UNIVERSITE JOSEPH KI-ZERBO

ECOLE DOCTORALE INFORMATIQUE ET CHANGEMENT CLIMATIQUE (EDICC)

BURKINA FASO

La Patrie ou la Mort, nous Vaincrons

Order N° : ....

MASTER RESEARCH PROGRAM

SPECIALITY: INFORMATICS FOR CLIMATE CHANGE (ICC)

MASTER THESIS

Subject:

Flood Risk Analysis for Anticipatory Action in Guinea

Presented on July 09, 2025, by:

BARRY Thierno Hamidou Mariama

Examination jury

President: OUIMINGA Salif, surname, Professeur, Université Joseph KI-ZERBO

Members :

- **ZONGO Sidiki**, Docteur, Univesité Joseph KI-ZERBO (external examiner)
- **DAHO Tizane**, Professeur, Université Joseph KI-ZERBO (supervisor);
- **Dr. GUIGMA Kiswendsida**, West Africa lead, Red Cross Climate Centre (co-supervisor)

Academic year 2024 - 2025

DEDICATION

With affection:

- To my dear parents, whose unwavering love and values are with me always. May Allah grant them paradise. AMIINE.
- To my wife, for her patience, love, and unwavering support.
- My children, my greatest pride, who push me to be better every day.

To my entire family, my loved ones, and friends, for their constant presence and support.

ACKNOWLEDGEMENTS

At the end of these two academic years, I first give thanks to Allah Subḥanahu wa Ta ala for His countless blessings in my life.

I would like to express my deep gratitude and sincere thanks to the following individuals and organizations for their unwavering support throughout the completion of this work:

The administrative staff of the Doctoral School of Computer Science for Climate Change (ED-ICC).

Prof. Amadé OUEDRAOGO, Director of ED-ICC, for his valuable advice.

Dr. Ousmane Coulibaly, Deputy Director of ED-ICC, for his availability and constant support since the beginning of the program.

Dr. Benewindé Jean-Bosco Zoungrana, Scientific Coordinator of ED-ICC.

All other members of the ED-ICC administrative team.

Prof. DAHO Tizane, my principal supervisor, for his rigorous guidance and support throughout this thesis.

Dr. Kiswendsida GUIGMA, my co-supervisor, who also proposed the theme of this thesis, for his dedication despite his many responsibilities, his critical feedback, his encouragement, and above all, his rigorous approach to work.

The German Federal Ministry of Education and Research (BMBF) for funding this program.

The West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL) for providing an exceptional framework for capacity building.

To my beloved wife, I owe my deepest gratitude for your love, support, encouragement, and above all, the time you dedicated to me during my studies.

To my parents and my brothers and sisters for their support and encouragement.

A heartfelt thank you to all my colleagues and friends with whom I shared a rich and rewarding experience during these two years of the program.

ABSTRACT

Like most West African countries, Guinea experiences recurrent flooding that severely affects its infrastructure, economy, and the lives of the population. These phenomena are exacerbated by climate change, and the country's vulnerability is particularly evident in poorly planned urban areas, where people often settle in high-risk flood zones. The main objective is to study flood anticipatory actions in Guinea through data-driven risk assessments. To better understand these risks, several types of data were combined: We used rainfall data from CHIRPS 1981 to 2024, river flow data 1992 to 2024, information on soil permeability, and risk exposure, vulnerability, and ability to adapt. Four main indicators are used to analyze flood risk: hazard, exposure, vulnerability, and Coping capacity. Hazard was measured using average annual precipitation, the 95th percentile of rainfall, and soil permeability coefficients, allowing for the evaluation of the intensity, frequency of extreme rainfall events and soil characteristics. Exposure was calculated based on the population, agricultural land, and livestock in risk-prone areas. Vulnerability was assessed through the Multidimensional Poverty Index (MPI), the presence of thatched or earthen roofs, and the number of vulnerable individuals (children under 4, the elderly, and people with disabilities). Lack of coping capacity was measured through access to essential services such as emergency services, health infrastructure, and communication networks. All data were processed and analyzed using Python and the R package.

The results showed that pluvial flood hazards (i.e., floods resulting from heavy rainfall) are concentrated in coastal areas and the southern part of the country, while fluvial flood risks (linked to rivers exceeding their capacity) occur throughout the country. The selection of vulnerability indicators also has a significant impact on the results. The analysis reveals that Kindia is the most affected region while presenting the highest flood risk.

Key words: Flooding; Risk; Analysis; Anticipatory Measures; Guinea.

RESUME

La Guinée, comme la plupart des pays d'Afrique de l'Ouest, subit de façon récurrente des inondations, affectant gravement ses infrastructures, son économie et la vie des populations. Ces phénomènes sont renforcés par le changement climatique, et la vulnérabilité du pays est particulièrement marquée dans les zones urbaines mal planifiées, où la population s’installe souvent dans des zones à haut risque d’inondation. L’objectif principal est d’étudier les actions anticipatives face aux inondations en Guinée à travers des évaluations des risques basées sur les données. Pour mieux appréhender ces risques, différentes sources de données ont été croisées. Cela inclut les données pluviométriques fournies par CHIRPS pour la période de 1981 à 2024, les mesures des débits fluviaux de 1992 à 2024, des renseignements sur la capacité d’infiltration des sols, ainsi que des indicateurs décrivant l’exposition, la vulnérabilité et les capacités d’adaptation. L’analyse des risques d’inondation repose sur plusieurs indicateurs essentiels : l’aléa, l’exposition, la vulnérabilité et la capacité d’adaptation. L’aléa a été mesuré à l’aide de la précipitation annuelle moyenne, du 95e percentile des précipitations et des coefficients de perméabilité des sols, permettant ainsi d’évaluer l’intensité, fréquence des épisodes de pluies extrêmes et caractéristiques du sol. L’exposition a été calculée en fonction de la population, des terres agricoles et du bétail présents dans les zones à risque. La vulnérabilité a été évaluée par l’indice de pauvreté multidimensionnelle (MPI), la présence de toits en chaume ou en terre, ainsi que le nombre de personnes vulnérables (enfants de moins de 4 ans, personnes âgées, handicapées). La capacité d’adaptation a été mesurée à travers l’accès aux services essentiels tels que les brigades de secours, les infrastructures sanitaires et les moyens de communication. Toutes les données ont été traitées et analysées à l’aide de Python et R package.

Les résultats ont montré que les aléas d'inondations pluviales (résultant de fortes précipitations) sont concentrés dans les zones côtières et le sud du pays, tandis que les risques d’inondation fluviale (liés au débordement des rivières) touchent l’ensemble du territoire. De plus, les choix d’indicateurs de vulnérabilité ont un impact significatif sur les résultats obtenus. Ainsi, l’analyse indique que la région de Kindia est la seule à être exposée aux deux types de risques, ce qui en fait la zone la plus vulnérable.

Key Word : Inondation ; Risque ; Analyse ; Mesures anticipatives ; Guinée.

LIST OF TABLES

Table 1 : Materials used 19
Table 2:Exposure sub-indicators...24
Table 3: Vulnerability sub-indicators...25
Table 4: Sub-indicators for Lack of Adaptive Capacity..26

List of figures

Figure 1:Four major component of Risk 8
Figure 2: Map of Guinea 14
Figure 3: Watercourse map of Guinea 16
Figure 4: Topography of Guinea 17
Figure 5: Average annual rainfall in Guin 29
Figure 6: climatology distribution from 1981 to 2024 30
Figure 7:95th annual percentile of precipitation 31
Figure 8:95th monthly percentile of precipitation 31
Figure 9: Soil permeability by region 31
Figure 10: Rainfall flood hazard 33
Figure 11: Soil permeability by region 33
Figure 12: 195th Percentile by region 33
Figure 13: annual cumulative by region 33
Figure 14: Average annual Flow rates by region 34
Figure 15: Return Time level duration 35
Figure 16:Return Time Level Based on GloFAS 36
Figure 17:Average Annual Flow by Region (m3/s) 36
Figure 18: River Flood Hazard 37
Figure 19: Population by Region 38
Figure 20: Animal Exposure normalize by region 39
Figure 21: Final Exposure 39
Figure 22: Standardized Agricultural Land Exposure 39
Figure 23: MPI by Region 40
Figure 24: Normalized Vulnerability of Housing 42
Figure 25: Normalized Vulnerability of People 42
Figure 26: Vulnerability by Region 42
Figure 27:Livelihood Vulnerability 42
Figure 28:Communications group 43
Figure 29: Normalized Disaster Management Sub-Indicators 44
Figure 30: normalized Infrastructure Sub-Indicators 44
Figure 31: Lack of Coping Capacity Map 45
Figure 32: Map of pluvial flood 46
Figure 33: Map of fluvial flood 47

Acronyms and Abbreviations

AHP	:	Analytical Hierarchy Process
AHPS	:	Hydrologic Prediction Service
AMHEWAS	:	African Multi-Hazard Early Warning and Early Action System
CDO	:	Climate Data Operators
CHIRPS	:	Climate Hazards Group InfraRed Precipitation with Station data
CNPC	:	National Flood Forecasting Center
DNH	:	National Directorate of Hydraulics
EFAS	:	European Flood Awareness System
FAO	:	Food and Agriculture Organization of the United Nations
FbF	:	Forecast-based financing
FEWS	:	Flood Early Warning Systems
FFWC	:	Flood Forecasting and Warning Centre
GDP	:	Gross Domestic Product
GIS	:	Geographic Information Systems
GloFAS	:	Global Flood Awareness System
IFRC		International Federation of Red Cross and Red Crescent Societies
MEDD	:	Methodical Exploration of Data and Decisions
MPI	:	Multi-dimensional Poverty Index
MSPQ	:	Ministry of Public Security of Quebec
NetCDF	:	Network Common Data Format
NWS	:	National Weather Service
OCHA	:	United Nations Office for the Coordination of Humanitarian Affairs
Red Cross	:	International Committee of the Red Cross
SAR	:	Synthetic Aperture Radar
UN	:	United Nations
UNDP	:	United Nations Development Program
UNHCR	:	United Nations High Commissioner for Refugees
UNISDR	:	United Nations International Strategy for Disaster Reduction
UVED	:	Virtual University for Environment and Sustainable Development
WMO	:	World Meteorological Organization

INTRODUCTION

The danger and high cost of flood risks necessitate simultaneous improvement in scientists' ability to assess these risks in Africa and globally (Mostafiz et al., 2022). A flood occurs when runoff water inundates land, potentially causing damage to crops, infrastructure and even loss of life (Hudson et al., 2014). Different climatic and non-climatic factors contribute to flooding, leading to river floods, flash floods, urban floods, sewer floods, glacial lake floods, and coastal floods (Kolawole O.M. et al., 2011). Historically, floods are among the oldest disasters on Earth, causing significant damage to property and people, including arable land, residential areas, and cities, which can impact a country's economy. These floods are triggered by processes such as heavy rainfall, poor drainage, discharges, and groundwater saturation. According to the World Meteorological Organization (WMO, 2006), floods account for 37% of natural disasters worldwide. Extreme weather disasters, including floods, result in significant economic losses, particularly in poor countries, as climate change progresses, extreme heat was responsible for 42% of recorded deaths, closely followed by floods, which accounted for 41% of fatalities (CRED, 2021). Globally, floods remain the most frequent type of disaster, with 201 events reported worldwide. These disasters affected 45.5 million people and caused major economic losses of about $92.7 billion (CRED, 2021). Many countries already face the effects of climate change due to irregular and unpredictable rainfall and an increased incidence of storms (WFP et al., 2009).

Flooding phenomena are recurrent in West African and result from rapid population growth, poorly managed urbanization, poverty, natural ecosystem degradation, inadequate urban planning policies, and climate change (Gemenne et al., 2014). In 2009, floods impacted over 600,000 people, leading in 250 deaths, and 35,000 homes lost, leaving 126,000 people in challenging conditions. They also exacerbated issues for vulnerable families already facing poverty, malnutrition, and violence (OCHA, 2009; Gaye, 2009). Future flooding risks will likely depend on climate changes (e.g., rainfall), land conditions, and exposure to losses. In this global context, West Africa, is characterized as the region most sensitive to floods (Vissoh et al., 2015). As many countries, West African Guinea has poor urbanization plan and widespread poverty obliging residents to settle in flooding-prone areas. This issue is made worse by the demand for land ownership and the need to access basic services. Consequently, many people settle in unsuitable, flood-exposed areas without considering the environmental impacts and associated risks (Tewa, 2020). This exposure, combined with increasingly intense rainfall, raises the risk and impact in the country, which can also be damaging. It is estimated that around 1.900 people were affected by floods in 2024 alone in the city of Siguiri (Renault, 2024).

Globally, managing disasters relies on Anticipatory Action (AA), which consists of preparing and responding to a forecasted hazard in advance to lessen its humanitarian impact before it strikes or before its worst effects occur. The response strategy relies on a joint risk assessment that anticipates the timing, location, and nature of the potential disaster (IFRC, 2020). AA aims to prevent disasters and provide rapid, cost-effective support while preserving dignity and promoting disaster risk reduction. It saves resources and protects development gains (IASC, 2024). AA has four main components: Risk assessment, trigger development, early action development and financial mechanisms. Any good AA program starts with a robust risk assessment, generally conducted at the national level to determine priority regions to focus on taking into account the hazard, exposure, vulnerability and coping capacity dimensions. There is an urgent need to strengthen flooding risks management in Guinea and AA could be a solution of choice. It should however, start with a risk assessment, encompassing various elements, including hazard, vulnerability, exposure, and risk assessment, as well as early warning systems, damage assessment, and risk mitigation planning. Successful risk management should include environmental, social, cultural, and economic factors and serve as a basis for planning flood prevention projects. Currently, warnings are limited to general information about rainfall, without sufficient details to protect people and property effectively. Flood forecasting is notoriously difficult. It depends on a complex mix of rainfall, soil moisture, and many other factors. Recent studies highlight advances in flood forecasting using weather data and image processing for hazard mapping (Syifa et al., 2019). Advance forecasts enable rapid evacuations, increased resilience, and better public awareness. They also reduce communication gaps, prevent infrastructure failures, and improve rescue coordination. These efforts support economic and social development (Watik et al., 2019).

Problem Statement

Guinea is endowed with a dense hydrographic system comprising 1,165 rivers that rise from the Fouta Djallon Highlands and the Guinean Ridge, spanning 23 river basins, including 14 that cross national borders (State & En, 2012). The country receives between 1,600 and 2,000 mm of rain each year, but in Conakry, it can go up to 4,349 mm, with daily amounts sometimes reaching 80 to 100 mm (Béavogui et al., 2011). This rainfall is vital for agriculture, water supply, and energy production as it influences the region's climate. However, in Guinea, communities living along these rivers regularly experience severe flooding during the rainy season. Furthermore, human developments in natural drainage areas, combined with flash floods, cause significant damage to livelihoods, infrastructure, and lives, particularly in cities like Conakry, Kankan, Kouroussa, Coyah, Kindia, Geckedou, etc. Flood issues in this region are often exacerbated by structural deficiencies, including the lack of proper drainage systems and non-compliance with urban planning regulations (Samoura et al., 2022). This situation, compounded by heavy rainfall and the recurrence and intensity of floods, represents a major challenge for the country's development (IFRC, 202). In this region, many large-scale floods have been recorded, such as the September 2020 floods that affected 26 of the 27 districts in the Kankan prefecture, causing significant damage to human lives and economic assets. According to the Red Cross, 49.536 households were affected, 657 houses destroyed, 1.363 people displaced, and 551 water points damaged.

The UNDP highlights that the implementation of the National Disaster Risk Reduction Strategy in Guinea remains incomplete. The country is exposed to several major hazards, such as floods, landslides, droughts, epidemics, and sociopolitical crises. These challenges, exacerbated by recent events like floods, hinder the effective application of this strategy. Since the adoption of the Sendai Framework in 2015, the understanding of risks, such as recurring floods, has improved. However, this knowledge is not systematically integrated into public and private decisions and investments. Although the framework calls for proactive risk management, many actors still neglect hazard analysis in their plans. Some progress has been made in risk management, with the establishment of early warning systems in 120 rural communes. These systems, while helpful in managing floods, remain insufficient, leaving a significant portion of the country exposed to unaddressed vulnerabilities (UNDP, 2016).

Literature reviews indicate that in Guinea, risks related to human-induced disasters and climate change, such as floods, are frequently addressed in development strategies, particularly in the country's priority sectors (Samoura et al., 2022). Beyond observations on damages and the limited capacity to cope with floods, research has been conducted on flood risk management in Guinea, highlighting that some stakeholders have focused on describing the impacts and analyzing floods and climate change (Mwasha & Robinson, 2021). Floods result from exceptional rainfall due to climate change effects, combined with the population's lack of interest in weather forecasts (Sylla, 2023). At the same time, others argue that the problem lies in the occupation of drainage channel easements and flood-prone areas in the city, although no scientific studies confirm this (Millimono, 2021). Studies have contributed to identifying and analyzing separately different components of flood risks without necessarily bringing them together. Furthermore, many are rather quantitative and none has focused on a data-centered approach. Furthermore, several studies did not cover the entire country with the aim of identifying the most at-risk areas, as should be the case in AA. In this context, this study aims to address the gaps identified in the literature and proposes adopting more data-driven approaches to analyze flood risks across the various regions of Guinea.

Research Questions, Hypotheses, and Objectives

- **Research questions**

Main research question:

What is the risk of floods in Guinea?

Specific questions

- ➢ What are the flood hazard characteristics in Guinea?
- ➢ What is flood exposure in Guinea?
- ➢ What is flood vulnerability in Guinea?
- ➢ What is the coping capacity to floods in Guinea?

- **Research hypotheses**

Main hypothesis:

Anticipatory actions based on risk analysis can reduce the impacts of flooding in Guinea.

Specific hypotheses:

- ✓ Floods are driven by intensified rainfall and inadequate drainage, worsened by climate change.
- ✓ Unplanned urbanization and infrastructure in risk zones increase flood exposure.
- ✓ Poverty, poor infrastructure, and limited risk awareness drive vulnerability.
- ✓ Limited by insufficient resources, weak institutions, and absent early warning systems.

- **Research Objective**

Main objective

The main objective is to study flood anticipatory actions in Guinea through data-driven risk assessments.

Specific objectives:

To achieve the main objective, we will:

- ✓ Describe the characteristics of flood hazards in Guinea.
- ✓ Analyze flood exposure in Guinea.
- ✓ Study flood vulnerability in Guinea.
- ✓ Evaluate the coping capacity for floods in Guinea.

CHAPTER 1: LITERATURE REVIEW

Floods are a persistent phenomenon in the West African region, particularly in Guinea, resulting in significant socio-economic and environmental impacts. Flooding risk management and improving its predictability are crucial for implementing effective preventive measures. For a better understanding of the scope of this research, it is essential to define certain concepts.

1.1 Definition and Concept of Flooding

Flooding is a hydrological hazard that occurs when water inundates land that is typically dry. This phenomenon arises from a combination of meteorological, hydrological, and anthropogenic factors. Heavy rainfall, excessive river discharge, dam failures, and rising groundwater levels are among the primary causes of floods (Oduoye et al., 2024). In many cases, flooding results from an imbalance between precipitation and the capacity of natural or artificial drainage systems, often leading to dike breaches and infrastructure failures. Additionally, seasonal variations such as prolonged precipitation, snowmelt, or storm surges can intensify flood events (Sutar et al., 2022). Floods represent the most frequent and devastating natural disasters worldwide, with disproportionate impacts on low-lying regions and communities located downstream of rivers and dams. These events result in significant loss of life, economic damage, and long-term environmental consequences (Grande, 2024). While floods cannot be entirely prevented, their risks can be mitigated through effective flood management strategies, including predictive modeling, early warning systems, and sustainable land-use planning (Joshua et al., 2021).

Flooding is rarely the result of a single contributing factor; rather, it often stems from the interaction of multiple mechanisms, making classification complex. The severity and nature of flooding depend on regional topography, land use, hydrological conditions, and climate variability. Lóczy et al. (2012) categorize floods into four primary types based on their causes and rate of onset:

- **Fluvial Floods (Riverine Flooding):** These occur when excessive rainfall or upstream water releases cause rivers, streams, or watercourses to overflow their banks. Unlike flash floods, river floods typically develop more gradually and are influenced by long-term hydrological patterns rather than immediate weather events.
- **Pluvial Floods (Rain-Induced Flooding):** These floods arise from intense, short-duration rainfall, independent of river overflow. Factors such as terrain slope, soil permeability, vegetation cover, and urban development significantly influence flash flood occurrences. Moist convection is a primary driver of rainfall-induced flash flooding, particularly in tropical and monsoon climates (Ki-, 2022).
- **Groundwater Floods:** Also known as water table rise floods, these develop slowly as subsurface water levels gradually increase beyond natural retention capacities. Typically occurring over weeks or months, they are strongly dependent on geological conditions and can lead to prolonged submersion, causing severe damage to infrastructure, agriculture, and ecosystems (Tewa, 2020).
- **Coastal Floods:** These floods result from storm surges, tidal fluctuations, or extreme weather events that push seawater inland. Coastal flooding is often exacerbated by concurrent riverine or groundwater flooding, complicating drainage processes and intensifying damage (Sandink et al., 2016).

Despite these categorizations, flood types frequently overlap, making it difficult to isolate a single causative factor. Simultaneous or sequential flood events can amplify their impact, challenging mitigation efforts and emergency response strategies (Sandink et al., 2016).

This study focuses on floods of pluvial and fluvial origin given their increasing frequency and serious consequences in urban and rural areas of Guinea. The selection of these types of flooding is especially important considering recent extreme weather events. In August 2024, torrential rains triggered devastating floods across multiple regions of Guinea. By October 2024, over 175,000 people had been severely affected, marking a more than tenfold increase compared to the same period in 2023. Moreover, 18 out of the country's 33 prefectures experienced severe flood-related disruptions (FAO, Govt. of Guinea, IOM, 2024). The intensification of flash floods in Guinea is largely attributed to urbanization patterns and inadequate drainage infrastructure. Many cities exhibit unregulated and rapid urban expansion, with critical infrastructure including roads, railways, and residential areas concentrated in flood-prone zones such as valleys and densely populated districts (Latrubesse, 2009). In these areas, impermeable surfaces reduce natural water absorption, increasing runoff and speeding up the onset of floods. Beyond physical and climatic drivers, socioeconomic vulnerabilities such as poor urban planning, weak governance, and lack of community preparedness further heighten flood risks.

1.2 Definition and Component of Flood Risk

According to UNISDR (2009), risk results from the probability of a hazard happening combined with its potential harmful impacts. Flood risk is a complex concept that arises from the interaction between the probability of flood events occurring and their potential negative impacts on human health, the environment, and economic activities (Eslamian et al., 2022). It integrates several dimensions, including physical, economic, social, and infrastructural aspects, relying on key elements such as hazard, exposure, vulnerability, and resilience (Tabasi et al., 2024). Flood risk is divided into tangible losses, measurable in financial terms, and intangible losses, such as human loss and impacts on mental health, which are often overlooked in traditional analyses (Eslamian et al., 2022). The complexity of flood risk is amplified by local hydrological conditions and community responses, which vary widely based on demographic characteristics and past experiences with flooding (Knighton et al., 2021). There is risk when a hazard meets vulnerability. The hazard alone cannot define risk, nor can vulnerability. Only their combined effect produces risk. For example, if no vulnerable area is exposed to a flood in an uninhabited flood-prone area, there is no risk. However, the same flood becomes a potential risk if it occurs in an environment with a high population density, along with buildings and infrastructure sensitive to flooding (UNISDR 2009).

According to the Ministry of Public Security of Quebec (MSPQ, 2008), risk consists of two main elements: the hazard, which depends on the intensity of the phenomenon, and vulnerability, which is related to the presence of stakes and their resilience capacity. So, risk comes from the combination of hazard, exposure, vulnerability, and the inability of human and natural systems to adjust, as shown in Figure 1. It reflects the degree of unpreparedness or inability of humans to manage a specific situation, such as a natural hazard, and can be represented in the following formula:

Risk = Hazard + Exposure + Vulnerability + Lack of Coping Capacity

Figure 1: IPCC Risk Framework

Source: Reisinger et al., 2020

A popular method of simplification states that the risk of flooding, like any other risk of calamity, can be described as the exposure of susceptible parties to a hazard, in this case, the transient presence of water. Land use, urbanization, meteorology, and other interrelated factors all have an impact on the primary factors (problems and risks).

1.2.1 Hazard

A hazard is a natural or human-made phenomenon that has the potential to cause a disaster, leading to human losses, injuries, or other health impacts. It can also cause material damage, loss of livelihoods, difficulties in accessing basic services, socio-economic disruptions, or environmental degradation (Guin, 2022). Among the natural hazards that threaten the Republic of Guinea and deserve particular attention are hydrometeorological risks (tornadoes, floods), geological risks (earthquakes, landslides), droughts, climate change, and oceanic risks (tidal waves, floodings of polders). The hazard, whether an event or a process, is characterized by three main elements: its intensity (why and how?), its spatial occurrence (where?), and its temporal occurrence (when and for how long?). Intensity reflects the magnitude of a phenomenon and can be measured (e.g., water height for a flood, magnitude for an earthquake) or estimated (e.g., duration of submersion, speed of movement). Spatial occurrence depends on predisposition or susceptibility factors, such as geological characteristics. However, estimating the spatial extent of a hazard remains complex (e.g., avalanches or landslides). As for temporal occurrence, it is influenced by triggering factors, whether natural or anthropogenic. It can be evaluated qualitatively (e.g., negligible, low, high) or quantitatively (e.g., return period of 10, 30, or 100 years). The duration of the phenomenon should also be considered, especially for rainfall events (UVED, 2006).

1.2.2 Exposure

It refers to the existence of people, livelihoods, animals, ecosystems, services, resources, infrastructure, or cultural, social, and economic assets in locations that may be affected or damaged (IPCC AR5). Exposure measures may include the number of people or the types of assets present in an area (Climate Change 2014 Synthesis Report Summary for Policymakers, 2014). It is widely recognized that exposure can be split into direct and indirect exposure. Direct exposure refers to the hazard being in the same area as people, buildings, or infrastructure. This type of exposure typically results in physical and mental harm, as well as material and financial losses. In contrast, indirect exposure relates to the consequences of a flood that extend beyond the flooded area itself. A region can be affected by a flood without being directly inundated. For instance, in rural areas, a flood may render a region completely inaccessible. Additionally, indirect exposure occurs when people are unable to reach their workplace, impacting productivity and income (From Flood Exposure to Flood Vulnerability, 2022).

1.2.3 Vulnerability

Vulnerability to floods refers to the susceptibility of communities and environments to suffer from the negative impacts of floods. It results from a complex interaction between environmental, social, and economic factors. This vulnerability is divided into three main aspects: exposure to flood risks, the sensitivity of people and infrastructure, and the ability to recover from the effects of floods (Chuan and Ros, 2021).

Understanding vulnerability helps identify the most effective ways to reduce it. Vulnerability assessment primarily aims to provide decision-makers and stakeholders with useful information to choose adaptation strategies in response to the impacts of flood risks (Douben, 2006). Over the past twenty years, the concept of vulnerability has significantly evolved in scientific literature, leading to numerous attempts to define and understand this concept. Originally, the term "vulnerability" comes from the Late Latin *vulnerabilis*, derived from *vulnerare* (to wound) and *vulnus* (wound), and refers to the capacity to be hurt or affected by harm (Rasse, 2009). In addition, it is linked to weakness when facing a threat. Different methodologies, such as the Analytical Hierarchy Process (AHP) and Geographic Information Systems (GIS), can be employed to assess vulnerability. These approaches highlight significant correlations between high-risk areas, population density, land use, and economic factors (Ibrahim et al., 2024). Understanding flood vulnerability is essential for designing effective mitigation and adaptation measures to minimize the impact of floods on affected communities (Ibrahim et al., 2024).

1.2.4 Lack of Coping Capacity

The lack of adaptive capacity refers to the insufficiency of resources and means available to individuals or communities to effectively cope with adverse conditions or disasters, thus increasing their vulnerability (Budiani et al., 2014). This concept plays a central role in disaster management and climate change adaptation, as it includes preparation, available resources, and necessary mechanisms to respond appropriately. For example, in the case of floods, communities with low adaptive capacity may face issues such as limited access to transportation and insufficient information, leading to ineffective evacuation strategies (Budiani et al., 2014). Moreover, coping capacity differs from proactive capacity, which involves preventive measures aimed at reducing risks. Instead, it focuses on immediate and reactive responses to crises (Tinch et al., 2015). Effective risk management requires incorporating coping capacities into assessments to highlight existing strengths and weaknesses, thus helping stakeholders prioritize risk reduction actions (Frischknecht et al., 2010). Ultimately, evaluating and understanding coping capacity is essential for enhancing resilience to various stressors (Yohe and Tol, 2002).

1.2.5 Anticipatory Actions for Flood Risk Reduction

Anticipatory actions are recognized as proactive measures taken in advance to minimize the effects of potential disasters by using advanced forecasts and risk data. This approach links climate forecasts with humanitarian efforts to provide timely assistance, thereby reducing suffering and improving the preparedness of at-risk populations (Chaves-Gonzalez et al., 2022). Anticipatory action is increasingly seen as a key strategy for reducing the impacts of climate disasters, particularly in complex crises marked by the combination of multiple hazards and limited forecasting capabilities. Anticipatory approaches have increased a lot in the past ten years and are now being developed in over 70 countries. Recent case studies have highlighted the effectiveness of anticipatory action in proactively addressing humanitarian needs. This is illustrated by early intervention pilot projects led by the UN in certain countries, which supported populations affected by conflict before the arrival of extreme floods (Easton-Calabria, 2024). The United Nations Office for the Coordination of Humanitarian Affairs (OCHA) has implemented actions in response to floods that have affected millions of people in several countries in Africa and worldwide, such as Burkina Faso, Nepal, Niger, Mali, Chad, Kenya, South Sudan, etc., highlighting the crucial role of reliable triggers and adaptable financing to ensure effective implementation (Chaves-Gonzalez et al., 2022). This is also demonstrated by the African Multi-Hazard Early Warning and Early Action System (AMHEWAS), which has created a framework that combines real-time information exchange and impact-based forecasts, encouraging proactive measures and improving resilience across the continent (Libertino et al., 2024).

Anticipatory innovation is becoming a key tool for managing uncertainties and shaping responses to future crises (Anticipatory Innovation, 2022). These anticipatory actions can be considered mitigation measures aimed at the effective management of flood risks through an approach that combines both structural and non-structural measures to strengthen community resilience, assisting authorities and organizations in facing crises and protecting their livelihoods while enhancing their preparedness to reduce future risks (Floods, 2022). However, these measures face challenges, such as setting up reliable triggers, flexible funding, and adjusting to changing disaster situations (Block & Bazo, 2023). Generally, the movement in favor of anticipatory action is expanding, thanks to initiatives such as forecast-based financing launched by the International Federation of Red Cross and Red Crescent Societies, among others (Wilkinson et al., 2018).

Furthermore, Anticipatory Actions consist of several key elements, including predefined action triggers based on forecast data and often combined with population-based criteria (determining when and where the first interventions will be deployed); a pre-established financing mechanism that is automatically activated when the trigger threshold is reached; as well as a set of early actions designed to reduce the impact of the anticipated shock (Gros et al., 2019).

Recently Guigma et al. (2022), have conducted studies in Burkina Faso on the feasibility of implementing forecast-based financing while considering Burkina Faso as a high-risk country that has experienced major climate and meteorological disasters. In the article, they highlight that this strong feasibility is also explained by the significant interest in FbF within many institutions, whether governmental or no. This has facilitated the determination of the Burkinabe Red Cross, which also has the necessary capacities to implement such a program in this country to prevent or reduce the impacts of hazards by carrying out relevant actions through an early action protocol before their occurrence With FbF, the financing mechanism allows for the automatic release of funds in anticipation of an extreme weather event. Globally, empirical data confirm that preventive actions significantly reduce the impact of disasters, emphasizing the importance of hydrological forecasts for rapid interventions (Enhancing anticipatory actions for disaster preparedness considering physical and social factors, 2022).

Research on flood risks in Guinea highlights significant challenges and opportunities for their management, particularly due to changing land use and climate variability. Several studies have examined various aspects of this issue, such as flood frequency, the influence of climatic factors and land-use changes, and the effectiveness of risk management measures. The study of flood frequency is a central research focus, revealing that Guinea, like other West African countries, regularly experiences recurring flood events. These events are influenced by a combination of local and regional climatic factors (Diop et al., 2025). This review presents a compilation of existing studies on the subject, highlighting the key findings of previous research to provide a comprehensive understanding of the phenomenon. One such study focused on the Konkouré River basin, revealing that the conversion of forested areas into built-up spaces has reduced soil infiltration capacity, leading to increased runoff and an expansion of flood-prone areas (*A Study on Land Use Changes and Their Impact on Flooding in the Konkouré River Basin, Republic of Guinea, 2022*). These findings emphasize the importance of sustainable land management practices to mitigate flood vulnerability.

Furthermore, research conducted on the Koliba/Corubal River basin has shown that the combination of rainfall variability and land-use changes has exacerbated flood risks. In particular, disruptions in the rainfall regime during the 1950s, 1960s, and 1980s led to significant precipitation deficits, thereby intensifying flood exposure (Sambou et al., 2020). Ghomsi et al. (2024) highlight, at the regional scale, that Guinea's vulnerability to flooding is exacerbated by its location in the Gulf of Guinea, a particularly sensitive area to sea-level rise. Projections show that, with high emissions, up to 95% of coastal areas could be flooded, threatening livelihoods and cultural heritage. These findings underscore the urgent need to implement targeted adaptation strategies, including effective early warning systems and integrated flood risk management approaches.

The study by Kabore (2024) on flood risks in the Coyah prefecture makes a significant contribution by enhancing the understanding of flood dynamics through cross-analysis of rainfall data, surveys, and satellite imagery. It identifies the relationships between precipitation, flooding, and land-use changes while highlighting local adaptation practices. By proposing flood hazard mapping using the Random Forest method, the study provides a crucial tool for local stakeholders in managing hydroclimatic risks. It also emphasizes gaps in flood risk communication, advocating for an integrated approach to strengthen community resilience against these disasters. Similarly, Kanté et al. (2020) highlighted those local studies have also provided valuable insights into the spatial and temporal variability of precipitation and its impact on flood risk. For example, an analysis of precipitation dynamics in Conakry, the capital of Guinea, using ERA-Interim data, revealed that the city experiences the highest rainfall during the peak of the rainy season. This intensity is primarily attributed to moisture convergence and orographic effects.

CHAPTER 2: MATERIALS AND METHODS

2.1 Study area

The Republic of Guinea is located in the southwestern sector of West Africa, encompassing an area of 245857 square kilometers with of 14 million population. This nation is classified as a coastal territory, featuring an extensive 300 kilometers of Atlantic shoreline, positioned equidistantly between the equator and the Tropic of Cancer, specifically between latitudes 7°05 N and 12°51 N, as well as longitudes 7°30 W and 15°10 W. To the northeast by Mali, to the north by Senegal, to the northwest by Guinea-Bissau, to the south by Liberia and Sierra Leone, with the Atlantic Ocean on the west. The country has four distinct natural regions: (1) Lower Guinea, with its lush coastal mangroves and lowlands; (2) Middle Guinea, home to the Fouta Djallon Mountain range; (3) Upper Guinea, known for its elevated savannahs that shelter the country's crucial Niger River watershed; and (4) Forest Guinea, defined by its rich, dense forests and dramatic mountains (Loua et al., 2020).

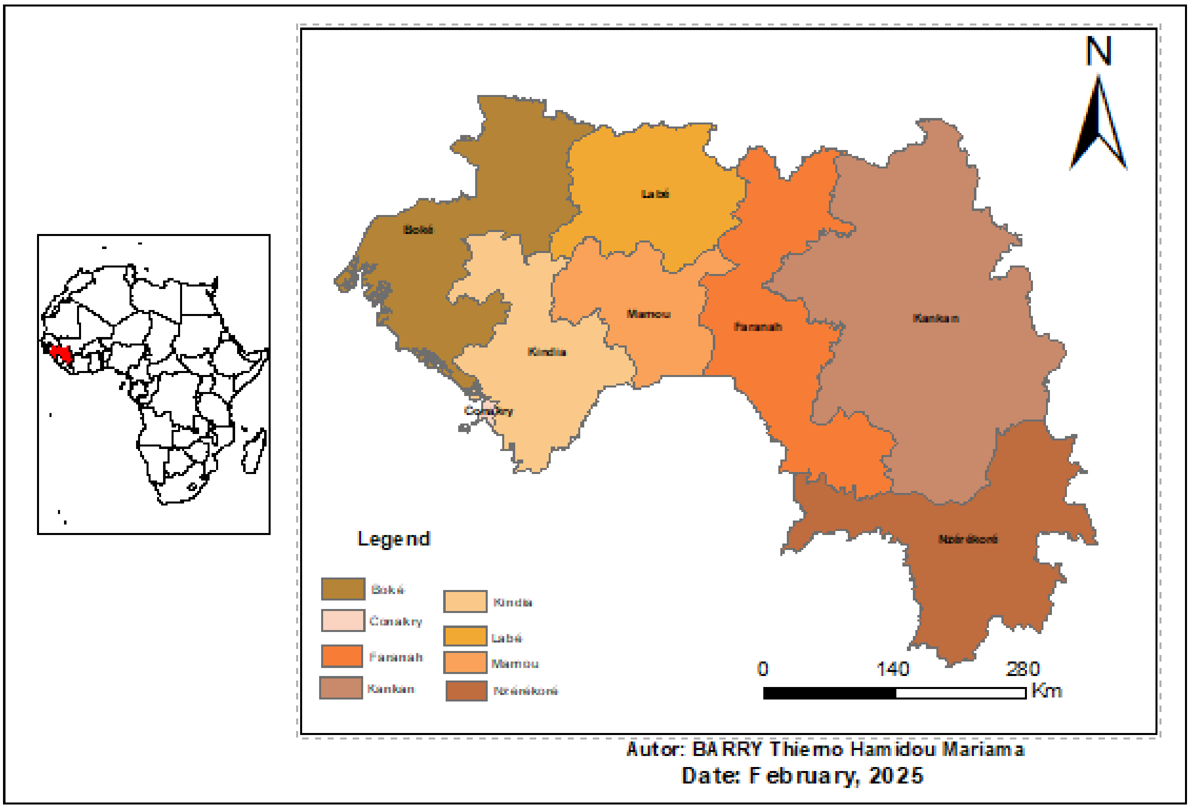


Figure 2: Map of Guinea

2.1.1 Climate

Guinea is divided into two climate zones: the tropical zone, which covers most of the territory, and the sub-equatorial zone, which covers the southeast of the country. The annual rainfall pattern is unimodal. The year is divided into two distinct seasons: a dry season and a rainy season, each lasting six months. The rainy season extends from May to October, and the dry season from November to April. Temperatures are consistently high, corresponding to the country's dry season. During this period, Guinea experiences Harmattan winds, which bring dry and dusty air from the Sahara, with little or no precipitation. Temperatures remain constantly high, especially in inland regions such as Kankan and Siguiri, where they often range between 35°C and 40°C. Coastal areas, like Conakry, are slightly cooler thanks to sea breezes. The country experiences notable climate variations, mainly due to the diversity of its landscapes. The sub-Guinean tropical climate of Lower Guinea is characterized by relatively stable average temperatures, ranging from 23 to 25°C, with heavy rainfall between 2,100 and 5,000 mm, and a monthly maximum of over 1,000 mm in August. In Middle Guinea, the mountainous tropical climate features roughly equal seasons, with rainfall ranging from 1,600 to 2,000 mm. Upper Guinea, located in the northeast of the country, experiences a dry and very hot climate starting in March. Forested Guinea, located in the southeast, has a tropical climate with very heavy rainfall starting in May. Guinea experiences diverse climatic influences, characterized by the annual alternation of Harmattan winds from the northeast and monsoon air masses from the southwest. This unique climate results in a distinct cycle that shapes the landscape (Loua et al., 2020).

2.1.2 Hydrography

The Fouta Djallon highlands provide vital water resources to several West African nations, which is why Guinea is often called the Water Tower of West Africa. This vast hydrographic network consists of 1,165 recognized rivers, including 14 international rivers that drain neighboring countries. Major rivers such as the Niger, one of the longest in Africa at 4,200 km, the Senegal River and the Gambia River, as well as their important tributaries such as the Tinkisso, Milo, Niandan and Falémé, demonstrate Guinea's vital water contributions. In addition, several coastal rivers bear the names given by 15th-century Portuguese explorers (e.g., Rio Nunez and Rio Pongo). Some of these rivers form deep estuaries, meandering through the mangrove ecosystems of maritime Guinea, a region that the French called Rivières du Sud at the beginning of colonization in the 19th century.

Currently, most rivers have an irregular flow regime due to factors such as topography, climate and anthropogenic activities (deforestation, slash-and-burn agriculture, bush fires, etc.). The country's hydrological richness is mainly due to the heterogeneity of its soils. Because of the rough terrain and seasonal rainfall changes, many rivers have irregular flows, becoming torrents during the rainy season and drying up in valleys during the dry season (Etat & En, 2012).

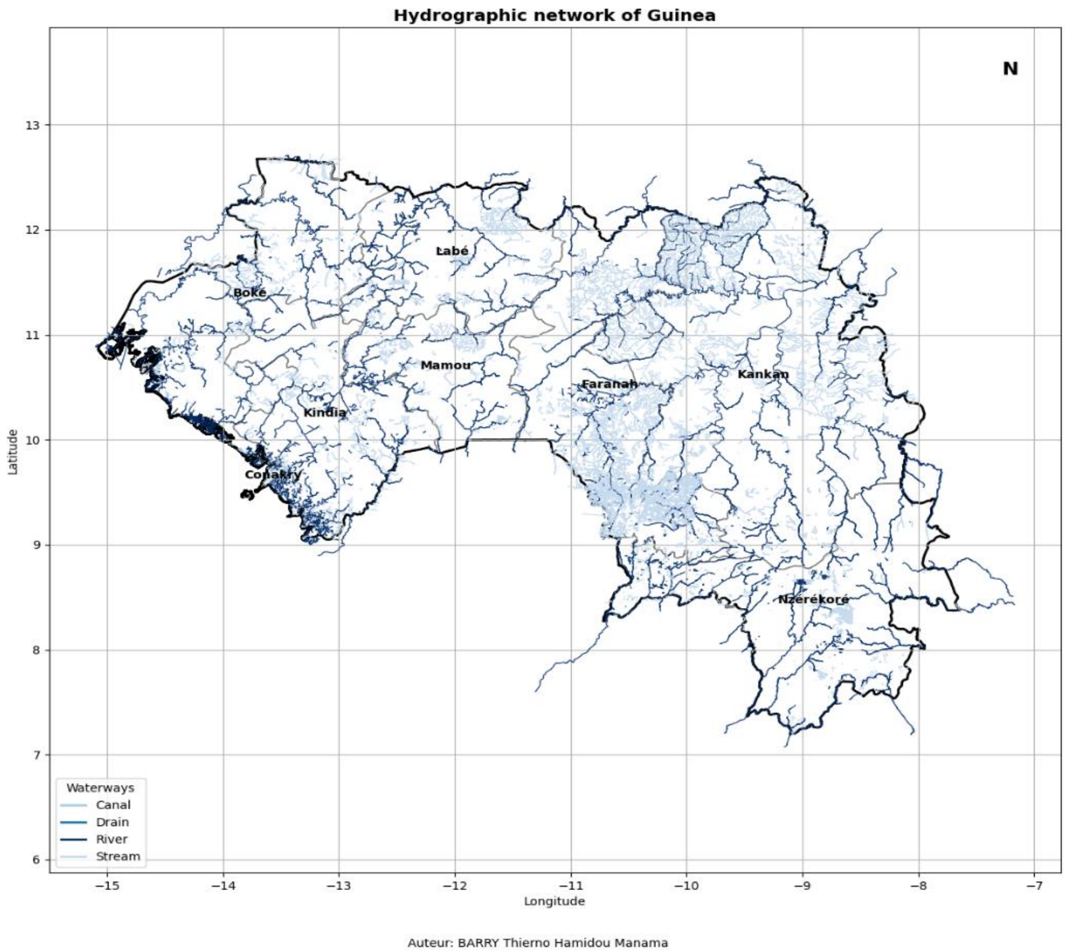


Figure 3: Hydrographic network map of Guinea

2.1.3 Relief

Guinea, a coastal region, is distinguished by its fertile coastal plains (Manchon, Koba, Kawas) and mountains such as Mount Gangan (1,117 m). Middle Guinea, dominated by the Fouta Djallon massif, has peaks such as Mount Loura (1,538 m) and plains in Pita and Gaoual. In Upper Guinea, the plateaus (Balayan, 1,025 m) and the plains along the Niger differentiate agriculture. As for Forest Guinea, it is home to the highest peaks, including Mount Nimba (1,752 m), surrounded by dense forests. This geographical wealth supports the country's economy and biodiversity (magoerevision.com, 2024). The most ancient geological structure in Guinea consists of a granite bedrock. From the point of view of mineral resources, Guinea is described by informed observers as a geological scandal. Guinea's geomorphological structure is highly complex and varied. It is in fact the result of several phenomena including tectonics and orogenic movements, the different processes of alteration of geological material, the importance of the vegetation cover and the mode of exploitation of the land by populations for decades (magoerevision.com, 2024).

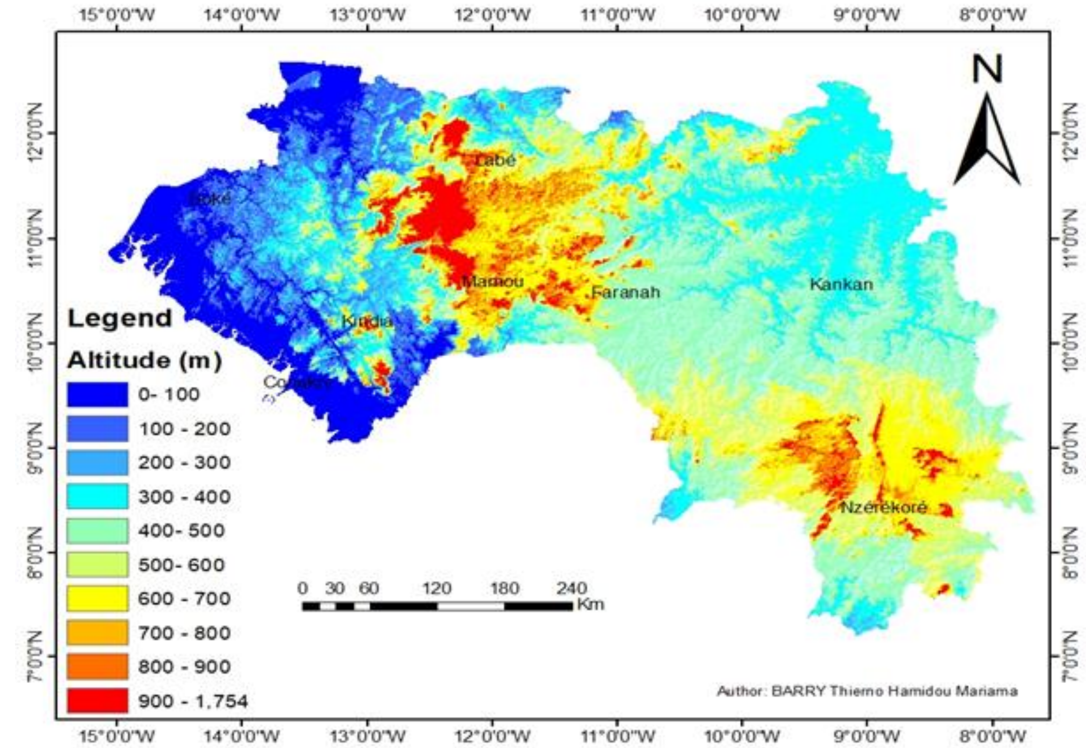


Figure 4: Topography of Guinea

2.1.4 Vegetation

Guinea’s vegetation is extremely diverse and varies according to its four major natural regions. In Lower Guinea, vegetation is mainly composed of mangroves along the coast, featuring mangrove species such as Rhizophora and Avicennia, along with coconut trees, oil palms, and fragmented coastal forests. In Middle Guinea, the vegetation consists of a mosaic of wooded and shrubby savannas, as well as gallery forests lining rivers. Common species include the néré (Parkia biglobosa), shea tree (Vitellaria paradoxa), kenkéliba (Combretum micranthum), and téli. Upper Guinea is characterized by Sudanian-type savanna vegetation, with wooded savannas dominated by Isoberlinia doka and Daniellia oliveri, and gallery forests along the Niger River, which are home to trees such as the baobab (Adansonia digitata), kapok tree (Ceiba pentandra), and shea tree. Finally, Forested Guinea contains the country's densest and most humid forests, particularly the classified forests of Ziama and Diécké, rich in valuable timber species such as mahogany (Khaya ivorensis), sipo (Entandrophragma cylindricum), fraké (Terminalia superba), and azobé (Lophira alata). However, this rich vegetation is increasingly threatened by deforestation, bushfires, and human pressure (FAO, 2001; National Environmental Documentation Center of Guinea, 2020).

2.1.5 Risk and Disaster Management

Guinea faces big challenges in handling disaster and risk, especially to help communities cope with climate problems. To improve its response ability, it created the National Agency for Emergency and Humanitarian Disaster Management (ANGUCH) by decree on June 23, 2022. This institution is run by the Ministry of Territorial Administration and Decentralization. ANGUCH makes national response plans, prepares for emergencies, organizes help, and gathers the needed resources. Its work is to protect people, property, and the environment from serious accidents, disasters, or catastrophes and their effects. Even though Guinea has made good steps in making disaster policies and risk reduction plans, its risk management still has big gaps in funding and identification. According to Samoura et al. (2022), these gaps hurt the climate resilience of communities. Research by Agrawal (2018) and Nirupama says good risk management needs a structured process: finding threats, analyzing how people are vulnerable, and using frameworks like the Hyogo Framework for Action. This helps local governments be stronger. In short, although Guinea has the right institutions and an agency for disaster management, it must improve stable funding, risk mapping, and adopt international standards for strong and integrated disaster management.

2.2 Tools

In the context of this study, several tools were used to facilitate data analysis, processing, and mapping. Each tool was selected based on its specific utility and relevance to the research objectives.

Table 1 : Materials used

Tools	Utility
ArcGIS	For the mapping study area
R language	Development of data analysis scripts; mapping
Python programming language	For data processing and analysis
CDO (Climate Data Operators)	To process and analyze scripts
Excell	For organizing data, performing basic calculations, and creating summary tables
Internet research	To find relevant scientific papers

2.2 Data collection

The research began by identifying the study area, which is Guinea. The data collected included rainfall, flow rates from ten hydrometric stations, soil structure data, and risk data. This enabled the analysis of risk components and the identification of areas at risk of flooding.

2.2.1 Hazard data

2.2.1.1 Precipitation Data

The daily precipitation data downloaded from CHIRPS (Verdin et al. 2020), through the website https://data.chc.ucsb.edu/products/CHIRPS-2.0/global_daily/netcdf/p25/, covers the entire planet and is available in NetCDF (Network Common Data Format). These data were collected and extracted using CDO (Climate Data Operators), selecting only the data corresponding to Guinea for the period from 1981 to 2024. These data were chosen due to the unavailability of daily weather station data, and also for their quality and relevance in analyzing high-resolution spatiotemporal precipitation, as noted by Müller et al. (2025).

2.2.1.2 Hydrometric data

The daily flow data from available hydrometric stations were collected from the National Directorate of Hydraulics of Guinea, covering the period from 1992 to 2024. These data were used to define the hydrological patterns of the ten hydrometric stations situated in Guinea's watersheds. The selection of historical data from these ten stations was based on data availability and quality. However, some stations had gaps, which were addressed using the random forest method in R packages. The advantage of this method is that it respects the trend and seasonality of the data, which simple linear regression cannot always achieve. Additionally, if several nearby stations exist, missing periods for one station can be estimated using data from neighboring stations. The evolution of the flows from the different stations was then analyzed to understand their trends. Additionally, another dataset was considered: the reanalysis provided by the Global Flood Awareness System (GloFAS) (Harrigan et al., 2020). This system integrates in-situ and satellite data with numerical models to produce optimal river flow estimates. Version v4 was used to assess the flood hazard from 1992 to 2024.

2..2.1.2 Soil Permeability

Soil permeability is influenced by texture. Data related to soil texture, including the proportions of sand, clay, and silt, are provided with a resolution of 250 meters from SoilGrids250m (Poggio et al., 2021). The data is freely accessible on the SoilGrids250m 2.0 website.

To better understand the permeability coefficient of different soil types based on their texture, additional data has been extracted from the FAO website: https://www.fao.org/soils-portal/en.

2.2.2 Exposure data

For the flood risk assessment, it was necessary to identify the sub-indicators for the exposure component, including: the population size, the number of cattle, sheep, goats, and pigs, as well as the cultivated areas of rice, fonio, maize, peanuts, cassava, and sweet potatoes. These sub-indicators were grouped into three categories: human population, agricultural land, and animals, with sub-indicators for each category. The data were extracted from the websites https://www.citypopulation.de/en/guinea/ and http://annuaire_statistique_de_l_environnement_2022_signe_vf.pdf, as well as various reports from the Ministry of Environment, the National Statistics Institute, and UNDP.

2.2.3 Vulnerability data

Just like for exposure, the various vulnerability sub-indicators were collected from reports by the National Statistics Institute and UNDP, including: the Multidimensional Poverty Index (MPI), children under 4 years old, people over 65 years old, people living with disabilities, the inactive population rate, thatched roofs, mud houses, and the number of farmers. The data where extracted from the following websites: https://data.humdata.org/dataset/guinea-mpi/ and https://www.citypopulation.de/en/guinea/.

2.2.4 Lack of adaptive capacity data

Similar to the previous two components, the sub-indicators for this indicator were selected from the reports of the National Statistics Institute's directory, and include the following: the number of rescue brigades, the illiteracy rate, health centers, health posts, the number of schools, the number of rural and community radios, structures managing internet access, structures managing vehicles, and the rate of paved roads. This data comes from the following website: https://www.stat-guinee.org/.

2.3 Data Processing

2.3.1 Precipitation Data Analysis

The filtered precipitation data were processed using R software. A monthly and annual climatological analysis was conducted to identify the most affected regions and estimate the average precipitation per locality. These data also highlighted extreme events through statistical analyses, including the calculation of climate indices based on the 95th percentiles recommended by the ETCCDI (Expert Team on Climate Change Detection and Indices) to characterize exceptional precipitation. It also helped determine the months when maximum and minimum precipitation levels are recorded in Guinea. Finally, figures were produced to illustrate precipitation trends and identify periods of heavy rainfall. The entire data processing, as well as the production of maps and graphs, was carried out using the R Package, enabling precise identification of the most vulnerable areas.

2.3.1.1 Hydrometric Data Analysis

This analysis also aimed to assess the impact of climate change through the study of monthly and annual flow variations, as well as extreme flows, in different regions of Guinea, based on the most comprehensive historical data set available, processed with Python. The extremes of river floods were characterized using the flow return levels provided by GloFAS, complemented by hydrometric flow data from the DNH.

2.3.1.2 Soil Permeability Data Analysis

To better understand soil texture and its components, we calculated how each type of soil allows water to pass through, which is called permeability. Equation 1 considers the amount of sand, clay, and silt in the soil. This calculation helps to know how water enters the soil, which is important for managing flood risk and protecting the environment. The formula is:

$$\boldsymbol{Coef_{Perm}} = \left[\left(\frac{\boldsymbol{P(silt)}}{\boldsymbol{6}}\right) + \left(\frac{\boldsymbol{P(sand)}}{\boldsymbol{3}}\right)\right] * (-\boldsymbol{1})$$

(Equation 1)

Where:

- Coef Prem is the permeability coefficient;
- P silt is the permeability of silt;
- P sand indicates the permeability level of sand.

2.3.1.3 Pluvial Flood Hazard Index Calculation

The pluvial flood hazard is related to precipitation and the capacity of soils to manage water. For its assessment, several sub-indicators were combined. The average annual precipitation cumulative measures the total amount of water that falls on a region each year. The 95th percentile of precipitation helps evaluate the frequency of extreme events, such as floods, by identifying periods when precipitation exceeds a certain threshold. In the end, these coefficients measure the soil's capacity to take in and drain water. All these sub-indicators are assessed by region. For the analysis of rainfall food hazard, a central method was used to combine several Sub-indicators with different dimensions and units, which were normalized to give them the same weight. The sub-indicators include the annual rainfall total, the precipitation level at the 95th percentile, and the soil's permeability. After normalizing the sub-indicators, we found their average and then divided it by three. Hence, the Following Hazard formula in Equation 2:

$$Pluvial\ Flood\ Hazard = \frac{(Average\ annual\ total + 95th\ percentile + Soil\ permeability)}{3}$$

(Equation 2)

2.3.1.4 <u>Fluvial Flood Hazard Index Calculation</u>

Fluvial flood hazard is related to the risk of flooding from rivers. It is evaluated through the return levels by region, which measure the probability of major floods over specific periods, such as a 1.5-year return level by region. This data is important for predicting flooding risks linked to extreme events. Additionally, the average river flows by region show the amount of water regularly flowing in rivers, helping to identify areas vulnerable to recurring floods. For the river flood hazard, all the sub-indicators were given equal weight. Then, the same process used for the rainfall hazard was applied. The data used includes return level flow rates and average flow rates of rivers by region. These data were combined, normalized, and then the regional average was calculated. At the end, the final number was halved to get the related figures. Here Is the formula used in Equation 3:

$$Fluvial\ Flood\ Hazard\ = \frac{(Return\ Period\ Flow\ +\ Average\ River\ Flow)}{2}$$

(Equation 3)

2.3.2 <u>Exposure Analysis</u>

These raw data were transformed using the natural logarithm, then normalized and weighted. The sub-indicators were grouped into three categories: the human population group, agricultural land, and animals, with each category having its sub-indicators. Regarding weighting, 50% of the exposure score was given to the population size, 25% to the agricultural land group (distributed among the different sub-indicators), and 25% to the animal group (distributed among the different sub-indicators) for the presence of all other sub- indicators in each group. Next, for each group and its sub-indicators, the coefficient value was determined by dividing the weighted total by the number of sub-indicators. Different weights were chosen for comparison purposes, which is why the Equation 4 was applied:

$$Exposure = \frac{Group(Population\ Size)}{2} + \frac{Group(Agricultural\ land)}{28} + \frac{Group(Animals)}{16}$$

(Equation 4)

Table 2:Exposure sub-indicators

Element (relative weight)	Group	Weight of the group
Population size (½)	Human population	1/2
– Rice Cultivated Area (1/28) – Fonio Cultivated Area (1/28); – Maize Cultivated Area (1/28); – Millennium Cultivated Area (1/28); – Peanut Cultivated Area (1/28); – Cassava Cultivated Area (1/28); – Sweet Potato Cultivated Area (1/28)	Agricultural land	1/4
– Number of cattle (1/16) – Number of sheep (1/16) – Number of goats (1/16) – Number of pigs (1/16)	Animals	1/4

2.3.3 Vulnerability Analysis:

This data, in its raw form, was also transformed using a natural logarithm, then normalized and weighted in the same way as for exposure. The sub- indicators were grouped into four sets: the MPI group, the housing-related vulnerabilities group, the people group, and the livelihoods group, with each group containing several sub-indicators. It is important to clarify that the calculation of the MPI is based on data extracted from external sources (2024 Global Multidimensional Poverty Index (MPI). In terms of weighting, 50% of the vulnerability score was allocated to the MPI group size, 25% to the housing-related vulnerabilities group (distributed among the different sub-indicators), 25% to the vulnerable people group (distributed among the different sub-indicators), and 25% to the livelihoods group (distributed among the different sub-indicators). Then, for each group with its sub-indicators, to obtain the coefficient value for each sub-indicator, the weighted value it represents was divided by the number of sub-indicators. It was decided that there would be different weights for the comparison, which is why the Equation 5 was used.

$$\text{Vulnerability} = \frac{Group(MPI)}{2} + \frac{Group(vulnerable\ people)}{12} + \frac{Group(vulnerable\ houses\ )}{8} + \frac{Group(Vulnerable\ livelihoods)}{8}$$

(Equation 5)

Table 3: Vulnerability sub-indicators

Element (Relative Weight)	Group	Weight of the group
MPI (1/2)	MPI	1/2
– Children under 4 years old, (1/12); – People over 65 years old, (1/12); – People living with a disability, (1/12)	Vulnerability People	1/4
– Thatched roofs (1/8) – Mud houses (1/8)) ;	Vulnerability of Housing	1/4
– Rate of inactive people (1/8) – Agricultural farmers' population (1/8);	Vulnerability of Livelihoods	1/4

2.3.4 <u>Lack of Adaptation Capacity Analysis</u>

The sub-indicators have been grouped into three categories: the communication group, the infrastructure group, and the disaster management group. For the communication and infrastructure groups, the sub-indicators within each group were divided by the total population by region, and for the disaster management group, the sub-indicators were divided by the area of the regions. These raw data were also transformed by normalization and weighting, in the same way as the previous ones. The weighting assigns 50% of the exposure score to the communication group (distributed across the different sub-indicators), 25% to the infrastructure group (distributed across the different sub-indicators), and 25% to the disaster management group (distributed across the different sub-indicators) for the presence of all other sub - Indicators in each group. Then, for each group with its sub-indicators, the value of the sub-indicator coefficient was calculated by dividing the weighted value it represents by the number of sub-indicators. It was decided that different weights would be used for comparison, which is why the Equation 6 was applied:

$$Coping\ Capacity = \frac{Group(Communication)}{6} + \frac{Group(Disaster)}{12} + \frac{Group(Infrastructure)}{12}$$

(Equation 6)

Table 4: Sub-indicators for Lack of Adaptive Capacity

Element (Relative Weight)	Group	Weight of the group
- Number of rural and community radios (1/6); - Paved road rate (1/6); - Illiteracy rate	Communication	1/2
- Health center (1/12); - Health post (1/12); - Number of schools (1/12);	Infrastructure	1/4
- Number of rescue brigades (1/12); - Structure managing internet access (1/12); - Structure managing vehicles (1/12)	Disaster management	¼

Another data processing methodology used is normalization, which is a scaling technique where values are shifted and resized to fit within a specific range, usually between 0 and 1, or in such a way that the average is zero and the standard deviation equals 1 (Analytics Vidhya, 2020). Normalization contributes in making the data consistent, improves the performance of learning models, and ensures that all features are fairly considered in the analysis process. After applying normalization, we combined all the sub-indicators of the different components together. It is important to note that normalization is done after calculating the average of the indicators in each region. To get the unique indicators of hazard, unique exposure indicators, unique vulnerability indicators, and unique adaptation capacity indicators, we used weighted averaging. It is at the level of the weighted averages that this normalization was applied to the different components, leading to the final Equation 7 as follows:

$$\text{Xnorm} = 1 + \left(\frac{\boldsymbol{X - X\,min}}{\boldsymbol{X\,max - X\,min}}\right) * 9$$

(Equation 7)

Where: (X) is the observed value of the indicator, (X min) is the smallest observed value, (X max) is the largest observed value and (X norm) is the normalized value, between 1 and 10.

Finally, regarding risk, it is divided into two parts, combining vulnerability, exposure, and lack of coping capacity, with the following Equation 8 and Equation 9:

$$Risk\ (Pluvial = Hazard(pluvial) + Exposure + Vulnerability + Lack\ of\ Coping\ Capacity.$$

(Equation 8)

$$Risk(fluvial = Hazard(fluvial) + Exposure + Vulnerability + Lack\ of\ Coping\ Capacity.$$

(Equation 9)

CHAPTER 3: RESULTS AND DISCUSSION

This chapter discusses results of our work at the national. The analysis of flood risks, including maps and vulnerable areas, will be shown in this section. The discussion section will focus on interpreting the results and comparing them with previous studies**.**

3.1 Results Hazard Analysis

This section will cover a quantitative analysis of the pluvial and fluvial hazards based on the sub sub-indicators defined in the methodology: for the pluvial flood hazard, it involves the mean annual precipitation cumulative, the 95th percentile of precipitation, and soil permeability coefficients, while for the fluvial flood hazard, the analysis will focus on the return flows of 1.5 years and the average flow rates of rivers by region.

3.1.1 Pluvial Flood Hazard

This section focuses on the pluvial flood hazard, which is evaluated using three main sub-indicators: the mean annual precipitation cumulative, the 95th percentile of precipitation, and soil permeability coefficients. These elements help analyze the intensity and impact of rainfall on flood risks.

3.1.1.1 Annual Climatology of Guinea from 1984 to 2024

The analysis of the results of Figure 5 shows that Guinea experiences an average annual rainfall ranging from 1000 mm to nearly 3000 mm, depending on the region. Precipitation is more abundant in certain areas, particularly in the West, a coastal region, where rainfall exceeds 3000 mm, and in the South, a forested region, where rainfall exceeds 2000 mm. The interior and northern regions receive less rainfall, around 1000 mm.

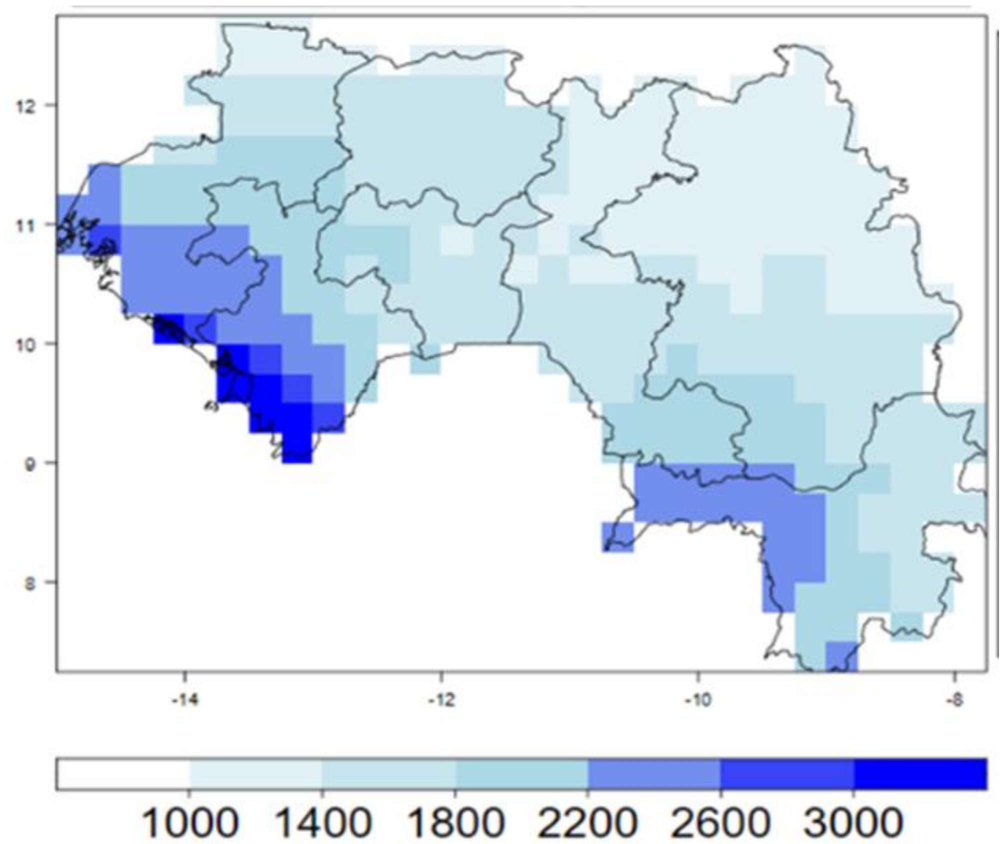


Figure 5: Average annual rainfall in Guinea in (mm)

3.1.1.2 Monthly Climatological Distribution in Guinea from 1981 to 2024

The analysis of the monthly rainfall distribution from 1981 to 2024 provides a detailed view of seasonal precipitation variations during this period. This seasonal distribution highlights the wettest months as well as the dry periods. As shown in Figure 6, the rainiest months are July, August, and September, corresponding to the wettest period (West African monsoon). The driest months are December, January, and March, during which rainfall is minimal. April, May, and June are the transitional months between the dry and rainy seasons.

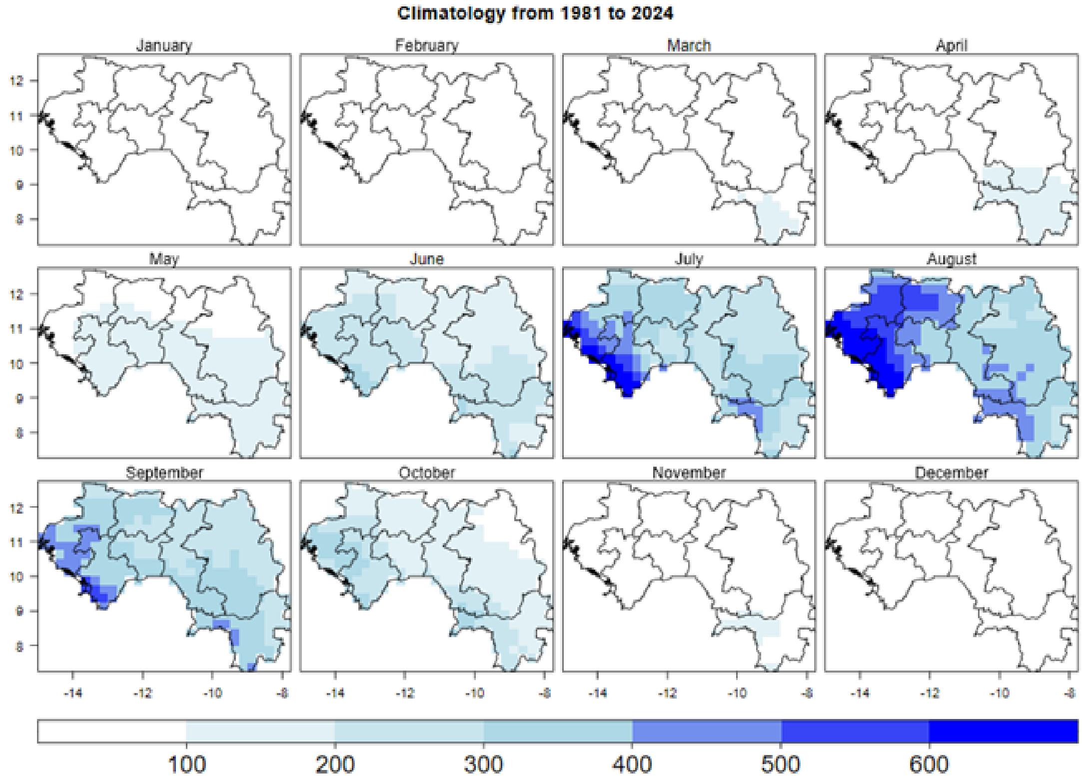
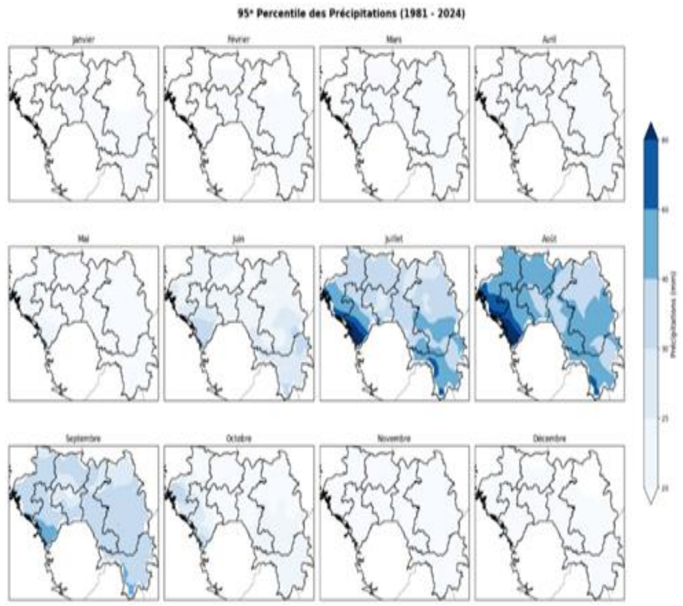


Figure 6: Climatology distribution from 1981 to 2024

3.1.1.3 95th Percentile Precipitation Indices

Geographical distribution analysis shows that the highest values of the 95th percentile are located in the west, particularly in the coastal area, and in the southwest, in the forested zones, indicating more extreme rainfall, as shown in Figure 8. In contrast, the center and east of the country exhibit lower values, suggesting few extreme rainfall events. Regarding seasonality, between November and April, extreme precipitation is very low, below 40 mm. However, between May and October, there is a gradual increase in rainfall starting in May, with particularly high values, peaking in August and July, where precipitation exceeds 100 mm, especially in the regions of Kindia, Conakry, and Boké. In September, rainfall decreases but remains significant, as shown in Figure 7.



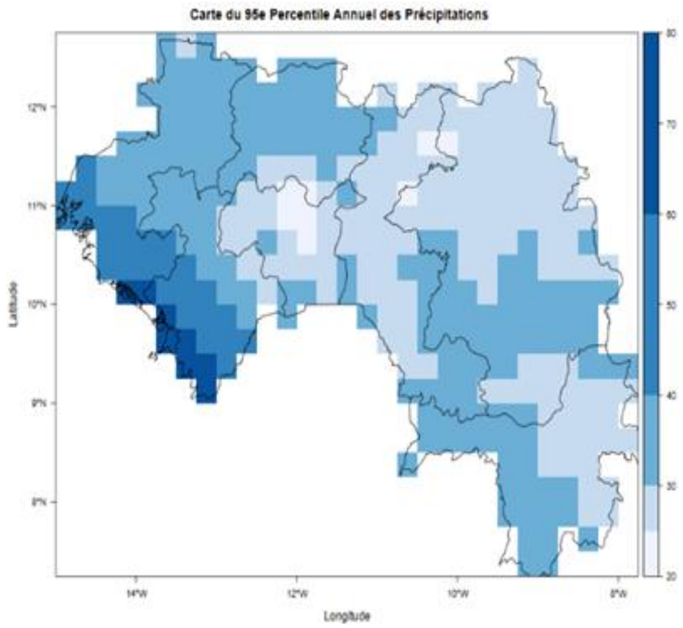


Figure 7:95th Monthly percentile of Precipitation

Figure 8:95th Annual percentile of Precipitation

3.1.1.4 Soil Permeability Coefficients Characteristics

Figure 9 shows the soil permeability by region. Boké, Labé, Kindia, and Conakry are characterized by very permeable soils with a coefficient ranging from -0.40 to -0.35, allowing for rapid water infiltration. Mamou and Faranah, with a range from -0.65 to 0.60, have moderately permeable soils that can retain a certain amount of moisture. Finally, Kankan and Nzérékoré have less permeable soils around -0.5, which limits water infiltration.

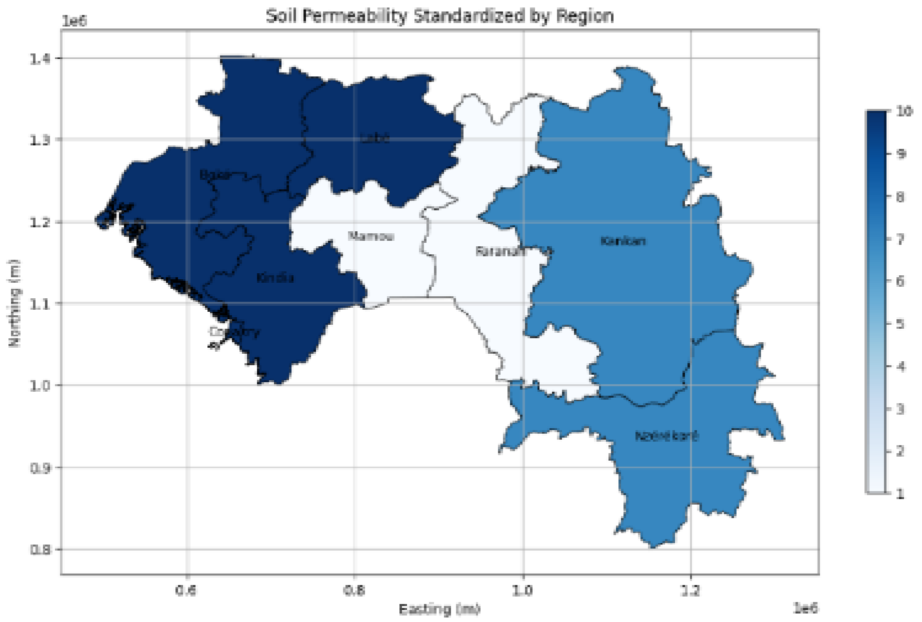


Figure 9: Soil Permeability by region

3.1.1.5 Composite sub-indicators of Pluvial Flooding:

Related to rainfall and the ability of soils to manage water, this hazard is particularly relevant in the context of flooding. The assessment is based on several important sub-indicators averaged over the area: the total mean annual precipitation, the 95th percentile of precipitation (which reflects extreme rainfall events often linked to floods), and soil permeability coefficients that indicate how well the soil can absorb and drain water. The analysis of the results of Figure 10, showing annual cumulative precipitation by region, reveals geographical disparities in the total annual rainfall amounts. Conakry stands out with high levels, surpassing Kindia, likely due to high rainfall, while northern regions like Labé, as well as the east and center (Kankan, Faranah), have lower amounts. The southern and northwestern regions show moderate levels.

As for the analysis of the results of Figure 11, of the 95th percentile of precipitation, marked disparities across Guinea are observed. Conakry has the highest value, indicating it experiences extreme rainfall events more often. Kindia follows with similarly high levels, reflecting intense and irregular rainfall. Boké and N'Nzérékoré register relatively high but more moderate values. In contrast, the regions of Kankan, Nzérékoré, Faranah, Labé, and Mamou show lower values, indicating less frequent and less intense extreme rainfall events. Regarding the results of Figure 12, of soil permeability by region, it is shown that Boké, Labé, Kindia, and Conakry have very permeable soils, allowing for rapid water infiltration. Mamou and Faranah have less permeable soils, capable of retaining a reasonable amount of moisture. Finally, Kankan and Nzérékoré have moderately permeable soils, which restrict water infiltration. Further, the analysis of the results of Figure 13, of the pluvial flood hazard shows that vulnerability to flooding varies significantly from region to region in Guinea. The regions of Faranah and Mamou are less exposed to the risks of pluvial flooding, meaning they are less likely to experience major flooding due to rainfall. In contrast, regions such as Labé, N'Nzérékoré, and Kankan have moderate vulnerability, indicating more frequent exposure to floods, though the risks are less severe than in other regions. Finally, Conakry is the most vulnerable, with higher risks of pluvial flooding, likely due to its higher rainfall. Kindia follows closely behind.

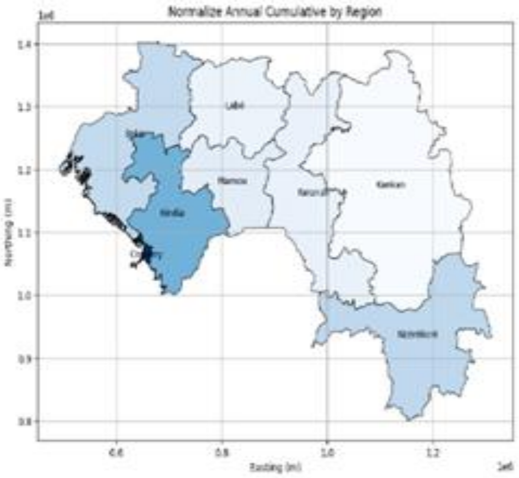


Figure 10: annual cumulative by region

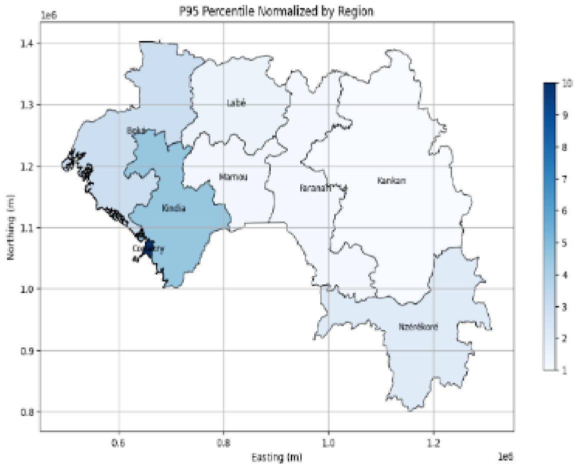


Figure 11: 195th Percentile by region

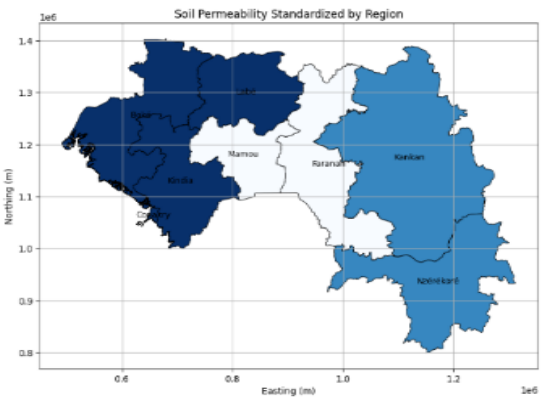


Figure 12: Soil permeability by region

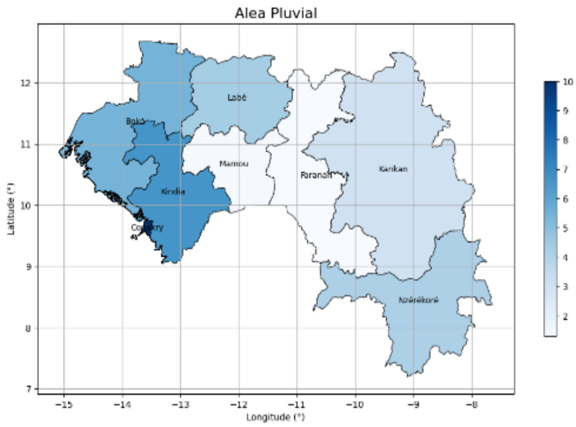


Figure 13: Rainfall flood hazard

3.1.2 Fluvial Flood Hazard

The fluvial flood hazard is assessed based on two main sub-indicators: the 1.5-year return flows, which measure the frequency of major floods, and the average river flows by region, which help assess the amount of water carried by rivers. These sub-indicators help understand the flood risks associated with waterways.

3.1.2.1 Average River Flow

Several major rivers flow through Guinea, including the Niger, Senegal, Gambia, Sankarani, and Konkouré. In connection with the rainfall regime, river flow exhibits significant seasonality. The analysis of river flow shows that Figure 14 illustrates the variations in average annual flows across different regions, highlighting areas with more or less significant hydrological flows. The Boké region, located in the Northwest, experiences the highest flows, followed by Kankan in the East, which also has significant flows. In contrast, Mamou and Conakry have relatively low flows, while the regions of Nzérékoré in the South, Labé in the North, and Faranah in the center display moderate flows.

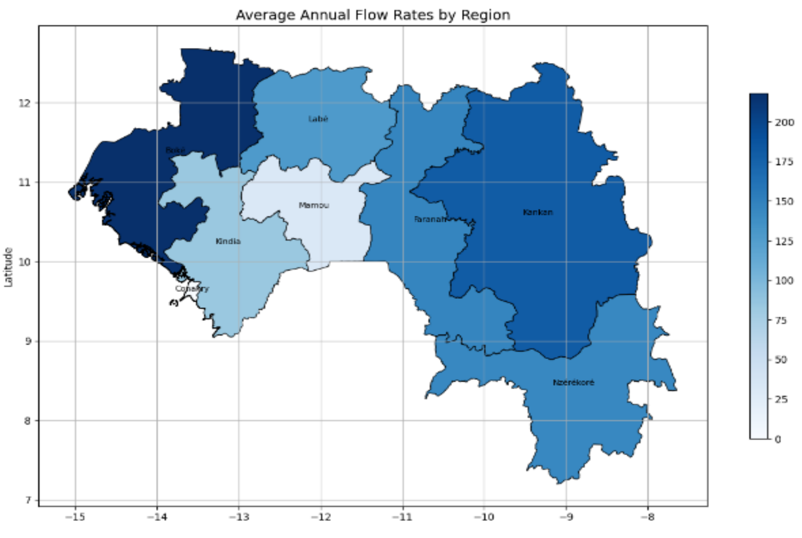


Figure 14: Average annual Flow rates by region

3.1.2.2 Extreme Flows and River Water Levels Based on GloFAS 1.5 (m^3/s)

The analysis of hydrometric stations reveals that flows vary significantly throughout the year. Extreme river floods are characterized by the return levels of river flow according to GloFAS and the water levels measured by the DNH. Looking at the results of Figure 1.5, the

GloFAS return level data provide a better understanding of the extreme water levels in Guinea's water bodies. It can be observed that Labé, located in the northern part of the country, experience less frequent extreme events, with a return level of 2 years, indicating a lower risk but potentially more severe impacts when these events occur. Boké and Mamou follow. In contrast, Kankan, Faranah, and Nzérékoré, located in the central and southern parts of the country, have shorter return level, close to 1 year or less, meaning these regions experience extreme events more frequently, thus exposing them more to flood risks.

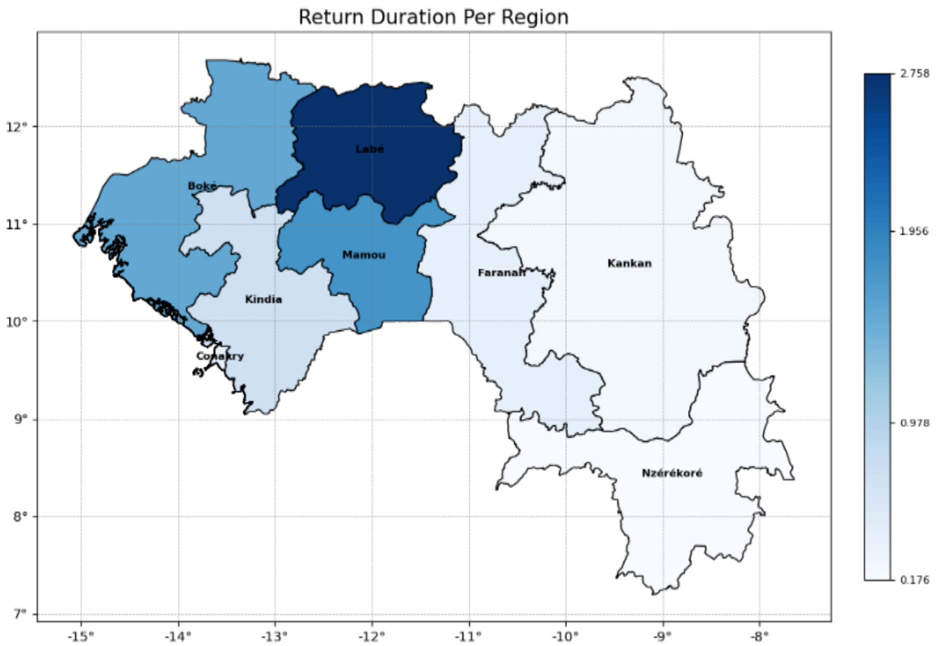


Figure 15: GloFAS Return Period Levels

<u>3.1.2.3 Composite sub-indicators of Fluvial Flooding:</u>

The analysis of the fluvial flood hazard involved equally weighting all sub-indicators, applying a process similar to that of the pluvial hazard. The data used includes return level as well as average river flows by region. This information was combined, normalized, and the regional average was calculated. The analysis of the results of Figure 16, of the average annual flow shows the distribution of the mean annual flow by region in Guinea. Conakry and Mamou have relatively low flows, with values close to 1 m³/s. Boké records the highest flows, with values ranging between 9 and 10 m³/s, followed by Nzérékoré, with values around 7 m³/s. Other areas, including Kankan, Kindia, Labé, and Faranah, have medium river flows between 2 and 6 m³/s.

As for the analysis of the results in Figure 17, return level by region in Guinea with a threshold of 1.5 years according to GloFAS, indicating the frequency of extreme events, it shows that Boké and Mamou experience extreme events less frequently, with return level over 1.5 years, meaning that extreme events are less frequent there. Labé also has less frequent extreme events, but with potentially more severe impacts when they occur. In contrast, regions like Conakry, Kindia, Faranah, Kankan, and Nzérékoré have return level close to 1.5 years or less, indicating that these regions experience extreme events more frequently, thus exposing them more to flood risks.

The analysis of the results of Figure 18, of the river flood hazard, shows that Conakry has a very low, almost negligible, fluvial risk level, indicating low exposure to fluvial floods. In contrast, the regions of Labé and Boké have a very high-risk level, meaning they are highly vulnerable to flooding. Ultimately, Kindia, Mamou, Kankan, Faranah, and Nzérékoré are classified as moderate-risk regions, showing a medium level of exposure to river flood hazards experiencing fewer extreme events than high-risk areas but more than those with low risk.

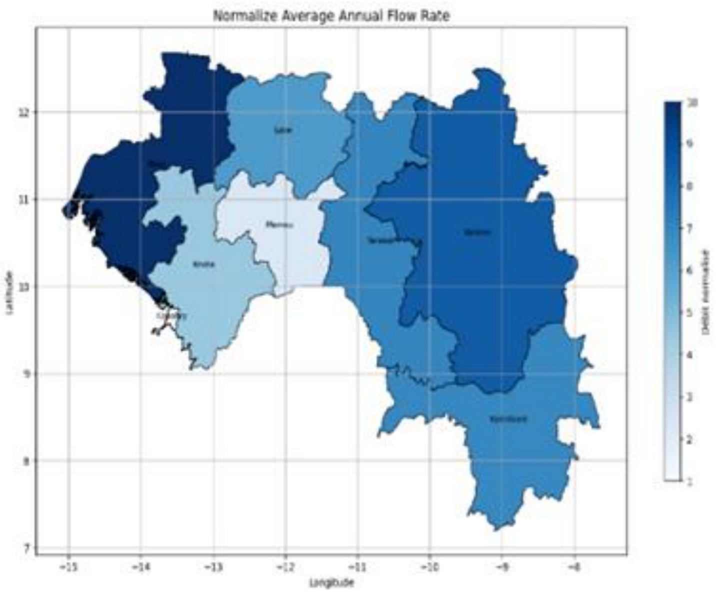


Figure 16: Average Annual Flow by Region (m3/s)

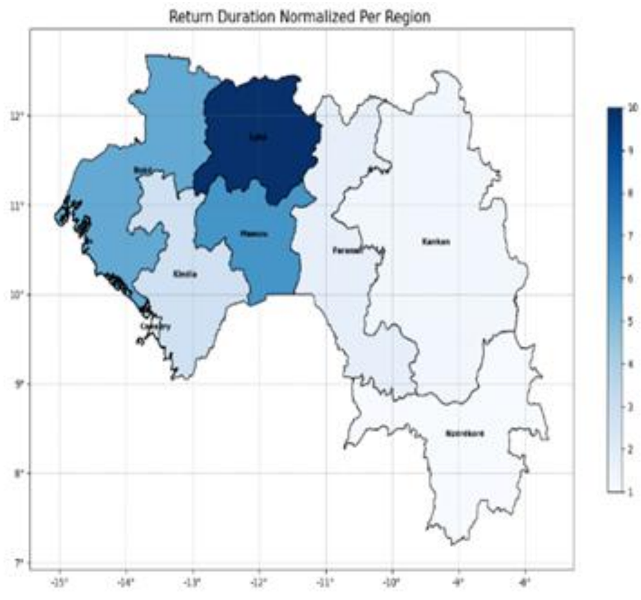


Figure 17: Return Time Level Based on GloFAS

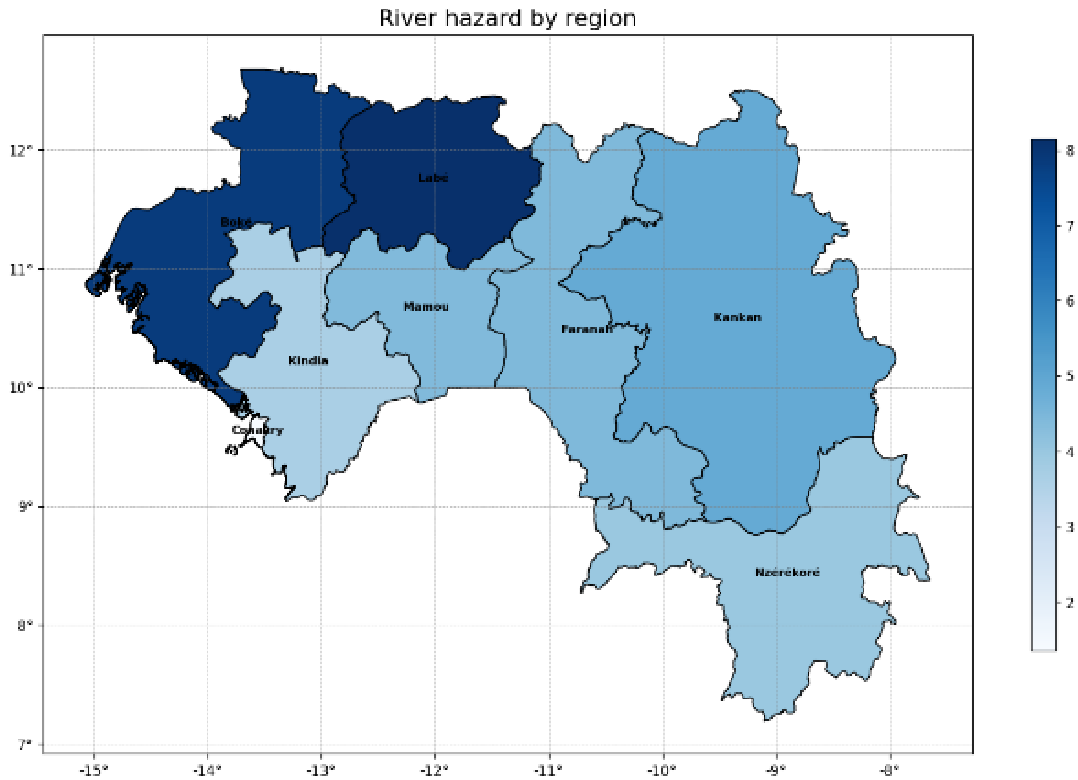


Figure 18: River Flood Hazard

3.1.3 Exposure

This section shows the results of evaluating exposure to river flood risks across various regions in Guinea. Exposure was measured using various sub-indicators, such as the human population, agricultural lands, and livestock. These normalized results are presented by region to identify the most vulnerable areas and better guide risk management actions. The analysis of the results of Figure 19, representing the population by region, highlights the demographic disparities across the country's different regions, where: Kankan stands out as the region with the highest population, followed by Conakry, Kindia, and Nzérékoré, which also have relatively large populations. In contrast, Mamou is the region with the lowest population, while regions like Boké, Labé, and Faranah have moderate populations, but less dense than those in other regions.

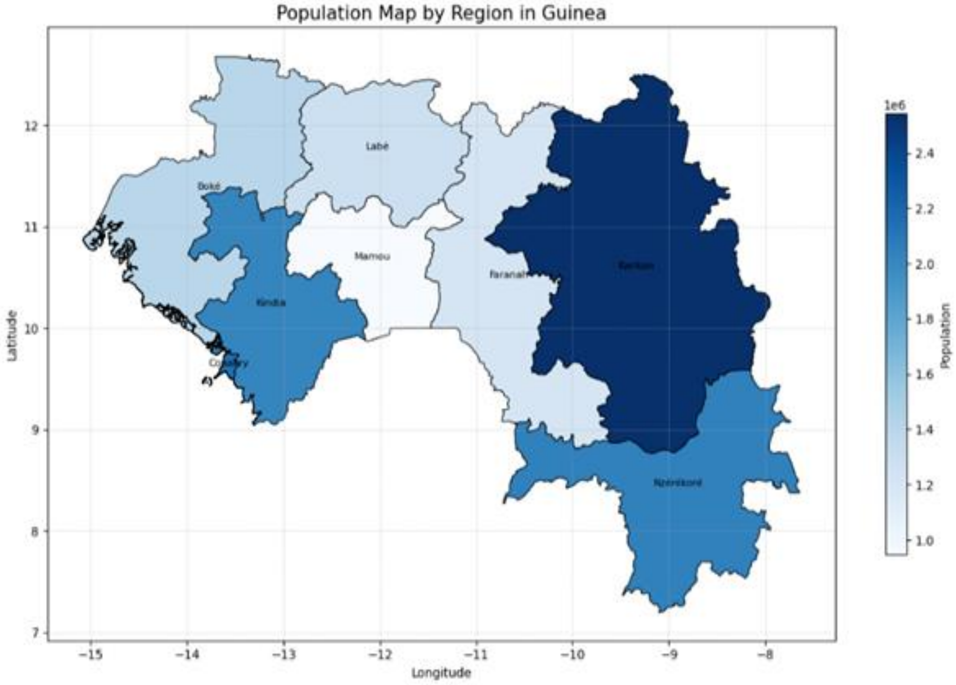


Figure 19: Population by Region

The analysis of the results of Figure 20 shows that the exposure of agricultural land, with sub-indicators such as sweet potatoes, peanuts, rice, maize, fonio, and millet, reveals variations across regions. Conakry, with the smallest cultivated areas, shows low exposure due to its lack of large-scale agricultural activity and its urbanization. Kankan, on the other hand, has high exposure, linked to large agricultural areas. Nzérékoré, Faranah, Kindia, and Boké are moderately exposed. The regions of Labé and Mamou also have limited areas, but their exposure is slightly higher than that of Conakry due to more agricultural activity.

The analysis of the results of Figure 21, shows that the Nzérékoré region has the highest animal exposure, including goats, cattle, sheep, and pigs, among all regions, with the largest number of animals. It is closely followed by Mamou and Boké, which also have significant animal exposure, though slightly lower than Nzérékoré. In contrast, Conakry, due to its high level of urbanization, has very low animal exposure, with the smallest number of animals. Finally, the regions of Labé, Kankan, Faranah, and Kindia have moderate animal exposure, with varying levels, but generally less concerning than those of Nzérékoré, Mamou, and Boké.

The study of the results of Figure 22, on exposure reveals that the region of Kankan bears the highest level of exposure among all regions, while the regions of Nzérékoré, Kindia, and Conakry show lower exposure than Kankan. The regions of Boké, Labé, and Faranah show a moderate level of exposure, while Mamou has the lowest, almost negligible, exposure level, indicating low vulnerability to flood risks.

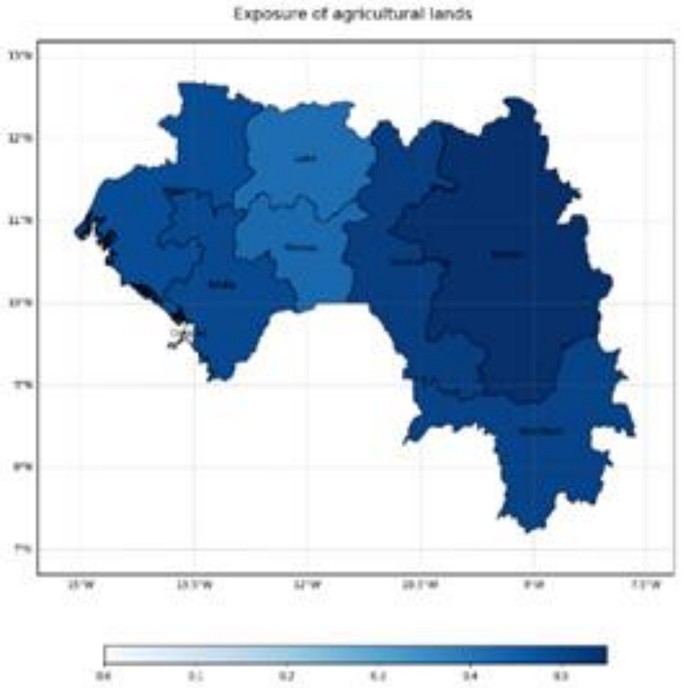


Figure 20: Normalized Agricultural Land Exposure

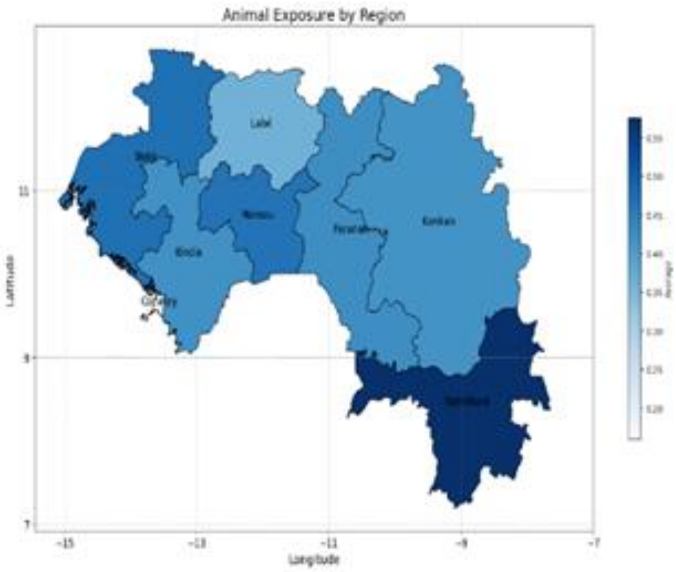


Figure 21: Animal Exposure normalized by region

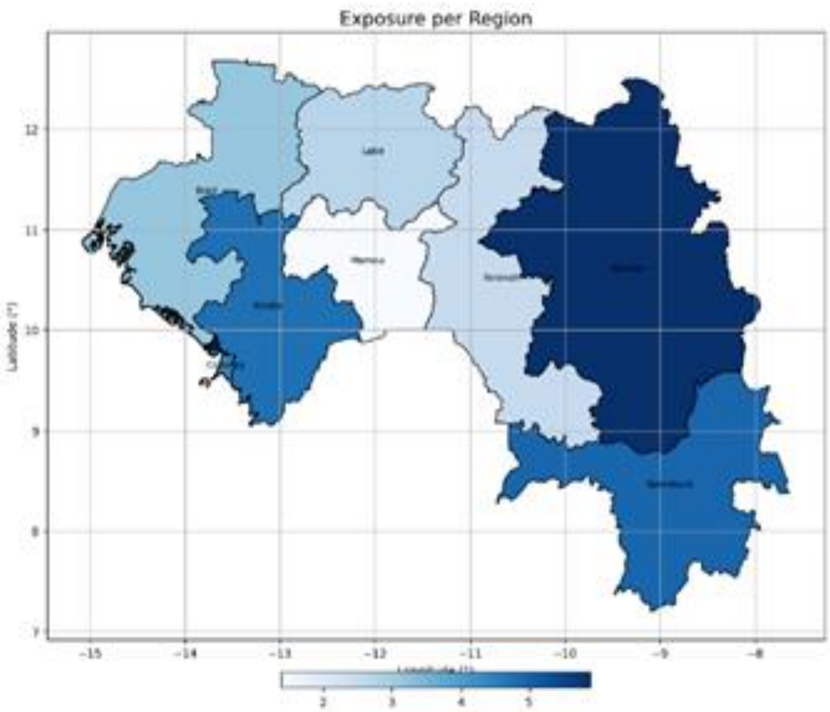


Figure 22: Final Exposure

3.1.4 Vulnerability:

In this part, we show how different regions in the country are affected by flood vulnerability. Vulnerability is analyzed through several dimensions, including the MPI group, the housing-related vulnerability group, the people group, and the livelihoods group, each with its sub-indicators. The analysis of the results of Figure 23, of the Multidimensional Poverty Index (MPI) by region reveals notable variations across the country. The regions of Labé and Faranah show high levels of multidimensional poverty, while Conakry stands out with the lowest poverty level compared to all regions, which is also less affected by poverty. The regions of Nzérékoré, Boké, Mamou and Kankan a show relatively moderate levels of poverty compared to other regions.

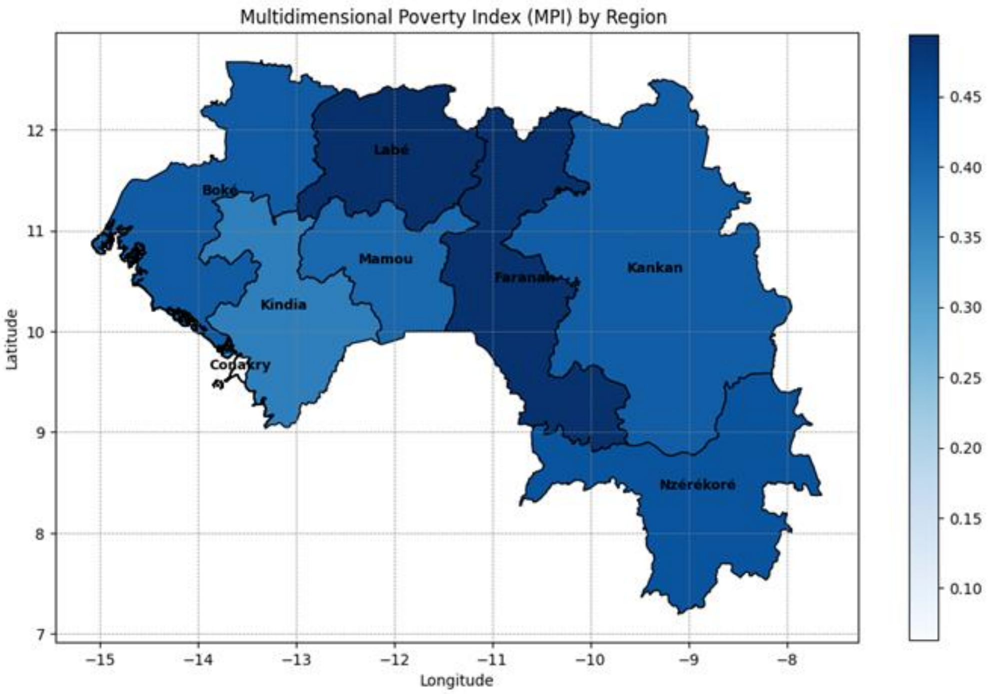


Figure 23: MPI by Region

The analysis of housing vulnerability in Figure 24, with sub-indicators such as thatched roofs and mud houses, shows that Conakry is the most exposed region, followed by Kindia, Mamou, Labé, and Kankan, which have lower vulnerability than Conakry. This reflects difficult living conditions, likely due to a lack of infrastructure. In contrast, the regions of Boké and Faranah show intermediate vulnerability, although lower than Kankan and Kindia. Finally, the Nzérékoré region in the south has low vulnerability, suggesting better living conditions compared to other regions in the country. This figure highlights the need for targeted interventions in the most exposed areas.

The analysis of the results of Figure 25 illustrates the vulnerability levels of vulnerable people, with its sub-indicators being: children under 4 years old, people over 65 years old, and people living with disabilities, by region, and reveals significant disparities. Kankan, in the northeast, stands out with the highest vulnerability levels, indicating particularly high exposure to risks. In contrast, Mamou shows very low vulnerability levels, signaling a lower exposure to threats. Conakry, Kindia, and Nzérékoré show moderate levels, suggesting a less severe but still present exposure to risks. Regions like Faranah, Boké, and Labé, although exhibiting higher vulnerability than Mamou, still require special attention.

The study of the livelihood Figure 26, consisting of sub-indicators such as the rate of inactive people and the number of farmers, shows that the regions of Conakry, Mamou, and Kankan have low vulnerability, meaning it is less exposed to things that make floods worse. Faranah, although close to these two regions, also shows less vulnerability. The regions of Boké and Nzérékoré have moderate vulnerability, while the Kindia region stands out with the highest vulnerability, followed by Labé, which also has high vulnerability, although slightly less pronounced.

The analysis of the results of Figure 27, vulnerability reveals that the most vulnerable areas of the country correspond to the regions of Labé, Faranah, and Kankan, which have high vulnerability. The moderately vulnerable areas include the regions of Kindia, Boké, N'Nzérékoré, and Mamou, characterized by moderate vulnerability. Finally, the region of Conakry stands out with low vulnerability, making it the least exposed to risk.

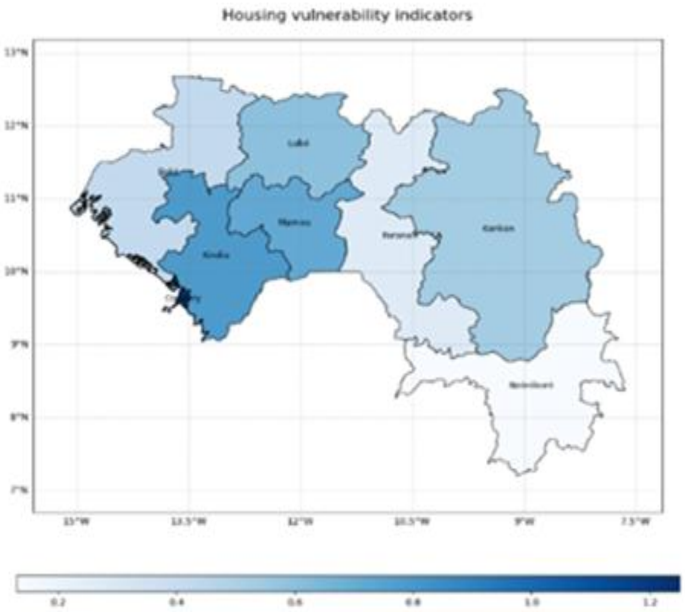


Figure 24: Normalized Vulnerability of Housing

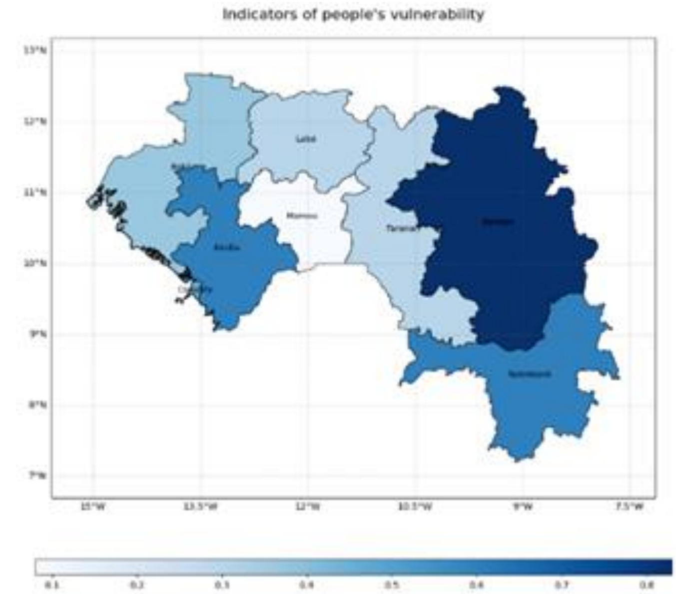


Figure 25: Normalized Vulnerability of People

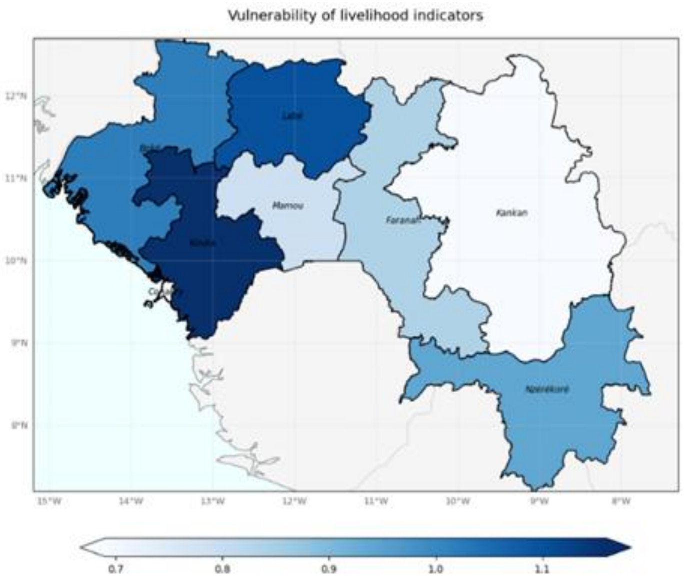


Figure 26*: Livelihood Vulnerability*

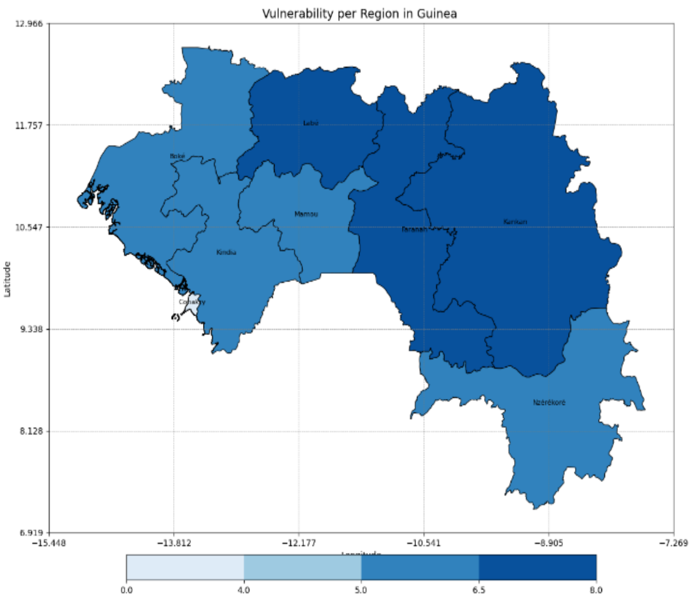


Figure 27*: Vulnerability by Region*

3.1.5 Lack of Adaptation Capacity

This section presents the main results from the analysis of the sub-indicators used to assess the lack of adaptation capacity in the regions, often related to limited access to information, education, and essential infrastructure. The analysis of the results in Figure 28, of the communication group, shows the following: Figure 28 shows that Labé and Nzérékoré have the best communication indicators, as they probably have more community radios and good access to information. Mamou has a medium level, while Kankan, Faranah, Boké, and Kindia are less well served in terms of communication. As for Conakry, it has a very low score, which could be explained by the centralization of media or a lack of local radios, despite being the capital.

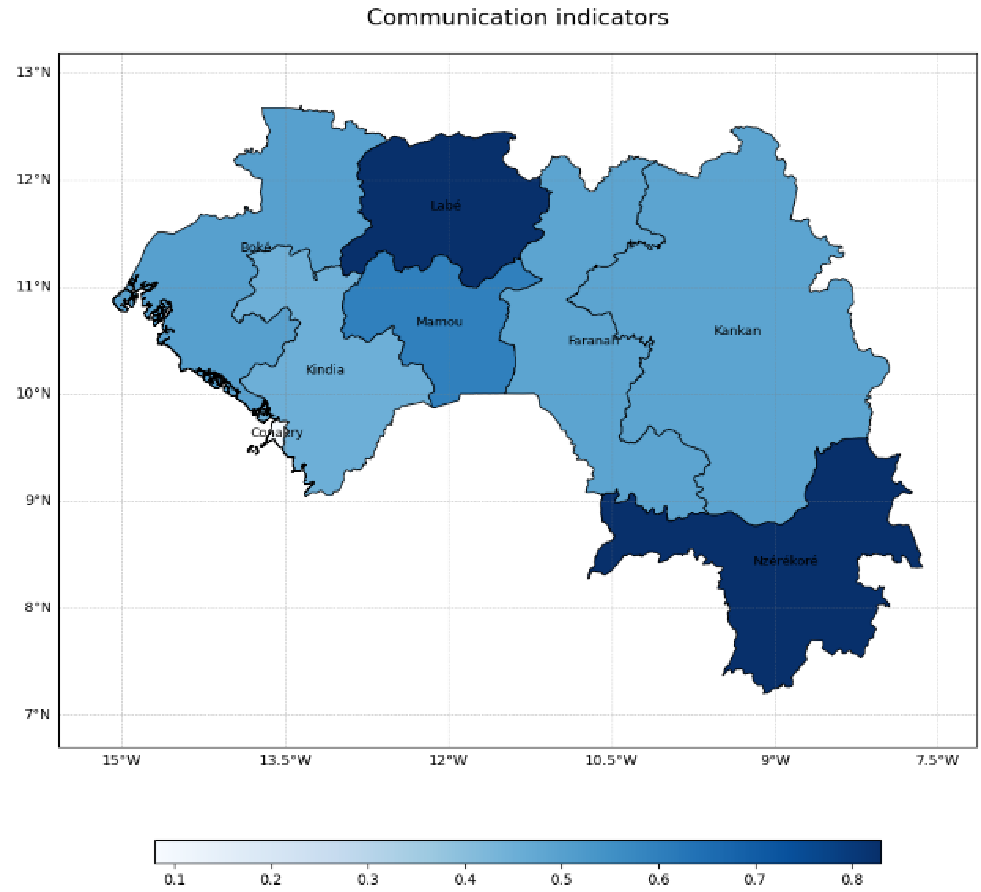


Figure 28: Communications Indicators

The analysis of the infrastructure sub-indicators in Figure 29, which include schools, health posts, and health centers, reveals the following points: Regarding general infrastructure, the Conakry regions record the lowest scores, indicating underdeveloped infrastructure, followed by Kindia, Boké, and Kankan. In contrast, Labé and Mamou present the highest scores, meaning they have the best infrastructure. As for other infrastructures, it has been observed that Nzérékoré and Faranah have the best moderate infrastructure and other essential services, while Nzérékoré and Faranah show more moderate infrastructure levels. The most vulnerable areas in terms of infrastructure remain in regions with low scores, such as Conakry and Nzérékoré.

The analysis of the disaster management sub-indicators in Figure 30 reveals marked differences between regions. Mamou and Conakry are the most advanced, with well-equipped rescue brigades, suitable structures, and internet access that allows for quick crisis management. Labé and Kindia follow with strong capacities, but are less optimized than those of Mamou and Conakry, particularly in terms of logistics and equipment. Kankan stands out with a lower level of disaster management, with limited resources in terms of emergency vehicles and infrastructure. Finally, the regions of Nzérékoré, Faranah, and Boké have moderate management, with rescue infrastructures in place but facing challenges in equipment and accessibility, particularly in terms of internet access and material resources.

The analysis of the results in Figure 31, regarding the lack of adaptation capacity, reveals significant regional disparities. The regions of Labé and Mamou stand out with the highest adaptation capacities. The region of Nzérékoré has an intermediate adaptation capacity, although lower than that of Labé and Mamou. The regions of Kindia, Conakry, and Faranah show a moderate level, while Kankan and Boké have the lowest adaptation capacity levels, indicating greater vulnerability to shocks and disasters.

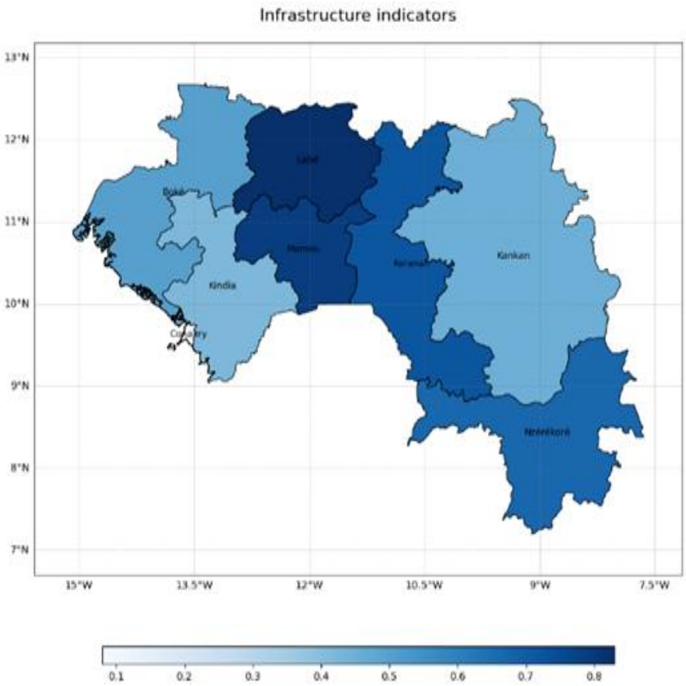


Figure 29: Normalized Infrastructure Sub-Indicators

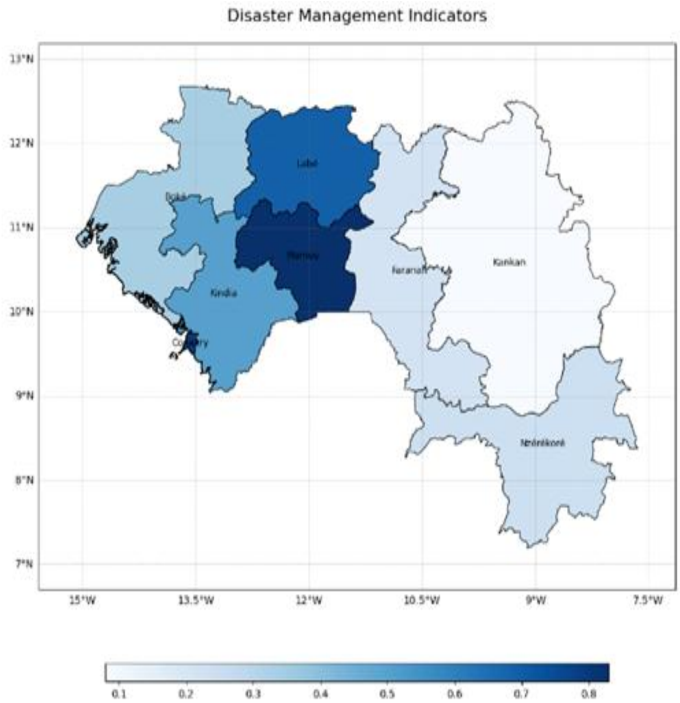


Figure 30: Normalized Disaster Management Sub-Indicators

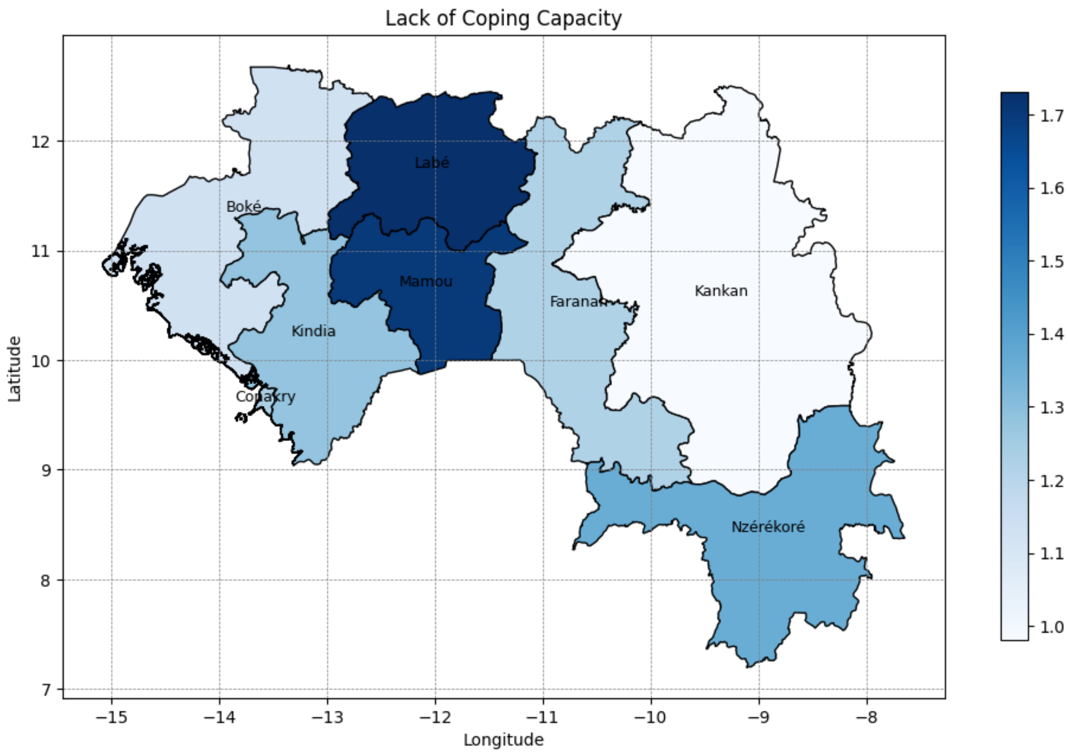


Figure 31: Lack of Coping Capacity Map

1.6 Risk assessment

At this stage, this section presents the main results of the risk assessment. It focuses on two major types of flooding identified: pluvial risks and fluvial risks.

3.1.6.1 Pluvial Flood Risk

In the context of our study, the pluvial risk was assessed by combining four main indicators: the pluvial flood hazard, exposure, vulnerability, and lack of adaptation capacity. This combination enables the creation of an overall index that synthesizes the risk level each region faces in relation to extreme precipitation. The analysis of the results in Figure 32, on pluvial risk, reveals marked disparities between regions. The region of Kindia displays a very high risk due, a high river overflow exposure. In contrast, Faranah and Mamou show a very low risk, which can be explained by geographic characteristics such as topography and rainfall. The regions of Nzérékoré, Conakry, and Labé fall into an intermediate zone with moderate risk.

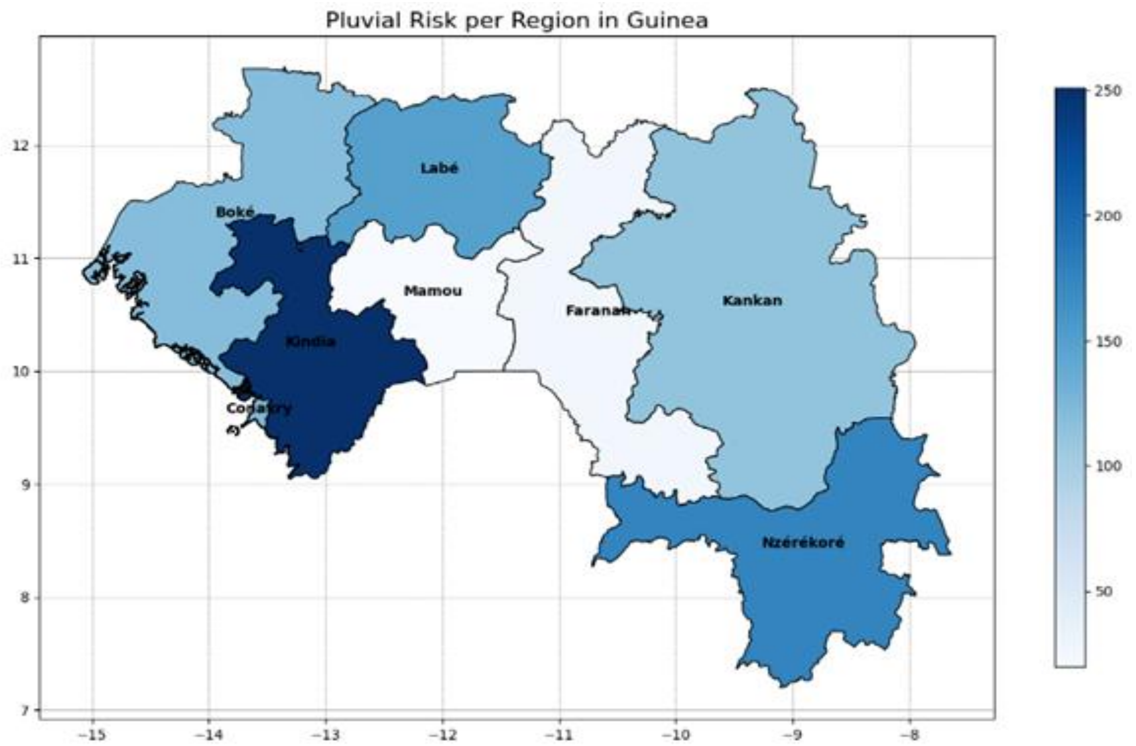


Figure 32: Map of pluvial flood

3.1.6.2 Fluvial Flood Risk

Similar to pluvial flooding, the risk of fluvial flooding heavily depends on the choice of vulnerability indicators. It was assessed by crossing four essential indicators: the fluvial flood hazard, exposure, vulnerability, and lack of coping capacity. This approach contributed to generating a synthetic risk index, taking into account the environmental, social, and institutional realities specific to each region. The analysis of the results in Figure 33, from this evaluation, showed that Guinea presents varying levels of fluvial risk across regions. The regions of Kankan, Nzérékoré, and Kindia stand out with very high flood risk. In contrast, Boké, Faranah, and Labé have a moderate risk. The regions of Conakry and Mamou, on the other hand, show very low risk, mainly due to their topography, the absence of large rivers, and their specific rainfall characteristics, which significantly reduce their exposure to river floods.

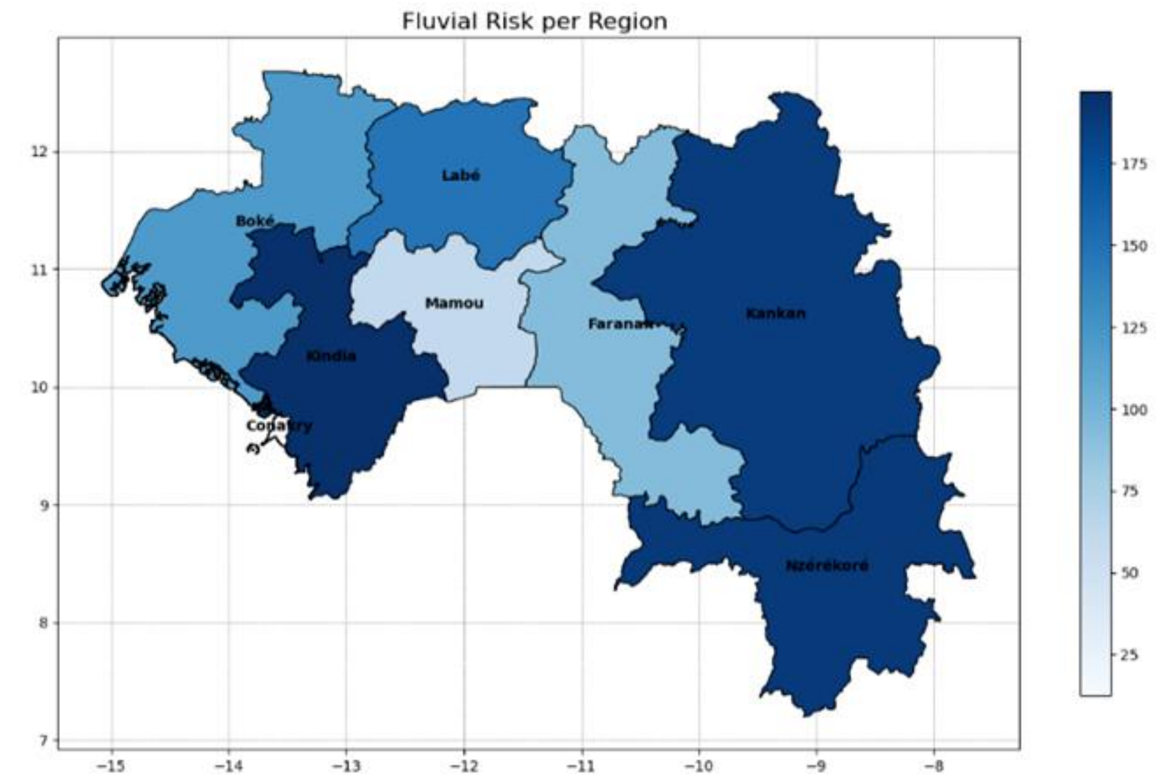


Figure 33: Map of fluvial flood

3.2 Discussion

The analysis of the relationship between rainfall events and flooding in Guinea shows a significant geographic and seasonal variability in rainfall. Annual rainfall varies from 1000 mm in the north to over 3000 mm in the south. The wettest months, from June to September, are associated with extreme rainfall, while the dry season lasts from December to March. These results are consistent with previous studies on rainfall in West Africa. For example, studies conducted in Sierra Leone and Liberia (Wadsworth et al., 2019; World Bank, 2021) also found a high concentration of rainfall in coastal areas and significant seasonal variability. These variations could be linked to climatic factors, such as the monsoon, as well as the country's topography, especially in the southeast, where the soil might increase the duration and intensity of rainfall. This supports findings from other related works (Le Lay & Galle, 2005; Diop et al., 2025; Sambou et al., 2020; Loua, 2020; Tewa, 2020).

Additionally, the analysis of river flow variations in Guinea has helped to better understand the impact of rainfall patterns on hydrological flows in different regions of the country. River flow seasonality, closely linked to rainfall, varies significantly from one region to another. Studies carried out by Camara et al. (2021) on the Tinkisso River in Guinea show marked variations in flow depending on the rainy seasons, with peaks during the wet season. However, according to a study by Ndiaye et al. (2020), the areas of Conakry and Mamou have relatively low flows, likely due to their topography and more moderate rainfall, unlike regions such as Boké and Kankan, where flows are much higher.

The analysis of soil permeability in the study of flood risks shows that very permeable soils, like those in Boké, Labé, Kindia, and Conakry, facilitate water infiltration but could lead to rapid runoff during heavy rains. While permeable soils are effective for infiltration, they can cause quick runoff when saturated, as confirmed by Kassim et al. (2020). On the other hand, less permeable soils in Kankan and Nzérékoré increase flood risk by limiting water infiltration, which is confirmed by Diallo et al. (2018) in their research.

Moreover, the statistical analysis of return level revealed that GloFAS data show Mamou and Labé, located in the north, experience less frequent extreme events (a return level of 2 years), with a lower risk but potentially severe impacts. In contrast, Kankan, Faranah, and Nzérékoré, in the center and south, have shorter return periods (close to 1 year), making them more exposed to frequent flooding. These results align with those of Bodian et al. (2020), who observed similar trends in the Senegal River basin, and Biao (2017), who studied river discharge dynamics in the Ouémé basin in Benin, highlighting significant variations linked to climate change.

The analysis of the pluvial flood hazard reveals a strong geographical disparity in flood vulnerability across Guinea, closely tied to rainfall and the soil's ability to absorb water. Coastal regions such as Conakry and Kindia have high rainfall levels, making them particularly vulnerable to extreme rainfall events. This phenomenon is well-documented in the research of Yéro et al. (2020), who observed that in high-rainfall areas, return level for extreme events are short, thus increasing the risk of frequent flooding. In contrast, northern and central regions like Kankan, Faranah, and Labé experience moderate rainfall and longer return level for extreme rainfall, explaining their moderate vulnerability to floods. This trend is corroborated by Tefera et al. (2024), who studied rainfall variability in West Africa, highlighting significant regional variations in precipitation and droughts, even in areas less exposed to extreme events.

However, the analysis of the fluvial flood hazard in Guinea reveals a contrasting spatial distribution of average annual flows. Boké records the highest flows (9–10 m^3/s), while Conakry presents values close to 1 m^3/s. This heterogeneity illustrates the complexity of regional hydrological processes. As observed by Bodian et al. (2016) in their findings, anthropogenic modifications of West African watersheds are transforming natural hydrological regimes, amplifying flood risks even during moderate rainfall events. The field observations confirm this hypothesis with the occupation of riverbeds and the obstruction of channels by waste. According to recent studies on Flood Management in Africa (2024) indicates that the illegal occupation of flood-prone areas is the main factor exacerbating fluvial risks, turning natural floods into urban disasters.

The analysis of flood risk exposure in Guinea reveals marked spatial disparities between regions, reflecting both the demographic, agricultural, and pastoral dynamics of the country. These disparities help identify the areas where the potential impacts of flooding would be most severe, in terms of both population affected and economic losses. The results show that Kankan is the most exposed region, combining a high population density, a vast area of cultivated agricultural land, and large livestock populations. This triple exposure makes the region particularly vulnerable to hydrological hazards. These findings align with those of Dao et al. (2024), who indicated that rural areas in West Africa, heavily dependent on rain-fed agriculture and pastoralism, are particularly vulnerable to climate shocks. In contrast, Conakry, despite its high population density, shows very low exposure to fluvial risks due to the absence of agricultural land and livestock. Similarly, Etengola Efeno et al. (2025) confirmed that densely populated urban areas, but with little involvement in agro-pastoral activities, show lower vulnerability to river-related flooding risks, although they remain exposed to other types of risks (runoff, soil saturation, etc.). Regarding livestock, the regions of Nzérékoré and Mamou host significant numbers of cattle and pigs, which would increase their economic and food security. The significant concentration of livestock in the regions of Labé and Boké, especially goats and sheep, would heighten their vulnerability to prolonged flooding. This situation is corroborated by the work of Ache Billah et al. (2024), who state that livestock loss during floods can lead to rapid impoverishment of households and harm community resilience. The analysis of agricultural land reveals that essential crops such as maize, fonio, peanuts, and cassava are highly exposed to flood risks in rural areas. This situation is in line with the findings of Dao et al. (2024), who emphasize the direct link between cultivated land in flood-prone areas and the severity of agricultural losses during rising waters.

The results of the analysis of the vulnerability of Guinea's regions to flooding show an uneven distribution, influenced by several dimensions such as multidimensional poverty, housing characteristics, demographic structure, and livelihoods. These factors reveal that some regions combine multiple vulnerability factors, thus increasing their fragility in the face of hydrometeorological disasters. The regions of Labé, Faranah, and Kankan appear to be the most vulnerable. This observation is reinforced by their high poverty rates, the significant proportion of houses made from poor materials (earth, thatched roofs), and the concentration of at-risk groups such as children under 4, the elderly, and people with disabilities. These findings align with the conclusions of Uwayisenga et al. (2025) in their Rwandan study on the vulnerability of rural households, which demonstrates that poor rural households are strongly affected by the lack of solid infrastructure. In contrast, Conakry stands out with relatively low vulnerability, due to better sub-indicators in housing, poverty, and agricultural dependence. However, this low material vulnerability does not mean the absence of risks, as the density of the urban population could exacerbate the effects of pluvial flooding, as confirmed by Dada, Almar & Morand (2024). For West African coasts, urban areas with high human density could remain exposed, particularly through impacts related to urban runoff. Furthermore, the analysis of the livelihoods group indicates that the rates of inactive people are particularly high in certain regions, suggesting an increased reliance on external aid or the informal economy, which worsens the situation in times of crisis. This profile aligns with the work of Collins & Cutter (2025), who show that social vulnerability is multidimensional and adjusted based on dependence on natural resources and the quality of housing. In contrast, the high proportion of farmers in regions such as Kindia, Kankan, and Labé increases their exposure to the direct impacts of flooding on production systems. As Ache Billah et al. (2024) state in their studies, any effective response to climate risks in West Africa must be rooted in a deep understanding of local vulnerabilities, integrating social, economic, and physical dimensions.

The results obtained from the analysis of the marked disparities in adaptation capacity, influenced by limited access to information, education, and essential infrastructure, show significant variations. For example, Labé has the highest number of rural and community radios but has the weakest road coverage, which would limit mobility and quick access to emergency services in the event of a disaster. Conakry, although benefiting from the highest density of paved roads and recording the highest literacy rate, has a low number of radios and health infrastructure. These disparities could be linked to the unequal distribution of resources and services between urban and rural areas, thus affecting resilience to flooding. This situation aligns with the findings of Sahani (2012), who showed that regions exposed to natural disaster risks, like floods, are often characterized by inadequate infrastructure and limited access to information. This is also supported by the work of Salehnia et al. (2020), which confirms that access to risk management infrastructure, such as rescue brigades and internet access, enhances adaptation capacity by enabling faster and better-informed responses to natural disasters. These findings are consistent with the conclusions of Armah et al. (2015), which emphasize the importance of diversifying infrastructure and improving access to information and health services to strengthen resilience to flooding.

The analysis of pluvial flood risk reveals marked disparities between regions. Kindia, Conakry, and Nzérékoré show a very high risk, which could be linked to their intense rainfall and exposure to overflow. This observation is confirmed by Foucher et al. (2022), who emphasize that areas with high rainfall and direct exposure to floods are more vulnerable to flooding. In contrast, Kankan and Boké present a moderate risk, due to significant rainfall but with more favorable geographical characteristics. Coulibaly et al. (2022) confirm that areas with moderate relief and better soil infiltration capacity are less exposed to flooding. Finally, Mamou and Faranah present the lowest risks, thanks to relief and rainfall conditions more suitable for water infiltration.

As with pluvial flooding, the risk of fluvial flooding heavily depends on the choice of vulnerability indicator. Using the composite vulnerability index, the regions of Kankan, Nzérékoré, and Kindia show the highest risks due to a strong correlation between vulnerability and exposure to river floods. Thus, these regions are the most at-risk areas in the country. At the bottom of the ranking, the regions of Conakry and Mamou show the lowest risks, mainly due to their specific topography that limits exposure to river overflow. A somewhat different ranking is obtained when poverty is used as a vulnerability indicator. Here, in addition to the high-risk regions mentioned above, Boké also presents a significant risk. For Kankan and Nzérékoré, the risk is primarily due to the high exposure created by major rivers, while for Boké, it is mainly the high poverty rates that constitute the primary explanatory factor. These observations are confirmed by the World Bank report (2020), which states that areas with a high population density of poor people are more vulnerable to flooding due to the lack of infrastructure and adaptation capacities. However, this relationship is nuanced by the IMF report (2024), which contradicts the idea that poverty is the only explanatory factor, emphasizing that climate policies and effective risk management can reduce vulnerabilities regardless of poverty. Additionally, the We Are Water Foundation (2021) supports this idea, stating that infrastructure management and climate adaptation systems play a major role in reducing vulnerability to floods.

It follows from the above that the regions of Guinea most affected by pluvial flooding are Kindia, Conakry, and Nzérékoré, while for fluvial flooding, the most affected regions are Kindia, Kankan, and Nzérékoré. The region of Kindia is the only one likely to be affected by both risks, meaning it presents the highest risk. After Kindia, Nzérékoré follows, also being highly exposed, but to a lesser extent than Kindia.

CONCLUSION AND PERSPECTIVES

This master's research enabled a detailed and structured analysis of flood risk in Guinea, with the primary objective of studying flood anticipatory actions in Guinea through data-driven risk assessment methodologies. The study confirmed that anticipatory actions can indeed help reduce the impact of floods by identifying vulnerable areas in advance and enabling the implementation of rapid response strategies. The main hypothesis that anticipatory actions can mitigate flood risks and their impacts in Guinea was validated through the use of climatic, hydrometric, and socioeconomic data to detect high-risk areas. However, the variability of results depending on the choice of vulnerability sub-indicators highlights the need to refine these components further in order to improve future analyses. To build on the work initiated in this master’s program, future research should focus on the following areas: the development of predictive models integrating machine learning algorithms for real-time flood forecasting; the integration of community-based early warning systems, particularly in peri-urban and rural areas; the inclusion of qualitative data from field surveys to better understand social vulnerabilities and community adaptation mechanisms; and the validation of results with local institutions to strengthen institutional frameworks and improve the implementation of anticipatory protocols. Moreover, the study highlighted structural challenges related to the availability and accessibility of data. Overcoming these obstacles will be essential to operationalizing early warning systems and transforming anticipatory frameworks into concrete disaster risk reduction tools.

The work carried out in this thesis thus provides a solid foundation for applied research, public policy development, and operational planning. It could be expanded within a doctoral program by integrating multi-hazard modeling, a cost-benefit analysis of anticipatory measures, and the use of real-time data from participatory. Such an extension would enhance the relevance and accuracy of flood risk management tools and contribute to Guinea’s efforts to strengthen its climate resilience and promote sustainable urban development.

REFERENCES

1. Ache Billah Kelei Abdallah, Abdoulaye Dieng, Yassine Doudoua, Koye Djondang. (2024). *Vulnerability of rural communities to climate shocks in West Africa*. AJAR. https://doi.org/10.5897/AJAR2024.16842
2. Adewumi, A. S. (2013). Analysis of Land Use/Land Cover Pattern along the River Benue Channel in Adamawa State, Nigeria. *Academic Journal of Interdisciplinary Studies, 2*(5), 95–108. https://doi.org/10.5901/ajis.2013.v2n5p95
3. Africa, W. (2023). *Uganda: Germany's contribution through the Special Fund for Emergency and Rehabilitation Activities – Anticipatory Action window*. Uganda: Germany's Contribution through the Special Fund for Emergency and Rehabilitation Activities – Anticipatory Action Window, 2022–2023. https://doi.org/10.4060/cc4125en
4. Aleksandrova, M., Balasko, S., Kaltenborn, M., Malerba, D., Mucke, P., Neuschafter, O., Radtke, K., Prutz, R., Strupat, C., Weller, D., & Wiebe, N. (2021). *World Risk Report 2021 Focus: Social Protection*. Institute for International Law of Peace and Armed Conflict (IFHV) Ruhr University Bochum. https://reliefweb.int/sites/reliefweb.int/files/resources/2021-world-risk-report.pdf
5. Analytics Vidhya. (2020, avril). *Feature Scaling in Machine Learning: Normalization & Standardization*. Analytics Vidhya. https://www.analyticsvidhya.com/blog/2020/04/feature-scaling-machine-learning-normalization-standardization/.
6. Avaligbé, H., et al. (2021). Perceptions and climate trends affecting shea parklands management in Benin. *Journal of Environmental Studies*. https://www.ajol.info/index.php/jens/article/view/211765
7. We Are Water Foundation. (2021). *Floods: Much Worse If You Are Poor*. Disponible sur wearewater.org
8. Banque Africaine de Développement (2024). Rapport sur la gestion des risques d'inondation en Afrique de l'Ouest. https://www.afdb.org/sites/default/files/documents/publications/burkina_faso_rapport_ees_inondations_ouagadougou_vf_24.05.2024.pdf
9. Banque mondiale. (2020). *People in Harm's Way: Flood Exposure and Poverty in 189 Countries*. World Bank. Disponible sur documents1.worldbank.org

10. Belay, A., J. R. T. W., & J. F. M. (2017). Proceedings of the International Conference on Impact of El Niño on Biodiversity, Agriculture, and Food Security, 23-24 February 2017 Haramaya University, Ethiopia. *Proceedings of the International Conference on Impact of El Niño on Biodiversity, Agriculture, and Food Security* (Issue July).
11. Bechler-Carmaux, N., Mietton, M., & Lamotte, M. (2000). Le risque d'inondation fluviale à Niamey (Niger). Aléa, vulnérabilité et cartographie // River flood risks in Niamey (Niger). Hazards, vulnerability and mapping. *Annales de Géographie, 109*(612), 176–187. https://doi.org/10.3406/geo.2000.1888
12. Biao, E. I. (2017). Assessing the Impacts of Climate Change on River Discharge Dynamics in Oueme River Basin (Benin, West Africa). *Hydrology*, 4(4), 47. https://doi.org/10.3390/hydrology4040047
13. Bodian, A., Diop, L., Panthou, G., Dacosta, H., Deme, A., Dezetter, A., Ndiaye, P. M., Diouf, I., & Vischel, T. (2020). Recent Trend in Hydroclimatic Conditions in the Senegal River Basin. *Water*, 12(2), 436. https://doi.org/10.3390/w12020436.
14. Camara, M., Diallo, O., & Barry, D. (2021). Variation saisonnière des débits fluviaux en Guinée : Cas du fleuve Tinkisso. *Revue des Sciences et Technologies*, 38(28), 816-827. Récupéré de https://revist.net/REVIST_38/28-ST-816.pdf
15. Cred. (2021). *Disaster Year in Review 2020 Global Trends and Perspectives*. Cred, May (62), 2020–2021. https://cred.be/sites/default/files/CredCrunch62.pdf
16. Collins, S. L., Rahman, A., & Tate, E**.** (2025). *Social vulnerability correlates of flood risk to crops and buildings*. Natural Hazards, 121, 8137–8158. https://doi.org/10.1007/s11069-025-07137-y
17. Corine, F., Wagner, J.-J., & Romerio-Giudici, F. (2010). Integrated risk analysis: How to consider coping capacity? 105–117. https://doi.org/10.1201/B10825-21
18. Daniel, L., Yu, C., & Faizah, C. R. (2021). Quantitative assessment of flood vulnerability in Malaysia. https://doi.org/10.1108/S2040-726220210000023009
19. Dao Abdalla, Flavien Houlboumi, Kady Y. Siri, Tégawendé O. Bonkoungou, Jacob Sanou, Ursula Frei. (2024). *Risk exposure and local coping strategies in flood-prone areas in Sub-Saharan Africa*. AJAR. https://doi.org/10.5897/AJAR2024.16774
20. Dada, O. A., Almar, R., & Morand, P. (2024). *Coastal vulnerability assessment of the West African coast to flooding and erosion*. Scientific Reports, 14(1), 890. https://doi.org/10.1038/s41598-023-48612-5

21. Descroix, L., Mahé, G., Olivry, J.-C., Albergel, J., Tanimoun, B., Amadou, I., Coulibaly, B., Bouzou Moussa, I., Maiga, O. F., Abdou, M. M., Yéro, K. S., Mamadou, I., Vandervaere, J.-P., Gautier, E., Diongue-Niang, A., Dacosta, H., & Diedhiou, A. (2017). Chapitre 7. Facteurs anthropiques et environnementaux de la recrudescence des inondations au Sahel. In B. Sultan, R. Lalou, M. A. Sanni, A. Oumarou, & M. A. Soumaré (Éds.), *Les sociétés rurales face aux changements climatiques et environnementaux en Afrique de l'Ouest* (pp. 145–161). IRD Éditions. https://doi.org/10.4000/books.irdeditions.12343.
22. Des, F., & Erard, C. (2024). 2006. 404–405.
23. Diop, S. B., Tramblay, Y., Bodian, A., Ekolu, J., Rouché, N., & Dieppois, B. (2025). Flood Frequency Analysis in West Africa. *Journal of Flood Risk Management, 18*(1), 1–19. https://doi.org/10.1111/jfr3.70001
24. Djoufack-Manetsa, V. (2011). Étude multi-échelles des précipitations et du couvert végétal au Cameroun : Analyses spatiales, tendances temporelles, facteurs climatiques et anthropiques de variabilité du NDVI (Doctoral dissertation). Université de Bourgogne; Université de Yaoundé.
25. Dr.S., J. K., Parthiban, A., Mukesh, P., Premd, M., & Kamaraj, P. (2021). Automated flood monitoring system using wireless sensor network. *Turkish Online Journal of Qualitative Inquiry, 12*(9).
26. Etat, S. U. R. L., & En, D. E. L. E. (2012). rap 2012_COSIE.
27. FAO, Govt. Guinea, IOM. (2024). Guinée : Plan de réponse d'urgence inondations - groupe de coordination intersectoriel, octobre 2024. https://reliefweb.int/report/guinea/guinee-plan-de-reponse-durgence-inondations-groupe-de-coordination-intersectoriel-octobre-2024 (consulté le 11/01/2024).
28. Food and Agriculture Organization (FAO). (2020). Global Forest Resources Assessment 2020. https://www.fao.org/3/ca9825en/CA9825EN.pdf
29. Forbes, H., Ball, K., & McLay, F. (2015). *Natural Flood Management Handbook*.
30. https://global-flood.emergency.copernicus.eu/
31. Guin, P. D. E. (2019). *République de Guinée*.
32. Gary, W., Yohe, R., & Tol, S. J. (2002). Indicators for social and economic coping capacity—moving toward a working definition of adaptive capacity. *Global Environmental Change - Human and Policy Dimensions, 12*(1), 25–40. https://doi.org/10.1016/S0959-3780(01)00026-7

33. Gros, C., Bailey, M., Schwager, S., Hassan, A., Zingg, R., Uddin, M. M., Shahjahan, M., Islam, H., Lux, S., Jaime, C., & Coughlan de Perez, E. (2019). Household-level effects of providing forecast-based cash in anticipation of extreme weather events: Quasi-experimental evidence from humanitarian interventions in the 2017 floods in Bangladesh. *International Journal of Disaster Risk Reduction, 41*(August), 101275. https://doi.org/10.1016/j.ijdrr.2019.101275
34. Haba, S., Bamba, Z., & Diaby, I. (2022). Caractérisation de la fluctuation pluviométrique de la Guinée à l'aide de l'indice standardisé de la précipitation (SPI). *21*(6), 102–112.
35. Hangnon, H., De Longueville, F., & Ozer, P. (2015). Précipitations "extrêmes" et inondations à Ouagadougou ; quand le développement urbain est mal maîtrisé. In *Actes du 28e Colloque International de l'Association Internationale de Climatologie* (pp. 497–502). Université de Liège.
36. Hudson, P., Botzen, W. J. W., Kreibich, H., Bubeck, P., & Aerts, J. C. J. H. (2014). Evaluating the effectiveness of flood damage mitigation measures by the application of propensity score matching. *Natural Hazards and Earth System Sciences, 14*(7), 1731–1747. https://doi.org/10.5194/nhess-14-1731-2014
37. International Federation of Red Cross And Red Crescent Societies. (2020). *Guinea: Floods in Kankan* (04 September 2021), 1–14.
38. IASC. (202x). GENEVIEVE BUTLER, JANE MCKEON. https://www.iasc.gov.au/node/1139 (cited 11/29/2024).
39. IFRC. (2020). *World Disasters Report 2020: Come Heat or High Water*.
40. IMF. (2024). *Natural Disasters and Climate Policies in Guinea*. International Monetary Fund. Disponible sur elibrary.imf.org
41. IPCC, Indices E. (2021). Annex VI: Climatic. May 2025, 2205–2214. https://doi.org/10.1017/9781009157896.020.2205
42. Judith Renoult. (2024). Guinée : les inondations à Conakry, conséquence de pluies diluviennes et de « décennies de négligence ». (Cited 11/24/2024).
43. K., N., Teja, V., Manikanta, V., Das, J., N., V., & Umamahesh. (2023). Enhancing the predictability of flood forecasts by combining Numerical Weather Prediction ensembles with multiple hydrological models. *Journal of Hydrology*. https://doi.org/10.1016/j.jhydrol.2023.130176

44. Latrubesse, E. (2009). Natural hazards and human-exacerbated disasters in Latin America: Special volumes of geomorphology. Elsevier.

45. Le Lay, M., & Galle, S. (2005). Variabilité interannuelle et intra-saisonnière des pluies aux échelles hydrologiques. La mousson ouest-africaine en climat soudanien. *Hydrological Sciences Journal, 50*(3), 509–524. https://doi.org/10.1623/hysj.50.3.509.65029

46. Lenaïck Lecknaï Etengola Efeno, Primus Azinwi Tamfuh, Georges Kogge Kome, Achille Ibrahim Roger Kogge Enang, Armand Ludovic Sylvain Wouatong. (2025). *Disaster vulnerability mapping in agricultural zones of Central and West Africa*. AJAR. https://doi.org/10.5897/AJAR2025.16856

47. Libertino, A., Alfieri, L., Poletti, L., Testa, N., Masoero, A., Gabellani, S., Massabò, M., Ouma, J., Amdihun, A., G., Kiriwai, J., Ambukeje, L., Rossi, L., Mouakkid Soltesova, K., & Beynon, H. (2024). Africa Multi-Hazard Early Warning and Early Action System for Strengthening Resilience to Natural Hazards. https://doi.org/10.5194/egusphere-egu24-5309

48. Loua, T., Bencherif, H., Nelson, B., & Mbatha, N. (2020). Surface Temperature Trend Estimation over 12 Sites. *Climate, 8*(68), 1–24.

49. https://www.diplomatie.gouv.fr/fr/dossiers-pays/guinee/presentation-de-la-guinee/view (consulté le 26/12/2024)

50. https://magoerevision.com/nosCours/fiches/single/?id=740 (consulté le 27/12/2024)

51. Chandellier, L. (2024). Renforcement de la résilience face aux inondations en Guinée : L'appui de l'OIM à travers le programme ARMP. https://guinea.iom.int/stories/renforcement-de-la-resilience-face-aux-inondations-en-guinee-lappui-de-loim-travers-le-programme-armp (consulté le 11/01/2024).

52. Millimono, J. (2021). Coyah : L'occupation anarchique des emprises du fleuve Sarinka, un véritable danger environnemental. Guineenews.org. https://www.guineenews.org/coyah-loccupation-anarchique-des-emprises-du-fleuve-sarinka-un-veritable-danger-environnemental/ (consulté le 24/12/2024).

53. Muhammad, I., Aidi, H., Waheed, U., Safi, U., Adnan, A., & Fangqian, Z. (2024). Flood vulnerability assessment in the flood prone area of Khyber Pakhtunkhwa, Pakistan. *Frontiers in Environmental Science*. https://doi.org/10.3389/fenvs.2024.1303976

54. Müller, J., Smith, A., & Dupont, L. (2025). Advances in data formats for climate research: A review of NetCDF and HDF5 applications. *Hydrology and Earth System Sciences*, 29, 85–102. https://doi.org/10.5194/hess-29-85-2025.

55. Mwasha, S. I., & Robinson, Z. (2021). Building livelihoods resilience in the face of climate change: Case study of small-holder farmers in Tanzania. In *African Handbook of Climate Change Adaptation* (pp. 829-848). Cham: Springer International Publishing.

56. Nasution, A. F. R., Azizah, D. N., Khairani, A., & Akbar, R. (2022). Vulnerability analysis of landslide disaster in Nagari Sungai Pinang, Sungai Nyalo and Mandeh, XI Tarusan Sub-District, Pesisir Selatan. *Epicentrum, 1*(02), 21–40. https://doi.org/10.54482/epicentrum.v1i02.181

57. Ndiaye, M., Faye, M., & Sow, A. (2020). Hydrologie et variations des débits dans les fleuves de la Guinée. *Journal of Hydrological Sciences*, 55(2), 45-56. Récupéré de https://fr.wikipedia.org/wiki/Gambie_%28fleuve%29

58. OCHA. (2009). Afrique de l'Ouest : Inondations 2009 rapport de situation no 2 - 9 Sep 2009. https://www.unocha.org/publications/report/benin/afrique-de-louest-inondations-2009-rapport-de-situation-no-2-9-sep-2009 (consulté le 14/11/2024).

59. Uwayisenga, A. J., Adelekan, I. O., & Oguge, **N.** (2025). *Vulnerability of rural households to flooding in Gicumbi District, Rwanda in Africa*. Journal of Applied and Natural Science, 17(1), 162–178. https://doi.org/10.31018/jans.v17i1.6203

60. Prieto, C., Patel, D., & Han, D. (2020). Preface: Advances in flood risk assessment and management. *Natural Hazards and Earth System Sciences, 20*(4), 1045–1048. https://doi.org/10.5194/nhess-20-1045-2020

61. Poggio, L., de Sousa, L. M., Batjes, N. H., Heuvelink, G. B. M., Kempen, B., Ribeiro, E., & Rossiter, D. (2021). SoilGrids 2.0: Producing soil information for the globe with quantified spatial uncertainty. *SOIL*, 7(2), 217–240. https://doi.org/10.5194/soil-7-217-2021.

62. Rahayu, B., Lestariningsih, S. P., & Gamayanti, P. (2014). Coping capacity masyarakat Das Gendol dalam menghadapi bencana erupsi Merapi (Coping capacity of Watershed Gendol community in facing the Merapi eruption). *JML, 21*(1), 106–113. https://doi.org/10.22146/JML.18518

63. Reisinger, A. et al., 2020: The Concept of Risk in the IPCC Sixth Assessment Report: A Summary of Cross-Working Group Discussions. Intergovernmental Panel on Climate Change, Geneva, Switzerland, 55 pp. Available at: https://www.ipcc.ch/site/assets/uploads/2021/02/Risk-guidance-FINAL_15Feb2021.pdf

64. Richardson, D. (2002). Flood risk - The impact of climate change. *Proceedings of the Institution of Civil Engineers: Civil Engineering, 150*(1 SPECIAL ISSUE), 22–24. https://doi.org/10.1680/cien.150.1.22.38543

65. Rob, T., Jill, J., Ines, O., Paula, A. H., Julia, W., & Robert, D. (2015). Applying a capitals framework to measuring coping and adaptive capacity in integrated assessment models. *Climatic Change, 128*(3), 323–337. https://doi.org/10.1007/s10584-014-1299-5

66. Rossella, G. (2024). Floods. 612–614. https://doi.org/10.1016/b978-0-323-80932-0.00098-7

67. Saint-Laurent, D., & Hähni, M. (2008). Crues et inondations majeures des villes de l'Estrie : Variations climatiques et modifications anthropiques (Québec, Canada). *Environnement Urbain, 2*(October 2008), 50–72. https://doi.org/10.7202/019221ar

68. Samanta, S., Koloa, C., Pal, D. K., & Palsamanta, B. (2016). Flood risk analysis in lower part of Markham river based on multi-criteria decision approach (MCDA). *Hydrology, 3*(3). https://doi.org/10.3390/hydrology3030029

69. Sambou, S., Dacosta, H., Diouf, R. N., Diouf, I., & Kane, A. (2020). Hydropluviometric variability in non-Sahelian West Africa: Case of the Koliba/Corubal River Basin (Guinea and Guinea-Bissau). *Proceedings of the International Association of Hydrological Sciences, 383*(1980), 171–183. https://doi.org/10.5194/piahs-383-171-2020

70. Samoura, D. A., Wahab, B., Taiwo, O. J., Diallo, A. I. P., & Younis, A. Y. I. (2022). Progress and challenges of Guinea's national service of risk management in building climate-induced disasters' resilience in Guinea Savanna communities. *Journal of Applied and Natural Science, 14*(4), 1400–1412. https://doi.org/10.31018/jans.v14i4.3973

71. Sri, R. B., Siti, P. L., & Priliani, G. (2014). COPING CAPACITY MASYARAKAT DAS GENDOL DALAM MENGHADAPI BENCANA ERUPSI MERAPI. *JML, 21*(1), 106–113. https://doi.org/10.22146/JML.18518

72. Syifa, M., Park, S. J., Achmad, A. R., Lee, C. W., Eom, J., & Eom, J. (2019). Flood mapping using remote sensing imagery and artificial intelligence techniques: A case study in Brumadinho, Brazil. *Journal of Coastal Research, 90*(sp1), 197–204. https://doi.org/10.2112/SI90-024.1

73. Sylla, M. (2023). Inondations à Coyah : Un météorologue explique le phénomène et alerte sur de nouveaux cas. https://guineenews.org/inondations-a-coyah-un-meteorologue-explique-le-phenomene-et-alerte-sur-de-nouveaux-cas/ (consulté le 24/12/2024)

74. Tefera, M. L., Seddaiu, G., Carletti, A., & Awada, H. (2024). Rainfall variability and drought in West Africa: challenges and implications for rainfed agriculture. *Theoretical and Applied Climatology*, 156(1), 41. https://doi.org/10.1007/s00704-024-05251-8,

75. Tewa, J. (2020). Vulnérabilité et performance des mesures endogènes d'adaptation au risque d'inondation dans un contexte de changements climatiques dans la commune urbaine de comme exigence partielle du doctorat en sciences de l'environnement.

76. WFP; FAO; IFRC; Oxfam; WHO; WVI; CARE; Caritas; SCF. (2009). Climate Change, Food Insecurity and Hunger Key Messages: Food Security Climate. *World Health*, November, 1–8.

77. Watik, N., & Jaelani, L. M. (2019). Flood evacuation routes mapping based on derived-flood impact analysis from Landsat 8 imagery using network analyst method. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives, 42*(3/W8), 455–460. https://doi.org/10.5194/isprs-archives-XLII-3-W8-455-2019

78. Wang, Y., Zhang, J., & Chang, Y.-H. (2024). A probability prediction model for flood disasters based on Multi-layer Perceptron. https://doi.org/10.21203/rs.3.rs-5250066/v1

79. Wang, J., Nie, Z., & Liu, L. (2023). Study on time stability on reinforced soil slope by anchor under flood loading effect. https://doi.org/10.21203/rs.3.rs-2446384/v1

80. yéro, I., Diop, M., Ndiaye, P., Wade, M., Djiondo, R., Diop, B., Efon, E., & Lenouo, A. (2020). Interannual Variability of Rainfall over the West Africa Sahel. *Journal of Geoscience and Environment Protection*, 8, 85-101. https://doi.org/10.4236/gep.2020.83007

Table: Permeability coefficient

Soil type	Clay proportion (score = 0)	Silt proportion (Score = 0.5)	Sand Proportion (Score = 1)	Permeability Ceef.
Ferrasols	0.2	0.5	0.3	-0.5
Luvisols	0.2	0.5	0.3	-0.5
Acrisol	0.4	0.3	0.3	-0.45
Iithosols	0.1	0.3	0.6	- 0.65
Cambrisols	0.3	0.4	0.3	-0.5
Nitrosols	0.4	0.3	0.3	-0.45
Planesols	0.4	0.40	0.2	–0.35

Table: Sub-indicators of exposure

Regions	Population	Cattle stock	Sheep stock	Goat stock	Pig stock	Rice area	Fonio area	Maize area	Groundnut area	Millet area	Cassava area	Sweet potato area
Boké	1403759	1.549	604	932	9389	120302	32537	13738	73476	1598	16268	1390
Conakry	2152715	0.35	15	11	4585	1	1	1	1	1	1	1
Faranah	1220365	1.203	463	435	4918	261360	111482	21887	71005	39050	29234	4242
Kankan	2543362	1.757	625	571	202	513255	117922	142197	144601	88318	33572	10854
Kindia	2022428	1.007	451	504	2785	164006	65328	1373	118417	11819	27852	608
Labé	1286939	1.248	521	1096	0	21894	120532	48207	88605	97690	30300	6794
Mamou	947236	0.755	422	465	7	31137	73252	21519	73021	52212	22113	1384
Nzérékoré	2045595	0.414	407	493	176042	224490	6944	17254	7187	1434	11829	1456

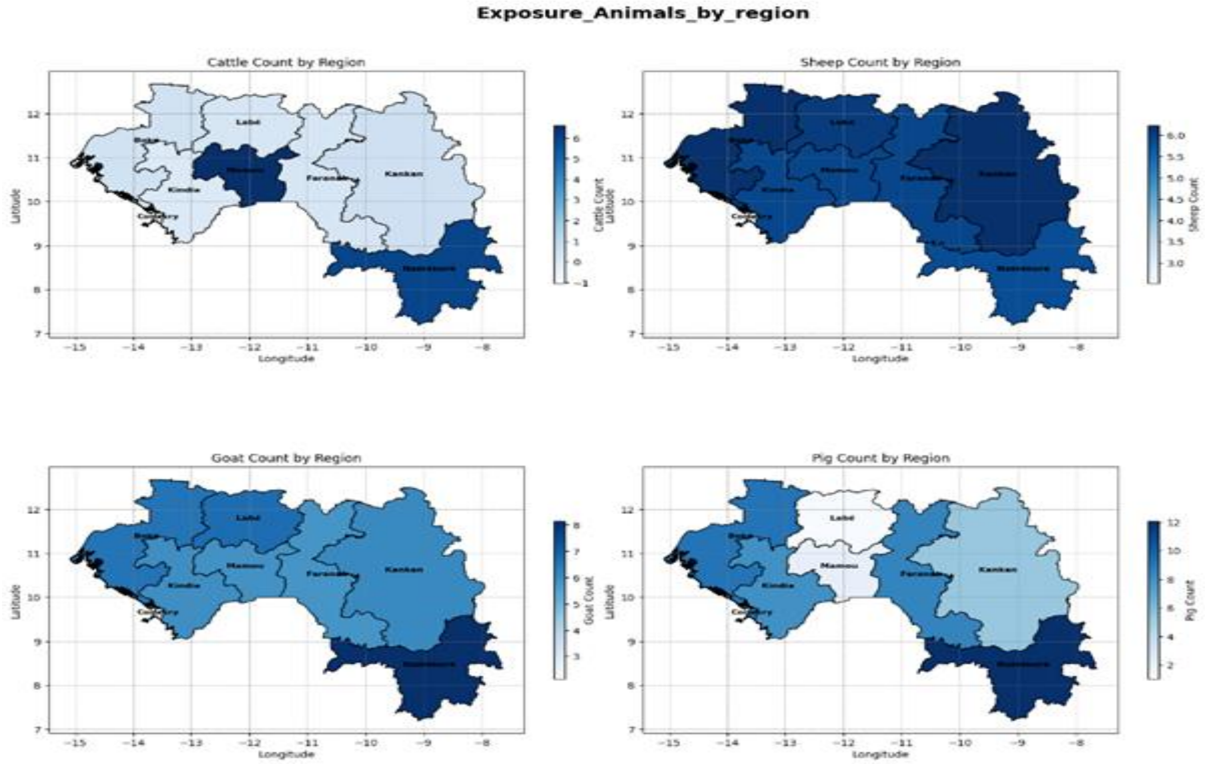
Table: Sub-indicators of vulnerability

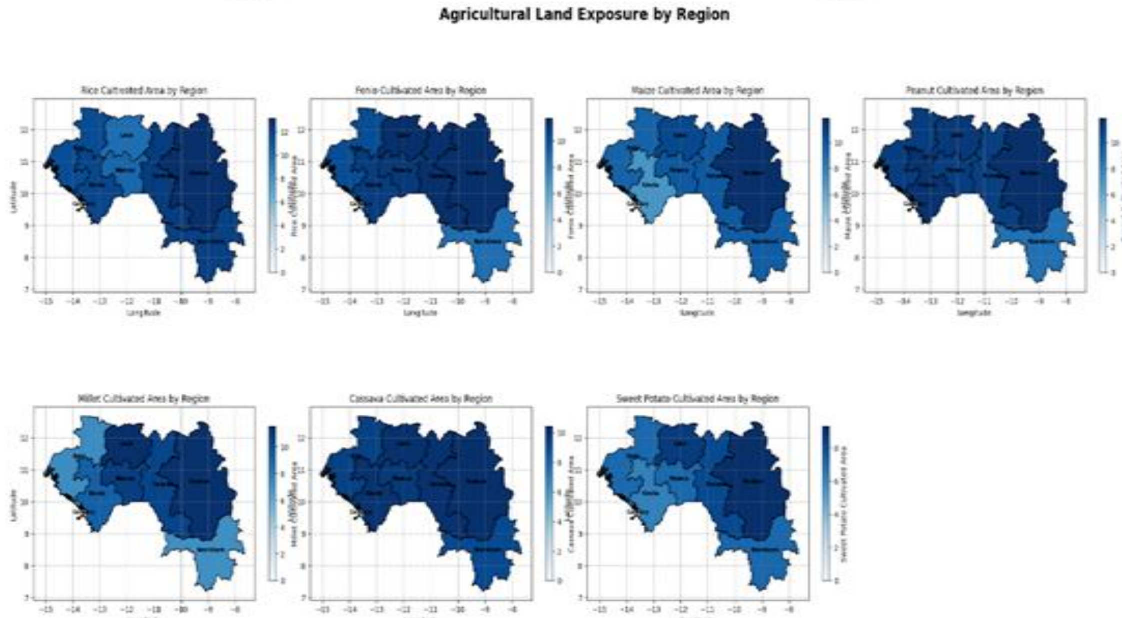
Regions	MPI	Children under 4	Elderly over 65	Disabled persons	Inactive rate	Straw roof percentage	Earthen houses percentage	Agricultural farmers	Unemployment rate
Boké	0.4221	222327	13071	15391	35.3	53.0	31.5	11500	0.16
Conakry	0.0632	255055	11494	22090	36.0	99.8	0.4	2750	1.0
Faranah	0.4888	195250	11978	14134	34.0	44.0	56.5	9750	0.0
Kankan	0.4171	475108	18094	24231	30.5	59.0	51.7	20500	0.18
Kindia	0.3637	325518	18764	25180	35.4	73.7	19.6	18750	0.19
Labé	0.4938	194035	19394	17206	35.2	63.2	36.8	16000	0.27
Mamou	0.4011	137037	17041	13285	33.4	69.6	37.9	10250	0.24
Nzérékoré	0.4336	321372	17308	24368	35.4	36.1	14.7	8500	0.1

Table: Sub-indicators of lack of coping capacity

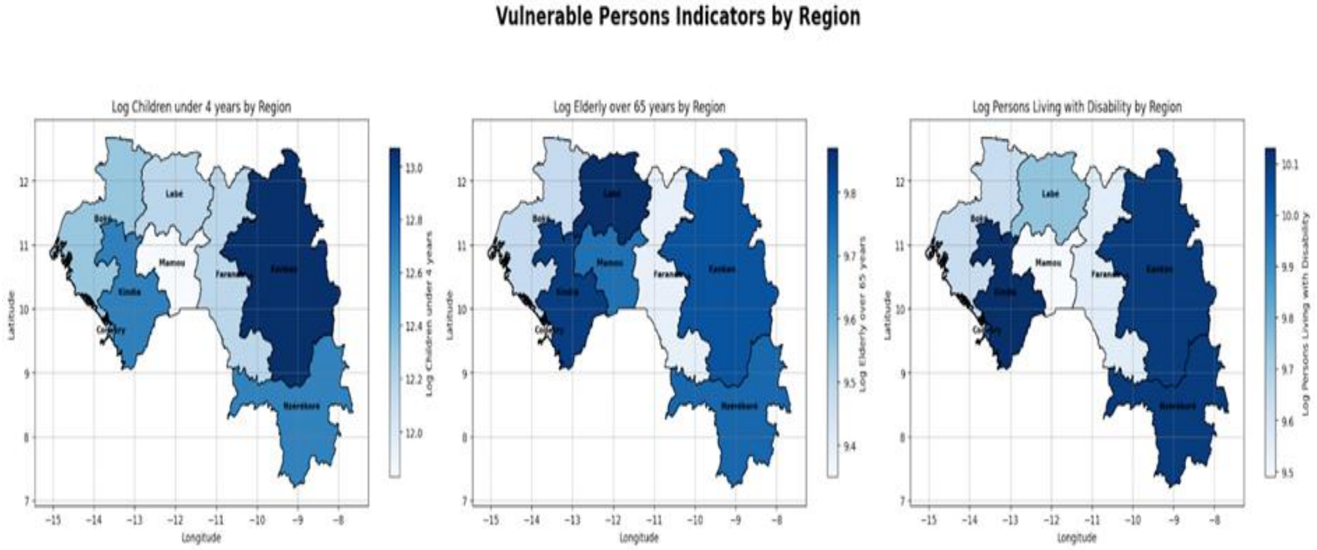
Regions	Rescue units	Unemployment rate	Illiteracy rate	Health centers	Health posts	Schools	Community radios	Internet access structures	Structures with vehicle	Paved road rate
Boké	23	2.3	40.6	44	206	1164	27	38	6	393.1
Conakry	68	14.1	72.1	29	4	6642	5	2	1	43.33
Faranah	15	0.1	23.3	49	207	723	23	43	5	398.2
Kankan	20	2.6	29.3	74	536	1553	48	59	6	550.2
Kindia	44	2.7	37.4	56	314	4091	35	47	6	362.5
Labé	36	3.9	24.7	58	407	935	42	55	6	42.2
Mamou	31	3.5	40.3	41	239	696	22	37	4	368.9
Nzérékoré	27	1.5	31.3	78	395	1910	32	67	7	443.1

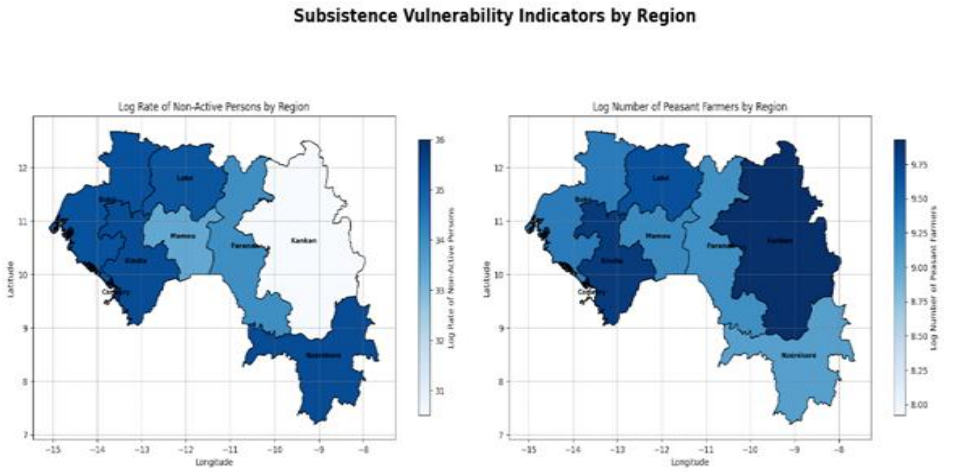
Sub-Indicators Exposure



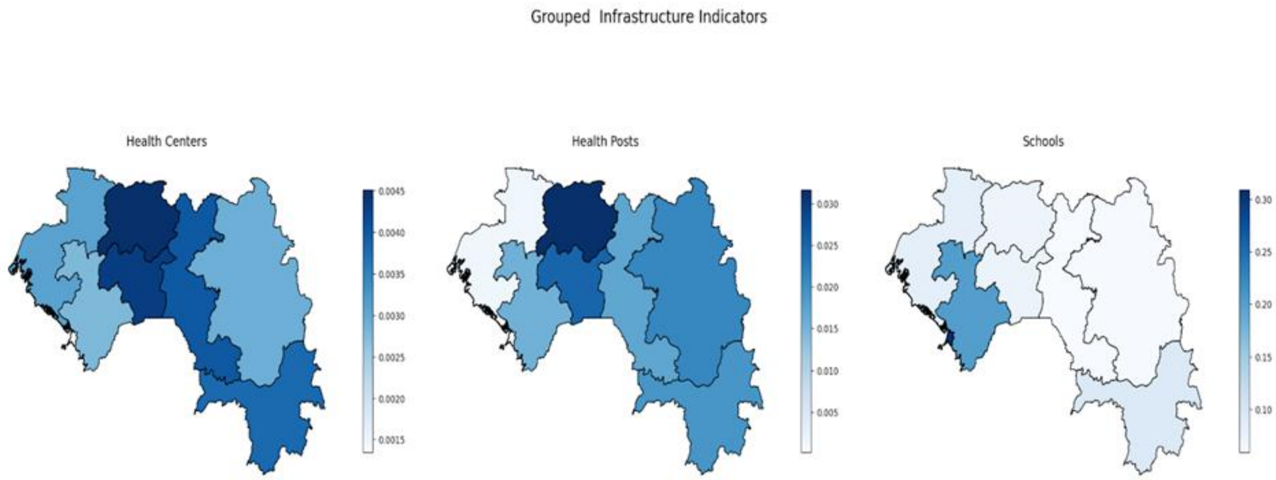


Sub-Indicators Vulnerability





Sub-Indicators Lack of Coping Capacity



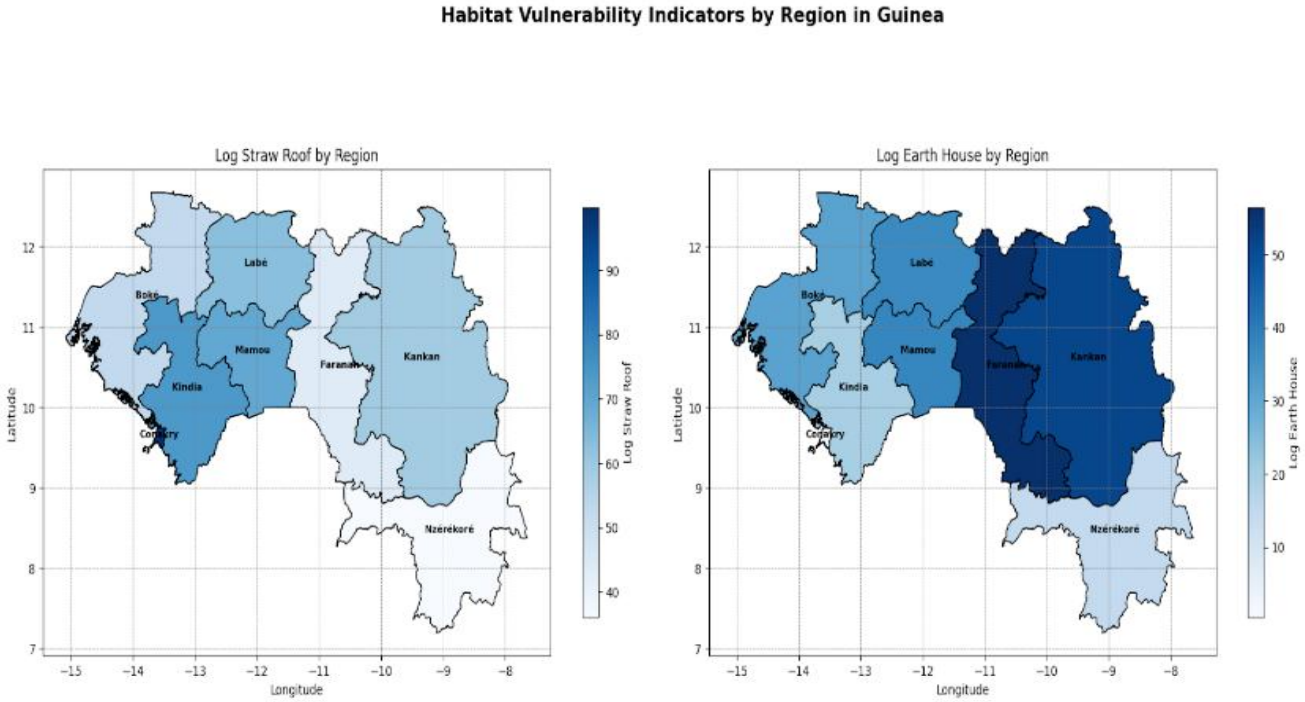


TABLE OF CONTENTS

DEDICATION i
ABSTRACT........ iii
RESUME iv
List of figures........ vi
Acronyms and Abbreviations........ vii
INTRODUCTION 1
Problem Statement........ 2
- Research questions........ 4

Main research question 4
- Research hypotheses 4

Main hypothesis:........ 4
Specific hypotheses:........ 4
- Research Objective 4

Specific objectives 5
CHAPTER 1: LITERATURE REVIEW........ 5
1.1 Definition and Concept of Flooding 5
1.2 Definition and Component of Flood Risk........ 7
1.2.1 Hazard........ 8
1.2.2 Exposure 9
1.2.3 Vulnerability 9
1.2.4 Lack of Coping Capacity 10
1.2.5 Anticipatory Actions for Flood Risk Reduction 10
CHAPTER 2: MATERIALS AND METHODS........ 14
2.1 Study area........ 14
2.1.1 Climate........ 15
2.1.2 Hydrography 15
2.1.3 Relief........ 16
2.1.4 Vegetation 17
2.1.5 Risk and Disaster Management 18
2.2 Tools........ 18
2.2 Data collection 19

2.2.1 Hazard data 19
2.2.2 Exposure data 20
2.2.3 Vulnerability data 20
2.2.4 Lack of adaptive capacity data 21
2.3 Data Processing 21
2.3.1 Precipitation Data Analysis 21
2.3.2 Exposure Analysis 23
2.3.3 Vulnerability Analysis: 24
2.3.4 Lack of Adaptation Capacity Analysis 25
CHAPTER 3: RESULTS AND DISCUSSION 28
3.1 Results Hazard Analysis 28
3.1.1 Pluvial Flood Hazard 28
3.1.2 Fluvial Flood Hazard 34
3.1.3 Exposure 37
3.1.4 Vulnerability: 40
3.1.5 Lack of Adaptation Capacity 42
1.6 Risk assessment 45
3.2 Discussion 48
CONCLUSION AND PERSPECTIVES 53
REFERENCES viii
ANNEXES xvi