

GIS AND REMOTE SENSING BASED FLOOD RISK MAPPING AND VULNERABILITY ASSESSMENT: A CASE STUDY OF T/A PEMBA IN SALIMA

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ABSTRACT

Floods are among the most destructive natural hazards in Malawi, and rural areas like Traditional Authority (T/A) Pemba in Salima District are particularly susceptible due to low elevation, high rainfall, and settlements situated near river networks. Despite the frequency of these events, disaster risk management often relies on broad-scale data, creating a need for detailed, community-level spatial assessments. This study assessed flood risk and community socio-economic vulnerability in T/A Pemba using Geographic Information Systems (GIS) and remote sensing. A mixed-methods research design was employed to integrate spatial analysis with socio-economic data. Physical flood risk was modeled using environmental variables, including elevation, slope, rainfall intensity, land use and land cover (LULC), flow accumulation, and distance to rivers. Socio-economic vulnerability was assessed through household surveys, evaluating indicators such as income level, education, livelihood type, household size, housing condition, and access to services. The Analytic Hierarchy Process (AHP) was utilized to determine the relative weights of these parameters.

The integration of these components, weighted at 75.0% for physical risk and 25.0% for socio-economic vulnerability, reveals a highly uneven spatial distribution of susceptibility. The results indicate that 77.1% of T/A Pemba falls within high or moderate susceptibility zones, primarily driven by proximity to river networks and widespread socio-economic constraints. Furthermore, 14.5% of the area is classified as very high susceptibility, representing critical spatial intersections where extreme socio-economic vulnerability overlaps with high physical flood exposure. In contrast, low susceptibility zones cover only 8.4% of the area. These findings demonstrate that while physical exposure dictates the spatial extent of flood hazards, community resilience is heavily constrained by socio-economic factors. The localized flood risk and vulnerability maps generated in this study provide actionable spatial data to support targeted mitigation measures, early warning systems, and resource allocation, directly aligning with Malawi Vision 2063, the Disaster Risk Management Bill (2023), and the Sendai Framework for Disaster Risk Reduction.

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ACRONYMS/ABBREVIATIONS

ASTER ..... Advanced Spaceborne Thermal Emission and Reflection Radiometer

DEM ..... Digital Elevation Model

DCCMS ..... Department of Climate Change and Meteorological Services

DoDMA ..... Department of Disaster Management Affairs

DRR ..... Disaster Risk Reduction

GIS ..... Geographic Information System(s)

GoM ..... Government of Malawi

HAND ..... Height Above Nearest Drainage

HEC-RAS ..... Hydrologic Engineering Centers River Analysis System

IPCC ..... Intergovernmental Panel on Climate Change

LISFLOOD-FP ..... Limburg Soil Floodplain Model

LULC ..... Land Use and Land Cover

MCA ..... Multi-Criteria Analysis

MW2063 ..... Malawi Vision 2063

NGO ..... Non-Governmental Organization

NPC ..... National Planning Commission

OCHA ..... United Nations Office for the Coordination of Humanitarian Affairs

PAR ..... Pressure and Release (Model)

QGIS ..... Quantum Geographic Information System

RS ..... Remote Sensing

SRTM ..... Shuttle Radar Topography Mission

TA ..... Traditional Authority

UNDRR ..... United Nations Office for Disaster Risk Reduction

USGS ..... United States Geological Survey

AHP..... Analytic Hierarchy Process

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1. CHAPTER 1: INTRODUCTION

1.1. Background

Floods are among the most destructive hydrometeorological hazards worldwide, causing loss of life, displacement, and damage to livelihoods and infrastructure. Between 2009 and 2019, floods affected about 510 million people globally and caused nearly 50,000 fatalities, making them the leading weather-related hazard (Garcin et al., 2022; Rentschler et al., 2022). The IPCC (2021) projects that extreme precipitation will become more frequent and intense, increasing both riverine and flash flood risks. In Sub-Saharan Africa, floods have increased significantly, affecting over 2.6 million people in 2022 alone and destroying infrastructure, crops, and livelihoods (Aliyu et al., 2023). Southern African countries such as Mozambique, Zimbabwe, and Malawi face recurrent floods that displace thousands and cause millions in economic losses (Saha & Praneeth, 2016; Hussein et al., 2023). Climatic variability, urbanization, poverty, weak infrastructure, and dependence on rain-fed agriculture exacerbate vulnerability and highlight the need for localized risk assessments (Mwalwimba, 2023). In Malawi, floods are frequent in low-lying areas like the Shire River Basin and central lakeshore regions, where flat terrain, dense populations, and rain-fed farming heighten exposure (Dewa, 2023). Between 2015 and 2023, major floods displaced tens of thousands (Msasa, 2024). In March 2023, floods from Tropical Cyclone Freddy displaced 553,600 people, caused 507 deaths, and affected over 100,000 residents (Hussein et al., 2023), demonstrating severe human, economic, and infrastructural impacts. Locally, Salima District particularly Traditional Authority (TA) Pemba is highly flood-prone due to low elevation, high rainfall, proximity to lake Malawi and settlements along rivers and wetlands. Communities frequently experience crop and housing destruction, displacement, and outbreaks of diseases like cholera (Mwalwimba, 2024). GIS and remote sensing support the integration of topographical, hydrological, land-use, and socio-economic data to generate hazard and vulnerability maps that guide preparedness and resilience planning (Li et al., 2023). This study is relevant because it directly supports key national and international frameworks for flood risk management. By providing localized data and insights, the study contributes to Malawi's Vision 2063,

which emphasizes resilience and sustainable development (MW2063). It also strengthens the objectives of the Disaster Risk Management Bill (2023), which aims to enhance disaster preparedness, response, and recovery at national and community levels (Malawi Government, 2021). Additionally, the study aligns with the Sendai Framework for Disaster Risk Reduction (2015–2030) by emphasizing hazard mapping, risk knowledge, and preparedness.

1.2. Problem Statement

Floods are among the most destructive natural hazards, causing loss of life, damage to homes, and disruption of livelihoods, particularly in rural areas like T/A Pemba in Malawi (Garcin et al., 2022; Rentschler et al., 2021). Although the Disaster Risk Management (DRM) Act provides frameworks for flood preparedness, response, and recovery, it often relies on broad-scale information and lacks detailed local-level data to support community-based risk reduction and early warning systems. Most flood studies in Malawi focus on large areas, such as districts or regions, and do not provide detailed information at the community level. As a result, there is limited understanding of where floods occur most frequently and which specific areas are at highest risk. There is a need for GIS- and remote sensing-based mapping that shows the exact locations and extent of flood-prone zones in places like T/A Pemba in Salima. Generating such localized flood risk maps is important because it allows authorities and communities to identify high-risk zones, plan targeted mitigation measures, and implement effective early warning systems, thereby enhancing preparedness and reducing potential losses. Many existing studies focus mainly on the physical aspects of flooding but give little attention to the social and economic conditions that make some communities more affected than others. This means there is limited understanding of which communities are most vulnerable and why, because past research rarely combines spatial data with information on livelihoods, housing quality, and access to services (there is lack of integration of socio-economic vulnerability into GIS-based flood assessments). Without this understanding, it is difficult to prioritize interventions, allocate resources efficiently, and support the most at-risk populations, which reduces the effectiveness of DRM strategies in enhancing adaptive capacity and building community

resilience. By applying GIS to integrate physical, hydrological, and socio-economic data, this study will produce localized flood risk and vulnerability maps.

1.3. Research Objectives

1.3.1. Main objective

To assess flood risk and community vulnerability in T/A Pemba using GIS and remote sensing.

1.3.2. Specific objectives

1. Delineate flood extents.
2. Evaluate socio-economic vulnerability of communities.
3. Develop integrated flood risk and vulnerability map
4. Develop flood impact assessment model

1.4. Research questions

1. What is the spatial distribution of flood-prone areas?
2. Which communities are most vulnerable to flooding, based on socio-economic data?
3. Which communities face the highest combined physical and socio-economic flood risk?
4. How can GIS and remote sensing be used to assess flood impacts and exposure within flood-prone areas?

1.5. Significance of the study

At the academic level, this study addresses a critical knowledge gap by generating localized, community-specific GIS-based flood risk and vulnerability maps for T/A Pemba. It contributes to scholarship on GIS applications in disaster management, demonstrating their effectiveness in data-scarce environments (Kombaitan & Yudoko, 2022). At the policy and humanitarian level, the study aligns with Malawi Vision 2063, emphasizing climate resilience for sustainable development (Government of Malawi, 2023). It complements the Disaster Risk Management Bill (2023) and supports the Sendai Framework for Disaster Risk Reduction (2015–2030) by providing localized data to inform preparedness plans, early warning systems, targeted interventions, and resource allocation for government authorities, NGOs, and humanitarian organizations (Malawi Government, 2023; UNDRR, 2015).

2. CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

The purpose of this literature review is to provide a critical and analytical overview of existing research on flood risk and vulnerability assessment, with particular attention to methodological and contextual gaps relevant to rural communities in Malawi. The review is structured thematically, beginning with conceptual and theoretical frameworks, followed by empirical studies on flood risk mapping and vulnerability assessment, highlighting gaps in current knowledge, and then ending with a conclusion of the review.

2.2. Conceptual and theoretical framework

Flood risk research is often underpinned by integrated frameworks linking hazard, exposure, and vulnerability. Two widely cited models are the Pressure and Release (PAR) model and the Access model, which highlight how socio-economic inequalities, governance structures, and limited resource access exacerbate vulnerability (Aziz, 2018; Michellier et al., 2020). Similarly, the hazard–exposure–vulnerability (HEV) chain emphasizes the interconnections between physical hazards and social systems, making it particularly relevant to community-level flood analysis (André et al., 2022). In addition to these theoretical models, national and international policy frameworks shape how flood risk is managed. In Malawi, the Disaster Risk Management Act (2023) mandates the Department of Disaster Management Affairs (DoDMA) to coordinate disaster preparedness and response (Development Bank, 2024). The country also aligns with the Sendai Framework for Disaster Risk Reduction (2015–2030), which emphasizes risk assessment, early warning, and community resilience (UNDRR, 2015). At the climate governance level, Malawi is a signatory to the Paris Agreement, which stresses adaptation measures for climate-driven hazards, including floods (Falkner, 2016). These theoretical and policy frameworks guide this study by situating flooding not only as a biophysical hazard but also as a socio-environmental process influenced by structural vulnerabilities, governance, and institutional capacity (Orchard et al., 2025). Building on these models, this study adopts a conceptual framework shown in Figure 1 that integrates flood hazard and socio-economic

vulnerability to guide GIS- and remote sensing-based flood risk assessment in TA Pemba, Salima District.

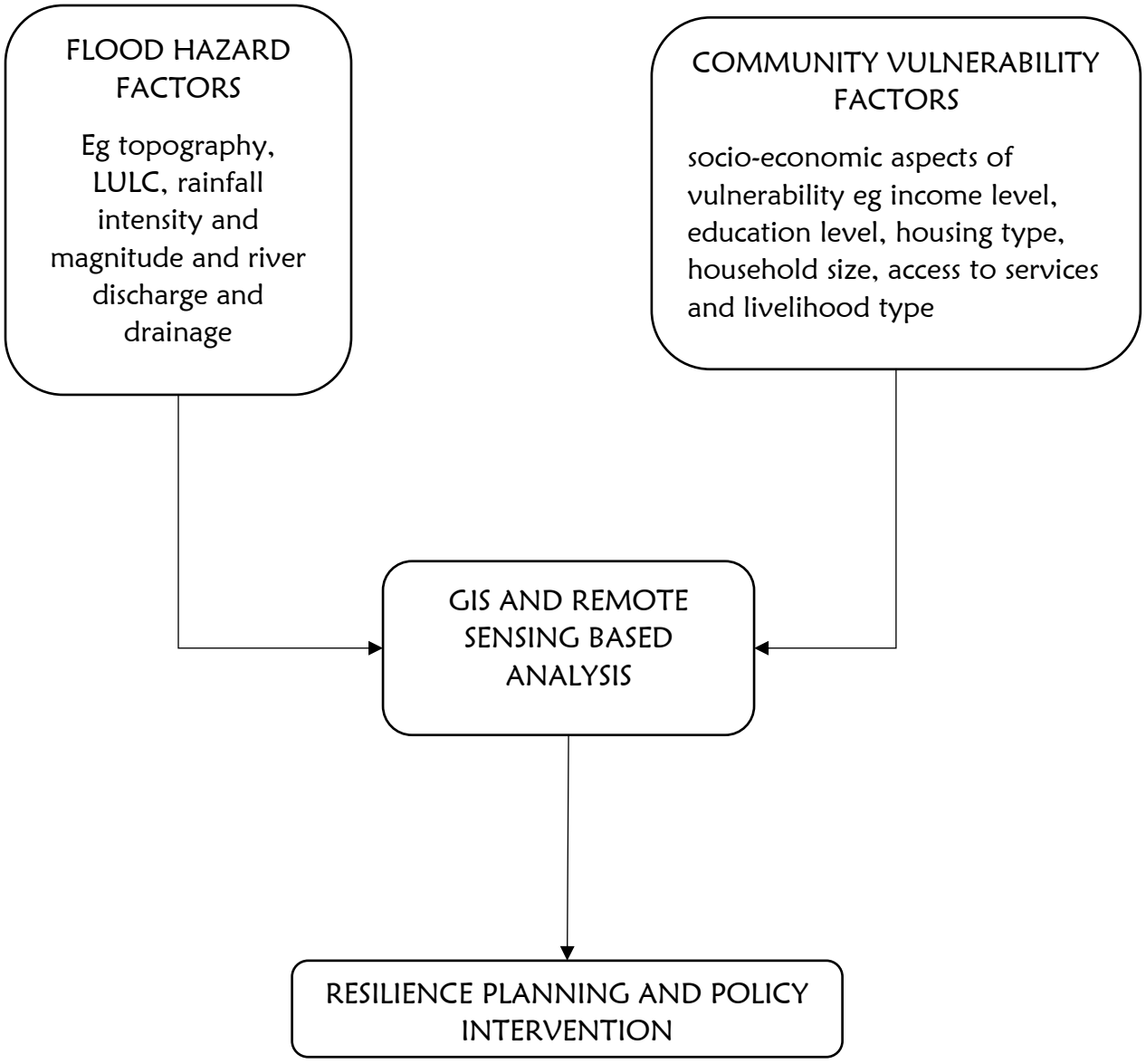


Figure 1 conceptual and theoretical framework

2.3. Empirical studies

2.3.1. Flood Risk Mapping

Flood risk mapping is widely applied to identify flood-prone areas and support mitigation planning. Globally, studies often integrate hydrodynamic modeling with spatial and

physical data to produce detailed flood hazard maps. For example, van den Bout et al. (2023) combined LISFLOOD-FP modeling with population and infrastructure data in West Bengal, India, while Orchard et al. (2025) applied similar approaches in Jakarta, Indonesia. These studies demonstrate that combining physical flood models with geospatial tools enhances the accuracy of identifying flood-prone zones and informs effective risk reduction strategies. However, challenges such as limited data resolution and the difficulty of accurately representing complex terrain or informal settlements are commonly reported (Li et al., 2023). Regionally, in Southern Africa, GIS and remote sensing applications using DEM-derived indices (e.g., HAND, slope, flow accumulation) alongside Sentinel-1 and Landsat imagery have shown improved spatial delineation of flood hazards (Shoko & Dube, 2024). These studies highlight the advantages of integrating geospatial analysis for hazard mapping, but methodological differences remain in terms of data processing, index selection, and the balance between accuracy and computational efficiency. At the national level in Malawi, GIS-based flood risk mapping studies have been conducted in Nsanje, Karonga, and Blantyre (Garcin et al., 2025; Tobias et al., 2024). These studies successfully delineate flood hazard zones using DEMs, historical flood records, and remote sensing data. Critically, some analyses assume uniform flood behavior across large areas, potentially oversimplifying flood dynamics. Limited attention has been given to the temporal variability of flood events and the integration of multiple hydrological events, which may affect the reliability of hazard predictions. Additionally, while technical mapping accuracy is often emphasized, there is minimal discussion on how uncertainties in input data or modeling assumptions could influence hazard delineation.

2.3.2. Flood vulnerability assessment

Flood vulnerability assessments aim to understand how communities are affected by floods, considering physical exposure, socio-economic conditions, and adaptive capacity. At the global level, Tran et al. (2017) conducted community-level vulnerability mapping in Vietnam's Mekong Delta by integrating hazard data with socio-economic and demographic information. Their methodology combined GIS-based spatial analysis with household survey data to assess exposure and adaptive capacity, revealing variations in

vulnerability across different communities. Gain et al. (2015) in Bangladesh developed vulnerability indices that incorporated both physical factors, such as flood depth and settlement location, and social and economic indicators, including income, education, and livelihood type, using a combination of remote sensing data and household surveys. Rojas et al. (2011) in Mozambique employed household surveys alongside flood hazard modeling to capture both social and physical vulnerability, emphasizing the role of access to emergency services and resource availability. While these studies provide valuable insights, differences in index weighting, hazard data resolution, and spatial scale limit the comparability of results and their applicability to other contexts. Regionally, analyses in Southern Africa have highlighted the influence of climatic drivers, such as extreme rainfall, cut-off lows, and La Niña events, in combination with infrastructural weaknesses including poor drainage and rapid urban expansion, in shaping flood vulnerability (Byaruhanga et al., 2025). These studies applied GIS and multi-criteria analysis approaches to integrate environmental and structural factors, but variations in methodology, including index selection and data processing techniques, lead to inconsistencies in vulnerability assessments across different studies. At the national level in Malawi, studies have predominantly focused on physical exposure and hazard-related factors. Mwalwimba et al. (2024; 2025) and Garcin et al. (2025) used GIS and historical flood records to map flood-prone areas and evaluate hazard frequency, while other studies examined topography, drainage patterns, and housing location as determinants of exposure (Mtembenuzeni & Kushe, 2018; Msasa & Manda, 2025). These studies provide useful insights and highlight patterns of flood hazard.

2.4. Critical analysis and research gaps

While significant progress has been made in flood risk research, several limitations remain. In Malawi, most flood risk mapping studies have focused on broad, district-level assessments, providing limited detail at the community level. This highlights the need for high-resolution, localized flood hazard maps that can accurately identify flood-prone areas and support targeted mitigation and more effective disaster risk management. At the same time, socio-economic aspects of vulnerability are rarely integrated into GIS-based

assessments, which limits understanding of which communities are most at risk, as spatial data are seldom combined with information on livelihoods, housing quality, and access to service

2.5. Conclusion of the literature review

The literature review shows that flood risk and vulnerability are shaped by both physical hazards and socio-economic factors. In Malawi, research remains largely district-level, with limited community-scale analyses and little integration of socio-economic vulnerability into GIS-based assessments. These gaps highlight the need for a community-focused, GIS-based approach that combines high-resolution flood mapping with socio-economic data to identify at-risk communities, which this study addresses through a methodology designed to provide actionable insights for local flood risk management.

3. CHAPTER 3: METHODOLOGY

3.1. Study Area

The study was conducted in Traditional Authority Pemba located in Salima District in the central region of Malawi as shown in Figure 2. The area lies within the lakeshore zone and is characterized by relatively low-lying terrain and the presence of seasonal rivers that drain into Lake Malawi. These geographical characteristics increase the susceptibility of the area to flooding, particularly during periods of intense rainfall. Flood events in the area frequently result in damage to infrastructure, destruction of agricultural land, and disruption of socio-economic activities within local communities. The majority of households in TA Pemba depend on subsistence agriculture and fishing as their primary sources of livelihood. These livelihood activities are highly sensitive to climate variability and hydrological hazards such as floods. Settlements located near river channels and low-lying areas are particularly exposed to flood hazards. Due to the frequency of flood events and the vulnerability of local communities, TA Pemba provides an appropriate setting for assessing flood risk and vulnerability using Geographic Information Systems (GIS) and remote sensing techniques.

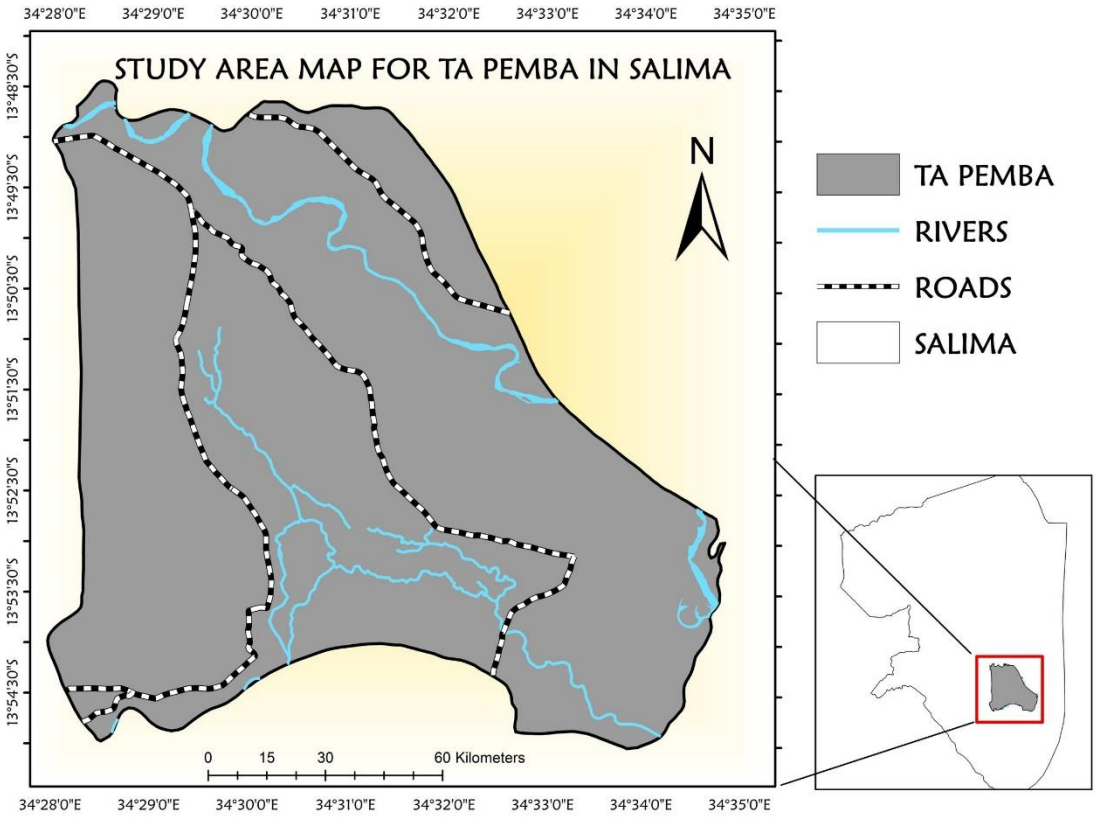


Figure 2 study area map

3.2. Research Design

This study adopted a mixed-methods research design integrating spatial analysis with socio-economic assessment. GIS and remote sensing techniques were used to analyze environmental factors influencing flood occurrence, while household surveys were conducted to assess the socio-economic vulnerability of communities to flood hazards.

The integration of these two approaches enabled the study to examine both the physical factors that contribute to flooding and the socio-economic characteristics that influence the capacity of households to cope with and recover from flood events. This approach therefore allowed for a comprehensive flood risk assessment by combining flood hazard mapping with socio-economic vulnerability analysis.

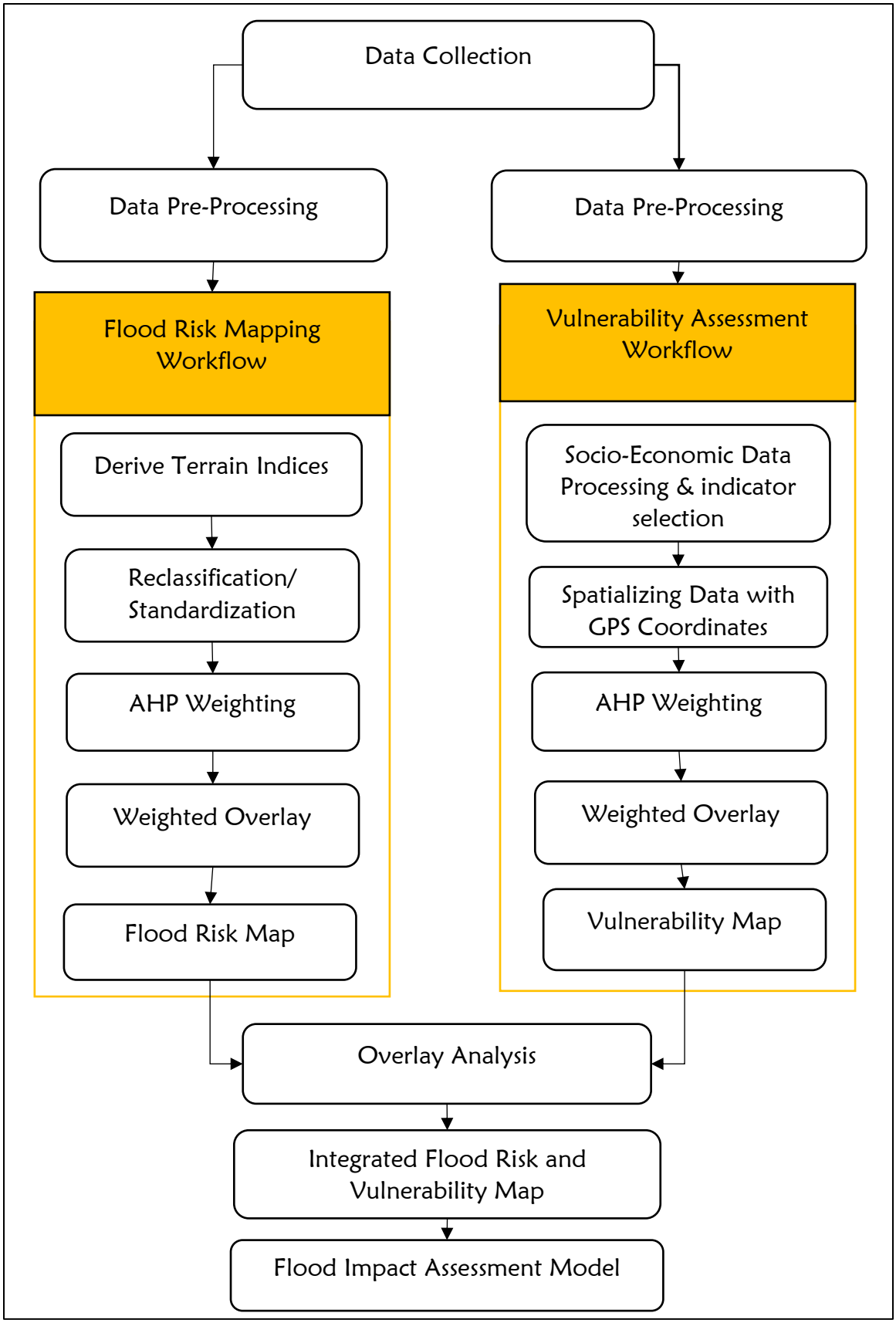

Data Collection
Data Pre-Processing
Data Pre-Processing
Flood Risk Mapping Workflow
Vulnerability Assessment Workflow
Derive Terrain Indices
Reclassification/ Standardization
AHP Weighting
Weighted Overlay
Flood Risk Map
Socio-Economic Data Processing & indicator selection
Spatializing Data with GPS Coordinates
AHP Weighting
Weighted Overlay
Vulnerability Map
Overlay Analysis
Integrated Flood Risk and Vulnerability Map
Flood Impact Assessment Model

Figure 3 schematic workflow

3.3. Sampling Technique and Sample Size Determination

This study employed a quantitative sampling approach to ensure that the selected respondents provided a statistically representative view of the study population. The sample size was determined using the Taro Yamane formula, which is widely used in social science research to calculate an appropriate sample size from a known population.

According to the National Statistical Office of Malawi, T/A Pemba in Salima District has a total population of 24,680 people and 5,345 households. Since this study targeted households as the unit of analysis, the total number of households (N = 5,345) was used in the sample size calculation.

The Taro Yamane formula is expressed as:

$$n = \frac{N}{1 + N(e^2)}$$

where:
n= required sample size
N= total number of households
e= margin of error (0.05)

Substituting the values into the formula:

$$n = \frac{5345}{1 + 5345(0.05^2)}$$

$$n = \frac{5345}{1 + 5345(0.0025)}$$

$$n = \frac{5345}{1 + 13.3625}$$

$$n = \frac{5345}{14.3625}$$

$$n \approx 372$$

The calculated sample size was therefore 372 households, which is considered sufficient to achieve a 95% confidence level with a 5% margin of error.

However, due to practical constraints such as time limitations, accessibility of some areas, and resource availability, a total of 50 households were successfully interviewed during the field survey. Despite the reduced sample size, efforts were made to ensure that the selected respondents were spatially distributed across the study area in order to capture variations in socio-economic conditions and flood exposure.

This approach ensured that the collected data remained relevant and useful for assessing socio-economic vulnerability within the study area, while acknowledging the limitations associated with the reduced sample size.

3.4. Data Collection

3.4.1. Data For Flood Risk Mapping

Flood risk mapping in this study was based on the integration of multiple environmental and hydrological variables, including elevation, slope, rainfall, land use and land cover (LULC), flow accumulation, and distance to rivers. These datasets were obtained from a combination of remote sensing products and institutional sources and were processed within a GIS environment to generate thematic layers for analysis.

Elevation data were obtained in the form of a Digital Elevation Model (DEM) from the United States Geological Survey, accessible via: https://earthexplorer.usgs.gov/. The DEM provided the basis for terrain analysis and was used to derive both elevation and slope layers. Elevation plays a critical role in flood occurrence, as low-lying areas are more prone to water accumulation and inundation. In this study, the DEM was processed in GIS to classify areas based on elevation ranges, with lower elevations assigned higher flood susceptibility.

Slope was derived from the DEM using spatial analysis tools in GIS software. Slope influences the movement of surface runoff, where flatter areas tend to accumulate water, increasing flood risk, while steeper slopes facilitate rapid drainage. The slope layer was

therefore generated and reclassified to reflect varying levels of flood susceptibility based on gradient.

Rainfall data were obtained from the Department of Climate Change and Meteorological Services. Rainfall is a key driver of flooding, as intense or prolonged precipitation increases surface runoff and river discharge. The rainfall data were spatially processed and classified to represent different levels of flood-generating potential, with higher rainfall amounts corresponding to increased flood risk.

Land use and land cover (LULC) data were derived from satellite imagery obtained from the United States Geological Survey and the European Space Agency. These datasets were accessed via: https://earthexplorer.usgs.gov/ and https://scihub.copernicus.eu/. LULC is an important factor in flood risk assessment, as different land cover types influence infiltration and runoff. For instance, built-up areas and bare land tend to increase runoff, while vegetation enhances infiltration and reduces flood potential. The imagery was processed and classified into relevant land use categories for analysis.

Flow accumulation was generated from the DEM using hydrological tools in GIS. This layer represents the accumulation of surface runoff within drainage networks and is useful for identifying areas where water converges. High flow accumulation values indicate zones where runoff is concentrated, which are more susceptible to flooding. The derived flow accumulation layer was reclassified to reflect varying flood risk levels.

Distance to rivers was calculated using river network data obtained from OpenStreetMap https://www.openstreetmap.org/. Proximity to rivers is a critical factor in flood risk assessment, as areas closer to river channels are more likely to experience flooding due to overflow. A distance analysis was performed in GIS to generate buffer zones around rivers, with areas closer to rivers assigned higher flood risk.

3.4.2. Socio-Economic Vulnerability Data

Socio-economic data were collected to assess the vulnerability of communities to flood impacts within the study area. Primary data were obtained through structured household questionnaires administered using the Kobo Collect platform. The questionnaire was designed to capture key socio-economic variables relevant to vulnerability assessment. These included income level, education level, livelihood type, household size, housing condition, and access to services. The questionnaire also included questions on previous flood experiences and household recovery capacity to provide additional context on vulnerability.

Data collection was conducted through field surveys, where selected households were interviewed using mobile devices equipped with the Kobo Collect application. Alongside the questionnaire, the spatial location of each household was recorded by capturing GPS coordinates using the GPS Essential application, which was critical for integrating the socio-economic vulnerability data into the GIS environment. The collected data were then uploaded to the Kobo server and exported in a spreadsheet format for further analysis.

Income level was used to assess economic capacity, with lower income levels indicating higher vulnerability. Education level was used as a proxy for awareness and preparedness, while livelihood type helped identify dependence on flood-sensitive activities such as agriculture. Household size was used to represent the level of dependency within households, and housing condition was used to assess structural resilience to flood impacts. Access to services, including proximity to health facilities and road accessibility, was used to evaluate the ability of households to respond to and recover from flood events.

3.5. Data Processing and GIS Analysis

3.5.1. Flood risk mapping

Flood risk mapping was conducted using a multi-criteria analysis approach that integrates several environmental and hydrological factors influencing flood occurrence. The analysis incorporated elevation, slope, rainfall intensity, land use and land cover, distance to rivers,

and flow accumulation as flood conditioning factors, all of which were derived from the datasets obtained for this study.

Each flood conditioning factor was reclassified into categories representing different levels of flood susceptibility. Areas with lower elevation, gentle slopes, higher rainfall intensity, high flow accumulation, and closer proximity to rivers were considered more susceptible to flooding compared to other areas.

The relative importance of these factors was determined using the Analytical Hierarchy Process. The weighting process incorporated expert knowledge and stakeholder consultation rather than relying solely on the researcher's judgement. Interviews and consultations were conducted with relevant experts and stakeholders including the District Risk Management Officer in Salima District, traditional authorities, village heads, and community members who have knowledge of historical flood events within the study area. In addition, relevant literature on flood risk assessment was reviewed to support the weighting process.

Pairwise comparison matrices were developed based on the information obtained from expert consultations and literature review. These matrices were processed using an AHP calculator implemented in Microsoft Excel to derive normalized weights and evaluate the consistency ratio of the judgments. The resulting weights were applied in a weighted overlay analysis within the GIS environment to integrate the different flood conditioning layers and generate a composite flood risk index. The final flood risk map was classified into low, moderate, and high flood risk zones.

3.5.2. Socio Economic Vulnerability Assessment

The vulnerability assessment focused on evaluating the socio-economic conditions that influence the ability of households to cope with and recover from flood hazards. The analysis utilized socio-economic indicators derived from household questionnaire data, including income level, housing condition, education level, access to services, livelihood type, and household size.

The weighting of these vulnerability indicators was determined using the Analytical Hierarchy Process. Similar to the flood hazard analysis, the weighting process incorporated expert consultations and literature review to ensure the reliability of the assigned weights. Consultations were conducted with local leaders, disaster management officials, and community representatives who possess knowledge of socio-economic conditions within the study area. Relevant literature on vulnerability assessment in disaster risk studies was also reviewed to guide the weighting process.

Pairwise comparison matrices were developed and processed using an AHP calculator implemented in Microsoft Excel in order to derive normalized weights and evaluate the consistency ratio of the judgments. To facilitate the spatial analysis, the spreadsheet containing the questionnaire responses was imported into the GIS software using collected GPS coordinates, effectively converting the tabular socio-economic data into spatial points. The resulting weights from the pairwise matrices were applied in a weighted overlay analysis within the GIS environment to integrate the different vulnerability indicators and generate a composite vulnerability index. The final vulnerability map was classified into low, moderate, and high vulnerability categories in order to identify communities that are more susceptible to the impacts of flooding.

3.5.3. Integration of Flood Risk Map and Vulnerability Map

The integrated flood risk and vulnerability map was developed to represent the combined effect of physical flood risk and socio-economic vulnerability within the study area. This was achieved using a weighted overlay analysis in a GIS environment, following the same procedure applied in the generation of the individual flood risk and vulnerability maps.

The flood risk map and the socio-economic vulnerability map were first standardized to a common scale to ensure consistency and comparability between the two datasets. Weights were then assigned to each layer based on their relative importance, as determined through the Analytical Hierarchy Process (AHP), with flood risk assigned a higher weight than vulnerability.

The standardized and weighted layers were subsequently combined using the weighted overlay tool to produce the integrated map. The final output was classified into different categories representing varying levels of combined flood risk and vulnerability across the study area.

3.5.4. Flood Impact Assessment Modelling

The flood impact assessment model was developed to identify areas, settlements, and infrastructure exposed to flooding within the 2 km buffer zone along the Lilongwe River in T/A Pemba. The model integrated flood risk outputs, rainfall scenario analysis, and exposure mapping using GIS techniques.

A 2 km buffer was created around the river centerline to focus on areas identified as highly vulnerable from the integrated flood risk assessment and field observations. Flood risk classes within the buffer zone were extracted from the flood risk map generated using the Analytical Hierarchy Process (AHP) and weighted overlay analysis.

Rainfall scenario analysis was then conducted using daily rainfall values derived from CHIRPS rainfall data. Three rainfall scenarios were considered, reduced rainfall scenario, current rainfall condition, and increased rainfall scenario.

The impact assessment further involved mapping settlements and infrastructure such as schools, boreholes, sanitation facilities, restaurants, and villages within the high flood impact zones using remote sensing imagery, field observations, and GPS coordinates.

Overlay analysis was subsequently applied to determine the exposure of communities and infrastructure to flooding under different rainfall conditions. The final flood impact assessment map was produced to support flood preparedness, spatial planning, and impact-based early warning.

3.6. Ethical Considerations

Ethical considerations were observed throughout the research process. Permission to conduct the study was obtained from relevant academic authorities as well as local

administrative leaders within TA Pemba. Community entry was facilitated through consultations with traditional authorities and village leaders to ensure cooperation from local communities.

Participation in the household surveys and stakeholder consultations was voluntary. Respondents were informed about the purpose of the research and the intended use of the information being collected before providing their consent to participate. Respondents were assured that the information they provided would remain confidential and would only be used for academic purposes.

All data collected during the research process were handled with integrity and confidentiality. Personal identifiers were not included in the analysis or reporting of results in order to protect the privacy of respondents.

4. CHAPTER 4: RESULTS AND DISCUSSIONS

4.1. Results

4.1.1. Flood Risk Mapping Results

4.1.1.1. Flow Accumulation Analysis

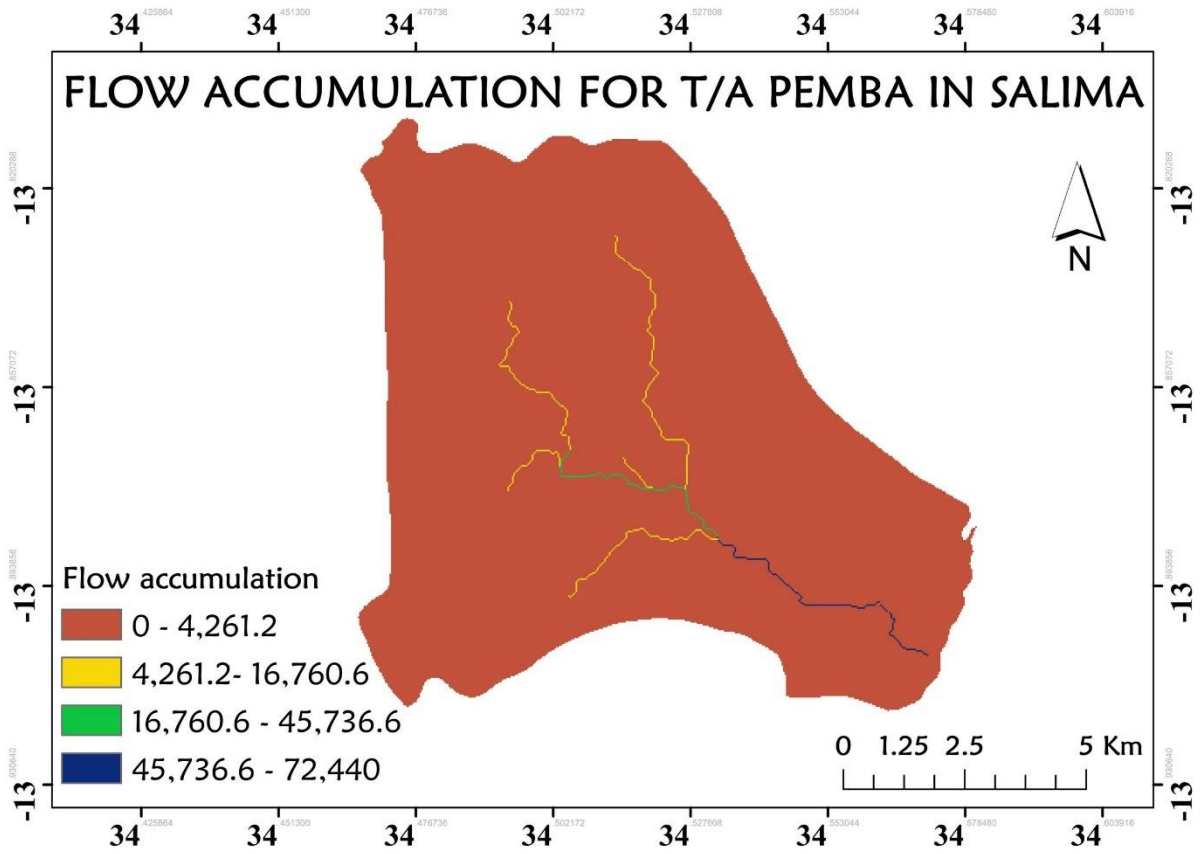


Figure 4 flow accumulation map

The flow accumulation map of the study area (Figure 4) indicates that the majority of the area falls within the lowest accumulation class (0–4,261.2), reflecting limited surface water convergence across most parts of the terrain. Distinct linear patterns of moderate to very high flow accumulation are observed along the main drainage channels. The highest accumulation values (45,736.6–72,440) are concentrated along the primary river network, while moderate accumulation zones extend outward along tributaries that feed into the main channels. These patterns show that surface runoff is concentrated along well-defined drainage paths rather than being evenly distributed across the landscape.

4.1.1.2. Slope Analysis

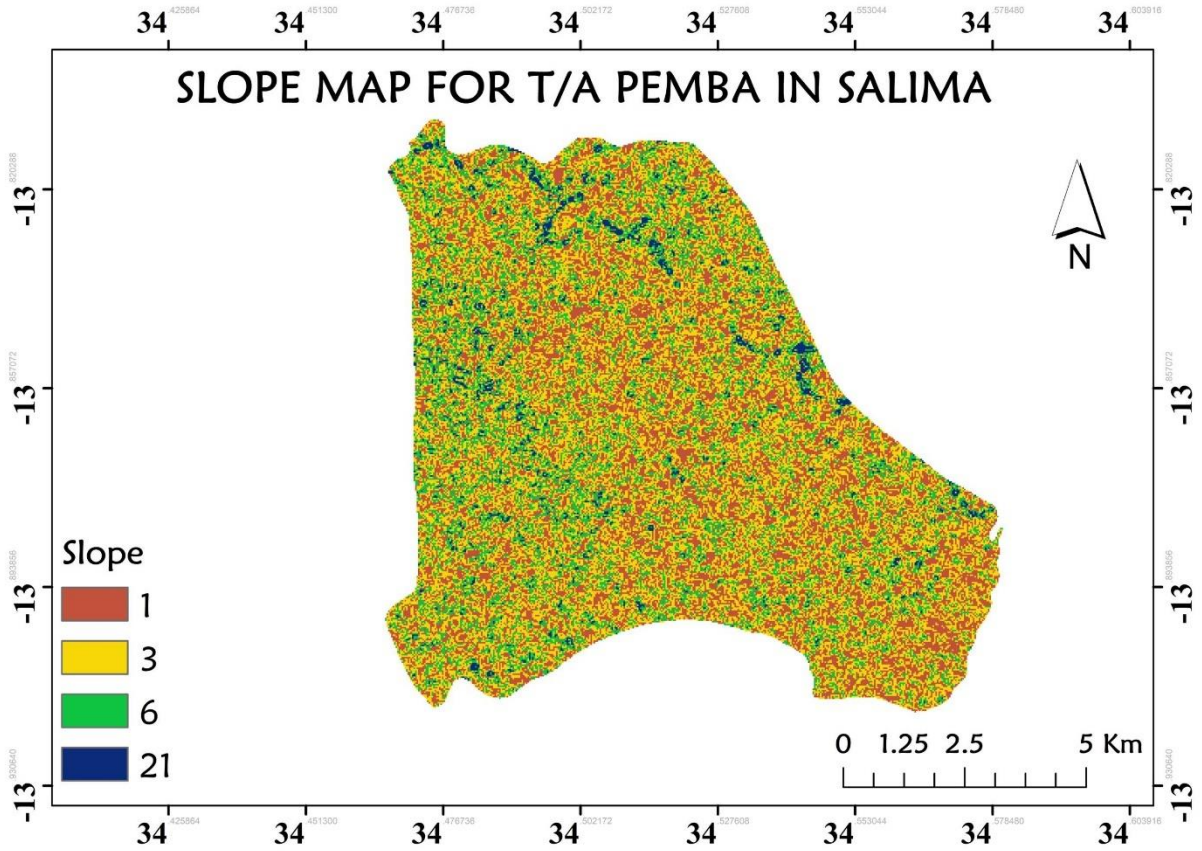


Figure 5 slope map

The slope map as shown in Figure 5 indicates that the study area is predominantly characterized by gentle to moderate slopes, with most values falling within the lower slope classes (1–6 degrees). Only a few isolated areas exhibit relatively higher slope values. The spatial distribution shows that much of the terrain has minimal variation in gradient, with relatively flat to gently sloping surfaces dominating the landscape.

4.1.1.3. Rainfall Analysis

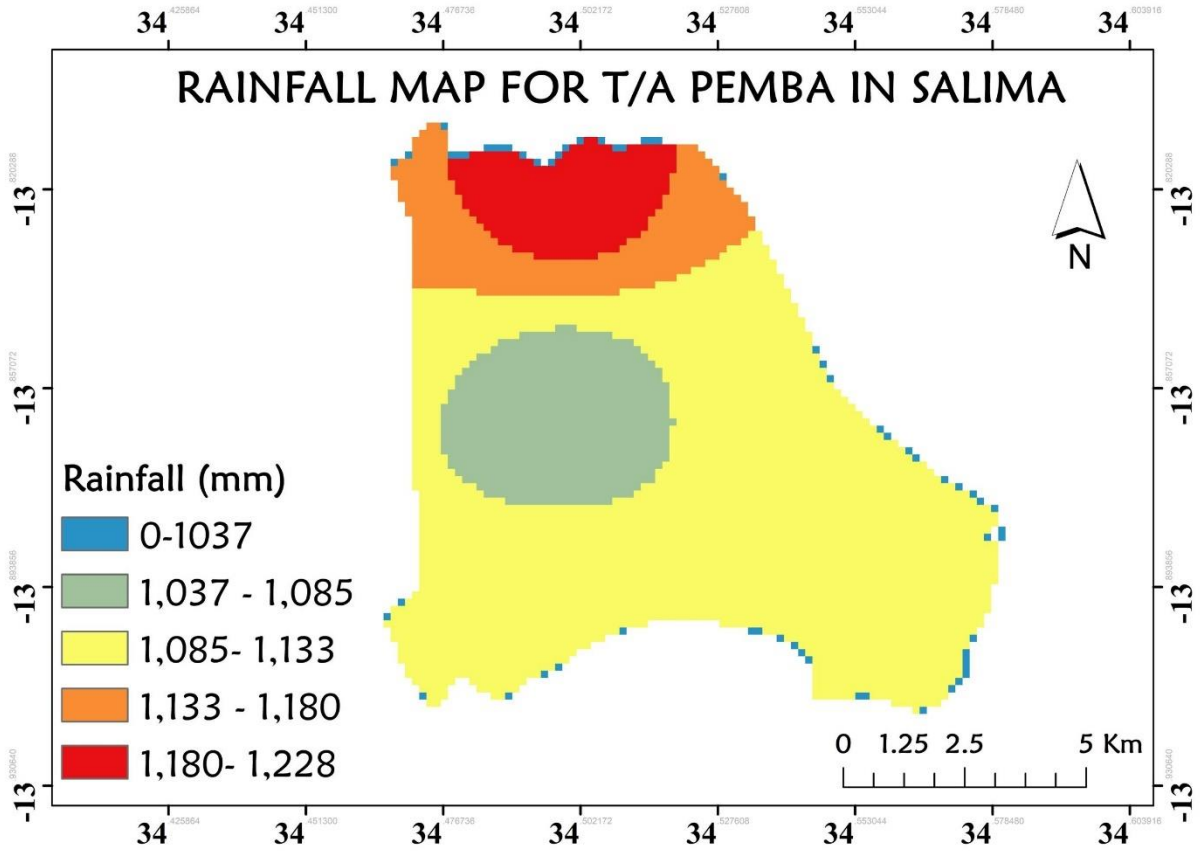


Figure 6 rainfall map

The rainfall distribution map as presented in Figure 6 shows spatial variability across the study area, with values ranging from approximately 0–1037 mm to 1180–1228 mm. Higher rainfall levels are concentrated in the northern part of the study area, while moderate rainfall dominates the central region. Lower rainfall values are observed in smaller, scattered areas along the boundaries. Overall, the map indicates a clear spatial gradient in rainfall distribution across the study area.

4.1.1.4. Elevation Analysis

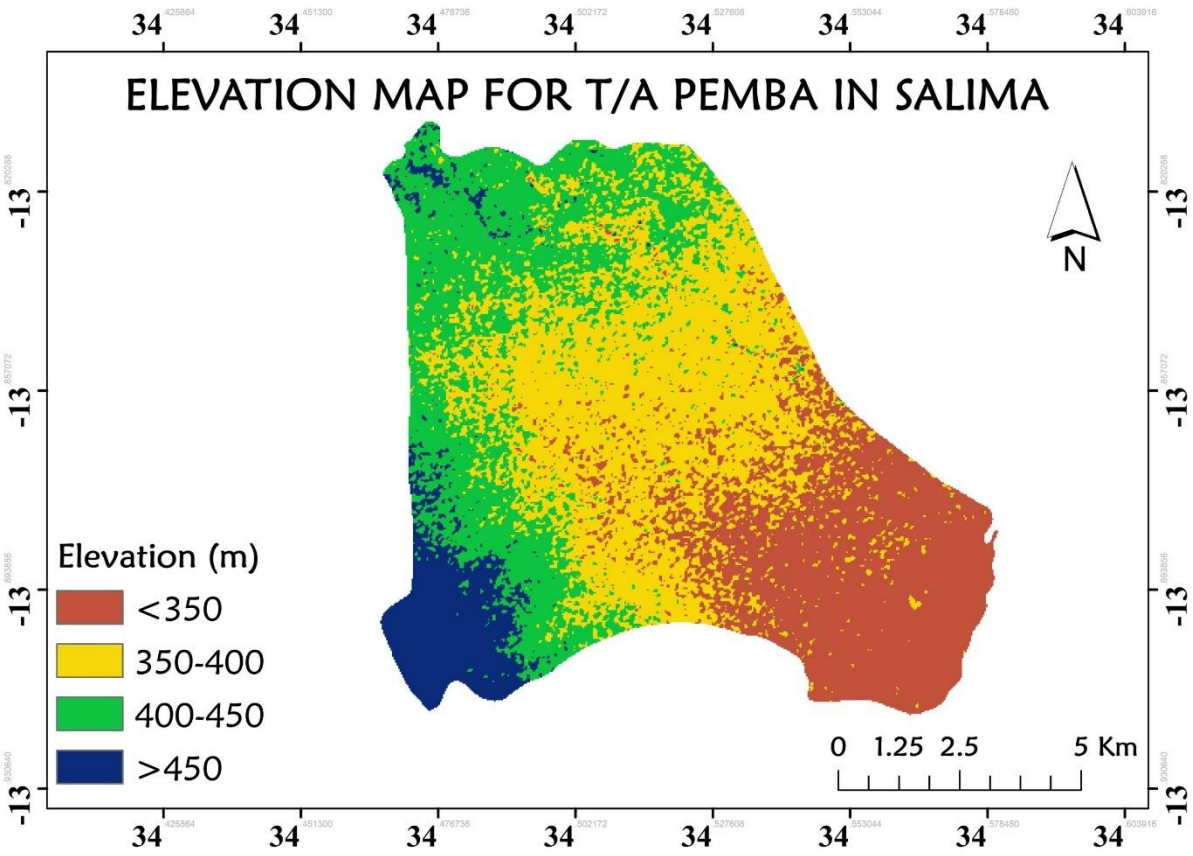


Figure 7 elevation map

The elevation map of the study area as shown in Figure 7 indicates a clear spatial variation in terrain height, with elevation values ranging from below 350 m to above 450 m. Lower elevation areas (less than 350 m) are predominantly located in the eastern and southeastern parts of the study area, while higher elevation zones (above 450 m) are concentrated in the southwestern region. Moderate elevation ranges (350–450 m) dominate the central and northern parts, forming a transitional zone between high and low terrain.

4.1.1.5. Distance to rivers analysis

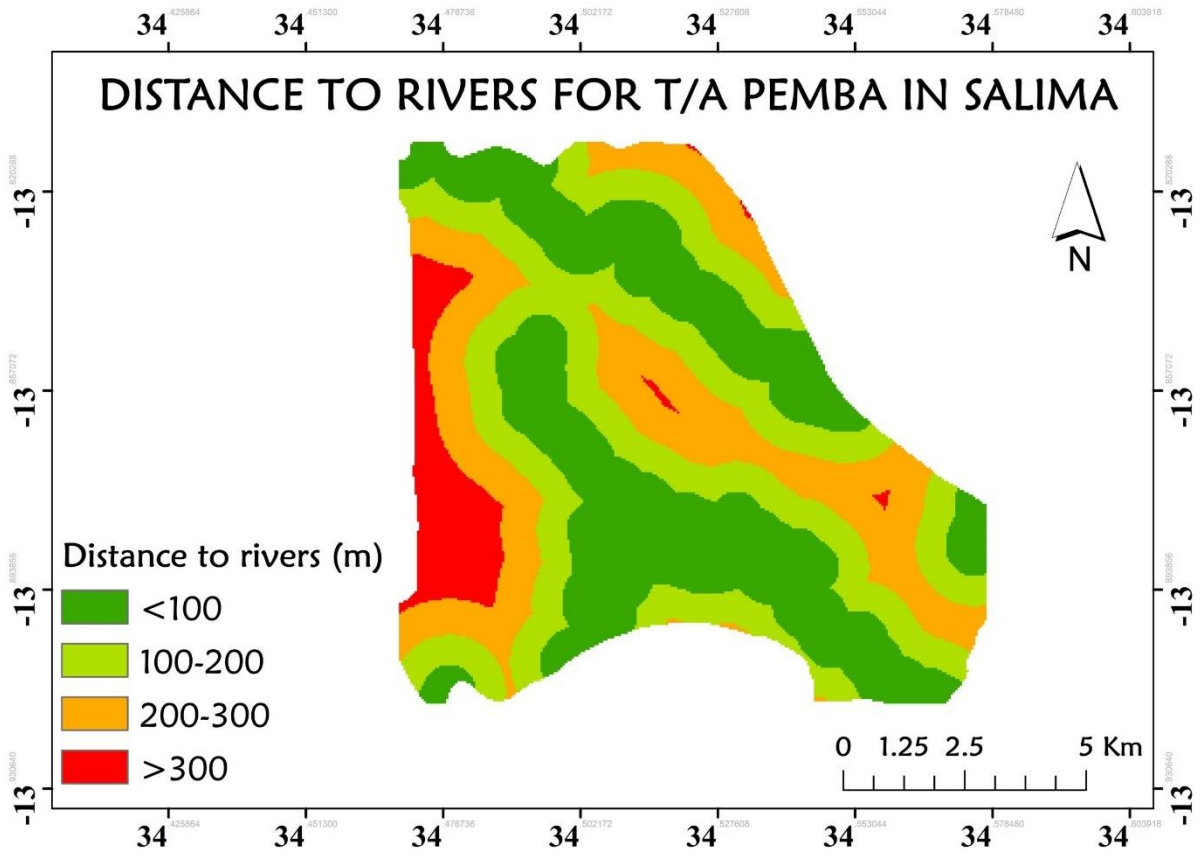


Figure 8 distance to rivers map

The distance to river map as illustrated in Figure 8 shows the spatial distribution of proximity to river channels within the study area, classified into four categories: less than 100 m, 100–200 m, 200–300 m, and greater than 300 m. Areas closest to rivers (less than 100 m) are mainly distributed along the central drainage network, forming continuous bands that follow the river channels. As distance increases, the zones extend outward, with areas beyond 300 m located further from the main drainage paths. The spatial pattern illustrates a clear gradient of increasing distance from the river channels across the study area.

4.1.1.6. Land Use and Land Cover Analysis

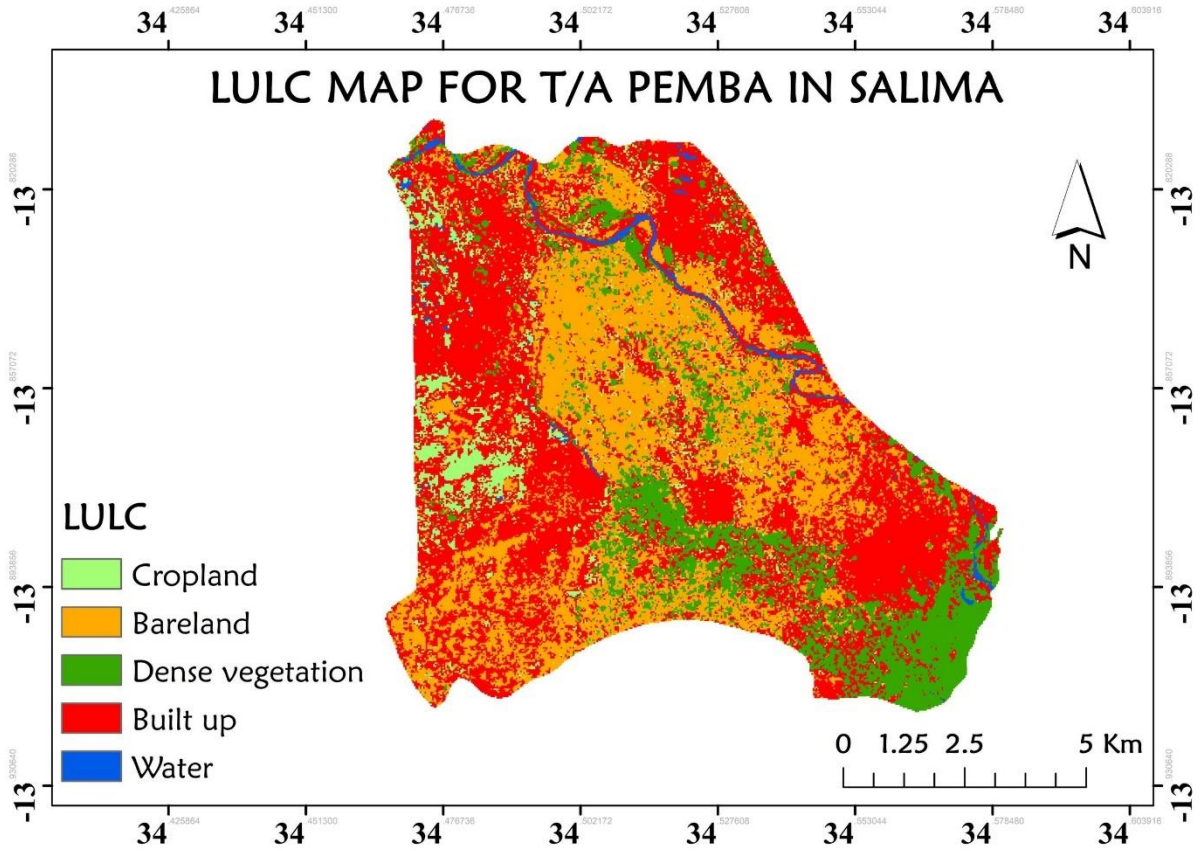


Figure 9 land use and land cover map

The land use and land cover map as depicted in Figure 9 shows that the study area is predominantly characterized by built-up areas and agricultural land, with smaller portions consisting of dense vegetation and water bodies. Built-up areas are widely distributed across the study area, while cropland is also extensively present, particularly in the central and southern regions. Dense vegetation is mainly concentrated in localized areas, and water bodies are limited to river channels and small surface water features. Overall, the map indicates that built-up and agricultural land uses dominate the landscape of the study area.

4.1.1.7. Weighting of Flood Conditioning Factors

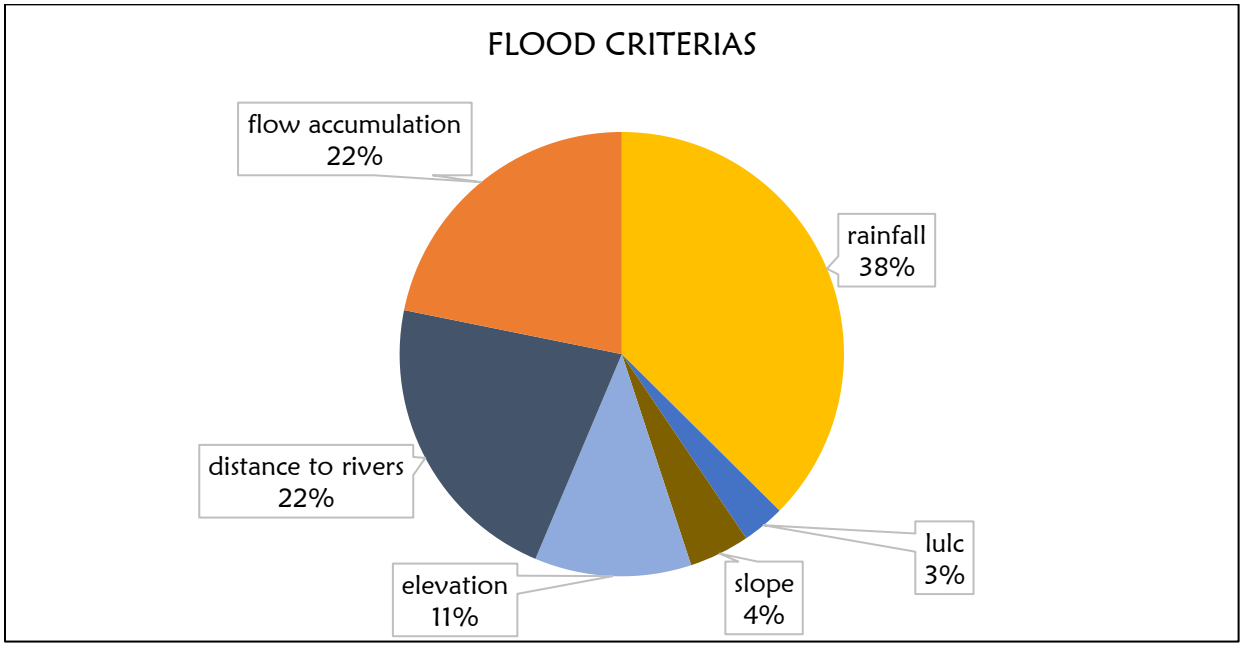
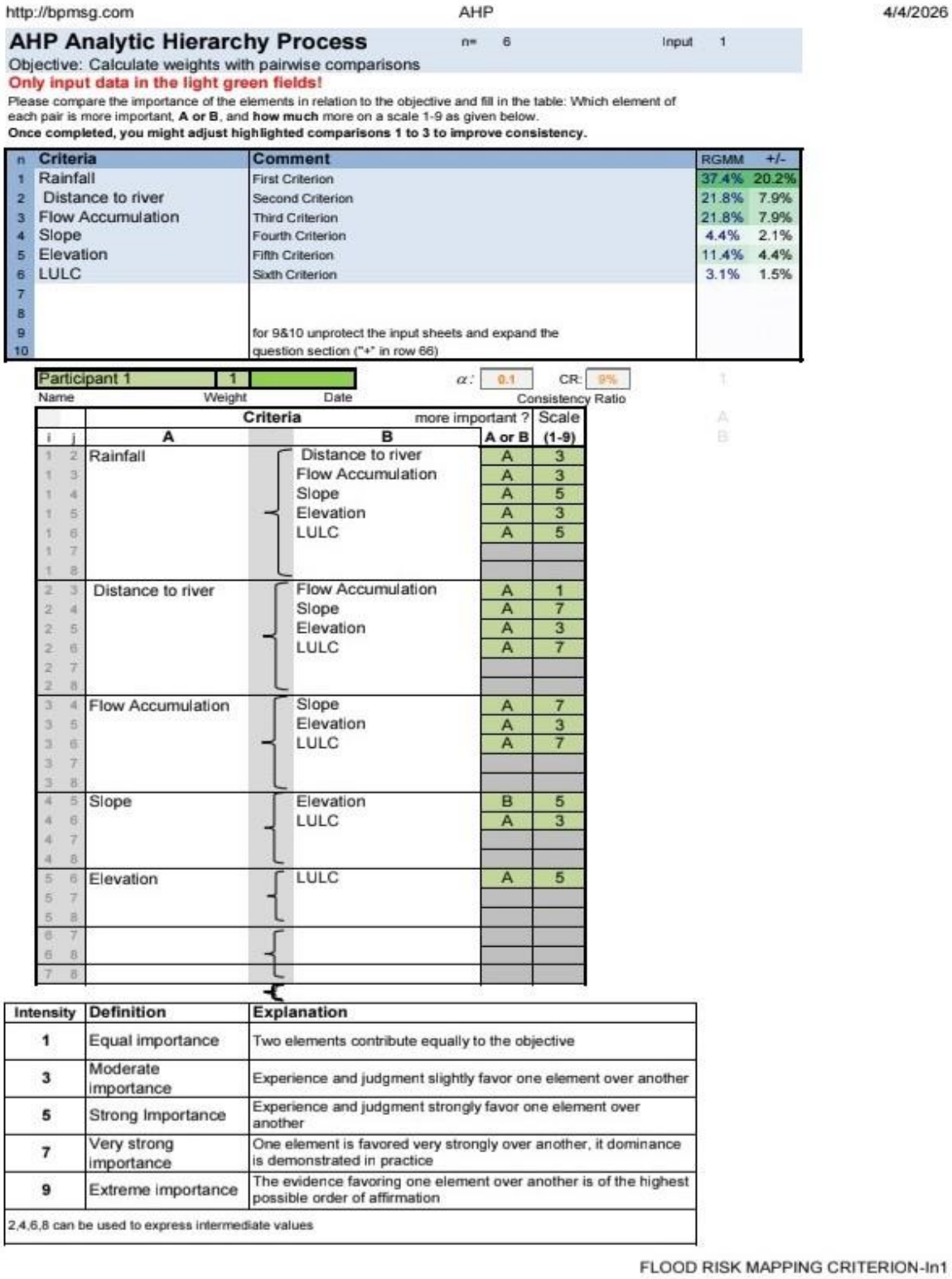


Figure 10 flood criteria weight in summary



http://bpmsg.com AHP 4/4/2026

AHP Analytic Hierarchy Process n= 6 Input 1

Objective: Calculate weights with pairwise comparisons

Only input data in the light green fields!

Please compare the importance of the elements in relation to the objective and fill in the table: Which element of each pair is more important, **A or B**, and **how much** more on a scale 1-9 as given below.

Once completed, you might adjust highlighted comparisons 1 to 3 to improve consistency.

n	Criteria	Comment	RGMM	+/-
1	Rainfall	First Criterion	37.4%	20.2%
2	Distance to river	Second Criterion	21.8%	7.9%
3	Flow Accumulation	Third Criterion	21.8%	7.9%
4	Slope	Fourth Criterion	4.4%	2.1%
5	Elevation	Fifth Criterion	11.4%	4.4%
6	LULC	Sixth Criterion	3.1%	1.5%
7				
8				
9		for 9&10 unprotect the input sheets and expand the		
10		question section ("+" in row 66)		

Participant 1 | 1 | | α: 0.1 CR: 9% 1

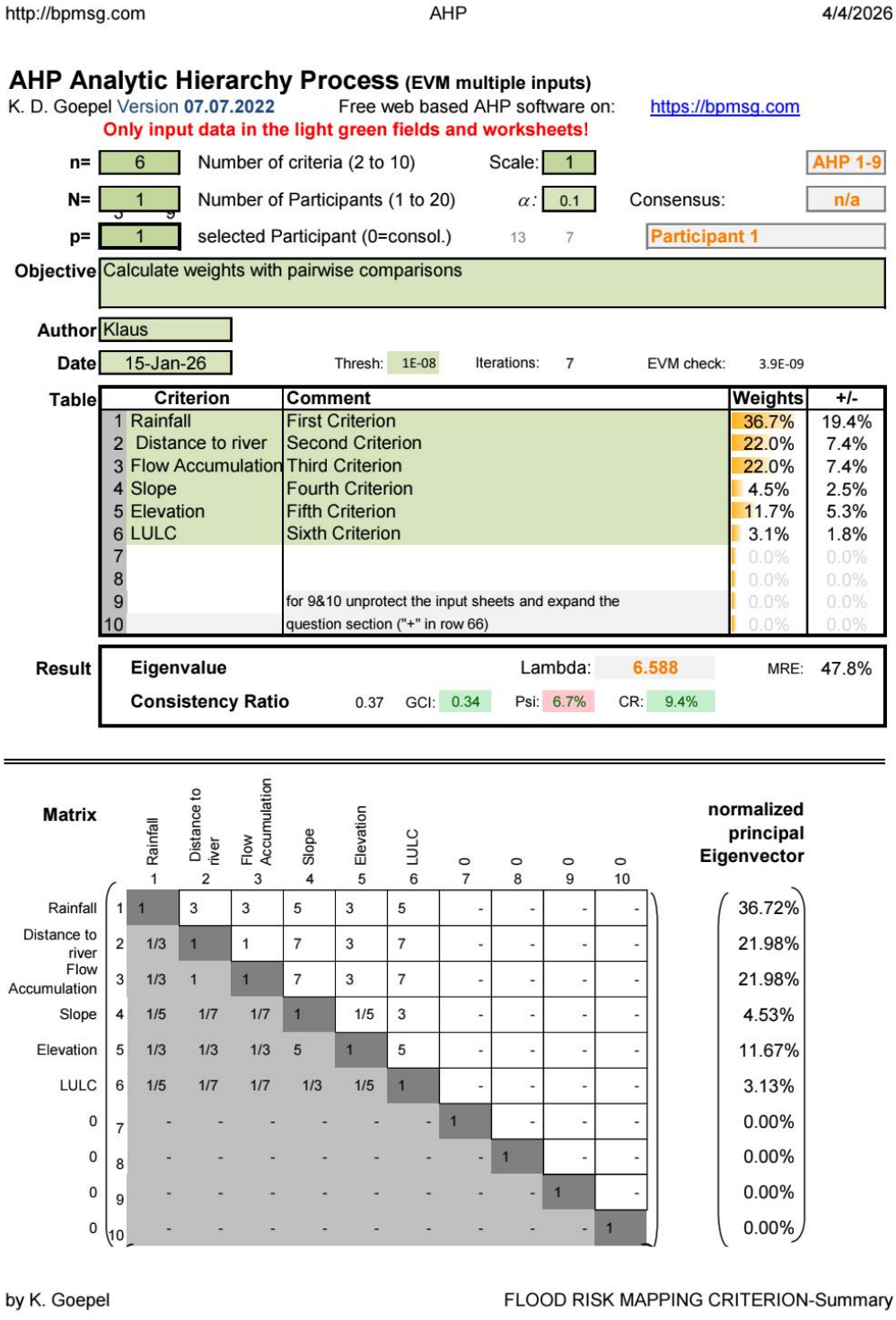
Name Weight Date Consistency Ratio

i	j	Criteria A	more important ? A or B	Scale (1-9)	Criteria B
1	2	Rainfall	A	3	Distance to river
1	3		A	3	Flow Accumulation
1	4		A	5	Slope
1	5		A	3	Elevation
1	6		A	5	LULC
1	7				
1	8				
2	3	Distance to river	A	1	Flow Accumulation
2	4		A	7	Slope
2	5		A	3	Elevation
2	6		A	7	LULC
2	7				
2	8				
3	4	Flow Accumulation	A	7	Slope
3	5		A	3	Elevation
3	6		A	7	LULC
3	7				
3	8				
4	5	Slope	B	5	Elevation
4	6		A	3	LULC
4	7				
4	8				
5	6	Elevation	A	5	LULC
5	7				
5	8				
6	7				
6	8				
7	8				

Intensity	Definition	Explanation
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one element over another
5	Strong Importance	Experience and judgment strongly favor one element over another
7	Very strong importance	One element is favored very strongly over another, it dominance is demonstrated in practice
9	Extreme importance	The evidence favoring one element over another is of the highest possible order of affirmation
2,4,6,8 can be used to express intermediate values		

FLOOD RISK MAPPING CRITERION-In1

Figure 11 pairwise comparison matrix



http://bpmsg.com AHP 4/4/2026

AHP Analytic Hierarchy Process (EVM multiple inputs)

K. D. Goepel Version **07.07.2022** Free web based AHP software on: https://bpmsg.com

Only input data in the light green fields and worksheets!

n=	6	Number of criteria (2 to 10)	Scale: 1		AHP 1-9
N=	1	Number of Participants (1 to 20)	α: 0.1	Consensus:	n/a
p=	1	selected Participant (0=consol.)	13 7		Participant 1

Objective: Calculate weights with pairwise comparisons

Author: Klaus

Date: 15-Jan-26 Thresh: 1E-08 Iterations: 7 EVM check: 3.9E-09

Table

	Criterion	Comment	Weights	+/-
1	Rainfall	First Criterion	36.7%	19.4%
2	Distance to river	Second Criterion	22.0%	7.4%
3	Flow Accumulation	Third Criterion	22.0%	7.4%
4	Slope	Fourth Criterion	4.5%	2.5%
5	Elevation	Fifth Criterion	11.7%	5.3%
6	LULC	Sixth Criterion	3.1%	1.8%
7			0.0%	0.0%
8			0.0%	0.0%
9		for 9&10 unprotect the input sheets and expand the	0.0%	0.0%
10		question section ("+" in row 66)	0.0%	0.0%

Result

Eigenvalue			Lambda:	6.588	MRE:	47.8%
Consistency Ratio	0.37	GCI: 0.34	Psi: 6.7%	CR: 9.4%		

Matrix

	1 Rainfall	2 Distance to river	3 Flow Accumulation	4 Slope	5 Elevation	6 LULC	7 0	8 0	9 0	10 0	normalized principal Eigenvector
1 Rainfall	1	3	3	5	3	5	-	-	-	-	36.72%
2 Distance to river	1/3	1	1	7	3	7	-	-	-	-	21.98%
3 Flow Accumulation	1/3	1	1	7	3	7	-	-	-	-	21.98%
4 Slope	1/5	1/7	1/7	1	1/5	3	-	-	-	-	4.53%
5 Elevation	1/3	1/3	1/3	5	1	5	-	-	-	-	11.67%
6 LULC	1/5	1/7	1/7	1/3	1/5	1	-	-	-	-	3.13%
7 0	-	-	-	-	-	-	1	-	-	-	0.00%
8 0	-	-	-	-	-	-	-	1	-	-	0.00%
9 0	-	-	-	-	-	-	-	-	1	-	0.00%
10 0	-	-	-	-	-	-	-	-	-	1	0.00%

by K. Goepel FLOOD RISK MAPPING CRITERION-Summary

Figure 12 AHP overview

The weighting of flood conditioning factors using the Analytical Hierarchy Process (AHP) as presented in Figures 10-12 indicates variation in the relative contribution of each factor within the study area. The results show that rainfall has the highest weight (37.4%), followed by distance to rivers and flow accumulation, each with a weight of 21.8%. Elevation accounts for 11.4%, while slope and land use/land cover have lower weights of 4.4% and 3.1%, respectively. Overall, the results indicate that rainfall, distance to rivers, and flow accumulation constitute the highest weighted factors, while elevation has a moderate contribution, and slope and land use/land cover represent the least weighted factors in the analysis.

4.1.1.8. Flood Risk Map

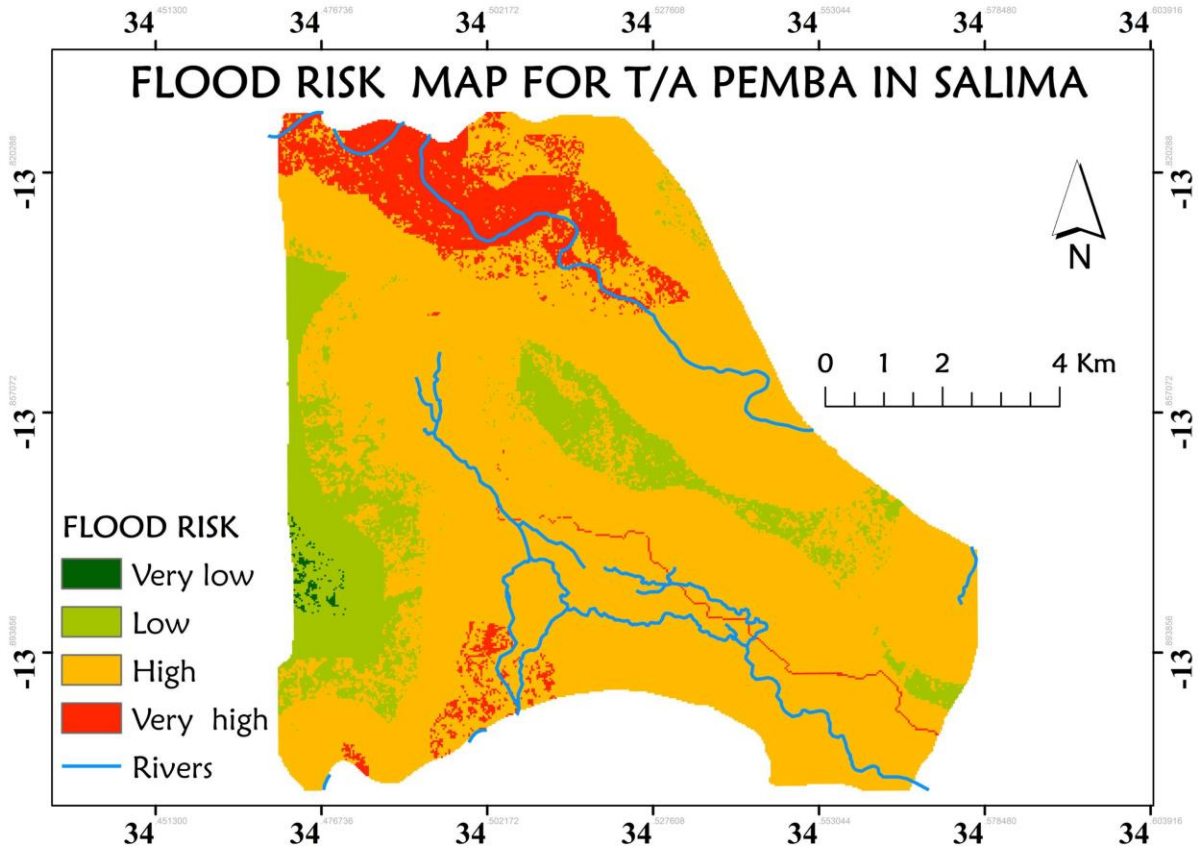


Figure 13 flood risk map

The flood risk map for T/A Pemba in Salima as presented in Figure 13 reveals a clear spatial variation across the study area, classified into four categories: very low, low, high, and

very high-risk zones. The results show that a significant portion of the study area falls under the high flood risk category, while localized areas are classified as very high risk. The very high-risk zones are concentrated primarily along the major river systems, particularly in the northern and central parts of the study area. This spatial pattern corresponds directly with the distance to rivers and flow accumulation maps, aligning with areas closest to river channels and zones of high-water convergence. The high-risk areas are widely distributed across the study area. Spatially, these areas correspond to regions that receive moderate to high rainfall and exhibit relatively gentle slopes.

Conversely, the low-risk zones are mainly found in areas that are located farther from rivers and exhibit moderate elevation. Similarly, the very low-risk areas are limited in extent and are primarily located in regions characterized by relatively higher elevations. The spatial distribution of the flood risk classes reflects the weighting of the conditioning factors derived from the Analytic Hierarchy Process (AHP) analysis. The widespread high-risk zones align spatially with the rainfall input layer, while the concentration of very high-risk areas closely tracks the distance to rivers and flow accumulation inputs. Elevation also shapes the observed pattern, with lower-lying topographic areas consistently falling into higher risk classification

4.1.1.9. Flood Risk Distribution (Area Statistics)

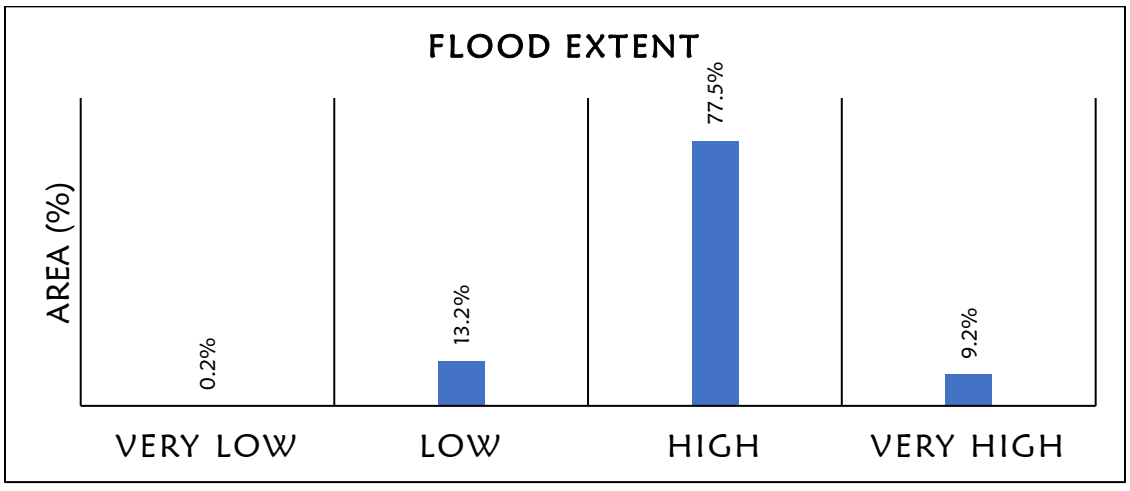


Figure 14 flood extent

The spatial distribution of the flood risk classes is further illustrated by the area statistics, which quantify the proportion of land under each category. The results in Figure 14 show that the high flood risk category covers the largest portion of the study area, accounting for approximately 77.5% of the total land. This is followed by low-risk areas, which cover 13.2%. The very high flood risk zones account for 9.2% of the total area and are spatially concentrated along the river channels. Finally, very low-risk areas cover the smallest proportion, accounting for only 0.2% of the study area.

4.1.2. Socio Economic Vulnerability Assessment Results

4.1.2.1. Socio Economic Characteristics of Respondents

4.1.2.1.1. Income Level

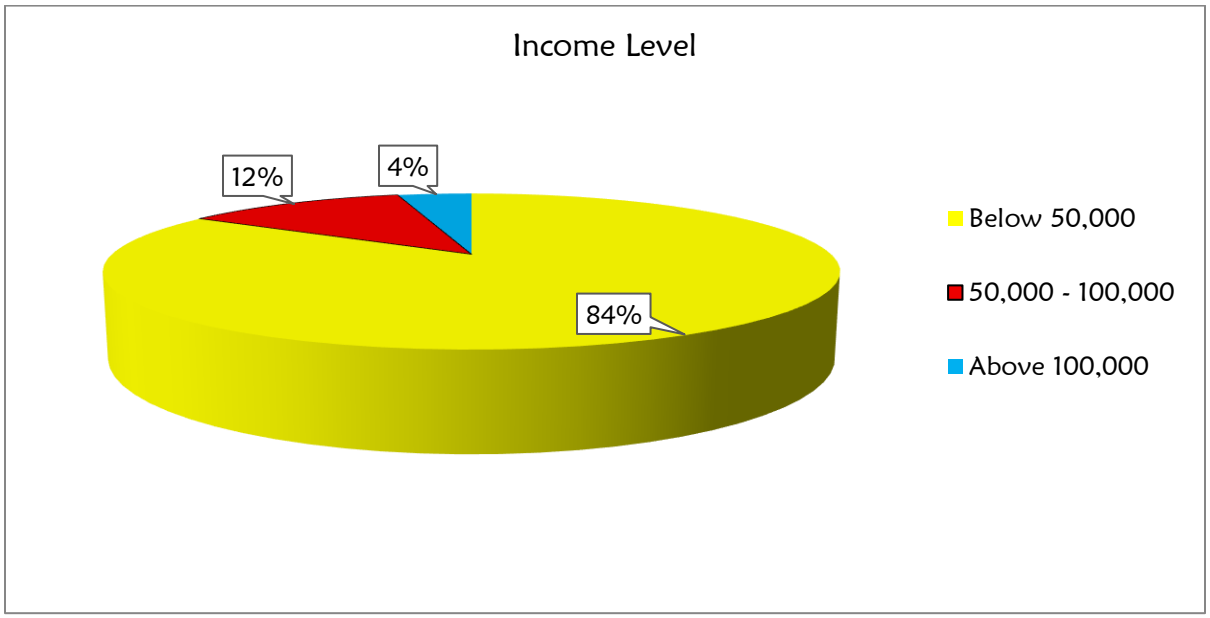


Figure 15 income level

The income data as indicated in Figure 15 reveals that 84% of the sampled households earn below MK50,000 per month. Additionally, 12% of the households fall into the MK50,000 to MK100,000 bracket, while only 4% report earning above MK100,000 per month.

4.1.2.1.2. Educational Level

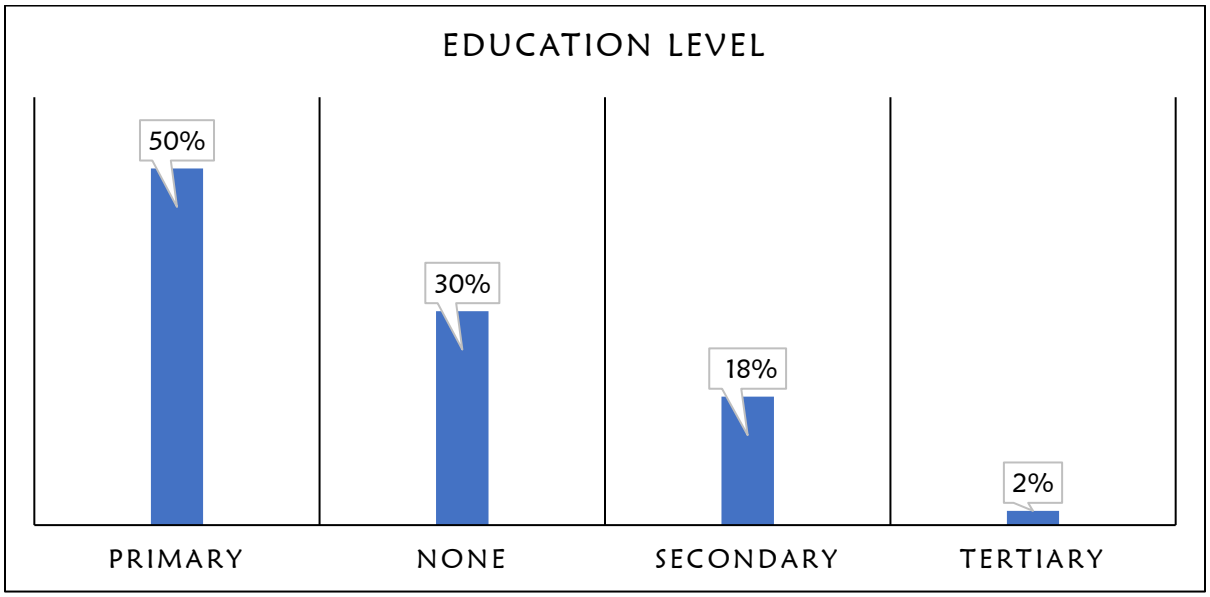


Figure 16 education level

The educational breakdown as observed in Figure 16 indicates that 50% of household heads attained a primary level of education, while 30% report having no formal education. Progression to higher educational tiers includes 18% of respondents reaching secondary school and 2% achieving tertiary education.

4.1.2.1.3. Household size

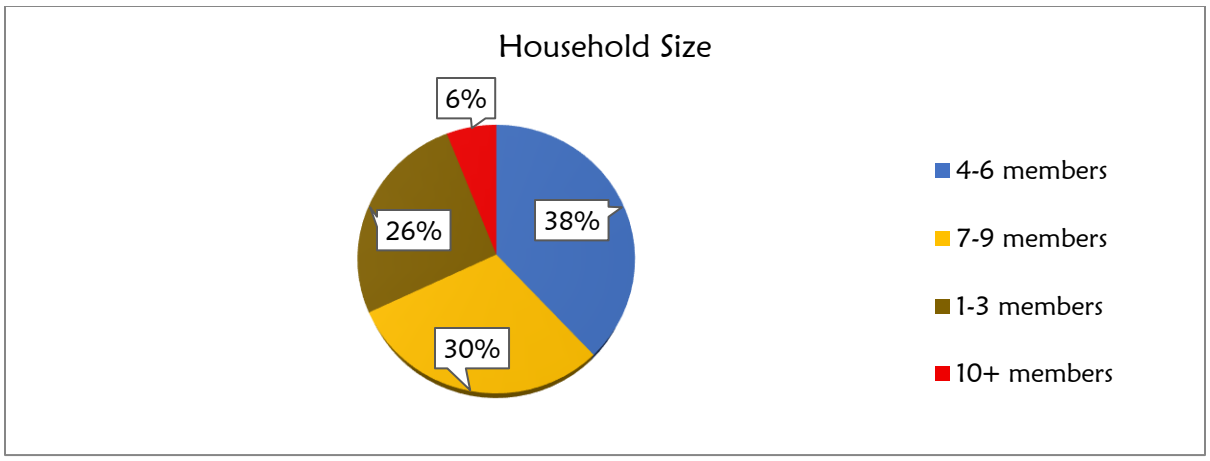


Figure 17 household size

Demographic data in Figure 17 indicates that 38% of the households have 4 to 6 members, followed by 30% with 7 to 9 members. Smaller families consisting of 1 to 3 members make up 26% of the sample, while households with 10 or more members account for the remaining 6%.

4.1.2.1.4. Livelihood Type

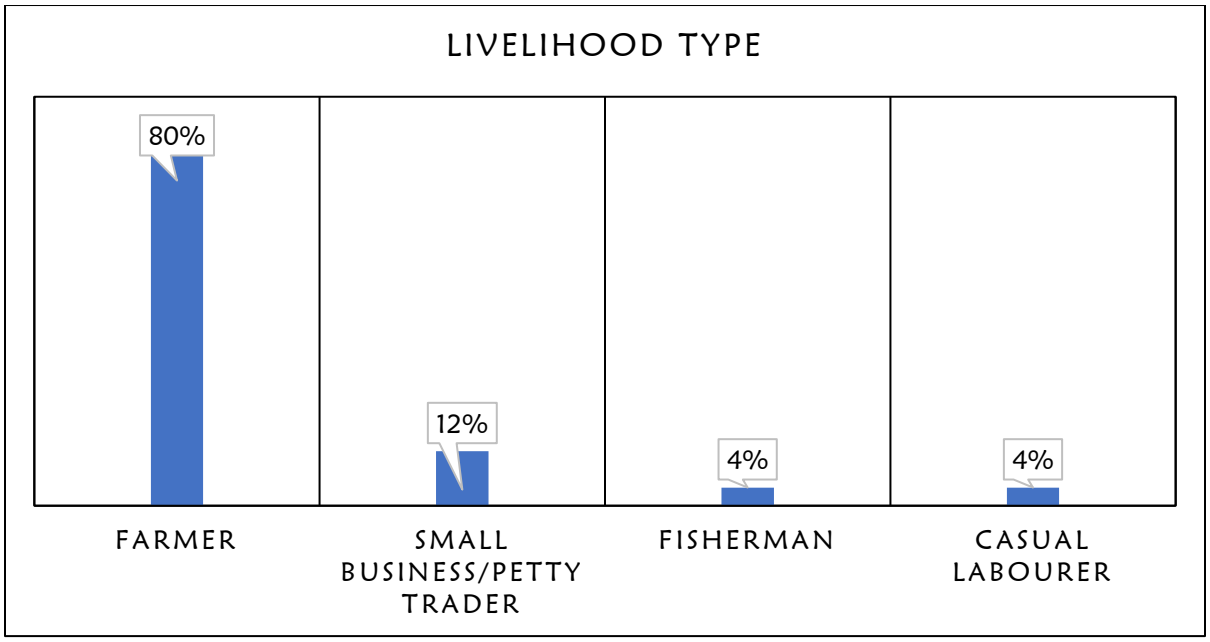


Figure 18 livelihood type

The employment data in Figure 18 indicates that 80% of the respondents identify farming as their primary occupation. The remaining 20% engage in alternative economic activities, with 12% involved in small businesses, 4% in fishing, and 4% working as casual laborers.

4.1.2.1.5. Housing Conditions

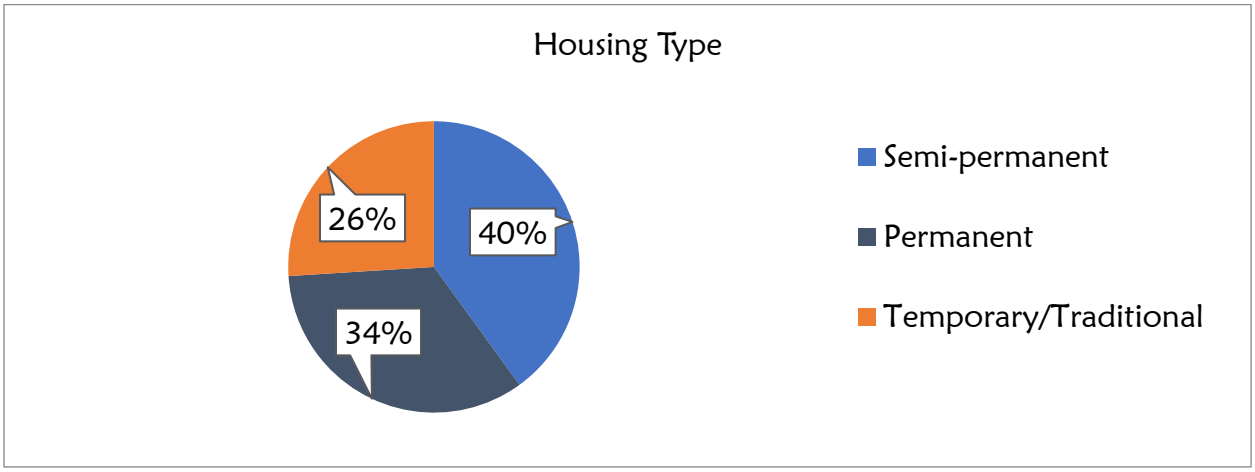


Figure 19 housing type

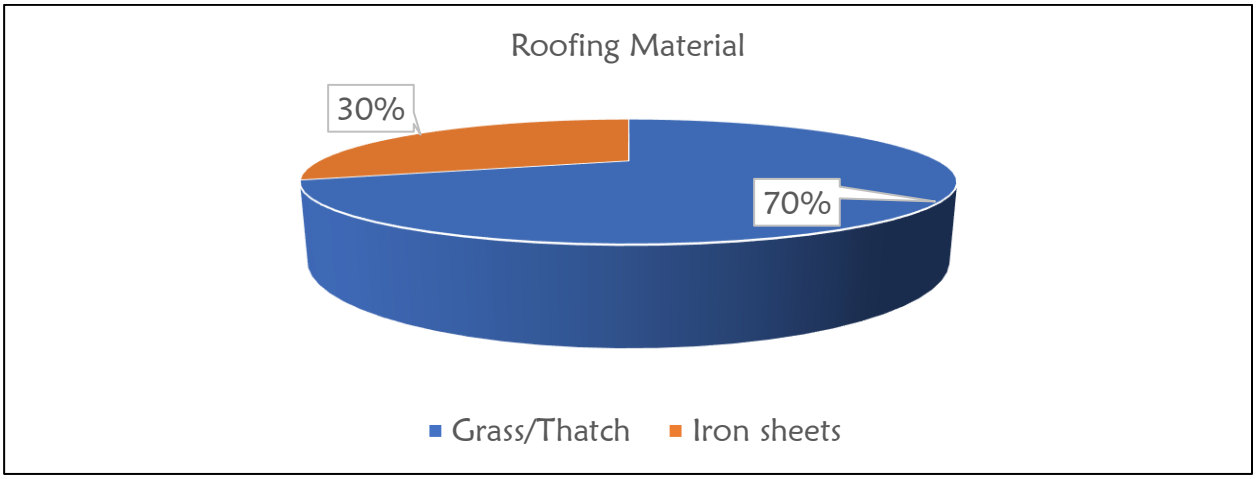


Figure 20 roofing materials

The housing statistics in Figures 19-20 indicate that 40% of the population resides in semi-permanent homes, 26% occupy temporary structures, and 34% live in permanent houses. Regarding roofing materials, 70% of the surveyed homes utilize grass or thatch, while the remaining 30% use corrugated iron sheets.

4.1.2.1.6. Visual Assessment of the Housing Conditions

Photographs were taken during the field visit as presented in Figure 21 to document the physical condition of the housing structures in the community. Most of the photographs show traditional and semi-permanent homes constructed with mud walls and grass or

thatch roofs. Conversely, a smaller portion of the photographs shows permanent houses built with fired bricks and corrugated iron roofs.



Figure 21 houses in T/A Pemba

4.1.2.1.7. Access to Services

4.1.2.1.7.1. Road Connectivity

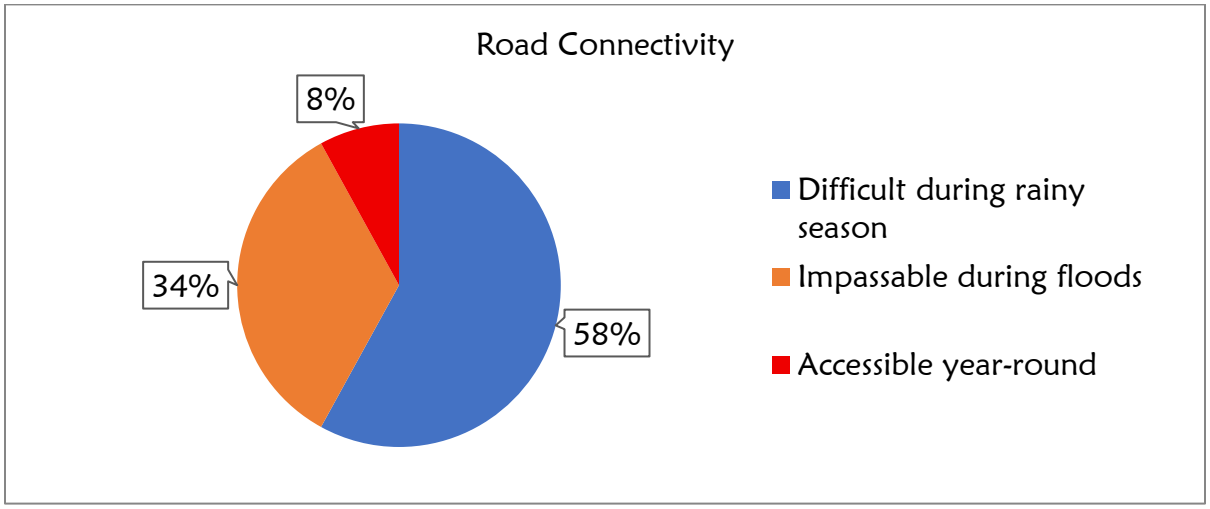


Figure 22 road connectivity

The data in Figure 22 reveals that 58% of the respondents report that roads become difficult to use during the rainy season, while 34% state that roads become completely impassable during floods. Only 8% of the surveyed households report having year-round road accessibility.

4.1.2.1.7.2. Health Care Access

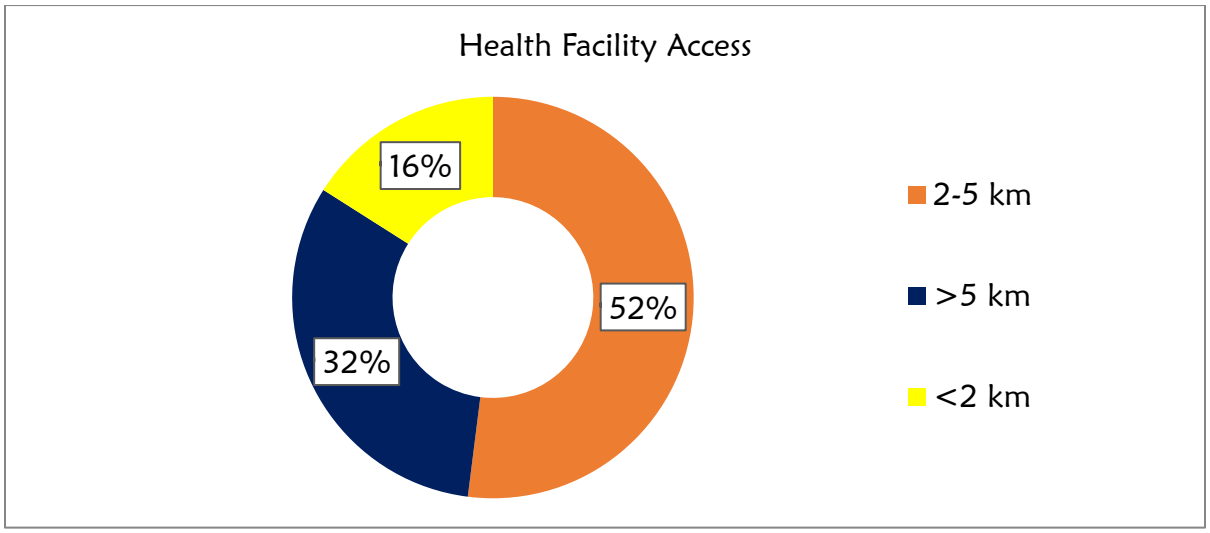


Figure 23 health care access

The data illustrated in Figure 23 regarding distance to medical facilities indicates that 52% of residents travel between 2 and 5 kilometers to reach a health clinic, and 32% travel more than 5 kilometers. The remaining 16% of the surveyed households have access to healthcare within a 2-kilometer radius.

4.1.2.1.7.3. Drinking Water

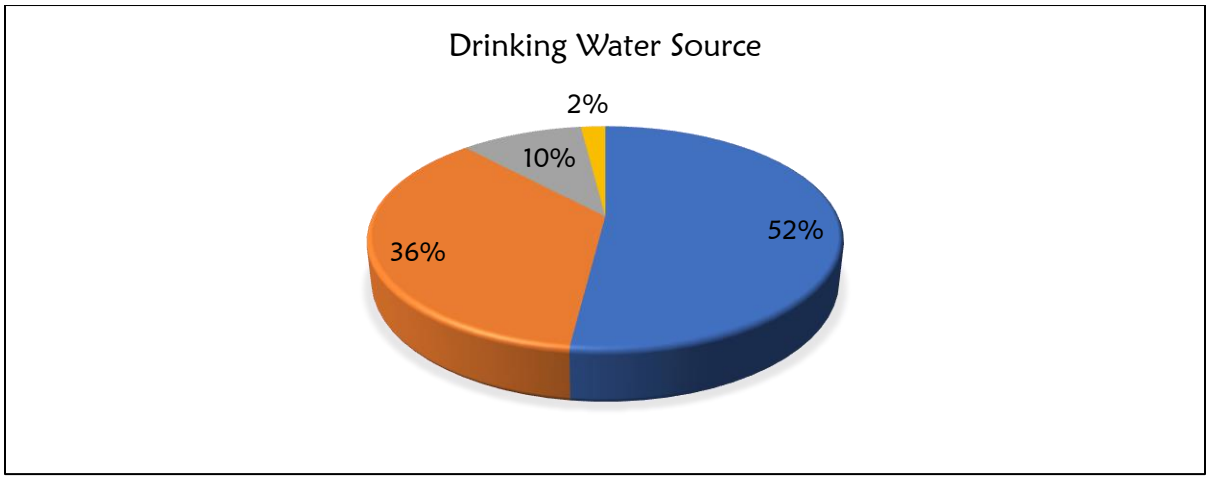


Figure 24 drinking water

The data indicated in Figure 24 depicts that 52% of the surveyed households use boreholes as their primary water source, and 10% use protected wells. Additionally, 36% of the households draw water from unprotected wells, while the remaining 2% utilize rivers or streams.

4.1.2.1.7.4. Sanitation Facilities

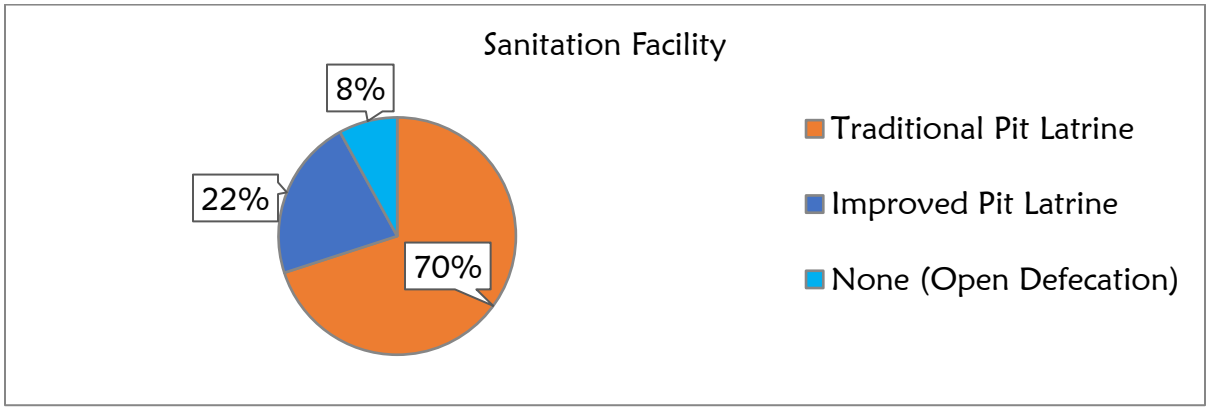


Figure 25 sanitation facility

The sanitation data in Figure 25 indicates that 70% of the surveyed households use traditional pit latrines, while 22% have access to improved pit latrines. The remaining 8% of households report having no sanitation facilities and practice open defecation.

4.1.2.1.7.5. School Access

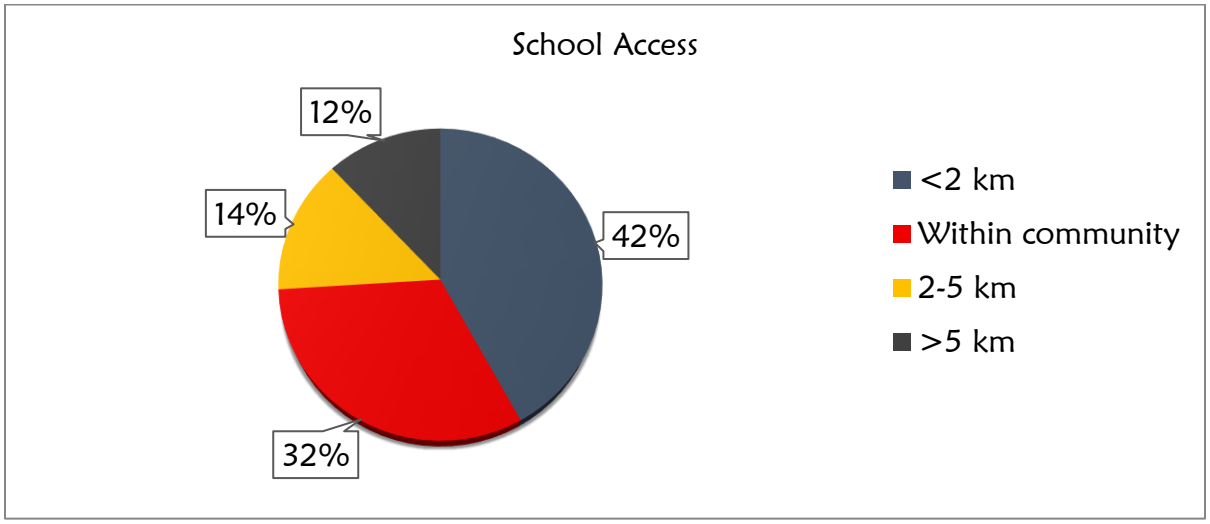
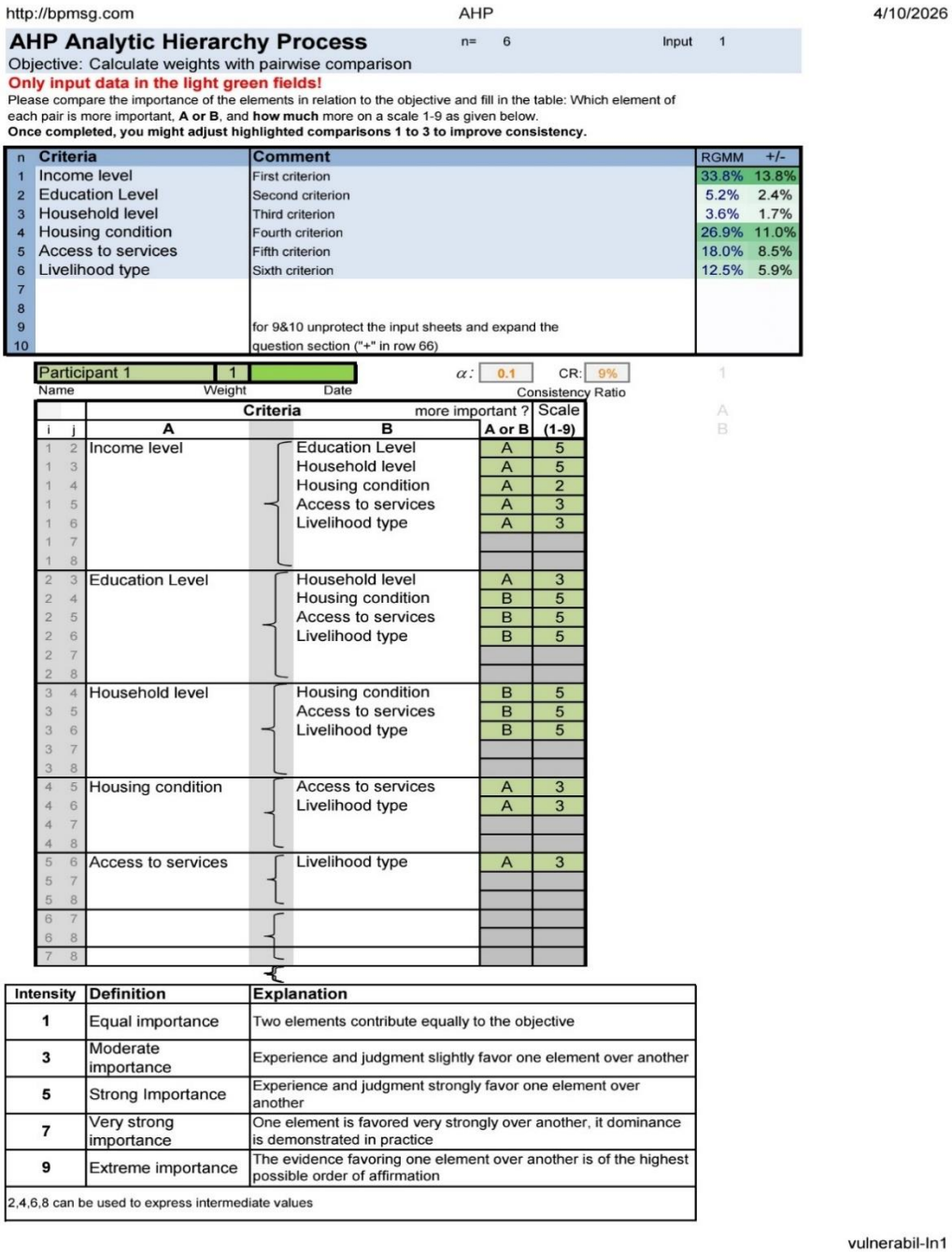


Figure 26 school access

Regarding access to primary education as shown in Figure 26, 32% of the surveyed households report having a school within their own community, and 42% are located within 2 kilometers of a school. The remaining households travel further distances, with 14% traveling between 2 and 5 kilometers, and 12% traveling over 5 kilometers.

4.1.2.2. Socio-Economic Vulnerability Weighting



http://bpmsg.com AHP 4/10/2026

AHP Analytic Hierarchy Process n= 6 Input 1

Objective: Calculate weights with pairwise comparison

Only input data in the light green fields!

Please compare the importance of the elements in relation to the objective and fill in the table: Which element of each pair is more important, **A or B**, and **how much** more on a scale 1-9 as given below.

Once completed, you might adjust highlighted comparisons 1 to 3 to improve consistency.

n	Criteria	Comment	RGMM	+/-
1	Income level	First criterion	33.8%	13.8%
2	Education Level	Second criterion	5.2%	2.4%
3	Household level	Third criterion	3.6%	1.7%
4	Housing condition	Fourth criterion	26.9%	11.0%
5	Access to services	Fifth criterion	18.0%	8.5%
6	Livelihood type	Sixth criterion	12.5%	5.9%
7				
8				
9		for 9&10 unprotect the input sheets and expand the		
10		question section ("+" in row 66)		

Participant 1 (Name) | 1 (Weight) | (Date) | α: 0.1 | CR: 9% (Consistency Ratio) | 1

i	j	A		B	Criteria more important ? A or B	Scale (1-9)
1	2	Income level		Education Level	A	5
1	3			Household level	A	5
1	4			Housing condition	A	2
1	5			Access to services	A	3
1	6			Livelihood type	A	3
1	7					
1	8					
2	3	Education Level		Household level	A	3
2	4			Housing condition	B	5
2	5			Access to services	B	5
2	6			Livelihood type	B	5
2	7					
2	8					
3	4	Household level		Housing condition	B	5
3	5			Access to services	B	5
3	6			Livelihood type	B	5
3	7					
3	8					
4	5	Housing condition		Access to services	A	3
4	6			Livelihood type	A	3
4	7					
4	8					
5	6	Access to services		Livelihood type	A	3
5	7					
5	8					
6	7					
6	8					
7	8					

Intensity	Definition	Explanation
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one element over another
5	Strong Importance	Experience and judgment strongly favor one element over another
7	Very strong importance	One element is favored very strongly over another, it dominance is demonstrated in practice
9	Extreme importance	The evidence favoring one element over another is of the highest possible order of affirmation
2,4,6,8 can be used to express intermediate values		

vulnerabil-In1

Figure 27 pairwise comparison matrix

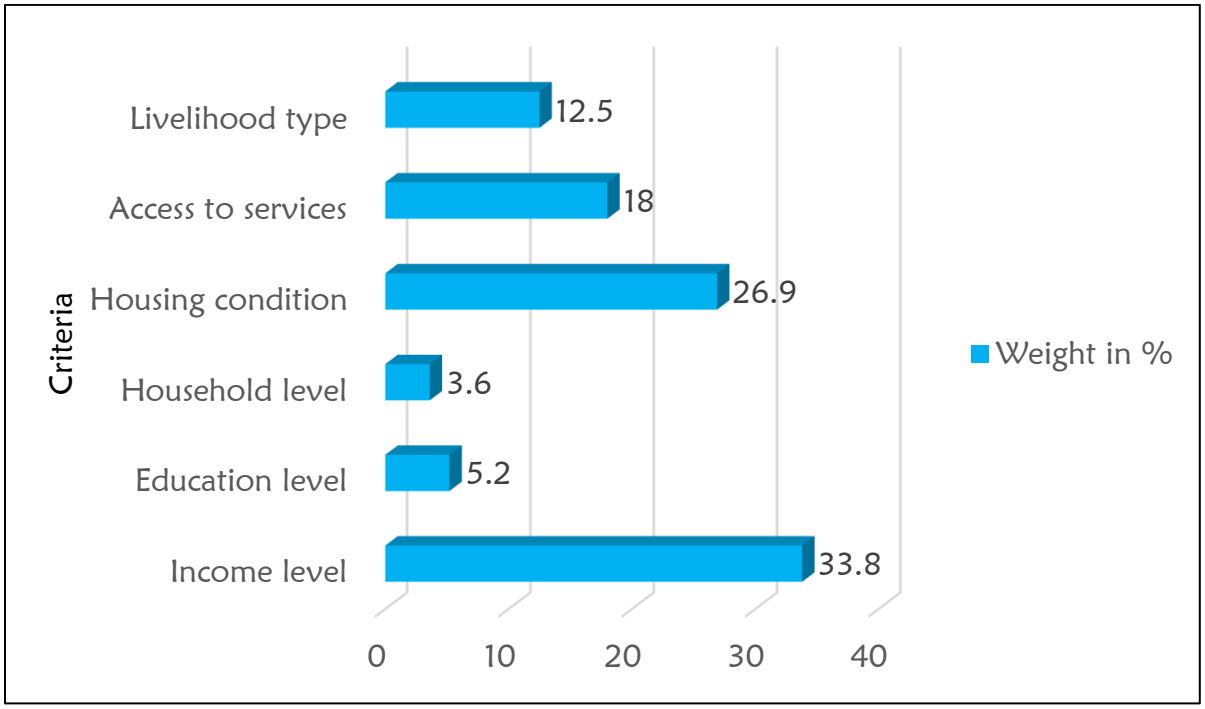


Figure 28 pairwise matrix results in summary

The results of the weighting process as indicated in Figures 27-28 reveal the relative distribution of the selected socio-economic factors. Income level carries the highest weight at 33.8%, followed by housing condition at 26.9%, and access to services at 18.0%. Livelihood accounts for 12.5%, education level for 5.2%, and household size contributes the lowest weight at 3.6%.

4.1.2.3. Spatial Distribution of Socio-Economic Vulnerability

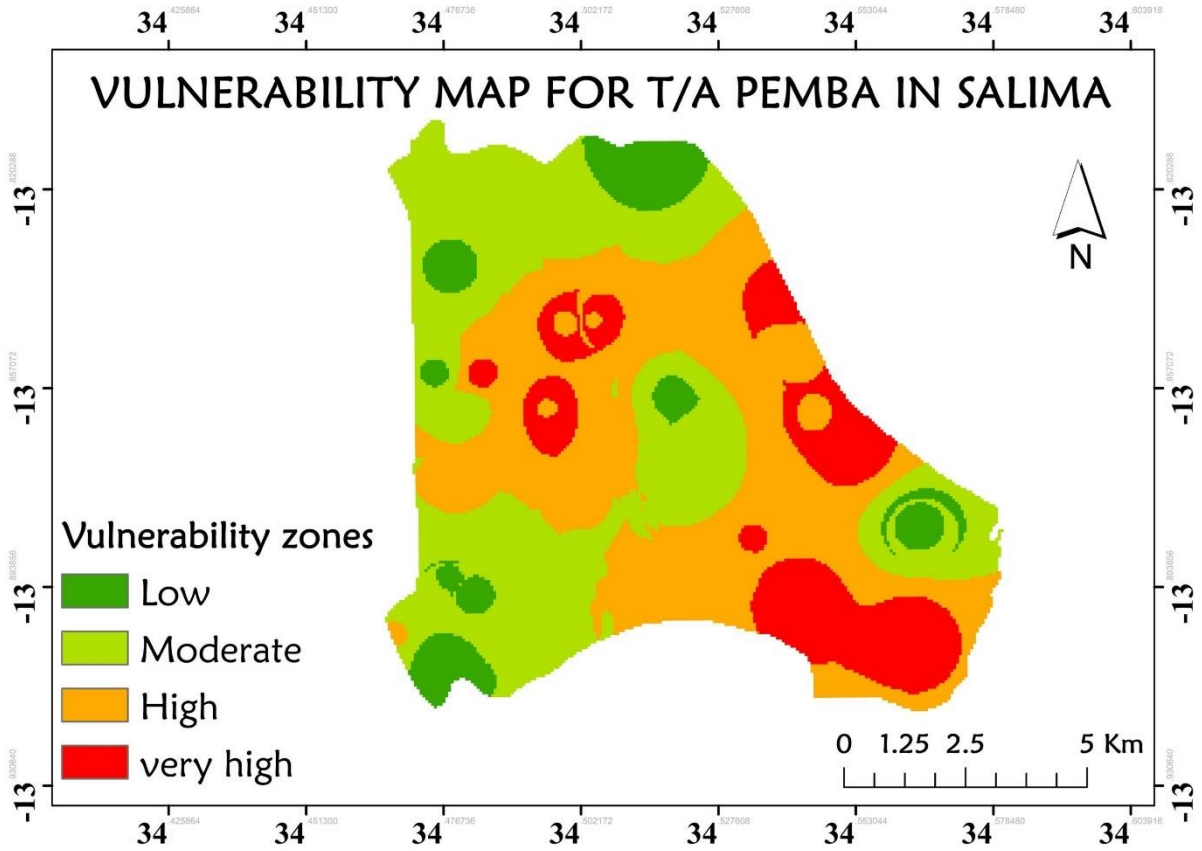


Figure 29 vulnerability map

The vulnerability map in Figure 29 categorizes the study area into low, moderate, high, and very high vulnerability zones based on the weighted AHP inputs: income level (33.8%), housing condition (26.9%), access to services (18.0%), livelihood (12.5%), education level (5.2%), and household size (3.6%). Areas classified as very high vulnerability spatially align with the lowest mapped income levels, non-permanent housing, and distant access to services. High vulnerability zones cover a considerable portion of the study area, driven primarily by the service access and livelihood layers. Moderate zones form transitional areas, while the limited and scattered low vulnerability zones directly correspond to locations mapped with higher income, permanent housing, and closer access to essential services. Overall, the map's gradient strictly reflects the spatial distribution of these underlying socio-economic input layers.

4.1.2.4. Vulnerability Categories Area Statistics

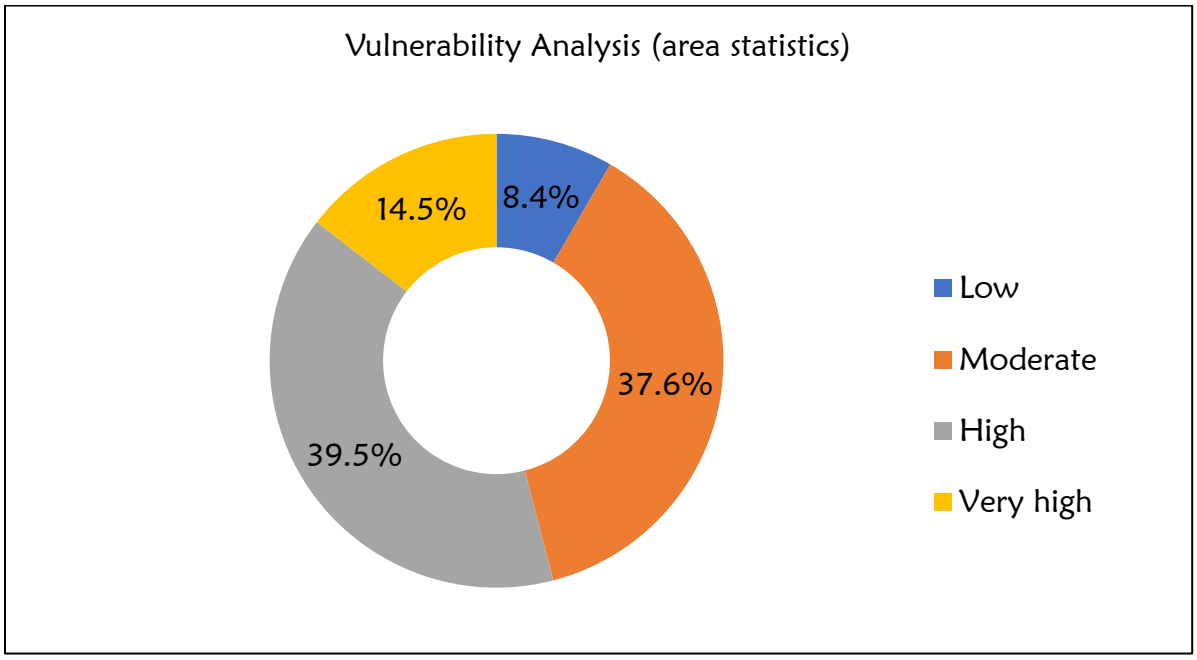


Figure 30 vulnerable area statistics

The area statistics as shown in Figure 30 indicate that 39.5% of the total study area is classified as high vulnerability, followed by moderate vulnerability at 37.6%. Together, these two categories account for 77.1% of the total land area. The very high vulnerability category occupies 14.5% of the area, while the low vulnerability category covers the smallest portion at 8.4%.

4.1.3. Integrated Flood Risk and Socio-Economic Vulnerability Results

4.1.3.1. Weighting process

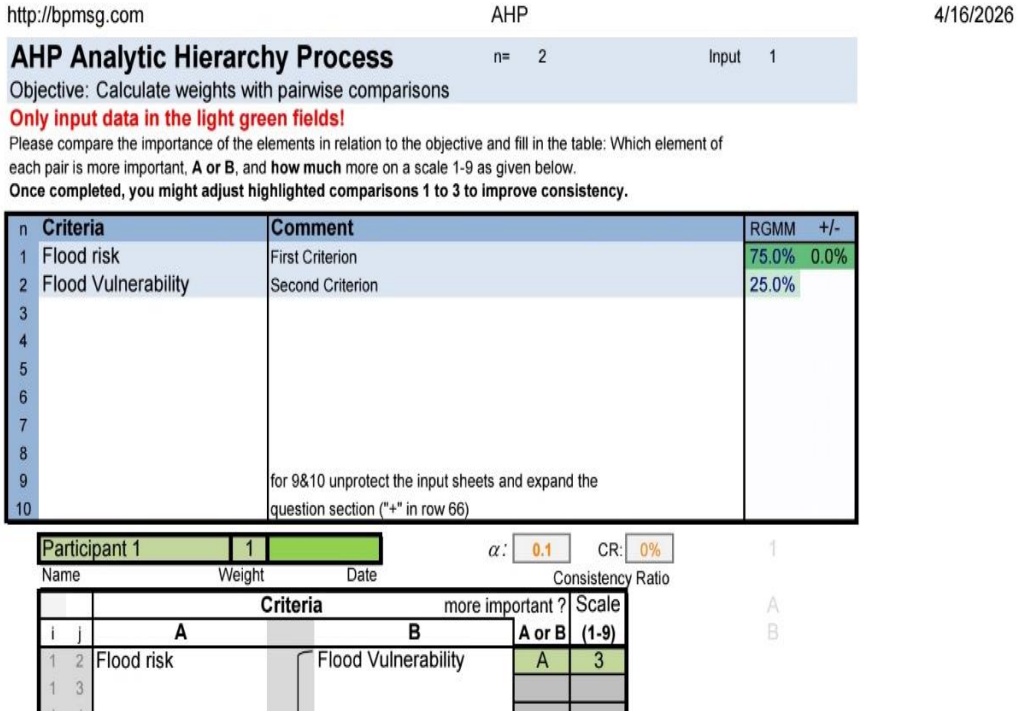


Figure 31 pairwise matrix

The results of the Analytic Hierarchy Process (AHP) as depicted in Figure 31 reveal the final weight distribution used to integrate the primary components of the model. Based on a pairwise comparison where Flood Risk was assigned a moderate intensity value of 3 in relation to Flood Vulnerability, the resulting weights are 75.0% and 25.0%, respectively. This distribution indicates that Flood Risk carries three times the weight of Flood Vulnerability in the final integrated output. Furthermore, the analysis yielded a Consistency Ratio (CR) of 0%, confirming that the assigned weights are mathematically consistent and free of contradictions.

4.1.3.2. Integrated Flood Risk and Vulnerability Map

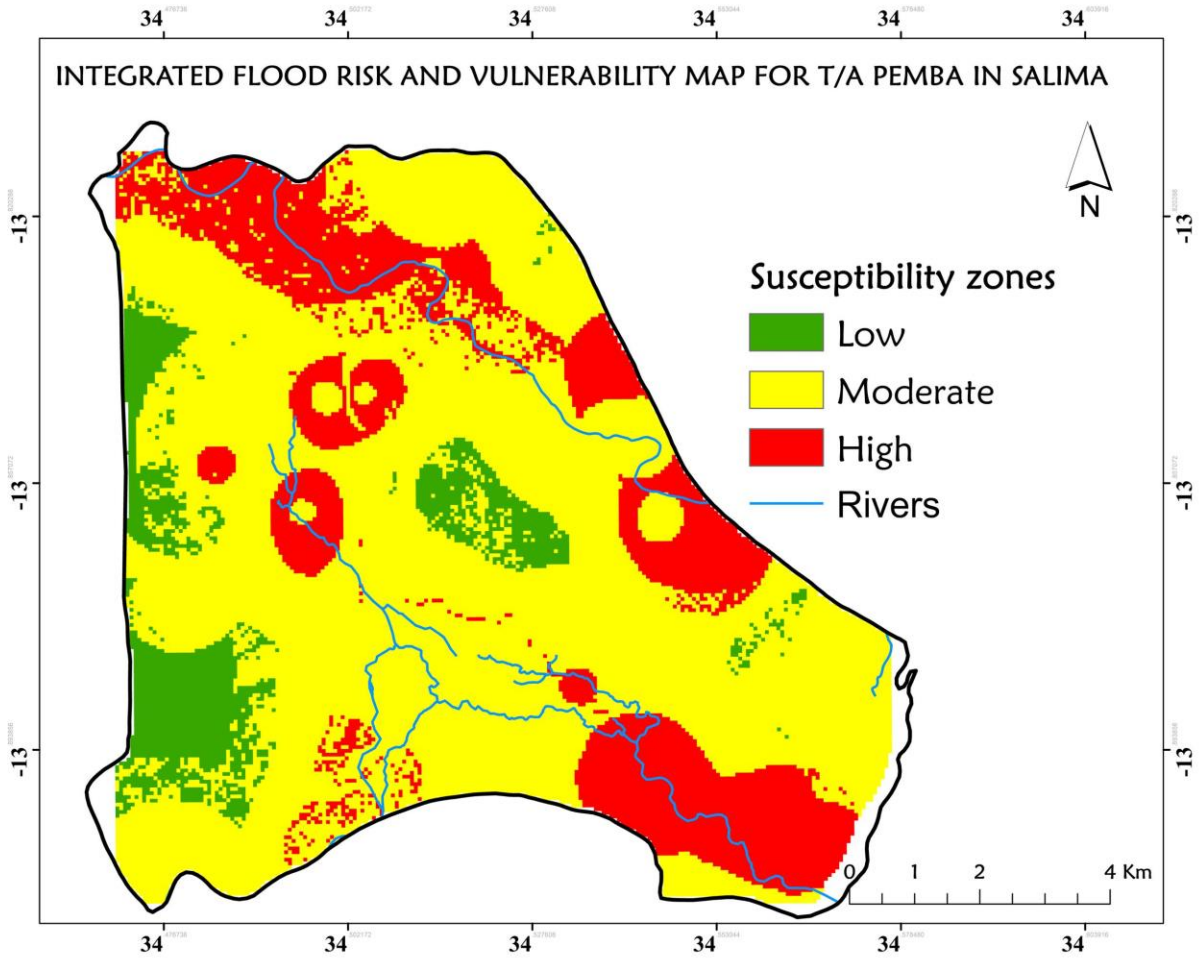


Figure 32 integrated flood risk and vulnerability map

The integrated susceptibility map for T/A Pemba as observed in Figure 32 presents the spatial distribution of combined physical risk and socio-economic vulnerability across the study area. This output is the result of the weighted overlay process where Flood Risk was assigned a 75.0% weight and Flood Vulnerability a 25.0% weight, as established by the AHP comparison matrix. High susceptibility zones, indicated in red, are predominantly located along the river channels in the northern and southeastern regions, as well as in specific central clusters, reflecting the heavy influence of the physical hazard data. Moderate susceptibility, shown in yellow, serves as the most widespread category, covering the majority of the landscape and acting as a transition between high-risk areas

and low-risk interiors. Low susceptibility zones, marked in green, are limited to the western and central-eastern portions of the area where both physical exposure and socio-economic factors are at their lowest levels. Overall, the map illustrates a susceptibility gradient that is primarily driven by proximity to river networks and moderated by the underlying socio-economic input layers.

4.1.3.3. Susceptible Zones Area Statistics

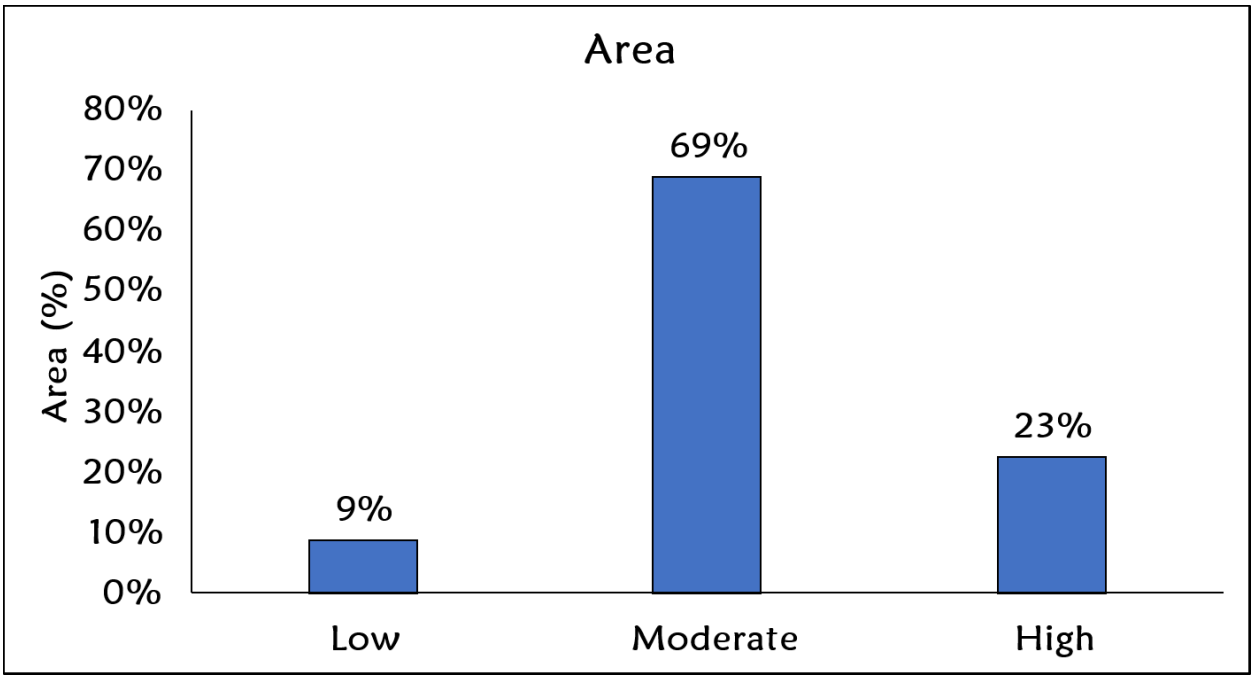


Figure 33 Susceptible Zone Area Statistics

The area statistics from the integrated flood risk and vulnerability map in Figure 33 above indicate that moderate susceptible zones cover the largest proportion of the study area, accounting for 69% of the total area. High susceptible zones account for 23%, while low susceptible zones constitute 9% of the mapped area.

4.1.4. Flood Impact Assessment Results

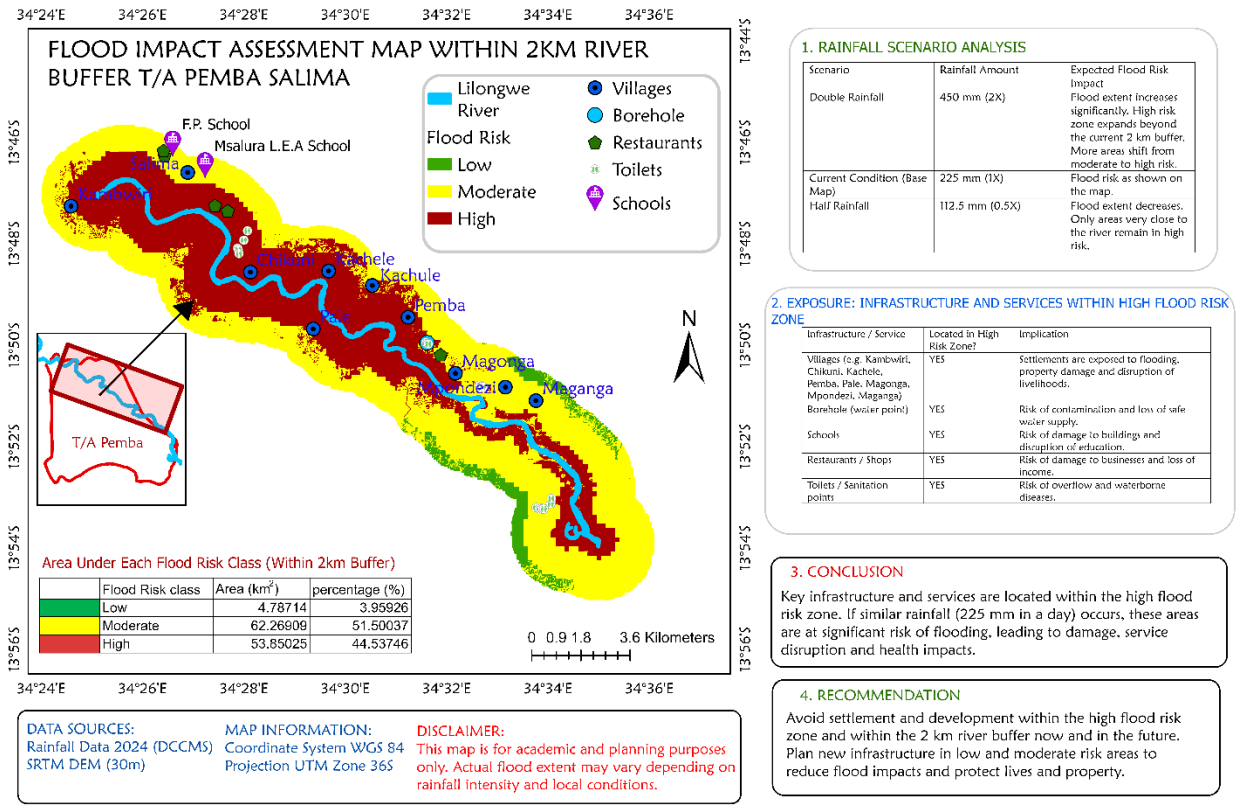


Figure 34 impact assessment map

The flood impact assessment map within the 2 km river buffer in Figure 33 shows the spatial distribution of flood impacts along the Lilongwe River in T/A Pemba, Salima. The results indicate that high flood impact zones are concentrated close to the river channel, while moderate impact zones extend outward across most parts of the buffer area. Low impact areas are limited and mainly occur farther from the river.

The area statistics further show that moderate flood impact areas cover the largest proportion of the buffer zone, accounting for 51.5% of the total area. High flood impact zones account for 44.5%, while low impact areas cover only 4.0% of the mapped area.

The rainfall scenario analysis indicates that the current flood impact pattern corresponds to a daily rainfall condition of approximately 225 mm/day. The results further show that

increasing the rainfall amount to 450 mm/day would increase the flood extent, causing more areas to shift into high flood impact zones. Conversely, reducing the rainfall amount to approximately 112.5 mm/day would decrease the flood extent, with high impact areas remaining concentrated near the river channel.

The exposure assessment indicates that several villages, including Kambwiri, Chikuni, Kachele, Pemba, Pale, Magonga, Mpondezi, and Maganga, are located within high flood impact zones. In addition, infrastructure and services such as boreholes, schools, restaurants, and sanitation facilities are also situated within areas of high flood impact.

4.2. Discussions

This study set out to assess the spatial distribution of flood risk and the socio-economic vulnerability of communities in T/A Pemba using GIS and remote sensing techniques. The findings demonstrate that flood risk in the study area is shaped by a strong interaction between environmental conditions and socio-economic characteristics, confirming that flooding is not only a physical hazard but also a socio-economic challenge.

The flood risk results indicate that a substantial proportion of the study area falls within high and very high-risk categories, accounting for 77.5% and 9.2% respectively. These areas are predominantly located along river channels and low-lying zones, reflecting the spatial influence of hydrological and terrain-related factors. The AHP weighting further supports this pattern, with rainfall (37.4%), distance to rivers (21.8%), and flow accumulation (21.8%) identified as the most influential factors. This demonstrates that flood occurrence within the study area is largely controlled by water availability and its movement through the drainage system. Similar findings have been reported by Mohammad Javad Tehrany et al. (2014), who identified rainfall intensity and proximity to river systems as primary determinants of flood hazard in GIS-based flood susceptibility mapping.

Although elevation and slope contribute to flood risk, their relative influence is comparatively lower, as reflected in their weights. Elevation (11.4%) plays a role in defining areas of lower terrain, while slope (4.4%) shows minimal variation across the study area,

indicating that much of the terrain is relatively flat. Land use and land cover (3.1%) also contribute less significantly in comparison to hydrological factors. This finding aligns with studies such as Biswajeet Pradhan (2010), which emphasize that while terrain characteristics influence flooding, hydrological factors tend to have a stronger impact in determining flood-prone areas.

The socio-economic vulnerability analysis reveals that the majority of households are characterized by low-income levels, with 84% of respondents earning below MK50,000 per month. This is coupled with limited access to essential services, reliance on agriculture as the primary livelihood, and varying housing conditions. The AHP weighting indicates that income level (33.8%), housing condition (26.9%), and access to services (18.0%) are the most significant contributors to vulnerability. These factors directly influence the capacity of households to cope with and recover from flood events. Households with lower income levels are often constrained in their ability to invest in resilient housing or access critical services, thereby increasing their exposure to flood impacts, as also highlighted by Ben Wisner et al. (2004).

The spatial distribution of vulnerability further indicates that a large portion of the study area falls within high (39.5%) and moderate (37.6%) vulnerability categories, with a smaller proportion classified as very high (14.5%) and low (8.4%). This distribution suggests that vulnerability is widespread, with only a limited proportion of the population having relatively lower susceptibility. These findings are consistent with the Pressure and Release (PAR) model, which explains how socio-economic conditions such as poverty and limited access to resources increase vulnerability to natural hazards (Wisner et al., 2004).

The integration of flood risk and socio-economic vulnerability provides a more comprehensive understanding of overall flood susceptibility within the study area. The results show that areas of greatest concern are those where high floods risk overlaps with high vulnerability. These areas are typically located near river channels and in zones with limited socio-economic capacity. The use of weighted overlay, with flood risk assigned a higher weight (75%) compared to vulnerability (25%), reflects the dominant role of

physical hazard while still accounting for the influence of human factors. This integrated approach supports the argument by Susan L. Cutter et al. (2003) that vulnerability is shaped by both biophysical and social dimensions.

The flood impact assessment further demonstrates the practical application of GIS and remote sensing in identifying exposed communities and infrastructure under different rainfall scenarios. The concentration of high flood impact zones along the Lilongwe River confirms the strong influence of river proximity and hydrological conditions on flood occurrence within T/A Pemba. The rainfall scenario analysis also indicates that increasing rainfall intensity significantly expands flood extent and exposure levels, while reduced rainfall decreases the extent of impacted areas. In addition, the exposure assessment identified several settlements and essential services, including schools, boreholes, sanitation facilities, and commercial services, within high flood impact zones. This suggests that flooding may result in disruption of livelihoods, reduced access to clean water and education services, and increased health risks. The integration of rainfall scenarios, flood extent, and exposure information therefore highlights the importance of impact-based flood assessment in supporting anticipatory action, spatial planning, and early warning initiatives. This finding further supports the argument by Susan L. Cutter et al. (2003) that disaster impacts are influenced by both physical hazard conditions and the exposure of people and infrastructure.

In relation to the research questions, the study has shown that flood-prone areas in T/A Pemba are primarily influenced by rainfall patterns, proximity to rivers, and drainage characteristics. It has also demonstrated that socio-economic factors, particularly income level, housing condition, and access to services, significantly affect the ability of households to cope with flood events. The combination of these factors explains the spatial variation in overall flood risk across the study area. This is in line with findings by Piers Blaikie et al. (1994), who argue that disaster risk is a product of both hazard exposure and vulnerability.

Overall, the findings highlight the importance of adopting an integrated flood risk management approach that addresses both environmental and socio-economic

dimensions. While structural interventions such as improved drainage systems may reduce flood hazard, efforts to improve household income levels, housing quality, and access to services are equally important in reducing vulnerability. This supports the broader understanding that effective disaster risk reduction requires a holistic approach that integrates both physical and social components of risk.

5. CHAPTER 5: RECOMMENDATIONS AND CONCLUSIONS

5.1. Conclusion

This study assessed flood risk and socio-economic vulnerability in T/A Pemba using a GIS-based multi-criteria analysis integrated with household-level socio-economic data. The findings demonstrate that flood risk within the study area is primarily influenced by hydrological and environmental factors, particularly rainfall (37.4%), distance to rivers (21.8%), and flow accumulation (21.8%), as determined through the Analytical Hierarchy Process (AHP). These factors collectively explain the spatial distribution of flood-prone areas, with 77.5% of the study area classified as high flood risk and 9.2% as very high risk.

In addition to physical exposure, the study revealed that socio-economic vulnerability plays a significant role in determining the severity of flood impacts. The majority of households were found to have low-income levels, with 84% earning below MK50,000 per month. The AHP-based vulnerability analysis identified income level (33.8%), housing condition (26.9%), and access to services (18.0%) as the most influential factors affecting vulnerability. The spatial analysis further showed that 39.5% of the area falls under high vulnerability, while 37.6% is moderately vulnerable.

The integration of flood risk and vulnerability provided a comprehensive understanding of overall flood susceptibility within the study area. The results indicate that areas of greatest concern are those where high floods risk coincides with high socio-economic vulnerability, particularly in zones located near river channels and characterized by limited economic capacity and infrastructure. This confirms that flood risk is not solely determined by environmental factors, but by the interaction between hazard exposure and human vulnerability.

The flood impact assessment modelling further demonstrated the practical application of GIS and remote sensing in identifying exposed settlements and infrastructure within high flood impact zones. Villages, schools, boreholes, sanitation facilities, and commercial services located near the Lilongwe River were identified as highly exposed to flood impacts under the simulated rainfall condition of 225 mm/day. The rainfall scenario analysis further

showed that increasing rainfall intensity would expand flood extent and exposure levels, while lower rainfall intensity would reduce the extent of impacted areas. This demonstrates the usefulness of impact-based flood assessment in supporting flood preparedness, spatial planning, and early warning initiatives.

Overall, the study demonstrates the effectiveness of integrating GIS-based flood risk mapping with socio-economic analysis and flood impact assessment in identifying priority areas for intervention. The findings provide a valuable basis for planning and decision-making aimed at reducing flood impacts, improving preparedness, and enhancing community resilience in T/A Pemba.

5.2. Limitation of the study

Despite the significant findings, the study was subject to certain limitations. The sample size for the household survey was limited to 50 respondents, which, although sufficient for the analysis, may not fully capture the diversity of socio-economic conditions across the entire study area. Additionally, the accuracy of the flood risk assessment is dependent on the quality and resolution of the spatial datasets used, such as DEM and rainfall data.

The weighting process using AHP is also subject to some level of subjectivity, as it relies on expert judgment in assigning relative importance to different factors. Furthermore, the study did not incorporate temporal variations in flood events, such as seasonal changes or long-term climate variability, which may influence flood patterns over time.

These limitations suggest that future studies could benefit from larger sample sizes, higher-resolution datasets, and the incorporation of temporal analysis to provide a more comprehensive assessment of flood risk and vulnerability.

5.3. Recommendations

Based on the findings of the study, the following recommendations are proposed:

Strengthening Community-Based Early Warning Systems (EWS):

- ✓ The study revealed that a large proportion of the study area falls within high (77.5%) and very high (9.2%) flood risk zones, yet preparedness mechanisms remain limited. There is a need for the establishment and strengthening of community-based early warning systems through collaboration between the Department of Disaster Management Affairs (DoDMA), local authorities, and NGOs. This aligns with the priorities of the United Nations Office for Disaster Risk Reduction under the Sendai Framework for Disaster Risk Reduction, which emphasizes enhancing disaster preparedness and early warning systems.

Integration of Risk Maps into Land Use Planning and Policy:

- ✓ Given that high-risk areas are concentrated along river channels and low-lying zones, it is essential that district authorities, particularly Salima District Council, integrate the flood risk and vulnerability maps into land use planning and zoning regulations. This will support controlled settlement and reduce exposure in high-risk zones. This recommendation is consistent with the Disaster Risk Management Act and the Malawi National Resilience Strategy, which advocate for risk-informed development planning.

Promotion of Flood-Resilient Housing and Infrastructure:

- ✓ With housing condition contributing significantly to vulnerability (26.9%), there is a need to promote resilient building practices, including the use of durable materials and improved structural designs in flood-prone areas. Government and development partners should support community-based housing improvement programs. This aligns with African Union's Agenda 2063, which emphasizes sustainable and climate-resilient infrastructure development.

Livelihood Diversification and Economic Empowerment:

- ✓ The findings indicate that 84% of households earn below MK50,000 and rely heavily on agriculture, increasing their vulnerability to flood impacts. There is a need to promote livelihood diversification through skills development programs, access to microfinance, and support for non-agricultural income-generating

activities. This supports the goals of the Government of Malawi under the Malawi Vision 2063, which prioritizes economic resilience and poverty reduction.

Improvement of Access to Essential Services and Infrastructure:

- ✓ Access to services contributed 18.0% to vulnerability, highlighting the need to improve infrastructure such as roads, health facilities, clean water supply, and sanitation services. Strengthening these services will enhance the capacity of communities to cope with and recover from flood events. This is in line with the Sendai Framework priority of strengthening disaster resilience through improved infrastructure systems.

Enhancement of Community Awareness and Disaster Preparedness:

- ✓ The presence of high and moderate vulnerability across a large proportion of the study area (39.5% and 37.6%) indicates the need for targeted community awareness programs. These should focus on flood preparedness, evacuation procedures, and risk communication. DoDMA and local stakeholders should intensify community-based disaster risk reduction initiatives in line with national DRM strategies.

Strengthening Data Collection and Integrated Risk Assessment Approaches:

- ✓ The study highlights the importance of integrating socio-economic and environmental data in flood risk assessment. Government agencies should strengthen data collection systems, including improving access to high-resolution spatial data and socio-economic databases. This will support more accurate and evidence-based planning, in line with global best practices promoted under the Sendai Framework.

Further Research and Advanced Modelling Approaches:

- ✓ Future studies should incorporate higher-resolution datasets and advanced modelling techniques to improve the accuracy of flood risk impact assessment.

Approaches such as machine learning and time-series analysis can enhance prediction and support more dynamic flood modelling.

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