-traditional approaches that use less conventional data would ensure the development of these mechanisms even in locations with scarce/no conventional observations. In this study, we investigated the usefulness of flood impact data to verify flood forecasts. Our findings show that although existing impact data have shortcomings, they also have the potential for flood event analysis and forecast verification and can be used in regions with no long-term hydrometeorological observations. These impact data may, however, require improvement to enhance their utility and make the forecast verification more acceptable and reliable. Among the recommendations outlined above, supporting the national institutions to streamline impact data collection, and expanding impact data using new technologies are of critical importance. Addressing these issues will, however, require a recognition of the role that impact data can play in verifying hydrometeorological forecasts and in identifying trends in extreme events to inform risk management. In addition, a collaborative effort among international humanitarian actors, disaster management institutions, the private sector, and local communities is needed to ensure that quality impact data are collected consistently and made available in near real-time.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

DATA AVAILABILITY STATEMENT

The GloFAS v3.1 reforecast are available from Copernicus Climate Change Service- Climate Data Store (https://cds.climate.copernicus.eu/). Impacts reports from DesInventar and EM-DAT are freely available from their respective web pages (https://www.desinventar.net/ and https://www.emdat.be/database). DFO reports are available upon request from the University of Colorado. The R-scripts used in forecast verification are available upon request from the authors.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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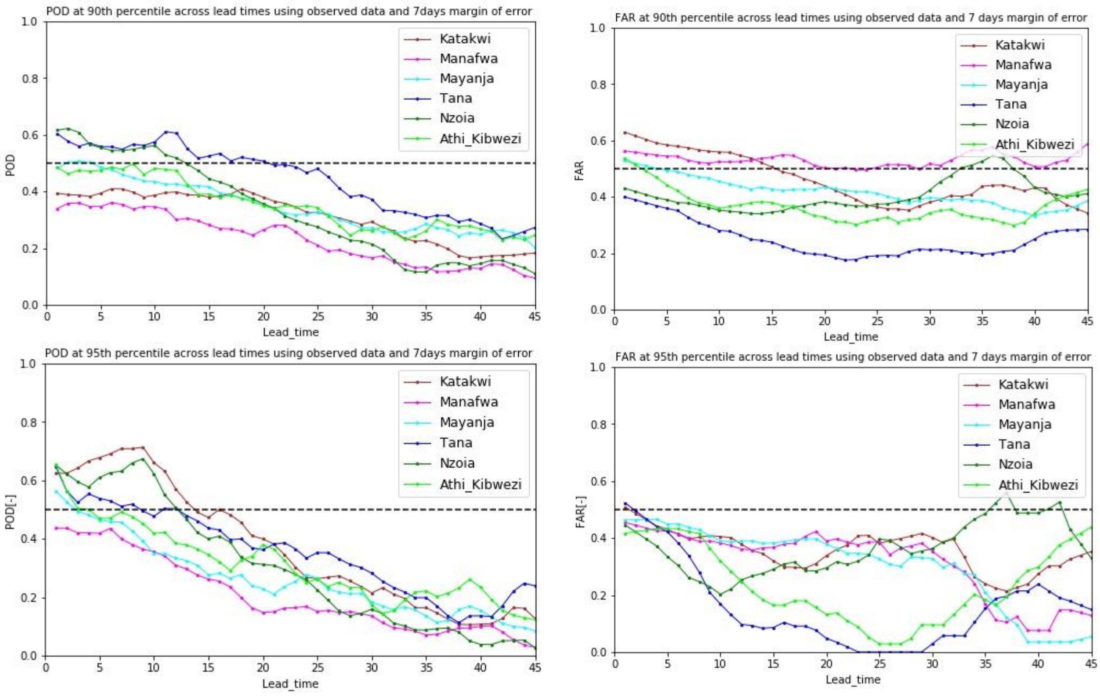
Appendix A3.1: Common parameters included in various data repositories.

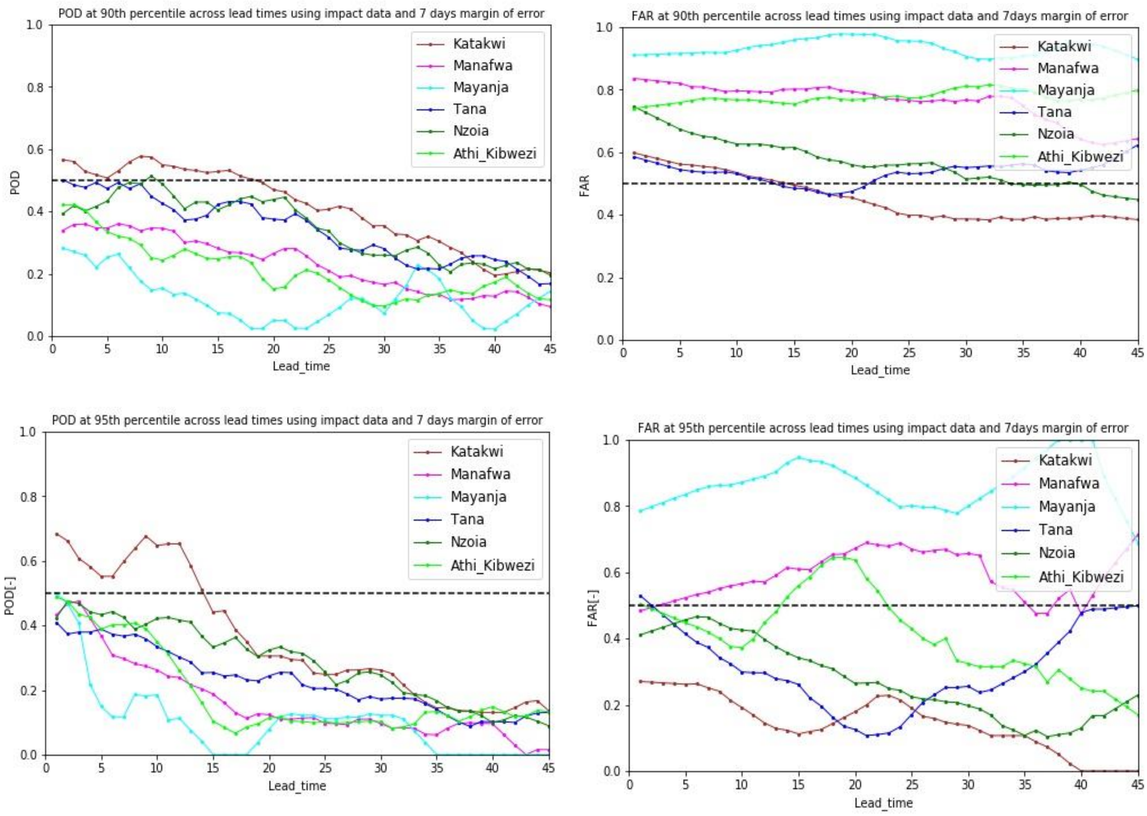
Data repository	**Parameters included**			
	Identifiers	Spatial and temporal	Quantitative	Qualitative
DesInventar	Serial number, district code, event type, cause of the impact, primary source of the data, magnitude,	location (district, sub-county, location), date (YMD)	Number of deaths, injured, missing, affected (directly and indirectly), evacuated, losses, damages in crops, houses damaged	Comment column that contains both quantitative and qualitative information on the impacts
EM-DAT	Dis no, origin (cause of impact), associated disaster	Names of districts affected, year, start date and month, end date and month,	Number of deaths, injured, affected, insured, homeless	No qualitative information
Dartmouth Flood Observatory (DFO)	ID, Glide number, severity, main cause	Country and other country, latitude and longitude of affected area, area, begin YMD and end YMD	Number dead, displaced,	No qualitative information

Appendix A3.2: Graphs of POD and FAR at (90th and 95th percentiles) using gauge-observations and impact data.

a) Gauge observations (POD and FAR at 90th and 95th percentile)



b) Impact data (POD and FAR at 90th and 95th percentile)



Appendix A4: Supplementary materials for Chapter 4

Appendix A4.1: Positive impacts of floods on fruit trees in the three villages in Katakwi District

Time of Year	December	January	February	March	April	May	June	July	August	September	October	November
Rainfall Season												
Fruit_trees/calendar	H	LAND PREP		PLANTING & WEEDING			HARVESTING [H]			PLANTING		H
Lemon												
Oranges												
Mango												
Papaya												
Jack fruit												

Appendix A4.2: pre-agreed early actions (from Uganda EAP) and the targeted early actions for Katakwi District

Pre-agreed Early actions (Drawn from EAP)
Community awareness on anticipated risks and selected early actions
Distribution of water purification chemicals, water storage vessels and soap
Distribution of Cash and Voucher Assistance to facilitate evacuation and meet other basic needs
Distribution of customized shelter kits
Cleaning water sources/desilting drainage channels/dredging in Urban and rural areas
Community mapping - (map out designated centres, evacuation roots and holding stores)
Early actions based on the crop calendar (derived from interviews with farmers.)

Months	March	April	May	June	July	August	September	October	November
Contextualized Early actions	Late planting of early maturing crops Draining water from farms to protect crops Farm management practices to improve soil drainage			Early harvesting of major crops such as cassava, sweet potatoes etc. Provide kits to ensure storage of harvests in a dry place			Late planting of early maturing crops Draining water from farms to protect crops		