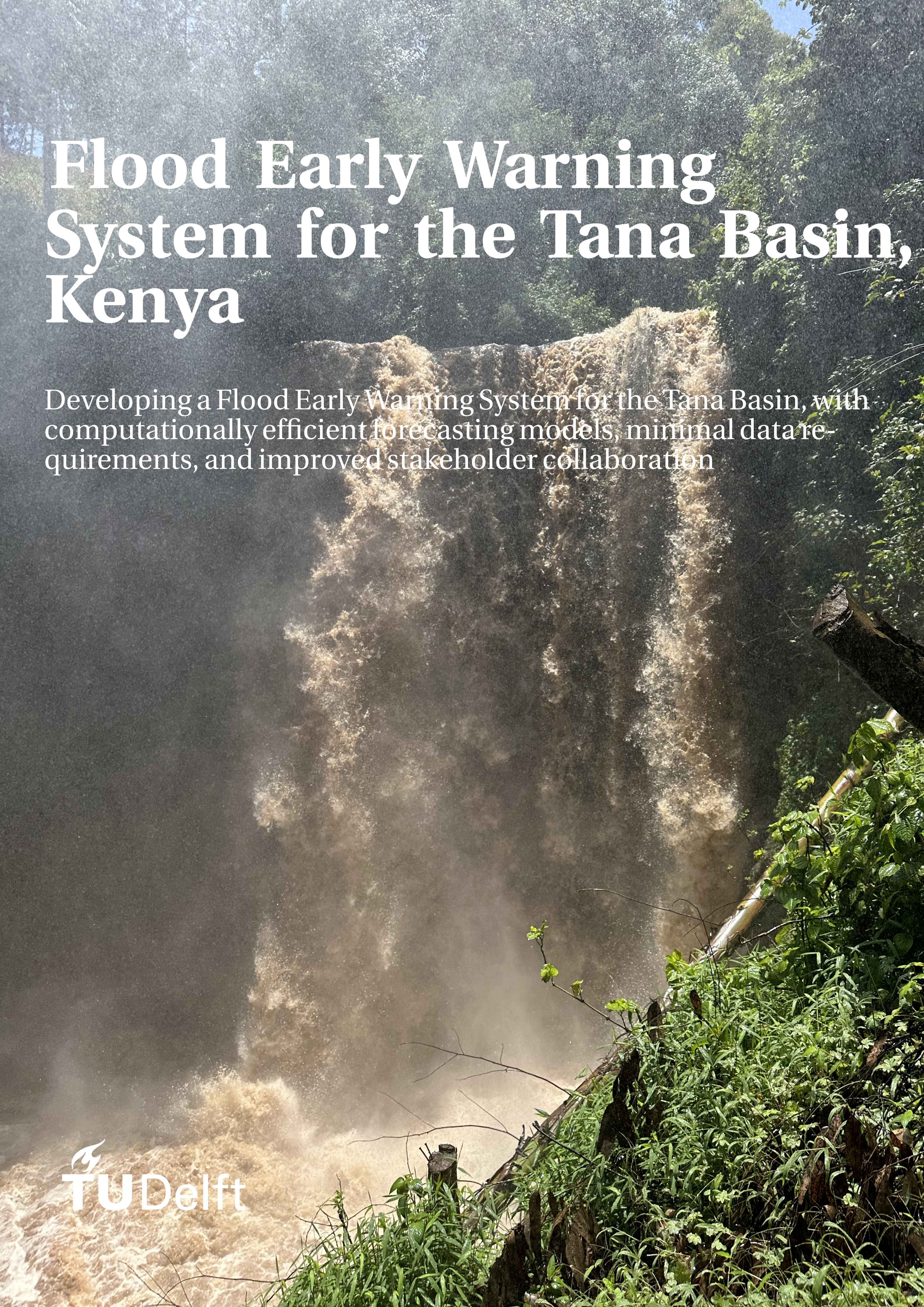
Flood Early Warning System for the Tana Basin, Kenya

Developing a Flood Early Warning System for the Tana Basin, with computationally efficient forecasting models, minimal data requirements, and improved stakeholder collaboration



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by

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Abstract

This report details the development of a Flood Early Warning System (FEWS) for the Tana Basin in Kenya, executed by a multidisciplinary team from the Delft University of Technology. Recognizing the Tana Basin's vulnerability to flood risks, exacerbated by climatic variability, limited funds, and limited available data, the project proposes a model that combines computationally efficient hydrological and hydrodynamic modelling with robust stakeholder collaboration. The study area comprises the entire Tana Basin, with a specific focus on the flood-prone area near Garissa used for validation. The FEWS developed incorporates local and scientifically derived knowledge to forecast floods, aiming to aid the transition from a technologically intermediate to a technologically advanced FEWS. Through an iterative process of model selection, validation, and stakeholder feedback, the system attempts to integrate the GR4J hydrological model in SuperflexPy and combines this with the Super Fast INundation of CoastS (SFINCS) model. Data sources include global remote sensing datasets like FABDEM & CHIRPS. Furthermore, it uses the water level gauge data provided by the Water Resource Authority of Kenya, as well as TAHMO weather station data.

The report concludes by reflecting on the modelling techniques for both the *hydrological* and *hydrodynamic* models and provides recommendations for the further development of a FEWS in the Tana Basin in Kenya. The implementation of the hydrological model was not able to propagate external flows through the network, making it poorly suited for use in the Tana Basin. The hydrodynamic model works decently well in flood conditions but overpredicts flooding during regular flow conditions. Recommendations on stakeholder engagements and data-sharing practices to foster a resilient flood management system in the Tana Basin include more comprehensive Memoranda of Understanding (MoU) and stricter adherence to the Disaster Risk Management Framework of the United Nations.

Acknowledgments

Travelling to Nairobi provides us as a group with a unique opportunity to develop and apply new skills regarding modelling, teamwork, and client cooperation. We are deeply grateful to our university, Delft University of Technology for providing us with this opportunity. We were supported by many people for whom we want to take this opportunity to extend our gratitude.

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Nomenclatura

CBDM Community Based Disaster Management

CHIRPS Climate Hazard Group InfraRed Precipitation with Station data

DCC District Commissioners

FEWS Flood Early Warning System

GoK Government of Kenya

GR4J Génie Rural a 4 paramètres Journalier

HEC-RAS Hydrologic Engineering Center's River Analysis System

ICPAC IGAD Climate Prediction and Applications Centre

JICA Japan International Cooperation Agency

KenGen Kenya Electricity Company

KMD Kenyan Meteorological Department

KRCS Kenyan Red Cross Society

MAM March-April-May

MoICNG Ministry of Interior and Coordination of the National Government

MoU Memorandum of Understanding

MSL Mean Sea Level

MWI Ministry of Water and Irrigation

NDMU National Disaster Management Unit

NGO Non Governmental Organisation

NMHS National Meteorological and Hydrological Services

OND Octobre-November-December

OPERA Observational Products for End-Users from Remote Sensing Analysis

SAGA Semi-Autonomous Government Agency

SFINCS Super Fast INundation of CoastS

TAHMO Trans-African Hydrological Meteorological Observatory

TARDA Tana & Athi Rivers Development Authority

TCA	Tana Catchment Area
WMO	World Meteorological Organization
WRA	Water Resources Authority
WRF	Weather Research and Forecastin model
WRMA	Water Resources Managament Authority

Contents

List of Figures

1 Introduction

Floods have a devastating effect on almost all socioeconomic activities and they are very common in Africa. Floods often occur unexpectedly in communities and disrupt transportation networks, affecting food security and market distribution systems. The impact of floods is devastating, very prevalent, and costly, with severe loss of life (human and livestock) and property, disruption of communication networks, and large economic losses. Floods are short-lived events that can happen suddenly (National Drought Management Authority, 2016), with little to no warning. The main cause of floods is intense precipitation that produces more run-off than the infiltration capacity to be subsequently stored or carried by a stream within its normal channel. Another reason for floods is when dams fail or landslides temporarily block a channel (Opere, 2013).

The size of a flood is based on its return period. This is determined by studying a long period of flow records in a stream. For example, a 5-year flood would occur, statistically, once every 5 years. The thing about floods is that they can occur at any time, but weather/climate patterns have a strong influence (Opere, 2013). Climate change is a global phenomenon that has been ongoing for some time now, exacerbating extreme weather events. However, the impact of climate change varies from location to location. Some regions experience more droughts, while others face increased precipitation (Serdeczny et al., 2017).

An effective Flood Early Warning System (FEWS) can play an important role in reducing risks posed by floods (Lumbroso, 2018). The FEWS can forecast flood events and allow warnings to be formulated based on scientific knowledge, monitoring, and consideration of the factors that affect disaster severity and frequency. This research focuses on developing a FEWS for the Tana Basin in Kenya, which has three flood-prone areas in the lower part of the basin.

This chapter is an introduction to the Multi-Disciplinary project we have been working on. First, we will introduce the Tana Basin in Section 1.1. Secondly, the problem analysis is explained in Section 1.2. Lastly, the scope and objective of this research are determined in Section 1.3.

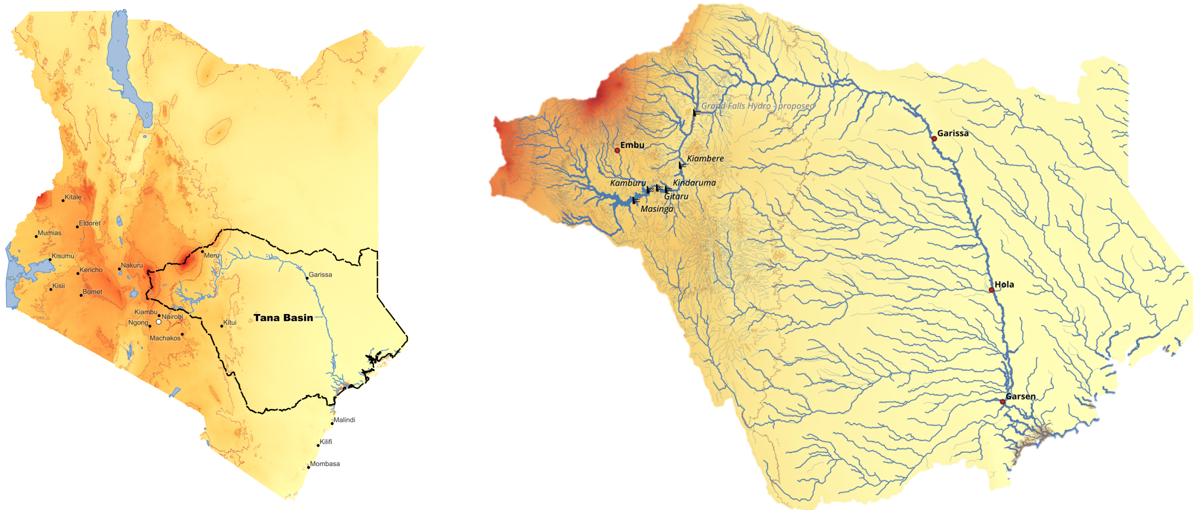
1.1. Study Area

The study area of this Multi-Disciplinary Project (MDP) is the Tana basin, Kenya. The Tana basin is the biggest supplier of fresh water for the capital of Kenya, Nairobi. Approximately 80% of the domestic water supply originates from this basin (Muthuwatta, Sood, Mccartney, Sandeepana Silva, & Opere, 2018). Besides water supply for Nairobi, the Tana Basin meets about 50% of Kenya's total electricity demand. This energy is generated by five dams, which are part of the Seven Forks Dams (Muthuwatta et al., 2018). The Tana basin is also an important source of food and employment. Fisheries and agriculture are the main sources for the 7 million people who live in that area (van Beukering & de Moel, 2015), and people from other parts of the country.

This section will discuss the topography, land use, and other important factors when building the required FEWS. It will also serve as an introduction to the Tana Catchment Area (TCA) and the diversity that is present within this region.

1.1.1. Regions and Subregions

The TCA is located in the Southeastern part of Kenya, as can be seen in Figure 1.1. With an area of 126,026 km^2 it covers about 21.9% of the country itself and contains the longest river in Kenya, the Tana River (Muthuwatta et al., 2018). The region itself contains a wide variety of landscapes, from the largest mountain in the country, Mount Kenya, at 5199 m above MSL to the coastline that is located at less than 50 meters above MSL. The region can best be subdivided into three subregions (upper, middle, and lower part) each with its own characteristics and main land uses.



(a) Overview of Kenya with the Tana basin outline.

(b) Tana basin region with the major tributaries.

Figure 1.1: Overview of the total study area.

The climate of the Tana Basin (and the whole of Kenya) is heavenly influenced by its location on/close to the equator. This brings the monsoon rains that are regulated by the north-south shift of the Inter-Tropical Convergence Zone (Byrne, Pendergrass, Rapp, & Wodzicki, 2018), meaning Kenya experiences two rain seasons per year. These seasons are referred to as long rains (March-May) and short rains (October-November) (**?**).

In general, the upper part of the Tana basin is fairly humid with large amounts of precipitation. The lower part contains mainly arid or semi-arid land. Figure 1.2 by Beck et al. (2018) shows the classification of land in Kenya as of 2018. Lawrence et al. (2023) showed that the areas of the Tana Basin that have been designated as arid or semi-arid have been decreasing significantly over the past 40 years.

In the National Water Plan 2030, by Government of Kenya (2013), proposals for the economic growth and development of the Kenyan economy and population are outlined, which has profound implications on the Tana Basin as well. The most important thing to consider when looking at the economic/climatological system of the Tana Basin is the fact that it plays out against an ever-increasing demand for water whilst experiencing an ever-decreasing amount of precipitation.

The following sections discuss the main characteristics of the Tana basin. The Tana Basin is divided into an upper, middle and lower part (Government of Kenya, 2013). The geography, climate and economy of each part are illustrated below (Government of Kenya, 2013; Sambalino & Steenbergen, 2012).

Upper Tana Basin

The Upper Tana basin is classified as any area above 1000 m compared to MSL. Of the three areas, it is the smallest catchment by size, with a total area of 17420 km^2 (Sambalino & Steenbergen, 2012).

Geograpy and climate: The Upper Tana Basin is largely characterized by smaller and seasonal tributaries like the Thika, Sagana, Thiba, and many more. The area also experiences the highest annual precipitation of the entire catchment area of around 1050 mm/year (Sambalino & Steenbergen, 2012) and up to 1600 mm/year around Mount Kenya (Government of Kenya, 2013). The Upper Tana is classified as a humid land. Parts of the

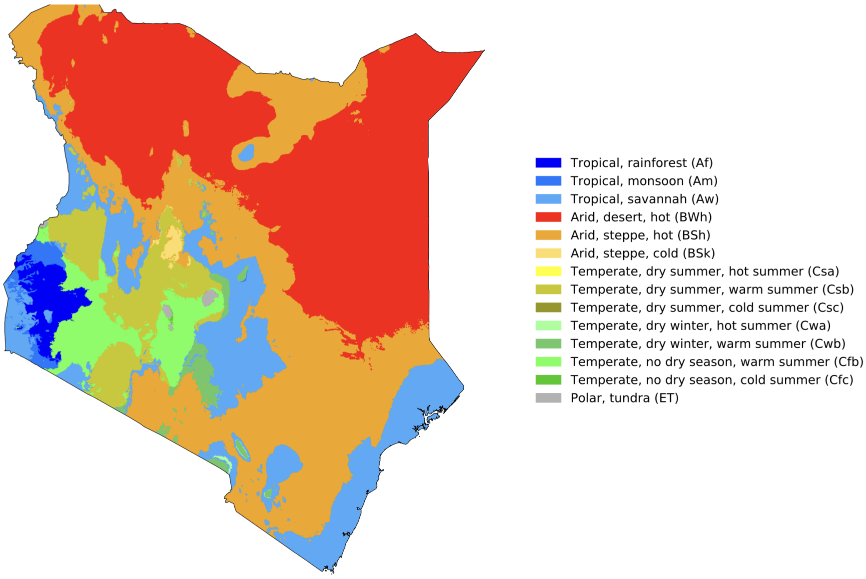


Figure 1.2: The classification of the land in Kenya done by Beck et al. (2018).

tributaries have been cut off by smaller dams, intending to divert the water towards the Athi basin in which, among others, Nairobi resides. (Muthuwatta et al., 2018).

This area experiences significant erosion and degradation of the soil (van Beukering & de Moel, 2015). The degradation is highest wherever the agricultural intensity is the highest, indicating a strong correlation between the two. The soil erosion in this area has large implications for the sediment transport in the Tana River.

Economics: The soil in the upper Tana area is mainly volcanic, which is rich in nutrients (Dijkshoorn, Macharia, Huting, Maingi, & Njoroge, 2010). As a result, this area is heavily used for the farming of rice, coffee, wheat, tea, and maize. Dairy production, poultry, and sheep farming also form a big part of the economic basis of this area (van Beukering & de Moel, 2015).

Furthermore, the upper Tana basin is characterized by a large number of hydro dams in the river, also known as the Seven Forks Stations. This is a series of hydrodams with a total capacity of 599.2 MW (KenGen, n.d.). It accounts for around 45% of the total power production of KenGen. There are further plans to build the High Grand Falls dam with a total installed capacity of 693 MW (Government of Kenya, 2013). Besides power generation, these dams also reduce the amount of sediment in the river, as well as the incidence and magnitude of floods, which has large implications for the characteristics of the river downstream (Snoussi et al., 2007).

Middle Tana Basin
The Middle Tana basin is classified as the basin area between 300 and 1000 m above MSL. It extends over the Tharaka, Kitui, Mwingi, and parts of Yatta district. Because of its limited precipitation and lower soil fertility, it is not as extensively used for crop production (Sambalino & Steenbergen, 2012).

Geograpy and climate: The Middle Tana is mostly classified as arid land, with the central part being classified as semi-arid. The area experiences much less precipitation, only around 500 mm/year. Several tributaries are present, but these are all seasonal (Government of Kenya, 2013). The soil is composed of cambisols and alkaline rocks (Sambalino & Steenbergen, 2012) which can be used for dryland farming

Economics The soil in the Middle Tana Basin can support dryland farming and the growing of crops such as cotton, tobacco, and beans. Furthermore, forestry is also possible in the area, but this is currently not strongly regulated (Sambalino & Steenbergen, 2012). This has led to deforestation, which in turn has aggravated flooding problems in the area. Lastly, sand mining is extensive in the Middle Tana Basin leading to reduced water buffering capabilities of seasonal streams.

Lower Tana Basin
The Lower Tana is classified as the area between 0 and 300 m MSL, including the river delta. Most of its land is taken up by two counties; Tana River County and Garissa County.

Geograpy and climate The coastal area of the Lower Tana is classified as semi-arid, with the remaining areas being classified as arid. The region experiences annual precipitation between 200 mm/year in the very arid regions and 800 mm/year near the coast (Baker et al., 2015).

Economics The Lower Tana basin is characterized by a rural population of about 1.4 million people, with unemployment rates of 28.4% and 42.8 % in Garissa and Tana River County respectively (Garissa County, 2018; Tana River County, 2018). Furthermore, in Tana River County 76.9% of its population is living in absolute poverty, compared to 36.1% of the country (Pape & Mejia-Mantilla, 2019). The unemployment figure for Garissa County is 28.4%.

Plans exist to try to lift people in both counties out of poverty, and one of the potential identified areas is increased farming activity in the region. Currently, only 2% of arable land in Tana River County is being irrigated, largely in large-scale schemes (Tana River County, 2018). Plans to further increase this irrigation percentage are described in the National Water Plan 2030 (Government of Kenya, 2013). If these plans are carried out it will have large implications for the water levels in the river and the quality of the existing soil. Garissa, being a more arid County has less irrigation potential and therefore no extensive schemes to increase the irrigated areas.

1.2. Problem Analysis

This section discusses the issues caused by floods in the Tana Basin. The section is divided into three parts. Section 1.2.1 discusses floods and their consequences, provides a historical overview, and discusses related trends and developments. Secondly, the current state of governance of flood risk management is discussed in Section 1.2.2. After that, the existing FEWS of the Tana Basin is examined in Section 1.2.3.

1.2.1. Floods

Floods cause the most economic damage of any natural hazard at 31% globally (UNISDR, 2015). Floods pose a significant risk to those living in flood-prone areas along the Tana (Baker et al., 2015; Government of Kenya, 2013; Kiptum et al., 2023), leading to loss of life and significant economic losses. Flooding Most of the agricultural activities, in Kenya, are concentrated along riverbanks, making crops more vulnerable to damage from floods resulting in food insecurity (National Drought Management Authority, 2016). Another consequence of floods is that stagnant water serves as breeding grounds for malaria or dengue fever outbreaks, which can increase the fatality rates of civilians and emergency workers (Snow et al., 2015). Kenya is mostly affected by floods during the rainy seasons as explained in Section 1.1. Most of the floods occur along wetland agroecological production systems (**?**). The Water Master Plan 2030 identifies nine flood-prone areas in Kenya (Government of Kenya, 2013), of which three are located in the Tana Basin: Garissa, Hola, and Garsen. These areas are located in the lower part of the basin. Section 1.1 provides the area analysis of these flood-prone areas of the Tana Basin.

One of the earliest well-documented floods was in 1997/1998 and was caused by an El Niño episode (Opere, 2013). Ngecu and Mathu (1999) performed the first research on floods and the socioeconomic impact of a flood in Kenya. During this El Niño event, Kenya experienced extreme precipitation between May 1997 and February 1998. This extreme precipitation resulted in landslides and flooding throughout multiple parts of the country. Human activity affected most of the landslides (Ngecu & Mathu, 1999). Apart from loss of life (human and livestock), property losses, and other socioeconomic losses, caused by landslides and floods, several health hazards ensued. These included outbreaks of gastroenteritis, respiratory infections, poisoning, communicable diseases, and epidemic diseases (cholera, diarrhoea, and dengue fever) (Okaka & Odhiambo, 2018). The World Bank estimated the replacement cost of the damage caused by the El Niño floods and landslides on the infrastructure at Ksh 64 billion (Mogaka, Gichere, Davis, & Hirji, 2005).

A more recent flood event during the MAM in 2018, also affected the Tana Basin. Over 150,000 people had to be evacuated, with 72 deaths and 33 injuries over the entire country. These floods led to disruptions of livelihood, 6000 livestock casualties, and submergence of 8450 acres of farmlands (**?**). In addition, UNICEF (2018) reported a high warning for Rift Valley fever, causing six deaths. In semi-arid and arid areas, extreme precipitation and flooding are vulnerable to the spread of this disease. Lastly, in several areas of the country, an active cholera outbreak was reported.

During the El Niño floods of 2023, 71 people were killed, 478,860 were affected, 17,600 acres of farmland were destroyed, and 13,400 livestock animals perished. In addition to these numbers, there is a high likelihood of trauma and communicable diseases. Thousands of homes have been washed away or are marooned, while farmland has been submerged and livestock drowned. The arid and semi-arid areas are the most vulnerable locations for floods (KRCS, 2023b). The areas most significantly impacted by the floods resulting from El Niño are those characterized as arid and semi-arid, similar to the Tana Basin. These areas were still recovering from the worst droughts in 40 years, which caused a lot of malnutrition.

Two types of floods occur in the Tana Basin: flash floods and riverine floods. The floods differ in their origins and properties. Flash floods occur as a result of sudden, intense precipitation events lasting from hours to days, leading to rapid rises in water levels within streams and seasonal rivers (Gourley et al., 2013; Laudan, Zöller, & Thieken, 2020). This short temporal scale creates a challenge in forecasting floods. In contrast, riverine floods arise from prolonged water accumulation, gradually saturating the soil and increasing groundwater levels until inundation ensues (Laudan et al., 2020). They have a greater predictability margin, but still cause extensive property damage (Muthuwatta et al., 2018).

The flood occurrences are influenced by changes in land cover, as explained in detail for the Tana Basin in Section 1.1, particularly the flash floods. This effect operates in two ways. Firstly, reductions in soil vegetation density resulting from changes in land cover within the basin decrease the drag forces exerted by ground vegetation on water streams. This facilitates accelerated water flow and reduces infiltration times, consequently exacerbating the severity of flash floods (Opere, 2013). Secondly, diminished original vegetation often corresponds with reduced soil infiltration rates, fostering increased surface runoff and amplifying flash flood frequency and intensity (Bartens, Day, Harris, Dove, & Wynn, 2008).

Beyond land cover changes, climate variations exert a discernible influence on flooding patterns. While annual precipitation is not projected to change, projections suggest a spatial and temporal redistribution of precipitation (Lawrence et al., 2023). Consequently, future flood management strategies must adopt adaptable frameworks to accommodate these shifts (Marigi, 2017). Notably, a study conducted by CIAT (2016) highlights a slight escalation in drought risks during the initial wet season (MAM) over the past four decades, as opposed to increased and more frequent precipitation occurrences during the subsequent wet season (OND). Projected climate models affirm the persistent vulnerability of Tana River County to both extreme drought and flood events.

1.2.2. Governance of Flood Risk Management

The government of Kenya should ensure coordination and implementation of policies, strategies, and actions aimed at reducing the impacts of flooding on communities, infrastructure, and the environment. However, effective flood risk governance typically involves multiple stakeholders at various levels, including government agencies, local authorities, community groups, non-governmental organizations (NGOs), and private sector entities. The disaster management cycle (UN-SPIDER, n.d.) is a conceptual framework that outlines the phases of managing disasters from preparedness and mitigation to response, recovery, and adaptation. It provides a systematic approach for governments, organizations, and communities to understand and address the various stages of disaster management, which will be discussed in more detail in Section 2.1. In the mitigation phase, stakeholders collaborate to implement zoning regulations and infrastructure improvements to reduce flood risk. For the preparedness phase, emergency management agencies, local government officials, and community leaders work together to develop evacuation plans. In the response phase, stakeholders including emergency services, medical personnel, and volunteer organizations coordinate efforts to provide immediate assistance to affected populations. In the recovery phase, stakeholders such as government agencies, insurance companies, and non-profit organizations collaborate to rebuild infrastructure and provide financial assistance.

Also in Kenya, flood risk management is fragmented across different institutions on national and county levels.

Next, a short overview of the most important stakeholders for flood risk management in the Tana River is presented.

Government of Kenya
As stated above, the Government of Kenya is mandated to consider and manage disaster mitigation at the national level. This generally entails coordinating and overseeing mitigation endeavours through various channels and utilizing a network of administrative officials including County Commissioners, District Commissioners (DCCs), Chiefs, Assistant Chiefs, and Village Elders County Government of Tana River (2021). The GoK has been putting a water sector reform into practice since the Water Act of 2002 was passed (Government of Kenya, 2013). The Water Resources Authority (WRA) was then founded in 2003 as the principal organization for national water resources management. The Water Act has been renewed in 2016 (Parliament of Kenya, 2016)

The GoK also introduced its national water master plan 2030, which outlines a comprehensive development plan for the country, emphasizing the crucial role of water resources in supporting its goals. Also, Kenya's challenges posed by climate change, including heightened risks of droughts and floods, prompted the government to develop adaptation strategies in this master plan. The National Water Master Plan 2030 is a collaboration between Kenya's Ministry of Water and Irrigation (MWI) and the Japan International Cooperation Agency (JICA) (Government of Kenya, 2013).

Water Resource Authority
The Water Resources Authority (WRA) is tasked with a range of functions aimed at the effective management and regulation of water resources in Kenya. These functions include formulating and enforcing standards, procedures, and regulations for water management and flood mitigation, as well as regulating the management and use of water resources. The Authority also plays a crucial role in receiving and processing water permit applications, determining permit issuance, and enforcing permit conditions (Parliament of Kenya, 2016; WRA, 2022).

The WRA plays a crucial role in addressing flood-related issues. This includes monitoring river flows (Section 1.2.3), observing flood events, and mapping areas at risk of flooding. (Kiptum et al., 2023; Weingärtner et al., 2019).

Kenya Meteorological Department
The role of the Kenya Meteorological Department (KMD) is to deliver timely early warning weather and climate information to ensure the safety of lives, safeguard property, and preserve the natural environment (**?**). This responsibility is firmly established within the framework of Executive Orders governing the structure and organization of the Kenyan government, as well as the World Meteorological Organization (WMO) convention. The convention specifically acknowledges National Meteorological and Hydrological Services (NMHSs), like the KMD, as the primary and authoritative entities for disseminating information on severe weather and extreme climate events among WMO member states (World Meteorological Organization., 2008).

For flood mitigation, flood forecasting is inherent. The Kenya Meteorological Department (KMD) is tasked with flood forecasting duties, which involve issuing warnings for extreme weather events. A Memorandum of Understanding (MoU) is in place to help ensure smooth flow of information and data between the WRA and KMD, but the extent of this memorandum and its effectiveness is somewhat unclear (Kiptum et al., 2023).

Local Government
Local (county) government (Tana River County, Garissa County) is tasked with developing policies and structures to enhance disaster preparedness, mitigation, and response (County Government of Tana River, 2021). In practice, these should be disaster contingency plans and response strategies. Disaster management is a joint responsibility between the national and county governments, but there has been a shift towards addressing these issues at the local level (County Government of Tana River, 2021).

KenGen and TARDA
KenGen operates the hydro dams in the Tana River. In total, they manage five hydropower dams and monitor the dam water levels. They are responsible for communicating the water levels with other stakeholders and issuing warnings before releasing large volumes of water (County Government of Tana River, 2021). These

warnings are issued to the public through TARDA, who are the legal owners of the hydropower dams. (Government of Kenya, 2013).

Kenya Red Cross Society
Established in 1965 through the Kenya Red Cross Society Act (Chapter 256 Laws of Kenya), the Kenya Red Cross Society (KRCS) operates as a voluntary aid organization, officially recognized by the Kenyan government. Serving as the exclusive National Red Cross Society in Kenya, it collaborates closely with public authorities to provide humanitarian assistance and support to those in need (KRCS, 2023a). Considering the disaster risk management cycle, the KRCS mainly operates within the preparedness and response phases. Still, given their position in the network, this stakeholder is often consulted by authorities regarding strategies or implementations of flood mitigation measures (Lino, Arango, Halima, & Abdillahi, 2021).

1.2.3. Flood Early Warning System
A Flood Early Warning System is a system that can make predictions on the flooding of certain areas using observational inputs. FEWSs are commonly agreed to consist of four components: (1) risk knowledge, (2) monitoring and forecasting, (3) warning dissemination, and (4) response capability (Cools, Innocenti, & O'Brien, 2016; Perera, Agnihotri, Seidou, & Djalante, 2020; UN, 2006; WMO, 2013). It has been shown that FEWS improve anticipation and preparation in the face of floods (Cools et al., 2016; Hallegatte, 2012). For an extensive review of and elaboration on FEWS and its components, see Chapter 2.

County Government of Tana River (2021) and Kiptum et al. (2023) provide an overview of the current status of the FEWS in the Tana basin. The previously mentioned components are implemented up to a varying degree in the Tana basin but do not constitute an official, operational FEWS. Below is an overview of the status of each component, along with some of the major challenges encountered. This analysis is conducted using the framework provided by UN (2006), which outlines both the essential components of FEWS and common challenges. Additionally, Kiptum et al. (2023) applied this framework to the various FEWS across Kenya.

(1) Risk knowledge
The Kenyan Water Master Plan delineates nine major, flood-prone zones in Kenya (Government of Kenya, 2013). Of these zones, four flood-prone areas are identified in the Tana Catchment Area (TCA). Three of these four areas are located in the Lower Tana, with Ijara being the remaining one. While the latter is technically located in the TCA, it is not flooded by the Tana itself but rather affected by local floods. When these areas are flooded, they are particularly susceptible to loss of life and economic damage.

Literature research indicated the following challenges or weaknesses regarding the risk knowledge component of the current FEWS.

- Lack of technical data on rivers. (UN, 2006)
- Absence of a return period database for all flood-prone areas. (Kiptum et al., 2023)
- Flood risks are not coupled to demographics. Demographic data is essential to determine vulnerability and exposure. (Kiptum et al., 2023; UN, 2006; Weingärtner et al., 2019)
- Absence of historical flood database. (Kiptum et al., 2023; UN, 2006)

(2) Monitoring and forecasting
The current system is referred to as a monitoring-based FEWS. This empirical system is based on upstream water levels to determine the downstream flood risks. Warnings are coupled to water level monitoring at Garissa, Hola, and Garson (Kiptum et al., 2023), as shown in Figure 1.3. Furthermore, warnings can be issued with a lead time of up to three days at Garissa through monitoring at Kathita rain gauge station (Government of Kenya, 2013), though no mention is made of specific warning strategies surrounding this station. A lead time of three days at Garissa is also secured when information is relayed from the Masinga dam. This lead time is increased to up to two weeks for the Tana Delta near the river mouth (Government of Kenya, 2013).

River level and by colour code	Actions
<3.0 m	Normal conditions
3.0–3.5 m	Alert conditions
3.5–4.0 m	Alarm
>4.0 m	Emergency

Figure 1.3: Warning levels coupled with respective water levels at Garissa gauge by Kiptum et al. (2023).

Currently, no forecasting models are used as the system solely relies on monitoring water levels. The mandate for the development of a FEWS does not have a clear responsible organisation. Various attempts have been made to develop a FEWS, but these models have not been fully implemented (yet). Achieving this necessitates robust collaboration between the WRA and KMD, with the former responsible for water level monitoring.

In total, the WRA operates a network of 43 water level gauges in the TCA as of 2010. Most of these stations are manually operated. Many stations lack rating curves or are not operational. Additionally, the WRA operates a total of 258 weather stations (12 telemetric) in the whole of Kenya. These were installed in collaboration with other instances (Government of Kenya, 2013). The KMD operates a network of 36 automatic weather stations (Government of Kenya, 2013). Despite the MoU (Section 1.2.2), information sharing has proven challenging. Finally, KenGen monitors water levels in the hydro dam reservoirs where they operate. This information is relayed to the regional offices of WRA each morning and evening according to sources in the local WRA Embu office.

Literature research and scoping interviews indicated the following challenges or weaknesses regarding the monitoring and forecasting component of the current FEWS.
Monitoring

- The monitoring network is limited, especially lacking telemetric stations. (Government of Kenya, 2013; Kiptum et al., 2023)
- The monitoring network has experienced maintenance issues, including problems relating to theft, operational costs (electricity, telecommunication), and sedimentation. (Government of Kenya, 2013)

Forecasting

- No operational forecasting system is in place. (Government of Kenya, 2013; Kiptum et al., 2023)
- Data exchange between different agencies has proven challenging, limiting the capacity for validation of forecasting models.

(3) Warning dissemination
According to MICNG and NDMU (2014), initial alerts for natural hazards or the immediate occurrence of disasters must first be issued by the appropriate early warning agency (e.g. KMD, WRA) or through an early warning system that is in place. This information must be quickly forwarded to the Director of the National Disaster Management Unit (NDMU) and the Permanent Secretary of the Ministry of Interior and Coordination of National Government (MoICNG) to initiate the required response actions as swiftly as possible. In case of flood, tsunami or cyclone hazard threat, the MoICNG is the lead agency for disaster risk management (MICNG & NDMU, 2014). Following the activation of MoICNG, the NDMU will oversee the dissemination of all warnings to the public. To ensure the public and relevant officials are adequately informed and prepared, the warnings will be communicated using the most effective media outlets and communication channels (MICNG & NDMU, 2014).

Several other instances currently have supporting responsibility for issuing flood early warnings. The KMD is responsible for general forecasting of weather. They provide flood warnings based on indicative heavy precipitation events. Separately, the Kenya Red Cross Society (KRCS) manages an Early Action Protocol that applies sub-seasonal to seasonal forecasts by GloFAS (Kiptum et al., 2023). Finally, KenGen provides warning information to the public through TARDA (dam owner) before releasing large volumes of water (Government of Kenya,

2013) from the hydropower reservoirs. As mentioned in the previous subsection, the warnings by KenGen provide local communities with a lead time between three days at Garissa to two weeks in the Tana Delta.

As pointed out in MICNG and NDMU (2014), early warnings should also be disseminated more directly.In 2021, the County Government of Tana River (2021) developed a proposed communication strategy as an outlook for future development. As outlined in this proposal, warning information currently travels through several separate modes to reach the local communities: National Government (KMD, WRA, and NDMU), County Government, NGOs, and (local) media. The County Government of Tana River (2021) provides a complete SWOT analysis of the current system and a future outlook and Lino et al. (2021) has conducted interviews with local stakeholders regarding their preferred communication modes.

At the national level, information is shared at community meetings (i.e. "bazaras"). The NDMU generates a monthly, weekly, and daily bulletin. Similarly, the KMD has monthly, weekly, and daily weather forecasts. At the county level, information is also shared through bazaras. However, in scoping interviews, persons affiliated with the WRA have pointed out that, in practice, warning information is mainly relayed through WhatsApp groups and radio broadcasts. Members of this WhatsApp group include the KRCS and sub-county coordinators, who relay information to local chiefs. This last stage of communication typically happens through informal means and unofficial water councils. Lino et al. (2021) found that most local leaders receive warning information through SMS.

Literature research and scoping interviews indicated the following challenges or weaknesses regarding the warning dissemination component of the current FEWS.

- Early warning information can be packaged and disseminated without consideration for the capacity of the receiver (County Government of Tana River, 2021; UN, 2006).
- Due to the absence of a complete formal dissemination network, some communities have poor access to flood warnings (County Government of Tana River, 2021; Kiptum et al., 2023).
- Coordination of flood early warning information dissemination can be poor and thus ineffective in timely reaching relevant actors and communities (County Government of Tana River, 2021; Kiptum et al., 2023; UN, 2006).
- Some communities have never experienced floods and are therefore unaware of potential impacts (County Government of Tana River, 2021; UN, 2006).

(4) Response capabilities
The capacity to respond to early warnings is dependent on the capacity of local communities and on the contingency plans maintained by local instances. Kiptum et al. (2023) argues the dependence of the former on the latter. They also argue that management protocols and contingency planning remain inadequate.
Government of Kenya (2013) has outlined a proposed community-based disaster management (CBDM) approach, consisting of "i) systematisation of communities and establishment of a flow of monitoring, information dissemination and evacuation in cooperation with the WRA Tana Regional Office, Lower Tana Subregional Office and local government offices, ii) construction of evacuation centres and evacuation routes by community involvement, iii) voluntary monitoring by members of the community by using simple rain and water level gauges, iv) community involvement in flood fighting activities, and v) construction of small-scale structural measures such as small revetments and culverts" (Government of Kenya, 2013). The objective of CBDM is to build disaster management capacity in local communities, specifically in the area downstream of Garissa. No publications have been made on this topic since its introduction, so its implementation status is unknown.

Literature research and scoping interviews indicated the following challenges or weaknesses regarding the response capabilities component of the current FEWS.

- Communities adhere to traditional/cultural practices and have become accustomed to floods. (County Government of Tana River, 2021; UN, 2006)
- Communities exhibit a lack of trust stemming from previous false alarms. (Tana River County, 2018; UN, 2006)
- Most affected communities do not have the resources to evacuate. (Tana River County, 2018; UN, 2006)
- Most lands are not legally demarcated and thus evacuation leads to fear of losing lands. (Tana River County, 2018)

- The county government has not established relocation grounds. (Tana River County, 2018; UN, 2006)

1.3. Scope and Objective

The scope of this MDP is defined by some boundaries; geographical, resources, capacity, safety, and time. The geographical boundary is determined by the location of the Tana Basin. The specific research area interesting for modelling can be further restricted by only considering the flood-prone areas, which are located in the lower part of the Tana Basin, approximately starting around Garissa. Availability of resources is a strict boundary. Financial resources to purchase modelling software are unavailable. Therefore, only open-source software can be used. Another resource that limits the research is the availability of data. Not all required data is openly available and must be requested from multiple organizations (e.g., WRA, KMD, TAHMO, KenGen). For the same reason, Garissa is the study area for this research. Additionally, the capacity of the research team is a constraint. A certain capacity is available for the implementation of hydrological and hydrodynamic models and the mapping of stakeholders and information flows. One of the last boundaries is the safety of the research team. Specifically, travel advice by the Dutch Government constrains the project from being executed in the TCA's flood-prone areas. Finally, the time constraint is determined by the limited time available for this project. Only 10 weeks are available to finish this project in Nairobi, Kenya. This timeframe allows the assessment and improvement of flood forecasting models and the required data-sharing mechanisms. This is achieved through literature research, interviews, and model validation through an event-based approach.

1.3.1. Objective

The MDP is divided into objectives aimed to be achieved at the end of the project. From these, the research question is obtained in Section 1.4.

The focus of the FEWS for the Tana Basin lies on the second and third components, discussed in Section 1.2.3. Specifically, it focuses on forecasting floods, with also some attention given to warning dissemination. We use predetermined flood-prone areas for flood modelling. Relating these to certain risk levels and demographics is better executed on a policy-making level. Flood forecasting lies within the group's capacity. Navigating inter-agency data exchange and using a limited monitoring network is an essential part of this process. While ample literature on warning dissemination is available, safety concerns prohibit the localization of this research. Warning dissemination is therefore researched on an institutional level. This also extends to response capabilities, which should preferably be addressed by socially oriented research.

Mapping the current system of stakeholders, mandates and existing FEWS is an integral part of the project. This system is navigated through a literature review and mainly scoping interviews.

Understanding the hydrological runoff process of the Tana Basin is imperative for the development of the model, as the hydrological runoff is the start of a flood. To achieve this goal it is necessary to get a good understanding of the area itself. The floods are mainly caused by heavy precipitation in the upper part of the Tana Basin, while the flood-prone areas are located in the lower part of the basin.

Another goal is to define which data is required for flood forecasts. Data can be scarce in developing countries (Leauthaud et al., 2013), but open-source remote sensing data may contribute significantly to the development of models. Moreover, various stakeholders are concurrently working on a FEWS. Yet, not all the requisite data for FEWS development is being actively exchanged.

With the help of some international organizations, the Nzoia FEWS was developed (see Section 2.6.4). This FEWS was sold to the WRA. However, they are facing some problems regarding maintenance and operating the system, relating both to physical gauges and maintaining models. Lessons from this Nzoia FEWS should be obtained through scoping interviews and incorporated into the Tana FEWS research. Resources are scarce and new FEWSs have not been implemented yet. The usage of open-source available software is important for the development of FEWS for the Tana Basin. Using open-source software reduces acquisition costs and enables local WRA staff to maintain and adjust the models if needed. For this capacity building for the WRA staff can be carried out, but this is not part of the research.

1.4. Research Question

The research question based on the objectives is:

How can a flood early warning system for the Tana Basin be improved with minimal data requirements, computationally efficient forecasting models, and enhanced stakeholder collaboration?

To answer this research question, three subquestions are defined. These questions will guide the answer to the main research question.

1. *What data is available in the Tana Basin for the development of a FEWS?*

For the development and improvement of the FEWS in the Tana Basin it is important to know what kind of data can be used. This is data about the catchment area itself and the available meteorological data for the catchment.

2. *What kind of computationally efficient, free-to-use models can be used for the development of a FEWS?*

Employees of the WRA must be able to run and make the models on the computers and laptops they have available at the moment. The models should be able to have the output within sufficient time, so an early warning can be shared in time.

3. *What information-sharing mechanisms exist between relevant stakeholders in the Tana Basin and how can this be improved?*

A FEWS consists of different parts, needing different types of information from stakeholders. For the development of a FEWS, it is important to know how the stakeholders interact with each other and if some interactions need some

1.5. Report Structure

This report will answer the research question by starting with a Literature Review in Chapter 2. This is followed by the Methodology in Chapter 3, where the model different models are discussed, together with the stakeholder analysis. The Results of this research are presented in Chapter 4. This is followed by a Discussion in Chapter 5 and the Conclusion in Chapter 6. Lastly, we present our recommendation towards the development of a FEWS for the Tana Basin in Chapter 7.

2

Literature Review

Between 2000 and 2024, floods accounted for at least 735 billion USD in damages and 130,000 deaths globally (CRED, 2024). This problem extends to Kenya, as discussed in Section 1.2.1, causing at least 1900 casualties and 500 million USD in damages (CRED, 2024).

The WMO (2013) emphasizes the potential of FEWSs to save lives and properties. This is also reflected in Sendai Framework Target G (UNDRR, 2015, 2022), where the emphasis is on multi-hazard early warning. Hallegatte (2012) estimated the potential avoided yearly asset losses through hydro-meteorological information production between USD 300 million and 2 billion USD for all developing countries with an additional 23,000 saved lives per year. In total, yearly benefits could reach between 4 and 36 billion USD, while yearly investments were estimated at a mere 1 billion USD. In conclusion, while a FEWS will not prevent floods, it can greatly reduce sustained economic losses and loss of lives.

This chapter examines the existing academic literature on Flood Early Warning Systems. First, a general overview of the general disaster risk management cycle will be given in Section 2.1. After that, a conceptual framework of FEWS will be given in Section 2.2. Next, both the models used in the scope of this research, the hydrological and hydrodynamic model are discussed in Section 2.3 and Section 2.4 respectively. After this, the methods and framework for dissemination of the warning are discussed in Section 2.5. The chapter will conclude with Section 2.6 discussing case studies of FEWS around the world, with a focus on the identification of challenges that surface during the implementation of a Flood Early Warning System.

2.1. Disaster Risk Management

Disaster risk management encompasses a broad spectrum of approaches and interventions. Hereby, the adverse consequences of both natural and human-induced hazards on susceptible communities and ecosystems are aimed to be reduced. It entails the systematic development and execution of inclusive strategies and policies to evaluate, diminish, prepare for, respond to, and recuperate from disastrous events (UNDRR, 2015). This is illustrated in the often cited disaster management cycle, see Figure 2.1.

Given the diverse array of disaster risks across the globe, the United Nations formulated the Sendai Framework for Disaster Risk Reduction. This framework offers comprehensive guidelines and actionable strategies to governments and stakeholders worldwide, addressing the multifaceted challenges posed by disasters (Nekoei-Moghadam, Moradi, & Tavan, 2024; UNDRR, 2015).

The Sendai Framework for Disaster Risk Reduction 2015-2030 represents a 15-year voluntary, non-binding, agreement that acknowledges the State's primary responsibility in reducing disaster risk while recognizing the shared responsibilities among various stakeholders, including local government and the private sector (UNDRR, 2015). The framework delineates seven specific targets, which center on achieving substantial reductions in disaster mortality, the number of affected individuals, direct economic losses, and damage to critical infrastructure. It also advocates for the enhancement of national and local disaster risk reduction strategies,

Figure 2.1: Disaster Risk Management Cycle from (Kemp et al., 2021).

increased cooperation with developing countries, and the expansion of multi-hazard early warning systems and disaster risk assessment capabilities.

Furthermore, the framework identifies four key priorities for action:

1. **Understanding disaster risk:** Emphasizing the importance of basing disaster risk management on a comprehensive understanding of vulnerability, capacity, exposure, hazard characteristics, and environmental factors, which can inform risk assessment, prevention, mitigation, preparedness, and response efforts (UNDRR, 2015).
2. **Strengthening disaster risk governance:** Highlighting the critical role of effective disaster risk governance at national, regional, and global levels in facilitating collaboration, partnership, and coordination across all phases of disaster management, including prevention, mitigation, preparedness, response, recovery, and rehabilitation (UNDRR, 2015).
3. **Investing in disaster risk reduction for resilience:** Advocating for both public and private investment in disaster risk prevention and reduction initiatives, encompassing both structural and non-structural measures. This serves to enhance the resilience of individuals, communities, nations, and their assets, as well as the natural environment, across economic, social, health, and cultural dimensions (UNDRR, 2015).
4. **Enhancing disaster preparedness for effective response and recovery:** Stressing the importance of strengthening disaster preparedness capacities at all levels to anticipate and respond to events effectively. Simultaneously, the opportunity presented during the recovery, rehabilitation, and reconstruction phase to "Build Back Better" by integrating disaster risk reduction principles into development initiatives and measures should be emphasized. (UNDRR, 2015).

Because of the economic, social, and development disparities between countries, the Sendai Framework cannot offer country-specific comprehensive implementation solutions (Nekoei-Moghadam et al., 2024). National governments should implement mitigation measures based on guidelines provided by this framework.

Flood mitigation measures can be classified as structural or non-structural (Hallegatte, 2012; Perera, Seidou, Agnihotri, Wahid, & Rasmy, 2019; UN, 2006; UNISDR, 2015; WMO, 2013). Examples of structural measures include levees, reservoirs, diversion channels, and spillways. Non-structural measures include flood early warning systems, land-use planning and zoning, rainwater harvesting, flood insurance schemes, and awareness campaigns (Perera et al., 2019). Both types of measures have the potential to reduce economic losses and loss of life.

Developing countries face significantly greater devastation compared to developed ones (Basha & Rus, 2007), and they often lack the resources to handle the aftermath of such disasters effectively. Therefore, attention to implementing FEWS is growing as early awareness of impending disasters could particularly aid developing countries by offering them the opportunity to safeguard assets and facilitate evacuations Basha and Rus (2007).

The Sendai Framework also emphasizes the importance of integrating FEWS to tackle the particular danger posed by floods (UNDRR, 2015). Furthermore, it stresses the need to incorporate these early warning systems into wider disaster risk management plans, fostering collaboration among stakeholders, and utilizing technology to ensure alerts are communicated effectively. Additionally, the framework underscores the importance of involving communities and enhancing their capabilities, which are fundamental aspects of implementing FEWS as they enable local communities to react swiftly and effectively to flood warnings.

2.2. Conceptual Framework of FEWS

FEWS are commonly agreed to consist of four components: (1) risk knowledge, (2) monitoring and forecasting, (3) warning dissemination, and (4) response capability (Cools et al., 2016; Perera et al., 2020; UN, 2006; WMO, 2013):

1. **Risk knowledge:** *systematic assessment of hazards and vulnerabilities, including mapping of their patterns and trends* (WMO, 2013).

Risk knowledge is essential to map risks and impacts on certain groups. Vulnerability is a key component and is quantitively assessed. It generally entails flood hazard maps, land-use analysis of downstream areas, demographic analysis, and financial analysis (Perera et al., 2019; UN, 2006). The UN (2006) highlights the importance of risk assessment to consider the cumulative effects of multiple hazards, for example, the outbreak of waterborne diseases associated with prolonged inundation. Using modern technologies such as remote sensing or better risk computing techniques could greatly improve risk knowledge.

Risk knowledge enables authorities to make informed decisions on acceptable risk levels and warning issuance.

2. **Monitoring and forecasting:** *accurate and timely forecasting of hazards using reliable, scientific methods and technologies* (WMO, 2013).

Monitoring and forecasting have to adhere to scientific standards to produce timely and accurate information (Perera et al., 2019; UN, 2006). Forecasting hydrometeorological information generally consists of a cascade of observations and models, which are summarized as meteorological observations and/or models, hydrological models, and hydrodynamic models. A more comprehensive consideration is provided in **??**. Progress with data gathering, sharing, and modeling techniques can greatly enhance the accuracy and reliability of monitoring and forecasting.

Monitoring and forecasting facilitate the provision of high-quality warnings with increased lead times (UN, 2006). Its effectiveness depends on technical capabilities, flood type, hydrometeorological models used, and the produced forecasts (Perera et al., 2019).

3. **Warning dissemination and communication:** *clear and timely distribution of warnings to all those at risk* (WMO, 2013).

Warnings are generated from the hydrodynamic forecasts. It is then essential to disseminate this to all at risk, commonly through a top-down approach (Perera et al., 2019). This generally involves a multitude of multi-level stakeholders that facilitate dissemination, ranging from governments to local NGOs. Generally, developed countries employ a nationwide push notification system, but this is often not in place in flood-prone developing countries (Perera et al., 2019). Improvements in these systems can often be made by increasing community engagement and incorporating developments made in information and communication technology.

4. **Response capability:** *national and local capacities providing knowledge about how to take appropriate actions when warnings are communicated* (WMO, 2013).

Response capabilities refer to the community's acceptance and responsiveness to early warnings (Perera et al., 2019). It is greatly dependent on the clarity of warnings and instructions, the availability of response measures, and the availability of contingency plans that include both pre-disaster and post-disaster emergency response and recovery (UN, 2006). Education on risks is essential at a community level, while the most important considerations at the management level are understandability of warning content by those at risk, safety and effectivity of public evacuation, and how to maintain order and security (UN, 2006).

Perera et al. (2020) found that the availability and status of FEWS worldwide, as well as their costs and advantages, difficulties, and emerging trends, are not well documented. They conducted a thorough online survey comprising more than 80 questions on a range of FEWS components, investments in FEWS, and their operational effectiveness, benefits, and challenges, to help close these gaps.

Depending on the presence and sophistication of FEWS components like hydrological data collection systems, data transfer systems, flood forecasting techniques, and early warning communication techniques, FEWS were categorised by Perera et al. (2020) as technologically "basic," "intermediate," and "advanced." Cools et al. (2016) showcased the good performance of well-implemented basic and intermediate systems compared to poorly implemented advanced systems. The problems with the latter generally stem from the mismatch in development level between FEWS components.

Table 2.1: Development level of a FEWS and corresponding characteristics from Perera et al. (2020).

Types of FEWS	Characteristics
Technologically basic	Manual data collection and transfer Qualitative forecast performed based on observations Community or local authority involved None of the following features is involved in this type of FEWS: Modern equipment, data collection, telemetric data communication, quantitative prediction, modelling
Technologically intermediate	Real-time data available from river and precipitation gauges No capacity for modeling-based flood forecasting Warnings issued based on data collected and past experiences
Technologically advanced	Telemetric data collection and transfer Modeling-based flood forecasting available Continuous monitoring and updates are provided once the flood warning is issued

Most flood early warning systems are built with a cascade of three different models: a meteorological, hydrological, and hydrodynamic model (Baker et al., 2015; Jain et al., 2018; WMO, 2011). The common structure is to have a meteorological model first. This model forecasts the spatial distributions of temperature and precipitation. This data is then used by a hydrological model, followed by a hydrodynamic model to predict floods. By using these models in tandem a risk assessment can be made as to if and where floods will occur. Figure 2.2 shows the common structure of a flood forecasting system.

Figure 2.2 presents the idealized situation in which each model is available and implemented. However, in practice, any of these components may be absent depending on the technological level of a FEWS (see Table 2.1. Another reason for the absence of certain components is that they are obsolete. For example, Cools et al. (2016) showcase a FEWS in Mali that does not use meteorological forecasts, since floods are driven by flows rather than local precipitation.

Since this report is focused on the hydrological and hydrodynamic model the meteorological model will not be discussed in depth. In short, the meteorological model is the first model in the cascade of FEWS models. The inputs for this model originate from the weather stations or satellite data (WMO, 2011). From this, both hourly forecasts (acute forecasts) and weekly or even monthly forecasts (seasonal forecasts) are made. On the other hand, the prediction will be more inaccurate the larger the timescale event.

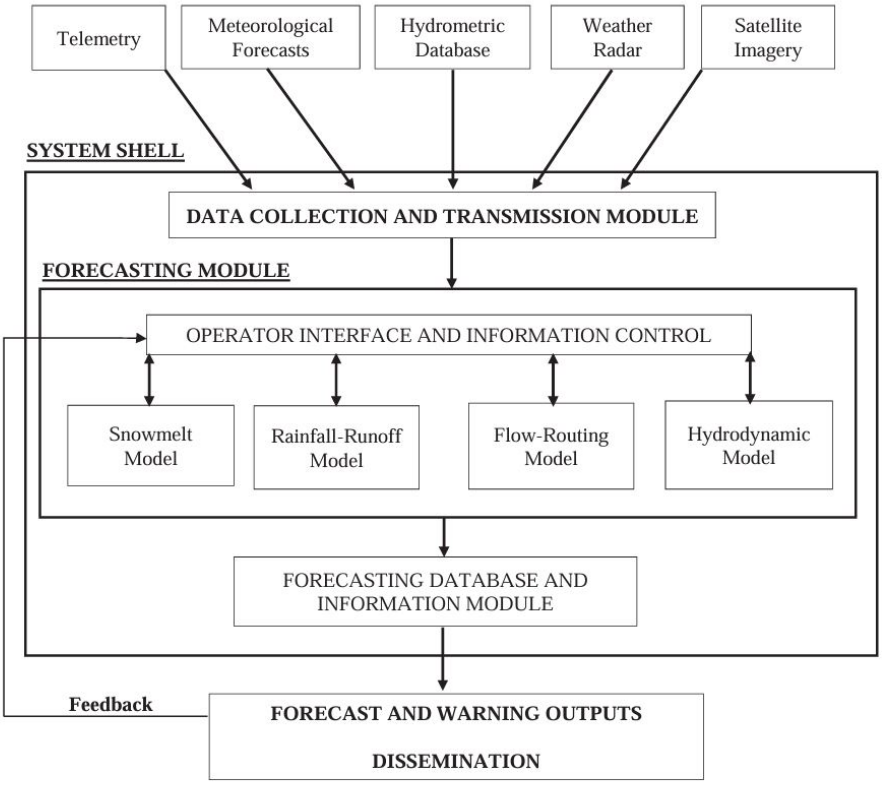


Figure 2.2: Components of a flood forecasting and warning system by WMO (2011).

2.3. Hydrological Model

The second model in a typical FEWS system is the Hydrological model. A hydrological model is a model that simplifies real-world hydrological systems (Devia, Ganasri, & Dwarakish, 2015). Understanding the Earth's environmental system will improve decision-making in water resource planning, flood prediction, irrigation practices, and groundwater development, among others (Devia et al., 2015; Pandi, Kothandaraman, & Kuppusamy, 2021). They are currently considered an important and necessary tool for water and environment resource management. A set of equations determines the runoff as a function of multiple parameters that describe the watershed characteristics. Two important input parameters for every hydrological model are precipitation and catchment area.

Different types of hydrological models are available. They can either be mathematically or spatial configuration-based (Devia et al., 2015; Wanzala, Stephens, et al., 2022). An overview of the two main categories with its subdivisions can be seen in Figure 2.3.

2.3.1. Mathematically Based Models

The different types of mathematically based models are explained in this section. Three main types of models are discussed here: Empirically based, Conceptual and Physical-based models. Table 2.2 gives a summary of the three different mathematically based models.

Empircal Models

This model distinguishes itself by primarily relying on observations to determine the response of the system, also known as data-driven models (Devia et al., 2015; Jackson et al., 2011). There is no physical understanding of the catchment and the model is only valid within the boundaries, e.g. unit hydrograph (Devia et al., 2015; Wanzala, Stephens, et al., 2022). Because of their simplicity, empirical models can be applied to catchments with limited gauges through regional analysis with relative ease. It is important to remember that empirical

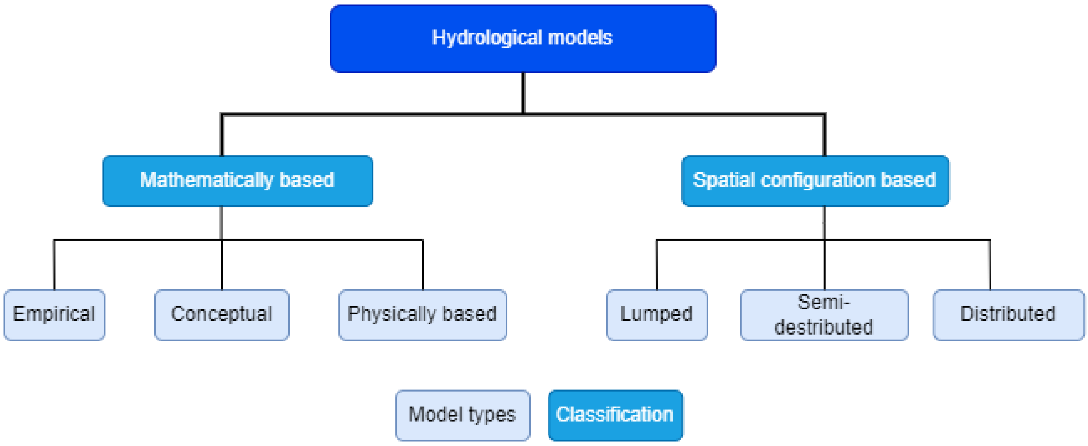


Figure 2.3: A visual representation of the classifications and model types of hydrological models based on Wanzala, Stephens, et al. (2022)

models depend on data availability, and although they have been used to extrapolate to extreme events or ungauged catchments, results are usually lacking in the formal specification of confidence limits (Jackson et al., 2011).

Conceptual Models

Conceptual models generally describe all components of hydrological processes (Devia et al., 2015; Jackson et al., 2011). They incorporate a conceptual representation of catchment information. For example, conceptual models can represent soil storage as leaky buckets and are usually characterized by parameters that have no direct physically measurable identity. (Jackson et al., 2011; Wanzala, Stephens, et al., 2022). Semi-empirical equations are used in this model and the model parameters are obtained through calibration using field data (Devia et al., 2015). A large dataset of meteorological and hydrological data is needed for this calibration. The complexity of this model varies significantly, and the general structure is determined by how schematic storages are applied (Jackson et al., 2011).

Physics-based Models

Physics-based models represent the components of hydrological processes (e.g., evapotranspiration, infiltration, overflows) using governing equations of motion (Jackson et al., 2011). It applies spatially and temporally distributed state variables and fluxes (Devia et al., 2015; Wanzala, Stephens, et al., 2022). Compared to the conceptual model, physics-based models do not require a lot of hydrological and meteorological data. However, spatial data about the catchment is required, which can be very expensive to observe and difficult to achieve sufficient resolution (Jackson et al., 2011; Wanzala, Stephens, et al., 2022). Therefore, these models average variables and parameters over a grid. Even a full physical representation does not represent the catchment heterogeneity (Jackson et al., 2011).

2.3.2. Spatial Configuration Based Models

The different types of spatial configuration-based models are explained in this section. Three main types of models are discussed here: Lumped, Semi-distributed and Physical models. Table 2.3 gives a summary of the three different spatial configuration based models.

Lumped Models

In a fully lumped structure, each (sub)catchment is represented as one single unit, with state variables that represent averages over an entire area (Das, Bárdossy, Zehe, & He, 2008; Jackson et al., 2011). All processes (precipitation, soil moisture, runoff responses), inputs, boundary conditions, and catchment geometric characteristics are computed separately for each sub-catchment (Das et al., 2008; Jackson et al., 2011). There are two primary advantages of using a lumped model (Wanzala, Stephens, et al., 2022):

- They provide a general picture of the functioning of the entire catchment since it is hard to predict the response if any natural land-surface
- Each building block of any distributed model is itself a lumped precipitation-runoff model.

The limitations of this model are in the determination of the event parameters for each catchment. If the parameter cannot be uniquely determined, then it cannot be connected to the catchment characteristics. This is a major problem for ungauged catchment areas. Another limitation is that it is not possible to represent the catchment change over time if the physical significance of the parameters is unclear (Wanzala, Stephens, et al., 2022).

Semi-distributed Models
In this model framework, spatial variation is accommodated for parameters, inputs, and outputs within a (sub)catchment (Wanzala, Stephens, et al., 2022). The (sub)catchments are subdivided into Hydrological Response Units (HRUs), each representing homogenous zones that may be determined based on diverse catchment characteristics such as topographic elevation, soil type, or land use (Das et al., 2008; Wanzala, Stephens, et al., 2022). Compared to the lumped models, semi-distributed and distributed models account better for the spatial variability of hydrologic processes, while lumped models present an entire river basin in one unit Wanzala, Stephens, et al. (2022).

Fully Distributed Models
In a fully distributed model, the catchment is divided into many cells where the physical properties are assumed to be homogeneous and characterized by a series of reservoirs. The reservoirs are linked vertically and represent the different hydrological processes (Das et al., 2008; Wanzala, Stephens, et al., 2022). Each cell represents the hydrological processes by linearised approximation of the non-linear differential equations (Wanzala, Stephens, et al., 2022).

Table 2.2: Summary of mathematically based hydrological models (Wanzala, Stephens, et al., 2022).

Model type/Characteristics	**Empirical-based models**	**Conceptual models**	**Physical-based models**
Description of hydrological processes	Mathematical equations deriving values from time series	Based on modelling of reservoirs and includes semi-empirical equations based on physics	Physical characteristics based on spatial distribution and evaluation
Data requirements for parameterization	Some consideration of features and processes of the system	Derived from field data and calibration	Data about the initial state of the models and morphology of the catchment is required
Required computer and power	High predictive power, low explanatory depth	Simple and can be easily implemented in computer code	Complex models, requiring human expertise and computational capability
Length of hydrometeorological data for calibration	Cannot be generated for other catchments	Much hydrological and meteorological data required	Affected by scale-related problems
Validity in applications	Only valid within the boundaries of a given domain	Calibration involves curve fitting, hard to interpret the physics	Valid for a wide range of situations

Table 2.3: Summary of spatial configuration based models (Wanzala, Stephens, et al., 2022).

Model type/Characteristics	**Lumped models**	**Semi-distributed models**	**Physical-based models**
Variability of input parameters	No spatial variability for the input parameters	Partial spatial variability for the input parameters	Full variability for the input parameters for the resolution
Output responses	Response only available at the output of each (sub)catchment	Response is evaluated for each smaller sub-catchment	Response is evaluated by dividing the catchment into very small sub-catchments
Simulating event-based processes	Not possible	In between of both models	Possible
Data requirements	Low	Medium	Large
Simplicity	Easy	Medium	Expert
Accountability of point hydrological processes	Prediction results are only available at the catchment outlet	In between both models	Prediction results can be obtained at any location and time
Computational speed and capacity	Simple in nature and require minimal computational time	In between both models	Require much computational power
Observations accuracy	Not very accurate simulations	In between both models	Highest accuracy is achieved if accurate data is available

2.4. Hydrodynamic Models

The hydrodynamic model, also known as the flood inundation model (Teng et al., 2017) or hydraulic routing model (WMO, 2011), is the final model of the cascade. The discharge modelled by the hydrological model is the input for a hydrodynamic model. A hydrodynamic model generally uses hydraulic forcing (e.g., flow, precipitation, sea level) and domain characteristics to model mass and momentum fluxes of water in the domain. Variables of interest are the spatially and temporally distributed depth and velocity, of which depth is of primary concern.

Riverine hydrodynamic models can be divided into two categories. Full physics and reduced physics models. Full physics models solve either the depth-averaged or full Navier Stokes equations to compute the hydrodynamics in a system and are known as 3D models (Teng et al., 2017). They are the most accurate type of models, but can often be very computationally expensive. Examples of this are Mike21 (Warren, Bach, & Warren, 1992) and DELFT3D-Flow (Lesser, Roelvink, van Kester, & Stelling, 2004). In reduced physics models simplified formulas are used for the calculations. These formulas are derived from the Saint-Venant equations and include for example the kinematic wave equations or the diffusive wave equations and can be in either one or two dimensions (1D or 2D) (Leijnse, van Ormondt, Nederhoff, & van Dongeren, 2021). The choice of equation depends on the function of the model and the required accuracy. The advantage of these reduced physics models is that the run-time is drastically decreased compared to their full-physics counterparts. The disadvantage however is that it also has reduced accuracy. This reduction in accuracy for reduced-physics models is shown to be in acceptable ranges by (Kumar, Sharma, Caloiero, Mehta, & Singh, 2023). From this criteria, it follows that a reduced physics model should be used such as HEC-RAS (Khattak et al., 2016), MIKE Flood (Tansar, Babur, Surchai, & Karnchanapaiboon, 2020),and SFINCS (Leijnse et al., 2021).

Many different model software packages exist to model floods. Kumar et al. (2023) provide a comprehensive overview of some of the most widely used models. It was found through scoping interviews that the following models are of interest: MIKE flood, HEC-RAS, and SFINCS. MIKE flood is part of recent efforts to implement FEWSs in the Tana and Athi catchments (Kiptum et al., 2023), HEC-RAS was indicated to be of interest for future FEWS efforts by the WRA, and SFINCS is part of a recent framework of implementing FEWSs in Sub-Sahara Africa by TEMBO Africa (N. van de Giesen, personal communication, February 28, 2024). In the next section, each model is further elaborated upon.

2.4.1. MIKE FLOOD

MIKE FLOOD integrates various MIKE software components designed for river systems, collection systems, and 2D surface flows, thereby offering a comprehensive flood modelling tool. Its widespread adoption across diverse geographical contexts and environmental settings is evident from its usage in numerous countries and environments (Li, Zhang, Mu, & Chen, 2018; Tho Dat, Quang Tri, Duc Truong, & Ngoc Hoa, 2019; **?**; **?**). In a comparative analysis of multiple flood modelling tools, Kumar et al. (2023) elucidates both the advantages and limitations of MIKE FLOOD, as depicted in Table 2.4. While MIKE FLOOD proves to be a valuable and user-friendly software solution in the long run, its initial implementation may require substantial effort due to its steep learning curve.

Table 2.4: Pros and Cons for MIKE FLOOD (Kumar et al., 2023)

Pros	**Cons**
A comprehensive and versatile flood study and prediction tool.	Steep learning curve for new users.
Capable of dealing with a broad range of hydrodynamic and hydrological processes.	Can be computationally intensive for large models or complex simulations.
Integrates with other MIKE software tools to provide a more comprehensive solution.	Requires a high level of technical expertise to use effectively.

2.4.2. HEC-RAS

HEC-RAS was designed by the US Army Corps of Engineers in 1995. It is a free-to-use software made to model hydrodynamics, sediment transport, and water quality. In terms of flood modelling, it allows for 1D, 2D, and coupled modelling and has extra features such as dam break analysis and calculation for special cross-sections such as bridges and culverts (US Army Corps of Engineers, 2024). Since its inception, it has been updated often and used widely for flood modelling (Basnet & Acharya, 2019; Ghimire, Sharma, & Lamichhane, 2022; Khattak et al., 2016; Mattos et al., 2022). Contrary to open-source models the free-to-use HEC-RAS does not allow access to view or modify the source code. It is a so-called black box model, similar to MIKE FLOOD. Kumar et al. (2023) also discusses HEC-RAS, as is seen in table 2.5. Compared to MIKE FLOOD, this option may be more limited in its application but is easier in its implementation.

Table 2.5: Pros and Cons for HEC-RAS (Kumar et al., 2023)

Pros	Cons
A user-friendly graphical interface for creating and visualizing models	Its ability to depict complex geometries and boundary constraints is limited.
Widely used and recognized throughout the engineering community.	Large models or complicated simulations can be computationally intensive.
Capability to simulate both steady-state and unsteady flows.	Its ability to manage interactions between water and the environment, such as sediment transport, is limited.

2.4.3. Super Fast INundation of CoastS (SFINCS)

SFINCS (Eilander et al., 2024; Leijnse et al., 2021) is a hydrodynamic model that can be used to simulate compound floods. It is a relatively new model (2021) and is subject to changes and updates. It has, however, been tested for multiple applications, including different combinations of fluvial, pluvial, and coastal forcing. Real-world applications include Sebastian et al. (2021), Grimley, Leijnse, Ratcliff, Sebastian, and Luettich (2022), and Eilander, Couasnon, et al. (2023).

SFINCS is based on the local inertial equations in two dimensions by Bates, Horritt, and Fewtrell (2010), but includes two extra terms in wind-stress and momentum advection. The latter was shown to be of less importance for most river floodplains while being the computationally most expensive term (Leijnse et al., 2021). The full governing momentum equation is given by

$$q_x^{t+\Delta t} = \frac{q_x^t - \left(g h_x^t \frac{\Delta z}{\Delta x} + \mathrm{adv}_x - \frac{\tau_{w,x}}{\rho_w}\right)\Delta t}{1 + g \Delta t n^2 q_x^t / h_x^{t^{7/3}}} \tag{2.1}$$

The continuity equation is discretized using backward Euler ($O(\Delta t)$) in time and central differences ($O(\Delta x^2)$) in space. The timestep is determined dynamically based on the CFL-condition (Leijnse et al., 2021). The advection term is discretized using an upwind method for gradients in x-direction and central differences for gradients in y-direction.

Since SFINCS is a compound flood model, it can be forced by river discharges, precipitation, tides, surges, and waves, with river and precipitation being the most important for the case of the Tana. These forcings are provided as time series in 1D (discharge, water levels) or 2D grids (precipitation, wind).

SFINCS handles three types of boundaries: water level, outflow, and incoming discharge. These are provided in the form of a mask file. As specified, boundaries should be provided with corresponding forcing time series. This mask also includes the active cells, which can be generated based on elevation.

Finally, SFINCS can be provided with multiple types of spatially varying terrain data. It readily interpolates any of this data to the specified grid. Input data includes a DEM, spatially varying roughness data (land use), and spatially varying infiltration rate (soil type). These maps can vary in resolution. The usage of high-resolution maps is facilitated by the use of sub-grids (Leijnse, Nederhoff, Dongeren, McCall, & Ormondt, 2022). Resolution can also be increased locally, using appropriate masks to prioritize a local, high-resolution dataset in areas of interest, e.g., LIDAR missions in flood-prone areas.

SFINCS supports rectangular and quadtree grids and makes use of a staggered grid (Leijnse et al., 2021). The computational efficiency is improved through the use of sub-grids, introduced by (Leijnse et al., 2022). This allows the user to use high-resolution elevation (and other) data while using a relatively coarse velocity grid. The latter improves computational efficiency while the former improves the accuracy of water level predictions.

The model inputs are summarized in Figure 2.4.

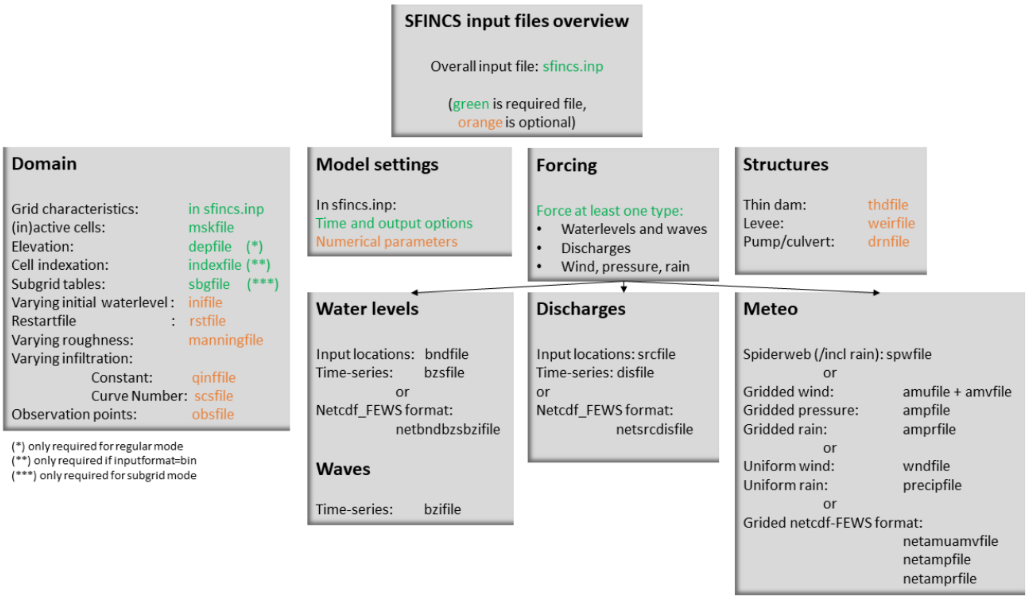


Figure 2.4: Overview of the inputs for the SFINCS model (Leijnse, 2023).

The advantages and disadvantages of the SFINCS model have been delineated in Table 2.6, drawing upon both our empirical observations and insights derived from the literature Leijnse et al. (2021). SFINCS is made available through a Python interface and a Graphical User Interface (GUI), which can be accessed via the Delft Dashboard. While instructions for the Python implementation are available online, they are not widely disseminated and usage examples are relatively scarce. Consequently, SFINCS necessitates a moderate proficiency in Python for effective utilisation. Furthermore, the absence of integration with warning integration software, specifically Delft-FEWS, implies that visualization currently relies on Python-based tools. However, it is anticipated that an adaptation for this software, given the shared origin of SFINCS and Delft-FEWS under Deltares, may become available in the foreseeable future.

Despite these limitations, SFINCS boasts several notable advantages over other hydrodynamic models. Its computational efficiency allows for swift simulations of vast geographical regions with minimal hardware requirements, making it particularly conducive to large-scale modelling applications. Additionally, its open-source nature fosters transparency, enhances collaboration, and affords flexibility in modelling practices. Moreover, its compatibility with Python facilitates seamless integration with hydrological models and data inputs from Application Programming Interfaces (APIs), further augmenting its utility and versatility.

2.5. Warning Dissemination

When creating a FEWS, considerable attention is typically devoted to ensuring the precision and dependability of the hydrological forecast (Kuller, Schoenholzer, & Lienert, 2021). However, the steps after a flood is forecasted should not be overlooked. Flood forecasts become ineffective if pertinent information does not reach

Table 2.6: Pros and Cons of SFINCS

Pros	Cons
You can use subgrids to make grids more detailed in the places where needed while saving computational time in unnecessary parts.	Relatively new, so not as established as other models.
Due to the lower computational time it is more easily implemented on bigger scales.	Proficiency in coding in Python is a prerequisite.
It is open-source software giving more transparency, flexibility and the ability to collaborate.	There is no good user interface outside of the Python environment making it hard to work with in the beginning.
It works through Python making it easy to integrate with other Python-based operations.	Currently no adaption yet for flood warning integration software such as Delft-FEWS.
	Little instructional material available.

the appropriate end-users in a clear and timely manner. The dissemination of information is a crucial part of any FEWS. For this, different methods can be used.

Kuller et al. (2021) present three components of flood warnings where they argue that the *"warnings are comprised of content (what, where, when, why), issued in a format (text, graphics, maps, face to face), which is distributed via a communication channel (radio, TV, Web page, SMS, etc.)"*. See Table 2.7 for their overview of the elements of flood warning communication. Thereby, the WMO (2013) has provided requirements and guidelines for presenting flood warnings to end-users. The warnings should contain comprehensible symbols, prioritize user-friendliness and effective design, and contain motivating language. Lastly, communities without access to the internet should be accounted for.

Table 2.7: Components and elements of flood communication from Kuller et al. (2021).

Content	Format	Channel
Source	Writing	Face to face
Location	Graphics	Telephone
Recommended Actions	Speech	Radio
Nature of Hazard	Maps	SMS
Time	Probabilities	TV
Predicted Impact		Social Media
Uncertainties		Sirens
Contact Information		Websites and Apps

Typically, an organization issues warnings internally to its staff and externally to other government departments, the press, the media, and the public (WMO, 2013). When integrated into a water management structure, internal warnings prepare staff for additional flood mitigation actions, including manning an incident control centre, deploying field observers for heightened reporting, alerting emergency maintenance teams for flood defence infrastructure, equipping public relations staff with incident information, and updating electronic media regularly (WMO, 2013).

External warnings target other government departments, local authorities, emergency services, NGOs involved in relief efforts, public information channels, press, media, and priority individual premises (WMO, 2013). It is for these types of warnings, that the effectiveness hinges on its ability to elicit specific intended behaviours from its recipients (i.e. preparation, relocation, evacuation, etc.)(Kuller et al., 2021). Message content for warnings should be simplified for end-users and delivered promptly to facilitate appropriate actions. Message delivery systems should be cost-effective, replicable, and straightforward. Recognizing the risk of false alarms is crucial, and the credibility of the message is vital for community acceptance of warnings (Kafle, 2019). The components and elements (see Table 2.7) should therefore be contextualized to end-users characteristics (e.g. demographics). Academic literature shows that the significance of a customized approach cannot be overstated, as there is no single solution that fits all situations (Kuller et al., 2021; WMO, 2013).

The effectiveness and efficiency of an early warning system also depend on the active involvement of local communities (Kafle, 2019). Various factors influence a community's decision to participate in flood early warning systems, including the hydrological characteristics of the area, the frequency of flooding, the community's level of interest and awareness, the potential for flood losses (as depicted by the hazard versus damage curve), the lead time provided by warnings versus the benefits, and the costs associated with implementing a system (Kafle, 2019; Kuller et al., 2021). Local governments are essential in spearheading community outreach efforts. Thereby, recognising that the community's largely intuitive and indigenous knowledge is just as valuable and reliable as technical and scientific expertise is crucial (Kafle, 2019). Therefore, before initiating community outreach activities, consultation with local government and selected community members is imperative.

The operation and maintenance of an early warning system often pose challenges to sustainability, as low-cost solutions and technical designs must align with realistic budgetary commitments (Kafle, 2019). Operational planning should encompass mock drills, community preparedness programs, and maintenance of all system components, including calibration and updates, either by the community collectively or by individuals over time (Kafle, 2019).

The WMO (2013) urges that the spatial delineation of warnings must also align with incident management and operational needs. This involves establishing a hierarchical structure for organizational areas, with the most local level facilitating coordination between warnings and immediate action, such as working with emergency labour teams, engaging with communities, and liaising with law enforcement. For strategic resource management and coordination during larger events, multiple smaller operational areas may be merged. Additionally, a national organization may exist above these levels to oversee and provide high-level coordination and reporting during significant events.

2.6. Case studies

To get a good idea of how to implement FEWS in the tana it is valuable to look at previous studies into FEWS. To do this FEWS systems in three different countries will be analysed.

- Belgium: well functioning, technologically advanced FEWS
- Egypt: Attempt for and advanced FEWS that turned out disappointing
- Namibia: Technologically basic system

By analysing these systems much can be learned by extracting the points of failure and success for the cases. At the end of the chapter, these findings will be combined with other, global FEWS research to highlight the most common pitfalls to be mindful of within the four different FEWS components

2.6.1. Flanders, Belgium

The FEWS in Flanders is a good example of a technologically advanced system. The first system was created in 2007 as a reaction to severe floods in earlier years and was eventually improved into the current system called FEWS-Flanders, in 2018 (Cools et al., 2016). As explained by Bogman, Gullentops, Smets, Deschamps, and Mostaert (2018) it uses three different numerical weather prediction models (ALARO, ICON EU and ECMWF) ranging in prediction from 60 hours to 10 days ahead. These models use astronomical data from 12 different weather stations. The weather data is validated to be fed into the model to run the hydrological and hydrodynamic models. The FEWS in Flanders uses the NAM model as the hydrological model and IJzer and the group Sigma, Zenne, Dender, Demer and LBSGJ are used as the hydrodynamic model. Both the hydrological and the hydrodynamic models are run with MIKE-11 software. Each weather model is run separately and used as input for the hydrological model. This simulation works simultaneously with two hydrodynamic models and is done multiple times per day. The management of the data flow and processes of all the integrated models is done in DELFT-FEWS. The predictions for water levels and flooding are available on the website waterinfo.be, up to 10 days ahead. The optimisation and validation are done by using 148 telemetric stations across the entire flood area by measuring the water levels (Vandenbruwaene et al., 2021). The system is operated by the

Flemish Department for Mobility and Public Works in cooperation with many different parties supplying input information for the models (Bogman, Buitrago, Smets, Gullentops, & Boeckx, 2016). Since the data transfer between the different actors is fully automatic this reduces possible communication problems drastically.

A system such as FEWS-Flanders won't be attainable in the near future for the Tana basin due to the high costs accompanying it. It can however function as a possible goal for a future system and could help to set guidelines for future standards in a path towards a more technically advanced system.

2.6.2. Egypt

Egypt's FEWS has been active since 2010, making it one of the first systems in Africa. The model is based on the Belgian FEWS system, developed with the help of Belgian researchers (Cools et al., 2016). As explained by Cools et al. (2012) the system started with meteorological data flowing through the usual components of FEWS (Section 2.2) up until the dissemination of flood information. The problem was that there were no water level gauges in the river and thus no data to validate the model. The model could still give predictions but the certainty of the predictions is unknown (Cools et al., 2016). A second problem occurred within the steps to raise a warning. The information from the model had to travel from the system operator to the 'Disaster and Crisis Centre' to organise a meeting with the 'Supreme Committee for Crisis Management'. The additional time to organise the meeting in combination with the poor reliability of the model, does not influence the model positively (Cools et al., 2016). The current model is only based on a meteorological model (WRF) that can forecast heavy precipitation that is considered to be reliable (El Afandi Gamaland & Morsy, 2020).

The Egyptian FEWS demonstrates that aiming for the most technologically sophisticated system may not necessarily be the best course of action. Achievability and the system's actual implementation are crucial elements that must be highly valued.

2.6.3. Namibia

The FEWS of Namibia falls under the type Technologically basic as described by Table 2.1. It is a nationally operated system that uses manual data collection as governing input combined with weather data (Mashebe, 2015). Four major parties are involved in running the current system. The Ministry of Agriculture, Water and Forestry is the head of the operation and is aided by two separate organisations for weather data and a fourth party provides the manually measured water heights. The data acquired by the ministry is subsequently transmitted to the Directorate for Disaster Risk Management for validation, which then forwards it to the Ministry of Information and Communication Technology for dissemination making it a time-consuming affair (Mandl et al., 2012).

Moises and Kunguma (2023) performed a critical gap analysis on the FEWS of Namibia focussing on governance, risk knowledge, monitoring and warning services, communication and dissemination and response capabilities. The report comes to an interesting conclusion. Although there is no actual model to predict floods, the monitoring and warning service scores the best out of all 5 categories. There is a will for a better forecasting system but this is not yet possible, mainly due to a lack of money and qualified personnel. Local villages often have their own forecasting and dissemination system based on traditional methods with relatively much success. The biggest challenges of Namibia's FEWS according to Moisès and Kunguma (2023) lie in the five different challenges

- Lack of qualified personnel
- Insufficient reliable information
- Insufficient equipment
- Inadequate financial investment
- Poor collaboration between authorities and communities

Most of these challenges are related to lower financial capabilities, a problem that many developing countries face concerning FEWS (Perera et al., 2019). However, fostering collaboration among various authorities and communities also stands as a crucial focal point.

2.6.4. Nzoia, Kenya

Currently (2024), there is only one functioning FEWS in Kenya. This FEWS is located in Nzoia, near Lake Victoria, and is part of a pilot project (Weingärtner et al., 2019). This pilot project aims to assess the feasibility of implementing this type of FEWS and if it can be implemented in other flood-prone areas in Kenya too.

The system in Nzoia uses GR4J as a hydrological model and the Galway Flood Forecasting System (GFFS) is used to estimate the river flow and water levels. The input data is provided by nine telemetric river gauging stations and 23 telemetric Automatic Weather Stations. The weather stations are operated by the KDM using the Weather Researching and Forecasting (WRF) model to forecast precipitation which is subsequently relayed to the WRA (Kiptum et al., 2023). The GR4J model is used for the hydrological model and Galway Flood Forecasting System (GFFS) is used to estimate the river flow and water levels. This system is coupled to warning levels automated through the Water Information Management and Ecosystem and Services (WIMES) interface (Kiptum et al., 2023). The system is operating well and is generally well-regarded.

It is important to note the cooperation between the WRA and the KMD respectively overseeing the river-related and weather-related aspects. Due to both organisations being involved their knowledge and measurement stations can be used to their full capacity creating the most optimal and robust FEWS. Although compared to other basins in Kenya there are far more telemetric stations in this basin it shows that with extra investment and good cooperation well working FEWS can be created.

2.6.5. Overarching Lessons

Besides learning from other FEWS systems worldwide there is also ample literature available that highlights good practices, common pitfalls and potential improvements for FEWSs. The UN (2006) created an overview of general functionality and common challenges per component. Golnaraghi (2012) highlights ten principles for a successful FEWS. Hallegatte (2012) discusses potential points of improvement for FEWS in developing countries as a cost-effective practice to reduce asset loss. Additionally, Perera et al. (2019) divides key challenges into technical, financial, political, and social challenges. They cite financial issues as an important contributor to each FEWS aspect, especially maintaining an effective monitoring and forecasting system. A comprehensive overview of components, their essential elements, recent opportunities, and common pitfalls and challenges is composed in Table 2.8.

Table 2.8: Common Pitfalls in the four FEWS components. (Golnaraghi, 2012; Hallegatte, 2012; Perera et al., 2019; UN, 2006)

Risk Knowledge	**Monitoring and Forecasting**	**Warning Dissemination and Communication**	**Response Capabilities**
• Insufficient focus on social, economic, and environmental vulnerabilities to map risks. • Lack of incorporation of community-perceived risks. • Lack of data on historical floods including observation systems, archives, and systematic post-flood data analysis. • Difficulty in assessing the financial value of assets at risk. • Lack of internationally agreed standards to classify early warnings as successful or unsuccessful. • Lack of effective feedback and improvement mechanisms.	• Insufficient coverage of observing systems for monitoring and validation. • Lack of monitoring equipment to model flash floods. • Insufficient forecasting capacity. • Mismatch between forecasting capacity and response capacity, both at institutional and community levels. • Lack of (international) data-sharing policies, i.e., MoUs, and international and interregional information access. • Poor interagency coordination and collaboration for improving forecasting systems and generating warning information.	• Inadequate communication systems to provide timely, accurate and meaningful forecasting and early warning information down to the level of communities. • Inadequate institutional arrangements and mandates. • Lack of political support to implement an early warning system and political reluctance to acknowledge disasters due, for example, to timing, and lack of contingency plans. • Warnings are not packaged and disseminated in an understandable format with complete information and context. • Inadequate standardization of warning levels and protocols on both an institutional and community level. • Cluttering of information due to the issuing of warnings by multiple institutions, leading to the lack of a single (or unified) recognized and authoritative source. • Insufficient use of media.	• Lack of multi-stakeholder arrangements at all levels. • Lack of collaboration and unclear roles of institutions from national to local levels. • Response facilities lack education on disasters, vulnerabilities, and warning systems, including simulations and evacuation drills at the local level and testing contingency plans and at the institutional level. • Disaster education lack of incorporation of local, traditional knowledge and concerns in early warning approach. • Lack of resources to facilitate evacuation.

3 Methodology

Common structures for FEWS are discussed in the Chapter 2. The importance of each of the four components was highlighted, but the main topics of this rapport are monitoring, information sharing, and flood forecasting. Monitoring generates data that serves as the input for any of the models. Forecasting is the final step before generating a flood warning. Since these responsibilities are shared between different instances, namely the WRA and the KMD respectively (and, to a lesser extent, KenGen/TARDA), information should flow smoothly between different organisations.

Forecasting was discussed to commonly consist of multiple sequenced models: meteorological, hydrological, and hydrodynamic. Currently, the KMD operates the only existing model in this sequence, WRF. The current monitoring-based FEWS lacks the hydrological and hydrodynamic models, as explained in Section 1.2.3. Selecting suitable models and creating, verifying and validating them are key steps in their implementation.

The importance of a smooth information flow and its implications for the second FEWS component when lacking was discussed in Section 2.2. Currently, water levels are monitored by the WRA, while weather is monitored and forecasted by the KMD. Both parties have initiated separate attempts at the implementation of a FEWS. Mapping current events, fostering collaboration, and implementing data-sharing policies aid in identifying challenges while highlighting opportunities.

This chapter describes the methodology to answer the research question. First, the selection of appropriate models is discussed in Section 3.1. This content is divided into two models: the hydrological model and the hydrodynamic model. Next, the implementation of the models is discussed in Section 3.2 and Section 3.3, respectively. Lastly, the approach to interview the stakeholders to get to understand their dynamics is discussed in Section 3.4.

3.1. Model selection

The selection of the models is mainly based on the following criteria. Firstly, the model should be able to predict flood events with sufficient accuracy to inform decision-making. Secondly, the model should not require too much computational power. Thirdly, software should be open source and/or freely available. Finally, the models should use data that is either freely available or through MoUs. Using remote sensing data, which is generally freely available on a global scale, can simplify the process of obtaining data. The following four requirements are now elaborated upon individually:

1. For a model to adequately inform decision-making, it should accurately predict flood events with sufficient lead time. Ideally, this also includes the inundation time to reduce the time spent away from livelihoods. The hydrological model should therefore be able to predict discharge extremes well in advance. The hydrodynamical model should accurately predict flood maps, maximum depths, and inundation times.

2. Developing countries can lack the resources to run advanced computational simulations, which is critical in a time-sensitive application such as flood modelling. This is exacerbated by the increased difficulty of interpreting such models and effectively communicating flood information to local communities (Cools et al., 2016; Lino et al., 2021). Also, a computationally cheap model allows for a probabilistic interpretation through Monte Carlo simulation (if the weather prediction has a probabilistic interpretation).

3. Lino et al. (2021) showed the difficulties in sustaining an advanced flood model in resource-poor countries. Furthermore, open-source software enables users to customize models to fit their needs, enhancing reusability across various systems. Therefore, using open-source software allows for the long-term sustaining and management of flood models. Only open-source models are considered within the model selection.

4. Remote sensing data is generally globally and freely available. The spatial resolution varies from relatively fine at 30 meters (Hawker et al., 2022) to relatively coarse at 250 meters (Jaafar & Ahmad, 2019). Using globally available datasets facilitates the extension to and applicability of the models to other areas, increasing reusability. This is especially beneficial if local data is scarcely available (Eilander, Couasnon, et al., 2023).

In the following sections, the model selection of the hydrological model is performed, followed by the hydrodynamic model.

3.1.1. Hydrological Model

The main considerations, explained in Section 3.1, evaluated for the implementation of the hydrological model are enumerated below. Each main criterion is explained in detail for the hydrological model. In addition, two extra criteria are added which are particular to the selection of the hydrological model.

1. The model should be accurate in predicting discharges in a large variety of landscapes due to the varied nature of the Tana Basin as discussed in Section 1.1.
2. The model should be inexpensive to run to facilitate rapid and timely predictions of potential floods occurring.
3. The model should be easily integrable with the hydrodynamic model selected in Section 3.1.2.
4. The model should be a user-friendly model for the local WRA staff to use, preferably one that has been used before. Multiple conversations with the staff have indicated a problem with receiving a new kind of model every time they get help from other organisations.

Different hydrological models have been examined, to determine which hydrological model meets these criteria best. The examination and explanation of the criteria, with respect to the different models, are provided below. Based on these four criteria the GR4J model was selected.

Accuracy

The accuracy of the GR4J model has been extensively compared to other models. The accuracy and error of different conceptual models vary by catchment and terrain size but are all sufficiently accurate in their discharge predictions (Ávila et al., 2022; Kunnath-Poovakka & Eldho, 2019; Tegegne, Park, & Kim, 2017). It is further concluded that the GR4J model is best in predicting the peak discharges for a large catchment in India (Kunnath-Poovakka & Eldho, 2019), making it more suitable for the FEWS.

Low Computational Power

Many different hydrological models are available (Wanzala, Stephens, et al., 2022). They can be divided into three main categories, as explained in Section 2.3. Only looking at the required computational power, the Conceptual model meets this requirement best. Secondly, the model has to be inexpensive, which means free-to-use models do have a preference over paid models. That leaves the following hydrological models that meet these requirements: GR4J, HBV model, TOPMODEL, and PDM.

To select one of the models that meet the requirements of low computational power, the amount of parameters needed to run the model is considered as well. Not every station measures the same (amount) of parameters, therefore it is desirable to need a few basic parameters as input for the hydrological model. When looking at the parameters of the different hydrological models, GR4J is the one with the least amount of parameters of 4 (Perrin, Michel, & Andréassian, 2003). The other models (HBV model, TOPMODEL, and PDM) require more input parameters (H. Lee, Balin, Shrestha, & Rode, 2010; Sigdel et al., 2011; Wawrzyniak, Osuch, Nawrot, & Napiorkowski, 2017). GR4J has the preference in using, considering the low computational power requirement.

Integration Hydrodynamic Model
The output of the hydrological model should be in line with the input of the hydrodynamic model. The chosen hydrodynamic model requires to be discharge data in the river as explained in Section 2.4.3. Sood and Smakhtin (2015) explains that the main output of all hydrological models discharge is. In addition, SFINCS uses Python as a programming language. To make the FEWS easier to understand, it would be preferential to have a Python implementation of the hydrological model as well.

WRA Preference
The local WRA staff indicated that the previous pilot in Nzoia with FEWS (see also Section 2.6.4) used GR4 as the conceptual hydrological model. This means that even if the SuperflexPy implementation (see Section 3.2.2) is not directly known to the local staff, the conceptual understanding of the GR4J should be helpful in capacity building for the entire FEWS.

After a review of various criteria encompassing factors such as model performance, computational efficiency, integration with the hydrodynamic model, and WRA preference, the decision has been reached to employ GR4J as the hydrological model.

3.1.2. Hydrodynamic model
Hydrodynamic (flood) models cover a large range of types, ranging from numerically solving the 3D Navier-Stokes equations to simple bathtub models. Determining the most suitable model is governed by often a consideration between required accuracy and available resources. Similarly to the hydrological model, the main criteria can be translated into application-specific criteria:

1. The model should effectively predict flood maps including inundation time to facilitate concise evacuation.
2. The model should only solve for the necessary dimensions to parsimoniously capture the necessary variables with minimal complexity.
3. The model should be freely available and preferably open-source.
4. The model should be well integrated with the hydrological model.
5. The model should perform well using remote-sensed data.

These criteria are used to determine a suitable hydrodynamic model. This is elaborated below. The selected model is SFINCS, which is completely described in section 3.3.

Dimensions
Several variables are of importance for decision-making during floods. Firstly, an inundation map is needed to determine the severity of a flood in space. To facilitate timely evacuation, flood-arrival times (FATs) should be determined. Finally, knowledge of inundation periods allows re-entry to the previously flooded area. These factors indicate the need for a temporal simulation instead of only determining the steady state. A temporal solution also shows the evolution of a flood (wave) along the river to determine FATs.

Costs
The costs of a model play an important factor. Computational costs as well as licensing costs should be kept to a minimum to guarantee continued operationality. Software that is paid for or that are subscription-based will not be taken into consideration. This leaves out the option to use MIKE FLOOD due to its subscription-based nature.

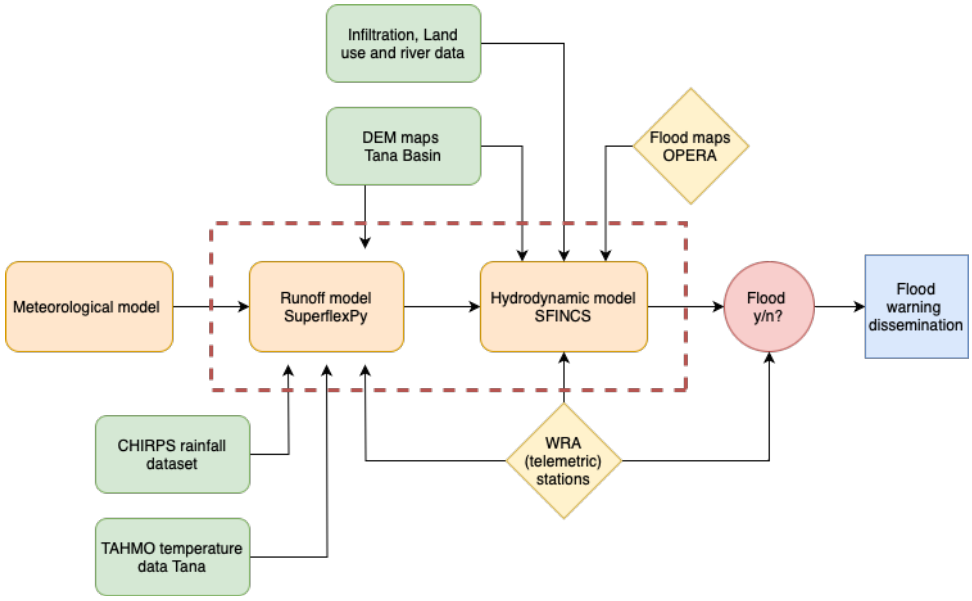


Figure 3.1: FEWS model structure, adapted from TAHMO framework. The scope of this research is outlined in red.

Integration
Superflexpy is an open-source framework that runs on Python. Integration of this system would not be exclusive to other Python-based software, but it would make the integration more fluent. This gives preference to the use of SFINCS.

Stakeholder Preference
Stakeholder preference is an important consideration when determining the preferred model. These preferences may be based on historical usage or one of the factors discussed previously. Historically, no hydrodynamic model has been used to predict floods, with all warnings being based on water levels and empirical risk levels. Preferences are thus based on other factors, among which experience in certain programming languages is among the most important.

The WRA has expressed the importance of using models that are not too resource-intensive. Furthermore, previous models were R-based and were not well understood. This motivates the switch to a different programming language. It has been indicated that models should be maintainable by local instances to avoid the cost of having a third party maintain the system.

Despite being a subscription-based software, MIKE FLOOD is available free of charge for the WRA (Water Resource Authority), courtesy of an agreement between the Nile Basin Initiative (NBI) and DHI, the developer of the MIKE software suite. The NBI has secured 300 licenses for the software, which are allocated to key stakeholders involved in water management and safety within the basin. However, the duration of the license validity remains uncertain, with stakeholders expressing varied opinions on the matter. Interviews conducted at ICPAC (Intergovernmental Authority on Development Climate Prediction and Applications Centre) indicate confidence in the continued cooperation, citing the successful collaboration over several years and the support of reputable financial institutions such as the World Bank, which lends stability to the NBI and, by extension, the availability of the MIKE software. Nevertheless, some employees at the WRA advocate for software solutions that offer long-term reliability and express reservations about the sustainability of the MIKE software.

Secondly, multiple stakeholders (e.i., KMD, TAHMO) have expressed their interest in using SFINCS. SFINCS is utilized by TEMBO Africa in one of their current projects or initiatives that focuses on implementing FEWSs. They provide the framework for flood modelling shown in Figure 3.1.

Summarizing, the above-mentioned criteria lead to the selection of SFINCS as the hydrodynamic model. The main advantages are the easier implementation of the hydrological model as well as the interest shown by other parties. That being said, the criteria do not show SFINCS to be the sole option as a hydrodynamic model. Other models such as HEC-RAS and TUFLOW could also be effective.

3.2. Model Génie Rural a 4 paramètres Journalier (GR4J)

This section starts with the description of GR4J, in Section 3.2.1, highlighting the conceptual framework and the belonging equations to gain an understanding of the model. Secondly, the model architecture is discussed in Section 3.2.2. The Python implementation within SuperflexPy and the data types utilized for the model are described under the model architecture. Lastly, the model validation is explained in Section 3.2.3.

3.2.1. Model Discription

GR4J is a daily lumped four-parameter rainfall-runoff model (Perrin et al., 2003). The GR4J model transforms precipitation into streamflow over a catchment using a structure with two stores (production and routing). These stores act as filters that transform one part of the precipitation input into the fast reservoir and the other part into the slow reservoir response (Drogue & Ben Khediri, 2016), as shown in Figure 3.2.

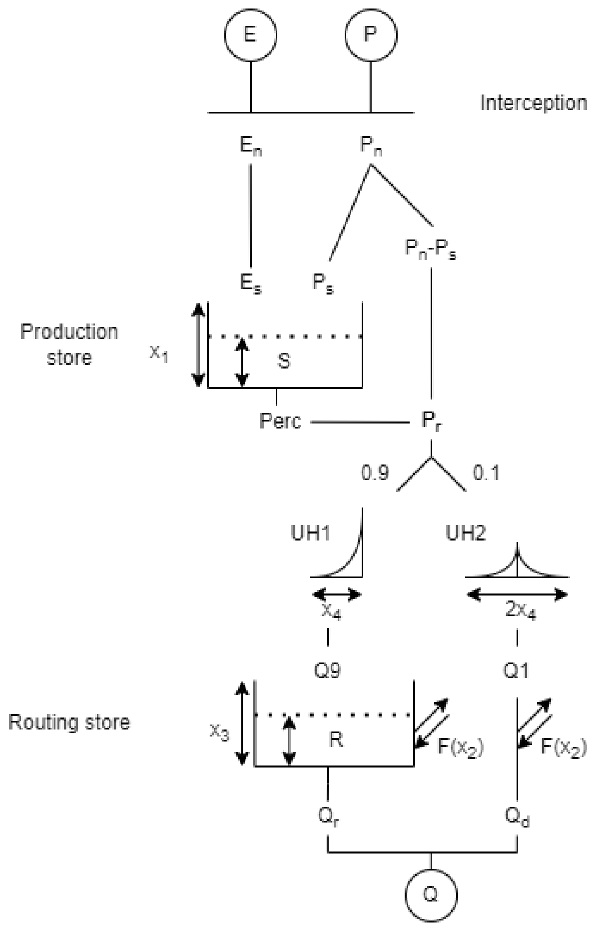


Figure 3.2: The conceptual water flow of the GR4J model through the production and routing store.

The two input values, at a given time step, are precipitation depth P and potential evapotranspiration E, both in mm. P is the calculated areal catchment precipitation estimate computed using the Kriging interpolation technique, which can be obtained using QGIS (ESRI, n.d.). The potential evapotranspiration is calculated using the Oudin equation,

$$P_e = \begin{cases} \frac{Re}{\lambda\rho}\frac{Ta+5}{100}, & \text{if } Ta+5>0 \\ 0, & \text{otherwise} \end{cases} \tag{3.1}$$

Re is the extraterrestrial radiation [MJ/m^2/day], λ is the latent heat flux of 2.45 [MJ/kg], λ is the water density [kg/m^3] and Ta is the mean daily temperature [°C] (Oudin et al., 2005). In the same research, performed by Oudin et al. (2005), it is concluded that using mean daily temperature and extraterrestrial evaporation for the determination of evapotranspiration is comparably accurate compared to more complex models.

Conceptually in GR4J, it is only possible to have either precipitation or evaporation. Therefore, the first step is to determine the net precipitation P_n or net evapotranspiration E_n by subtracting the potential evaporation from the precipitation.

If P_n is not equal to zero, P_s, a part of P_n, fills the production store. P_s is determined by (Dal Molin, Kavetski, & Fenicia, 2021b)

$$P_s = P_n(1-(\frac{S_{UR}}{x_1})^{\alpha}) \tag{3.2}$$

Another scenario arises when E_n is not equal to zero, indicating the presence of an actual evaporation rate determined by the level in the production store. In this case, the quantity E_s of water evaporating from the store is calculated as

$$E_s = E_n(2\frac{S_{UR}}{x_1}-(\frac{S_{UR}}{x_1})^{\alpha}) \tag{3.3}$$

The water content in the production store is determined by calculating all the fluxes in and out of the reservoir, which are the precipitation or evaporation and the percolation out of the reservoir (Perrin et al., 2003).

The water content cannot exceed x_1. Filling out this equation with the formulas used for P_s, E_s and $Perc$ will lead to the primary ODE determining the storage change in the reservoir.(Dal Molin et al., 2021b)

$$\frac{dS_{UR}}{dt} = P_n(1-(\frac{S_{UR}}{x_1})^{\alpha}) - E_n(2\frac{S_{UR}}{x_1}-(\frac{S_{UR}}{x_1})^{\alpha}) - \frac{x_1^{1-\beta}}{(\beta-1)}\nu^{\beta-1}S_{UR}^{\beta} \tag{3.4}$$

The amount of water that reaches the routing functions is then once again given by a simple mass balans(Perrin et al., 2003)

$$P_r = Perc + (P_n - P_s) \tag{3.5}$$

From here on the the water will be divided into two flow components. A fixed split is used for this diversion; 90% of P_r is routed by a unit hydrograph UH1 and then a non-linear routing store, and the remaining 10% of P_r are routed by a single unit hydrograph UH2. Both unit hydrographs depend on the same parameter x_4, expressed in days. UH1 has a time based on x_4 days, whereas UH2 has a time based on $2x_4$ days (Perrin et al., 2003).

The output of UH1 is the input of the routing store, which is a reservoir controlled by

$$\frac{dS_{RR}}{dt} = Q_{UH1} - \frac{x_3^{1-\gamma}}{(\gamma-1)}S_{RR}^{\gamma} - \frac{x_2}{x_3^{\omega}}S_{RR}^{\omega} \tag{3.6}$$

The second term is the output of the reservoir and the last is a gain/loss term (called Q_{RF}) (Dal Molin et al., 2021b),

$$Q_{RF} = \frac{x_2}{x_3^{\omega}} S_{RR}^{\omega} \tag{3.7}$$

The gain/loss term is also subtracted from the output of UH2, even though it is a function of the state S_{RR}. The fluxes Q_{RR}, Q_{RF} and Q_{UH2} are then combined to obtain the final output of the model.

3.2.2. Model Architecture

The GR4J model is just a conceptual model, meaning it can be implemented in different ways. Because the model should be open source and Python was most familiar to the development team, an implementation using a Python package called SuperflexPy was used. In Section 3.2.2 this implementation is outlined, followed by a discussion of the datasets used for the hydrological model.

SuperflexPy

The GR4J model is built using SuperflexPy. SuperflexPy is a new flexible framework for building hydrological models. A wide range of structural complexity can be accommodated in this framework (Dal Molin et al., 2021b). To create this kind of flexibility, SuperflexPy has four different levels, also known as components, shown in Figure 3.3 (Dal Molin et al., 2021a).

1. *Elements*: An element is the basic building block of the model and is used to create reservoirs, lag functions, and connections. It can be used to represent an entire catchment, a specific hydrological process, or a response mechanism within the catchment (Dal Molin et al., 2021a, 2021b).

   The *reservoir* element is used to conceptualize processes involving the storage and release of water and other fluxes. In most conceptual models, the reservoir elements have a single state variable (water storage).

   The *lag function* element represents delays in the transmission of fluxes. There is a mathematical correspondence between reservoirs and lag functions. Depending on the requirements of the model, the element specification can be selected in SuperflexPy.

   The *junction* and *splitter* connect two or more *elements* when a direct connection is not possible. They are used when a flux needs to be split among multiple elements downstream (splitter) or vice versa (junction). There is one particular type of junction element, the transparent, which simply outputs the same fluxes it receives as inputs. This element is needed for the structure of SuperflexPy.

2. *Unit*: A unit is a collection of multiple connected elements and is generally applied for a lumped model, like GR4J. These connected elements can either be directly connected or with connection elements (junction, splitter or transparent element) (Dal Molin et al., 2021a, 2021b).

3. *Node*: A node is a connection of one or multiple units that operate in parallel. The node can represent a single catchment and the units can be used to describe multiple landscape elements. Each unit in a node is characterized by a weight and its contribution to the outflow of the node. The weights are used to combine the output fluxes from units into the total output flux of the node (Dal Molin et al., 2021a, 2021b).

4. *Network*: A network connects multiple nodes into a tree structure and it can generate discharge predictions at internal sub-catchment locations. It routes fluxes from upstream nodes to the final downstream node. Routing delays in the river network can be simulated by feeding the node outputs into lag function elements. The area of each node (a sub-catchment) is used to determine its contribution to the total outflow of the network. It is only possible to have one network in SuperflexPy (Dal Molin et al., 2021a, 2021b).

The GR4J model is explained in Section 3.2. The implementation of GR4J is slightly different than the conceptual framework of GR4J itself, as can be seen in Figure 3.4.

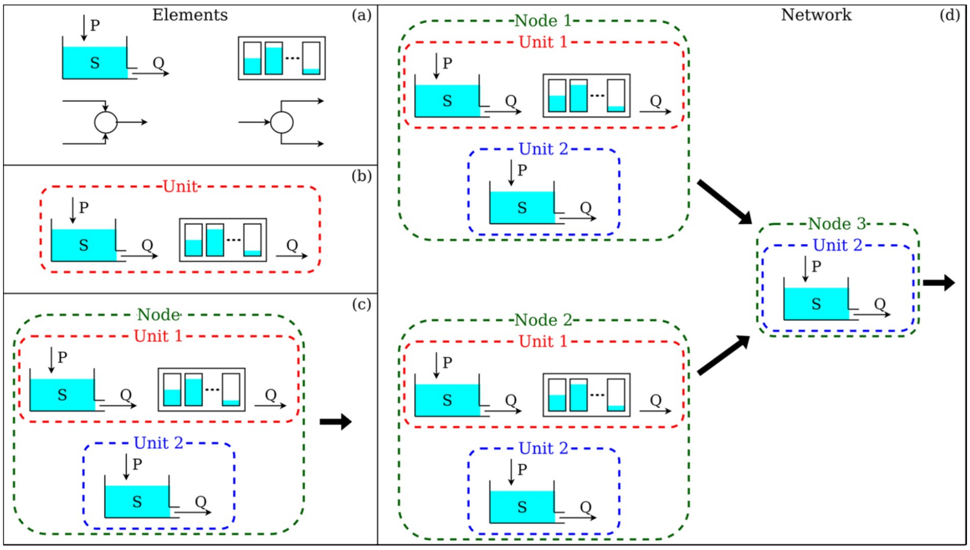


Figure 3.3: The four levels of SuperflexPy, named by their components. a) *Elements* represents the hydrological processes/catchment response mechanisms. b) *Units* connect multiple elements. c) *Nodes* connect multiple units that operate in parallel representing a sub-catchment. d) *Network* connects multiple nodes to put them all together (Dal Molin et al., 2021a)

The potential evaporation and precipitation are filtered by an interception element (interception filter). This element calculates the net fluxes by setting the smallest to zero and the largest to the difference between the two fluxes (Dal Molin et al., 2021b). This is the same as in the conceptual framework of GR4J.

The first difference between the conceptual framework and SuperflexPy implementation is within the *production store*. The part that flows into the production store and the part that goes to the routing store are both functions of the state reservoir. These fluxes cannot be calculated before the reservoir is solved. SuperflexPy calculates this by taking all precipitation into the unit that incorporates with the production store. The precipitation is divided into the different parts inside the element (Dal Molin et al., 2021b). The output of the unit is the sum of percolation and the bypassing precipitation.

The splitter element divides the flux into UH1 and UH2. For GR4J the deviation between the UHs is set, as explained in Section 3.2. The output of UH1 is the input for the routing store. The calculations for the routing store are performed in this unit. The gain/loss term that is subtracted from UH1 and UH2, will be subtracted in the flux aggregator element. It is not possible to do this in the same unit layer in SuperflexPy. The junction element combines the outputs of the routing store, the gain/loss term and the output of UH2 to each other. The transparent element, added after UH2 is needed to balance the model, it is not possible to have an uneven amount of building blocks for a parallel section in SuperflexPy.

Data

For the development of the hydrological model, three different types of data are needed. The input data for GR4J is precipitation and evaporation, as explained in Section 3.2. Besides that, the Tana Basin has to be divided into sub-catchments. This is done using a digital elevation method. The different data types are discussed below.

The precipitation and evaporation data can be obtained from different organisations. Depending on the location and availability of data, numerical weather predictions, remote sensing data or actual station data can be utilised. For the usage of this model, the data must be easily accessible. Therefore it is chosen to use remote sensing data, even though remote sensing data is known for overestimating and underestimating (Dinku et al., 2018). CHIRPS remote sensing is known for overestimating the precipitation data in Eastern Africa (Dinku et al., 2018). However, it is the most suitable dataset that can be used for precipitation in Kenya (Macharia, Ngetich, & Shisanya, 2020).

The evaporation is calculated using the Oudin evaporation, as explained in Section 3.2. Therefore, tempera-

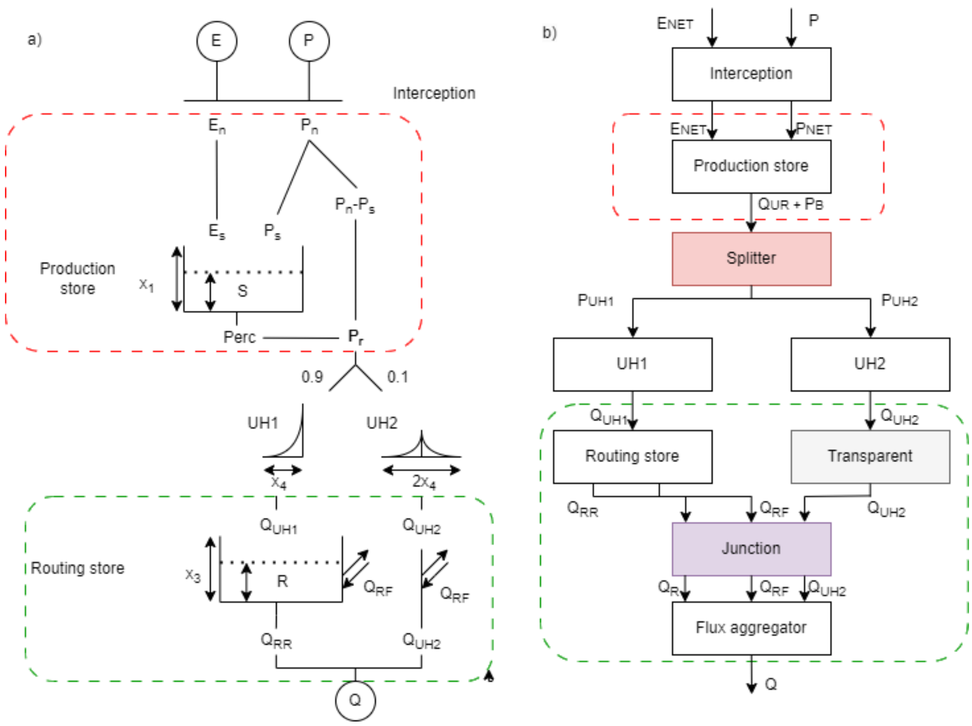


Figure 3.4: a) The conceptual framework of GR4J. b) The adaptation of GR4J in SuperflexPy using the different elements.

ture data is needed. The temperature data is obtained from the stations of TAHMO. The Trans-African Hydro-Metrology Organisation is an organisation with an extensive network of weather stations across many parts of Africa including Kenya. TAHMO (2023) enables unrestricted access to raw data for scientific research and governmental applications, aligning with the regulations set forth by the WMO. With Kriging interpolation the spatial temperature data is determined. Kriging interpolation was preferred over other interpolation techniques as the results are more accurate than, for example, Tiessen Polygons (Sergio, Ongel Saz-Sanchez, & Cuadrat, 2003; Tatalovich, Wilson, & Cockburn, 2006). For the interpolation, the Ordinary Kriging method was used as the spatial correlation and mean were unknown.

With the Kriging interpolated temperature data it is possible to calculate the Oudin evaporation for the Tana Basin. Besides temperature, the extra-terrestrial radiation for that area has to be determined, to know the evaporation. This is done using the equation in FAO56 to determine the extraterrestrial radiation (R. G. Allen & Pereira, 1998). For simplicity and after a discussion with the stakeholders, it is decided to average the evaporation for the entire area for five years.

In the SuperflexPy implementation of the GR4J model, each node represents a sub-catchment of the Tana basin. The actual catchment cutoff areas are based on the SRTM30 digital elevation model (NASA Shuttle Radar Topography Mission, 2013). The model has a spatial resolution of 30 meters, which is sufficient for the hydrological model as only discharge needs to be calculated which is less sensitive to a more accurate DEM (Ginting, Lidyana, Christopher, Yudianto, & Yuebo, 2024). This DEM is then used to calculate the runoff direction of flow at any given pixel. From this, the network of streams and rivers in the Tana basin is generated. With this information, a Strahler order is assigned to each part of the river (Strahler, 1952). Based on the available data a certain number of the Strahler tree is cut off to reach a desirable amount of catchments. This means that the amount chosen provides sufficient accuracy while also being possible to calibrate on the available data. Furthermore, it is also based on the physical representation of the area by comparing the map of streams to the OpenStreetMap for the area. For the Tana Basin, four levels of Strahler order were kept resulting in a total of 263 catchments, as can be seen in Figure 3.5.

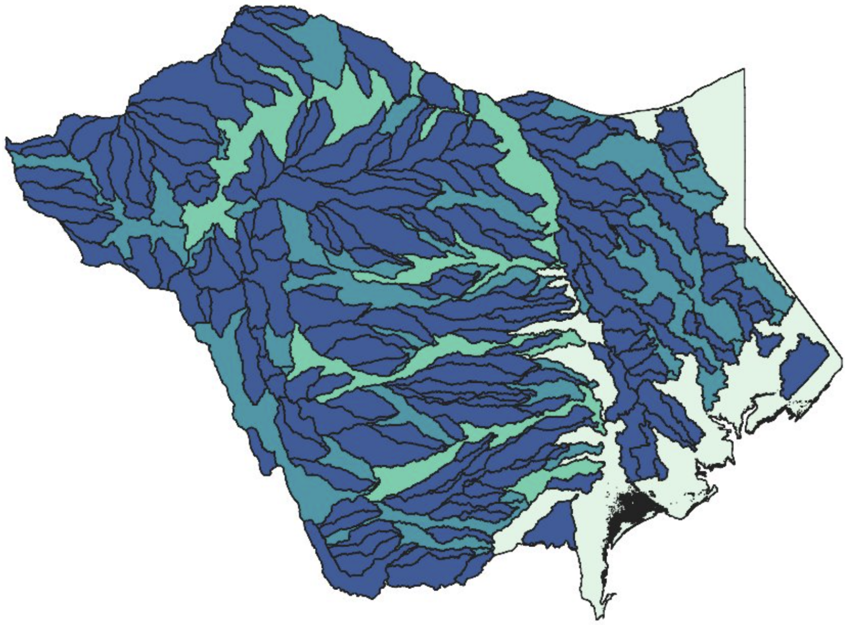


Figure 3.5: Selected sub-catchments for the Gr4J model, totalling 263. Lighter blues/greens indicate higher Strahler orders. Four levels of Strahler orders were selected based on OpenStreetMap and practical considerations for the number of catchments.

3.2.3. Model Validation

As the complete FEWS consists of multiple models, each one should be individually validated on the intended application. The goal of model validation is to determine if the model performs within predetermined limits. For the hydrological model, the model performance can be determined by comparing the model results to the actual discharges. The model validation for the hydrodynamic part of the FEWS is explained in Section 3.3.2.

The calibration and validation can be done at the station located in Garissa. The two most widely used criteria for calibration and evaluation of hydrological models are the mean squared error (MSE) and the Nash-Sutchliffe efficiency (NSE) (Gupta, Kling, Yilmaz, & Martinez, 2009; Traore, 2014).

NSE can be used as a good first try for the calibration of the model. However, it should be used carefully. The NSE is very sensitive to high seasonal variabilities, which can result in a volume balance error in the model (Gupta et al., 2009). The Tana Basin is dealing with wet and dry seasons, causing a high variability in runoff. The water level at Garissa can vary between 2m and 7m, during the wet season, as can be seen in Figure 3.6.

The parameter calibration using NSE is as follows

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^{n}(Q_{obs,i} - \overline{Q_{sim,i}})^2} \tag{3.8}$$

$Q_{obs,i}$ and $Q_{sim,i}$ are the observed and simulated flow rates at time step i, $\overline{Q_{sim,i}}$ is the average of the observed flow rates and n is the number of time steps. The NSE performance is explained in Table 3.1 (Ritter & Muñoz-Carpena, 2013). A value of 1 means that the simulated flow rate is the same as the observed values, and zero means that the simulated flow rate is the same as the average value of the observed flow (Gupta et al., 2009).

Other methods for model calibrations have to be considered as well, because of the sensitivity of the NSE for high seasonal variabilities. Adeyeri, Laux, Arnault, Lawin, and Kunstmann (2020); Mohammadi, Safari, and Vazifehkhah (2022); Shin and Jung (2022); Wanzala, Ficchi, et al. (2022) show different calibration methods for the GR4J model for different areas around the world. Wanzala, Ficchi, et al. (2022) used Kling Gupta Efficiency (KGE) for the calibration of the four parameters of GR4J for a case study in Kenya. The KGE is used as the objective function and the observed river discharge data of the different catchments as reference data. The

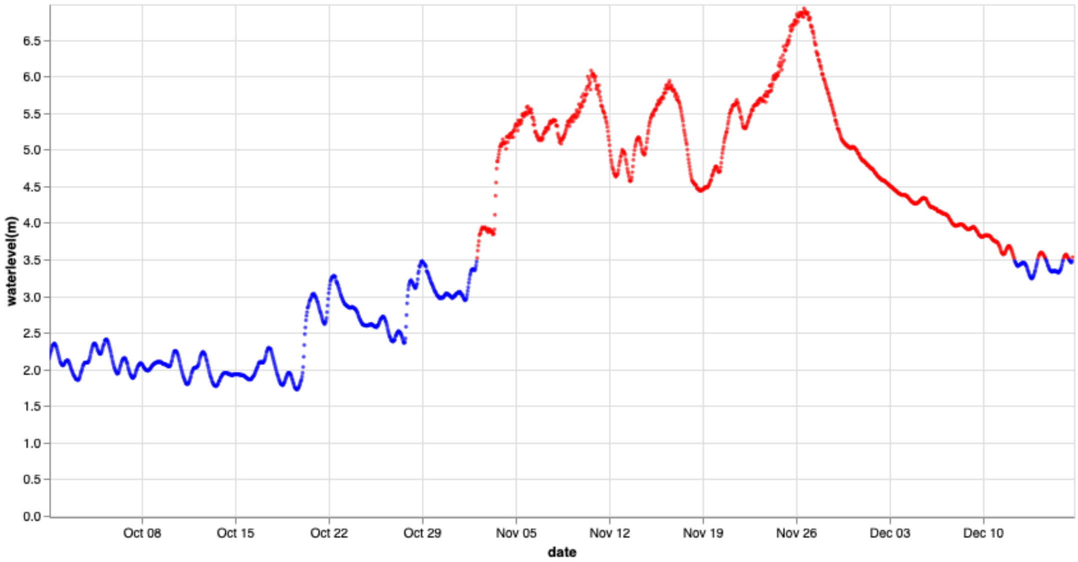


Figure 3.6: Water level measurements by the telemetric station at Garissa.

Table 3.1: Model Performance Rating based on Nash-Sutcliffe Efficiency (NSE) Value (Ritter & Muñoz-Carpena, 2013)

Performance Rating	**NSE Value**
Very good	≥ 0.90
Good	$0.80 - 0.90$
Acceptable	$0.65 - 0.80$
Unsatisfactory	≤ 0.65

objective function of KGE represents a weighting of three different components; bias, correlation and variability. This is to make sure the KGE is sensitive to errors in the overall distribution of streamflow (Adeyeri et al., 2020; Kling, Fuchs, & Paulin, 2012). To determine the hydrological model performance data for the calibration and validation periods, KGE can be helpful. The suitability of various reanalyses as input to simulate river flows is assessed by comparing the hydrological model's performance with reanalysis datasets (Wanzala, Ficchi, et al., 2022). The KGE is determined by

$$\begin{aligned} KGE &= 1 - ED \\ ED &= \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2} \end{aligned} \tag{3.9}$$

where ED is the Euclidian distance from the ideal point, r is the maximum potential value for KGE, β is the ratio between the mean simulated and mean observed flows (β represents the bias). In optimization, KGE is subjected to maximization, with an ideal value of 1 for α (Gupta et al., 2009).

After the calibration and validation of the hydrological model, GR4J, a sensitivity analysis has to be performed. The parameters obtained by the NSE or KGE are the target functions and the observed data at Garissa are the reference values. According to Wanzala, Ficchi, et al. (2022) and Shin and Jung (2022) the global Sobol sensitivity can be performed. The variance within the model results is decomposed in this sensitivity analysis. After that, the relative effect of each parameter and the interaction between the parameters on the variance of the results. By identifying the most important parameters, performing this sensitivity analysis will enable a reduction in the number of parameters (Wanzala, Ficchi, et al., 2022), which, in places where data is scarce, can be quite helpful. The input parameters for the sensitivity analysis are sampled from a uniform distribution, with little to no prior data available (Nossent, Elsen, & Bauwens, 2011). Sensitivity Indices (SI) are calculated resulting in a single value for each parameter. The output variance is used to describe the relative importance of each parameter, and the number of sensitivity parameters is counted to determine whether over-parameterization may be an issue (Wanzala, Ficchi, et al., 2022).

3.3. Super Fast INundation of CoastS

The following section will begin with a discussion of the model architecture, followed by an explanation of the validation method used. A full description of the SINCS model can be found in Section 2.4.3.

3.3.1. Model Architecture

The Super Fast INundation of CoastS (SFINCS) model is usable through either a GUI or Python. The latter makes use of HydroMT (Eilander, Boisgontier, et al., 2023), which is a package that facilitates Python implementations of several of Deltares' software packages. Using this package eliminates the need to learn new software, simplifying the model setup process and improving the understanding of underlying processes during model setup. It is also easily connected to the GR4J implementation in SuperflexPy.

Since SFINCS is a relatively new model, the availability of documentation is limited, but Deltares provide a detailed SFINCS-HydroMT tutorial(Couasnon et al., 2023), outlining the steps in setting up a SFINCS model through HydroMT. Summarizing, these steps consist of creating a data library, specifying a region and creating a grid, loading in datasets on this grid (e.i., digital elevation model, roughness, infiltration data, rivers to burn into the grid), adding masks to specify active cells and boundary conditions, adding forcing (e.i., precipitation, discharges, water levels), and adding observations points (water levels) and lines (discharges). Furthermore, Eilander, Couasnon, et al. (2023) provide a framework for modelling compound floods. They also provide an overview of global, remote-sensing, open-source data that are useful when only limited data is available. This frameworks generally consist of similar steps to what was outlined by (Couasnon et al., 2023), albeit on an older version of HydroMT SFINCS. The steps are also accounted for in the upcoming section.

Firstly, the region is specified. As discussed in Section 1.3, Garissa is used as the study area. Due to the limited availability of validation data (see Section 3.3.2), the domain of the validation set is used with a 5 km buffer, created using QGIS. A 5km buffer is enough to ensure the complete immersion of the floodplains in the domain, only allowing water to leave the domain at the most downstream position. The domain encompasses most of Garissa. It also includes a secondary seasonal river.

Accuracy and computational efficiency are the main considerations when determining grid size. A grid size of 100 meters is used, which is a common starting point also used by Eilander, Couasnon, et al. (2023). After creating a grid, several global datasets are loaded onto the grid. This includes a digital elevation model (DEM) (Hawker et al., 2022), land use (Buchhorn et al., 2020), and infiltration (Jaafar & Ahmad, 2019). These (gridded) datasets are projected onto the grid, but loss of information is minimized through subgrids.

The DEM contains the topography of the study area. It has been proven to be a crucial component for the accuracy of flood model (Cobby, Mason, & Davenport, 2001). It is essential in both the hydrological as well as the hydrodynamic model. In the former, it is used to define catchments and the flow of precipitation from the land towards the river. In the latter, it is used to predict which parts of the floodplains will be inundated due to their elevation. Coarser DEMs have been shown to lead to more errors (Xu et al., 2021). Hawker et al. (2022) used machine learning to remove buildings and forests at 1-arcsecond resolution (30$meters$), $whichledtotheFABDEMdataset.TheT$
$performingdataset(Ali, Popescu, Jonoski, \&Solomatine$, 2023).

Floodplain surface roughness is the second most important parameter to calculate flow in flooded areas besides DEM (Medeiros, Hagen, & Weishampel, 2012). Land use is a proxy for spatially varying Manning roughness (Kalyanapu, Burian, & Mcpherson, 2009). Land use data is obtained from collecting three of the Global Land Cover maps from 2019 (Buchhorn et al., 2020). This dataset has a spatial resolution of 100 meters and differentiates between 23 different land cover types which are subsequently translated to Manning roughness coefficients.

Finally, spatially varying infiltration is determined through curve numbers (K. K. F. Lee, Ling, & Yusop, 2023). Curve numbers are used to estimate precipitation runoff. They are obtained from the Global Curve Number 250 meter resolution dataset (GNC250) by Jaafar and Ahmad (2019). These curve numbers are split into three

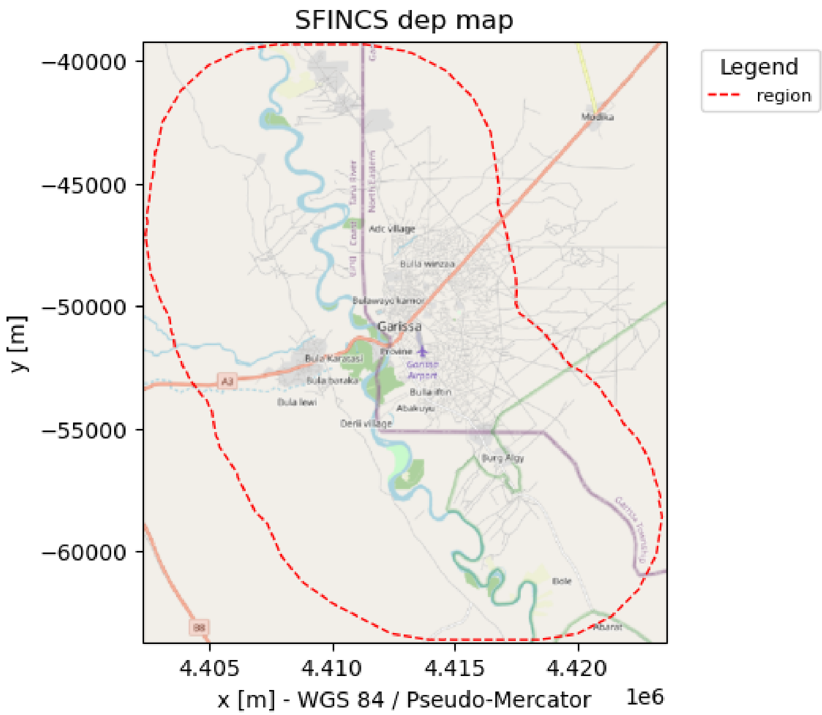


Figure 3.7: Model domain of Garissa overlayed on OpenStreetMap.

datasets for wet, average, and dry conditions. Any of these states may be used as an initial condition for the model, with average being the default state. To test the effect of varying the initial soil state, the models are created with wet and average soil moisture.

Masks are used to determine active and inactive cells. These can be automatically generated through minimum and maximum elevation thresholds (Leijnse et al., 2021). Minimizing the amount of active cells by ignoring cells that are deemed irrelevant is beneficial for computational efficiency. Examples of areas that are not of interest may include areas in the sea or areas with a high elevation where water can never reach. Including or excluding local precipitation is an important consideration in the latter. Since a relatively small domain is considered, all cells are considered active.

DEMs typically lack representation of bathymetric data (Eilander, Couasnon, et al., 2023), necessitating a separate integration method for river bathymetry within the model. River centerlines can be inferred from a DEM, using the nearest steepest slopes through a similar procedure as defining catchments for the GR4J model, see Section 3.2.2. Instead of newly creating these, a high-fidelity dataset by Yamazaki et al. (2019) is used, MERIT-Hydro. This dataset also contains upstream drainage areas and river widths, though, for river widths, the more Global River Widths from Landsat (GRWL) mask by G. H. Allen and Pavelsky (2018) is used. This is extended through the global database by Lin et al. (2019), who used machine learning on the GRWL and MERIT-Hydro datasets to find two-year return period discharges and river widths.

River centerlines and inflow points are determined using the MERIT-Hydro dataset. SFINCS offers the functionality to set minimum river length and upstream area thresholds for inferring centerlines based on D8-flow directions. Through trial and error, thresholds of 100 km^2 for upstream area and 100 km for river length were identified, yielding satisfactory results with two identified upstream inflow points. Alternatively, river centerlines can be directly obtained using the dataset by Lin et al. (2019).

Eilander, Couasnon, et al. (2023) used this dataset, estimating bankfull discharge as two-year return period discharges, to find river depths using a power-law:

$$h = aQ^b$$

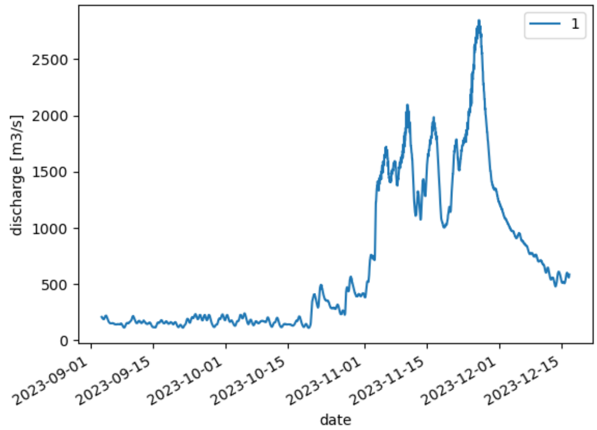


Figure 3.8: Discharge measured at the telemetric station in Garissa. This discharge is used to force the inflow points of the SFINCS model.

This makes sense when modelling multiple rivers with different two-year return period discharges. However, when only modelling a single river, this approach unnecessarily complicated the problem. Discharge is barely added over the model domain, so it can be assumed that the depth is more or less constant, only varying based on the river width. Adding the discharges from tributaries would warrant this approach since it can be used as a single approach to approximate all bathymetries of the tributaries. In that case, calibration is required for coefficients a and b.

The river exhibits a distinct roughness compared to the floodplains, typically featuring a smoother surface that facilitates a more efficient water flow. Consequently, a higher Manning roughness coefficient in the river results in increased resistance, exacerbating the risk of flooding (Yamazaki, Kanae, Kim, & Oki, 2011). To mitigate this and enhance model accuracy, the Manning coefficient for the river is fixed at 0.03 $m^{1/3}s$ (Di Baldassarre, Schumann, & Bates, 2009; Eilander, Couasnon, et al., 2023; Yamazaki et al., 2011).

As outlined in Section 3.1.2, SFINCS incorporates subgrid capabilities, enabling the utilization of finer resolution data while maintaining a relatively coarse computational velocity grid (Leijnse et al., 2022). With a grid resolution of 100 meters and the finest data resolution at 30 meters, employing a subgrid of four pixels effectively captures the highest resolution details, as each subgrid has dimensions of 25x25 meters.

SFINCS supports two boundary types: water levels and outflow. A water level is used as forcing, for example by tides. Downstream water levels also constitute upstream conditions in the case of subcritical flow. However, water levels are not known downstream of the study area. Outflow also supports subcritical flow and can therefore be used for the application of river flood modelling.

The model is forced by two upstream inflow points. Inflow discharge may be obtained through the GR4J model, or by using measured time series. Section 1.2.3 discussed the monitoring network operated by the WRA. This includes a telemetric station at Garissa, for which water level and discharge data are available. The latter is computed through a rating curve. Technically, this point is located at Garissa, but since most local precipitation barely adds to the total discharge, the local discharge can be used as forcing. Leauthaud et al. (2013) showed that the upper Tana accounts for 95% of the discharge, validating this assumption. This discharge does not account for the tributary that is also used as a secondary inflow point. This inflow is fed by the runoff model, GR4J. The discharge forcing is shown in Figure 3.8.

Since the model can not easily be given initial conditions for water height in the river the models will be run with data from at least two months prior to the flooding event, which is found to be more than sufficient to account for the spin-up time. Therefore, the models are run from September 2023 until (and including) December 2023. A more detailed account of the flood during this period is provided in Section 1.2.1.

Finally, SFINCS supports the addition of several geodata input types, which the user supplies. This includes observation points to specifically monitor the water level at a single point, observation lines to monitor dis-

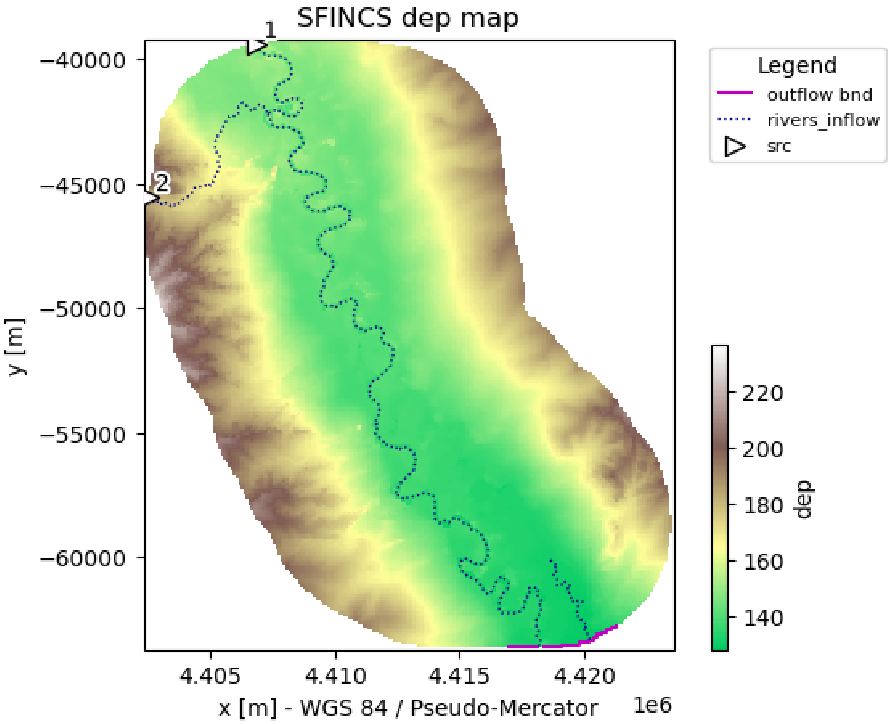


Figure 3.9: Overview of the SFINCS model, including boundaries, discharge forcing points, and observation points/lines.

charge that passes a certain cross-section, and weir files to represent impenetrable boundaries such as levees. Of these, only observation points are of interest. The domain only has one actual river (with tributaries), but discharge is not distributed between several routes and the discharge in the river is thus a simple sum of the input. Furthermore, dyke breaches are not identified as the specific failure mechanism that leads to flooding. For a smaller-scale, urban flooding model, the discharge that is flowing into the city and passing a certain cross-section would be of interest to use as input for this model.

An observation point is added at the telemetric gauge location. This makes validation of water levels possible, which is of interest when using inflow by GR4J.

The complete overview of the SFINCS model is shown in Figure 3.9, including boundaries, discharge forcing points, and observation points/lines. In this case, centerlines were generated from the DEM. An overview of the used remote sensing datasets is provided in Table 3.2.

Table 3.2: Overview of (global) remote sensing datasets used in the SFINCS model.

Variable	**Dataset type**	**Dataset name**	**Resolution [m]**	**Source**
Topography	Digital elevation model	FABDEM	30	Hawker et al. (2022)
		SRTM30	30	NASA Shuttle Radar Topography Mission (2013)
River centerlines	-	MERIT-Hydro	90	Yamazaki et al. (2019)
		Global estimate [...]	-	Lin et al. (2019)
River width	Mask	GRWL	30	G. H. Allen and Pavelsky (2018)
Roughness (land)	Land use	Copernicus Global Land Service	100	Buchhorn et al. (2020)
Curve numbers	-	GCN250	30	K. K. F. Lee et al. (2023)

The **?** outlines two calibration methods for flood forecasting models: i) trial and error calibration and ii) automated (parameter) optimization calibration. The latter is rather data-intensive, necessitating a calibration and validation set, while the former is more intuitive. Trial and error calibration is employed, time and data availability being major constraints.

3.3.2. Model Validation

Flood models are historically validated through flood frequency analysis and/or event-based modelling (Filipova, Lawrence, & Skaugen, 2018). The former requires well-gauged sites and extrapolation to long return periods. The latter is widely used due to its simplicity, but a prominent limitation is the lack of applicability to extremes with a different return period than the simulated event. It is, however, a good starting point when validating a flood model. Filipova et al. (2018) also notes the potential of using other randomly distributed variables (e.g., precipitation) in Monte Carlo methods to obtain a more probabilistic interpretation of flood models.

Validating a flood model for a wide range of flood events is often challenging since finding data on flood events can be scarce (Molinari, De Bruijn, Castillo-Rodríguez, Aronica, & Bouwer, 2019). Two sources of validation data are identified: water level gauges and remote-sensed flood maps.

Gauge data is obtained from the WRA. The study area contains one telemetric station operated by the WRA. However, this data is also used as inflow data, so multiple stations would be required to spatially verify water levels. Moreover, this gauge is used when validating GR4J and SFINCS in sequence, since this does not require the gauge as an input.

Bauer-Marschallinger et al. (2022) showed the potential of using remote sensing data to validate flood maps. The SFINCS model is validated by comparing flood maps from satellite imagery with model runs for the same days. The available and modelled flood maps are compared at Garissa since it is the place with the best satellite data as well as the only telemetric station in the Tana.

Acquiring useful flood maps from satellite imagery poses significant challenges. Primarily, the infrequent coverage by flood-detecting satellites, occurring fewer than once a week, hinders the availability of up-to-date data. Moreover, to verify flood maps accurately, images must coincide with peak flooding, which is often not feasible. Another obstacle is the presence of trees throughout the Tana basin's floodplains, obscuring flooded areas and resulting in incomplete maps unsuitable for validation. Additionally, the temporal accuracy of flood models is constrained by the morphologically dynamic nature of the Tana River. Consequently, flood maps older than 5 years are disregarded. Cloud coverage further complicates matters, obstructing satellite views and impeding flood detection. Since floods are caused by excessive precipitation, clouds often interfere with satellite imagery, despite the majority of the discharge being generated far upstream. Six usable flood maps have been identified despite these challenges, as highlighted in Table 3.3. These flood maps are obtained from OPERA (2023). OPERA Dynamic Surface Water Extent Provisional imagery layer is a product based on satellite imagery of the Sentinel 2A, Sentinel-2B, and Landsat 8. It has a spatial resolution of 30 meters and differentiates five classes: Not Water, Open Water, Partial Surface Water, Snow/Ice, and Cloud/Cloud Shadow. Other sources, such as GloFAS (Copernicus, n.d.), proved unusable due to the various aforementioned reasons. Even during days of low cloud coverage, trees prove to be a major hindrance for this tool.

Table 3.3: Dates of acquired flood maps.

Source	**Dates**
Opera	12-10-2023
	11-11-2023
	21-11-2023
	26-11-2023
	29-11-2023
	01-12-2023

The flood maps from OPERA (2023) and the output of the SFINCS model need to undergo several pre-processing and post-processing steps, respectively.

Firstly, the OPERA flood maps are projected onto the model (sub)grid by employing nearest-neighbour interpolation, similarly to Eilander, Couasnon, et al. (2023). Depending on the satellite coverage, i.e., Landsat 8, Sentinel-2A, or Sentinel-2B, data values differ. The data is mapped to -1 to indicate no data/clouds, 0 for land, 1 for permanent water, and 2 for flooded grid cells. A permanent water mask is obtained from OPERA (2023) by taking a reference date on which no flooding occurred: 12-10-2023 (see Table 3.3). It is assumed that there have been no significant changes in the morphology of the area between this reference date and the modelled floods.

The SFINCS results are mapped to the previously discussed values. SFINCS output is generated each hour. The closest time is selected to compare the flood maps. A permanent water mask is obtained similarly to the satellite map by using the same reference date and time as the reference flood map.

The modelled flood extent is determined by applying a threshold of 15 cm of inundation, consistent with water mask depths generated from satellite imagery (O. E. Wing et al., 2017).

Following O. E. Wing et al. (2017) four values are computed for validation. These statistics provide insight into the model performance and enable comparison with benchmark models. In these statistics, the subscript 1 denotes wet pixels and 0 denotes dry grid cells for the model (M) and the Benchmark (B). Consequently, M_1B_0 signifies a false positive, M_0B_1 a false negative, and M_1B_1 a true positive.

The hit rate (H) signifies how much of the inundation of the flood maps is correctly predicted by the model.

$$H = \frac{\sum M_1B_1}{\sum M_1B_1 + \sum M_0B_1}$$

The false alarm ratio F is the ratio of correctly predicted inundated grid cells and the total predicted inundated grid cells.

$$F = \frac{\sum M_1B_0}{\sum M_1B_0 + \sum M_1B_1}$$

Thirdly, the Critical Success Index (CSI) is a measure to sum up the effectiveness of the model ranging from 0 to 1 and works for both under and overshooting models. It is computed by dividing the number of correctly modelled grid cells by the sum of all wetted grid cells of either the model, benchmark, or both.

$$CSI = \frac{\sum M_1B_1}{\sum M_1B_1 + \sum M_0B_1 + \sum M_1B_0}$$

Fourthly, the error bias (E) gives insight into the tendency of the model to either underpredict or overpredict flooding.

$$E = \frac{\sum M_1B_0}{\sum M_0B_1}$$

3.4. Stakeholder Interviews

The interactions between the various stakeholders in the multi-stakeholder arena, where their competing and varied interests are at play, contribute to the issue's complexity. To fully understand the dynamics at play in the Tana River flood forecasting and preparedness strategy, it is imperative to analyze the individuals involved in the decision-making process. This report will assess the flood early warning infrastructure in three parts: stakeholder roles, data-sharing mechanisms and dissemination strategies.

Firstly, the current network of stakeholders regarding flood forecasting and management in Kenya, specifically for the Tana River region, is examined. Here, each of the stakeholder's roles (i.e., legal mandates, responsibilities, and general operationalities) will be disclosed. This information will help determine which stakeholders have the resources to contribute to introducing a FEWS in the Tana River. Also, it helps determine the possibilities and limitations of this FEWS. Involving these stakeholders and receiving their point-of-views, will ensure that the needs and specific requirements of a FEWS are clear.

Secondly, given the fact that multiple parties have ownership of important data, the sharing of information amongst stakeholders is reviewed. The sharing of data is important to support government agencies in providing weather data and/or flood warnings. However, it is unclear who possesses which data, and information sharing is in many instances inefficient. This information will also help understand the network of stakeholders and the functionalities of current FEWS. On top of that, it also helps understand responsibilities, incentives, and possible bottlenecks.

Lastly, the dissemination of flood early warnings will be inspected. Some stakeholders distribute the warnings and other stakeholders are receiving these. Next to that, other stakeholders fulfill roles that follow up on the warnings. Determining their roles will help with drawing up the requirements for an efficient FEWS.

To achieve the outlined objectives, stakeholder interviews will be conducted with key individuals representing various entities involved in flood forecasting and management in the Tana River region. Interviews will primarily target personnel affiliated with the WRA, KMD, ICPAC, and KRCS. Additionally, interviews will be conducted with residents from affected counties, specifically focusing on Garissa. These interviews aim to capture the perspectives, experiences, and insights of communities directly impacted by flooding events.

The key informant interviews will be semi-structured, according to the interviewee's occupation, expertise and affiliation towards FEWS. The following range of topics outlines the (variable) structure of the interview.

1. Current practices and challenges in flood forecasting and management
2. Existing data-sharing mechanisms and their effectiveness.
3. Perspectives on the feasibility and potential benefits of implementing a FEWS in the Tana River region.
4. Suggestions for improving collaboration and coordination among stakeholders.

4

Results

The focus of this research lies in the methods of gathering data, setting up forecasting models, and mapping the information flows between stakeholders. The results are discussed following the structure of the research questions: discussing available and required data, assessment of models, and mapping information/data flow. The methods for this research were discussed in Chapter 3. The results of this research are provided in this chapter. While some results are still preliminary, they are provided as comprehensive as possible. The formulation of results is split into several parts. The hydrological model will be discussed qualitatively, and the hydrodynamic model both qualitatively and quantitatively. The qualitative model results entail usability, modelling process, and data requirements. Formulating and assessing these parts are integral to the total assessment of the forecasting approach in Chapter 5. Quantitative results entail model performance assessed through the previously discussed score indicators. This facilitates model assessment, providing insight into the actual applicability to the research area and specific case study.

Model results of GR4J and SFINCS are discussed in Section 4.1 and Section 4.2, respectively. Improving the current FEWS entails mapping current stakeholder relations and existing policies. This is approached through interviews as discussed in Chapter 3 and is presented in Section 4.3.

4.1. Hydrological Model

The results of the hydrological model are mostly based on the implementation of GR4J in SuperflexPy. This is the main step for the development of the hydrological part of the FEWS.

The network for GR4J is built in SuperflexPy, but the external flows are currently not propagating through the network. The network is connected by determining the outflow point of each sub-catchment and feeding the output of the subcatchment into the downstream neighbour using the routing functions of SuperflexPy. The building blocks within SuperflexPy provide a clear overview of how GR4J for each sub-catchment can be implemented. Each node of the network represents one of the 263 sub-catchments of the Tana Basin.

Due to time limitations, it was not possible to finalise the GR4J model. The following steps have to be taken to finish the hydrological model and obtain an input value that can be used for the hydrodynamic model: First of all, as there is currently no flow propagating through the network, this has to be solved. Next, the non-converging network problem has to be solved. After this, the model can be validated and calibrated for the station at Garissa. Then the model can produce the input values for the hydrodynamic model at the required locations.

As the model is currently not propagating flows through the network it is not possible to validate the model. Furthermore, it is difficult to validate the 1052 parameters of the hydrological model (4 per catchment) on the limited data that is available. This is one of the issues that has to be addressed before a technologically advanced model can be fully set up.

4.2. SFINCS

The SFINCS model mainly requires data obtainable through remote sensing. Several global datasets are available, their resolutions ranging between 30 and 250 meters. Generally, all data is obtainable either through free-to-use tools or by using output from GR4J. The recency of available datasets varies from 2018 to 2023, introducing some discrepancies in the model, especially when validating the models on specific events.

The calibration of the SFINCS model is trial-and-error based. The nature of the datasets provided some difficulties in the calibration process. Most parameters are not straightforwardly altered, e.g., topography, spatially varying land use, and curve numbers, which exhibit strong spatial correlation. Eilander, Couasnon, et al. (2023) performed a sensitivity analysis to research the effect of varying different parameters. They identified river depth and roughness as minor and fluvial forcing as of major importance. In this case, varying river depth proved an important calibration factor during visual calibration. Furthermore, the topography data was varied between FABDEM and SRTM30. Two methods of burning river bathymetry into the grid were discussed. Firstly, centerlines were inferred from flow directions as discussed in Section 3.3.1. Secondly, a global database for river centerlines was used. These were subsequently burned into the grid with a constant depth, which was varied between models. Varying the initial soil moisture content between dry, average, and wet proved to be of minor influence on model results. Finally, the effect of adding a buffer around the inflow point was researched. This buffer ensures that water does not flow out of the domain around the inflow point. The models are summarized in Appendix C.

SFINCS was originally only validated for the water level as opposed to both water level and velocity. In accordance, six satellite flood maps are compared to SFINCS flood maps. These are shown in Appendix B and Appendix D, respectively. A threshold inundation depth of 15 cm is used for the SFINCS flood maps to distinguish between wet and dry grid cells.

Firstly, a visual comparison is made between the flood maps produced by SFINCS and the remote-sensing flood maps. A first observation is that the river's width in the SFINCS model consistently exceeds the river's width in the remote-sensing flood maps. This discrepancy does not affect the scores since permanent and non-permanent water are both classified as part of the flood. It is also noted that some of the SFINCS models exhibit flooding of the floodplains during times of relatively low to normal discharge. This is not necessarily confined to the digital elevation model and occurs in both FABDEM and SRTM30. Finally, some outliers are noted in the OPERA maps. These cells are located away from the river and are still identified as wet.

The inundation maps are scored based on the four criteria discussed in Section 3.3.2: hit rate, false alarm ratio, critical success index, and error bias. These are plotted over time and shown in Figure 4.1. These measures are computed at each time step and for each model.

The models generally exhibit little variation. Most variation occurs at the start, which is attributed to the discrepancy in permanently flooded pixels discussed previously. These variations all but completely disappear towards the period that flooding occurred. Variations between models are negligible compared to variations observed between different timesteps. Each measure exhibits a peak or valley when flooding is most extreme towards the end of November.

The model's hit rate ranges from ~ 0.77 to 0.90. Conversely, the false alarm ratio varies from ~ 0.65 under normal conditions to 0.15 during floods. The critical success index varies from ~ 0.2 during normal conditions to 0.75 during maximum flooding. Finally, error bias varies from $\sim 6 - 11$ during normal conditions to ~ 2 during maximum flooding. confirming the tendency to overpredict flooding.

4.3. Evaluation of Flood Early Warning Infrastructure

This section identifies gaps, challenges, and obstacles in the current network for flood warnings (i.e. adequate infrastructure, community engagement, communication barriers, etc.). Findings from interviews and literature regarding stakeholders' perceptions of the system and its limitations are discussed. These problems contribute to the overall challenges in flood management and explain the need for improvement by introducing a more effective FEWS.

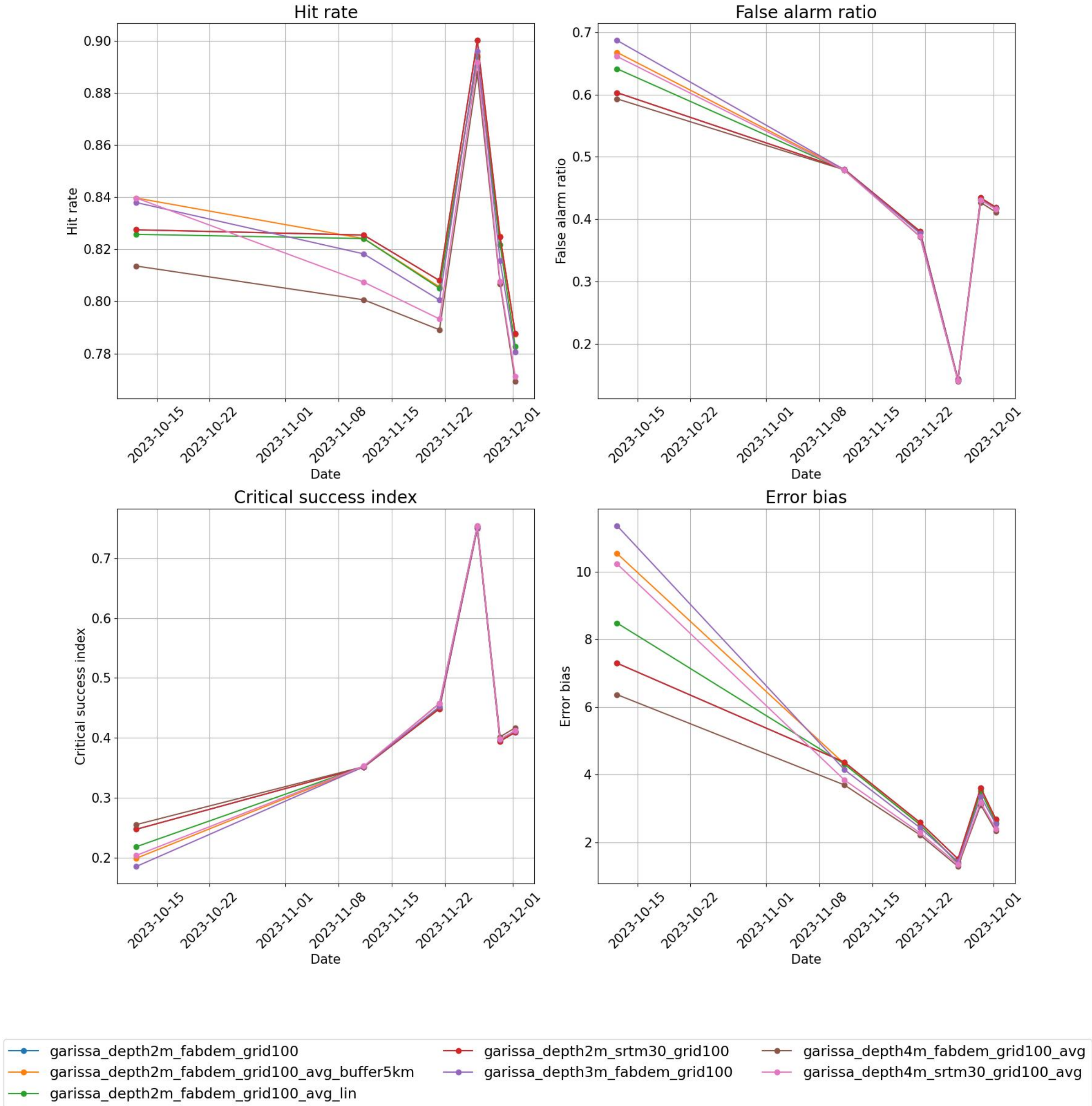


Figure 4.1: Performance metrics computed from confusion matrix of inundation maps of SFINCS and OPERA, including metrics at the reference date, 12-10-2023.

4.3.1. Unclear Mandates

The WRA is established under The Water Act, see Appendix A, Figure A.1. Research shows that regarding FEWS, its primary role is to develop and enforce standards, procedures, and regulations for water resource management and flood mitigation, see Table A.1. Besides this, the WRA operates (telemetric) measurement stations across Kenya, which monitor stream gauges for the respective rivers. The Water Act furthermore prescribes one of the powers of the authority to collect, analyze and disseminate information on water resources. Various interviewees point out that the mandate established in the Water Act does not sufficiently explain the role of the WRA regarding FEWS. As a FEWS is seen as a mitigation measure, the following discrepancies can be interpreted:

1. Regarding flood mitigation, the description of the role of the WRA can be seen as limited to developing

standards procedures and regulations.

2. The power of dissemination of information (e.g. early warnings) appears limitedly described for water resources and does not mention floods.

To develop a technologically advanced FEWS for the Tana River, the inclusion of modeling-based flood forecasts is paramount(Table 2.1). Such models rely on two primary data streams: water level data, monitored by the WRA and meteorological data, overseen by the KMD (Table A.1). The KMD, forthcoming from the ratification of the WMO Convention, is the single and authoritative voice concerning severe weather and climate events. Furthermore, the Government of Kenya instructs the KMD to deliver prompt and accurate weather and climate forecasts to ensure the safety of lives, safeguard property, and preserve the natural environment. In an interview, residents of Garissa have noted significant improvements in flood communication over the years, with particular mention of the efforts by KMD. However, other individuals affiliated with KRCS, WRA and ICPAC mention that it is not clear whether the KMD has the legal mandate to establish a FEWS. The literature review has been inconclusive regarding this, since a mandate for FEWS also entails managing and operating river telemetric stations (now operated by WRA). Individuals affiliated with KMD aswell are uncertain about this mandate.

Meteorological Bill

The challenges mentioned above are subject to change after the introduction of the new Meteorological Bill (Government of Kenya, 2023). If passed, the Bill would herald significant changes for the Kenya Meteorological Department, which would then be known as Kenya Meteorological Services Authority (Etyang, 2023; Government of Kenya, 2023; Nyarangi, 2023). The legal framework should effectively transition the KMD into a Semi-Autonomous Government Agency (SAGA). According to individuals associated with the KMD, this transition has been discussed for the past 20 years and should introduce more comprehensive strategies to tackle major meteorological challenges and advocate for an integrated method in the planning and implementation of different measures. It suggests establishing a legal and institutional framework along with governance measures to fulfil its objectives. Furthermore, it would emphasise a coordinated effort for better monitoring, pooling of resources, and governance in meteorology, aiming for a more efficient and effective management of meteorological services in Kenya (Etyang, 2023; Nyarangi, 2023). It is for these matters, that KMD affiliates are looking forward to the introduction of the Meteorological Bill.

4.3.2. Data sharing

Most interviewees view a collaboration between KMD and WRA as crucial for the development of a comprehensive FEWS. WRA representatives stress that such a FEWS would require the integration of both WRA and KMD datasets (i.e. meteorological data and water level data). However, insights from interviews with all individuals affiliated with the WRA suggest a notable absence of collaboration between the two entities. It appears there may be some hesitation, if not a preference for discretion, within the KMD regarding the sharing of its meteorological data. Delays often occur, with requests for compensation being a recurring hurdle. Despite the presence of a MoU between the KMD and the WRA, its efficacy in fostering cooperation between the two entities seems to remain limited. The MoU, intended to outline terms of collaboration, has not translated into tangible improvements in data-sharing practices.

ICPAC primarily focuses on training government institutions and organizes conferences to discuss the latest developments in climate forecasting (Table A.1). Being an international organization, they mainly interact with ministries and government institutions such as KMD and WRA, providing training and information about FEWS. ICPAC has noticed efforts from both KMD and WRA to establish FEWS but acknowledges that collaboration between them appears to be lacking. They recommend that KMD and WRA focus on fostering their relationshop to improve the effectiveness of FEWS implementation.

KRCS also acknowledges a significant gap between KMD and WRA in terms of information sharing and collaboration. In response to a suggestion of them being a third party to help improve relations between the two institutions, KRCS responded positively. They pointed out that organizations like ICPAC might be too high-level, operating mainly at the ministry level, and that NGOs, while helpful, might lack the capacity to fulfil such a role effectively. However, KRCS, with its strong national and regional presence and better legal mandates, is well-positioned to enhance collaboration for flood mitigation.

4.3.3. Dissemination of Warnings

As of early 2024, legal mandates for the establishment of a FEWS remain unclear. The Ministry of Interior is seen as legally responsible for flood risk management and should oversee the dissemination of warnings. Officially, information about forecasted floods from KMD, WRA, or other disaster forecasting organizations is relayed to higher-ups in the ministry, who then strategize in accordance with the disaster management cycle. However, key informants from WRA and KRCS indicate that information about impending severe weather or floods is also distributed informally through various organizations and institutions like KRCS, local county governments, and NGOs, ensuring that communities likely to be affected are warned well in advance.

4.3.4. Stakeholder engagement

The importance of the involvement of stakeholders is recognized by most interviewees. However, determining the extent of their engagement is difficult. Inadequately engaging stakeholders causes insufficient utilization of technological advances (i.e. implementing a new FEWS). Even though legal mandates for developing a FEWS in the Tana River are shared between the KMD and the WRA, many more stakeholders are closely connected to implementing such a system (e.g. local government, ICPAC, KRCS, KenGen, TARDA, etc.). These actors do not have their interests fully aligned. As discussed above, FEWS in Kenya, and along the Tana River, have proven difficult to be established due to inadequacies between stakeholders.

Furthermore, it can be interpreted that knowledge is not adequately shared even though it is present (i.e. about weather forecasting, hydrological & hydrodynamic models, and warning dissemination). Besides, interviews show that many of the stakeholders cannot cultivate this knowledge as a result of lacking capacity.

5

Discussion

This chapter focuses on the interpretation of the results presented in Chapter 4, forming the foundation for the link between the research questions and the results. Summarizing, the main research question aims to improve the existing FEWS, with the subquestions relating to data availability, selection of forecast models, and information sharing mechanisms, respectively.

In the results, it was found that the information available to calibrate the GR4J model was insufficient at the current time. Furthermore, issues with network structure provided difficulties with running the entire model. SFINCS and remote-sensing flood maps were compared on six different dates, progressing from relatively normal discharges to peak flow. These were analyzed through the computation of four error measurements. Stakeholder interviews, as discussed in the results, pointed towards four main issues in establishing a FEWS for the Tana River: unclear mandates, data-sharing, dissemination of warnings, and stakeholder engagement.

The discussion is structured as follows. Firstly, the data requirements are discussed in Section 5.1 in terms of source, quality, and obtainability. Part of the objective relates to finding suitable models to employ in flood forecasting, so the model usability and performance are discussed in Section 5.2. Finally, the information flow and decision-making process for a FEWS is discussed in Section 5.3.

5.1. Data Requirements

Meteorological and possibly hydrodam data is required to feed the hydrological and hydrodynamic models. This can be obtained from different institutions, depending on their relationship (i.e., WRA, KMD, TAHMO, KenGen, or TARDA). If an effective MoU exists, the required data for the hydrological model can be easily shared. However, not all organisations presently have these MoUs in place, which leads to difficulties in the integration of the datasets for use in the hydrological model.

Precipitation data can be obtained through KMD, TAHMO, or freely available remote sensing. As described in section Section 2.6.4 there is good collaboration between the KMD and WRA for the FEWS system in the NZOIA river. However, such a level of collaboration was not observed outside of this region raising doubt to the short-term availability of this KMD data. Therefore two other options are available to receive this data, either through TAHMO (with an MoU (van de Giesen, Hut, & Selker, 2014a)) or from remote sensing data (CHIRPS or similar datasets). The quality of the data sets depends on the source and how they have been interpolated.

Remote sensing is known for its high uncertainties in predicting precipitation data. This depends on the type of remote sensing and area. The CHIRPS dataset is known for overestimating the precipitation in Eastern Africa (Dinku et al., 2018). However, it is the most suitable dataset that can be used for precipitation in Kenya (Macharia et al., 2020). A different data source for precipitation data is using station data. The spatial distribution and interpolation methods have the biggest influence on the quality and reliability of the data. The station density is bigger in the upper part of the Tana Basin compared to the lower part, resulting in a better spatial resolution in the upper part of the basin.

Validation of the GR4J model was possible through telemetric gauge data courtesy of the WRA. Moreover, this allows for the research of error propagation when using GR4J output as input for SFINCS, though this analysis was not performed. This data was made readily available, and the WRA emphasised the power of data when shared openly. Telemetric data is available at Garissa. While other (manual and automatic) stations exist, relaying of measurements is infrequent. Furthermore, some stations have rating curves that have not been updated since at least 1980, making them unusable for the model as the river is dynamic. These factors led to the decision to only use telemetric gauge data from Garissa and limit the study area to Garissa only. It should be noted however that the reliability of this station has not been validated as part of this study.

Limiting the study area to Garissa allowed the usage of gauge data as input for the SFINCS model since the implementation and connection of GR4J proved infeasible. This restricted the validation possibilities of the hydrograph, which was already used as input, necessitating the recourse to remote sensing inundation maps by OPERA. While this alternative facilitated the computation of various performance metrics, it also resulted in the omission of flood arrival time validation. The latter is exacerbated by the limited satellite coverage (see Table 3.3). A bigger domain along with the utilization of GR4J output would have facilitated this validation. In that case, the presence of additional telemetric stations along the Tana, for example at flood-prone areas Hola and Garson, would allow the validation of arrival times at several locations.

SFINCS to a large extent depended on the recency of global data sets, which ranged from 2018 (river mask: G. H. Allen and Pavelsky (2018)) to 2023 (infiltration: K. K. F. Lee et al. (2023)), as summarized in Table 3.2. The morphologically dynamic nature of the Tana discourages the use of outdated datasets, which may have partly caused the discrepancies in river width between the SFINCS model and the OPERA inundation maps.

Furthermore, the resolution of these maps is often highly limited, capping out at 30 meters. This restricts the applicability for small-scale applications, for example, urban flooding, for which the model has to be supplied with higher-resolution data. This also requires additional validation on a local scale. At this scale, global inundation maps are not available at a sufficient resolution.

5.2. Model Performance

The following criteria were selected to base model choice on (see Section 3.1):

1. Models should accurately predict flood events with sufficient lead time.
2. Models should be computationally efficient.
3. Models should be open-source.
4. Freely available remote sensing data should constitute a major part of model input.

Additionally, the application of these models allows for reflection on their usability and practicality.

This section considers the used models in the above regard, mainly discussing the performance and usability of GR4J and SFINCS sequentially.

5.2.1. Hydrological Model

The main problem with the SuperflexPy implementation of GR4J is that the flows are not propagating through the network structure, meaning flows in the Tana River Basin are not aggregated while moving downstream. While the creator of SuperflexPy did supply a method to create custom nodes that incorporate both internal and external flow (Dal Molin & Fenicia, 2021), it is currently not operational due to bugs in the source code of SuperflexPy. This problem can be solved, but the developer of SuperflexPy is not actively working on the project at this time. However, the advantage of using an open source model means that all source code is available and this problem is solvable, provided substantial programming knowledge is present. This makes the model less suitable for the Tana River Basin based on the model selection criteria outlined in Section 3.1.1.

Another issue is that the model parameters are currently the same for each catchment, which results in the model not converging even after a large amount of iterations ($\geq 100,000$). If different parameters were used for different catchments the convergence errors are likely able to be fixed, but this is difficult due to the scarcity of the available data. With only a single telemetric station and some infrequently updated stations, it is not possible to properly calibrate the model.

Evaporation
Currently, the evaporation data is strictly based on an Ordinary Kriging interpolation using the TAHMO temperature data. However, research has shown that improved results can be achieved by incorporating both information on elevation from the DEM and location data to increase the accuracy of the interpolation Sergio et al. (2003). Furthermore, by averaging all evaporation to a single value for 5 years some seasonal variation is lost, which could lead to less accurate predictions on the discharge.

Usability of the model
The original choice for the combination of GR4J and SuperflexPy was based on the fact that WRA staff is already familiar with GR4J from the Nzoia system. SuperflexPy is a computationally efficient, free, and open-source implementation which made it a logical choice for the project. However, the lack of clear documentation and practical examples in the literature makes it difficult to implement unless substantial programming knowledge in Python is present. Furthermore, consulting a programming expert revealed that bugs are present in some of the objects and methods in SuperflexPy, meaning the source code needs to be modified to apply the model. This adds even more complexity, which is not desirable for the implementation in the Tana River.

5.2.2. SFINCS

We start with an interpretation of the visual inspection and comparison of the SFINCS and satellite flood maps. Secondly, the error metrics are discussed. Finally, we reflect on the usability of the model.

The remote-sensing maps exhibit occasional noise, with instances of permanent water spuriously occurring through the domain. Similarly, the floods depicted in the maps are not always restricted to areas adjacent to the river, raising questions on whether they stem from localized precipitation events or represent noise within the data. Limitations of the OPERA product are known to include the increase in commission errors in the presence of shadows cast by trees, buildings, or clouds, thick canopy, and low sun angles (Jones, 2019). The latter may be exacerbated by the overpass time, generally around 7:30 AM. Additionally, forest and vegetation are prevalent near the Tana (Buchhorn et al., 2020; Droogers & Immerzeel, 2006), while building cast shadows may be present in Garissa.

It is found that the SFINCS maps on the reference date feature flooding while no known flooding occurred, suggesting that the river bathymetry does not offer the capacity that is required under normal flow conditions. This may also be influenced by the bed roughness, with a lower roughness facilitating flow, though the expected influence of bed roughness is low Eilander, Couasnon, et al. (2023). However, it is observed that a bankfull depth of 4 meters does not offer the required capacity either, since some flooding is still observed at the reference date for the SRTM30 digital elevation model, while FABDEM does offer the required capacity. This may indicate errors in either the SRTM30 DEM itself or the way it is combined with the bathymetry. Rivers are burned into the grid based on a quantile parameter, which determines the relative height of river banks compared to the surrounding land. Decreasing this should burn the river deeper into the DEM, thus reducing floods.

Interestingly, it is noted that adding a 5 km buffer around the inflow point to prevent water from flowing out of the domain, increases the amount of flooding at the reference date. This is concluded by comparing the FABDEM 2-meter burned river depth model with the same model including a 5 km buffer. This suggests the outflow of water from the inflow boundary since adding a buffer increases the amount of water in the study domain.

Four error metrics were computed over time for each model: hit rate, false alarm ratio, critical success index, and error bias. Each metric offers valuable insights into the models' inclinations toward overprediction or underprediction, as well as their overall performance. Since several other studies have used the same four metrics (Bernhofen et al., 2018; Eilander, Couasnon, et al., 2023; Horritt, Bates, Fewtrell, Mason, & Wilson, 2010; Pappenberger et al., 2006; O. E. Wing et al., 2017; O. E. J. Wing et al., 2021), a consensus exists on the performance that constitutes a good model. Since the CSI provides a general measure of performance, this is the focus of this comparison. The other metrics then indicate the inclination to underprediction and overprediction. Well-calibrated models 2D models based on remote-sensing data can show CSI values between 0.7 – 0.8 with good calibration but can reach down to 0.3 in some cases, with < 0.5 considered poor and > 0.7 considered good.

The CSIs vary from 0.2 during normal conditions to 0.75 during maximum flooding, approximating 0.4 at the onset and towards the end of the floods. As discussed in Section 4.2, a consistent disparity exists between the width of the river in the SFINCS model and that observed in the satellite imagery, resulting in smaller CSI scores during normal conditions. This discrepancy is particularly pronounced due to the limited amount of wet grid cells, amplifying the influence on the CSI. However, not counting the reference river results in a lower CSI during flood conditions, since much less flooded grid cells are found due to the increased river width of the SFINCS model. Summarizing, the SFINCS model performs well during floods, but poorly during normal conditions, though large improvements are expected through a good calibration of the river widths.

The models' hit rates, ranging from 0.77 to 0.90, indicate a successful representation of flooded grid cells, and generally little tendency to underpredict flooding. The false alarm ratios varied between 0.65 under normal conditions and 0.15 during floods, showing the models' inclinations to overpredict flooding during normal conditions. This was also concluded previously during visual inspection. Finally, error bias varies from $\sim 6-11$ during normal conditions to ~ 2 during maximum flooding, confirming the inclination to overprediction of flooding. Generally, the models perform better during floods than normal conditions, due to their propensity to overpredict.

In reflection on the usability of the SFINCS model, it offers notable advantages, as elaborated upon in Section 3.1, such as rapid computational speed and compatibility with other Python-based software tools. Nevertheless, there are compelling reasons to explore alternative hydrodynamic models, such as HEC-RAS, which is discussed in the next part.

The first concern is regarding the intuitiveness of SFINCS. The software lacks a user-friendly interface, posing challenges for users unfamiliar with Python coding. A significant level of Python proficiency is required to create a custom model from scratch, presenting a barrier to adoption for institutions with no Python experience. Almost all interviewees and other employees met had little to no Python experience, making it hard to roll out soon for these organizations. In contrast, alternative models such as HEC-RAS offer more intuitive interfaces. While SFINCS benefits from various Python libraries for data visualization, the process still demands a considerable understanding of Python.

The limited availability of use cases exacerbates the usability problem. SFINCS offers documentation for each method, though few examples are available. SFINCS' recency compounds this issue, with methods often shuffled or removed, while documentation lags. This can result in prolonged troubleshooting periods, sometimes spanning multiple days for a single issue. Additionally, many hydrodynamic modelling tools offer extensive tutorial resources, including video tutorials, facilitating a smoother learning curve. The recency of SFINCS also presents limitations in terms of its establishment. Established models like HEC-RAS and MIKE benefit from years of refinement and validation across diverse environmental contexts. Furthermore, the lack of establishment is seen in the limited knowledge of, for example, common pitfalls. SFINCS is also not supported by integration software, e.g., Delft-FEWS, but it is expected that it will be in the future (see Section 3.1).

5.3. Stakeholders and FEWS

The GoK and the WRA have clearly stated that introducing FEWS along the Tana River is of the highest priority as flooding becomes more frequent. A significant challenge is to be recognized: there is limited time available to achieve consensus regarding implementing a FEWS, despite the critical importance of such consensus to the decision-making process. Under these circumstances, deferring the decision-making process is not a viable option, as delaying decisions may result in stakeholders becoming committed to a particular course of action without adequate consideration. This has been learned from the Nzoia FEWS and from the earlier efforts along the Tana River. Here, software was introduced with help from third-party experts from foreign countries on request from WRA and/or KMD. These companies were allegedly paid big sums of money and left after implementing closed-sourced software (e.g. MIKE Powered by DHI). Even though successful, it left the WRA and all other stakeholders highly dependent on them and not in the capacity to resolve any bugs or flaws in the system. Moreover, there is a risk that decisions made hastily may face substantial criticism from other stakeholders. Thus, it becomes imperative for stakeholders to make decisions that minimize the potential for regret. Such decisions should avoid entrenching stakeholders in inflexible positions and should instead allow ample room for future decision-making processes to unfold effectively.

The introduction of the meteorological bill brings some points of attention. The KMD reestablished as the National Meteorological Service Authority within the Ministry of Environment and Forestry, remains the authoritative source for weather, climate, and hydrological updates, including advisories for air quality and tsunamis (Etyang, 2023; Nyarangi, 2023). While extreme precipitation, cyclones, and tsunamis are explicitly addressed, floods are not specifically mentioned in this bill. Besides that, the bill describes data and information sharing with various sectors (i.e. maritime, transport, private), but the WRA is not mentioned. Further research is needed to assess the extent of the meteorological bill and its consequences for collaboration with the WRA.

Collaboration between KMD and WRA seems crucial for establishing a FEWS. Information sharing, as mentioned above, appears to be inefficient. While bureaucratic processes, commercial interests and resource constraints are possible factors that may contribute to these challenges, the exact underlying reasons remain unclear. It is imperative to navigate these complexities with sensitivity, recognizing the complexities of bureaucratic systems and the need for constructive dialogue to foster collaboration and ensure the successful implementation of a FEWS.

6
Conclusions

Having discussed the results and their implications, the report is continued by formulating the conclusions. Conclusions are formulated based on the research questions in Section 1.4. Summarizing, the objective is to enhance the flood forecasting system of the Tana Basin. First, each research question is answered sequentially, subsequently ending with the answer to the main research question.

1. *What data is available in the Tana Basin for the development of a FEWS?*

In the Tana basin, many different data sources are available for the development and training of a FEWS, but not one organisation has access to all the data, hindering the development of a technologically advanced FEWS.

River gauges are operated and maintained by the WRA. These are essential in the calibration of the catchments of the GR4J model. One operational telemetric station is located at Garissa. This station can be used to validate the hydrological model, however, it does not suffice to calibrate the large number of sub-catchments required to accurately model the Tana Basin. Therefore, more telemetric stations are necessary. The exact locations depend on the division of the TCA into sub-catchments, but it is advisable to place the stations at the downstream end of the catchment to most accurately match the output of the model. The number of sub-catchments is dependent on the availability of data and computational power. More sub-catchments could increase the accuracy of the model, but more research needs to be done to verify this.

Meteorological data is gathered by the KMD. They are also responsible for meteorological forecasts. Data requests resulted, sequentially, in no data and insufficient data. However, the analyzed data is promising. The KMD operates a wide network of weather stations. Furthermore, they make numerical weather predictions, which can provide high-fidelity input to GR4J and, subsequently, SFINCS. The WRA and KMD have both seen efforts to improve the FEWS for the Tana Basin, but neither can succeed without the other's data. Any development in FEWS should thus be a joint effort.

TAHMO data proved feasible to obtain in large quantities by using their API. Their (provisionally) coarse network of weather stations facilitates the calibration of higher-resolution remote sensing datasets, like CHIRPS. They do not, however, make numerical weather predictions, rendering their data supplementary to the KMD. However, considering an event-based approach to model calibration and validation, their data proved useful due to the high temporal resolution. The network is expected to keep on growing so the data should be incorporated into the model.

KenGen and TARDA are the final important institutions regarding data. Efforts to obtain data did not prove successful, so no conclusions can be made regarding data quality. It is known, however, that discharges are monitored and thus available.

Several remote sensing datasets were identified to be useful for developing GR4J and SFINCS models. Globally available datasets included digital elevation models, several river databases, land use, soil types, and precipitation. For discharge, this is a bit more problematic. While advancements are being made in flux estimation through remote sensing (e.g., Wang et al. (2021)), this is obsolete when discharge measurements are available directly from KenGen or telemetric water gauges.

The global DEM proved useful to derive sub-catchments, while also forming a solid base for the topography of a SFINCS model. To inform decision-making on a local scale, this should be supplied with higher-resolution topography data, since a 30-meter resolution does not suffice at this scale. Similarly, while global river datasets proved able to accurately capture river centerlines, the bathymetry is not accurately obtained by those and should be supplied with local measurements. These may be as straightforward as an estimate for the bankfull depth and width to implement as a rectangular profile.

2. *What kind of computationally efficient, free-to-use models can be used for the development of a FEWS?*

Several models were considered. SuperflexPy's implementation of GR4J and Hydro-MT's implementation of SFINCS were selected after considering the criteria presented in Section 3.1.

GR4J has been shown to work well in other applications like for example the Nzoia FEWS in Kenya itself. However, the SuperflexPy implementation of this model, while open source and computationally efficient, has significant problems. The main problem is the fact that natively SuperflexPy does not support routing through networks. The noted workaround for this problem by the author lacks documentation and contains bugs Dal Molin and Fenicia (2021). In general, the documentation for this implementation is limited and examples are not widely available. These factors make SuperflexPy not the most suitable for deployment in the Tana Basin.

Several SFINCS models were developed, each varying one or a few parameters. This did not constitute a full formal sensitivity analysis but adhered to the findings by Eilander, Couasnon, et al. (2023). The models were validated using several performance metrics. It was found that the models perform well during flood conditions, but overpredict flooding during normal conditions. This is seen in a relatively high false alarm ratio, particularly during normal flow conditions. Furthermore, while some differences in performance metrics are visible between several model instances during normal conditions, these are quite literally washed during flood conditions.

This inclination towards overprediction is attributed to two major factors: the increased river width of the SFINCS models compared to the OPERA maps and the discrepancies between the height of the river banks in the model and reality. Another factor to consider, albeit of lesser importance, is the presence of outliers in the OPERA maps. These outliers skew the results of any subsequent analysis through an increased number of artificial false negatives and should therefore be addressed through pre-processing steps.

The increased river width of the SFINCS models compared to the OPERA maps is visible when comparing Appendix B and Appendix D. A potential solution is to manually decrease the river widths of the SFINCS model, for example to constant widths for each river segment. Another approach is to measure, physically or through sources like OpenStreetMap, river widths. SFINCS only supports rectangular bathymetries, which may complicate this method, so calibrating the river on bankfull discharges using available rating curves is another option.

The discrepancies in river bank heights between the model and reality become apparent when referencing specific dates. Flooding on these dates is observed across several SFINCS model instances. This is attributed to the manner in which river geometry is burned into the DEM (Eilander, Couasnon, et al., 2023), which is primarily controlled by the "quantile for river bank estimation" (Couasnon et al., 2023), which can result in the misplacement of river banks relative to the surrounding topography. Consequently, even temporary rises in water levels above the river banks may lead to instances of flooding.

SuperflexPy and SFINCS are relatively new models, seen in the relatively few documentation and usage cases, complicating straightforward implementation. Specialized knowledge and experience with the model are necessary to implement and validate, with no known cases in which either model is applied in a FEWS. However, SFINCS seems promising due to its good performance during flood conditions and its computational efficiency, facilitating potential upscaling to a much larger domain, discussed in Section 7.5. Very recent efforts by Kiptum, Antonarakis, Todd, and Guigma (2024) have focussed on a hydrological model only. Since water levels are readily computed directly from discharges and most discharge stems from the upper Tana, it is worth considering not using a hydrodynamic model. The issuance of a flood warning then directly stems from discharge predictions coupled with water levels through the available rating curves. However, this removes the possibility of incorporating flood retention times and may have difficulty in capturing the relation between different inflow points.

3. *What information-sharing mechanisms exist between relevant stakeholders in the Tana Basin and how can this be improved?*

The evaluation of the current flood warning infrastructure reveals several significant gaps, challenges, and obstacles hindering its effectiveness:

1. **Unclear Mandates:**
   - Ambiguities persist regarding the roles and responsibilities of key stakeholders, particularly the WRA and the KMD.
   - While the Water Act assigns regulatory functions to the WRA, its role in FEWS is not clearly defined.
   - Similarly, the KMD's mandate regarding FEWS implementation remains uncertain, leading to challenges in collaboration and data-sharing between the two entities.
   - The impending introduction of the Meteorological Bill poses both opportunities and challenges for FEWS implementation.
   - While the bill aims to strengthen meteorological services and governance, uncertainties exist regarding its implications for collaboration between the KMD and the WRA, as well as its explicit mandate for FEWS development and operation.

2. **Limited Collaboration and Information Sharing:**
   - Despite the presence of Memoranda of Understanding (MoUs) between relevant stakeholders, including the KMD and the WRA, collaboration and information-sharing practices remain inadequate.
   - Delays and reluctance in sharing meteorological data between the KMD and the WRA impede the integration of essential datasets necessary for the development of a comprehensive FEWS.

3. **Inadequate Stakeholder Engagement:**
   - The involvement of stakeholders in the FEWS implementation process is crucial but remains insufficient.
   - Many stakeholders, including local governments, NGOs, and affected communities, are not adequately engaged in decision-making processes, leading to gaps in knowledge dissemination and capacity building.

4. **Dissemination of Warnings:**
   - Despite efforts by various organizations, including the KRCS and local county governments, challenges persist in the timely dissemination of flood warnings to affected communities.
   - Informal communication channels often supplement official channels, highlighting the need for improved coordination and information-sharing mechanisms.

Addressing these gaps, challenges, and obstacles is essential for enhancing the effectiveness of flood warning systems in the Tana River region. A coordinated effort involving clear mandates, improved collaboration, robust stakeholder engagement, and a supportive legal and institutional framework is necessary to overcome existing barriers and ensure the successful implementation of a comprehensive FEWS.

Finally, with all the subquestions answered the main research question of this report can be answered.

How can a flood early warning system for the Tana Basin be improved with minimal data requirements, computationally efficient forecasting models, and enhanced stakeholder collaboration?

The subquestions are answered above and will help formulate the answer to the research question. The data needed for this model is freely available or can be available through a MoU. Secondly, the current FEWS can be improved by developing a FEWS using open-source models only. The models that are used for this FEWS, are not the most suitable models to use. As the network structure in SuperflexPy is not functioning for GR4J, a different implementation of GR4J might work better. The SFINCS implementation is working but understanding the program requires considerable Python knowledge as well. Considering the amount of data available for this model and the knowledge at WRA, a different model might be more suitable for a FEWS. Lastly, in our opinion, the collaboration between WRA and the KMD can be improved to support the development of a FEWS. Since both parties need each other for the development of a FEWS, this is a crucial step.

7 Recommendations

The report is finalized by providing recommendations for further research and/or actions regarding the implementation of a flood forecasting system. This is needed to make the following steps in the development of a FEWS in the Tana basin. First, the calibration of the hydrological model is discussed in Section 7.1, which is strongly related to the availability of data. Next, recommendations to better record the river bathymetry are done in Section 7.2, which are needed for better performance of the hydrodynamic model. The recommendation to implement the impact of the hydro dams on the Tana Basin is discussed in Section 7.3. The extension of the model into a probabilistic model is discussed in Section 7.4. The recommendations to upscale the hydrodynamic model to the entire Tana Basin are discussed in Section 7.5. Lastly, potential improvements for stakeholder engagement are discussed in Section 7.6.

7.1. Hydrological Model Calibration and Data Availability

One of the most important factors preventing the Tana Basin from having a technologically advanced FEWS system is the limited amount of measurement stations. The most crucial of these are the telemetric water level gauges, as they can relay water levels in near-realtime. Currently, only the water gauge at Garissa is a telemetric station, meaning it is not possible to properly calibrate the model, nor to feed it the data to make accurate predictions.

Two strategies are proposed to circumvent the limited availability of data, with a combination likely to give the best results.

1. Even though each catchment is different, it could be possible to group similar types of catchments and use both the same initial guesses as calibration steps for these catchments. Grouping could occur based on area, land use, geography, or a combination of these factors.
2. Adding more (telemetric), frequently updating water gauges to the system would greatly improve the calibration of the model for specific catchments. This way, the model would be more accurate in predicting small-scale floods as a smaller sub-catchment would be properly calibrated on the input data.

7.1.1. Grouping Catchments

Grouping catchments could be based on various properties of which land use, soil type, and geography are the most logical because these affect how water is routed through the network. The area of the sub-catchment could be used as a scaling parameter to relate similar, but different-sized catchments together. From there, the reduced set of unique catchment parameters is calibrated on the available data.

Another shortcut to calibrate the model is the use of transfer learning. If the catchments and parameters of another GR4J model are known it can serve as a good starting point for further calibration. In the case of the WRA, the Nzoia FEWS can be used as a starting point for the calibration of the Tana FEWS. A more extensive literature study may also give insights into the starting parameter values of the Gr4J model.

7.1.2. Adding Telemetric Stations

Increasing the number of telemetric water gauges in the Tana basin is a critical step in accurately calibrating the model. These water stations will serve two purposes. The first purpose is to allow the model to be calibrated on one or a few individual sub-catchments, increasing its predictive accuracy. Secondly, it can also serve as an input parameter for the hydrodynamic model, reducing the uncertainty band of the high water wave propagating downstream.

Adhering to Krabbenhoft et al. (2022), it should be prioritized to place these gauges in strategic locations, which is, counterintuitively, not necessarily in big cities. This complicates management and maintenance, but the priority should be placement around junctions in agreement with the division of the TCA into sub-catchments. Singhal et al. (2024) emphasize the need to identify critical nodes for gauge placement. Placing gauges at the junctions between sub-catchments Section 3.2.2 should be a priority moving forward, with the identification of sub-catchments (and the corresponding agreeance with a hydrological model) an integral component.

7.2. Bathymetry Measurements

Several discrepancies were noted between the representation of rivers in the SFINCS model and the OPERA maps. In particular, river widths were noted to vary between them. SFINCS river widths were obtained from the GRWL river mask (see Section 3.3.1). It is not known whether river widths are more accurately represented by GRWL or OPERA, especially during reference conditions. Improvements in the bathymetry representation in hydrodynamic models have been shown to greatly increase model accuracy (J. C. Neal et al., 2015).

These measurements could be made in some different ways. Detailed cross-section measurements could be made with sonar, but this is a costly procedure (Cook & Merwade, 2009). In the absence of such measurements, several avenues exist to estimate river bathymetry. For example, J. Neal et al. (2021) introduced a gradual flow solver to improve bathymetry estimates on a large scale. However, the preferred course of action is local measurements. The river can be simplified to a rectangular profile (in the case of SFINCS), which has to be verified locally. The application of other hydrodynamic models may allow more complex profiles. Local measurements of width, bank height and, normal depth allow for more accurate calibration and parameter selection. Down the line, LIDAR measurements can improve the accuracy of predicted floodplains. LIDAR measurements have higher spatial accuracy and have been shown to increase the accuracy of the modelled floodplain with CSI values up to 0.9 given a good working model (Bates et al., 2006; Bermúdez et al., 2017).

As noted in Section 3.3.2, the Tana is considered morphodynamically active. River dimensions and flood conveyance are subject to relatively much change over time, leading to the misrepresentation of bathymetry in hydrodynamic models. This can lead to failing to the model failing to predict incoming floods (Pender, Patidar, Hassan, & Haynes, 2016). To counter degradation in model performance the DEM should be updated with newer versions whenever possible. This means that the model with the new DEM should be validated again, potentially including the re-derivation of river centerlines from this DEM.

7.3. Hydro Dams

As discussed in Section 1.1 the upper Tana is characterized by the large amount of hydrodams present in Kenya, producing about half its current power. Furthermore, there are plans to double this capacity with the Grand Falls hydro dam. These dams are currently not implemented in the model, and depending on collaboration with the dam operator KenGen two main continuation strategies are proposed.

1. Use KenGen discharge data as input for SFINCS. If KenGen has an accurate schedule for the power generation and spillway usage, a predicted discharge can be inferred from this. Subsequently, this can be used as a discharge forcing in the SFINCS model. The advantage of this strategy is that fewer data stations are required as we can leave out all sub-catchments that feed into the dam reservoirs. However, if KenGen is not able to predict discharge and water level at least a few days in advance, this method becomes unfeasible.

2. Use the hydrological model to predict reservoir levels and predict reservoir discharge based on the model. By using this method the KenGen data becomes obsolete, which simplifies the process of obtaining data from stakeholders. However, due to differing power demands or unpredictable spillway

behaviour, this method may turn out to be unreliable. Before implementing this solution, more research into the accuracy of his method should be done.

Combining these two methods would likely yield the best results and could benefit both the WRA and KenGen. As such, it is recommended to expand the collaboration between the WRA and Kengen. If the hydrological model of the WRA could inform decision-making for the discharge schedule of the Seven Forks Hydro dams, KenGen would be more inclined to share this discharge schedule. Furthermore, large usage of the spillway can potentially be reduced, leading to lower water levels in the Tana River. This way, more timely predictions can be made for the lower Tana.

7.4. Probabilistic Flood Modelling

Currently, the models are fully deterministic. Hindcasted meteorological data is used as input, propagated through SuperflexPy, to finally arrive at a flood forecast (although this cascade is not fully operational, as discussed). Additional research may provide uncertainty in this data, allowing a probabilistic interpretation for an event-based approach but this was not included in this research. The deterministic model in this research computes flood exposure but does not give insight into flood risk or probability. This is important information necessary for making well-informed decisions regarding floods, since currently, the inherent uncertainty of the output (due to uncertainty in the input data) is not quantified, making it impossible to give probabilities to certain events occurring (i.e., the water is 80% certain to reach a certain level) and relating this to predetermined risk maps. This informs decision-makers to act based on the forecasted flood probability combined with (un)acceptable risk levels.

The weather data used in models, especially with weather forecasts is subject to uncertainty. The further ahead the weather predictions are made, the bigger the uncertainty in these predictions. To get a better understating of the uncertainties in the model a probabilistic interpretation should be included in modelling efforts. A probabilistic interpretation in numerical weather forecast is commonly done through ensemble forecasting (Palmer, 2000). Similarly, flood model runs can be ensembled to include a probabilistic interpretation, either through sampling from the meteorological forecast (using the probability density function) or by sequentially feeding the ensemble into the flood models. Probabilistic flood models are based on a Monte Carlo framework and have been done in many different flood models (Thompson & Frazier, 2014). It uses a probability distribution of the different inputs, taking the covariance into account, and models all different possibilities to give a flood risk assessment.

Probabilistic modelling has been applied in the context of SFINCS by (W. Lee, Sun, & Scanlon, 2024) but has been applied to many flood models (e.g., Domeneghetti, Vorogushyn, Castellarin, Merz, and Brath (2013) for IHAM). SFINCS's computational efficiency facilitates this approach since many models are run in a relatively short time span.

A probabilistic interpretation facilitates the creation of risk maps, which are part of the first FEWS component as described in Section 2.2. Models are then run for several 1-in-T-year floods to determine the flooding under several design conditions (Bodoque, Esteban-Muñoz, & Ballesteros-Cánovas, 2023). Flood impact is based on both probabilities as well as the costs associated with such a flood, including loss of life, affected households, and asset loss. Combining the probability with the estimated costs generates a flood impact or risk map. These are used for effective decision-making to identify the most important flood-prone areas on different scales. Specialized flood impact models offer tailored solutions for these calculations, seamlessly integrated with various flood models. These tools are specifically designed to assess and quantify the potential impacts of flooding events, providing valuable insights for decision-makers and stakeholders involved in disaster management and mitigation efforts. One notable flood impact model is Delft-FIAT, developed by Deltares. This Python-based tool is freely available and enjoys widespread adoption worldwide. Much like SFINCS, Delft-FIAT can be accessed through the Hydro-MT library in Python. Several studies have applied Delft-FIAT in conjunction with SFINCS (Bader, Bricker, Sebastian, & Leijnse, 2018; Eilander, Boisgontier, et al., 2023; Parodi, 2019).

7.5. Upscaling

One of the main advantages of SFINCS is its ability to efficiently model compound flooding, taking into account water level forcing, waves, storm surges, pluvial, and fluvial forcing. An SFINCS model is thus not only upscalable to similar, but bigger, domains but also to coastal settings. Furthermore, SFINCS is a computationally efficient model, thus facilitating upscaling.

Upscaling the SFINCS model entails several key points to incorporate into the model, which we discuss in the following section. Finally, an alternative approach is also proposed.

Firstly, water levels downstream should be incorporated through wave spectra and sea level measurements. Currently, sea levels are monitored by the Kenya Marine and Fisheries Research Institute and are openly available Magori, Ndirangu, Kosieny, Ochengo, and Onsare (2015), allowing for validation using historical records of water levels as forcing. To incorporate these in a forecasting model, sea level forecasts are also required.

Secondly, increasing the domain size may increase the influence of pluvial forcing, since more precipitation is included in the domain. Since discharge stems from upstream, the need to incorporate pluvial forcing should be researched to determine whether local pluvial forcing is still negligible compared to fluvial forcing. Obtaining precipitation data has proven difficult during the course of this project, but future endeavours may see the KMD providing meteorological forecasts, resulting in the ability to incorporate local precipitation.

Finally, upscaling to a larger domain adds more inflow points to the model. Figure 7.1 is an example of what this would entail, with multiple inflow points located along the Tana. Identifying the necessary inflow points is key when upscaling. This should be done in collaboration with the hydrological model, which should supply discharges at these points. Dividing the catchment into the desired amount of sub-catchments and accompanying sub-catchments with respective gauges to calibrate this model is detrimental to upscaling since a large and complex model should be equipped with the possibility to calibrate smaller sections of the total catchment area.

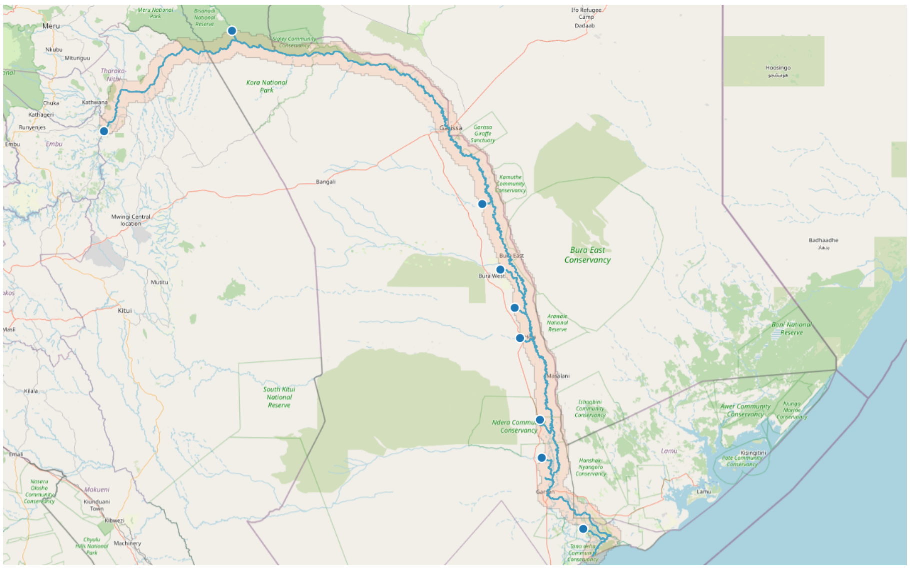


Figure 7.1: An illustration of a model domain for upscaling to the entire Tana basin, potentially incorporating water level forcing at the outflow point into the sea. In the Figure, blue markers represent inflow points where discharge time series should be provided. The number and locations of these inflow points may vary based on model parameters and can be adjusted manually.

Obviously, maintaining computational efficiency is an important consideration. The model shown in Figure 7.1 was run for a total of 5 months at a resolution of 1000 meters, taking approximately 90 seconds. This resolution is too coarse to accurately inform decision-makers, so research is necessary into using smaller grid sizes. SFINCS supports quadtree grids, providing another avenue to improve computational efficiency.

Another possibility to upscale without severely impeding computational efficiency is through fragmented upscaling. Empirically, the velocity at which flood waves propagate is well known, and flood arrival times are generally well described by Government of Kenya (2013). It is therefore possible to only create SFINCS models for the areas of interest, i.e., the identified flood-prone areas. The times at which the discharge forcing is applied are then known through the empirical arrival times. However, the potentially complex interplay between different inflow points may complicate this. Similarly as discussed for local precipitation, the influence of upstream discharge compared to the secondary inflow points should be researched, and multiple inflow points should then potentially be aggregated to one inflow point.

7.6. Stakeholder Engagement

In a cooperative game of establishing a FEWS in Kenya, the KMD and WRA can be identified as key players. However, their efforts to collaborate and share data, essential for the effective functioning of a comprehensive FEWS, are interpreted to have been hindered by institutional challenges. These challenges include weak governance structures, coordination issues, and a lack of funding. Despite the existence of a Memorandum of Understanding (MoU) outlining terms of collaboration, the cooperation between KMD and WRA seems limited.

Amidst these challenges, a potential third player should be recognized: the IGAD Climate Prediction & Applications Centre (ICPAC), an organization actively involved in training government institutions, including KMD and WRA. In interviews, ICPAC has observed that while both organizations are making efforts, they operate as isolated entities, functioning as "islands." Although ICPAC has not yet formally assumed the role of a third player in this cooperative game, their involvement could offer significant opportunities for facilitating collaboration and addressing institutional challenges.

ICPAC's potential role as a mediator or facilitator could help bridge the gap between KMD and WRA, fostering cooperation and shared decision-making. By leveraging their expertise and experience in training government institutions, ICPAC could offer valuable insights and resources to support the establishment of robust FEWSs in Kenya. Moreover, their involvement could help align the interests and objectives of all stakeholders involved, including international NGOs and other agencies.

While ICPAC emerges as the most logical candidate due to its international stature and expertise, other stakeholders such as KRCS and various NGOs could also fulfil this role. The KRCS holds significant leverage in such a cooperative game, given its established network and comprehensive knowledge of the local area. With a strong presence in disaster management and response, KRCS possesses the capacity to facilitate coordination among stakeholders and contribute valuable insights into the specific challenges faced in Kenya and the Tana River. Furthermore, KRCS's potential to secure funding for such projects adds a crucial dimension to its role as a third player, providing essential resources to support the establishment and operation of a comprehensive FEWS.

Additionally, other NGOs present viable candidates for the role of a third player in the cooperative game. Organizations like BlueDeal, specializing in capacity-building initiatives, offer valuable expertise and resources to enhance the capabilities of government institutions such as KMD and WRA. By leveraging funding opportunities from other countries, facilitated through partnerships or grants, NGOs can play a pivotal role in strengthening institutional capacity and coordination. While ICPAC may have the advantage of being an international organization, the diverse capabilities and networks of NGOs make them valuable contributors to the collaborative efforts aimed at mitigating flood risks and enhancing disaster resilience in Kenya.

Ultimately, by recognizing the potential of a third player in this cooperative game (e.g. ICPAC, KRCS, Bluedeal), stakeholders can work towards overcoming institutional challenges, improving coordination, and achieving more effective collaboration in establishing a comprehensive FEWS in Kenya.

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A

Stakeholder Overview

A.1. List of stakeholders

This section briefly introduces the relevant stakeholders. Furthermore, the formal relations between them are listed.

In this section, an initial list of stakeholders is presented.

Government of Kenya (GoK)

The Government of Kenya holds the mandate for considering and managing disaster mitigation at the national level. One of its primary responsibilities is to undertake comprehensive disaster mitigation efforts across the country, such as the implementation of FEWS. This generally entails coordinating and overseeing mitigation endeavours through various channels (i.e. WRA, KMD, etc.) and utilizing a network of administrative officials including County Commissioners, District Commissioners (DCCs), Chiefs, Assistant Chiefs, and Village Elders County Government of Tana River (2021). These officials serve as key partners for the GoK in the implementation of mitigation strategies and initiatives at the grassroots level. By leveraging this multi-tiered approach, the government strives to strengthen the resilience of communities and enhance their capacity to cope with and mitigate the impacts of disasters.

Water Resource Authority (WRA)

The Water Resources Authority (WRA) in Kenya is responsible for managing water resources and addressing flood-related issues. This includes monitoring river flows, observing flood events, and mapping areas at risk of flooding. To support these efforts, the WRA has established the National and Regional Flood Mapping and Impact Assessment Centres (FMIAC). These centres focus on collecting data and conducting assessments to better understand and manage flood risks both nationally and regionally. The WRA plays a crucial role in water resource management and flood mitigation in Kenya (Kiptum et al., 2023).

Kenya Meteorological Department (KMD)

The Kenya Meteorological Department (KMD) is tasked with flood forecasting duties, which involve issuing warnings for extreme weather events. Flood advisories and alerts are then distributed to disaster response agencies, including both national and county governments, as well as humanitarian organizations. Recently, the Water Resources Authority (WRA) and the Kenya Meteorological Department (KMD) have entered into a 5-year Memorandum of Understanding (MoU) to ensure the seamless integration of their respective activities in managing flood-related risks and responses (Kiptum et al., 2023).

County Governments (Tana River & Garissa)

County governments have been tasked with developing policies and structures to enhance disaster preparedness, mitigation, and response. As disaster management is a joint responsibility between the national and county governments, there has been a shift towards addressing these issues at the local level. However, much of the focus in Tana River and Garissa counties has been on response rather than proactive measures such as preparedness and mitigation. Efforts have been made to improve early warning systems for floods, emphasizing the production, dissemination, and feedback of early warning information. Additionally, initiatives have been undertaken to establish flood early warning systems and enhance community capacity in managing disaster risks County Government of Tana River (2021).

Tana and Athi Rivers Development Authority (TARDA)
Tana and Athi Rivers Development Authority's (TARDA) duties and obligations involve coordinating and planning various development projects across the Tana and Athi River Basins, with a specific emphasis on implementing initiatives for the sustainable use and conservation of water and soil resources in the region. Consequently, TARDA's objectives encompass hydro-power generation, environmental conservation, natural resource planning and management, as well as fostering economic development in rural areas to address regional disparities. TARDA oversees the dams and reservoirs in the Tana River (TARDA, n.d.).

Kenya Red Cross Society (KRCS)
The Kenya Red Cross Society (KRCS) already has put in efforts to improve early warning systems in Kenya. Also in the Lower Tana (and Athi basins), with an emphasis on Garissa, Kilifi, and Tana River counties. The KRCS, in collaboration with the British Red Cross (BRC), has been carrying out the Strengthening Early Response Capacity (StERC) project with funding from the European Civil Protection and Humanitarian Aid Operations (ECHO) (Kiptum et al., 2023). This project ultimately aimed for effective disaster preparedness and ensuring effective response to sudden onset emergencies by the KRCS. In their assessment, they also provide recommendations for the other stakeholders involved in FEWS.

KenGen
KenGen operates the hydro dams in the Tana River. In total, they manage five hydropower dams and monitor the dam water levels. They are responsible for communicating the water levels with other stakeholders and issuing warnings before releasing large volumes of water. These warnings are issued to the public through TARDA, who are the legal owners of the hydropower dams(County Government of Tana River, 2021).

Organized Community Groups
Organized Community Groups, also named Water Resource Users Associations (WRUAs), are community-based organizations that work together to manage water resources at the sub-catchment level and to settle disputes related to resource use County Government of Tana River (2021). They also play a big role in the dissemination of flood warnings to local communities.

Affected communities
The are many local communities who have lived on and around the floodplains of the Tana River. The biggest urban areas are Garissa, Hola and Garsen. The main ethnic groups present in this area are Pokomo (farmers and fisherfolk), Orma, Wardey and Somali(nomadic pastoralists), Wata (hunter-gatherers), Giriama (farmers and fisherfolk), Luo (fisherfolk), Luhya (farmers and fisherfolk), and Kikuyu (farmers) (Okoko, 2022). On one hand, floods are the lifeblood of many communities, providing support for all of the county's economic endeavours. On the other hand, many local communities each year are displaced because of these (flash)floods.

BlueDeal (BD)
The BlueDeal is a stakeholder which is formed out of a partnership between the Dutch Water Authorities and the WRA. Originally, the objective of this collaboration was the enhancement of quantitative water management in Kenya's upstream Tana River regions. BD has since focussed on creating strategies for the allocation and management of water in the Upper Tana sub-catchments, specifically Upper and Mid Thika (Alphen, 2021). Due to these ongoing projects, BD has acquired a strong position in the network. Furthermore, BD has been involved in earlier efforts to introduce FEWS along the Tana River.

TAHMO
TAHMO (Trans-African Hydro-Meteorological Observatory) is an organisation that aims to develop a network of hydro-meteorological measurement stations in sub-Saharan Africa (van de Giesen, Hut, & Selker, 2014b).

ICPAC
ICPAC (IGAD Climate Prediction and Applications Centre) is a climate centre that offers its services to eleven East African countries. These services focus on building resilience in areas prone to climate change and extreme weather. Accredited by the World Meteorological Organization they are also committed to researching FEWS in the Greater Horn Of Africa (Alfieri et al., 2024).

A.2. Formal Relations

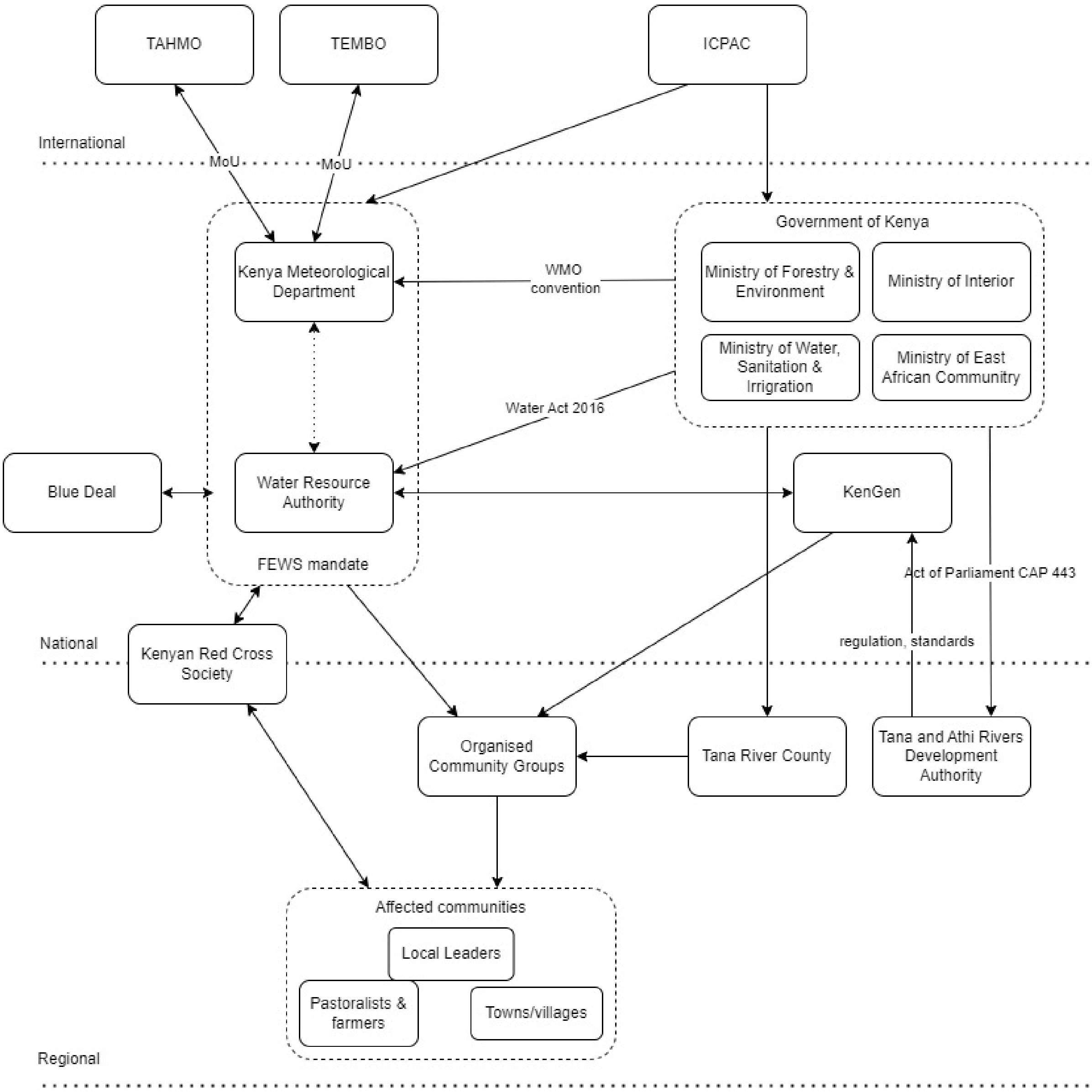

Figure A.1: Formal chart.

A.3. Stakeholder resources

Table A.1: Stakeholders and Their Resources/Roles

Stakeholder	**Resources/Role**
Government of Kenya (GoK)	Authority regarding regulatory frameworks. Legitimacy Subsidies and funding.
Water Resource Authority (WRA)	Authority regarding regulation of water resources. Information on water levels and discharge.
Kenya Meteorological Department (KMD)	Meteorological data. Weather forecasts
County Governments (Tana River + Garissa)	Local Authority Budgeting and allocation of funds. Relations with local communities. Knowledge of the area.
IGAD Climate Prediction Applications Centre (ICPAC)	Knowledge of climate forecasting Position in network Capacity Building
NGO's (TAHMO + TEMBO + BlueDeal + other)	Knowledge and information. High temporal resolution data from weather stations across sub-Saharan Africa (TAHMO) Knowledge of the area Capacity building
Kenyan Red Cross Society (KRCS)	Knowledge of the area. Position in the network Funding for humanitarian aid
Dam operators (KenGen + TARDA)	Information on water levels and discharge surrounding Seven Forks Dams.
Affected communities	Knowledge of the area.

Kenya Meteorological Department

P.O. Box 30259-00100, Ngong Road, Dagoretti-Corner, Nairobi.
Tel: +2542038567880-5, +254724255153-4 Email: director@meteo.go.ke

Heavy rainfall Advisory

Message Type:	Heavy Rainfall
Message Update No.:	Four
Advisory No.:	04/2024
Date of Issue:	1^{st} April, 2024 4pm
Validity:	From 2^{nd} April, 2024 2pm to 4^{th} April, 2024 6pm
Urgency:	Expected
Severity:	Moderate
Certainty:	Probability of occurrence (33% to 66% Chance)

Message Description:

Heavy rainfall of more than 30mm in 24hrs is expected over several parts of the Lake Victoria Basin, the Rift Valley, Highlands West and East of the Rift Valley including Nairobi area on Tuesday 2^{nd} April, 2024. The heavy rainfall is likely to intensify to more than 40mm in 24hrs and spread to Southeast Lowlands, coast and northern sector on Wednesday 3^{rd} April, 2024. It is likely to reduce in intensity on Thursday 4^{th} April, 2024. The heavy rainfall is likely to be accompanied by gusty winds.

Area(s) of Concern:

Counties: Nyamira, Nandi, Kericho, Bomet, Kakamega, Vihiga, Bungoma, Siaya, Kisumu, Homabay, Busia, Migori, Narok, Baringo, Nakuru, Trans-Nzoia, Uasin-Gishu, Elgeyo-Marakwet, West-Pokot, Turkana, Samburu, Nyandarua, Laikipia, Nyeri, Kirinyaga, Murang'a, Kiambu, Meru, Embu, Tharaka-Nithi ,Nairobi, Machakos, Kitui, Makueni, Kajiado, Taita-Taveta, Mombasa, Tana-River, Kilifi, Lamu,Kwale, Marsabit, Mandera, Wajir, Garissa and Isiolo.

Instructions:

Residents in all the mentioned areas are advised to be on the lookout for potential floods and flash floods. Residents are advised to avoid driving through, or walking in moving water or open fields and not to shelter under trees and near grilled windows to minimize exposure to lightning strikes. Gusty winds may blow off roofs, uproot trees and cause structural damages. Updates on the ensuing weather will be provided promptly.

Message Addressed to:

The Presidency, Cabinet Secretary: Ministry of Environment Climate Change and Forestry; Principal Secretary: State Department for Environment and Climate Change, National Intelligence Service, Kenya Red Cross, Kenya Maritime Authority, Kenya Ports Authority, Kenya Airport Authority, National Disaster Operations Centre, National Disaster Management Unit, Media, Various Government Ministries, Council of Governors, County Directors of Meteorological Services (CDMs).

Originator:

Dr. David Gikungu

Director, Kenya Meteorological Department

Figure A.2: Heavy Rainfall Advisory from KMD

Tana and Athi Rivers Development Authority (TARDA)

PRESS RELEASE

FOR IMMEDIATE RELEASE

April 9th, 2024: Flood Alert In Counties In The Upper And Lower Tana Basins

The Tana and Athi Rivers Development Authority (TARDA) is issuing an urgent flooding alert for residents of the Upper and Lower Tana River Basins. According to the latest forecast from the Kenya Meteorological Department dated April 5, 2024, heavy rainfall persists, heightening the risk of flooding across the region. Of particular concern is the surge in rainfall within the Nyambene Hills catchment area, spanning Meru and Tharaka Nithi counties, resulting in a significant increase in the flow of the Tana River. As a consequence, this has caused a substantial rise in the Tana River flow overtopping the banks at Garissa and inundating the adjacent areas towards the Tana Delta.

The rapid surge in water levels along the Tana River at Garissa have surpassed the 4-meter flood alarm threshold by over 1 meter within the last 24 hours:

- **08/04/2024: 4.91m at 06:00hrs, 5.11m at 09:00hrs, and 5.14m at 18:00hrs**
- **09/04/2024: 4.85m at 00:00hrs and 4.92m at 03:00hrs**

Additionally, Mount Kenya and Aberdare catchments have witnessed substantial rainfall, leading to swift rises in the levels of Seven Forks dams. As of 09/04/2024 at 05:00hrs, Masinga and Kiambere dam levels were reported at 1.41m and 1.03m respectively below their full supply capacity. TARDA is actively monitoring the dam levels along the Tana River, ensuring the safety and well-being of all communities in the area.

TABLE 2: STATIONS WITH SIGNIFICANT SEVEN-DAY RAINFALL TOTALS

STATION	COUNTY	SEVEN-DAY TOTAL RAINFALL (mm)
MERU METEOROLOGICAL STATION	MERU	262.0
MUKAA RAINFALL STATION	MAKUENI	249.6
KIANAMU RAINFALL STATION	EMBU	221.1
IKISAYA PRIMARY SCHOOL RAINFALL STATION	KITUI	214.8
NJUKI-INI FOREST RAINFALL STATION	KIRINYAGA	206.3
MIAD KANDONGU RAINFALL STATION	KIRINYAGA	195.1
MATERI GIRLS HIGH SCHOOL RAINFALL STATION	THARAKA NITHI	185.5
GITII-NGURA RAINFALL STATION	EMBU	175.5
KIIMA KIU RAINFALL STATION	MAKUENI	172.0
NYERI METEOROLOGICAL STATION	NYERI	169.3

Rainfall from The Last Seven Days To Date

In light of these developments therefore, we urge residents to remain vigilant and prepared. It is crucial for communities residing within the Lower and Upper Tana Basins to heed the warnings that have been issued by the relevant authorities and to take the necessary precautions to safeguard their families and property.

TARDA remains committed to working in collaboration with various stakeholders across the board from various sectors to assess the flood situation and provide essential advice on relocating to safer areas in collaboration with the relevant agencies.

For any further inquiries, please contact us on **020 3341781/82/90**, or email us on info@tarda.go.ke.

MANAGING DIRECTOR

Figure A.3: Press release for flood alert from TARDA

B

Flood Maps: Opera

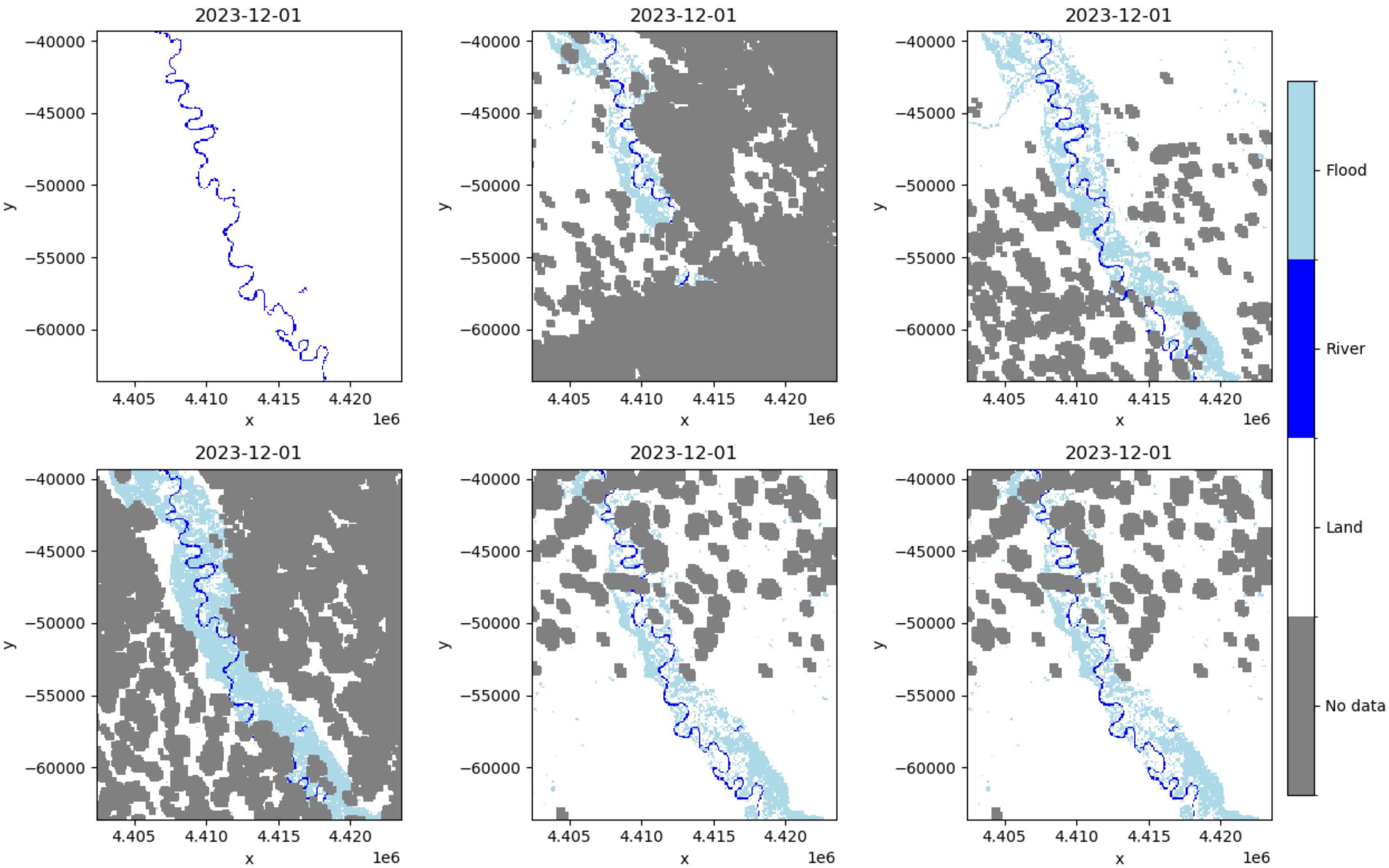

Figure B.1: OPERA flood maps generated through satellite imagery of Sential-2A, Sentinel 2B, and Landsat-8. The used coordinate reference system is EPSG:3857.

C
Overview SFINCS Models

Model name	Digital elevation model	River centerline method	Constant river depth	Initial soil moisture content
garissa_depth2m_fabdem_grid100	FABDEM	Inferred from DEM	2 meter	Wet
garissa_depth2m_fabdem_grid100_avg_buffer5km	FABDEM	Inferred from DEM	2 meter	Average
garissa_depth2m_fabdem_grid100_avg_lin	FABDEM	Centerlines by Lin et al. (2019)	2 meter	Average
garissa_depth2m_srtm30_grid100	SRTM30	Inferred from DEM	2 meter	Wet
garissa_depth3m_fabdem_grid100	FABDEM	Inferred from DEM	3 meter	Wet
garissa_depth4m_fabdem_grid100_avg	FABDEM	Inferred from DEM	4 meter	Average
garissa_depth4m_srtm30_grid100_avg	SRTM30	Inferred from DEM	4 meter	Average

Table C.1: Overview of models with varied parameters.

D

Flood Maps: SFINCS

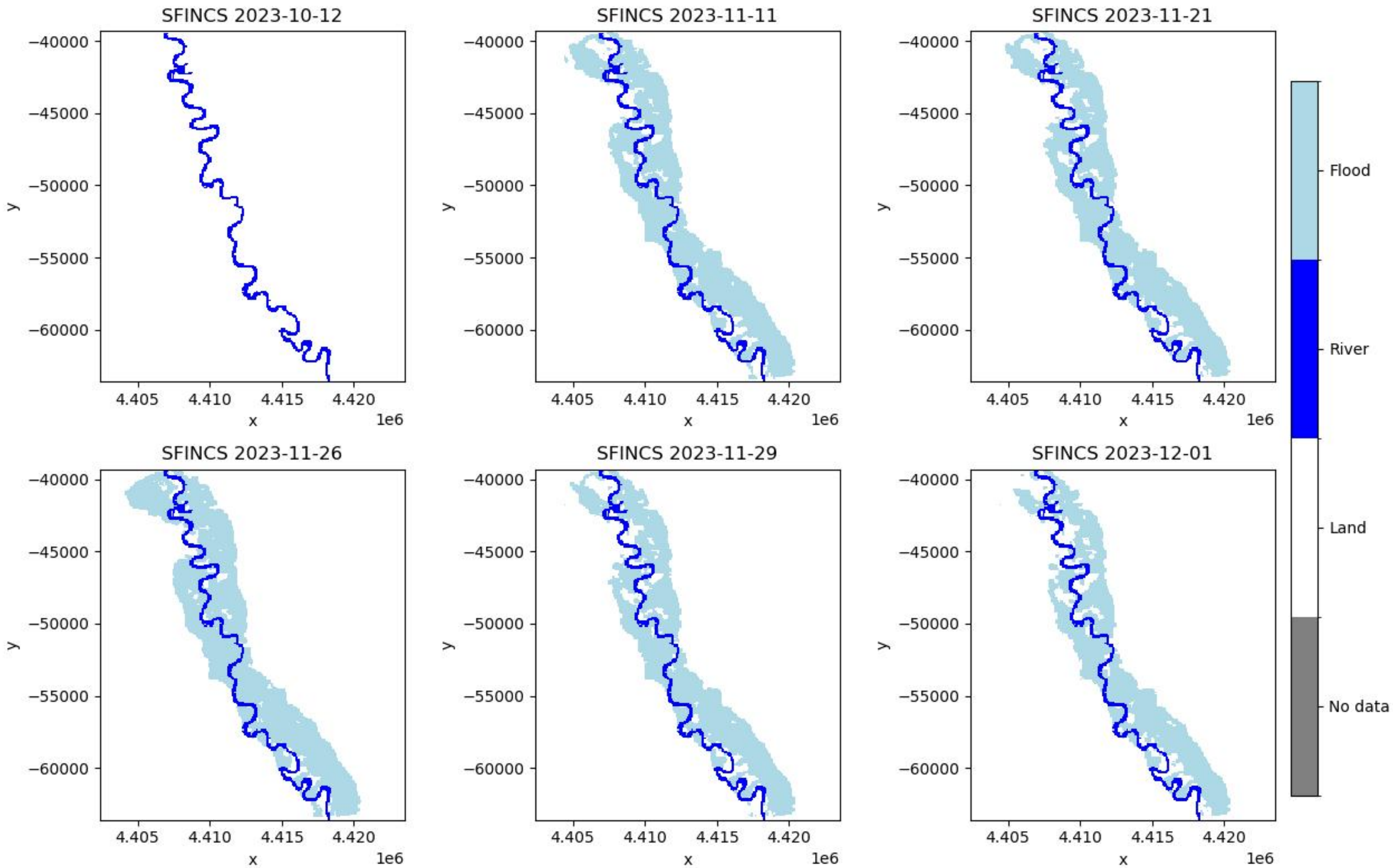

Figure D.1: SFINCS generated inundation maps for model: garissa_depth2m_fabdem_grid100. The used coordinate reference system is EPSG:3857.

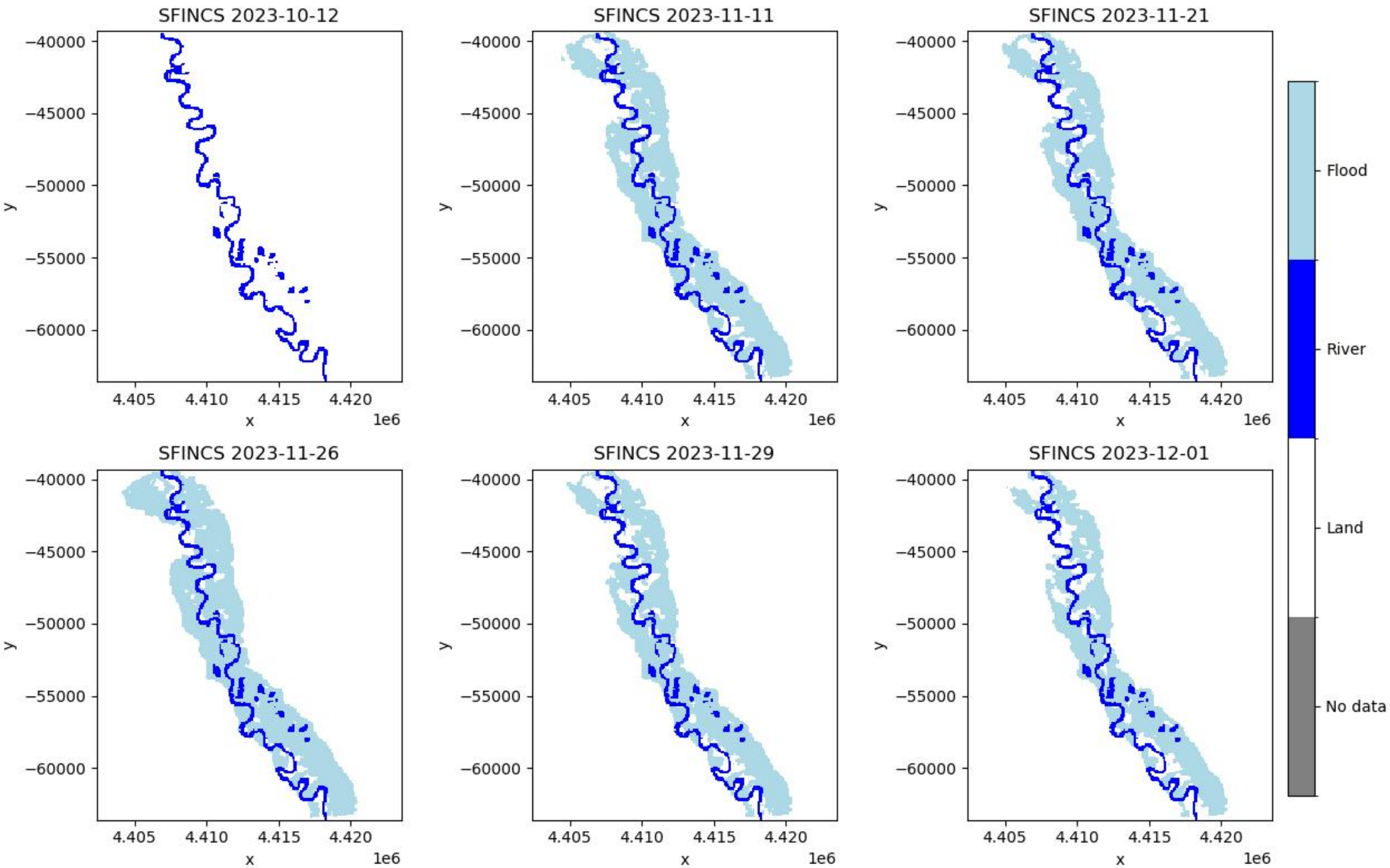

Figure D.2: SFINCS generated inundation maps for model: garissa_depth2m_fabdem_grid100_avg_buffer5km. The used coordinate reference system is EPSG:3857.

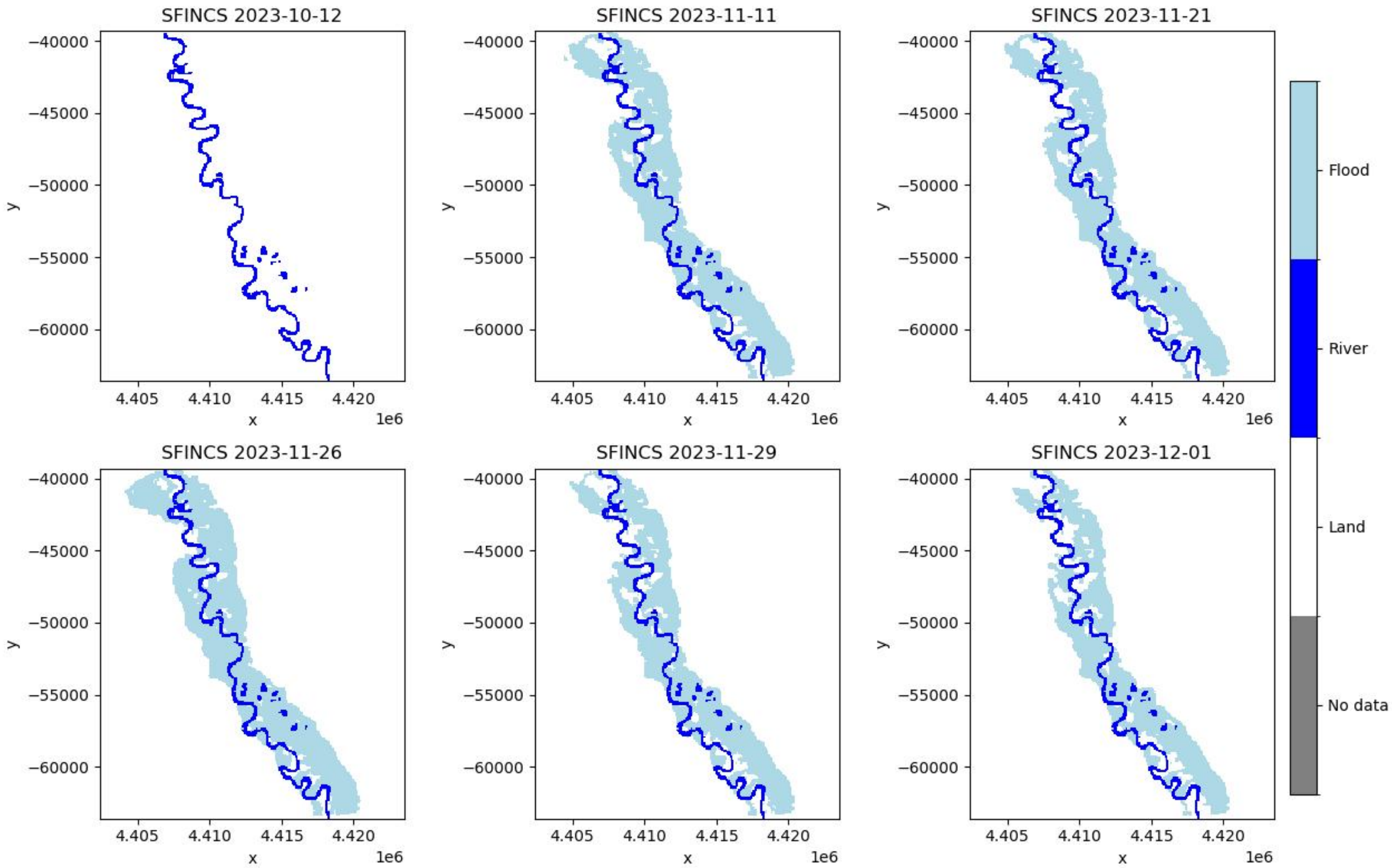

Figure D.3: SFINCS generated inundation maps for model: garissa_depth2m_fabdem_grid100_avg_lin. The used coordinate reference system is EPSG:3857.

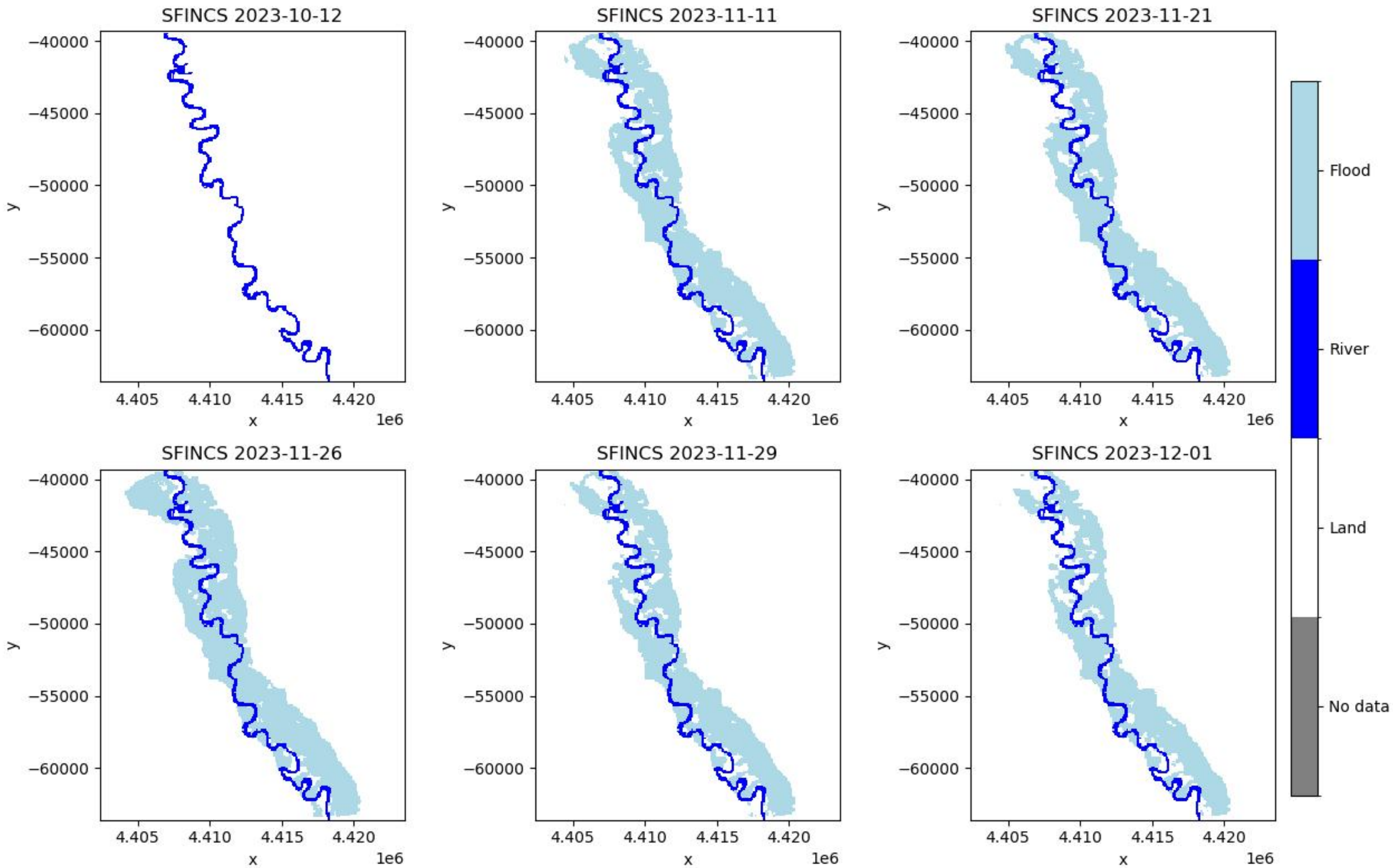

Figure D.4: SFINCS generated inundation maps for model: garissa_depth2m_srtm30_grid100. The used coordinate reference system is EPSG:3857.

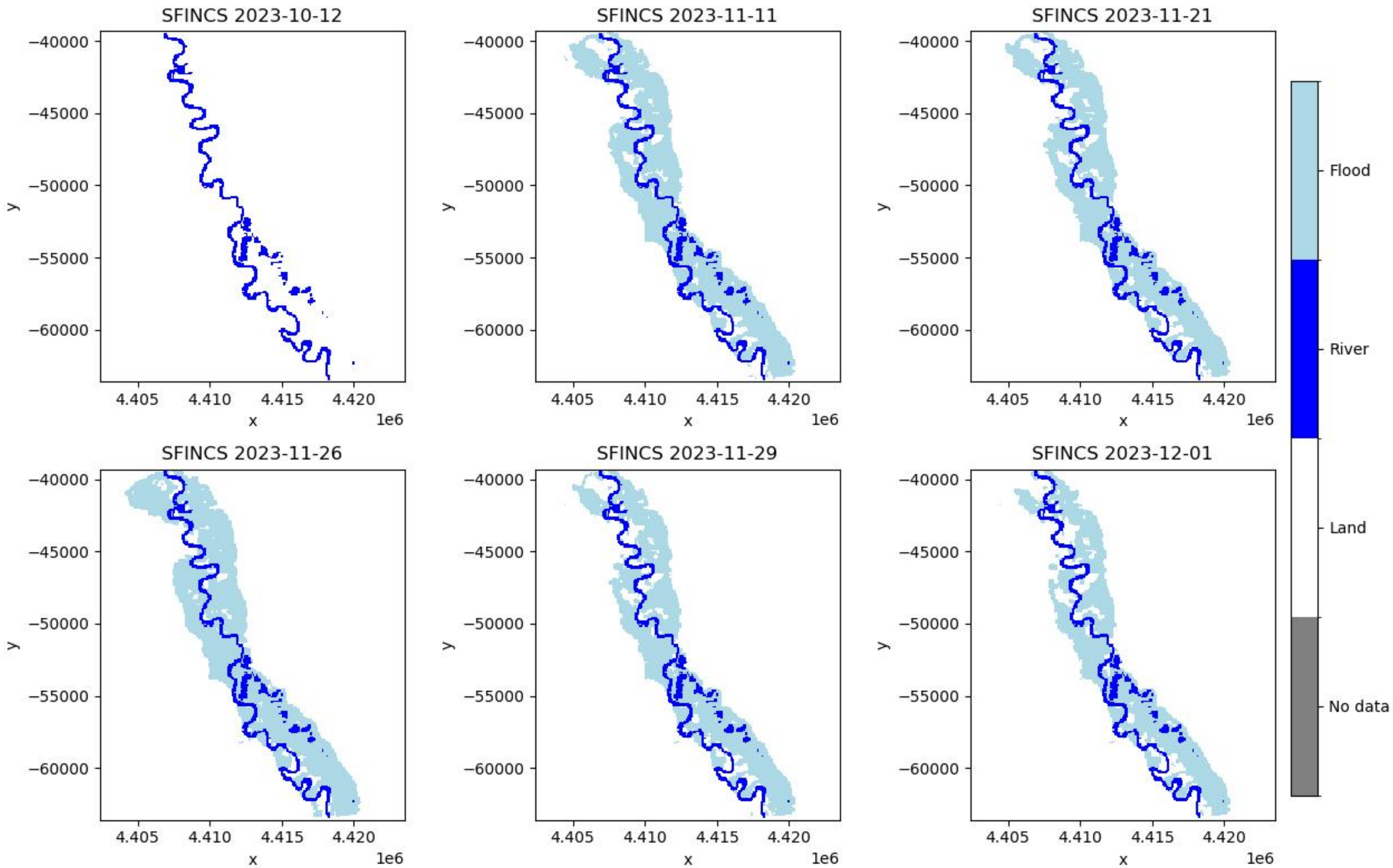

Figure D.5: SFINCS generated inundation maps for model: garissa_depth3m_fabdem_grid100. The used coordinate reference system is EPSG:3857.

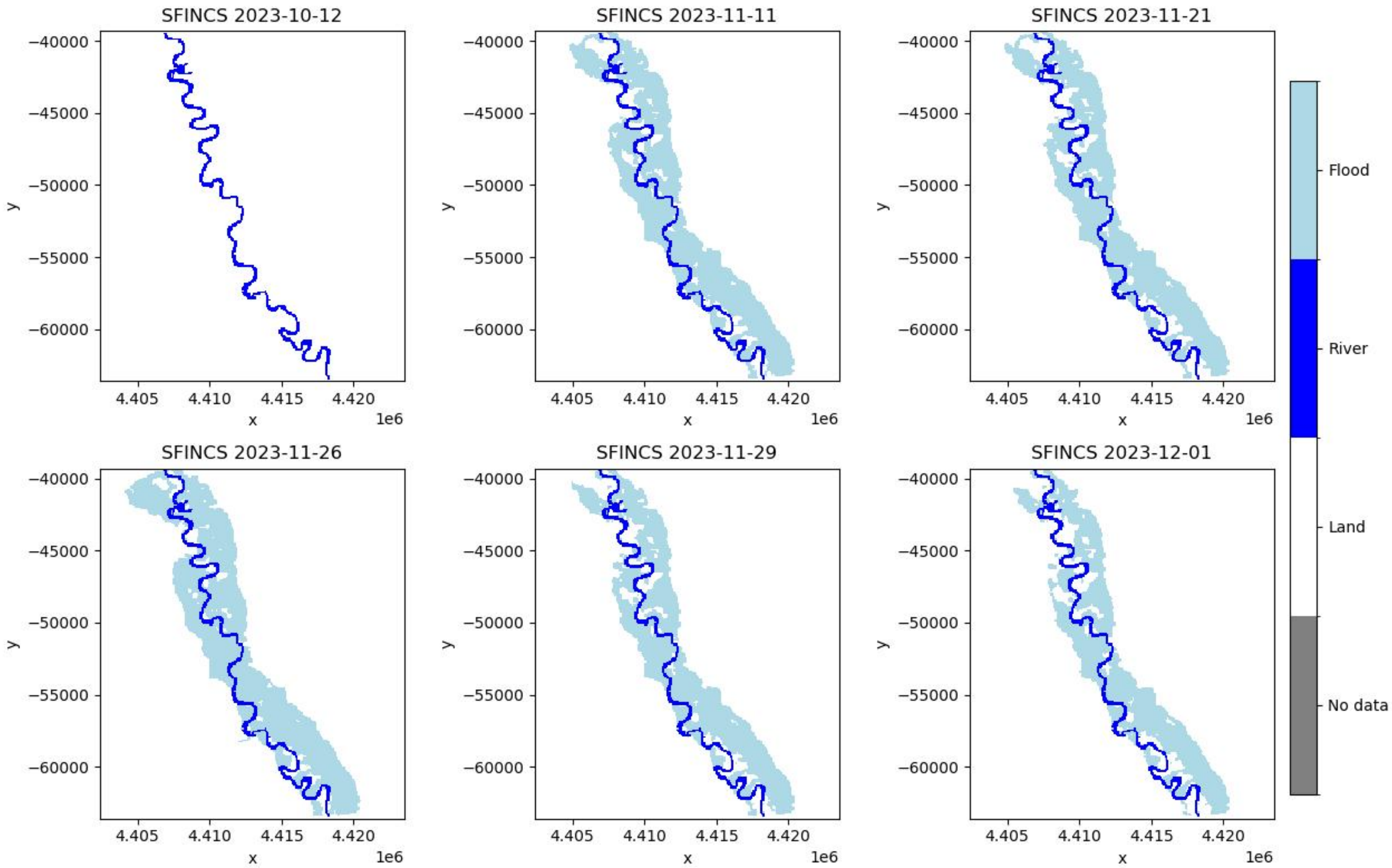

Figure D.6: SFINCS generated inundation maps for model: garissa_depth4m_fabdem_grid100_avg. The used coordinate reference system is EPSG:3857.

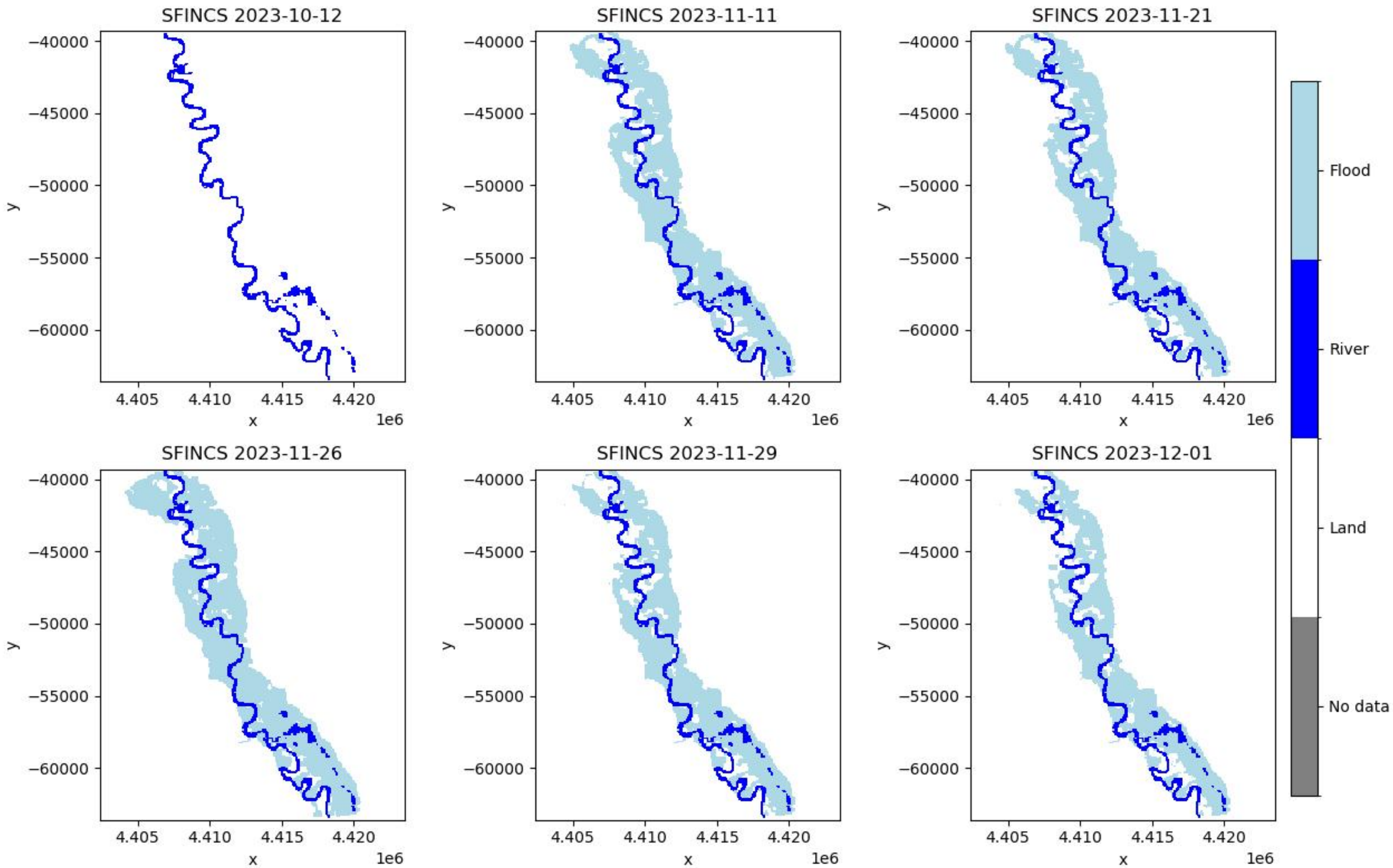

Figure D.7: SFINCS generated inundation maps for model: garissa_depth4m_srtm30_grid100_avg. The used coordinate reference system is EPSG:3857.