Optimisation of strategies using spatial approaches to manage flood risk in Thailand

Karuna Pimprasan

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of Sheffield Hallam University
for the degree of Doctor of Philosophy

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Candidate Declaration

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College	Social Sciences and Arts
Director(s) of Studies	Dr Jonathan Bridge Dr Rebecca Sharpe

Abstract

Flooding poses a major and escalating threat across Thailand, particularly within the Chao Phraya River Basin where complex hydrological processes interact with rapid urbanization, socio-economic inequality and long-standing governance challenges. While GIS-based flood risk assessment is widely applied internationally, limited research has examined model transferability, data sensitivity and the integration of expert knowledge in data-constrained environments. This thesis develops an optimized GIS-based flood risk assessment framework intended to support evidence-based decision-making for Thai local authorities. The research integrates three components: a UK pilot study to examine model behavior in a data-rich environment, a full transfer and localization of the model to Thai conditions using publicly available hazard, exposure and vulnerability datasets, and an expert-elicitation phase involving practitioners from key national and provincial agencies. Statistical methods including Principal Component Analysis (PCA), Ordinary Least Squares (OLS), and Geographically Weighted Regression (GWR) were applied to diagnose variable behavior, minimize multicollinearity and identify robust predictors of flood risk. The results show that flood frequency is the strongest hazard indicator, while vulnerability variables, especially education, income and savings, consistently outperform exposure factors in explaining spatial patterns of flooding. Expert consultations support many of these findings while also highlighting aspects of long-term experiential knowledge that are not fully captured by statistical relationships alone. Comparative mapping shows that expert weightings tend to broaden mid-range classifications, whereas GWR produces sharper and more localized clusters of risk, indicating stronger analytical reliability. The research contributes to the academic literature by demonstrating the transferability of GIS-based flood risk modelling across contrasting international contexts and by providing a practical framework for managing uncertainty and integrating expert knowledge within quantitative spatial analysis. Overall, the research provides a transferable and data-efficient flood risk modelling approach suited to the constraints of Thai local governance and offers practical guidance for sub-district planning, early warning development and climate-resilient flood management.

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Chapter 1: Introduction

1.1 Introduction

Recent scientific evidence shows that flood hazards are increasing worldwide as a direct consequence of climate change and the rising frequency of extreme weather events (IPCC, 2021). Global datasets indicate a substantial increase in the number of reported floods, storms and related natural disasters since the early twentieth century, reflecting both improved monitoring and an actual intensification of climate-driven hazards (Our World in Data, 2025). Projections suggest that global exposure to a one-in-one-hundred-year flood could rise from roughly 1.6 billion people today to almost 1.9 billion by 2100, demonstrating how both population growth and climate change will significantly expand global flood vulnerability (Rentschler et al., 2022; Rogers et al., 2025). Current global estimates further indicate that more than 1.8 billion people are already living in areas where a major flood event could inundate homes, infrastructure and farmland (Rentschler et al., 2022).

Climate change is reshaping hydrological behavior in several ways. Warmer air holds more moisture, increasing the intensity of heavy rainfall events, while rising sea levels amplify storm surges. The combined influence of tidal cycles, extreme precipitation and storm-driven winds has also increased the frequency of compound flood events in many regions worldwide (NOAA, 2025). Scientific work such as Darlington et al. (2024) provides detailed evidence of how future climate scenarios can dramatically increase flood exposure. Using a high-resolution five meters flood model, their study demonstrates that areas currently considered low risk may become significantly exposed under projected changes in rainfall intensity and sea-level rise. The research also shows that continued urban expansion amplifies exposure by placing more people, buildings and critical assets in flood-prone areas.

Recent flood events illustrate these trends clearly. In Thailand, recurrent flooding linked to intensified monsoon rainfall continues to affect multiple regions, reflecting increasing hydroclimatic variability (World Bank, 2021; Asian Development Bank, 2022). For example, the 2011 flood in Thailand, one of the most severe disasters in the country's history, affected more than 13 million people and caused economic losses exceeding USD 46 billion (World Bank, 2012). Similar catastrophic floods have occurred elsewhere. In Nigeria, the 2022 floods were among the most devastating on record, affecting millions of people and causing widespread damage across most states, driven by extreme rainfall and river overflow (World Bank & NEMA, 2022). In Pakistan, the 2022 floods caused large-scale devastation and were associated with exceptionally high monsoon rainfall, with some regions experiencing several times the normal precipitation levels (WorldBank et al., 2022). Attribution studies indicate that climate change increased the likelihood and intensity of such extreme rainfall events. Together, these cases demonstrate that flood frequency, magnitude, and impacts are increasing across diverse global regions, consistent with broader evidence linking climate change to intensified hydrological extremes.

In view of the escalating risks associated with climate-related flooding, the development of accurate, timely and climate-informed flood risk assessment methods has become critically important. Contemporary analytical approaches must consider not only the intensification of physical flood hazards but also the social, economic and environmental conditions that shape vulnerability and long-term resilience (IPCC, 2021). These global trends highlight the value of GIS applications, which can provide accessible and practical tools for supporting evidence-based planning, strengthening disaster risk management and guiding climate adaptation strategies without necessarily requiring complex hydrological modelling systems or highly specialized technical expertise (Moel et al., 2015; Sahraei et al., 2022). As flood hazards continue to intensify, the availability of practical and effective tools to understand, assess and manage flood risk is becoming increasingly essential for supporting long-term resilience and sustainable development.

Despite the growing body of literature on GIS-based flood risk assessment, several important research gaps remain. Much of the existing research has been developed within data-rich environments where high-resolution hydrological, infrastructural and socio-economic datasets are readily available, resulting in models that often rely on complex calibration procedures, proprietary datasets or computationally intensive approaches that are difficult to replicate in developing countries with limited technical and institutional capacity (Kreibich et al., 2015; Merz et al., 2007). In addition, relatively limited attention has been given to understanding how variations in data quality, spatial resolution and variable selection influence the sensitivity and reliability of GIS-based flood risk models across different geographical and socio-economic contexts. Existing studies also frequently apply standardized vulnerability indicators without sufficiently accounting for local governance structures, social conditions and spatial variability (Cutter et al., 2003). Furthermore, although flood risk is widely recognized as both a physical and social process, fewer studies have systematically integrated statistical modelling, spatial analysis and local expert knowledge within a transferable and data-efficient flood risk assessment framework (Islam & Meng, 2024). This thesis addresses these gaps by developing and evaluating a GIS-based flood risk assessment approach designed specifically for data-constrained environments, with particular emphasis on model transferability, parameter sensitivity, uncertainty and local contextual relevance within Thailand.

1.2 Flood risk modelling as a spatial problem

Flood risk assessments commonly adopt the concept of the “risk triangle,” which includes three interrelated components: hazard, exposure, and vulnerability. This framework provides a structured way to evaluate flood risk by considering the probability of flood events (hazard), the concentration of people and assets in potentially affected areas (exposure), and the degree to which those elements are susceptible to harm (vulnerability) (Crichton, 1999). Its integrative nature has made the risk triangle one of the most widely used models in disaster risk reduction because it allows multi-dimensional risk factors to be combined within a spatially explicit analytical approach (Papathoma-Köhle et al., 2016).

Understanding flood risk through this framework requires recognizing that it represents a fundamentally spatial problem. Harvey (1968) explains that spatial problems arise when a phenomenon cannot be fully understood without considering its geographic distribution, underlying spatial patterns, and interactions across locations. In such cases, spatial processes and spatial patterns are closely connected, meaning that analysis must account for how conditions vary from place to place, how scale influences interpretation, and how neighboring areas influence each other.

Flooding clearly demonstrates this type of problem. Flood hazard is shaped by terrain, drainage pathways, floodplain morphology and land use, meaning that the intensity and extent of flooding depend on the physical characteristics of specific locations (Moel et al., 2015). Exposure is also spatial since populations, buildings, infrastructure and economic assets are unevenly distributed across landscapes. Vulnerability similarly varies geographically because socio-economic conditions, coping capacities and local governance structures differ between communities. Hartmann and Driessen (2017) emphasize that flood risk governance is inherently spatial because decisions relating to development, land use and water management directly influence how risk is created and distributed across space.

Recognizing flooding as a spatially structured phenomenon highlights why GIS provides an appropriate analytical tool. GIS enables the integration of hazard, exposure and vulnerability datasets into a single spatial environment, allowing the geographic intersection of these components to be examined directly. This capability aligns closely with Harvey's (1968) argument that spatial patterns, processes and scales must be analyzed together. Through multi-layer and multi-scale analysis, ranging from catchment-level hydrological patterns to sub-district socio-economic variations, GIS offers a coherent method for representing and quantifying flood risk as a geographically variable and interacting process.

Given the complex, multidimensional and nonlinear nature of flooding, the role of GIS in flood risk assessment has become increasingly significant. GIS allows diverse datasets including topography, hydrology, land use, demographic indicators and socio-economic conditions to be incorporated into models that generate detailed flood hazard and vulnerability maps. These outputs are especially valuable in urban environments where spatial variability is high and decision-making requires detailed geographic information (Sahraei et al., 2022). As a result, GIS has become a core technology for supporting sustainable and evidence-based flood risk management (Gurav et al., 2016).

Although short-term flood forecasting and early-warning systems are vital for minimizing immediate impacts, long-term resilience relies on robust GIS-based flood maps and comprehensive risk assessments supported by a clear and consistent definition of flood risk. Flood risk is generally understood as the interaction between the probability of a flood occurring at a particular location and the severity of its potential consequences for people, assets, infrastructure and the environment. This understanding is formalized in the European Floods Directive (2007/60/EC), which requires Member States to assess both flood likelihood and the expected effects on human health, cultural heritage, economic activity, infrastructure and ecosystems. Recent evaluations demonstrate uneven progress across Europe, highlighting ongoing challenges in ensuring consistent implementation of these principles (Arvidsson & Johansson, 2024).

1.3 Flood risk modelling as a social problem

Flood risk modelling is often viewed as a technical or hydrological exercise, yet it is fundamentally a social issue because the impacts of flooding are shaped as much by social conditions as by physical processes. Although models quantify hazard, exposure and vulnerability, these components reflect underlying social realities, including inequality, governance capacity and uneven resource distribution. As Islam and Meng (2024) highlight, vulnerability to flooding arises not only from physical exposure but also from socio-economic status, demographic characteristics, political and institutional contexts and the capacity of communities to cope with and adapt to hazards. These dimensions combine to create persistent disparities in who is most at risk, with disadvantaged groups experiencing disproportionate impacts due to structural inequalities, historical settlement patterns and uneven investment in hazard prevention.

Within this context, flood risk modelling itself becomes a social process because the variables used to represent vulnerability are social constructs that reflect how communities are organized, how public resources are allocated and how planning decisions distribute risk across space. Decisions about data selection, spatial boundaries, classification thresholds and weighting systems are shaped by institutional priorities, political considerations and power relationships. As Cutter et al. (2003) argue, social vulnerability arises from demographic characteristics, economic constraints, political marginalization and access to knowledge, all of which influence a community's ability to prepare for, respond to and recover from flooding. Because economically disadvantaged communities often reside in low-lying or poorly serviced areas due to restricted livelihood opportunities and historical planning decisions, model outputs can unintentionally reproduce or obscure these social inequities unless such dynamics are carefully integrated into the analytical framework.

Recognizing flood risk modelling as a social problem therefore expands its role beyond prediction. Modelling becomes a tool for identifying patterns of marginalization, informing targeted interventions and guiding policy towards fairness and protection of vulnerable populations. As demonstrated by Islam and Meng (2024), understanding socio-economic and demographic drivers of vulnerability is essential for developing equitable and context-appropriate resilience strategies, since these variables explain a substantial proportion of who becomes most exposed and least able to recover from flooding events. Effective flood risk models must therefore combine geospatial and hydrological analysis with social science perspectives, stakeholder engagement and local knowledge to ensure that flood management policies are technically robust, socially just and responsive to the lived realities of communities facing chronic flood stress.

1.4 Research motivation and challenges

The 2011 flood in Thailand, particularly across the Chao Phraya River Basin, is widely recognized as one of the most devastating hydrological disasters in the country's recent history. It resulted from an extended period of unusually intense monsoonal rainfall, combined with uncoordinated water releases from major reservoirs and rapid urban expansion into high-risk floodplain areas. Large parts of central Thailand were submerged, affecting approximately 13.6 million people and causing more than 800 deaths. Sixty-five of the nation's seventy-seven provinces experienced significant flooding, with the central plains, which contain many of Thailand's major industrial zones, suffering the most extensive damage (Komori et al., 2012). The economic consequences were severe, with total losses exceeding USD 45 billion, placing the event among the costliest global disasters recorded in 2011 (Haraguchi & Lall, 2015). Several industrial estates were inundated, interrupting worldwide supply chains in sectors such as automotive manufacturing and electronics for several weeks, and exposing the vulnerability created by highly concentrated industrial activity in poorly protected floodplain settings.

Beyond the substantial economic and human impacts, the 2011 flood illuminated critical shortcomings in Thailand's water governance systems, land use planning and disaster preparedness. Challenges included weak coordination among responsible agencies, limited public understanding of flood risks and reliance on outdated flood management strategies (Sayama et al., 2015). The disaster ultimately served as a turning point that encouraged national efforts to strengthen integrated flood risk management, promote risk reduction and enhance resilience. Subsequent reforms aligned more closely with global frameworks for disaster risk governance, including the Sendai Framework for Disaster Risk Reduction (UNDRR, 2015).

Thailand adopted the Sendai Framework for Disaster Risk Reduction (2015–2030) to enhance its national strategy for disaster risk governance, marking a shift from reactive disaster response to proactive and preventive risk management (UNDRR, 2015). Effective implementation of this framework requires a thorough understanding of the root causes of disaster risk and the identification of hazard-prone and vulnerable areas. In the context of Thailand, where geographical features vary significantly from mountainous northern regions to low lying flood-prone central plains standardized, one size fits-all policies are often ineffective (Marks & Lebel, 2016). To ensure success, flood risk management must be tailored to the specific geographic, hydrological, and socio-economic characteristics of each locality. This highlights the need to strengthen local-level risk governance through decentralized planning and capacity building (Field & Kelman, 2018).

A major challenge in flood risk assessment lies in accurately modeling and selecting appropriate variables to generate flood risk maps that reflect both the underlying drivers and the severity of risk across multiple dimensions. Variable selection is a critical component, as these factors ranging from topographic and hydrological characteristics to socio-economic conditions and infrastructural capacity determine the spatial variability of flood risk (Merz et al., 2007). The same variable can have different levels of influence depending on local context, making it difficult to apply a one size fits all model. Consequently, flood risk modeling requires regionally adaptive approaches that account for the complexity and diversity of geographic and social conditions, as well as limitations in data availability and resolution (Kreibich et al., 2015).

1.5 Research questions

This study seeks to develop an efficient flood risk assessment model, focusing on the assessment of factors affecting model reliability by synthesizing approaches from different international contexts that differ in terms of geography, socio-economic conditions, and data availability. The model is designed using GIS technology and can be applied at the sub-district level, which is the smallest administrative unit in

Thailand with data availability, to support the operations of local government agencies, thus providing an effective flood risk management tool.

Research questions related to this challenge include:

1) What is the availability (coverage and quality) of data necessary for GIS-based flood risk assessment?
2) What criteria determine 'success' in flood risk modelling and to what extent do these vary depending on context (location, jurisdiction, management objectives)?
3) How sensitive is a model output to differences in data quality/availability in the inputs?
4) How do uncertainties in GIS-based flood model outputs affect the process of making risk management decisions?

1.6 Aims and objectives

This research aims to investigate an optimal approach to the design and application of flood risk assessment models linked to GIS to guide local authorities in Thailand to manage flood risk appropriately in their area of responsibility.

Overall objectives:

1. Compile a comprehensive audit of data availability for flood risk mapping in Thailand and assess this robustly against international comparators to identify priorities for data collection.
2. Determine a set of ‘success criteria’ for flood risk assessment relative to Thai contexts and demonstrate these by means of a screening process to test model approaches.
3. Develop and apply an expert evaluation protocol to assess impacts of data quality/availability/uncertainties on model outputs and use ability.

1.7 Structure of the thesis

The structure and content of each subsequent chapter in this thesis are summarized as follows.

Chapter 2 presents a review of the relevant literature in this research. It consists of two main parts: the conceptual design of the model and the challenges of parameter selection. Parameterization is a key factor in ensuring the reliability of the designed model results. For example, the availability of data with different contexts in each country includes the definition of conditions, characteristics, constraints, and public services. It also discusses the limitations and uncertainties of the model resulting from the specific characteristics and qualities of the parameters in each area. This is one of the answers to the research question on the uncertainty in the model results (4).

Chapter 3 contextualizes the transferability of the selected models and variables to the Thai case study by presenting an integrated overview of Thailand's physical, socio-economic, and policy conditions relevant to flood risk. It examines the causes, impacts, and long-term consequences of the 2011 flood to illustrate the hydrological characteristics and systemic vulnerabilities of the study area, while also outlining the nature and limitations of available datasets, particularly in terms of quality, availability, and spatial consistency (3). These constraints highlight the sensitivity of the models to input data and the resulting uncertainties in model outputs, which have important implications for decision-making in flood risk management (4).

Chapter 4 describes the main steps and conceptual framework used in the process of evaluating the evidence from the literature review in Chapter 2 and the Thai context study in Chapter 3. The process is described in detail, including data preparation methods, criteria used for consideration, weighting, data analysis and precautions to avoid uncertainty in the results, and the construction of flood risk maps for presentation of the results.

Chapter 5 presents the results of hypothesis testing used in the model design using a case study in Sheffield, UK, to study the sensitivity and uncertainty of the model built when the economic and social data used as input data change. Techniques used to critically evaluate the performance of the models are demonstrated, and the sensitivity of the GIS approach to the input data is demonstrated. In addition, this chapter provides guidance for refining the model to ensure its appropriate and efficient transfer to the Thai context. It examines how differences in data quality, availability, and structure influence model performance, thereby addressing the sensitivity of the model to variations in input data (3).

Chapter 6 presents model results and the transferability of socio-economic datasets to characterize flood risk and vulnerability across national contexts, with validation and comparisons between the UK and Thailand. This chapter highlights the conceptual, cultural and logistical challenges of porting GIS-based flood risk assessments and provides a clear examination of data issues within the Thai context. This chapter provides a clearer answer to the research question on assessing the availability (1) and quality of data required for GIS-based flood risk assessment and model uncertainty influenced by poor quality input data (3).

Chapter 7 presents the results of an expert elicitation process designed to include local knowledge of social exposure and vulnerability parameters in respect of flood risk, and to compare model iterations developed incorporating these insights with models parameterized using global academic research literature. This chapter address research question (2) on understanding local conditions and criteria determining success in coupled hydro-socio-economic flood risk modelling.

Chapter 8 summarizes the key findings and contribution of the thesis and critically assess limitations in the approach and recommends solutions.

Chapter 2: Literature Review

2.1 Basic concepts of flood risk assessment

Flood risk assessments are widely guided by the “risk triangle” framework, which conceptualizes risk as the interaction between three fundamental components: hazard, exposure, and vulnerability (Crichton, 1999). This framework is particularly useful for structuring spatial and quantitative assessments of flood risk, and it is commonly applied in both academic research and disaster risk management policy (UNDRR, 2015). The risk triangle model demonstrates that flood risk is not determined by hazard alone, but by the combined and spatially overlapping presence of hazard, exposure, and vulnerability. For example, a high hazard in an uninhabited area constitutes low risk, whereas moderate hazard in a densely populated area with low adaptive capacity can result in very high risk.

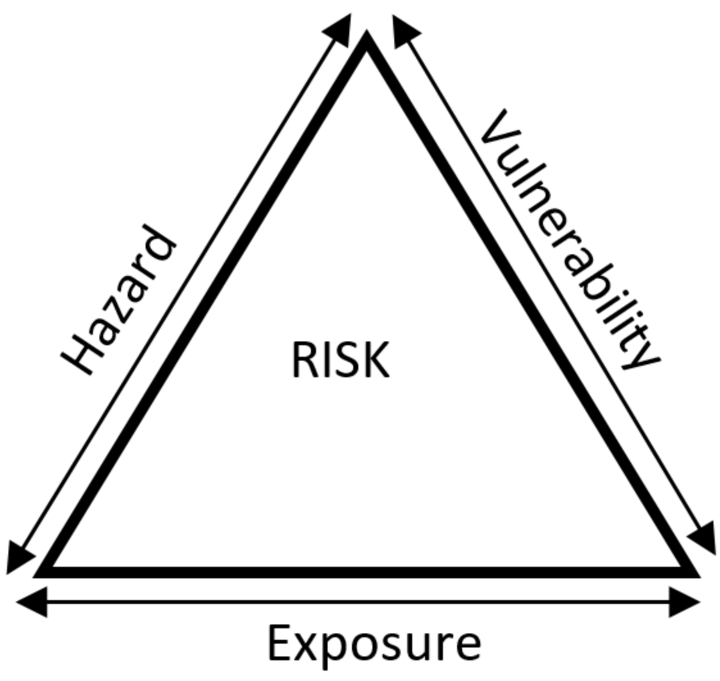


Figure 1.1. The concept of risk triangle (Crichton, 1999)

This insight supports a balanced approach to risk reduction, where risk can be reduced by mitigating hazards (e.g., flood defenses), limiting exposure (e.g., zoning regulations), or strengthening resilience (e.g., education, early warning systems). In practical applications, the risk triangle is often operationalized in a GIS-based environment, where the three components are mapped and overlaid to produce composite flood risk maps (Alfieri et al., 2017). Such spatial analysis allows local governments and planners to prioritise interventions and allocate resources effectively. A comprehensive understanding of the fundamental components of flood risk namely hazard, exposure, and vulnerability and the complex interactions between them is indispensable for conducting rigorous flood risk assessments. Such understanding is critical not only for accurately identifying areas and populations at risk but also for informing spatial planning decisions and developing effective disaster risk reduction strategies aimed at minimizing potential flood impacts (Birkmann et al., 2013; Crichton, 1999).

2.1.1 Hazard

Flood hazard refers to the likelihood and characteristics of flood events occurring in a given area, encompassing key physical attributes such as the spatial extent of inundation, water depth, flow velocity, duration, and frequency (Moel et al., 2015). Flood hazards manifest in various forms depending on their origin, including riverine floods caused by excessive rainfall and river overflow, coastal floods driven by storm surges and sea-level rise, urban flash floods resulting from intense precipitation combined with inadequate drainage, and groundwater floods due to rising water tables (Alfieri et al., 2017). The nature and severity of these hazards are governed by a complex interplay of climatic conditions, geomorphological features, soil properties, and human interventions such as dams, levees, and urbanization (Alfieri et al., 2017). Furthermore, ongoing climate change has introduced greater variability and extremes in weather patterns, thereby intensifying flood hazards and complicating their prediction and management (Parmesan et al., 2022).

Flood hazard assessment is a systematic process that identifies, quantifies, and spatially represents the characteristics and probabilities of flood events in a region. This process is foundational to flood risk analysis and management, as it establishes where flooding is likely to occur and how severe it might be under different scenarios. Typically, flood hazard assessment employs a combination of hydrological models that simulate runoff generation and river discharge, and hydraulic models that replicate the flow of water through channels and floodplains, thereby producing estimates of flood extent, depth, and velocity (Apel et al., 2004). These outputs are often visualized as flood hazard maps, which delineate areas prone to inundation under specified flood return periods, such as 1-in-10-year or 1-in-100-year or 1-in-1000-year events. Such maps are critical tools for urban planners, emergency managers, and policymakers to inform land use decisions, infrastructure development, early warning systems, and flood mitigation strategies (Jongman, Ward, et al., 2012).

Flood return periods, also known as recurrence intervals, are statistical estimates used to describe the frequency or probability of flood events of a certain magnitude occurring over time. Specifically, a return period refers to the average interval of time between floods of a given size or greater. For example, a "100-year flood" refers to a flood event that has a 1% probability of being equaled or exceeded in any given year, while a "1,000-year flood" has a 0.1% annual probability (Katz et al., 2002). This concept is central to hydrological analysis and flood risk management because it provides a standardized method for assessing and comparing the likelihood of extreme flood events. It is important to note that the term "100-year flood" does not mean such a flood will occur only once every 100 years. Rather, it means that each year there is a 1% chance of such a flood occurring. Therefore, multiple 100-year floods can occur in a short span of time, particularly under changing climatic or hydrological conditions. (Merz et al., 2007).

The 1-in-100-year and 1-in-1000-year flood return periods are widely adopted in flood risk assessment due to their regulatory importance, engineering relevance, and communicative simplicity. The 1-in-100-year event (1% annual exceedance probability) is commonly used to define flood-prone zones, inform land-use planning, and set standards for building codes and insurance requirements(de Moel et al., 2015b). In contrast, the 1-in-1000-year event (0.1% probability) is typically applied to the design of critical infrastructure where the consequences of failure would be catastrophic (Jongman, Ward, et al., 2012). These return periods are also useful for communicating risk to non-expert audiences by translating probabilistic flood hazards into intuitive terms, despite common misinterpretations (Kundzewicz et al., 2014). While limitations exist particularly the assumption of hydrological stationarity, they remain central to floodplain management, disaster mitigation, and policy development (Merz et al., 2007).

GIS constitute a critical instrument in flood hazard assessment by facilitating sophisticated spatial analyses and the visualization of flood risk associated with various return periods, notably the 1-in-100-year and 1-in-1000-year events. By integrating heterogeneous datasets comprising hydrological records, topographical features, land use classifications, and infrastructure distributions GIS enables the production of detailed flood hazard maps that underpin informed decision-making in urban planning, disaster mitigation, and emergency response (Moel et al., 2015). Advances in remote sensing technologies and the proliferation of high-resolution digital elevation models have considerably enhanced the spatial accuracy and resolution achievable in flood mapping within GIS platforms (Goodchild, 2007). Nonetheless, the robustness of GIS-based flood assessments is contingent upon the comprehensiveness and quality of input data, as well as the traditional assumption of stationarity in flood frequency and magnitude, a premise increasingly questioned due to ongoing climate change, urban expansion, and alterations in land use (Kundzewicz et al., 2014). Addressing these limitations, contemporary GIS applications increasingly incorporate probabilistic, dynamic, and non-stationary modeling frameworks to more accurately capture the complexity of present and projected flood hazards (Mokrech et al., 2015).

2.1.2 Exposure

Exposure assessment is a core element of flood risk analysis, concerned with systematically identifying and quantifying people, assets, and infrastructure situated within areas vulnerable to inundation. Unlike hazard, which describes the probability and intensity of flood events, or vulnerability, which relates to the susceptibility of elements to damage, exposure specifically denotes the spatial distribution and presence of elements potentially affected (Crichton, 1999). The assessment process typically involves superimposing flood hazard maps often based on defined return periods onto spatial datasets capturing land use, population density, economic activities, and critical facilities. GIS have become essential tools for this purpose, as they enable the integration of diverse data sources and facilitate visualization of exposed elements at multiple scales (Moel et al., 2015). This geospatial approach allows decision-makers to quantify exposure not only in terms of the number of people and infrastructure units at risk but also in relation to economic value and the potential for service disruption (Jongman, Ward, et al., 2012).

Building on this foundational perspective, recent advances in exposure modelling highlight a transition from static representations toward dynamic frameworks that account for temporal variability. These contemporary approaches recognize that exposure is not fixed but evolves over time due to rapid urban growth, demographic shifts, and environmental change (Jongman et al., 2014). The expansion of settlements into floodplains, wetlands, and low-lying coastal areas increases concentrations of population and assets, often in contexts where infrastructure and regulatory oversight are inadequate. Dynamic models address these challenges by integrating time-dependent datasets that capture evolving land-use patterns, projected climate impacts, and socioeconomic trends. For instance, the integration of high-resolution satellite imagery with scenario-based projections, such as the Shared Socioeconomic Pathways, allows planners to explore how development pathways and policy decisions will shape exposure in coming decades (Mondal & Tatem, 2012; Winsemius et al., 2018). This scenario-based approach helps identify future hotspots of risk and assess which populations are most likely to be affected, particularly in fast-growing cities where adaptive capacity is limited (Douglas et al., 2008). As a result, dynamic exposure modelling underpins forward-looking planning, supporting the incorporation of disaster risk reduction into development and infrastructure investment (Hallegatte et al., 2013).

Closely aligned with this evolution, probabilistic and non-stationary modelling techniques have significantly enhanced the capacity to assess risk under conditions of uncertainty. Probabilistic methods capture a wide range of possible outcomes by incorporating variability in flood frequency, magnitude, and extent. In contrast to deterministic approaches that yield single-value estimates, probabilistic frameworks produce distributions of scenarios, enabling risk to be expressed as probability rather than certainty (Moel et al., 2015). This probabilistic perspective is essential for designing resilient infrastructure, calibrating insurance products, and planning contingency measures.

Non-stationary models further advance the field by explicitly integrating changing climatic conditions, socioeconomic development, and evolving land use, acknowledging that historical records may no longer provide reliable predictors of future hazard patterns (Jongman et al., 2012). Incorporating drivers such as sea-level rise, more frequent extreme precipitation, and rapid urbanization, these models support proactive adaptation and risk management strategies (Milly et al., 2008). Collectively, these methodological innovations mark a paradigm shift toward more flexible, anticipatory approaches to flood risk assessment, particularly relevant in rapidly urbanizing and climate-sensitive regions where conventional models risk underestimating emerging threats (Hallegatte et al., 2013).

Nevertheless, despite substantial methodological progress, persistent challenges constrain the accuracy and comprehensiveness of exposure assessments. Data limitations such as inconsistent spatial resolution, outdated inventories, and the scarcity of disaggregated, regularly updated information remain particularly acute in low- and middle-income countries (Jongman et al., 2012). In addition, informal settlements and undocumented infrastructure are often omitted from official datasets, resulting in significant underestimation of actual exposure and further marginalizing already vulnerable populations (Douglas et al., 2008). Institutional fragmentation and weak coordination across sectors, including urban planning, water management, and disaster risk governance, further complicate efforts to harmonize and integrate exposure data (UNDRR, 2015). Addressing these gaps will require strengthened data governance frameworks, the adoption of standardized, interoperable geospatial infrastructures, and investment in capacity building to support comprehensive and inclusive exposure assessments (Teng et al., 2017).

To comprehensively assess flood risk, it is essential to examine the multiple dimensions of exposure, each of which captures a distinct aspect of how and to what extent elements are subject to potential inundation (Koks et al., 2015). These dimensions include spatial location, temporal variability, physical characteristics, functional importance, economic value, and social attributes (Aerts et al., 2018). Together, they provide a nuanced perspective on the scale, distribution, and implications of exposure, informing the development of evidence-based strategies for risk reduction, urban planning, and climate adaptation (Hallegatte et al., 2013). Dimensions of exposure in flood risk encompass multiple, interrelated aspects that together shape the scale and nature of potential impacts:

- **Spatial exposure** refers to the geographic location, spatial distribution, and extent of people, buildings, infrastructure, and economic activities situated within flood-prone areas. This includes both the areal extent of exposed assets and their proximity to rivers, coastlines, or other hazard sources, which directly influences the likelihood and severity of inundation (UNDRR, 2015).

- **Temporal exposure** captures how exposure changes over time due to seasonal variations, diurnal population movements, and long-term trends such as urban expansion, land-use conversion, and demographic growth. For example, some regions experience significant fluctuations in exposure during tourist seasons or agricultural cycles (Jongman et al., 2014).
- **Physical exposure** relates to the structural attributes and material characteristics of exposed elements, including building types, construction quality, elevation, and maintenance condition. These factors largely determine how susceptible structures are to damage during flood events and influence repair and reconstruction costs (Koks et al., 2015).
- **Functional exposure** recognizes the critical importance of specific facilities and infrastructure networks that provide essential services to society, such as hospitals, power stations, water supply systems, and transportation corridors. Disruption of these functions can produce cascading impacts well beyond the directly affected area, amplifying social and economic consequences (Aerts et al., 2018).
- **Economic exposure** reflects the financial value of exposed assets, including residential, commercial, and industrial properties, as well as the potential magnitude of economic disruption. Economic exposure assessments often consider insured and uninsured losses, replacement costs, and the indirect effects of interrupted business activities (Hallegatte et al., 2013).
- **Social exposure** encompasses the characteristics of populations living in hazard-prone areas, including their socioeconomic status, age distribution, health conditions, and capacity to prepare for, respond to, and recover from floods. Social exposure also relates to inequality and marginalization, which can exacerbate the impacts of flooding among vulnerable groups (Cutter et al., 2003).

A comprehensive understanding of these dimensions is essential for accurate flood risk assessments and the development of targeted strategies that integrate hazard mitigation with economic protection and social equity considerations.

2.1.3 Vulnerability

General vulnerability assessment refers to a structured approach aimed at systematically identifying, analyzing, and appraising the factors and attributes that increase the susceptibility of individuals, communities, assets, or systems to harm when exposed to hazardous events. This process incorporates physical, social, economic, environmental, and institutional dimensions to evaluate the degree to which a system may be negatively impacted by potential threats (Birkmann et al., 2013; Cutter et al., 2003). The overarching objective of vulnerability assessment is to provide an evidence base for risk reduction planning, enhance preparedness strategies, and inform adaptive measures by clarifying which elements are most at risk and elucidating the reasons for their vulnerability (Birkmann et al., 2013).

Building upon this general foundation, vulnerability assessment in the context of flood risk specifically involves examining the factors that determine why certain populations, infrastructures, or systems are disproportionately exposed to and affected by flooding hazards. This includes analyzing the physical aspects of exposure, such as proximity to flood-prone areas and elevation, as well as the sensitivity of buildings and infrastructure (e.g., construction quality and design standards). Additionally, it considers social and economic determinants such as income levels, demographic characteristics, and access to early warning systems that shape the capacity to prepare for, respond to, and recover from flood events (Cutter et al., 2003; Merz et al., 2007). Typically, these assessments integrate spatial analysis of flood hazard zones with indicators of social vulnerability to create a comprehensive perspective on the distribution and drivers of flood risk (Birkmann et al., 2013; Fekete, 2019).

To guide these assessments, a range of conceptual frameworks has emerged to address the complex interactions between physical hazards and social processes that produce unequal outcomes. While early approaches emphasized exposure and biophysical susceptibility (Cutter et al., 2003), later perspectives highlighted that vulnerability is socially constructed and shaped by broader systems of inequality and governance (Adger, 2006). Models such as the Pressure and Release (PAR) framework and coupled human–environment systems situate vulnerability at the intersection of exposure, sensitivity, and adaptive capacity (Turner et al., 2003). More recently, the MOVE framework has advanced understanding by recognizing vulnerability as multidimensional, dynamic, and context-specific, requiring integrated assessments that combine quantitative data, qualitative insights, and spatial analysis (Birkmann et al., 2013).

The dimensions of vulnerability in flood risk consist of multiple, interrelated factors that together influence the extent to which individuals, communities, and systems are exposed to, affected by, and able to recover from the adverse impacts of flooding. These dimensions encompass not only the physical characteristics of places and infrastructure but also the underlying social, economic, institutional, and environmental conditions that shape differential capacities to anticipate, withstand, and adapt to flood hazards (Birkmann et al., 2013; Cutter et al., 2003):

- **Physical vulnerability** relates to the inherent characteristics of the built environment, infrastructure, and geographical location that increase susceptibility to flood damage. Settlements located in low-lying areas, floodplains, or coastal zones are subject to higher levels of exposure and more frequent inundation (Cutter et al., 2003; Koks et al., 2015). The materials and structural integrity of buildings such as the use of non-reinforced masonry, inadequate anchoring, or lack of elevated foundations also significantly affect the likelihood and severity of flood impacts. Additionally, the presence or absence of protective infrastructure, including levees, drainage systems, and flood barriers, can either mitigate or exacerbate physical vulnerability (Birkmann et al., 2013).
- **Social vulnerability** refers to the demographic, cultural, and socioeconomic characteristics that determine how people are differentially affected by floods. Factors such as poverty, limited education, age (particularly young children and the elderly), disability, and lack of social networks can restrict access to information, reduce mobility during evacuations, and impede recovery (Cutter et al., 2003; Fekete, 2019). Marginalized populations often occupy high-risk areas

due to economic necessity and may have limited voice in planning and decision-making processes, further compounding their vulnerability (Adger, 2006).

- **Economic vulnerability** captures the degree to which households, businesses, and communities rely on livelihoods and assets that are sensitive to flood disruptions. Those engaged in informal economies, subsistence agriculture, or small-scale enterprises often lack insurance or financial reserves, making it difficult to absorb losses and rebuild after an event (Birkmann et al., 2013). Economic marginalization can also limit investments in preparedness measures and reduce the capacity to relocate from hazardous areas (Bubeck et al., 2019).
- **Institutional vulnerability** reflects the adequacy and effectiveness of governance systems, policies, and institutional capacities that support flood risk management. Weak regulatory frameworks, fragmented responsibilities among agencies, poor enforcement of building codes, and inadequate emergency response systems all contribute to heightened vulnerability (Adger, 2006; Bubeck et al., 2019). Institutional capacity also includes the ability to disseminate timely warnings, coordinate evacuations, and deliver post-disaster assistance equitably and efficiently (Birkmann et al., 2013).
- **Environmental vulnerability** arises from the degradation or loss of natural ecosystems that traditionally provide flood mitigation and buffering functions. Wetlands, mangroves, forests, and natural floodplains can slow floodwaters, enhance drainage, and reduce downstream impacts. When these systems are altered by urban development, deforestation, or pollution, communities lose important protective services and become more exposed to flood hazards (Jongman et al., 2012).

Understanding that these dimensions are interdependent is essential for designing comprehensive flood vulnerability assessments. For example, even well-constructed infrastructure (low physical vulnerability) may still be at risk if institutional frameworks are weak or if social inequalities limit adaptive capacity (Birkmann et al., 2013; Cutter et al., 2003).

Flood risk emerges from the interaction of hazard, exposure, and vulnerability, each of which varies across space and time. Hazards encompass the probability and characteristics of flood events, such as depth and duration, and are identified using historical data, hydrological models, and climate projections (Jongman et al., 2012). Exposure reflects the presence and distribution of people, infrastructure, and economic assets in flood-prone areas, providing a measure of what could potentially be affected (Moel et al., 2015). Vulnerability captures how susceptible these exposed elements are to harm and their capacity to respond and recover, incorporating both physical and social dimensions (Birkmann et al., 2013). The interplay among these components explains why some areas experience minimal impacts despite frequent hazards, while others face severe consequences from less frequent events. This interdependence underscores the importance of integrated, multidimensional assessments to inform land-use planning, disaster preparedness, and climate adaptation (Gallina et al., 2016).

2.2 Computational modelling of flood risk

2.2.1 Brief history of hydrological modelling and flood risk analysis

Early hydrological modelling and flood risk analysis were based primarily on empirical observations and descriptive records, drawing on anecdotal evidence and simple correlations such as stage–discharge relationships derived from gauging station measurements (Singh & Frevert, 2010). These methods typically involved manual recording of river stages, estimation of flood extents through local knowledge and surveys, and the compilation of historical flood chronicles. While such approaches provided valuable baseline information about flood-prone areas and the recurrence of extreme events, they lacked the capability to simulate underlying hydrological processes or predict flood responses under changing conditions. Their reliance on observed data meant that extrapolation beyond measured extremes was highly uncertain, particularly in ungauged catchments or rapidly evolving landscapes (Shaw, 1994). Nevertheless, these empirical techniques laid the foundations of modern hydrological science, informing the design of early flood defenses and motivating the development of systematic, process-oriented modelling frameworks.

Building on these early empirical methods, the middle decades of the twentieth century marked a transformative period with the emergence of conceptual rainfall–runoff models. The Stanford Watershed Model introduced structured methodologies to simulate processes such as evapotranspiration, infiltration, and soil moisture dynamics, reflecting a shift towards more mechanistic representations of catchment hydrology (Singh & Woolhiser, 2003). Around the same time, the HBV model in Sweden was further refined and applied across Europe as a flexible framework for streamflow forecasting and catchment-scale water resource management (Lindström et al., 1998). Progress in computational technology during the 1970s and 1980s further accelerated this evolution, moving modelling practices beyond simple lumped systems toward distributed and semi-distributed approaches. Notable examples include physically based models such as SWAT and TOPMODEL, which allowed the explicit incorporation of spatial heterogeneity in land cover, soil infiltration characteristics, and runoff pathways (Arnold et al., 1998; K. Beven & Kirkby, 1979). Simultaneously, probabilistic techniques for flood frequency estimation gained prominence, supporting the quantification of flood magnitudes and recurrence intervals essential for designing protection infrastructure and insurance schemes.

This foundation set the stage for more sophisticated tools. By the late twentieth and early twenty-first centuries, hydrological modelling became increasingly integrated with hydraulic simulation software, representing a significant advancement in flood risk assessment methodologies. Tools such as HEC-RAS and MIKE FLOOD enabled the coupling of rainfall–runoff models with one- and two-dimensional hydraulic models to simulate water surface profiles, flow velocities, and inundation extents across complex floodplain topographies (Fewtrell et al., 2008; Horritt & Bates, 2002). These platforms allowed practitioners to account not only for the volume of runoff generated but also for its dynamic propagation through river channels and urban drainage systems.

At the same time, the growing use of GIS significantly reshaped the practical application of hydrological and hydraulic models. GIS platforms offered a powerful environment for combining diverse spatial datasets, such as land use information, digital elevation models, soil characteristics and remotely sensed rainfall estimates, within a single modelling framework (Goodchild, 2007; Teng et al., 2017). This capability enhanced the spatial detail of hazard mapping and made it possible to conduct scenario testing and visualize potential flood impacts more effectively. These improvements strengthened decision-making processes in urban planning, infrastructure development and emergency management. Together, these technological advances provided a strong foundation for more evidence-driven approaches to disaster risk reduction and climate adaptation.

Globally, the implementation of hydrological models has exhibited considerable regional variation shaped by differences in climate, data availability, institutional capacity, and regulatory standards. In Europe, LISFLOOD emerged as a central modelling framework for large-scale flood forecasting, water balance analysis, and assessments of climate change impacts (Roo et al., 2000). The European Commission has employed LISFLOOD extensively for pan-European flood hazard mapping and policy development under the EU Floods Directive. Many countries combine LISFLOOD outputs with high-resolution terrain data and regional climate projections to guide adaptive risk management (Alfieri et al., 2013).

In England, flood risk assessment has developed into a highly structured and systematically regulated discipline overseen by the Environment Agency (Environment Agency, 2022). Hydrological modelling approaches for rainfall–runoff estimation are routinely combined with advanced hydraulic solvers such as LISFLOOD-FP to simulate inundation dynamics with high spatial precision (Alfieri et al., 2017; Wing et al., 2017). These frameworks, underpinned by LiDAR-derived topographic data and GIS, support spatial planning, infrastructure design, and insurance underwriting, with regulatory requirements mandating climate change allowances and thorough uncertainty analyses.

In the United States, the Hydrologic Modeling System (HEC-HMS) and River Analysis System (HEC-RAS) have become cornerstones of regulatory processes, including FEMA’s National Flood Insurance Program (Horritt & Bates, 2001).These tools are frequently applied together to model rainfall–runoff generation and hydraulic flow routing across river networks and floodplains (Cook & Merwade, 2009). Their flexibility, open access, and compatibility with high-resolution spatial datasets have contributed to widespread adoption by federal, state, and local agencies.

In regions such as Africa and Latin America, limited hydro meteorological monitoring networks often necessitate simpler conceptual models like HBV and NAM, valued for their modest data requirements and operational practicality (Di Baldassarre et al., 2010). To compensate for sparse observations, satellite-derived rainfall products and globally available DEMs such as SRTM are widely employed for calibration and catchment delineation (Huffman et al., 2007). Despite inherent uncertainties, this approach has enabled the development of early warning systems and seasonal forecasting capacity in many data-scarce contexts (Thiemig et al., 2012).

Conversely, in Asia, physically based hydrological models such as SWAT and MIKE SHE has become integral to assessing runoff, sediment transport, and the impacts of climate variability, particularly in monsoon-dominated regions undergoing rapid urban expansion (Gosain et al., 2006; Shrestha et al., 2018). In Thailand, these models gained traction after the 2011 floods exposed and the limitations of earlier floodplain mapping efforts (Komori et al., 2012). The combination of hydrological and hydraulic simulations with high-resolution elevation datasets and GIS platforms has markedly enhanced the spatial accuracy and operational relevance of flood risk assessments (Baldassarre et al., 2010). GIS now plays a pivotal role in merging land use, soil, and population data to create hazard, exposure, and risk maps that inform zoning, insurance, and emergency planning (Sayama et al., 2015).

Building on these advances, heightened awareness of climate change and land-use transitions has further accelerated the adoption of non-stationary, scenario-based modelling frameworks that rely on GIS to manage and analyse large, spatially distributed datasets (Bates et al., 2021). By integrating regional climate projections, socioeconomic scenarios, and Shared Socioeconomic Pathways, these approaches enable practitioners to evaluate future flood risks under deep uncertainty (Hirabayashi et al., 2013). Recent progress in high-resolution satellite imagery and machine learning has enhanced capabilities for near-real-time flood forecasting and probabilistic inundation mapping within GIS environments (Wing et al., 2018). Collectively, these developments illustrate how hydrological modelling has evolved into a dynamic, spatially explicit foundation for evidence-based planning, disaster risk reduction, and climate adaptation worldwide.

2.2.2 Comparison of hydrological models and GIS

Comparing modelling approaches is essential for developing credible and defensible flood risk assessments because models are underpinned by diverse theoretical concepts, data requirements, and computational methods that can yield substantially different estimates of hazard, exposure, and overall risk, even when applied within the same catchment (Teng et al., 2017). A wide range of hydrological and GIS-based models has been developed to address this complexity, each offering distinct capabilities and areas of expertise.

Physically based hydrological models such as the Soil and Water Assessment Tool (SWAT) and MIKE Surface Hydrology Europe (MIKE SHE) are designed to simulate detailed watershed processes, including rainfall–runoff generation, evapotranspiration, and groundwater–surface water interactions (Arnold et al., 1998). These tools excel at quantifying the timing and volume of runoff in response to precipitation and land-use change but typically require extensive calibration and high-quality input data. In contrast, hydraulic models like HEC-RAS and LISFLOOD-FP focus on representing the movement of water through river channels and across floodplains, calculating inundation extent, flow velocity, and water depth at high spatial resolutions (Horritt & Bates, 2002; Neal et al., 2012).

While hydrological and hydraulic simulations can operate independently, Geographic Information Systems (GIS) provide the essential spatial framework to integrate and visualize terrain data, land cover classifications, and socioeconomic exposure indicators, supporting the development of comprehensive flood hazard and risk maps (Goodchild, 2007). Platforms such as ArcGIS and QGIS are particularly effective at managing and analyzing these datasets and can link directly to hydrological and hydraulic model outputs to assess risk under different scenarios (Teng et al., 2017). The key distinction lies in their primary focus: hydrological models emphasize runoff generation and catchment water balance, hydraulic models specialize in flow routing and inundation dynamics, and GIS platforms bring together these diverse outputs into formats accessible for decision-making and planning (Wing et al., 2018).

This integration has become a cornerstone of contemporary flood risk management, as it enables consistent, transparent, and reproducible assessments that combine diverse data sources. For example, digital elevation models, land use data, and socioeconomic indicators can be merged within GIS environments to generate detailed flood hazard maps that inform zoning regulations, infrastructure design, and emergency preparedness (Teng et al., 2017). The ability to visualize and compare scenarios also facilitates communication with stakeholders and supports the identification of vulnerable areas under both current and projected climate conditions (Bates et al., 2021). The urgency of adopting and comparing these modelling frameworks has intensified in recent years, as climate change increases the frequency and severity of extreme precipitation events and rapid land-use change alters runoff regimes and flood hazard patterns globally (Hirabayashi et al., 2013). Traditional empirical or deterministic methods often fall short of capturing the uncertainty and non-stationarity inherent in future flood risk projections (Bates et al., 2021). Consequently, selecting robust, scalable tools capable of incorporating high-resolution remote sensing data, climate scenarios, and socioeconomic projections is fundamental to supporting evidence-based risk management and adaptation strategies (Wing et al., 2018).

Table 2.1. A comparative summary highlighting key hydrological model typologies.

Model Type	Description	Examples	Main Focus	Strengths	Limitations
1) Conceptual	Conceptual models represent the hydrological cycle as a series of interconnected reservoirs or "boxes," with simplified rules governing the transfer of water between components such as interception, soil moisture, groundwater, and surface runoff. These models rely on empirical or semi-empirical relationships calibrated against observed flow data (Lindström et al., 1998; Seibert, 1997)	The HBV hydrological model, originally developed in Sweden, has been widely used in many regions worldwide and has also been applied in parts of northern Thailand. Its parsimonious structure and modest data requirements make it well suited to basins with limited hydrometric monitoring and sparse observational records, conditions that describe several catchments in the northern region (Sriwongsitanon & Taesombat, 2011).	Analysis of runoff behavior under different land cover conditions	The HBV model performed well in data-scarce basins because its simple structure and low input requirements allowed effective simulation even with limited hydrometric observations.	Model accuracy was constrained by the sparse availability of calibration data, which reduced its ability to capture complex hydrological processes in heterogeneous catchments.
2) Physically Based	Physically based hydrological models simulate catchment behaviour by representing the underlying physical laws that control hydrological processes, typically using conservation equations for mass, momentum and energy. These models divide the watershed into grid cells or hydrological response units and compute process rates explicitly, allowing for a detailed representation of infiltration, surface runoff, evapotranspiration and channel flow (Keith J. Beven, 2012).	SWAT and MIKE SHE In Thailand, the SWAT model has recently been coupled with machine learning approaches, such as Long Short-Term Memory (LSTM) networks, to enhance the prediction of flow rates in the Chao Phraya River Basin and improve the accuracy of runoff simulations under changing land-use and climate conditions (Phetanan et al., 2024). Similarly, MIKE SHE has been coupled with MIKE 11 to enable integrated simulation of surface runoff,	Represent hydrological systems by explicitly simulating processes such as infiltration, runoff generation and channel flow using fundamental physical laws.	Their main strength lies in their ability to capture detailed spatial and temporal variability, making them suitable for scenario testing and assessing the impacts of land-use or climate change.	They require extensive datasets, high computational effort and careful parameterisation, which can limit their applicability in data-scarce basins.

Model Type	Description	Examples	Main Focus	Strengths	Limitations
		channel hydraulics, and groundwater interactions, delivering a robust platform for evaluating flood hazards, planning irrigation systems, and supporting decision-making in river basin management (Thompson et al., 2009).			
		HEC-RAS has been widely used in Thailand for hydraulic flood modelling and flood-risk mapping, particularly in riverine environments where detailed simulations of water levels, discharge and inundation extents are required. In the Chao Phraya River Basin, HEC-RAS has been applied to simulate unsteady flow conditions, analyze flood scenarios and evaluate inundation patterns under different hydrological situations, demonstrating its importance for floodplain assessment and early warning applications (Chuanpongpanich et al., 2012).	Support early flood-warning operations.	HEC-RAS effectively simulates unsteady river flow and inundation patterns, providing a practical framework for operational flood forecasting.	Model performance was constrained by limited data availability and the one-dimensional nature of HEC-RAS, which reduces accuracy in complex floodplain environments.
3) Stochastic	Stochastic hydrological models use probabilistic techniques to represent the inherent variability and uncertainty of hydrological processes, particularly rainfall and streamflow. Rather than	ARMA models, Markov For example, stochastic rainfall generators and Markov chain approaches have been used in Southeast Asia to reconstruct precipitation time series and	Reproducing the statistical behavior of hydrological time series in order to characterize variability and uncertainty in	Their main strength is the ability to capture natural randomness in hydrological records and	They cannot explicitly represent physical processes within a catchment, which limits their usefulness for

Model Type	Description	Examples	Main Focus	Strengths	Limitations
	simulating processes through physical equations, these models aim to reproduce statistical patterns found in observed time series, such as mean values, variances and autocorrelation structures (Koutsoyiannis, 2000).	estimate design flood magnitudes in data-scarce catchments, thereby improving the reliability of hydrological analyses and infrastructure design (Srikanthan & McMahon, 2001).	processes such as rainfall and streamflow.	generate realistic synthetic sequences for forecasting, risk analysis and scenario testing.	detailed spatial analysis or process-based interpretation.
4) GIS Platforms	GIS are not hydrological models per se, but they serve as powerful platforms for managing, analyzing and visualizing the spatial datasets required in flood risk assessment. They support key tasks such as preprocessing input layers including DEMs, land use and soil maps, overlaying flood extents with exposure information, producing hazard and risk maps and conducting spatial statistical analyses and scenario comparisons (Moel et al., 2009; Sanyal & Lu, 2004)	ArcGIS and QGIS are central to modern flood risk assessment because they integrate diverse spatial datasets, including remote sensing rainfall products, LiDAR-based elevation models, exposure layers and socio-economic indicators, within a single geospatial environment. This integration enables the generation of detailed flood hazard and risk maps that support land-use planning, zoning, infrastructure protection and disaster management, while improving the precision, consistency and transparency of flood risk evaluations (Costache et al., 2020).	Integrate and manage spatial datasets so that hazard, exposure and vulnerability information can be analyzed together within a single geospatial framework.	GIS offers powerful tools for combining high-resolution elevation data, remote-sensing observations and socio-economic layers to produce detailed hazard and risk maps that enhance planning and disaster management.	GIS depends heavily on the quality and resolution of input data and must be paired with external hydrological or hydraulic models, as it cannot simulate physical flood processes on its own.

Understanding the theoretical principles behind hydrological and GIS models is crucial for selecting suitable methods tailored to data availability, catchment features, and management goals (Beven, 2012). Because modeling frameworks rely on different assumptions about hydrological processes and spatial variability, their applicability varies across regions. In contexts like Thailand, where strong monsoonal variability, rapid urban expansion, and widespread land-use change converge with limited ground-based hydro meteorological observations, combining physically based and conceptual models with GIS platforms enables robust, spatially explicit flood risk assessments (Gosain et al., 2006; Shrestha et al., 2018).

From the comparison results, it is clear that hydrological modeling tools such as SWAT, HBV, MIKE SHE, autoregressive moving average (ARMA) models, and Markov chain models each present limitations related to data requirements, software complexity, parameter calibration, and the need for specialized expertise in hydrological data processing (Arnold et al., 1998; Lindström et al., 1998). These factors often pose significant challenges for local agencies with limited technical capacity or access to high-resolution datasets. In contrast, GIS offer a practical alternative for flood risk assessment when reliable secondary data are available, as they generally demand lower levels of technical expertise (Goodchild, 2007). With appropriate training and awareness of model uncertainties, parameter limitations, and data constraints, local government officials can use GIS tools to independently identify and evaluate flood-prone areas (Jonkman et al., 2008). This capability empowers local authorities to support planning and disaster preparedness without relying on complex hydrological modeling systems.

2.3 Flood risk analysis

Flood risk analysis is a fundamental component of integrated flood management and climate adaptation planning. It involves a systematic evaluation of flood hazards, exposure, and vulnerability to quantify both the probability of flood occurrence and the magnitude of its potential consequences (UNDRR, 2015). Unlike traditional flood hazard assessments that emphasize the likelihood and extent of inundation, modern flood risk analysis adopts a more comprehensive and decision-oriented framework that accounts for the interplay between physical hazards and societal impacts (Apel et al., 2004; Merz et al., 2007). This approach enables stakeholders including government agencies, insurers, and urban planners to assess potential losses under various scenarios and evaluate the effectiveness of different mitigation and adaptation strategies (Moel et al., 2009; Jongman et al., 2012).

2.3.1 The concept of flood risk assessment using GIS

To support this multidimensional analysis, contemporary flood risk assessments integrate hydrological and hydraulic models with GIS, remote sensing, and socio-economic data (Aerts et al., 2014; Schumann et al., 2009). GIS-based spatial analysis enables high-resolution mapping of flood-prone areas and the identification of exposed populations, offering critical insights for risk reduction planning, particularly in data-scarce regions (Moel et al., 2009; Schumann et al., 2009). Remote sensing technologies provide critical inputs such as precipitation estimates, land cover, and flood extents, while socio-economic datasets help quantify exposure and vulnerability based on population density, infrastructure, and economic value (Moel et al., 2009). To manage the inherent uncertainties in flood modeling especially in areas undergoing rapid urban change or lacking historical records probabilistic and scenario-based methods are increasingly employed (Beven, 2012; Jongman et al., 2015).

Given the diverse spatial contexts in which flood risks occur, assessments must be tailored to different scales. Flood risk can be evaluated at the global, regional, national, and local levels, each offering unique insights and challenges (Jongman et al., 2015; Jongman et al., 2012). While global assessments are useful for identifying broad risk patterns and informing transboundary policy, detailed local-scale analyses are essential for operational planning, infrastructure design, and community-level preparedness (Moel et al., 2009; Merz et al., 2007). Each scale presents varying demands in terms of data resolution, modeling approaches, and stakeholder involvement, necessitating flexible and context-specific methodologies (Apel et al., 2004; Winsemius et al., 2016).

In addition to technical and spatial considerations, policy frameworks significantly influence how flood risk assessments are designed and implemented. They establish regulatory standards, define acceptable levels of risk, and shape data governance and institutional coordination (UNDRR, 2015). For example, many national policies prescribe design return periods, risk thresholds, and mandates for participatory planning processes (Merz et al., 2007). Policies also determine resource allocation and inter-agency collaboration, which in turn affect the methodological depth and spatial scale of analysis (Hartmann & Driessen, 2017).

A prominent example of policy-driven risk assessment is the European Commission's Floods Directive (Directive 2007/60/EC), which requires EU member states to develop flood hazard and risk maps for all river basins and sub-basins with significant flood risk. These maps form the foundation for coordinated risk management plans aimed at prevention, protection, and preparedness (European Commission, 2007). The Directive adopts a conceptual framework that defines flood risk as the combination of three components: hazard, exposure, and vulnerability (UNDRR, 2015). In this framework, hazard encompasses the physical and statistical properties of flood events such as depth, extent, velocity, and duration. Exposure refers to the presence of populations, assets, and infrastructure within flood-prone zones, while vulnerability describes the susceptibility of these elements to damage, depending on structural, social, and economic factors (Moel et al., 2015; Merz et al., 2007). This structured approach facilitates scenario comparisons and supports prioritization of mitigation strategies at both strategic and operational levels.

A key example of policy-driven flood risk assessment is the European Floods Directive (Directive 2007/60/EC), which mandates EU Member States to develop flood hazard and risk maps but does not mandate a standardized methodology, allowing flexibility based on each country's geographic, hydrological, and socio-economic conditions (European Commission, 2007). This has led to diverse modeling approaches across Europe, ranging from deterministic to probabilistic methods, with varying levels of complexity and data requirements (Albano et al., 2015). The Directive defines flood risk as the interaction of hazard, exposure, and vulnerability (UNDRR, 2015). In this framework, hazard refers to the physical characteristics of flood events such as depth, extent, and duration while exposure includes populations and assets located in flood-prone areas, and vulnerability represents the susceptibility of those elements to harm, shaped by structural, social, and economic factors (Moel et al., 2015; Merz et al., 2007). Although fully probabilistic models offer comprehensive risk assessments (Apel et al., 2004), their use is often limited by data and resource constraints. Consequently, effective flood risk modeling must balance methodological rigor with a spatial understanding of risk, commonly conceptualized through the risk triangle framework (Kaźmierczak & Cavan, 2011).

In GIS-based flood risk assessment, the conceptual equation commonly applied is:

$$Flood\ Risk = Hazard \times Exposure \times Vulnerability \tag{1}$$

Equation (1) represents the risk triangle model (Crichton, 1999; UNDRR, 2015), where each component is spatially represented using GIS layers:

- Hazard layer: Derived from hydrological and hydraulic modeling (e.g., HEC-RAS, SWAT, MIKE SHE), it includes flood extent, depth, and return periods.
- Exposure layer: Maps the spatial distribution of population, infrastructure, land use, or economic assets at risk.
- Vulnerability layer: Represents the susceptibility of exposed elements to damage, often based on socio-economic data, building materials, elevation, or access to services.

In GIS, the risk equation is implemented through raster or vector overlay operations, where normalized values or indices are combined using weighted or multiplicative approaches:

$$Flood\ Risk\ Index\ (FRI) = H_i \times E_i \times V_i \qquad (2)$$

Where:

H_i is the hazard index at location i,

E_i is the exposure index at location i,

V_i is the vulnerability index at location i.

Equation (2) multiplicative formulation reflects the principle that risk increases jointly with the intensity of the hazard, the concentration of exposed assets and the susceptibility of affected populations or systems (Crichton, 1999).

Flood risk assessment in GIS typically begins with the integration of hazard, exposure and vulnerability datasets, and this process is often guided by Multi-Criteria Decision Analysis techniques. One of the most widely used approaches is the Analytic Hierarchy Process, which provides a rigorous method for structuring decision problems by arranging criteria hierarchically and deriving numerical weights through pairwise comparisons, a procedure formalized by Saaty (1987). Because AHP quantifies expert judgement in a consistent ratio scale, it is especially useful in flood studies where practitioners must determine the relative importance of terrain features, hydrological factors or socio-economic indicators and translate this information into spatial weights suitable for GIS overlay operations.

When data are uncertain, imprecise or involve gradual transitions, fuzzy logic provides an alternative decision framework. The foundation of fuzzy set theory, introduced by Zadeh (1965), allows values such as elevation, slope or drainage proximity to be expressed as degrees of membership rather than strict categorical boundaries. This is particularly beneficial in flood modelling because vulnerability or hazard conditions often change progressively across space, and fuzzy membership functions allow these transitions to be captured more realistically than crisp classification. As a result, fuzzy methods enable GIS users to represent ambiguous or continuous environmental conditions in a way that aligns more closely with physical processes.

To complement these expert-based methods, Principal Component Analysis offers a statistically objective tool for reducing large sets of correlated variables. PCA identifies new orthogonal components that explain the dominant sources of variance in the data, providing a compact representation of the system without redundancy. This method is particularly advantageous in flood risk assessment because many environmental and socio-economic variables exhibit strong inter correlation, and transforming them into principal components improves computational efficiency and reduces the risk of multicollinearity, as explained by Jolliffe and Cadima (2016). The conceptual basis and mathematical properties of PCA are further elaborated by Abdi and Williams (2010), who highlight its ability to reveal underlying patterns that may not be immediately apparent in the raw data.

After criteria have been weighted through AHP, represented through fuzzy membership functions or reduced through PCA loadings, GIS provides the environment in which these layers are combined. Raster algebra and weighted overlay operations form a central component of GIS-based multi criteria analysis, allowing multiple spatial criteria to be integrated into a single decision surface as discussed by Malczewski (2006). Through these operations, hazard, exposure and vulnerability layers are combined to generate composite flood risk indices that express the joint influence of each factor on overall risk.

These composite surfaces are typically classified into meaningful categories to support planning, zoning, evacuation design and infrastructure prioritization, reflecting the long-standing role of GIS as a platform for organizing and analyzing spatial decision problems, as outlined by Malczewski (2006). The classification of risk values into levels such as low, moderate, high or very high allows complex model outputs to be communicated in ways that are accessible to planners, local authorities and non-technical stakeholders, ensuring that spatial information can be directly applied to land-use regulation and hazard mitigation strategies. Because GIS environments allow analysts to adjust weighting schemes, redefine classification thresholds and incorporate new datasets as they become available, GIS-based flood risk assessment remains highly adaptable to changing hydrological conditions, revised land-use patterns and updated demographic information. This adaptability is emphasized throughout the GIS-MCDA literature, where GIS is described as a dynamic decision-support framework capable of iterative model refinement, scenario testing and continuous calibration as environmental and socio-economic data evolve. In practice, this means that flood risk maps can be regularly updated to reflect emerging patterns of exposure or vulnerability, enabling authorities to maintain accurate and policy-relevant spatial assessments that support real-time and long-term risk management.

The ability of GIS to manage and process extensive spatial datasets enables complex modelling approaches to operate within a detailed geographic context. This facilitates iterative scenario analysis, sensitivity testing and the comparison of alternative weighting strategies, supporting the examination of how different modelling assumptions influence risk patterns, a function highlighted in decision-analysis discussions by Malczewski (2006). As new elevation data, rainfall records or demographic datasets become available, GIS allows models to be recalibrated so that risk maps remain current and reflective of evolving exposure conditions, landscape change and socio-economic development. In this way, GIS functions as the operational platform through which AHP, fuzzy logic and PCA-based analyses are translated into practical, policy-relevant flood risk outputs.

Table 2.2. Comparison of GIS-Based Flood Risk Assessment Techniques

Technique	Advantages	Disadvantages	Limitations	References
AHP (Analytic Hierarchy Process)	• Structured and transparent decision-making process • Effective for integrating expert judgement • Produces ratio-scale weights suitable for spatial modelling	• Subjective; influenced by expert bias and inconsistency • Time-consuming when many criteria require pairwise comparison	• Pairwise comparisons become impractical with large numbers of indicators • Less suitable for purely data-driven or statistical modelling	Saaty (1987); Malczewski (2006)
Fuzzy Logic	• Captures uncertainty and imprecision inherent in environmental data • Represents gradual transitions between risk classes • Well suited to variables lacking clear boundaries	• Requires careful design of membership functions • Interpretation can be complex for non-specialists	• Difficult calibration without strong empirical data • Less transparent for policy-oriented decision making	Zadeh (1965); Malczewski (2006)
PCA (Principal Component Analysis)	• Reduces redundancy and multicollinearity • Enhances computational efficiency • Provides objective, data-driven variable reduction	• Components may be abstract and not directly interpretable • Requires statistical expertise for analysis	• Performs best in data-rich settings • May exclude variables with low variance but high conceptual importance	Jolliffe & Cadima (2016); Abdi & Williams (Abdi & Williams, 2010)
Ordinary Least Squares (OLS) regression	• Straightforward implementation and widely understood statistical method • Provides baseline global relationship between dependent and independent variables • Enables diagnostic testing (e.g., multicollinearity, significance of predictors)	• Assumes spatial stationarity, meaning relationships are constant across the study area • Sensitive to multicollinearity and outliers • Does not explicitly account for spatial dependence in the data	• Cannot capture local variations in relationships • Residuals may exhibit spatial autocorrelation, reducing model validity • May oversimplify complex spatial processes relevant to flood dynamics	(Anselin, 1999; Brunsdon et al., 1998; Kutner et al., 2005)

Technique	Advantages	Disadvantages	Limitations	References
	• Useful for initial screening of variables before spatial modelling			
WLC (Weighted Linear Combination)	• Simple and intuitive for combining weighted criteria • Allows compensatory trade-offs • Easy to implement in raster GIS	• Sensitive to subjective weight selection • Assumes uniform relationships across space	• Cannot represent spatially varying relationships • Oversimplifies complex flood processes	Malczewski (2006)
Raster Algebra	• Straightforward implementation • Integrates hazard, exposure and vulnerability layers • Useful for exploratory spatial modelling	• Lacks statistical foundation • Manual classification choices may be arbitrary	• Produces deterministic outputs with no uncertainty estimation • Not suitable for modelling interactions or predictions	Malczewski (2006)
GWR (Geographically Weighted Regression)	• Captures local spatial variation in predictor influence • Improves spatial resolution of risk estimates • Useful in heterogeneous landscapes	• Computationally intensive • Sensitive to bandwidth and kernel selection	• Requires dense and well-distributed data • Can be unstable in areas with sparse observations or strong outliers	Fotheringham et al. (2011); Shafapour Tehrany et al. (2013)

2.3.2 State of the art in GIS-based flood risk modelling

Recent developments in flood risk modelling demonstrate that Geographic Information Systems (GIS) have evolved into a central platform for integrating hazard, exposure and vulnerability information within spatially explicit risk assessment frameworks. Since 2020, advances in Earth observation technologies, cloud computing platforms and geospatial analytics have significantly improved the accuracy, scalability and accessibility of flood risk assessments (Tellman et al., 2021; Wing et al., 2022). Contemporary GIS-based flood models increasingly combine satellite-derived flood observations, high-resolution digital elevation models (DEMs), socio-economic datasets and climate projections to support decision-making across multiple spatial scales. For example, Tellman et al. (2021) developed the Global Flood Database using satellite observations from 913 flood events worldwide, demonstrating substantial increases in population exposure to flooding over recent decades. Similarly, Wing et al. (2022) showed that advances in large-scale flood inundation modelling have improved the assessment of current and future flood risks under changing climatic conditions. These developments illustrate a shift from traditional flood hazard mapping towards integrated, data-driven and decision-oriented risk assessment frameworks that consider both physical flood processes and social vulnerability characteristics.

In Europe, GIS-based flood risk assessment continues to be strongly influenced by the implementation of the European Floods Directive, which promotes the integration of hazard, exposure and vulnerability information within basin-scale flood risk management plans (European Commission, 2007). Recent studies increasingly utilise high-resolution terrain data, land-use information, infrastructure inventories and climate-change scenarios to assess present and future flood risks (Alfieri et al., 2017; Dottori et al., 2018).In the United Kingdom, national flood models are increasingly combined with geospatial exposure datasets and resilience planning frameworks to support land-use planning, emergency preparedness and infrastructure management (Wing et al., 2022). In the United States, advances in

HEC-RAS-based floodplain modelling and geospatial analytics continue to support regulatory flood mapping and risk management applications (Wing et al., 2017).

Meanwhile, in data-scarce regions across Africa, South Asia and Southeast Asia, GIS-based approaches increasingly utilise satellite imagery, remote sensing-derived flood extents, global digital elevation models and open-access socio-economic datasets to overcome limitations in conventional hydrological observations (Tellman et al., 2021). Advances in Earth observation technologies have improved the availability and spatial coverage of flood-related information, enabling more accurate assessments of flood hazards, exposure and vulnerability in regions with limited monitoring infrastructure (Merz et al., 2021). Consequently, GIS-based flood risk modelling has become an increasingly important tool for supporting flood risk management, disaster preparedness and climate adaptation planning in developing and climate-vulnerable countries (Parmesan et al., 2022; UNDRR, 2020).

A major trend in the current state of the art is the increasing use of hybrid approaches that combine hydrological or hydraulic modelling with spatial statistical and multi-criteria decision-support techniques (Teng et al., 2017). Methods such as Analytic Hierarchy Process (AHP), fuzzy logic, weighted linear combination, raster algebra, Principal Component Analysis (PCA), Ordinary Least Squares (OLS) regression and Geographically Weighted Regression (GWR) are widely applied to structure, weight, classify and analyse flood risk indicators within GIS environments(Lu et al., 2011; Malczewski, 2006). AHP and weighted overlay approaches are particularly useful where expert judgement is required to determine the relative importance of variables (Saaty, 1987), while fuzzy logic supports the representation of gradual transitions in flood susceptibility rather than fixed categorical thresholds (Zadeh, 1965). These techniques allow GIS-based flood risk assessment to integrate both quantitative analysis and expert-based decision-making within a single spatial framework.

Among these approaches, OLS, PCA and GWR continue to play an important role because of their complementary strengths in addressing data complexity, statistical robustness and spatial heterogeneity. OLS provides a global statistical framework for evaluating relationships between flood occurrence and explanatory variables, identifying multicollinearity and screening predictors before spatial modelling (Anselin, 1999; Fotheringham et al., 2017). PCA reduces dimensionality by transforming correlated environmental and socio-economic variables into a smaller number of independent components while retaining most of the original variance within the dataset (Jolliffe et al., 2016). Recent flood risk studies have continued to demonstrate the value of PCA for reducing redundancy and improving the interpretability of vulnerability indicators and composite risk indices (Jolliffe et al., 2016). GWR extends conventional regression by allowing relationships between flood risk and explanatory variables to vary spatially, thereby capturing local heterogeneity that cannot be represented through global models alone (Brunsdon et al., 1998; Lu et al., 2011). Recent applications of GWR in flood risk assessment have demonstrated significant improvements in model performance and have revealed spatially varying drivers of flood vulnerability, exposure and resilience across heterogeneous landscapes (Jolliffe et al., 2016). Together, OLS, PCA and GWR provide a robust analytical framework in which OLS establishes statistical validity, PCA optimises data structure and GWR enhances spatial precision. These characteristics make the combined approach particularly suitable for GIS-based flood risk assessment in data-limited environments where both statistical rigour and spatial adaptability are required.

2.3.3 Incorporation of expert knowledge in GIS-based flood risk assessment

Alongside technical and statistical advances, the incorporation of expert knowledge has become increasingly important in flood risk modelling because flood risk maps are not purely technical products, but are influenced by decisions regarding variable selection, weighting, classification and interpretation (Kaźmierczak & Cavan, 2011; UNDRR, 2015). Expert knowledge can therefore help identify locally relevant indicators, refine assumptions, interpret uncertain outputs and validate whether modelled risk patterns reflect real flood experience (Birkmann et al., 2013). This is particularly important in data-constrained contexts where official datasets may be incomplete, outdated or unable to capture local coping capacity, informal settlement patterns, drainage problems or community-level vulnerability (Cutter et al., 2003). In GIS-based flood risk assessment, expert input is commonly incorporated through AHP pairwise comparison, Delphi surveys, stakeholder workshops, participatory GIS, local validation exercises and structured interviews with practitioners (Malczewski, 2006; Saaty, 1987).

International examples demonstrate several ways in which expert knowledge can improve flood risk mapping. Participatory GIS studies often involve local residents and officials identifying historically flooded areas, evacuation constraints and critical facilities that may not appear in formal datasets (Mccall, 2008). In MCDA-based flood studies, experts from hydrology, planning, disaster management and local government are frequently used to assign weights to hazard, exposure and vulnerability indicators (Fernández & Lutz, 2010). In validation-focused studies, flood maps are compared with local flood records, community memory, field observations or stakeholder assessments to determine whether model outputs reflect realistic flood conditions (Brito & Evers, 2016). Expert knowledge is also valuable for refining vulnerability indicators because social vulnerability is highly context-specific and may not be fully captured by standardized census variables (Cutter et al., 2003). This supports a coproduction approach in which flood risk maps are developed through interaction between scientific modelling, GIS analysis and practical knowledge from communities and practitioners who understand local flood conditions (Pattison & Lane, 2012).

For this thesis, the incorporation of expert knowledge is particularly important because the research aims to produce a GIS-based flood risk assessment framework that is transferable, data-efficient and locally relevant to Thailand. Expert input can therefore support not only parameter weighting but also the coproduction, validation and refinement of flood risk maps. This is especially relevant in Thailand, where flood risk varies considerably across physical, socio-economic and administrative contexts, and where local authorities and practitioners possess contextual knowledge regarding flood history, drainage conditions, vulnerable populations and institutional capacity that may not be fully represented within secondary datasets. Integrating expert knowledge alongside GIS-based statistical and spatial modelling therefore strengthens both the technical reliability and practical legitimacy of flood risk assessment outputs (Birkmann et al., 2013; UNDRR, 2015).

2.4 Challenges in model parameterization

One of the primary challenges in flood risk model parameterization is the limited availability and resolution of spatial and temporal data. Accurate model parameterization depends on reliable hydrological, topographical, and socio-economic datasets to characterize hazard, exposure, and vulnerability. However, many regions particularly in the Global South suffer from sparse or outdated data, which restricts the accuracy of model inputs and often forces reliance on proxies or generalized indicators (Jongman et al., 2012; Merz et al., 2007). Even in data-rich contexts, selecting appropriate variables requires careful consideration to ensure they are representative of local flood dynamics and social conditions. Inconsistent or incompatible data formats across agencies also complicate integration, undermining spatial precision and comparability across regions (Moel et al., 2009).

Parameter uncertainty arises from natural variability, incomplete knowledge of system processes, and simplifications embedded in model design. Hydrological models, for example, require assumptions about rainfall-runoff relationships, soil infiltration, and channel flow all of which vary spatially and temporally (Beven, 2009). If model parameters are poorly calibrated or transferred from different regions without adjustment, predictions may diverge significantly from actual flood behavior. Sensitivity analysis and uncertainty quantification are essential to test the robustness of flood risk estimates (Apel et al., 2009). However, these steps are often omitted due to computational costs or a lack of validation data, especially for rare or extreme events. Consequently, the absence of systematic parameter calibration can erode confidence in risk outputs, particularly when used to inform public policy or investment decisions.

Flood risk models that integrate biophysical and socio-economic indicators often encounter multicollinearity, a condition in which input variables are highly correlated, producing unstable coefficient estimates and potentially misleading results. For instance, variables such as population density and urban land cover may both reflect exposure, and including them simultaneously without adjustment can distort the weighting structure of composite risk indices. Principal Component Analysis is frequently applied to address this issue because it transforms correlated variables into orthogonal components that retain the dominant variance structure of the dataset, thereby reducing dimensionality and mitigating collinearity problems (Abdi & Williams, 2010; Jolliffe et al., 2016). While PCA is effective for simplifying complex datasets, the resulting components are statistical abstractions that may reduce transparency and make interpretation more difficult for planners and stakeholders who are unfamiliar with the underlying mathematical transformations.

Spatial heterogeneity presents another key challenge in model parameterization, especially in large or ecologically diverse regions. Global models often assume a uniform relationship between variables and flood risk, which oversimplifies local variability. For instance, the impact of slope or land use on flood susceptibility may vary significantly between urban and rural settings. Geographically Weighted Regression (GWR) addresses this limitation by generating location-specific coefficients, enabling the model to reflect spatial non-stationarity (Brunsdon et al., 1998; Lu et al., 2011). However, GWR requires high-quality, spatially dense data and presents computational challenges. If improperly implemented, it can introduce overfitting or misinterpret spatial trends. Therefore, while GWR improves spatial realism, it demands careful parameter selection, bandwidth calibration, and diagnostic testing to ensure credible results.

Accurate flood risk assessment depends fundamentally on the identification and integration of appropriate spatial variables that represent the three core elements of the risk triangle: hazard, exposure, and vulnerability. Each of these components encompasses a distinct set of parameters that reflect the physical dynamics of flood events, the distribution of assets and populations at risk, and the socio-economic and structural susceptibility of affected communities (Merz et al., 2010; UNDRR, 2015). The quality, resolution and contextual appropriateness of the variables used to represent hazard, exposure and vulnerability exert a strong influence on the accuracy and reliability of flood risk models. Variable selection is particularly important because poorly chosen or low-quality indicators can propagate uncertainty throughout the modelling process and weaken decision-making outcomes. As Beven (2009) notes, hydrological and environmental modelling is highly sensitive to data uncertainty, and careful scrutiny of input variables is essential for producing credible risk estimates. Within GIS-based multi criteria assessment, Malczewski (2006) emphasizes the need for systematic evaluation of criteria used in spatial decision-making to ensure that each contributes meaningfully to the overall analytical framework. A structured review of the key variables aligned with each component of the risk triangle is therefore necessary to support robust, evidence-based flood risk assessment.

2.4.1 Hazard Parameters (Flood Characteristics)

The hazard component of flood risk assessment refers to the physical and statistical characteristics of flood events, including their magnitude, frequency, spatial extent, depth, and velocity. These parameters determine the intensity and probability of flooding and are essential for understanding where and how floods may occur. Accurate characterization of flood hazards supports the creation of flood hazard maps, which form the foundation for effective flood risk management and spatial planning (Merz et al., 2007; UNDRR, 2015). Table 2.3 on the following pages summarizes key parameter characteristics derived from global research literature.

Table 2.3. Comparison of Hazard Parameters in GIS-Based Flood Risk Assessment

Parameter	Description	Level of risk	Indicators/Classes	Key Reference
Flood Frequency	Flood frequency refers to how often floods occur in a given area. Higher frequency indicates repeated exposure, increasing cumulative risk and long-term damage. Areas with annual or near-annual floods often face persistent disruption, especially if resilience and recovery capacities are limited.	Frequent events (≥5/year) signal chronic exposure and high hazard potential. Infrequent events may still be damaging but offer longer recovery periods.	- High (≥8 years between events) - Medium (4–7 years) - Low (≤3 years)	Kron (2005); Jonkman & Kelman (2005)
Return Period / Probability	The return period, or probability, describes the statistical likelihood of a flood event occurring in any given year (e.g., 1-in-100-year flood has a 1% annual chance). Lower-probability, high-magnitude floods (e.g., 1-in-1000-year) may be rare but cause extensive damage, while more frequent events pose ongoing risk.	Lower return period (higher probability) → High hazard	- High1-in-100-year zone - Medium 1-in-1000-year zone - Low Outside mapped floodplain	Winsemius et al. (2016); Ward et al.(2013)
Flood Depth	Flood depth is one of the most important determinants of flood damage because the vertical height of inundation strongly influences structural failure, internal damage, and risks to human safety. As water depth increases, damage severity rises disproportionately, especially for single-storey buildings and critical services located at ground level. This depth–damage relationship is well established in flood-risk research	Greater depth → Higher flood hazard	- High >1.5 m - Medium 0.5–1.5 m - Low <0.5 m	Merz et al. (2010); Jongman et al (2012)
Flood Duration	Flood duration is a major factor influencing flood impact because multi-day inundation leads to greater structural weakening, increased contamination risks and more severe economic disruption. Evidence from national flood-loss studies and large-scale hydrologic modelling shows that floods that persist for long periods generate substantially higher cumulative damage than short-lived events. Prolonged inundation associated with slow-moving storms, snowmelt or repeated high flows consistently results in higher hazard levels and more extensive losses.	Longer duration → Greater damage potential	- High >72 hrs - Medium 24–72 hrs - Low <24 hrs	Wobus et al. (2017); Changnon (2008)

Parameter	Description	Level of risk	Indicators/Classes	Key Reference
Flow Velocity	Flow velocity refers to the speed of moving floodwater. High-velocity flows exert greater force on structures and can result in rapid erosion, scouring, and physical injury. Fast-moving water is especially dangerous in urban areas and steep terrains.	Higher velocity → More destructive force	- High >2 m/s - Medium 1–2 m/s - Low <1 m/s	Apel et al. (2004); Jonkman & Kelman (2005)
Inundation Extent	Inundation extent is the total area covered by floodwaters during an event. Larger extents affect more people, infrastructure, and economic assets. Spatial analysis of extent helps identify the geographical scale of flood exposure.	Wider extent → More assets exposed	- High >75% of built area inundated - Medium 30–75% - Low <30%	Ward et al. (2013); Dottori et al. (2017); UNDRR (2015)
Soil Saturation / Runoff	Higher antecedent soil moisture greatly increases flood potential because saturated or nearly saturated soils have minimal infiltration capacity, causing rainfall to convert rapidly into runoff. Experimental catchment studies consistently show that once soil moisture exceeds key thresholds, stormflow rises sharply, making saturated areas more likely to generate floods. Soil-moisture mapping is therefore essential for identifying zones with elevated runoff potential and for improving flood-forecasting accuracy.	High saturation → Reduced infiltration, increased	- High Soils fully saturated - Medium Partially saturated soilssaturated - Low Dry soil	L. Brocca, Melone, & Moramarco (2007); Penna, Tromp-Van Meerveld, Gobbi, Borga, & Dalla Fontana (2011); Western et al.(2004)
Storm Surge	Storm surge refers to the abnormal rise of sea level caused by storm winds, often coinciding with high tides. It poses a major hazard to coastal areas, inundating large areas and damaging critical coastal infrastructure.	High surge → Severe coastal flood risk	- High >3 m surge - Medium 1–3 m - Low <1 m	Muis et al. (2016); Hinkel et al. (2014); Vousdoukas et al. (2020)
Flash Flood Potential	Flash flood potential describes the likelihood of sudden, high-intensity flooding in small catchments or urban areas, typically driven by short-duration extreme rainfall combined with steep slopes or highly impermeable surfaces. Because flash floods develop rapidly and offer minimal warning, they often cause severe erosion, structural damage and loss of life. Areas with steep terrain or dense urbanization are particularly susceptible, as rainfall is converted quickly into concentrated runoff, producing fast-moving, destructive flows	High flash flood risk in steep or urban terrain	- High High-intensity rainfall in steep terrain - Medium Moderate - Low Gentle terrain	Borga et al. (2014), Gaume et al.(2009); Marchi et al., (2010)

2.4.2 Exposure Parameters (Elements at Risk)

The exposure component in flood risk assessment refers to the spatial distribution and characteristics of people, infrastructure, economic assets, and ecosystems that lie within flood-prone areas. It determines what is at stake when a flood event occurs and is thus essential for estimating potential losses and guiding mitigation priorities (Moel et al., 2009; UNDRR, 2015). Unlike hazard, which describes the physical nature of flooding, exposure focuses on the presence and value of elements that may be adversely affected.

Table 2.4 on the following pages summarizes key parameter characteristics derived from global research literature.

Table 2.4. Comparison of Exposure Parameters in GIS-Based Flood Risk Assessment

Parameter	Description	Level of risk	Indicators/Classes	Key Reference
Population Density	Population density reflects the concentration of people in a given area and directly influences flood exposure. Densely populated areas face higher risks of casualties, overcrowding in shelters, and strain on emergency services during flood events. High density can also complicate evacuation efforts and amplify the human impact of inundation. Mapping population density helps identify zones where large numbers of individuals are at risk.	High – Low	- High >10,000 people/km² - Medium 1,000–10,000/km² - Low <1,000/km²	Cutter et al. (2003); Jha et al. (2012); UNDRR (2015)
Building Density	Building density indicates the intensity of built-up structures within a flood-prone area. High building density increases the potential for widespread property damage and economic losses during floods. It also reflects the value of physical assets at risk and can hinder water drainage, worsening flood severity. Dense urban areas require targeted flood mitigation strategies due to their high exposure and limited open space.	High – Low	- High >80% built-up area - Medium 30–80% - Low <30%	Koks et al. (2015); Hallegatte et al. (2013) ; Ward et al. (2013)
Household Size	Larger household sizes often correlate with increased vulnerability during floods due to the complexities of evacuating and sheltering multiple dependents. Overcrowded living conditions can also elevate health risks and reduce the capacity for in-home preparedness. Household size is an important demographic variable for assessing both exposure and response needs in disaster planning.	High – Low	- High ≥6 persons/household - Medium 4–5 - Low 1–3	UN-Habitat (2015); Birkmann (2013); Gall et al. (2009)
Land Use / Land Cover	Land use and land cover (LULC) determine the types of assets exposed to flooding and influence the hydrological behavior of landscapes. Urban and industrial areas have high exposure due to infrastructure concentration, while agricultural lands face crop damage and food security risks. LULC classification in GIS allows risk planners to distinguish between zones with different flood sensitivities and economic consequences.	High – Low	- High Dense urban area - Medium Agriculture / peri-urban - Low Forest / open land	Dewan et al. (2012); Thieken et al. (Merz et al., 2010); Jonkman et al. (2005)
Economic Assets	Economic assets include commercial, industrial, and financial centers exposed to flood hazards. Damage to these areas can result in significant direct losses and cascading impacts on employment and regional economies. High-value economic zones in floodplains require robust risk reduction measures due to their critical role in local and national development.	High – Low	- High High-value industrial/commercial zone in floodplain - Medium Mixed-use - Low Rural	Hallegatte et al. (2013); Jongman et al. (2005); UNDRR (2015)

Parameter	Description	Level of risk	Indicators/Classes	Key Reference
Critical Facilities	Critical facilities such as hospitals, schools, emergency shelters, and fire stations are essential for disaster response and recovery. Their exposure to flooding can disrupt emergency operations and increase mortality and recovery delays. Protecting critical infrastructure is a priority in flood risk planning to maintain life-saving services during and after emergencies.	High – Low	- High Within flood-prone zone - Medium Partial exposure - Low Outside flood zone	(Samuels & Gouldby, 2009)Samuels & Gouldby (2009); Cutter et al. (2003); UNDRR (2015)
Transportation Networks	Transportation infrastructure, including roads, railways, and bridges, is vital for evacuation, relief delivery, and post-flood recovery. When these networks are disrupted by floods, entire communities may become isolated, hindering emergency response. Assessing the exposure of transportation routes is essential for ensuring accessibility and continuity of critical movement during flood events.	High – Low	- High Major transport hub in floodplain - Medium Peripheral exposure - Low No exposure	Koks et al. (2015); Jongman et al. (2012); Thieken et al. (2005)
Utility Infrastructure	Utility infrastructure includes power generation, water supply, telecommunications, and sewage systems. Flood exposure can cause widespread service disruptions, affecting both individual households and institutional operations. Infrastructure failure during floods can compound impacts and delay recovery. Mapping utility exposure helps identify priority areas for system protection and redundancy planning.	High – Low	- High Critical systems in flood zone - Medium Localized systems - Low Not exposed	Balica et al. (2012); Ward et al. (2013)

2.4.3 Vulnerability Parameters (Susceptibility to Damage)

In flood risk assessment, vulnerability refers to the degree to which exposed elements such as populations, infrastructure, or economic systems are susceptible to damage when a flood occurs. Unlike hazard and exposure, which describe the physical characteristics of flooding and the spatial distribution of assets at risk, vulnerability captures the internal characteristics that influence how severely those assets will be affected (Birkmann et al., 2013). It is shaped by a variety of socio-economic, structural, and institutional factors, including building materials, floor elevation, and age of infrastructure, poverty levels, and access to services. In GIS-based flood modeling, these factors are spatially represented through thematic layers and integrated into composite risk indices to identify communities with the highest likelihood of suffering adverse impacts (Cutter et al., 2003; Fekete, 2019).

Table 2.5 on the following pages summarizes key parameter characteristics derived from global research literature.

Table 2.5. Comparison of Vulnerability Parameters (Susceptibility to Damage)

Parameter	Description	Level of risk	Indicators/Classes	Key Reference
Population Age	Population age structure significantly influences flood vulnerability. Children under 5 and adults over 65 are at greater risk due to limited mobility, physical frailty, and higher dependency on caregivers. These groups struggle with evacuation, access to information, and recovery, and are more prone to health complications during and after flood events. Areas with a high proportion of these age groups are considered more socially vulnerable, making age structure a crucial parameter in GIS-based flood risk assessments and disaster preparedness planning.	Higher % of dependents → High vulnerability	- High >30% population under 5 or over 65 - Medium 15–30% - Low <15%	Gall et al. (2009); UNDP (2014); Cutter et al. (2003)
Gender	Gender significantly influences vulnerability to floods through unequal access to resources, decision-making, and coping mechanisms. Women and gender minorities often face restricted mobility, caregiving responsibilities, and limited access to financial, informational, and institutional support. These constraints heighten their exposure and reduce their ability to respond effectively during and after flood events.	Higher % of females → High vulnerability	- High High gender disparity in education or income - Medium Moderate disparity - Low Low disparity	UNDRR (2015); Birkmann (2013); Tate (2012)
Literacy / Awareness	Literacy and awareness reflect a population's capacity to understand and act upon flood-related information, such as warnings and preparedness guidance. It is commonly measured as the percentage of people aged 7 and above who can read and write. Low literacy rates hinder the ability to respond effectively to disasters, increasing vulnerability especially in rural or under-resourced communities where alternative communication strategies may be limited.	Lower literacy → High vulnerability	- High Literacy Rate - Medium >90%), - Low 70–90%	UNDP, (2014); Paul & Bhuiyan, (2010)
Less Hi School	Education plays a critical role in reducing vulnerability to floods. Higher levels of education improve individuals' capacity to comprehend early warning systems, interpret risk information, and implement appropriate preparedness and response actions. Communities with stronger educational attainment are more likely to participate in disaster planning, access emergency support, and recover more effectively after flood events. In contrast, lower levels of education are often linked to limited awareness, restricted access to information, and reduced adaptive capacity, particularly in rural or disadvantaged areas. Therefore, strengthening education is a key component in enhancing long-term resilience to flooding.	Lower education → High vulnerability	- High <60% completed primary education - Medium 60–85% - Low >85%	Cutter et al. (2003); Birkmann (2013); UNDP (2014);

Parameter	Description	Level of risk	Indicators/Classes	Key Reference
Unemployment	Unemployment increases flood vulnerability by limiting individuals' financial capacity to prepare for, respond to, and recover from flood events. Without a stable income, affected populations may struggle to afford protective infrastructure, emergency supplies, or insurance. Unemployed individuals are also more likely to live in poorly constructed housing or informal settlements, which are typically located in high-risk flood zones. Additionally, unemployment can reduce social participation and access to critical information, further weakening adaptive capacity and resilience to floods.	High unemployment → High vulnerability	- High >15% unemployment rate - Medium 5–15% - Low <5%	Gall et al. (2009); UNDP (2014); Cutter et al. (2003)
Socioeconomic Status/ Income	Socioeconomic status is a core determinant of vulnerability to flood risk. Low-income individuals and communities often reside in high-risk areas due to affordable land constraints and have limited resources for preparedness, insurance, or recovery. Economic constraints also reduce access to safe housing, healthcare, education, and transportation, compounding exposure and delaying recovery. These populations may lack political representation and are often overlooked in disaster planning. Addressing socioeconomic inequality is therefore essential for equitable and effective flood risk reduction strategies.	Lower income → High vulnerability	- High Low income, informal jobs - Medium Moderate income - Low High income	Cutter et al. (2003); Tate (2012); Koks et al. (2015);
Low Savings (Recovery Capacity)	Low savings reflect limited household financial reserves available for coping with and recovering from flood impacts. Households with little or no savings are less able to repair damaged property, replace essential goods, or afford temporary shelter and medical costs. This economic constraint significantly delays recovery and increases dependence on external aid, making such populations more vulnerable to long-term socioeconomic disruption after flooding events.	Low savings → High vulnerability	% with no or low savings; - High >60% - Medium 30–60% - Low <30%	Hallegatte et al. (2013) Rufat et al. (2015)
Health Access / Insurance	Access to healthcare and insurance plays a vital role in reducing flood vulnerability. Populations with limited or distant access to medical facilities face higher health risks during and after floods, especially in cases of injury, waterborne disease, or chronic illness. Health insurance provides financial protection that supports faster recovery and reduces the long-term impacts of disasters. Inadequate access to health services and coverage increases both physical and economic vulnerability, particularly in low-income or rural areas.	Poor health access/disability → High vulnerability	- High >5 km from health facility / no insurance - Medium 2–5 km - Low <2 km	Chen (2020); UNDRR (2015); Cutter et al. (2003)
Health/Disability	People with disabilities or chronic health conditions are particularly vulnerable to floods due to physical limitations, medical dependencies, and reduced mobility. These individuals may require assistive devices,	High disability → High vulnerability	- High >15% disabled population - Medium 5–15%	Cutter et al. 2003); UNDP

Parameter	Description	Level of risk	Indicators/Classes	Key Reference
	medication, or caregiver support, which are often difficult to access during emergencies. Without inclusive evacuation planning and accessible shelter facilities, their safety and well-being are at higher risk. Integrating disability-sensitive measures into disaster risk reduction strategies is essential for ensuring equitable		- Low <5%	(2014); Chen et al. (2020)
Previous Flood Experience	Previous flood experience can have both positive and negative effects on vulnerability. Communities that have experienced floods may be more aware of risks and better prepared. However, repeated exposure without adequate support or adaptation can lead to cumulative damage, economic strain, and psychological distress—ultimately increasing vulnerability. The impact of past experience depends on recovery capacity, institutional support, and whether lessons have been effectively integrated into local practices.	Lack of experience → High vulnerability	- High >2 major floods in last 10 years - Medium 1 event - Low No event	Sahana et al. (2019); Tran et al. (2009); UNDRR (2015)
Housing Tenure (Owner/Renter)	Housing tenure influences vulnerability by shaping control over housing quality and access to recovery resources. Renters often live in lower-quality housing with limited ability to invest in flood-proofing or maintenance. They may also be excluded from insurance benefits, compensation schemes, or post-disaster assistance aimed at homeowners. This lack of control and support heightens the vulnerability of renter populations, particularly in urban and informal settlements.	Higher % renters → High vulnerability	- High High % renters - Medium Mixed tenure - Low High % owners	Tate (2012); Fekete (2009); UNDRR (2015)
Proximity to Emergency Services	Proximity to emergency services—such as hospitals, shelters, and fire stations is a key factor in reducing flood vulnerability. Communities located far from such facilities face delays in receiving medical care, evacuation assistance, and relief services during flood events. Poor accessibility, especially in rural or densely built areas, increases the risk of loss of life and prolongs the recovery process. Mapping service accessibility is crucial for identifying spatial inequalities in emergency preparedness.	Greater distance → High vulnerability	- High >5 km / >30 mins travel - Medium 2–5 km - Low <2 km	Fekete (2009); Chen et al. (2020); Gall et al. (2009)
Building Material	Building material is a direct indicator of physical vulnerability to floods. Structures built with weak, non-engineered materials such as mud, bamboo, or thatch are highly susceptible to water damage and collapse. In contrast, buildings constructed with reinforced concrete or brick are more resistant to inundation. Poorer communities often rely on low-cost, high-risk materials due to affordability, increasing their exposure and damage potential during flood events.	Weaker material → High vulnerability	- High Mud, bamboo, thatch - Medium Brick, wood - Low RCC, concrete	Papathoma et al. (2016); Koks et al. (2015); Sahana et al. (2019)

Parameter	Description	Level of risk	Indicators/Classes	Key Reference
Building Age / Condition	Older and poorly maintained buildings are generally more vulnerable to flood damage. Over time, structural components may weaken due to material fatigue, weathering, or lack of maintenance. Buildings constructed before the enforcement of modern flood-resilient building codes are especially at risk. Structural vulnerability increases with age unless retrofitting or reinforcement measures are implemented, making building age a critical parameter in flood risk mapping.	Older structure → High vulnerability	- High >40 years old - Medium 20–40 years - Low <20 years	Birkmann et al. (2013); UNDRR (2015); Cutter et al. (2003)

Chapter 3: Flood Risk in Chao Praya River Basin, Thailand

3.1 Study area

The Chao Phraya River is Thailand's principal river system, formed in Nakhon Sawan Province by the confluence of the Ping, Wang, Yom, and Nan Rivers. Flow within the basin is regulated by the Chao Phraya Dam in Chai Nat Province, Thailand's largest water diversion structure, which plays a critical role in irrigation management, water supply, and flood regulation (Spring, 2022). During the 2011 flood, the dam discharged water at a peak rate of 3,721 cubic meters per second to protect the structure from failure. However, these releases intensified downstream flooding, contributing to floodgate breaches in Sing Buri and extensive inundation in Ang Thong (HII, 2011). This demonstrates how large-scale hydraulic infrastructure, while essential for water management, can also increase downstream flood risk during extreme hydrological events. Consequently, provinces in the Central Plain, particularly Chai Nat, Sing Buri, and Ang Thong, became some of the most severely affected areas during the 2011 Thailand flood (Figure 3.1), highlighting the interconnected nature of basin-wide hydrological processes and local flood vulnerability.

As shown in Figure 3.1, Chai Nat Province lies in the upper Central Plain, defined by lowland terrain intersected by the Chao Phraya, Tha Chin, and Noi Rivers, along with major irrigation canals such as Khlong Anusasanan and Khlong Maharat (MOAC, 2021). Administratively, Chai Nat comprises 8 districts and 53 sub-districts, with agriculture serving as the main livelihood. In 2011, floodwaters inundated 1,288 km^2, equivalent to 52 percent of the province's land area (HII, 2011). Vast rice fields, livestock farms, and rural infrastructure were damaged, leaving smallholder farmers with heavy debts and food insecurity. Limited financial capacity and dependence on seasonal harvests made recovery slow and uneven, reinforcing long-term vulnerability (Poaponsakorn et al., 2015). The province's position upstream of the

Central Plain places it at the center of flood management, as water releases from the Chao Phraya Dam help protect national infrastructure but impose localized costs. This dynamic creates a clear linkage to Sing Buri, where converging rivers and flat terrain intensified the 2011 inundation.

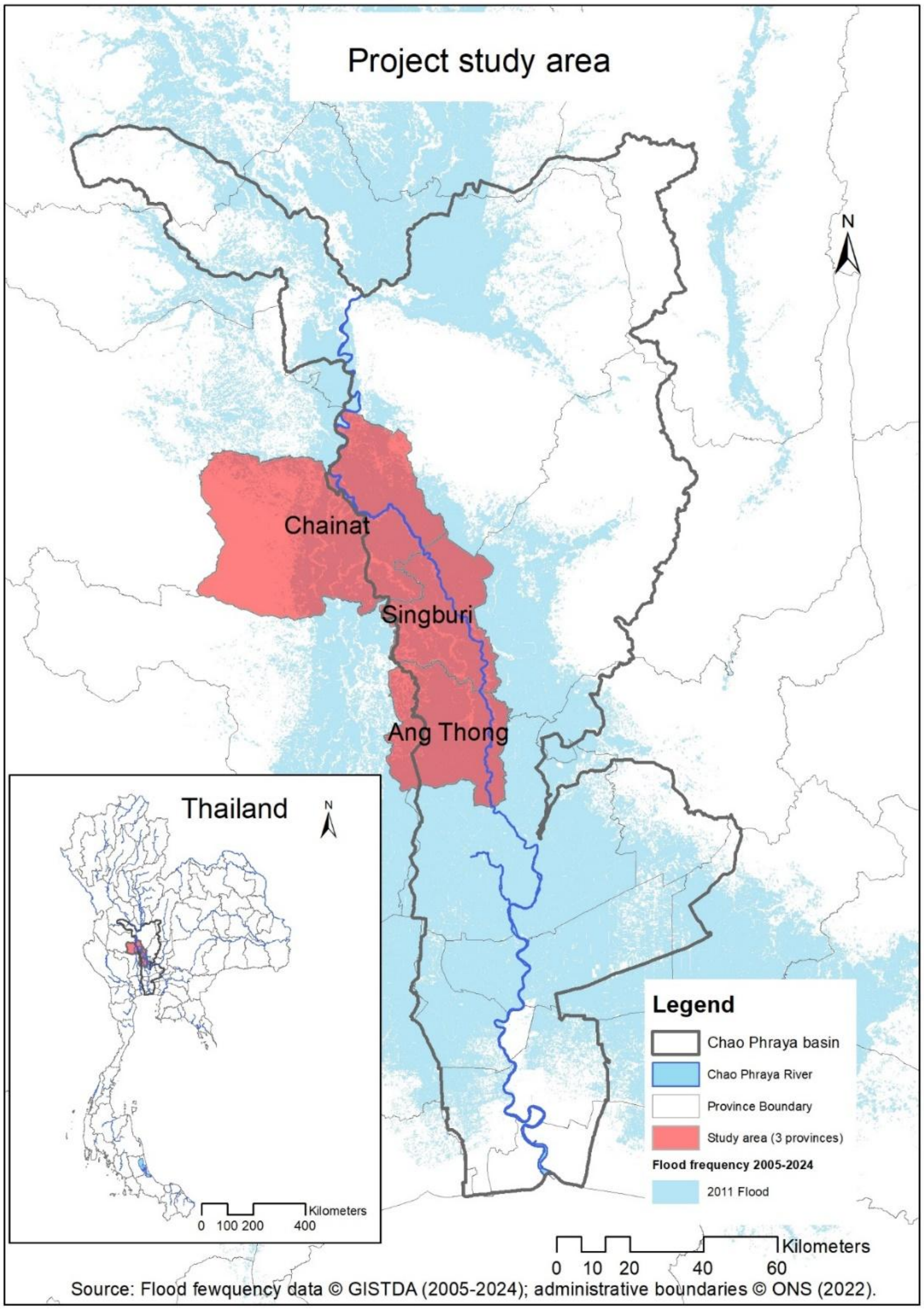


Figure 3.1. Project study area (GISTDA, 2025)

Geomorphologically, the study area is dominated by low-gradient alluvial floodplains, meandering river systems, natural levees, backswamps, and extensive sediment deposits associated with the Chao Phraya River and its distributaries (Komori et al., 2012; UNEP, 2015). Over long periods of seasonal flooding and sediment accumulation, the basin has developed broad depositional plains composed mainly of fertile clay-rich alluvial soils that support intensive rice cultivation but are also highly susceptible to prolonged inundation (Marks & Lebel, 2016). The very gentle slope of the Central Plain reduces drainage efficiency and slows floodwater movement, particularly during periods of intense monsoon rainfall (ESCAP, 2000). As a result, floodwaters frequently overflow riverbanks and spread across extensive flood basins before gradually draining toward the Gulf of Thailand (Dutta, 2011). An example of its physical characteristics is shown in Figure 3.2.

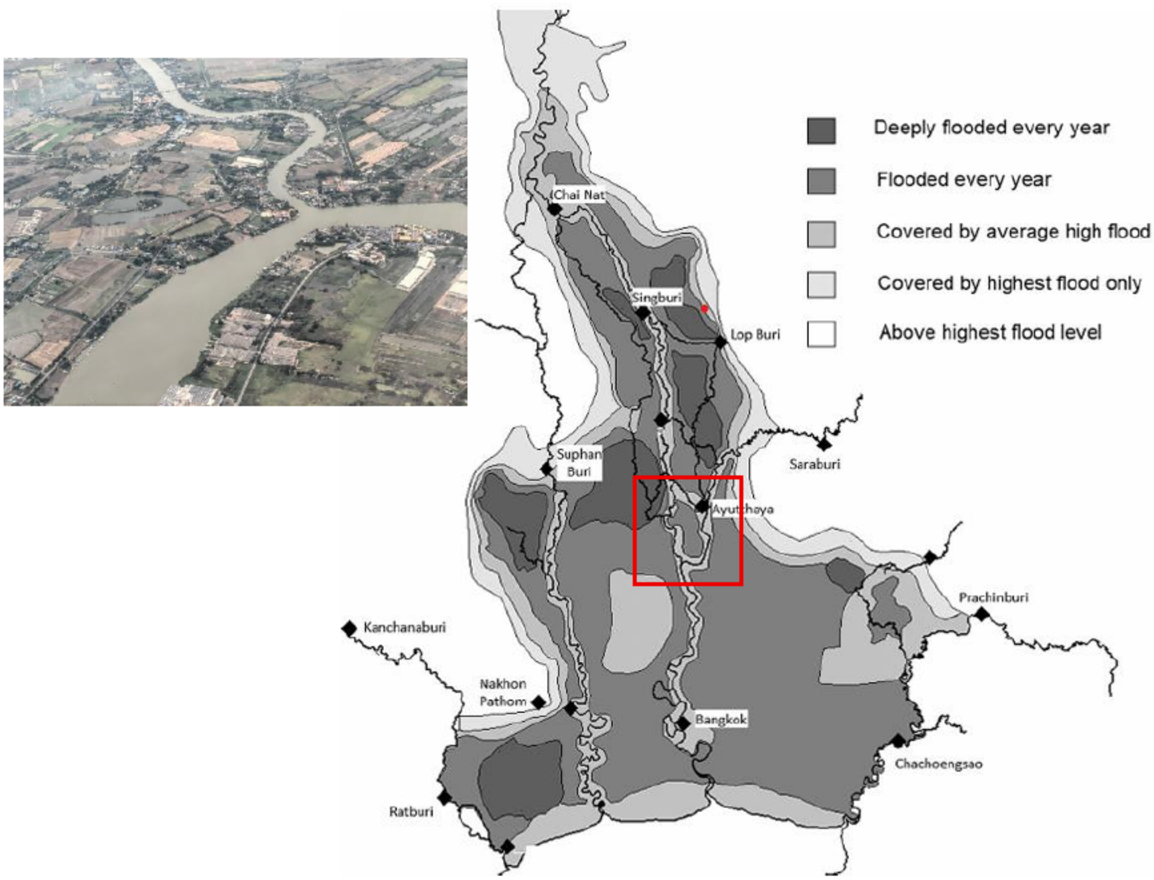


Figure 3.2. Geomorphological features of the Chao Phraya River (Molle et al., 2021)

The meandering morphology of the Chao Phraya and Noi Rivers further reduces channel conveyance capacity during high-flow conditions, increasing the likelihood of overbank flooding and prolonged water retention (Komori et al., 2012). In provinces such as Sing Buri and Ang Thong, flat terrain, shallow channel gradients, interconnected irrigation canals, and natural floodplain depressions create significant retention areas where floodwaters can persist for weeks or months after major flood events (HII, 2011). These geomorphological characteristics were clearly observed during the 2011 flood, when large parts of the lower Central Plain experienced prolonged inundation (World Bank, 2012). In addition, human modification of canals, floodways, and agricultural landscapes has altered natural drainage patterns and increased the complexity of flood behavior throughout the basin (Marks & Lebel, 2016). Together, these geomorphological and hydrological characteristics strongly influence flood extent, depth, duration, and spatial distribution across the Chao Phraya River Basin.

Sing Buri Province, located immediately downstream, consists of flat alluvial terrain shaped by centuries of sedimentation from the Chao Phraya River. More than 80 percent of its land is level with minimal slope, making the province highly flood-prone (MOAC, 2021). It is divided into 6 districts and 43 sub-districts, with the Chao Phraya, Noi, and Lop Buri Rivers flowing through its territory. In 2011, floodwaters covered 748.8 km², or nearly 85 percent of the province, submerging agricultural land, homes, and local markets (HII, 2011). Rice fields were devastated, and communities faced prolonged water retention, which delayed recovery. Rural populations dependent on farming bore significant losses, while small towns experienced disruptions to local trade and transport. Compared with Chai Nat, where flooding was driven by dam regulation, Sing Buri's challenges were exacerbated by its location as a downstream convergence zone. This geographic disadvantage connects directly to Ang Thong Province, where basin-like topography further amplified disaster impacts.

Ang Thong Province, situated south of Sing Buri, features basin-like topography with fertile clay soils suitable for rice farming, orchards, and field crops. The province is divided into 7 districts and 73 sub-districts, and is traversed by the Chao Phraya and Noi Rivers, which act as major floodways (MOAC, 2021). In 2011, Ang Thong endured some of the most severe damage, with 846.4 km² or 87 percent of its land area inundated (HII, 2011). Prolonged flooding submerged farmland, disrupted schools, and damaged transport and irrigation networks. Thousands of households were displaced, with rural communities facing long recovery periods. Smallholder farmers, lacking insurance or capital reserves, were the hardest hit, while limited provincial resources strained emergency and recovery operations. Compared with Sing Buri, Ang Thong's basin-like geography intensified both flood depth and duration, worsening impacts across communities. Together, Chai Nat, Sing Buri, and Ang Thong illustrate how geography, river morphology, and governance converge to shape the scale and distribution of flood disasters in the Chao Phraya Basin.

As shown in Figure 3.3 illustrates the topography and river network of the Lower Chao Phraya Basin study area, encompassing Chainat, Sing Buri, and Ang Thong provinces. The Digital Elevation Model (DEM) reveals a distinct contrast between the higher terrain in the eastern and northeastern parts of Chainat and the extensive low-lying floodplains that dominate Sing Buri and Ang Thong. Elevations range from approximately 36 to 776 metres above mean sea level, with the Chao Phraya River flowing north to south through the centre of the basin and connected to a dense network of tributaries and irrigation canals. The study area is characterised by broad alluvial floodplains and very gentle slopes, particularly in Sing Buri and Ang Thong, where elevations are generally below 50 metres. These geomorphological conditions facilitate the accumulation and slow drainage of floodwaters during periods of high river discharge. Runoff generated from the higher upland areas of Chainat is conveyed downstream to the flat floodplain zones, which function as natural water retention and storage areas. Consequently, floodwaters can spread widely and remain inundated for extended periods due to limited drainage gradients. The figure therefore highlights the strong influence of topography and hydrological connectivity on flood behaviour and provides an important physical basis for understanding flood susceptibility and flood risk across the Lower Chao Phraya Basin (Royal Irrigation Department, 2020).

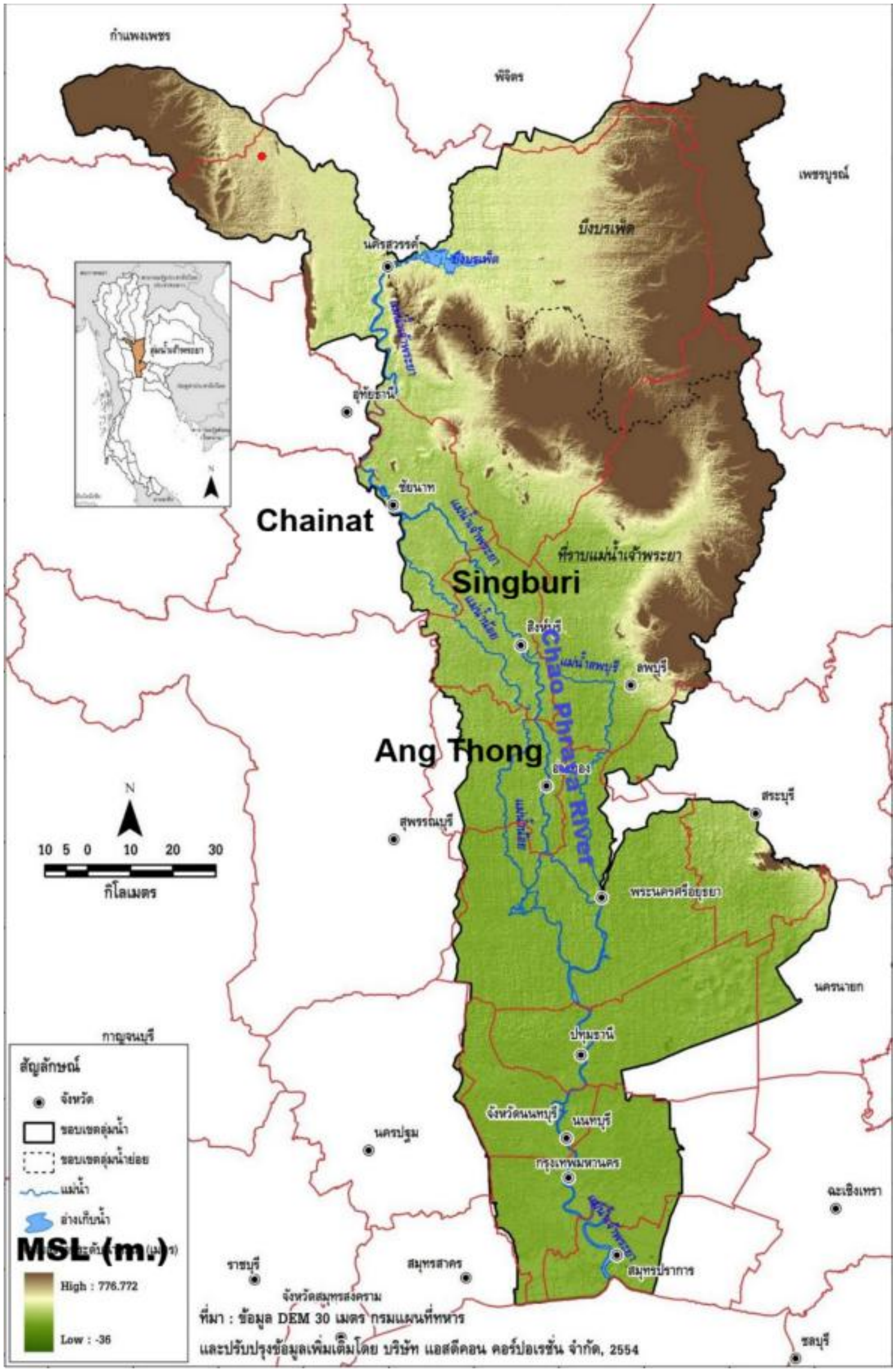


Figure 3.3. Topography and River Network of the Lower Chao Phraya Basin Study Area (Royal Irrigation Department, 2020)

3.2 Characteristics of Thailand

3.2.1 Geography, Topography and climate conditions

Thailand occupies a key position in mainland Southeast Asia, covering about 513,000 km² and bordered by Myanmar, Laos, Cambodia, and Malaysia. The country also has extensive coastlines along the Gulf of Thailand and the Andaman Sea, which are crucial for fisheries, transport, and trade (ESCAP, 2000). Geographically, it is divided into four regions: the mountainous and forested North, the fertile central plain dominated by the Chao Phraya River Basin, the elevated and semi-arid Khorat Plateau in the Northeast, and the southern peninsula with its coastal plains. The central plain, often called the “rice bowl of Asia,” is highly productive due to fertile alluvial soils but also vulnerable to seasonal inundation because of its low elevation and natural river convergence (Marks & Lebel, 2016). This geographical framework underpins the diversity of Thailand’s landscapes and establishes the foundation for its varied topographic patterns, which strongly influence water flow, agricultural use, and flood risk.

Thailand’s topography varies from rugged mountains in the North and West to the elevated Khorat Plateau in the Northeast and narrow coastal plains in the South. The most critical feature is the central plain shaped by the Chao Phraya River Basin, a vast lowland formed by centuries of sediment deposition (ESCAP, 2000). The basin spans about 159,000 km², nearly 30% of Thailand’s land area, and is home to around 40% of the national population, including Bangkok, the country’s economic and political hub (UNEP, 2015). Its funnel-shaped terrain directs runoff from northern highlands into the plain before reaching the Gulf of Thailand, often resulting in extensive inundation during the southwest monsoon. The plain’s flat relief and intensive land use increase its flood vulnerability despite its agricultural productivity (Marks & Lebel, 2016). This topographic setting, particularly the central plain, forms the link between Thailand’s geographical structure and its monsoon-driven climate, which together determine patterns of flood risk.

Thailand’s climate is dominated by the tropical monsoon, with the southwest monsoon (May–October) bringing intense rainfall that frequently causes flooding in the central plain, while the northeast monsoon (November–February) produces drier conditions (ESCAP, 2000; UNEP, 2015). Rainfall varies spatially, averaging about 1,000 mm in the Northeast but exceeding 2,000 mm in the southern peninsula and along the west coast. Coastal ecosystems such as mangroves and wetlands once buffered against floods but are being replaced by aquaculture and urban development, reducing natural resilience. Bangkok and surrounding provinces face particular flood risk due to low elevation, rapid urbanization, and groundwater extraction. Uneven rainfall distribution also contributes to water scarcity in some regions while amplifying flood hazards in others, requiring region-specific adaptation strategies (World Bank, 2012). The interaction of Thailand’s geography, topography, and climate thus creates spatially diverse flood risks, where natural conditions and human pressures combine to shape national vulnerability.

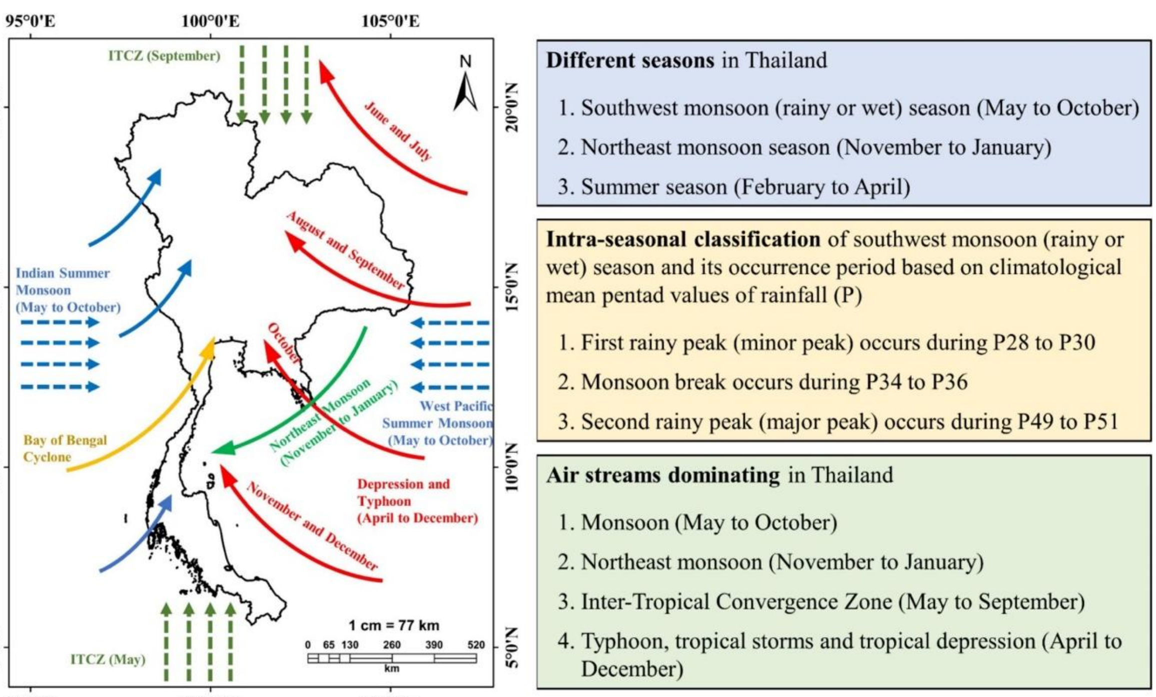


Figure 3.4. Wind currents that bring moisture into Thailand and classification of seasonal rainfall in Thailand (Madolli et al., 2025)

3.2.2 Socioeconomic conditions

Thailand is divided into 77 provinces with uneven population and economic distribution. The country has about 70 million people, with over 10 million concentrated in the Bangkok Metropolitan Area, which generates more than 40% of national GDP (World Bank, 2012). Agriculture employs around 30% of the workforce but contributes only about 10% of GDP, while industry and services dominate the economy, accounting for roughly 40% and 50% respectively (ESCAP, 2000). Rural households, particularly in the Northeast, earn six times less on average than urban households in Bangkok, reflecting persistent inequality (UNEP, 2015). Over 60% of the population lives in rural areas, heavily dependent on agriculture and therefore highly vulnerable to climate shocks such as floods and droughts. These socioeconomic disparities mean that rural provinces often lack resources for flood preparedness, while urbanized provinces face concentrated risks from dense populations and critical infrastructure.

Thailand’s rapid economic growth has also driven environmental transformation. Between 1980 and 2010, urban areas expanded by more than 150%, while mangrove forests were reduced by almost 50%, largely due to aquaculture and industrial development (World Bank, 2012). The loss of wetlands and natural floodplains has significantly reduced natural storage capacity and storm protection. Road networks, housing projects, and industrial estates built in flood-prone zones have altered drainage systems, increased runoff and shortening flood retention times. In Bangkok, groundwater extraction for industries and domestic use has caused land subsidence of up to 10 cm per year, compounding flood and sea level rise risks (UNEP, 2015). These statistics highlight how economic expansion, while beneficial to growth, has reshaped natural systems in ways that amplify flood hazards and reduce resilience.

3.2.3 Policy conditions

Thailand's flood management policy has evolved significantly, particularly after the catastrophic 2011 floods that inundated over 20,000 km² of farmland and caused more than USD 45 billion in damages, exposing weaknesses in centralized governance (World Bank, 2012). For decades, water management was dominated by structural interventions such as dams, dikes, and diversion channels, largely overseen by the Royal Irrigation Department (RID). These projects reduced localized flooding but also disrupted natural flood retention areas and encouraged settlement in vulnerable zones (Marks & Lebel, 2016). Recognizing these shortcomings, recent policies have begun to integrate non-structural measures, including early warning systems, disaster education, and ecosystem-based adaptation such as wetland restoration. Thailand has also aligned its strategies with the Sendai Framework for Disaster Risk Reduction, emphasizing preparedness and resilience rather than reliance on engineering solutions alone (UNDRR, 2015). This shift reflects a broader move from "flood control" to "flood risk management," combining structural defenses with adaptive governance.

A major institutional reform has been decentralization, transferring responsibility for disaster management from central agencies to provincial, municipal, and sub-district levels. Local governments are tasked with developing risk maps, regulating land use, and implementing community-based disaster preparedness plans. For example, the Bangkok Metropolitan Administration has introduced urban drainage and land subsidence monitoring programs, while sub-district governments in flood-prone northern provinces have piloted participatory risk assessments (ESCAP, 2000). Despite these initiatives, challenges remain: many local authorities lack technical expertise, financial resources, and timely hydrological data. More than 30 national agencies continue to share overlapping mandates, creating fragmentation and coordination gaps (Marks & Lebel, 2016). Without stronger institutional capacity and resource allocation, local governments often struggle to enforce zoning laws or invest in sustainable flood defenses. Strengthening multi-level governance, expanding technical training, and improving data-sharing across agencies are now widely recognized as essential steps toward effective, locally driven flood risk management (World Bank, 2012).

3.3 The Great 2011 flood in Thailand

3.3.1 Narrative

The Great Flood of 2011 was Thailand's most devastating disaster in modern history, triggered by record monsoon rainfall between July and October and intensified by Tropical Storm Nock-ten. Heavy precipitation across the northern and northeastern provinces saturated soils and filled major reservoirs such as Bhumibol and Sirikit beyond safe levels, forcing emergency discharges. These releases, combined with continuous runoff, overwhelmed the Ping, Yom, Nan, and Wang rivers, while the Chi and Mun rivers in the Northeast also overtopped their banks. According to Komori et al. (2012), this chain reaction produced extensive overland flooding across multiple catchments. Gale and Saunders (2013) further note that La Niña-driven anomalies strengthened the monsoon, extending rainfall duration and raising the probability of extreme flooding beyond historical averages. The resulting hydrological convergence channeled unprecedented water volumes into the Central Plain, inundating agricultural land, provincial towns, and eventually Bangkok, exposing the acute vulnerability of interconnected river basins.

By mid-October, 65 of Thailand's 77 provinces were disaster zones. The North suffered flash floods and landslides in Chiang Mai and Lampang, which destroyed homes and transport links. In the Northeast, Mekong tributaries caused prolonged inundation that devastated rice paddies and livestock. Southern provinces such as Nakhon Si Thammarat endured storm surges that compounded inland flooding. The Central Plain bore the brunt: Ayutthaya's historic city and surrounding industrial estates remained under water for weeks, while northern Bangkok districts faced widespread disruption. The crisis revealed how basin-wide connectivity and infrastructure exposure magnified flood severity, turning a meteorological hazard into a systemic disaster affecting multiple regions simultaneously (World Bank, 2012).

The flood persisted for nearly six months, from July 2011 to January 2012, making it one of the longest disasters in Thai history. More than 13 million people were affected and over 800 lives were lost. Approximately 6 million hectares of farmland were submerged, reducing food security and rural incomes. Critical infrastructure, including electricity generation, highways, and water supply, suffered extended interruptions. Economic losses were estimated at US$46.5 billion, placing the event among the costliest floods globally. Haraguchi and Lall (2015) argue that the disaster highlighted institutional weaknesses, particularly fragmented water governance and poor inter-agency coordination, which delayed response efforts and intensified the crisis. Beyond physical damages, the event exposed the high stakes of Thailand's development model, where concentrated populations, industries, and assets in flood-prone areas amplify both national importance and vulnerability.

3.3.2 Impacts

Rural populations bore severe consequences, especially smallholder farmers in the Central Plain and Northeast. Over 6 million hectares of rice fields were inundated, wiping out harvests, livestock, and stored seeds, which forced many households into debt (Poaponsakorn et al., 2015). Farmers without irrigation systems or insurance were most vulnerable, while large agribusinesses recovered more quickly due to diversified assets and stronger financial reserves. Gall et al. (2011) stress that the flood deepened rural poverty, as poorer households lacked the capacity to adapt or rebuild. Particular concern arose for elderly residents, who faced heightened risks due to limited mobility, health issues, and dependence on family support, conditions consistent with broader evidence of elder vulnerability during climate-induced disasters (Adelekan, 2010). These overlapping pressures increased social dependency within households, as younger members migrated to seek income elsewhere, leaving the elderly and women disproportionately burdened with both agricultural recovery and caregiving responsibilities. The strain on rural livelihoods set the stage for parallel challenges in urban centers.

Urban areas faced contrasting hardships, particularly in Bangkok and its surrounding provinces. Informal settlements along canals and flood retention zones were submerged for weeks, cutting access to clean water, sanitation, and electricity. Residents without legal land tenure were often excluded from compensation schemes, limiting recovery (Marks & Lebel, 2016). Migrant workers and renters near industrial estates were disproportionately affected, losing both housing and employment with little formal support. Alderman et al. (2012) note that floods frequently trigger surges in waterborne diseases such as leptospirosis, diarrhea, and dengue, which spread rapidly in overcrowded shelters and poorly drained neighborhoods. These patterns were evident in Bangkok, where weak sanitation systems compounded public health risks. Wealthier districts, protected by private barriers and backed by insurance, restored services more quickly. This uneven recovery exposed sharp socioeconomic divides. Moreover, urban disruptions fed directly into broader economic losses, as industrial estates and infrastructure critical to national and global supply chains lay at the heart of the flood zone.

Industrial and infrastructure losses were severe, crippling Thailand's economy and exposing systemic dependence on flood-prone zones. Industrial estates in Ayutthaya and Pathum Thani, home to major firms such as Toyota, Honda, and Western Digital, were inundated for over a month, halting automobile and electronics production (Haraguchi & Lall, 2015). The 2011 Thailand floods disrupted global supply chains, causing worldwide shortages of cars and computer hard drives as inundated industrial estates forced major manufacturers to halt production (Haraguchi & Lall, 2015). Small and medium-sized enterprises and informal businesses experienced the most severe and prolonged impacts because they lacked insurance coverage, financial reserves and alternative facilities for recovery, unlike multinational corporations that were able to resume operations more quickly through diversified resources and institutional support (Meechang et al., 2021; Srinivas & Nakagawa, 2007). Infrastructure damage compounded the crisis: highways, bridges, and railways were submerged, isolating rural provinces, while power plants and water treatment facilities sustained critical damage, causing service breakdowns across multiple regions (World Bank, 2012). The disruption of industries, transport, and utilities demonstrated that the 2011 flood was not only a humanitarian disaster but also a global economic shock.

3.3.3 Long-term consequences

The long-term consequences of the 2011 flood reshaped Thailand's water governance and disaster management frameworks. The unprecedented scale of damages exposed weaknesses in centralized decision-making, as fragmented coordination between national agencies and local authorities delayed timely responses (World Bank, 2012). In its aftermath, Thailand shifted from reactive flood control toward integrated risk management, emphasizing prevention, preparedness, and multi-stakeholder engagement (Marks & Lebel, 2016). New institutions, such as the Water and Flood Management Committee (WFMC), were created to strengthen planning and coordination, while investments in flood forecasting, warning systems, and structural defenses increased significantly (Komori et al., 2012). However, policy debates remain polarized between advocates of large-scale infrastructure, such as dams and diversion canals, and proponents of ecosystem-based approaches. This institutional learning process illustrates how extreme events can catalyze governance reforms but also highlights persistent tensions between technocratic control and community-centered resilience building. The 2011 flood thus acted as both a turning point and a continuing challenge for disaster governance in Thailand.

At the community level, the flood had lasting socioeconomic consequences, particularly for vulnerable households. Millions of smallholder farmers and informal workers faced long-term income losses, deepening rural indebtedness and widening inequality (Poaponsakorn et al., 2015). Flooding produces long-lasting social and psychological impacts that extend far beyond the immediate physical damage. Evidence from urban poor communities shows that displacement weakens social networks and disproportionately harms vulnerable groups such as the elderly, women, migrants and low-income households, who face persistent livelihood disruption and reduced coping capacity (Adelekan, 2010). Mental-health effects are substantial: the Health Protection Agency's review highlights elevated levels of stress, anxiety, depression and ongoing psychosocial distress, driven by both the initial trauma and prolonged secondary stressors such as housing loss, slow recovery and administrative challenges (AP, 2011). Educational disruption further deepens inequalities, while longer-term recovery often reshapes migration patterns, with younger and more mobile residents relocating and older or poorer groups remaining. As emphasized in international disaster-risk literature, these combined effects erode human capital and heighten vulnerability unless addressed through inclusive recovery planning and strong social protection systems (Wisner et al., 2011).

From an economic perspective, the 2011 flood left an enduring imprint on Thailand's development trajectory and global supply chains. With damages estimated at US$46.5 billion, it became one of the costliest floods in modern history (Haraguchi & Lall, 2015). The prolonged shutdown of industrial estates in Ayutthaya and Pathum Thani disrupted international production of automobiles, electronics, and hard drives, prompting multinational firms to diversify supply chains away from Thailand (Ye & Abe, 2012).This loss of investor confidence pressured the government to prioritize flood resilience in economic planning, including stricter zoning regulations and higher investment in protective infrastructure. Yet small and medium-sized enterprises (SMEs), which lacked the resources to relocate, faced protracted recovery, reinforcing structural economic inequalities (Lim & Skidmore, 2019). Beyond direct damages, the flood altered global perceptions of disaster risk in Southeast Asia, elevating resilience as a key factor in trade and investment decisions. Thus, the disaster not only reshaped Thailand's economic landscape but also influenced broader global risk governance.

3.4 Overview of flood risk in the Chao Praya River Basin

The Chao Phraya River Basin is Thailand's most important hydrological and economic region, covering nearly one-third of the national territory and supporting more than 40 percent of the population (Komori et al., 2012). Its fertile Central Plain underpins agricultural productivity, particularly rice cultivation, while major urban centers such as Bangkok and Ayutthaya anchor industrial and commercial activity. This concentration of population, economic assets, and infrastructure within a low-lying environment heightens exposure to hydrological extremes. Seasonal floods have long shaped settlement patterns and agricultural cycles, but the Great Flood of 2011 revealed how extreme monsoon rainfall, upstream runoff, and human interventions like reservoir operations can escalate localized hazards into a nationwide crisis (World Bank, 2012). Addressing flood risk in the basin therefore requires an integrated perspective that considers hazards, exposure, vulnerabilities, and governance.

3.4.1 Geographic and Hydrological Setting

Understanding the geographic and hydrological setting provides the foundation for analyzing these risks. The basin's hydrological structure is defined by four major tributaries, the Ping, Wang, Yom, and Nan Rivers, which converge at Nakhon Sawan to form the Chao Phraya River before discharging into the Gulf of Thailand. This funnel-shaped configuration channels runoff from the mountainous north and west into the Central Plain, a highly productive yet flood-prone alluvial region. With more than 25 million residents and key hubs such as Bangkok, Pathum Thani, and Ayutthaya, the area illustrates how economic growth is intertwined with hazard exposure (UNEP, 2015).

Hydrologically, the basin is shaped by the tropical monsoon, producing sharp seasonal variations in rainfall. The southwest monsoon, from May to October, often brings widespread flooding, while the northeast monsoon, from November to February, brings drier conditions occasionally intensified by cyclones. Reservoirs such as Bhumibol and Sirikit regulate water, yet extreme rainfall increasingly exceeds storage capacity (Gale & Saunders, 2013). Meanwhile, urban expansion and wetland conversion reduce natural retention. These physical processes frame the discussion of exposure, since where people live, work, and cultivate land within this hydrological system determines their degree of flood risk.

3.4.2 Exposure Dimensions

The Chao Phraya Basin is one of Thailand's most densely populated regions, placing millions at risk of recurrent flooding. Bangkok, with more than 10 million residents on low-lying deltaic terrain, is highly vulnerable to both riverine and coastal floods (Marks & Lebel, 2016). Other centers such as Ayutthaya, Pathum Thani, Chainat, Singburi, and Ang Thong also face recurring inundation, as their role as retention areas prolongs flooding and disrupts agriculture and urban activity. More than 6 million hectares of farmland are regularly exposed to flood hazards, underscoring the national-scale consequences for food security (Poaponsakorn et al., 2015).

Industrial and infrastructural assets intensify exposure. The 2011 flood submerged estates in Ayutthaya and Pathum Thani, crippling local communities and disrupting global supply chains (Haraguchi & Lall, 2015). Informal settlements near canals and retention zones faced inundation without secure housing or compensation (World Bank, 2012). The overlap of dense population, agriculture, and industry highlights systemic exposure. Yet exposure alone does not determine flood outcomes. Vulnerability shapes how severely different groups are impacted, as explored in the next section.

3.4.3 Vulnerability Profile

Vulnerability in the Chao Phraya Basin is deeply shaped by socioeconomic inequalities. Rural farmers in provinces such as Chainat, Singburi, and Ang Thong are highly dependent on rice cultivation in flood-prone lowlands. Crop and livestock losses often push households into debt, especially without insurance or irrigation support (Poaponsakorn et al., 2015). The elderly face mobility and health challenges during disasters, while women and children experience disproportionate caregiving and educational disruptions (Matlakala et al., 2024). Such groups consistently bear the heaviest burden of floods.

In contrast, urban and peri-urban populations encounter vulnerabilities linked to settlement patterns and governance gaps. Informal communities in Bangkok, Ayutthaya, and Pathum Thani lack durable housing and secure tenure, excluding them from formal assistance (Marks & Lebel, 2016). Migrant workers in flood-prone industrial zones face dual vulnerability through loss of both employment and housing during floods (World Bank, 2012). Health risks are elevated by outbreaks of waterborne diseases during prolonged inundation (Alderman et al., 2012). These disparities reveal how governance plays a decisive role in shaping resilience, providing a bridge to the discussion of risk management frameworks.

3.4.4 Governance and Risk Management

Thailand's flood governance has long relied on centralized, structural measures led by agencies such as the Royal Irrigation Department (RID) and the Department of Disaster Prevention and Mitigation (DDPM). Large dams, dikes, and diversion channels dominated policy, but the 2011 flood exposed weaknesses, including poor coordination and limited local authority. Provinces such as Chainat, Singburi, and Ang Thong struggled to manage retention zones effectively, illustrating gaps in decentralization (Marks & Lebel, 2016).

More recent strategies for managing flood risk in the Chao Phraya River Basin increasingly prioritize integrated water resources management and disaster risk reduction in accordance with the Sendai Framework for Disaster Risk Reduction (UNDRR, 2015). These approaches integrate structural measures such as embankments, retention areas and upgraded drainage with non-structural measures including zoning reform, ecosystem restoration and community-based early warning systems, which are widely recognized as essential for long-term resilience in large river basins (Dutta, 2011).International partners have played a central role in advancing basin-wide planning. The Asian Development Bank has supported integrated flood-risk management and climate-resilient water-resource initiatives through recent basin-modelling and coordination programs in Thailand (Asian Development Bank, 2024), while the Japan International Cooperation Agency has contributed significantly through its Comprehensive Flood Management Plan for the

Chao Phraya River Basin, which outlines long-term structural and non-structural flood mitigation strategies (JICA, 2013). Despite these efforts, rapid urbanization, weak enforcement of land-use regulations and the expansion of industrial zones in provinces such as Ayutthaya and Pathum Thani continue to heighten exposure, a pattern highlighted in post-2011 flood governance analyses (Poaponsakorn et al., 2015). These persistent governance challenges indicate that without stronger regulatory systems and coordinated basin-wide planning, climate change and ongoing development pressures are likely to compound future flood risk.

3.4.5 Future Outlook

Flood risk in the Chao Phraya Basin is expected to worsen because climate change, rapid urban growth and socioeconomic pressures are acting together to increase hazard levels. More intense rainfall and rising sea levels heighten exposure in Bangkok and nearby provinces, while land subsidence caused by prolonged groundwater extraction further increases the depth and extent of flooding. Research shows that parts of the city have subsided by several centimeters per year, creating a substantial elevation deficit that amplifies flood severity. Modelling studies also confirm that the combined effects of subsidence, sea-level rise and storm surge will significantly expand future flood inundation across the metropolitan region (Duangyiwa et al., 2015; Phien-wej et al., 2005). Urban growth in floodplains, particularly in Pathum Thani and Ayutthaya, reduces natural retention capacity. Unless mitigated, these factors will amplify systemic risks for communities, agriculture, and industry (Gale & Saunders, 2013).

Future resilience will depend on governance reform and community-based approaches. While structural solutions remain central, experts emphasize balancing them with non-structural measures such as insurance, zoning, and early warning systems (Dutta, 2011). Decentralization is critical for empowering local governments in provinces such as Chainat, Singburi, and Ang Thong, which serve as floodways but often lack resources. Regional cooperation on upstream flows and stronger alignment with the Sendai Framework will also be vital (UNDRR, 2015). Thailand's ability to adapt will rest on balancing structural and non-structural measures, strengthening governance, and reducing inequality to build systemic resilience against future floods.

Flood risk in Thailand's Chao Phraya River Basin reflects the combined pressures of natural hazards, concentrated exposure, and uneven social vulnerability. The 2011 flood, which inundated two-thirds of the country and caused over US$46 billion in damages, underscored how heavy monsoon rainfall and limited institutional coordination can transform seasonal flooding into a nationwide disaster (World Bank, 2012). The basin's role as the country's agricultural and industrial core intensifies systemic risk, as densely populated urban centers, critical industries, and extensive farmland are concentrated in flood-prone areas. Vulnerability is heightened for groups such as smallholder farmers, migrant workers, and informal settlers, who lack the resources and institutional support to recover quickly (Marks & Lebel, 2016; Poaponsakorn et al., 2015). While reforms aligned with international frameworks like the Sendai Framework have promoted more integrated risk management, significant gaps remain in decentralization, land-use regulation, and ecosystem-based approaches (Dutta, 2011; UNDRR, 2015). Building long-term resilience requires reducing inequality, improving governance, and balancing structural defenses with adaptive, community-centered strategies.

3.5 Selecting a pilot area for model testing.

3.5.1 Shared Characteristics Supporting Model Transferability

This research adopts the River Don catchment in Sheffield, England, as a pilot study area to develop and test the flood risk assessment methodology before transferring it to Thailand. The selection of Sheffield was based on three key considerations: the availability of high-quality secondary data, the suitability of the catchment for GIS-based flood risk modelling, and the existence of previous flood risk research that provides a basis for comparison and validation. The River Don flows through a densely populated urban environment where flood risk is influenced by the interaction of hydrological processes, land use patterns, socio-economic conditions, and historical river modifications. Sheffield has experienced several significant flood events, including the widespread floods of 2007, which highlighted the vulnerability of communities located along the River Don and its tributaries and stimulated extensive flood risk research and management initiatives within the catchment (Environment Agency, 2010).

As a result, the River Don catchment has become one of the most extensively studied river basins in the United Kingdom, with a wealth of publicly available hydrological, topographical, environmental, demographic, and socio-economic datasets provided by organisations such as the Environment Agency, the UK Census, and local authorities (Environment Agency, 2010). These datasets provide a data-rich environment for evaluating model performance, testing methodological assumptions, and assessing the sensitivity of flood risk models under conditions where data limitations are minimal. Previous studies in Sheffield have also demonstrated the value of integrating hazard, exposure, and vulnerability indicators within GIS-based flood risk assessments and provide an important methodological benchmark for the present research (Chen, 2021).

The River Don catchment also shares several characteristics with the Chao Phraya River basin. Although the Chao Phraya basin is substantially larger and characterised by low-gradient alluvial floodplains, both river systems experience flood risk arising from the interaction of physical flood processes, human settlement patterns, and socio-economic vulnerability. Consequently, the River Don catchment provides a suitable environment for developing and refining a transferable flood risk assessment framework. As discussed in Chapter 5, the Sheffield pilot study enabled the evaluation of data requirements, the identification of appropriate variables, and the assessment of model sensitivity to different input datasets. The findings established the methodological foundation for applying the framework to the flood-prone provinces of Chai Nat, Sing Buri, and Ang Thong in Thailand.

3.5.2 Contextual Differences for Understanding the Study Areas

An important consideration when transferring the flood risk assessment framework from Sheffield to Thailand is the contrasting relationship between society and flooding in the two study areas. Flood risk is not determined solely by hydrological and physical processes but is also shaped by historical land-use practices, flood management strategies, and societal perceptions of flooding. These factors influence how communities adapt to, respond to, and coexist with flood hazards.

In Sheffield and many parts of the United Kingdom, flood management has traditionally focused on reducing flood occurrence through engineered solutions, including flood walls, embankments, channel modifications, and upstream flood storage schemes (Environment Agency, 2010). Urban development has generally been planned with the expectation that rivers will remain within defined channels and that flood defences will provide a specified level of protection. Consequently, flooding is often viewed as an abnormal or extreme event that occurs when the capacity of flood management infrastructure is exceeded. This approach has contributed to substantial investment in flood defence systems and flood risk management policies throughout the River Don catchment following major flood events such as those experienced in 2007 and 2019.

In contrast, the Chao Phraya River basin has historically developed as a floodplain society in which seasonal inundation is an inherent part of the natural environment and agricultural system (Molle, 2007). The low-lying alluvial plains of Chai Nat, Sing Buri, and Ang Thong contain natural levees, flood basins, wetlands, and extensive agricultural areas that have traditionally functioned as water retention zones during the monsoon season. Rather than completely preventing flooding, water management practices have often focused on accommodating and regulating floodwaters across the landscape. As a result, rivers may naturally overtop their banks in some locations, including areas occupied by settlements and agricultural land, without necessarily being regarded as a failure of the flood management system. The severe flooding of 2011 demonstrated both the importance and limitations of this floodplain-based approach, highlighting the complex interactions between river management, flood retention areas, human settlement, and economic development throughout the basin (Komori et al., 2012).

These differences illustrate that the River Don catchment and the Chao Phraya basin represent distinct flood management contexts. While the Sheffield pilot study provides a valuable environment for testing GIS-based flood risk assessment methods under a highly managed flood regime, the transfer of the framework to Thailand requires consideration of a landscape where periodic flooding remains a natural component of the hydrological system. Understanding these contextual differences is essential for interpreting model outputs and ensuring that the flood risk assessment framework remains applicable within the social, environmental, and institutional conditions of the Chao Phraya floodplain.

As show in Figure 3.5. Hydrological features and riverbank environments in the Chao Phraya Basin and River Don Catchment (Komori et al., 2012; Shaw et al., 2016). (a) The confluence of the Ping, Wang, Yom, and Nan Rivers at Nakhon Sawan, forming the Chao Phraya River. (b) Major tributaries of the River Don catchment in northern England. (c) Natural riverbanks and riverside settlements along the Chao Phraya River, illustrating the traditional relationship between communities and the floodplain landscape where periodic inundation is a recognised part of the hydrological system. (d) Reinforced riverbanks and flood protection infrastructure along the River Don in Sheffield, reflecting a flood management approach that emphasises engineered protection and channel containment. Together, these images demonstrate how differences in physical geography, flood management practices, and historical adaptation have shaped distinct riverine environments in the two study areas.

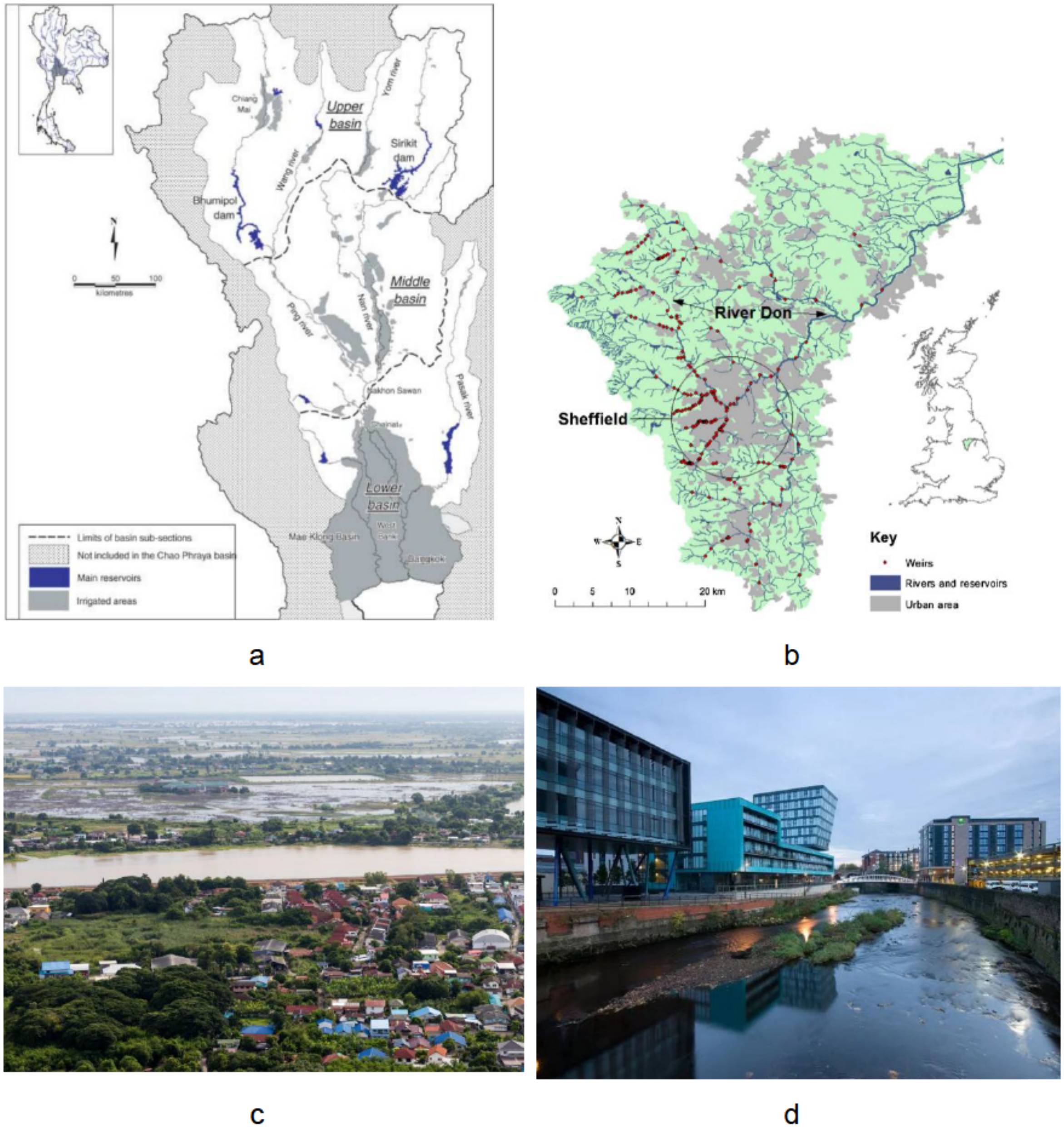


Figure 3.5. Comparison of River Confluences and Riverbank Environments in the Chao Phraya and River Don Basins

3.6 Conclusion

Critical issues for flood vulnerability and flood-risk estimation in Thailand

- Structural and environmental pressures have intensified vulnerability, including rapid urbanization, wetland loss, land subsidence and the expansion of settlements and industry into natural floodplains. These changes reduce natural retention capacity and amplify the effects of monsoon-driven flooding.
- Socioeconomic inequality and demographic characteristics create uneven vulnerability. Smallholder farmers, informal settlers, migrant workers, elderly residents and low-income households face greater exposure, weaker coping capacity and slower recovery, making vulnerability highly spatially and socially differentiated.
- Governance fragmentation and data limitations constrain accurate flood-risk estimation. Overlapping institutional mandates, limited local technical capacity, weak enforcement of land-use regulations and inconsistent hydrological and socioeconomic datasets reduce the effectiveness of modelling and coordinated basin-wide planning.
- The Chao Phraya Basin and the River Don Catchment differ considerably in scale, topography, floodplain characteristics, and flood management practices. However, both river systems experience flood risk arising from the interaction of hydrological processes, land use patterns, population distribution, and socioeconomic vulnerability, providing a suitable basis for methodological comparison and model transferability.
- The contrasting environmental, social, and institutional contexts of the two study areas highlight the importance of developing a flexible GIS-based flood risk assessment framework. Such a framework must be capable of incorporating locally available data while maintaining a consistent approach to evaluating hazard, exposure, and vulnerability across different geographical settings.

Chapter 4: Methodology and Methods

4.1 Rationale for theory and model selection

This study employed a GIS-based multi-criteria flood risk assessment framework integrating Ordinary Least Squares (OLS) regression, Principal Component Analysis (PCA), and Geographically Weighted Regression (GWR) to explore spatial relationships among hazard, exposure, and vulnerability variables to Identify flood risk areas. The modelling framework emphasizes a quantitative, data-driven approach to minimize the subjectivity associated with expert-based weighting and to assess the sensitivity and relative importance of key variables within each component of the flood risk model. This approach was selected for its ability to integrate heterogeneous geospatial and statistical datasets, capture spatial variability in flood dynamics, and enable comparative assessment at both regional and sub-district scales. Moreover, it strengthens spatial decision-making in data-scarce environments typical of developing countries such as Thailand. To validate the methodological robustness and cross-context applicability, the framework was first tested in a pilot study conducted in Sheffield, United Kingdom, allowing for examination of model sensitivity, parameter stability, and transferability across differing geographic and socio-economic conditions (Merz et al., 2007; Shrestha et al., 2018).

All research activities were conducted in full compliance with the university's ethical and data governance standards. Secondary datasets, including hydro-meteorological data, physical data and socio-economic data, were obtained from authorized government and open-access sources to ensure compliance with privacy and data protection requirements. No personally identifiable or sensitive information was included in analyses or modelling. Consultations with experts and local stakeholders were undertaken through informed consent, guaranteeing voluntary participation and confidentiality of responses. All procedures for data storage, processing, and analysis followed the University's Research Ethics Committee protocols and aligned with the principles of the GOV UK (2018) and General Data

Protection Regulation (GDPR). Ethical clearance was granted before commencing data acquisition and spatial analysis.

This methodological framework is grounded in established theoretical and policy principles of flood risk research, notably the Risk Triangle Model (Crichton, 1999), the EU Floods Directive (2007/60/EC), and the framework promoting integrated assessment of hazard, exposure, and vulnerability (UNDRR, 2015). It incorporates a hybrid spatial analysis approach, combining multi-criteria evaluation with Geographically Weighted Regression (GWR) to capture spatial heterogeneity and local variations in flood dynamics. This integration strengthens the model's capacity to reflect complex environmental and socio-economic interactions influencing flood risk. By aligning international methodologies with local spatial structures, the framework enhances both conceptual coherence and analytical robustness, facilitating its application at the sub-district level in Thailand for more context-sensitive flood risk management (Cutter et al., 2003; Jongman et al., 2015).

4.2 Conceptual framework

The conceptual framework is organized into 3 main stages to provide a systematic approach to flood risk assessment. The first stage involves gathering, selecting, and preparing secondary data from government sources and published materials. Quantitative techniques are applied to identify the most relevant variables associated with flood hazard, exposure, and vulnerability, supported by literature review and expert consultation. The second stage applies Ordinary Least Squares (OLS) regression and Principal Component Analysis (PCA) to analyze statistical relationships and assess the sensitivity of each variable, while Geographically Weighted Regression (GWR) captures spatial variability and highlights areas of high flood susceptibility. The final stage integrates the findings from the hazard, exposure, and vulnerability analyses to develop composite flood risk maps that present a clear spatial understanding of flood patterns and support data-driven decision-making at both regional and sub-district levels. The conceptual framework is shown in Figure 4.1.

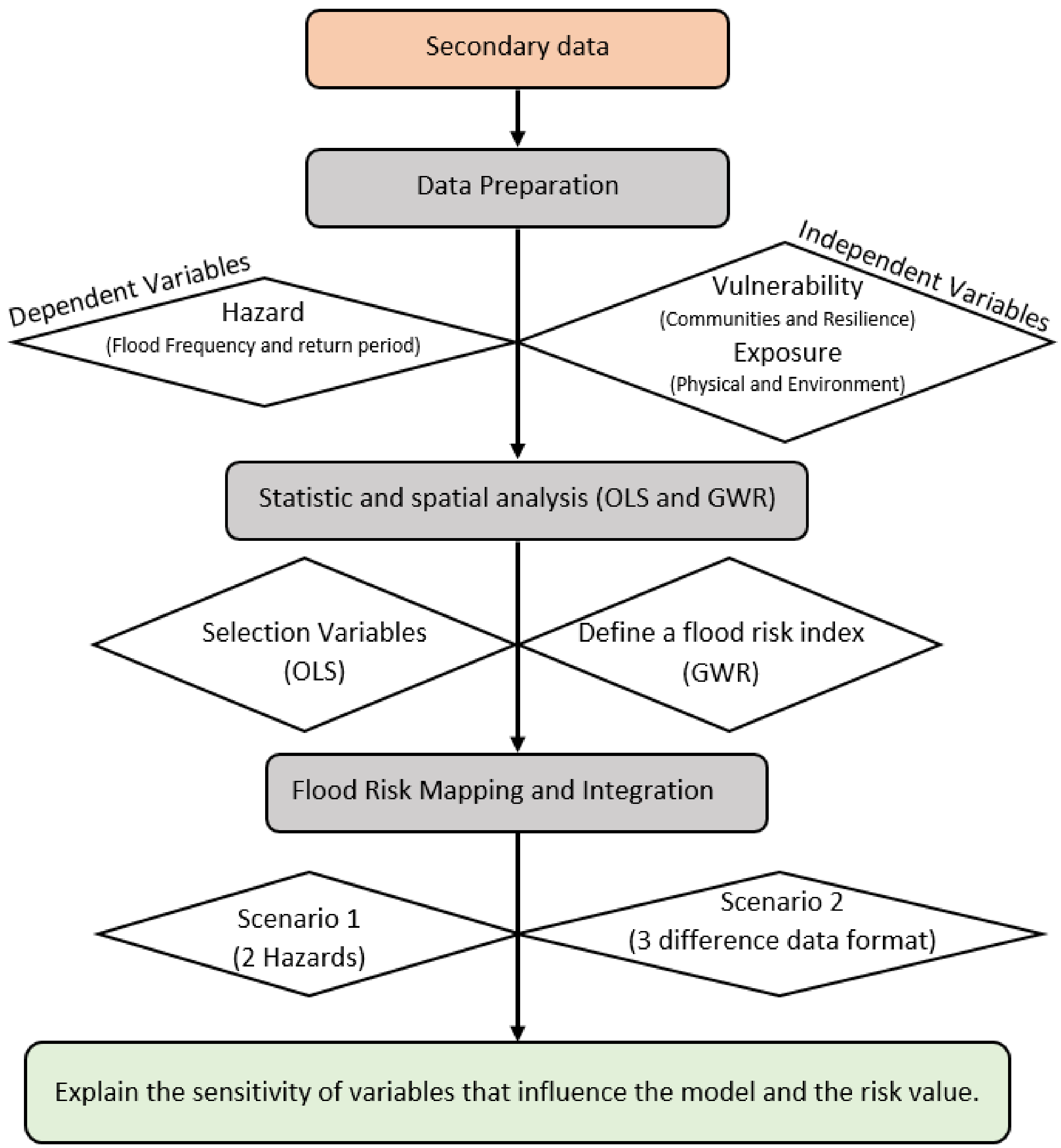


Figure 4.1. The conceptual framework

4.2.1 Sheffield Pilot Study as a Methodological Validation Stage

Prior to transferring the flood risk assessment framework to Thailand, a pilot study was conducted in Sheffield, United Kingdom, to evaluate the methodological robustness, sensitivity and transferability of the proposed GIS-based modelling approach. The pilot study served as an intermediate validation stage between the theoretical review presented in Chapter 2 and the application of the framework in Thailand.

The selection of Sheffield was justified by several methodological considerations. First, Sheffield provides a data-rich environment with high-quality and openly accessible datasets relating to flood hazards, demographic characteristics, building stock and socioeconomic conditions. Such data availability enabled rigorous testing of statistical procedures and model behaviour before application in a more data-constrained environment. Second, the city has a documented history of river flooding associated with the River Don catchment, making it an appropriate case for examining interactions between hazard, exposure and vulnerability. Third, the presence of detailed flood-risk studies and previous GIS-based assessments provided opportunities for comparison and validation against established findings.

A particular objective of the pilot study was to evaluate alternative approaches for variable selection and model construction. Three analytical techniques were examined: Principal Component Analysis (PCA), Ordinary Least Squares (OLS) regression and Geographically Weighted Regression (GWR). PCA was initially explored as a dimensionality-reduction technique to identify dominant patterns within the socioeconomic variables and to minimise redundancy among candidate indicators. However, PCA alone provides limited information regarding the direct statistical relationship between individual variables and flood-risk outcomes and may reduce interpretability when transferred across different geographical contexts.

Consequently, OLS was adopted as the primary modelling and diagnostic technique within the research framework. OLS provides a transparent and statistically robust method for evaluating variable significance, identifying multicollinearity through Variance Inflation Factor (VIF) diagnostics, assessing model performance through measures such as adjusted R^2 and Akaike Information Criterion (AIC), and determining the relative contribution of individual predictors. These capabilities directly support the study objectives of assessing data quality, parameter sensitivity and model uncertainty. Furthermore, OLS offers a consistent and transferable framework that can be applied across different datasets and national contexts, making it particularly suitable for comparing the Sheffield and Thailand case studies.

The pilot study also demonstrated that flood-risk relationships exhibit significant spatial heterogeneity that cannot be fully captured by a global regression model. Therefore, Geographically Weighted Regression (GWR) was selected as the final modelling technique because it allows regression coefficients to vary spatially, thereby capturing local variations in the relationships between hazard, exposure and vulnerability factors. The role of OLS was therefore to provide the primary statistical screening and diagnostic framework, while GWR was employed to model spatially varying relationships and generate the final flood-risk index.

The findings from Sheffield informed several methodological refinements subsequently applied in Thailand. These included the adoption of OLS-based variable selection procedures, the use of diagnostic thresholds for variable screening, the selection of GWR as the final spatial modelling approach and improvements to flood-risk classification methods. Consequently, the pilot study provided an essential foundation for evaluating model transferability and reducing uncertainty associated with cross-context application. This is explained in Chapter 5.

4.2.2 Expert Knowledge Integration and Parameterisation

Although the core modelling framework was developed using quantitative and statistically driven methods, this research recognizes that flood risk is influenced by local environmental processes, socioeconomic conditions and governance factors that may not be fully represented within secondary datasets. Therefore, expert knowledge was incorporated as a complementary component of the methodological framework.

Expert involvement was deliberately positioned at the parameterisation stage of model development. The conceptual structure of the flood-risk model, including the hazard exposure vulnerability framework, was established through the literature review and refined through the Sheffield pilot study. Similarly, model performance was evaluated using statistical diagnostics rather than expert judgement. Consequently, expert participation focused on assessing the relevance of variables, interpreting local conditions and evaluating the practical significance of different indicators within the Thai context.

Experts were selected from disciplines relevant to flood-risk management, including hydrology, flood modelling, GIS and spatial analysis, disaster management, local government planning and community-level flood experience. Their knowledge was used to assess the appropriateness of candidate variables, identify locally significant factors and assign relative importance scores to hazard, exposure and vulnerability indicators. These assessments were subsequently converted into weighting values that were incorporated into the modelling framework and compared against statistically derived results.

The integration of expert knowledge served two methodological purposes. First, it provided contextual validation of variables derived from international literature and statistical analysis. Second, it enabled evaluation of the extent to which expert-informed parameterisation influences spatial patterns of flood risk compared with purely data-driven approaches. This comparison contributes directly to understanding uncertainty, model sensitivity and the role of local knowledge in flood-risk assessment, particularly in environments where data limitations may constrain conventional modelling approaches.

4.3 Data preparation

Data preparation focuses on the identification and collation of a suitable set of data layers sufficient to characterize the 3 components of the risk triangle. This is not a trivial task as data availability varies geographically and over time.

4.3.1 Data source

This study uses publicly available secondary data to ensure transparency, reproducibility, and practical value for local government agencies engaged in flood risk management. All datasets were obtained from official Thai government sources and cross-checked with open-access repositories to maintain accuracy and consistency. Flood hazard data, including flood frequency, depth, and spatial extent, were collected from the Geo-Informatics and Space Technology Development Agency (GISTDA) for the period 2005-2024, while flood return period data were obtained from the United Nations Office for Disaster Risk Reduction (UNDRR). These datasets were used to support hazard mapping, model calibration, and scenario evaluation. Census data from the Community Development Department provided socio-economic and demographic variables such as population density, household size, education, income, savings, and occupation, which informed vulnerability and exposure analyses. Building footprint and density data were derived from the Google Open Buildings Dataset, and administrative boundary data from the Office of the National Statistics (ONS) were used for spatial referencing and sub-district level analysis. All datasets were standardized, georeferenced, and integrated into a Geographic Information System (GIS) to ensure spatial consistency and produce comprehensive flood risk maps at both regional and local levels.

Building on these datasets, the study emphasizes the importance of using the sub-district level as the primary spatial unit for analysis. Thailand's administrative system comprises provinces, districts, sub-districts, municipalities, and villages, with the sub-district representing the smallest officially recognized unit with defined geographic boundaries. Census data at this level provide high spatial precision and allow reliable integration with other datasets such as hazard, building, and infrastructure data. For this research, sub-district level census datasets from 2023 and 2024 were selected as the most complete, up-to-date, and publicly accessible sources available through government open data platforms. Their consistency in classification and spatial reference ensures accurate comparisons across administrative areas and supports robust, replicable flood risk assessments at both regional and local scales.

The study area encompasses three provinces within the Chao Phraya River Basin, comprising a total of 169 sub-districts: Ang Thong (73 sub-districts), Sing Buri (43 sub-districts), and Chainat (53 sub-districts). Each province features diverse watershed conditions and varying exposure levels to flooding. The average population per sub-district ranges from 100 to 900 residents, reflecting mainly rural and semi-urban communities that are critical for localized flood risk analysis. However, considerable spatial heterogeneity within the basin presents challenges in processing certain variables. Differences in sub-district size, land use distribution, and socio-economic profiles can create inconsistencies in data comparability. For instance, a small sub-district with 5–10% industrial land use may demonstrate disproportionately higher flood risk compared to predominantly agricultural areas. As a result, some variables with incompatible spatial scales or incomplete representation could not be uniformly applied across the study area.

Table 4.1. Candidate variables and data sources

Component / Variables	Description	Criteria	Year	Data Source
Hazard				
H1 Hazard zone by frequency of flood	Represents the rate of flood occurrence in a given area over time. High flood frequency indicates repeated exposure, increasing the likelihood of cumulative damage and erosion of community resilience. (Long et al., 2025)	Weighting of Flood (2008-2024)	20 y (2005-2024)	Thailand Flood Monitoring System, GISTDA, Thailand (GISTDA, 2026) https://disaster.gistda.or.th/flood
H2 Hazard zone by return period	Represents the statistical probability of a flood event of a given magnitude occurring in any year (e.g., 1-in-100-year flood = 1% annual probability). (Albano et al., 2017).	Flood recurrence rate: 3 High (1 in 100 chances of flooding) 2 Medium (1 in 100 chances of flooding) 1 Low (Outside mapped floodplain)	2015	UNDRR (UNDRR, 2020). https://risk.preventionweb.net/
Exposure				
E1 Building density	In high-density residential areas, incident response emergency services may be overloaded (Cutter et al., 2003).	Building density per km^2	2022	Google Buildng (Google, 2026).https://sites.research.google/gr/open-buildings/

Component / Variables	Description	Criteria	Year	Data Source
E2 Population density	Population density is often linked to low-income housing, which in overcrowded areas tends to have poor drainage and inadequate infrastructure (Rinc et al., 2018).	Population density per km^2	2y (2023-2024)	Thailand Census data (CDD, 2024). https://dashboard66.cdd.go.th/Home/DashBoardPublic
E3 Size of household	Families with many dependents often have limited funds to care for their dependents from outside. Therefore, they are responsible for working and taking care of family members. All effect resilience and recovery from danger (Cutter et al., 2003).	Population number per household	2y (2023-2024)	Thailand Census data (CDD, 2024). https://dashboard66.cdd.go.th/Home/DashBoardPublic
Vulnerability				
V1 AGE	Measures the proportion of vulnerable age groups (e.g., children <5 and elderly >60) who are more susceptible to injury, mobility constraints, or health impacts during floods. (Cutter et al., 2003).	Children under 5 years and elder over 60 years	2y (2023-2024)	Thailand Census data (CDD, 2024). https://dashboard66.cdd.go.th/Home/DashBoardPublic
V2 Gender	Gender imbalance (especially high proportion of females) may indicate greater vulnerability due to socioeconomic roles, caregiving responsibilities, or reduced mobility. (Cutter et al., 2003).	Women in the population	2y (2023-2024)	Thailand Census data (CDD, 2024). https://dashboard66.cdd.go.th/Home/DashBoardPublic

Component / Variables	Description	Criteria	Year	Data Source
V3 No Education	A proxy for awareness of disaster risks and capacity for preparedness and adaptation actions. (Cutter et al., 2003).	No qualification or No Education	2y (2023-2024)	Thailand Census data (CDD, 2024). https://dashboard66.cdd.go.th/Home/DashBoardPublic
V4 Less hi school	Education level affects the ability to understand warnings, prepare for floods, and recover. Low education correlates with poor flood response capacity. (Cutter et al., 2003).	Level of qualification with primary school	2y (2023-2024)	Thailand Census data (CDD, 2024). https://dashboard66.cdd.go.th/Home/DashBoardPublic
V5 Un Employed	Unemployed populations often lack the financial resilience to cope with flood damages. (Cutter et al., 2003).	Unemployed ratio of all economically active	2y (2023-2024)	Thailand Census data (CDD, 2024). https://dashboard66.cdd.go.th/Home/DashBoardPublic
V6 Income	Low-income populations are less able to invest in protection, preparedness, or recovery. (Kaźmierczak & Cavan, 2011).	Household with income less than 40,000 bath/years	2y (2023-2024)	Thailand Census data (CDD, 2024). https://dashboard66.cdd.go.th/Home/DashBoardPublic
V7 LowSaving	Households with low or no savings are unable to recover quickly from flood damage, replace assets, or pay for temporary housing or repairs. (Kaźmierczak & Cavan, 2011).	Household with low saving less than 10,000 bath	2y (2023-2024)	Thailand Census data (CDD, 2024). https://dashboard66.cdd.go.th/Home/DashBoardPublic

4.3.2 Scenario generation

In this research, scenarios are used to test the model's robustness and capture variations in flood risk caused by both physical and socio-economic factors. The scenarios are divided into 2 main groups.

4.3.2.1 The hazard scenario

The flood hazard is derived from two sources: the 20-year flood frequency (ScH1) and the flood return period (ScH2). This approach enables the model to capture both the temporal variability and intensity of flood events under different hydrological conditions. The 20-year flood frequency represents the long-term trend and recurrence of floods, reflecting the historical magnitude and spatial distribution of flood hazards across the study area (Ward et al., 2013). Conversely, the flood return period highlights the probability of extreme flood occurrences and the likely duration required for environmental and infrastructural recovery (Merz et al., 2007). Integrating these two perspectives strengthens the hazard assessment by encompassing both frequent, low-intensity floods and rare, high-impact events, thereby improving the accuracy of spatial hazard classification and the weighting of flood severity across sub-districts(Jonkman et al., 2008; Winsemius et al., 2016).

4.3.2.2 The exposure and vulnerability scenario

Exposure and vulnerability scenarios include three conditions: (1) raw data (ScEV1) obtained directly from secondary sources based on criteria established in the literature, (2) grouped data (ScEV2) categorized into 5 severity levels using the Natural Breaks (Jenks) classification method (Hudson, 1979), and (3) averaged data (ScEV3) that combine values from the 2023 and 2024 census datasets. This scenario design enables evaluation of how different data preparation and aggregation approaches influence the accuracy and sensitivity of model outcomes. The raw data scenario retains the original variability of the indicators, allowing for detailed spatial differentiation (Kubal et al., 2009). The grouped data scenario ensures comparability across sub-districts by applying standardized classification thresholds, thereby improving interpretability and consistency in GIS-based spatial analysis (Wu et al., 2022). Meanwhile, the averaged data scenario minimizes annual fluctuations and reflects a more stable representation of socio-economic and demographic conditions, which is critical for understanding long-term vulnerability trends (Birkmann et al., 2013; UNDRR, 2015). Together, these scenarios enhance model calibration and sensitivity analysis, supporting the identification of the most consistent and reliable approach for local-level flood risk assessment.

4.3.3 Data acquisition and preprocessing

Data preparation in Geographic Information Systems (GIS) is a critical stage in ensuring the accuracy, consistency, and reliability of flood risk assessment models. All datasets collected from public sources were first examined for completeness, spatial resolution, and temporal consistency prior to integration. Each dataset representing hazard, exposure, and vulnerability components was standardized to a common coordinate system (WGS 1984 UTM Zone 47N) to maintain spatial compatibility. Preprocessing tasks included data cleaning, reclassification, interpolation, and format conversion between raster and vector layers to ensure analytical consistency. Attribute tables were structured to allow variable normalization, classification, and cross-comparison among sub-districts. Finally, all processed layers were integrated and overlaid within the GIS environment to produce harmonized datasets for multi-criteria analysis and flood risk mapping at both regional and sub-district scales (Goodchild et al., 2018; Wyszomierski et al., 2021).

This research is divided into 2 groups, dependent and independent variables, because this distinction clarifies the relationship between influencing factors and outcomes in the flood risk assessment model. The Dependent Variables include hazard data, representing flood characteristics such as frequency and return period that directly indicate the level of flood hazard in each sub-district (Merz et al., 2007; Samuels & Gouldby, 2009). The Independent Variables include exposure and vulnerability data, which describe the socio-economic, physical, and environmental conditions that influence the degree of potential impact (Cutter et al., 2003; UNDRR, 2015). This classification enables a systematic evaluation of how exposure and vulnerability contribute to variations in flood hazard levels across different areas (Crichton, 1999; Winsemius et al., 2016). See list of dependent and independent variables in Table 4.2 below.

Table 4.2. List of dependent and independent variables.

Type	Component	List of variables	Feature type	Scenario
Dependent	Hazard	H1 Hazard zone by frequency of flood	Vector (Polygon)	ScH1
		H2 Hazard zone by return period	Raster (Grid)	ScH2
Independent	Exposure	E1 Building density	CSV (Point)	ScEV1, ScEV2, ScEV3
		E2 Population density	Excel	ScEV1, ScEV2, ScEV3
		E3 Size of household	Excel	ScEV1, ScEV2, ScEV3
	Vulnerability	V1 AGE	Excel	ScEV1, ScEV2, ScEV3
		V2 Gender	Excel	ScEV1, ScEV2, ScEV3
		V3 No Education	Excel	ScEV1, ScEV2, ScEV3
		V4 Less hi school	Excel	ScEV1, ScEV2, ScEV3
		V5 Un Employed	Excel	ScEV1, ScEV2, ScEV3
		V6 Income	Excel	ScEV1, ScEV2, ScEV3
		V7 LowSaving	Excel	ScEV1, ScEV2, ScEV3

4.3.3.1 Dependent Variables

The dependent dataset in this research represents the *hazard scenario*, defining the spatial distribution and intensity of flood hazards across sub-districts. It comprises two datasets: the 20-year flood frequency (ScH1) and the flood return period (ScH2), which serve as the dependent variables in the GIS-based model. The 20-year flood frequency dataset was developed using time-series analysis of flood occurrences from 2008 to 2024, identifying areas repeatedly inundated and therefore under chronic hydrological stress (Ward et al., 2013). The flood return period dataset captures the probability of rare but severe flood events (e.g., 1-in-100-year floods) and represents low-frequency, high-impact conditions (Merz et al., 2007; Winsemius et al., 2016). Together, these datasets reflect both recurrent and extreme flood phenomena, providing a comprehensive representation of spatial hazard intensity.

To assign relative importance among hazard indicators (e.g., flood frequency, duration, depth, and extent), an Analytic Hierarchy Process (AHP)-based weighting approach was applied using literature-derived ranking criteria rather than expert judgment. This rule-based system ensures objectivity and reproducibility while aligning with established flood risk assessment frameworks (Brito & Evers, 2016). The weighted layers were integrated through a Weighted Linear Combination (WLC) method, normalized, and classified into five hazard levels using the Natural Breaks (Jenks) method to emphasize meaningful spatial distinctions in hazard intensity (Hudson, 1979). This process captures both frequent, lower-intensity floods and rare, high-impact events, thereby improving the interpretability and accuracy of hazard zoning for local-level flood risk assessment (Jonkman et al., 2008).

The Natural Breaks (Jenks) classification method is a GIS-based data clustering technique that identifies natural groupings within a dataset by minimizing variability within classes and maximizing differences between them. It is particularly suitable for environmental and socio-economic datasets, which often exhibit uneven or skewed distributions. In flood risk assessment, Jenks classification supports the identification of meaningful thresholds for hazard, exposure, and vulnerability variables by reflecting inherent data patterns rather than applying arbitrary or equal-interval breaks. This enhances the accuracy and clarity of spatial outputs, enabling clearer differentiation between low, medium, and high-risk areas and improving decision-making for flood management (Hudson, 1979).

1) Flood frequency data

This study utilized historical flood data from the Geo-Informatics and Space Technology Development Agency (GISTDA) of Thailand, covering a 20-year period from 2005 to 2024. The dataset consisted of annual flood extent polygons for each year, which were converted into point samples to facilitate spatial analysis. These points were used to quantify both the frequency of flood occurrences and the relative importance of each flood event, determined by the proportion of total area affected in each year. This approach allowed for the construction of a comprehensive flood inventory dataset, representing the spatial and temporal distribution of flooding across the study area. The preparation of the flood-frequency hazard data in this research is based on the methodological approach used by Long et al. (2025). The processing steps are outlined as follows:

- Rasterization of Flood Inventory: Each of the 20 annual flood inventory layers was converted from polygon to raster format to ensure uniform spatial resolution across all datasets. In the resulting raster, cells representing flooded areas were assigned a value of 1, while non-flooded cells were assigned a value of 0.

- Frequency-Based Raster ($R_{frequency}$): A frequency-based raster layer, referred to as $R_{frequency}$, was created by summing the raster values of all 20 annual flood layers. This process produced a composite raster in which each cell value indicates the total number of years (ranging from 0 to 20) that flooding occurred at a specific location. The resulting $R_{frequency}$ layer effectively represents the spatial distribution and recurrence of floods throughout the 20-year observation period. See in equation (3). The resulting is shown in Figure 4.2a.

$$R_{frequency} = R_{2005} + R_{2006} + \cdots + R_{2024} \tag{3}$$

- Area-Weighted Raster ($R_{weighted}$): To incorporate the relative magnitude of flooding in each year, an area-weighted raster ($R_{weighted}$) was developed. For this purpose, each annual flood extent raster was weighted according to the proportion of its flooded area relative to the total cumulative flood area across all 20 years. These weighted rasters were then summed to produce the final ($R_{weighted}$) layer, in which each cell value reflects both the frequency and the relative spatial significance of flooding over the study period. See in equation (4):

$$R_{weighted} = W_{2005} * R_{2005} + W_{2006} * R_{2006} + \cdots + W_{2024} * R_{2024} \tag{4}$$

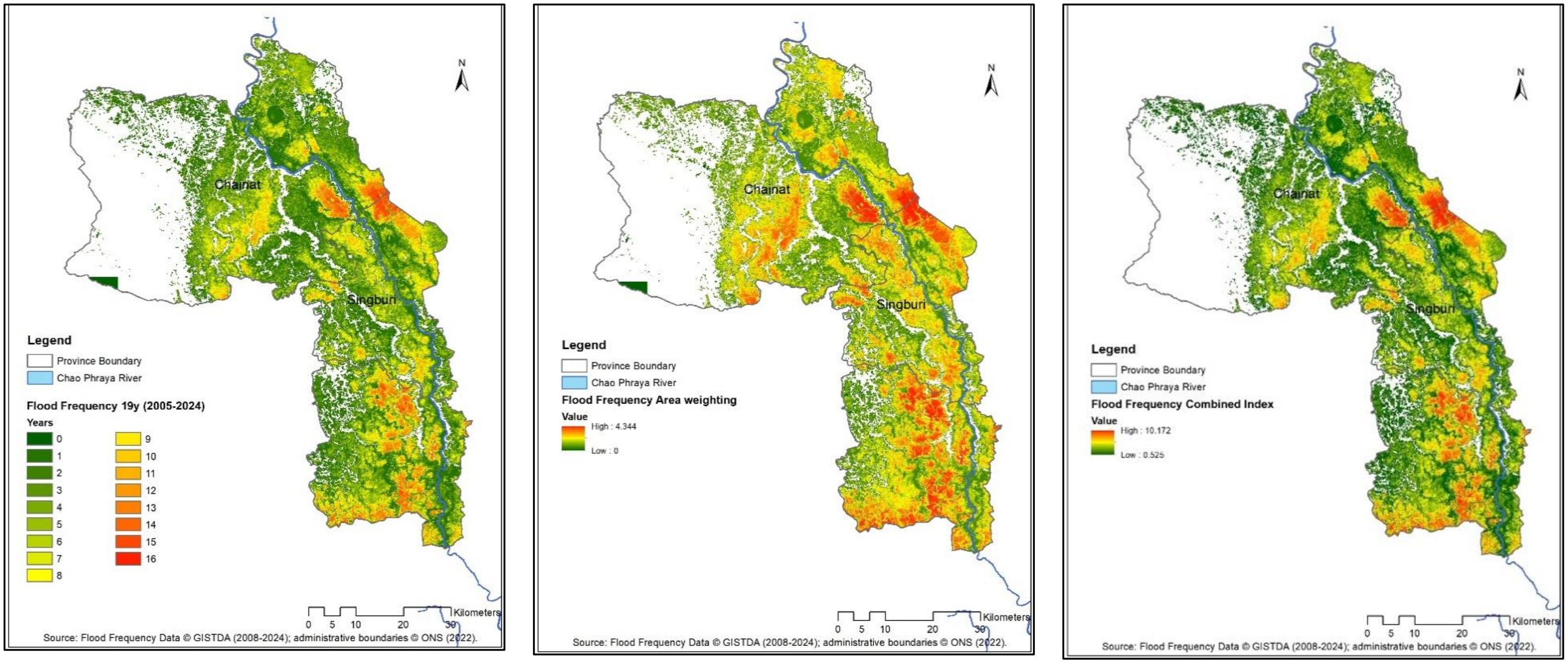
Where (W_i) denotes the weighting factor associated with the flood extent in year i , meaning that years experiencing larger inundated areas receive higher weights. The resulting area-weighted flood extent surface is presented in Figure 4.2b. The computed index values range from 0 to 1, with values approaching 0 representing lower flood severity and values closer to 1 indicating higher flood severity over the study period.

- Combined Aggregation Raster: A composite raster ($R_{combined}$): was produced by assigning equal weights (α = 0.5 and β = 0.5) to both the frequency-based and area-weighted raster. This ensures that flood recurrence and flood extent contribute equally to the final flood inventory representation. The resulting combined flood extent surface is shown in Figure 4.2c. The aggregation index ranges from 0.525 to 10.172, with lower values indicating limited flood occurrence over the study period and higher values reflecting areas more consistently and extensively affected by flooding. See in equation (5):

$$R_{\text{combined}} = \alpha * R_{\text{frequency}} + \beta * R_{\text{weighted}} \quad (5)$$

The results of the flood frequency analysis were categorized into five threshold levels using the Natural Breaks (Jenks) method to enhance the distinction between varying degrees of flood occurrence. This classification technique minimized internal variance within each group while maximizing differences between groups, ensuring a more accurate representation of spatial variations in flood frequency. The 5 levels, defined as very low (1), low (2), moderate (3), high (4), and very high (5), were established based on the statistical distribution of flood frequency analysis. The resulting flood hazard layer is shown in Figure 4.3.

After classification, the threshold values were joined with the GIS database at the sub-district level using a unique administrative code. This integration allowed for spatial analysis and visualization of flood frequency across all sub-districts, creating a standardized dataset for flood hazard mapping and severity evaluation.



(a) $R_{frequency}$ (b) $R_{weighted}$ (c) $R_{combined}$

Figure 4.2. Developing a flood hazard layer from flood frequency data

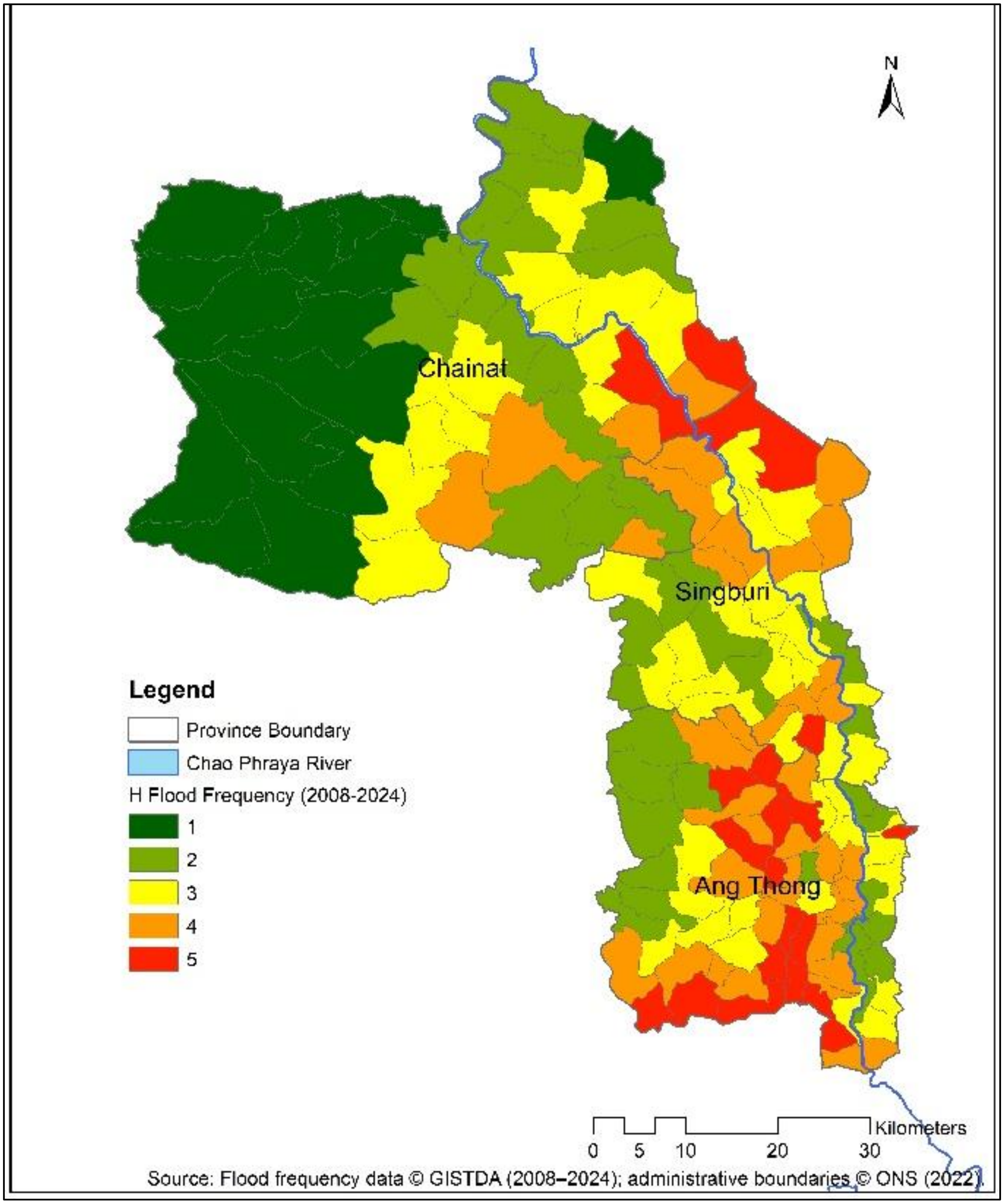


Figure 4.3. Flood Hazard layer derived from historical Flood Frequency

2) Flood return period data

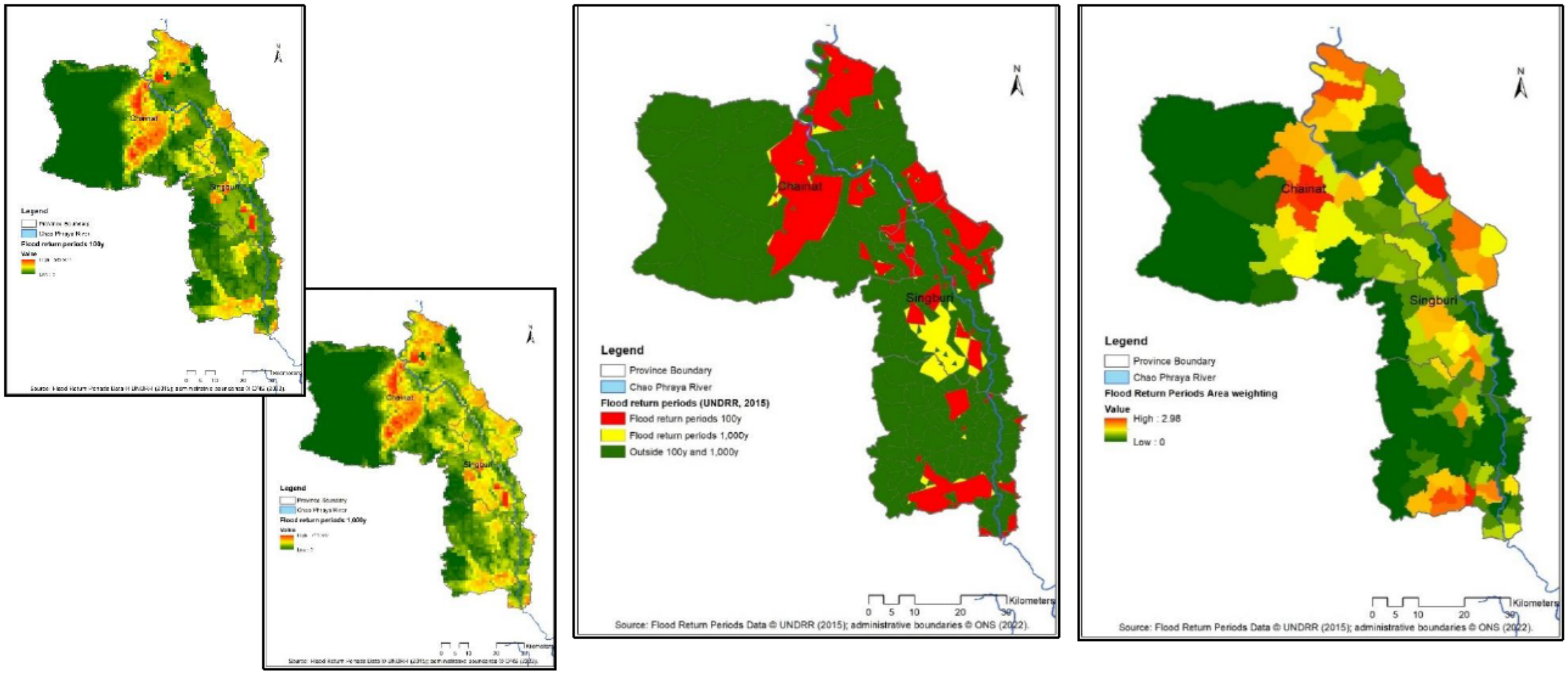
The flood return period dataset represents the probability of extreme flood events and is essential for understanding long-term flood hazard conditions. Publicly available flood hazard layers were utilized to ensure transparency and alignment with open-data practices. Consistent with guidance from the United Nations Office for Disaster Risk Reduction (UNDRR) on risk-informed planning. These return periods are widely used in flood risk modelling and infrastructure planning due to their relevance for preparedness, prevention, and long-term adaptation. The processing steps are outlined as follows:

The raw return-period data were provided as raster grids with a spatial resolution of 1 km. The dataset was subsequently harmonized and resampled to match the spatial resolution of the flood frequency layer, ensuring consistency in spatial analysis and comparability across all sub-district-level hazard inputs within the GIS model. This dataset supports scenario-based assessment of high-impact flooding. Following established literature, three flood probability classes were applied: 1-in-100-year floods, 1-in-1,000-year floods, and areas located outside mapped flood-prone zones. The resulting is shown in Figure 4.4a.

The results of the flood return period analysis were defined into three levels of severity high, moderate, and low based on criteria established in the literature and weighted according to their influence within each sub-district. The weighting process ensured that areas with shorter recurrence intervals and higher flood probabilities received greater importance in the hazard evaluation. The resulting is shown in Figure 4.4b.

The classified layers were then combined using a Weighted Linear Combination (WLC) technique to produce a composite hazard index. This technique integrated multiple dependent parameters, including frequency, return period, and depth, assigning each a weight according to its relative contribution to overall flood hazard. The resulting is shown in Figure 4.4c.

Following this classification, the weighted flood return period data were further processed and reclassified into five threshold levels using the Natural Breaks (Jenks) method to enhance the differentiation of flood risk intensity across the study area. This approach minimized variation within each class and maximized differences between classes, providing a clearer representation of flood recurrence patterns. The final classified dataset was then joined with the GIS database at the sub-district level using a unique administrative code, enabling spatial integration, mapping, and analysis of flood severity across the local scale. The resulting is shown in Figure 4.5.



(a) raw return-period data

(b) Flood return-period classify by litterature

(c) Flood return-period weighting by area

Figure 4.4. Developing a flood hazard layer from flood return period derived from a global flood model

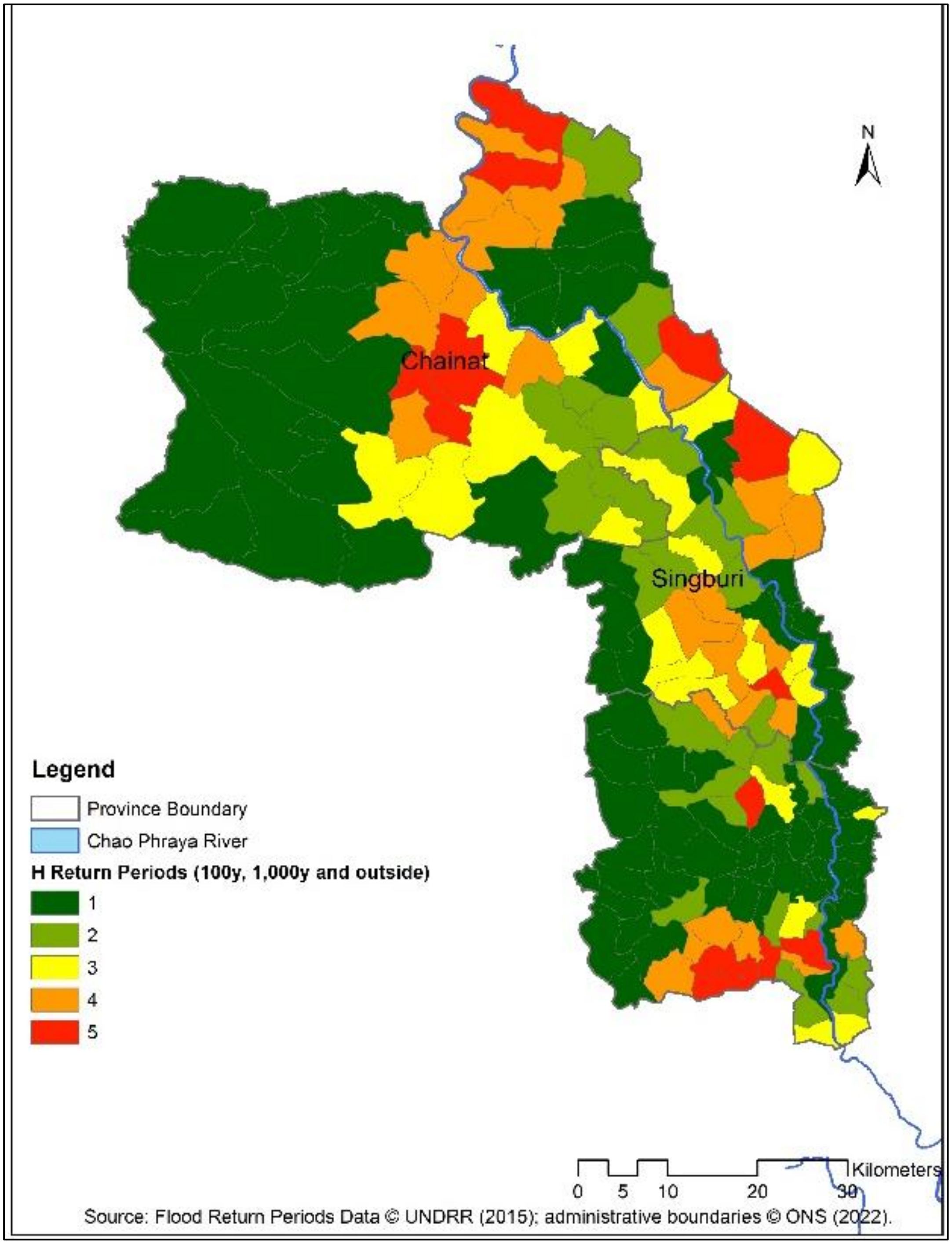


Figure 4.5. Flood Hazard layer derived from global modelled Flood Return Period

4.3.3.2 Independent Variables

Independent data in flood risk assessment provide the quantitative foundation for evaluating exposure and vulnerability by capturing the physical, environmental, and socio-economic factors that determine how populations and assets are affected by floods. These datasets explain variations in potential loss, damage, and disruption across flood-prone areas. Physical parameters such as elevation, slope, and distance from rivers describe terrain characteristics that influence flood depth and flow accumulation. Environmental factors, including land use, vegetation cover, and soil type, affect infiltration, runoff, and water retention capacity. Socio-economic indicators such as population density, household size, building materials, education level, income, and access to essential services reflect the community's capacity to prepare for and recover from flood events. Combining these quantitative datasets provides a holistic understanding of exposure and vulnerability, enabling more accurate flood impact estimation and targeted risk reduction planning (Jongman et al., 2015; Merz et al., 2007).

The preparation of independent data is a fundamental step in developing a reliable and consistent flood risk assessment framework. This process ensures that variables representing exposure, and vulnerability are accurately structured, standardized, and spatially aligned for analysis within the GIS environment at the sub-district level. The data preparation followed a three-scenario approach to improve comparability and sensitivity testing across datasets from multiple sources. All independent datasets were collected in various formats, including Excel spreadsheets (.xlsx), CSV tables, and GIS shapefiles (.shp) from different agencies. These datasets contained physical, environmental, and socio-economic indicators such as building density, population, household size, age, gender, education, income, unemployed and saving. The data were cleaned, reformatted, and imported into the GIS platform. Each variable was geocoded and joined with the sub-district boundary shapefile using a unique administrative code to create an integrated spatial database. All layers were standardized to a common coordinate reference system (WGS 1984 UTM Zone 47N) and projected to ensure spatial uniformity. Attribute tables were reviewed to verify data consistency and completeness before subsequent analysis.

Scenario 1: Raw Data Based on Literature Criteria

In the first scenario, raw data were maintained according to the original measurement units and classification criteria established in previous studies and national datasets. This scenario served as the baseline dataset, allowing direct comparison with existing research methodologies and ensuring alignment with literature-based parameter thresholds.

Scenario 2: Grouping Data by Natural Breaks (Jenks)

In the second scenario, variables were reclassified using the Natural Breaks (Jenks) method into 5 threshold groups (very low, low, moderate, high, and very high). This approach identified natural data groupings and minimized variance within each class while maximizing differences between classes. For instance, population density, building density, and socio-economic data were categorized into 5 severity levels representing progressive risk intensity. The Natural Breaks classification enhanced interpretability by grouping values into meaningful intervals and was particularly effective for spatial visualization of exposure and vulnerability patterns.

Scenario 3: Averaged Data from 2023–2024 Census

The third scenario employed averaged census data from 2023 and 2024 to represent updated socio-economic and demographic conditions. This approach minimized temporal bias by smoothing short-term fluctuations in population, income, or household statistics. For each sub-district, mean values were computed and spatially joined with the GIS database to produce representative indicators of exposure and vulnerability. Averaging provided a stable dataset suitable for model calibration and regression analysis, ensuring that temporal variations did not distort long-term flood risk patterns.

This multi-scenario data preparation process ensured robust analysis by testing the sensitivity of results under different data aggregation strategies. It enhanced the reliability of the exposure and vulnerability assessment while maintaining transparency and reproducibility in GIS-based flood risk modelling.

4.4 Statistic and spatial analysis

A structured statistical and spatial analysis framework was applied to strengthen the development of the flood risk assessment model. The process began with Ordinary Least Squares (OLS) regression to identify statistically significant predictor variables and evaluate their global relationships with flood occurrence patterns, supported by diagnostic tests to assess model fit, multicollinearity, and residual behavior. To further refine the dataset and minimize redundancy among highly correlated indicators, Principal Component Analysis (PCA) was implemented, allowing the extraction of the most influential components while preserving key variance in the data.

Following variable selection and dimensionality reduction, a flood risk index was established using Geographically Weighted Regression (GWR), which incorporates spatial heterogeneity by allowing coefficient estimates to vary across geographic locations rather than assuming uniform relationships. This integrated approach enhances the methodological rigor of the model by combining statistical significance testing, dimensionality reduction, and spatially adaptive analysis, resulting in a flood risk index that more accurately reflects local variations in hazard, exposure, and vulnerability at the sub-district level.

4.4.1 Selection of variables

The selection of variables in this study followed a rigorous statistical and spatial screening framework to ensure that only relevant, reliable, and meaningful indicators were incorporated into the flood risk model. Initial statistical analysis assessed the suitability and distribution of potential variables, examining normality, variance, multicollinearity, and correlation strength to ensure that each variable behaved appropriately for spatial modelling and demonstrated strong explanatory capacity.

Variables were further evaluated based on statistical significance, theoretical support from established flood risk literature, and the availability of consistent data at the sub-district scale, ensuring both scientific validity and practical relevance. To capture the multidimensional nature of flood risk, indicators were selected across hazard, exposure, and vulnerability domains, providing a comprehensive and balanced representation of flood-related factors.

To strengthen the reliability and robustness of the variable selection process, this study applied two complementary statistical techniques, Ordinary Least Squares (OLS) and Principal Component Analysis (PCA), before implementing Geographically Weighted Regression (GWR) for spatial modelling. OLS was used to identify significant predictors, evaluate the strength and direction of relationships, and examine diagnostic indicators such as multicollinearity and residual distribution. Following this, PCA was employed to reduce dimensionality by detecting correlations among variables and retaining those with the highest explanatory contribution.

These preparatory steps ensured that the selected indicators were statistically sound and appropriate for spatially adaptive regression. The combined use of OLS and PCA is well established in hydrological and spatial modelling studies as an effective approach for improving model efficiency, enhancing interpretability, and minimizing redundancy among variables (Ouma & Tateishi, 2014). The screened and refined variables were subsequently integrated into the GWR model to account for spatial heterogeneity in flood risk relationships. This staged analytical framework, incorporating OLS, PCA, and GWR, provides a balanced integration of statistical rigour our and spatial sensitivity, aligning with recognized best practices for flood risk assessment and disaster risk reduction (UNDRR, 2015).

4.4.1.1 Ordinary Least Squares (OLS)

Ordinary Least Squares (OLS) is a fundamental regression technique commonly applied in GIS-based spatial analysis to evaluate the strength and direction of relationships between a dependent variable and multiple explanatory variables. In a spatial context, OLS provides a global model, assuming that relationships remain constant across the entire study area. It is widely used to assess variable significance, quantify model performance, and detect statistical issues such as multicollinearity, non-normal residuals, and spatial autocorrelation. Key diagnostics, including Variance Inflation Factors (VIF), residual plots, and the Adjusted R^2, help determine whether variables are appropriate for spatial modelling. OLS often serves as a preliminary analysis step before applying local spatial techniques such as Geographically Weighted Regression (GWR), which account for spatial heterogeneity when OLS diagnostics indicate spatial non-stationarity. Overall, OLS provides a rigorous statistical foundation for selecting meaningful variables and validating model structure within a GIS environment. The steps for OLS analysis are as follows:

1) Define the Dependent and Independent Variables. The first step is to identify the dependent variable (e.g., flood frequency or flood return periods) and select appropriate independent variables (e.g., population density, building density, household size, age, gender, education, less hi school, unemployment, income, low saving). Variables should be theoretically relevant and spatially aligned to the same coordinate system and resolution within the GIS environment.
2) Data Preparation and Standardization. All input datasets are cleaned, normalized, and converted into compatible spatial formats (e.g., raster or vector). This ensures that each variable can be accurately compared and spatially overlaid.
3) Run the OLS Regression Model. The OLS equation is expressed as (6):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \tag{6}$$

Where Y is the dependent variable, X_i are the independent variables, β_i are the coefficients, and ε is the residual error term. The model estimates the coefficients that minimize the sum of squared residuals.

4) The results are obtained in two forms: statistical and map representation in a GIS. The results are then evaluated for statistical diagnosis.

Key statistics used to evaluate the model are as follows:

- Check for Multicollinearity. Multicollinearity occurs when two or more independent variables are highly correlated. The Variance Inflation Factor (VIF) is used to detect it. Variables with a VIF value greater than 7.5 (or 10, depending on the literature) are usually removed or combined to avoid distortion in the regression results.
- Adjusted R^2: Measures how well the independent variables explain the dependent variable.
- P-values: Assess the statistical significance of each coefficient (typically significant if $p < 0.01$).
- Jarque–Bera Test: Checks the normality of residuals.
- Koenker (BP) Statistic: Tests whether relationships are consistent across the study area (spatial stationarity).
- Akaike's Information Criterion (AIC): Used to compare model performance.

5) The map results of an OLS analysis visually express how well the regression model explains the spatial variation of the dependent variable (such as flood frequency or flood risk) and help diagnose model performance. Typically, OLS map outputs show:
   - Predicted Value Map. Displays the model-estimated values of the dependent variable across space. This map helps identify spatial patterns in predicted flood risk or hazard and compare them with observed patterns.
   - Residual Map. Shows the difference between observed and predicted values.
     - High positive residuals = model underestimates (higher observed than predicted)
     - High negative residuals = model overestimates

    - Random residual patterns suggest a good model fit, while clustered residuals indicate spatial non-stationarity and the need for GWR.
- Standardized Residual Map Visualizes residuals on a standardized scale to easily detect outliers and local model errors.
- Coefficient Maps (if exported manually). Reflects the strength and direction of influence of each variable.
    - Positive coefficients: variable increases flood risk (e.g., impervious surface, rainfall)
    - Negative coefficients: variable reduces flood risk (e.g., elevation, vegetation)
- R^2 or Local Goodness-of-Fit Surfaces (diagnostic layer from GIS tools). Shows how well the model explains spatial variation. Higher values indicate better explanatory power in those areas.

The OLS analysis produced several essential diagnostic indicators, including the Variance Inflation Factor (VIF), Adjusted R^2, P-values, Jarque–Bera Test, Koenker (BP) statistic, and Akaike's Information Criterion (AIC), which are widely used to assess model robustness and accuracy (Brunsdon et al., 1998; O'Sullivan & Unwin, 2010). Each indicator provided valuable insight into model quality and performance. The VIF values were applied to detect multicollinearity and ensure that predictors were not excessively correlated (Kutner et al., 2005), while the Adjusted R^2 measured the proportion of variation in flood risk explained by the model. P-values tested the statistical significance of each factor, confirming their contribution to the regression (Gujarati & Porter, 2009).

The Jarque–Bera and Koenker (BP) statistics examined the normality and heteroscedasticity of residuals, ensuring model assumptions were met. AIC was employed to compare model efficiency and select the optimal structure with minimal information loss (Burnham & Anderson, 2003). Interpreting these diagnostics facilitated refinement of variable selection, enhancing model validity before applying spatially adaptive techniques such as Geographically Weighted Regression (GWR).

Therefore, this research conducted Ordinary Least Squares (OLS) analysis to evaluate both the overall model performance and the statistical relationships among variables influencing flood risk. OLS served as a global regression technique that supports systematic screening of predictors and assessment of model reliability (Gujarati & Porter, 2009; O'Sullivan & Unwin, 2010). The model performance assessment considered key diagnostic indicators, including the Adjusted R^2, Jarque–Bera Test, Koenker (BP) statistic, and Akaike's Information Criterion (AIC), which collectively measure explanatory power, normality, heteroscedasticity, and overall model efficiency (Burnham & Anderson, 2003).

The variable evaluation process focused on detecting multicollinearity and determining statistical significance. A Variance Inflation Factor (VIF) greater than 7.5 was used as a threshold to identify problematic multicollinearity, following common guidance in regression diagnostics (Kutner et al., 2005). P-values were used to test the significance of each variable, with values below 0.01 typically indicating meaningful contributions to the model (Gujarati & Porter, 2009). This approach ensured that only robust, statistically valid variables were retained for subsequent spatial analysis.

4.4.1.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) plays an important role in GIS-based modelling by simplifying complex spatial datasets and preparing variables for advanced spatial analysis such as Geographically Weighted Regression (GWR). In a GIS context, PCA reduces dimensionality by transforming correlated variables into a set of independent principal components that capture the majority of variance in the data. This process helps remove redundancy, highlight dominant spatial patterns, and improve interpretability when working with multiple environmental and socio-economic indicators. PCA is also particularly useful as a preparatory step before applying GWR. Since GWR is sensitive to multicollinearity among explanatory variables, PCA provides cleaner and more independent inputs, leading to more stable model coefficients and stronger spatial diagnostic results. By reducing noise and preventing overfitting, PCA enhances the efficiency and accuracy of GWR in capturing spatially varying relationships. In combination, PCA and GWR allow researchers to build statistically robust and spatially explicit models that better explain local variations in flood risk and other spatial phenomena.

Additionally, PCA has limitations when the dataset exhibits excessive dispersion or high levels of noise. In such cases, irregular variance patterns can hinder the method's ability to identify meaningful components, resulting in outputs that are unstable or difficult to interpret. This issue arises because PCA assumes that the directions of maximum variance correspond to the most informative features, which may not hold true when the data contain random variability or outliers (Abdi & Williams, 2010; Jolliffe et al., 2016). The steps for PCA analysis are as follows:

1) Data Preparation. Relevant variables are selected and prepared in a consistent GIS format by converting all variables into raster grids. The variables are then standardized to comparable scales, particularly when they are measured in different units. Standardization transforms each variable to have a mean of zero and a standard deviation of one, preventing variables with large ranges from disproportionately influencing the analysis.
2) Run the PCA Model. The standardized raster data are input into the PCA algorithm to identify underlying patterns and reduce dimensionality. Import all variables from independent variables that have been converted to raster. The PCA computation generates principal components that represent combinations of the original variables.
3) Extract PCA Outputs. The PCA process generates several key outputs that are critical for interpretation and further analysis. These include:
    - Component loadings, which quantify the contribution of each original variable to each principal component and indicate the strength and direction of relationships.
    - Component scores, representing the transformed values of each observation (or raster cell) in terms of the new principal components, which can be spatially mapped in GIS.

- Explained variance and cumulative variance, which indicate how much of the total data variability is captured by each component and help determine how many components to retain.
- Scree plots and eigenvalue tables, which visualize the rate of variance decline across components, assisting in component selection. These outputs collectively allow the identification of the most influential variables and the dominant factors driving spatial patterns in the data.

4) Analyze Eigenvalues and Eigenvectors. Eigenvalues and eigenvectors are essential elements of PCA that describe how variance is distributed and oriented in multidimensional space. Eigenvalues represent the amount of variance explained by each principal component, where higher eigenvalues indicate that a component accounts for a larger proportion of the total variance. Components with small eigenvalues contribute little to explaining variability and are often excluded. Eigenvectors define the direction of maximum variance and determine how much weight each original variable contributes to forming the components. By analyzing both eigenvalues and eigenvectors, researchers can identify the most influential components and interpret the relative contribution of each variable. In GIS, this analysis helps detect dominant spatial gradients, clusters, and relationships among environmental and socio-economic factors relevant to flood risk.
5) Select Principal Components. The PCA results identified three principal components for the vulnerability variables based on the Kaiser criterion (eigenvalues greater than 1), collectively explaining approximately 75% of the total cumulative variance. This level of explained variance aligns with established PCA theory, which suggests retaining components that capture a substantial portion of variance to preserve information while reducing dimensionality (Jolliffe et al., 2016).

4.4.2 Geographically Weighted Regression (GWR) to define a flood risk index

Flood risk assessment in this study is designed to quantify and map the spatial distribution of flood risk at the sub-district scale by integrating hazard, exposure, and vulnerability components within a GIS framework. In line with recognized disaster risk reduction principles, flood risk is understood as the interaction between the probability and intensity of flood events (hazard), the presence of people, property, and essential systems in flood-prone areas (exposure), and the susceptibility of communities and infrastructure to harm and loss (vulnerability). This multidimensional perspective reflects international frameworks, including the Sendai Framework definition of risk, which highlight that flood impacts arise not only from physical flood processes but also from socio-economic conditions and system resilience.

Accordingly, the methodology applies a structured, data-driven approach that incorporates diverse spatial datasets, comprehensive variable screening, and advanced spatial modelling techniques to produce a robust and evidence-based flood risk index. Hazard conditions are represented using long-term flood frequency data and flood return-period scenarios to capture both recurrent and extreme events. Exposure is assessed by mapping population, buildings, and critical facilities within flood-prone zones, while vulnerability is evaluated through socio-economic and infrastructure indicators that reflect sensitivity and adaptive capacity. These datasets are harmonized, standardized, and processed in GIS, and subsequently filtered using statistical diagnostics and dimensionality-reduction techniques to ensure that only relevant, non-redundant variables are included. Through this integrated methodology, the resulting flood risk maps reveal spatial patterns of risk variation across sub-districts and enable the identification of priority areas for mitigation, preparedness, and resilient planning.

This research uses Geographically Weighted Regression (GWR) to determine the flood risk index by capturing the spatially varying relationships between hazard, exposure, and vulnerability factors across sub-districts. GWR is chosen because flood-related processes are inherently spatial and non-stationary; the influence of physical and socio-economic characteristics on flood risk changes from one location to another. In contrast to global regression models, which assume uniform relationships across the entire study area, GWR calibrates a local regression equation for each spatial unit, allowing the coefficients to vary depending on geographic context. This enables a more accurate and context-specific assessment of flood risk, reflecting local differences in terrain, land use, infrastructure conditions, and community characteristics.

Through this approach, GWR produces spatially explicit parameter estimates that quantify the strength and direction of influence for each risk component. These outputs are used to generate a continuous flood risk index surface and visualize localized hot spots where certain variables exert disproportionately high influence. By integrating GWR results into the risk-mapping process, the methodology enhances model sensitivity, ensures a more realistic representation of spatial risk patterns, and supports evidence-based prioritization of high-risk areas for targeted mitigation, planning, and resource allocation.

Steps for Applying Geographically Weighted Regression (GWR)

1) Prepare Spatially Referenced Data. All selected hazard, risk and exposure variables are organized in GIS and adjusted to the corresponding spatial resolution and geographic coordinate system. All dependent variables (hazard scenarios) and independent variables (exposure and vulnerability scenarios) data are saved to a single database file so that they can be accessed in the GWR model run.
2) Validate Inputs Using Global OLS Diagnostics. Before running GWR, a global Ordinary Least Squares (OLS) model is estimated to verify the suitability of input variables. This step ensures that only statistically reliable and stable predictors are included in the spatial modelling process.

- Diagnostic tests are conducted, including checks for Variance Inflation Factors (VIF) to detect multicollinearity, assessment of residual normality, and evaluation of spatial autocorrelation using Moran's I. Multicollinearity is controlled by examining VIF values, with a commonly accepted threshold of VIF less than 7.5 to avoid unstable or inflated coefficient estimates (Kutner et al., 2005).
- The statistical significance of predictors, typically based on p-values below 0.01, and model performance indicators such as the Adjusted R^2 and Akaike Information Criterion (AIC) are also reviewed. In addition, Moran's I is used to test whether residuals exhibit significant spatial autocorrelation, since spatially random residuals indicate that the global model meets the assumptions required for valid inference (Getis & Ord, 1992). Variables that meet all diagnostic requirements, including low multicollinearity, statistical significance, normal and spatially independent residuals, and satisfactory global model fit, are retained for GWR to ensure accurate and meaningful spatial coefficient estimation.

3) Select GWR Kernel Type and Bandwidth. In Geographically Weighted Regression (GWR), the choice of kernel function (fixed or adaptive) and bandwidth selection method (Akaike Information Criterion corrected, AICc, or Cross-Validation, CV) determines how spatial proximity influences the weighting of observations in each local regression. The kernel function controls how weights decline as distance increases, shaping the degree of local influence within the model, while the bandwidth defines the spatial scale of the neighborhood used for calibration at each location. Together, these settings determine the balance between capturing fine-scale spatial variation and maintaining statistical stability. Appropriate kernel and bandwidth selection is therefore essential for producing reliable spatially varying coefficients and avoiding model over-smoothing or excessive local noise (Brunsdon et al., 1998; Lu et al., 2011). This research takes into account the substantial variation in the size and spatial distribution of sub-districts in Thailand. For this reason, an adaptive kernel is the most suitable option, as it adjusts to local spatial density

and reduces the risk of having too few neighboring units for reliable estimation. Bandwidth optimization using AICc is recommended because it identifies the most statistically efficient spatial scale, minimizes information loss and enhances the stability of local coefficient estimates across different socioeconomic conditions and multi-year hazard scenarios. In contrast, a fixed bandwidth is not appropriate, as it cannot respond to the uneven geographic and demographic characteristics of the sub-districts and may lead to unstable or biased local regressions.

4) Output of GWR. The outputs of GWR model provide both statistical diagnostics and spatially explicit results that support the evaluation and interpretation of flood risk patterns across sub-districts.
    - Model Diagnostics. GWR produces several diagnostic indicators that measure model performance and help assess whether spatial variation improves explanatory power relative to a global regression approach. Key diagnostics include the corrected Akaike Information Criterion (AICc), local and global R^2 values, and residual summaries. A lower AICc compared to the global OLS model suggests improved model fit, while higher local and global R^2 values indicate stronger explanatory capability. Residual analysis, including spatial distribution checks, helps confirm whether the local model has reduced spatial autocorrelation and improved explanatory accuracy. Together, these metrics provide evidence that the GWR model captures spatial non-stationarity and yields robust, location-specific relationships between flood risk variables.
    - Generate Spatial Outputs. Beyond statistical measures, GWR produces spatially explicit coefficient surfaces and diagnostic maps that visualize how the influence of independent variables varies across space. Key outputs include local coefficient maps, local R^2 maps, and residual maps. Coefficient surfaces display the magnitude and direction of each predictor's effect at each location, revealing spatial patterns in hazard, exposure, and vulnerability influences. Local R^2 maps highlight areas where the model performs better or worse, providing insight into spatial heterogeneity and model reliability.

Residual maps help identify locations where the model over or under predicts, supporting further refinement or local interpretation. These spatial outputs collectively enable the creation of a continuous, locally weighted flood risk surface and facilitate the identification of high-risk hotspots and spatial clusters, supporting targeted mitigation and community-level planning.

5) Derive the Flood Risk Index from GWR Results The final stage of the modelling process involves deriving the Flood Risk Index (FRI) from the results of the Geographically Weighted Regression (GWR) analysis. The FRI represents the integrated spatial outcome of the hazard, exposure, and vulnerability relationships as captured by the GWR model. The GWR-generated predicted values were used as the basis for constructing the flood risk index, as they incorporate locally weighted coefficients that reflect spatial variations in the intensity and influence of each risk component across the study area. These predicted values serve as a continuous representation of flood risk, accounting for both statistical relationships and spatial heterogeneity in the underlying variables. To facilitate interpretation and spatial comparison, the predicted FRI values were reclassified into 5 threshold levels using the Natural Breaks (Jenks) classification method. This method identifies natural groupings within the data by minimizing variance within classes and maximizing variance between classes. The resulting categories very low (1), low (2), moderate (3), high (4), and very high (5) flood risk provide a clear and data-driven classification of relative flood risk intensity across sub-districts. The Natural Breaks method is widely applied in GIS-based environmental modelling because it reflects the inherent distribution of spatial data rather than imposing arbitrary intervals, leading to more meaningful and realistic risk zoning (Brewer & Pickle, 2002). The predicted values were selected for classification instead of raw or composite variable scores because they represent the model’s integrated output, capturing both local variations in variable influence and spatial dependencies between flood risk components. This approach ensures that classification reflects the actual spatial behavior of flood risk as estimated by the calibrated GWR model. By basing classification on predicted values, the resulting flood risk map accurately

identifies areas where the combined effects of hazard, exposure, and vulnerability converge, thereby supporting data-driven decision-making for flood preparedness, land-use planning, and resource prioritization at the sub-district level.

4.5 Flood Risk Mapping and Integration

Flood risk mapping and integration form the final stage of the methodological framework, where the spatial relationships identified through the Geographically Weighted Regression (GWR) model are translated into an interpretable and policy-relevant form. This process integrates the three fundamental components of flood risk: hazard, exposure, and vulnerability, following the risk triangle concept proposed by Crichton (1999). In this framework, flood risk is conceptualized as the interaction among these three elements, expressed by the general relationship. See equation (7):

$$Flood\ risk\ map = hazard\ map + exposure\ map + vulnerbility\ map \tag{7}$$

This equation illustrates that flood risk increases when any one of these components intensifies, and decreases when any component is reduced through effective management or mitigation. Hazard represents the probability and magnitude of flooding events, exposure indicates the presence of people, infrastructure, and assets within flood-prone zones, and vulnerability describes the susceptibility of these elements to harm and their capacity to recover.

The GWR predicted values, which represent the spatially varying influence of hazard, exposure, and vulnerability, were used to generate the Flood Risk Index (FRI). This continuous surface was then classified into five levels, ranging from very low to very high risk, using the Natural Breaks (Jenks) method to establish data-driven thresholds that reflect the natural distribution of flood risk across the study area.

All spatial analyses were performed in a GIS environment. GIS was used to manage, process, and overlay spatial datasets, ensuring that all layers shared consistent projection, resolution, and extent. The final flood risk map provides a spatially explicit representation of the relative flood risk distribution across sub-districts. This integrated approach enables the identification of high-risk zones and supports the prioritization of flood mitigation measures. By combining GWR modelling, spatial data integration, and the risk triangle concept, the flood risk map enhances both the analytical accuracy and policy relevance of flood risk assessment.

Chapter 5: Sensitivity of GIS-based flood risk modelling to variations in data inputs – case study in Sheffield, England

This chapter presents a pilot study undertaken to develop and validate the proposed GIS-based flood-risk assessment model, emphasizing methodological robustness and cross-context applicability. The model was first applied in Sheffield, United Kingdom, a hydrologically comparable urban catchment influenced by the River Don system, varied topography, and mixed residential-industrial land-use patterns. Sheffield's history of fluvial and pluvial flood events, including the 2007 flood, provides a relevant empirical setting for testing model behavior and data performance under real-world flood conditions (Pitt, 2008). By applying the model in Sheffield, this study evaluated model sensitivity, parameter stability, and the transferability of spatial indicators to new socio-environmental contexts. The pilot also tested integration of hazard, exposure, and vulnerability layers within a GIS environment, supporting evaluation of technical scalability and transferability before implementation in Thailand. Dataset sources included publicly available administrative, hydrological, and land-use datasets, enabling assessment of data structure consistency and interoperability between UK and Thai datasets.

5.1 Pilot project

A key challenge in flood-risk research lies in selecting variables and analytical structures capable of capturing the complex, multi-dimensional nature of risk, including hydrological processes, built-environment characteristics, and socio-economic vulnerability. Producing an accurate flood-risk surface requires identifying causal factors of risk and linking them to spatial patterns of exposure and sensitivity. In Thailand, topographical variation between downstream deltas, mid-basin floodplains, and mountainous headwaters, combined with socio-economic inequalities and rapid urbanization, increases model complexity. Therefore, careful selection and testing of flood variables is essential to ensure representative, context-sensitive outputs. The research responds by developing and trialing a multi-criteria GIS approach that integrates hazard metrics, demographic vulnerability, infrastructure exposure, and land-use patterns, aligning with established frameworks such as the EU Floods Directive and the “risk triangle” (Albano et al., 2015; Crichton, 1999). The pilot case informed decisions on parameter selection, data standardization, and uncertainty interpretation to ensure suitability for sub-district-level flood governance in Thailand.

This chapter outlines the core theoretical foundations and methodological procedures that structure the research, while introducing results from the pilot study conducted in Sheffield. The Sheffield case provides a controlled and evidence-rich environment, supported by publicly available secondary datasets and documented flood studies, enabling systematic evaluation of the model’s operational performance under real flood conditions. The pilot study functions as a methodological proving ground, allowing assessment of data processing workflows, spatial weighting techniques, and integration of hazard, exposure, and vulnerability indicators within a GIS-based framework. Comparative analysis with findings from Chen (2020) using a similar modelling approach supports validation of model logic and analytical consistency, while also identifying areas requiring refinement. Insights from the pilot are used to examine model sensitivity, stability of variable weighting, and sources of uncertainty associated with spatial and socio-economic inputs. These results provide an empirical foundation to enhance model robustness and guide necessary adjustments prior to full deployment in Thailand, ensuring that the assessment framework is context-responsive, technically reliable, and suitable for decision-making at local government level.

5.2 Methodology of Pilot project

The modeling method begins with a literature review to compare the assumptions, objectives, performance, and data requirements of different modelling approaches. Literature reviews show that hydrological models use a large amount of specialized hydrological data that is difficult to access for the general researcher. On the other hand, most of the data used in the GIS model is publicly available, which is easier to use. However, as noted above there remains considerable challenge in determining how best to combine and apply these data. In addition, the study compared the use of different approaches to assess risk indexes and determine risk areas under the conditions of a quantitative approach (Albano et al., 2015).

Data preparation focuses on the identification and collation of a suitable set of data layers sufficient to characterize the three components of the risk triangle. This is not a trivial task as data availability varies geographically and over time. The impacts of this on model formulation are explored briefly in the pilot project. This project uses the same methods and simulation testing areas as a previous study on Sheffield flood risk (Chen, 2021), but the difference is the variables. Generic variable prioritization uses a qualitative method where experts rank and rate the variables. A qualitative approach is useful in simplifying the assessment. In this way, citizens can support decision-makers with local knowledge and experiences from previous floods (Harclerode et al., 2016). On the other hand, it has been mentioned in some studies that experts with different knowledge experience can create conflicts of variable priorities that could affect the identification of vulnerable areas (Aydi et al., 2013). Therefore, the quantitative method is preferable to assess risk, as it can quantify the risks that arise in terms of environmental, economic or life losses. There are several ways to prioritize parameters using GIS tools, such as Principal Component Analysis (PCA), the Analytical Hierarchical Process (AHP) and GIS modeling with the Fuzzy AHP process. It is an effective risk assessment method that uses questionnaires to collect expert responses to prioritize parameters (Chen, 2021).

The important and challenging step of this research was to collect and screen variables to suit the area. When the locations are different, there are also different variables due to the terrain, society, environment and culture (European Commission, 2007). Therefore, in this research, emphasis is placed on variable screening, which can be changed with changes in location in order to achieve locally appropriate policies for reducing flood risk. In the pilot project, Principal Component Analysis (PCA) approach was used to remove redundancy to critical variables and to screen only variables influencing flood risk (Mavhura et al., 2017). The next step is to assess the risk indicators in each area to rank flood risk with the variables selected and assign a flood risk index to each area. This research uses the theory PCA, which is a quantitative method to determine the key variables in the vulnerability component for flood risk assessment (Mavhura et al., 2017). The advantage of PCA is one of the statistical methods used to analyze the relationship between candidate variables which simplifies variable analysis by reducing dimension (Chen, 2021). Therefore, PCA is used to eliminate redundancy to leave only the critical variables for the next step in flood risk assessment. PCA may not be applicable to some vulnerability variable analysis because some variants still require expert with a qualitative approach to ranking and rating variables (Dash & Sar, 2020).

In the pilot project, Geographically Weighted Regression (GWR) is used to create a geographic regression by evaluating the dependent variable at any location with a set of independent variables defined at a known location (Calzada et al., 2012). The known location here refers to the flood zone predicted based on analysis of historical flood data. Therefore, one of the criteria for success of data collection is assumed to be the acquisition of flood zone or repetitive flood zone data. The shape and size of bandwidth depend on user input for kernel type, bandwidth method, distance, and number of neighbor parameters (Chen, 2020). The difference between GWR and multiple linear regression is that GWR combines the spatial nature of complex parameters and allows the resulting regression to be weighted according to geolocation. The advantages of GWR are used to model spatial heterogeneous relationships (Mentzafou et al., 2017). GWR is unable to organize indicators in a hierarchy which is a disadvantage of this approach. Therefore, it is not possible to obtain partial results in each branch from this analysis (Calzada et al., 2012).

The final step was to combine the risk outcomes from the three components of the risk triangle with the GIS tool. The GIS tool was used to analyze the relationship between variables and areas to assign risk indices to each area and to create flood risk maps (Armenakis et al., 2017). The spatial risk index for each unit area within each flood hazard zone was estimated using a spatial overlay operation between the hazard and the flood impact spatial layer. The consequent layer is created based on the spatial intersection of the vulnerability and the spatial intersection exposure layer operates under the risk triangle concept. Thus, the Flood Risk (RF) map is the spatial intersection of flood hazards overlapped with exposure risks and the vulnerability risks of social and economic (Armenakis et al., 2017).

The flood risk maps generated from the model were then compared with results from other studies using the same method and area but using different variables (Chen, 2020). To assess the effectiveness of the model created and discuss the results for further application. In addition, the validation of the risk areas obtained from the model. It will use the review to compare it with flood data and the most severe flood damage in the year (Dash & Sar, 2020). Therefore, in the process of model testing, it is necessary to use the data at a time that corresponds to the data used in the audit. The methodology is shown in Figure 5.1.

5.2.1 Data preparation

The resources of this study were compiled from publicly available sources in the form of a GIS data layer. All variables were performed under the Lower Layer Super Output Area (LSOA) which is a small area unit in England and Wales which broadly corresponds to the scale of organization of local government of Thailand. The candidate variables are grouped according to the components of the risk triangle: hazard, exposure, and vulnerability. The hazard component uses three

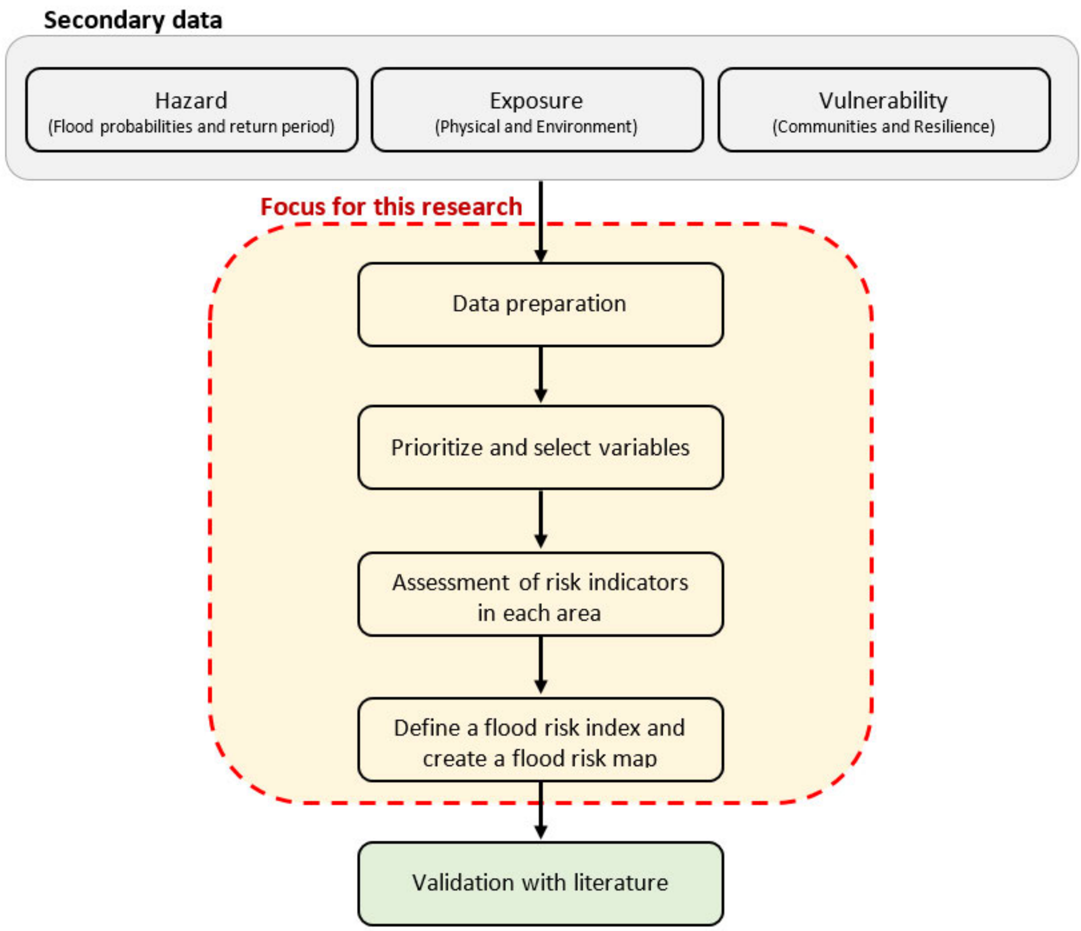


Figure 5.1. Pilot project methodology

variables from Environment Agency 2021, which are variables for defining flood zones (Chen, 2020). Zone3 is the most vulnerable zone due to the probability of flooding 1 in 100. Zone 2 is a zone with a probability of flooding 1 in 1,000, which is less than Zone 3. Zone 1 is defined as an area without flood risk by subtracting the total area by the areas of Zones 3 and 2. The zone is assigned a value of LSOA, which is a hazard indicator from 3 to 1. The exposure component comprises two variables, building density and population density, which are important factors influencing the sensitiveness of an area (Rinc et al., 2018).

The data was then taken for initial statistical analysis to characterize each variable and stored as individual GIS layers at the LSOA level. The vulnerability component in this study selected seven relevant variables to represent a group of socioeconomic variables (Cutter et al., 2003). Then every variable is stored as GIS layer and under LSOA level. It can be seen that there is a large number of variables in this component, where only the variables that influence the risk of each area are selected in the next step by PCA and GWR methods. See a list of the candidate variables in Table 5.1.

5.2.2 Prioritize and select variables

In this research, PCA was used to eliminate redundancy and to define only the variables critical for flood risk assessment. There are 7 candidate variables for this analysis. It starts with converting the storage format to a raster format as an input for PCA tools in ArcGIS software. Then set the number of elements equal to the number of input variables and choose to save the output file for further analysis. The Vulnerability Element PCA report is shown in Table 5.2, which identifies the eigenvalues and eigenvectors of seven variables (v1-v7). The key variables influencing the principal components can be determined in the flood area using eigenvalues and eigenvectors. PCA report of the vulnerability component is generated as shown in Table 5.2.

This report can be used to classify the importance of variables influencing local flooding. The PCA report splits the principal component (PCs) into three for the Kaiser Criteria vulnerability variable (eigenvalues > 1) and approximately 75% of the total cumulative variance based on the PCA theory (Tabachnick & Fidell, 2007). Therefore, the eigenvector greater 0.45 in the 1, 2, 3, 4 and 7 PCs for the vulnerability component in Table 2 is defined as the five main variables: Age (V1), Education (V2), Unemployment (V3), Diversity (V4) and Renter (V7).

Table 5.1. Characteristics of candidate variables classified by risk component.

Component	Variables	Description	Criteria	Unit
Hazard (Possibility of flooding from past events)	Flood Zone 3 (H1)	A flood hazard is considered the probability that it will occur at a given time and in some areas the flooding is of some severity. The hazard is closely related to a statistical quantity known as the return period. In general, the probability of these happening decreases as the return time increases but the severity tends to increase. For example, an event with a return period of 100 years has a probability of occurring at 1% in a year. So, there is a 10% probability in a year that there will be repeat flooding in that area (Albano et al., 2017).	1-in-100 chance of flooding	Specified score
	Flood Zone 2 (H2)		1-in-1,000 chance of flooding	Specified score
	Zone 1 (H3)		Outside of Zone 2 and Zone 3	Specified score
Exposure	Density of Buildings (E1)	In high-density residential areas, incident response emergency services may be overloaded (Cutter et al., 2003).	Building density per km^2	%of building density
	Population density (E2)	Population density is often linked to low-income housing, which in overcrowded areas tends to have poor drainage and inadequate infrastructure (Rinc et al., 2018).	Population density per km^2	%of population density
Vulnerability	Age (V1)	Age affects movement out of harm's way who can create barriers to movement during floods and evacuation operations, which increases the burden of care and lacks flexibility (Clark et al., 1998).	Children under 4 years and elder over 75 years (Kaźmierczak & Cavan, 2011)	% people age in the population
	Education (V2)	The study was linked to socioeconomic status and ability to understand warning information and access to rescue information (Cutter et al., 2003).	Level of qualification; no or level 1 qualification (Kaźmierczak & Cavan, 2011)	%people with no or level 1 qualification

Component	Variables	Description	Criteria	Unit
	Unemployed (V3)	The loss of employment results in slower recovery from disasters, such as repairing homes and equipment in preparation for the next flood (Cutter et al., 2003).	Unemployed ratio of all economically active	% Unemployed
	Diversity (V4)	In the case of certain ethnic minorities, cultural differences may hinder support from emergency services due to misunderstandings and communication problems (Cutter et al., 2003).	not British ethnic group	%not British ethnic group
	Income (V5)	The ability to recover from losses faster due to various insurance and entitlement programs to cope with flooding (Kaźmierczak & Cavan, 2011).	People with low income	%people deprived in terms of their income
	Health problem (V6)	People with long-term health problems or disabilities may have limitations in their awareness of alerts and evacuations (Kaźmierczak & Cavan, 2011).	Long-term health problem or disability; Day-to-day activities limited a lot	% people whose health was not good
	Renter (V7)	People who rent housing because they are temporary. They often do not have access to information about financial assistance during recovery in the event of severe damage (Kaźmierczak & Cavan, 2011).	households rented from private landlords	%tenant

Table 5.2. Eigenvalues and eigenvectors of PCA for the vulnerability component

Principal Component Layers	1	2	3	4	5	6	7
Eigenvalues	268.50	63.86	46.10	4.04	0.83	0.34	0.00
Input Layer	Eigenvectors						
1	0.00	0.00	0.15	0.88	0.43	0.13	0.00
2	0.35	0.54	0.72	-0.20	0.12	0.10	0.00
3	0.09	0.00	0.05	0.02	0.24	-0.97	0.01
4	0.50	-0.79	0.35	-0.03	-0.06	0.04	0.00
5	0.00	0.00	0.00	0.00	0.00	-0.01	-1.00
6	0.07	0.15	0.14	0.42	-0.86	-0.19	0.00
7	0.78	0.25	-0.56	0.07	0.04	0.05	0.00
Accumulative of Eigenvalues (%)	69.98	86.62	98.63	99.69	99.91	99.99	

5.2.3 Assessment of risk indicators in each area

Geographically Weighted Regression (GWR) was used to analyze the relationship between flood risk in the area of interest and exposure and vulnerability components. It considered the spatial relationship between flood risk factors and areas of interest, such as areas that had undergone risk mitigation recovery and areas with frequent flooding. In this project, rehabilitation areas were used to reduce flood risk from Chen's research ideas to compare whether changing variables in this project affects the flood risk assessment (Chen, 2020).

First, the scope of the GWR was determined using 172 LSOA, which is a zone 3 area of the hazard map and flood prevention remediation area. See 172 LSOA selected in Figure 5.2. Then, spatial regression of exposure and vulnerability was analyzed using the GWR method in ArcGIS. The exposure component analysis with the GWR determines the dependent variable (172 LSOA that has assigned the risk of hazard), explanatory variables (Building density and population density), kernel type (adaptive), bandwidth method (bandwidth_parameter), and number of neighbors (40). As these parameters are optimal (Chen, 2020), the results of R^2 and AIC (0.74 and 394.37) are shown in the Table 3. The vulnerability component analysis with the GWR tool uses the system defaults: the dependent variable (172 LSOA that has assigned the risk of hazard), explanatory variables (Age (V1), Education (V2), Unemployment (V3), Diversity (V4) and Renter (V7)), kernel type (Fixed), bandwidth method (AICc), and number of neighbors (30). The results of R^2 and AIC (0.46 and 879.99) are shown in the Table 5.3.

Table 5.3. Report of the GWR for the exposure and vulnerability components

Variable	exposure	vulnerability
Neighbors	40	30
Residual Squares	56.15	231.07
Effective Number	54.21	23.67
Sigma	0.82	0.85
AICc	394.37	879.99
R^2	0.74	0.46
R^2 Adjusted	0.58	0.42

In Table 5.3, the R^2 comparison showed that the exposure was higher than the vulnerability, meaning that the exposure variable had a more spatial correlation than the vulnerability. The GWR results were used to predict exposure component risk scores in LSOA. The scores were divided into three equal ranges, corresponding to low, medium, and high exposure levels of flooding, respectively. See a map of exposure risk map shown in Figure 5.3. In Figure 5.4, the vulnerability risk map is shown.

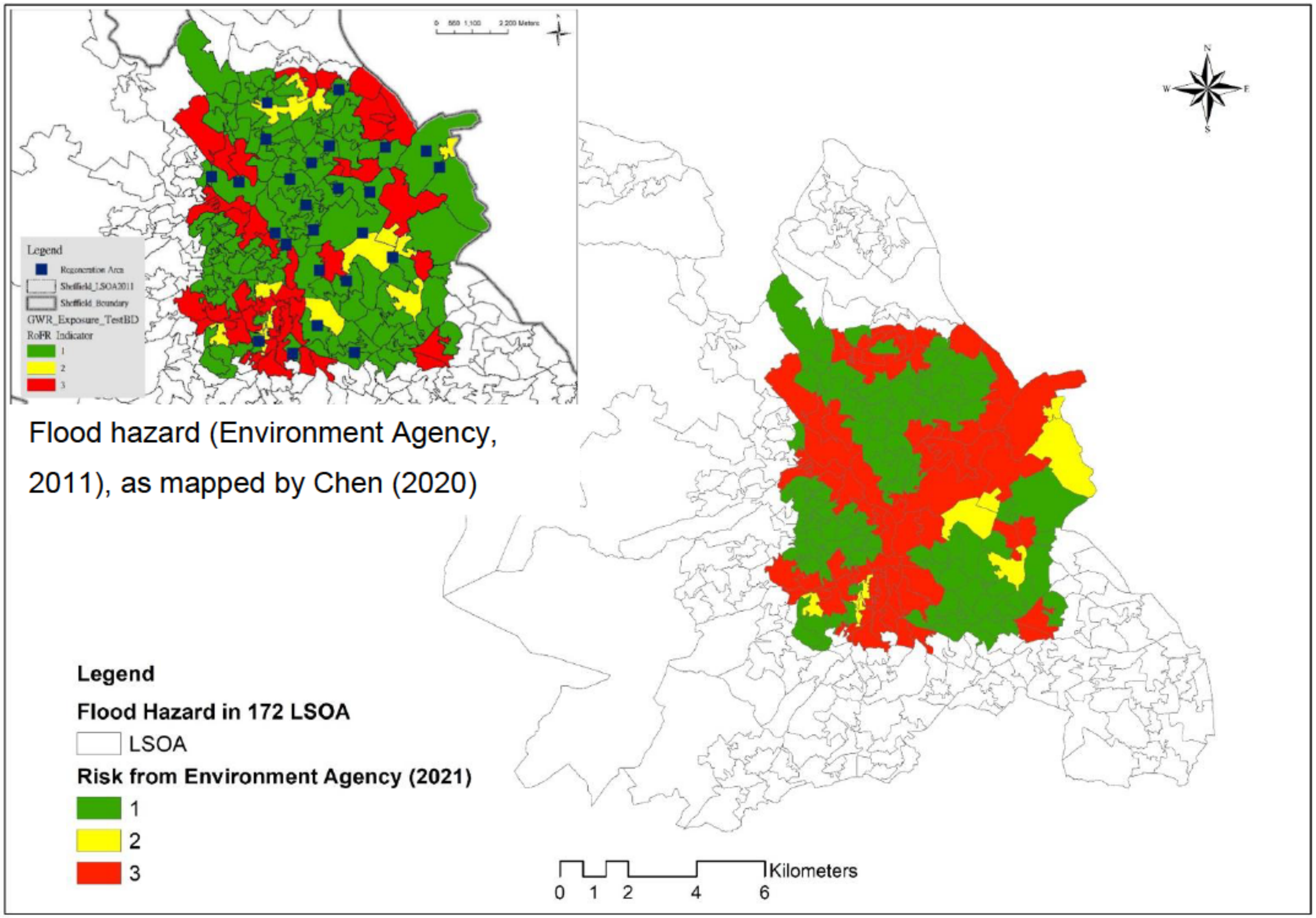


Figure 5.2. Hazard risk map in Sheffield

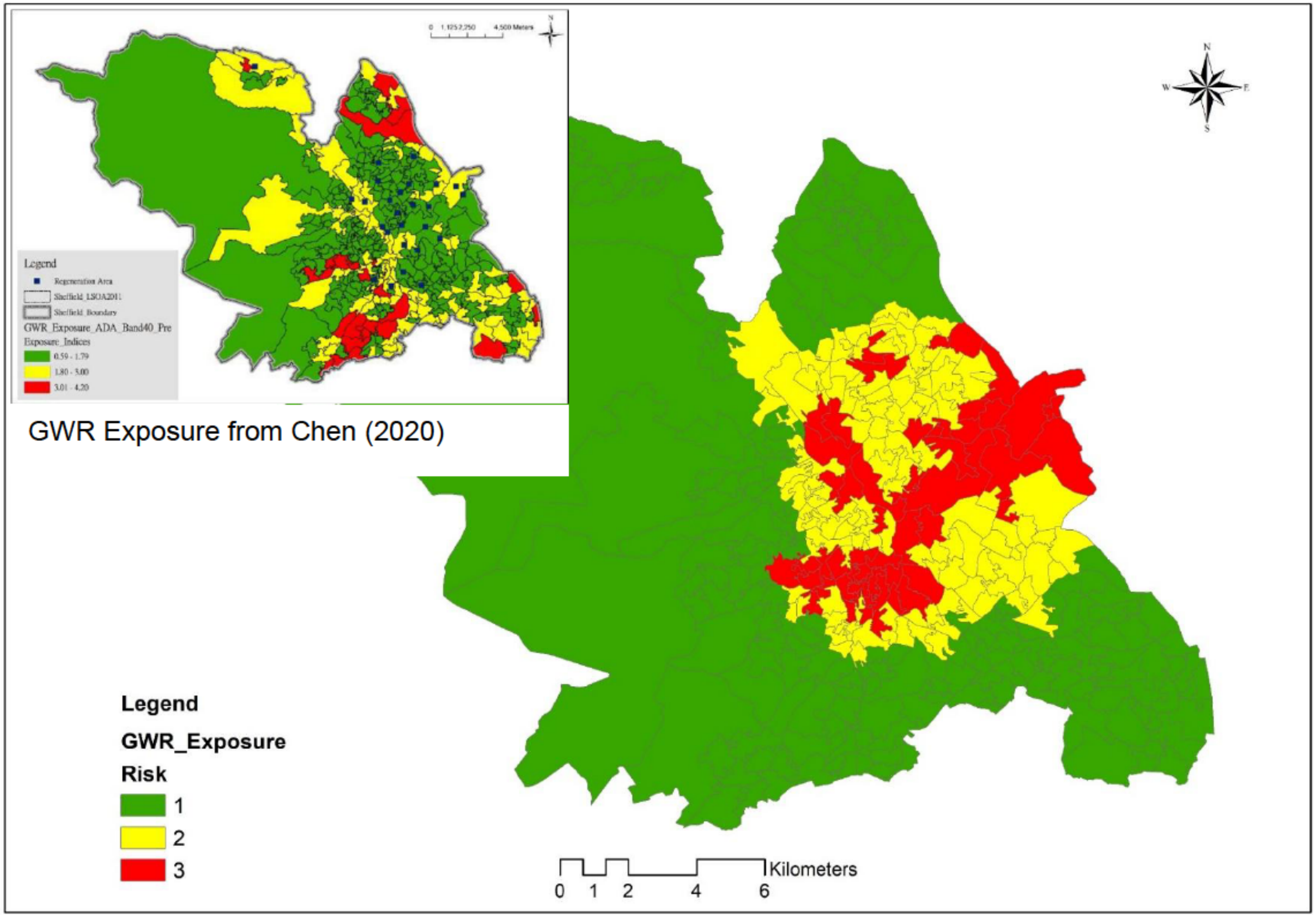


Figure 5.3. Exposure risk map in Sheffield

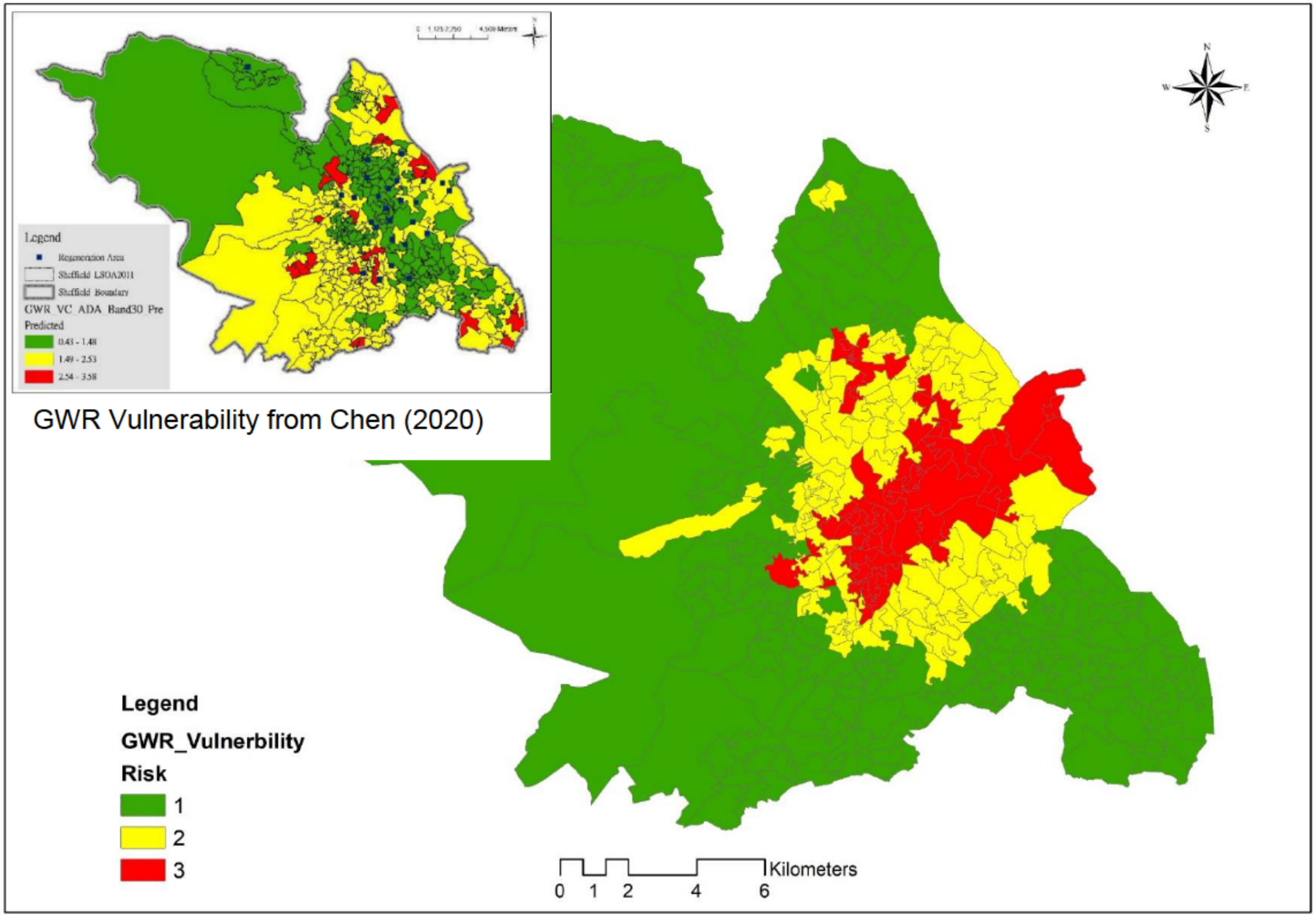


Figure 5.4. Vulnerability risk map in Sheffield

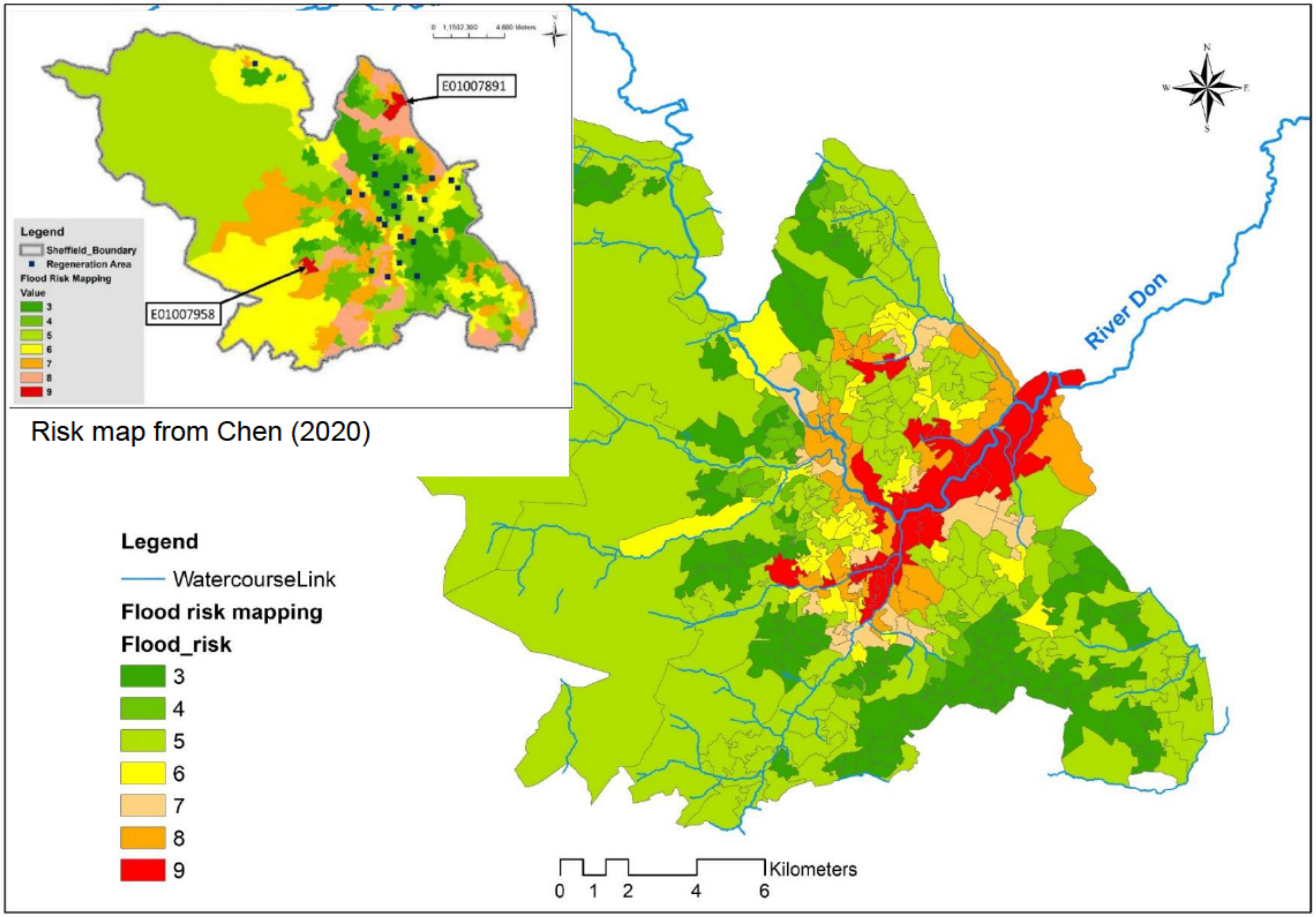


Figure 5.5. GIS-modelled Flood risk map for Sheffield

Table 5.4. Summary statistics of the key variables and risk index for the 8 LSOA in this study, compared to Chen's (2020) analysis of 2 high risk LSOA

Item	Mean	Data (Pilot model)								Chen's risk area	
LSOA		E01007 877	E01007 885	E01007 904	E01007 913	E01033 262	E01033 268	E01033 269	E01033 270	E01007 891	E01007 958
Hazard variable		3	3	3	3	3	3	3	3	3	3
Exposure variables		3	3	3	3	3	3	3	3	1	1
Density of Buildings (E1)	30.44	27.00	22.00	29.00	17.00	43.00	24.00	32.00	20.00	10.00	25.00
Population density (E2)	40.10	48.73	36.37	49.41	45.04	3.50	25.31	42.99	19.17	51.27	51.99
Vulnerability variables		3	3	3	3	3	3	3	3	1	1
Age (V1)	13.78	19.64	11.43	16.99	17.29	1.60	12.90	15.11	8.15	13.8	17.54
Education (V2)	37.93	50.15	51.11	63.69	54.89	10.90	35.59	54.45	27.73	35.87	12.25
Unemployed (V3)	3.61	8.13	8.82	6.81	10.06	3.29	4.93	11.56	7.75	0.91	0.65
Diversity (V4)	15.30	63.00	30.83	48.03	72.11	47.86	32.49	79.05	49.80	2.97	6.76
Renter (V7)	39.46	42.49	78.23	67.24	46.32	88.32	87.83	82.02	90.98	6.71	9.12

5.2.4 Defining a flood risk index and creating a flood risk map

As per the methods outlined in Section 4.4 the hazard, exposure and vulnerability layers were combined into a flood risk map to present the LSOA area-specific flood risk index. The flood risk map index is divided into seven scales from 3 to 9 through a combined score of three components. There are 21 areas with a risk index of 9, meaning that the area has the highest flood risk. The flood risk map is shown in Figure 5.5.

A further investigation of the area revealed that only 8 areas on the Don River crossing were subject to overflow during floods. Table 5.4 provides summary statistics of the key variables for the 8 LSOA risk area sample. It is evident that Diversity (V4) and Renter (V7) in these LSOAs are above Sheffield average, where these areas are vulnerable to cultural differences and the majority of residents are tenants.

5.2.5 Validation with literature

The designed flood risk assessment model was tested in Sheffield using a GIS tool, which was determined under the conditions of the risk triangle component. The results of the pilot project presented in Sheffield's 21 LSOA and 8 LSOA are the Don River flow areas consistent with past flood events. The results compare the results of the risk assessment with that of Chen's research, which uses the same methodology and the same area, but has changed the variables used in both the vulnerability assessment and the exposure assessment. This may have been the reason for the difference in results this time. From Table 5.4, a comparison of the results area from Chen's research found that the area had variables that were lower than the mean of the whole Sheffield data, namely: Density of Buildings (E1), Education (V2), Unemployed (V3), Diversity (V4), and Renter (V7). Differences are possible because categorization, grouping, and modernization of variables are different, which may lead to differences in results this time.

This comparison is very useful in identifying the weaknesses and strengths of this model. If a variable changes, this results in a changeable risk area. An analysis of the Chen's variable selection revealed a number of observations that may have caused the variability of the outcomes. For example, assigning a unit to a variable, many of which are assigned to units other than percent. Therefore, if they are calculated together, there may be inaccurate results. In addition, variables in the vulnerability components of the Chen (2020) present many variables, which have redundant conditions such as age, poverty and health problems. Therefore, groups should be clearly grouped to screen for the use of redundant variables. Variable consideration is essential for the implementation of this model. It also leads to recommendations for implementing this model in Thailand. This may require further consideration on the number of variables, variable selection and grouping criteria.

5.3 Experience from pilot projects to improvements

This section synthesizes the key experiences and insights gained from the pilot model application, highlighting how empirical testing informed methodological refinement and strengthened the model's reliability. The pilot results underscored the importance of variable selection, standardization, and grouping, as the model demonstrated significant sensitivity to changes in input parameters. Comparative analysis with Chen's approach revealed critical issues such as inconsistent measurement units and overlapping socio-economic indicators, which contributed to variability in risk outputs and potential double-counting within vulnerability components.

These observations emphasize the need for clear indicator classification, standardized units, and the removal of redundant variables to enhance accuracy, interpretability, and transparency. Lessons learned from the pilot directly inform targeted adjustments to improve model stability, weighting logic, and data integration procedures. This provides a foundation for adapting the framework to Thailand's local-government context, ensuring that the model is both methodologically robust and contextually suitable for sub-district-level flood-risk assessment and decision-support systems.

5.4 Conclusion

- The pilot study showed that the model is highly sensitive to variations in input variables, as demonstrated in Table 5.5, where shifts in exposure and vulnerability indicators produced clear changes in LSOA risk rankings. This finding emphasizes the need for stronger variable screening and standardization, providing a direct foundation for the methodological refinements introduced in the next chapter.
- Results presented in Table 5.5 indicate that certain variables, such as education, unemployment and renter proportions, exert a consistently stronger influence on the risk index than others. This highlights the importance of prioritizing statistically dominant indicators and reducing redundancy, which informs the transition to a refined variable-selection process in the following chapter and ensures better alignment with Thailand's socio-economic context.
- The comparison with Chen's model, summarized in Table 5.5, revealed that inconsistencies in measurement units, grouping logic and socio-economic categorization can significantly alter flood-risk outputs. These observations underline the necessity of establishing a coherent variable-design framework before applying the model in Thailand. The next chapter builds directly on this insight by implementing a more context-appropriate and technically consistent indicator set.

Table 5.5. Comparison between pilot project and the next step of project

Key points	Pilot	Guideline to Full project
Methodology	• Set up the model • Demonstrate the implementation in the test area. • Discuss the relationship and strength/weakness of the technique and variables. • Discuss the suitability of the model to the test area for further implementation of the model in the study area.	• Apply modeling techniques such as adding statistical analysis to analyze the quality of variables before using them in the model. • Apply modeling to additional variables such as economic and environmental variables. • Characterize variables, group them, and assign units to them. • Discover the subtleties and limitations of various techniques, some of which may not be applicable in Thailand.
Technique	Only quantitative • Principal component analysis (PCA) • Geographically weighted regression (GWR) **Why?** This is a quantitative method that is simpler than a qualitative method. There are no potentially complex and personal interviews or questionnaires. Additionally, most of the secondary data (Census, IMD, and Digimap) is collected from the UK Government's open data. Therefore, it is more suitable for use as a pilot technique in studies to expand the results to other areas more easily.	Quantitative + Qualitative (expert opinion) • Principal component analysis (PCA) • Geographically weighted regression (GWR) • Statistical analysis • Ordinary least squares (OLS) • Quantitative methods in this study priorities the use of publicly available secondary data. By relying exclusively on open and accessible datasets, the model ensures transparency, replicability, and accountability in its analytical processes. This approach allows the methodology to be safely reproduced by other practitioners and researchers, supporting consistent application and fostering confidence in the model's reliability and validity. • Qualitative approaches may also be employed to illustrate variations in outcomes, thereby strengthening confidence in the performance and suitability of the quantitative methods.

<table>
<tr><th>Key points</th><th>Pilot</th><th>Guideline to Full project</th></tr>
<tr><td>Input Data</td><td>• Hazard (Flood Zone)
• Exposure (buildings, Population density)
• Vulnerability</td><td>• Assign variables according to different techniques (Hazard, Vulnerability, Exposure)
• Create scenarios to analyze the sensitivity of variables.</td></tr>
<tr><td>Output</td><td>• Pilot model
• Condition/Strength/weakness of the technique and variables for implementation in Thailand.</td><td>• The best model for Thailand
• Condition/Strength/weakness of each technique and variables</td></tr>
<tr><td>Study area</td><td>River Don catchment</td><td>Chao Phraya River Basin, Thailand (The area will be selected later.)</td></tr>
<tr><td>Type of model</td><td>GIS Model</td><td>GIS Model</td></tr>
<tr><td>Software</td><td>ArcGIS/Open-source software</td><td>ArcGIS/Open-source software</td></tr>
<tr><td>Reference research</td><td>(Chen, 2020)
Similarity
• Technique (PCA and GWR)
• Methodology
• Some variables
• Study area (LSOA)
Difference
• Variables
• Update and Classification of variables
Why? Learn how to use this technique to create a suitable model and study the sensitivity of using variables.</td><td>(Chen, 2020)
Similarity
• Technique (GWR)
• Methodology
• Some variables
• Study area (LSOA)
Difference
• Variables
• Update and Classification of variables</td></tr>
</table>

Chapter 6: Availability, assembly and assessment of data inputs for flood risk quantification in Thailand

This chapter evaluates the availability, quality and suitability of the datasets required to implement the GIS-based flood risk model in Thailand. It assesses how well hazard, exposure and socio-economic vulnerability data can be assembled and transferred into the modelling framework, drawing comparisons with the UK pilot to highlight differences in data structure, completeness and reliability. The chapter also examines the conceptual, cultural and logistical challenges involved in porting GIS-based flood risk assessments across national contexts, showing how Thai data conditions affect variable stability, model behavior and overall uncertainty. In doing so, it directly addresses the research questions on the availability and quality of data for flood risk assessment (RQ1) and the influence of poor-quality inputs on model uncertainty (RQ3), establishing the foundation for interpreting the Thailand model results in later sections.

6.1 Impact of socio-economic data transfer on model uncertainty

The transfer of socio-economic data across spatial and temporal contexts introduces considerable uncertainty into flood risk modelling. Socio-economic indicators such as population density, household income, education level, and infrastructure condition are often collected under different methodologies, administrative boundaries, or policy frameworks, which can result in inconsistencies when integrated into models (Merz et al., 2007; Winsemius et al., 2016). When datasets of differing resolutions or representativeness are transferred or combined, they can distort estimates of exposure and vulnerability, leading to biased or misleading risk outcomes. Temporal mismatches between socio-economic and hazard data further compound these errors, particularly in rapidly urbanizing regions where land-use and demographic patterns change quickly (Ward et al., 2013). Such inconsistencies also influence the weighting of indicators in multi-criteria analyses, including OLS, PCA, or GWR, altering the statistical relationships among variables. To minimize these effects, the use of spatial resampling (set scenarios), statistical harmonization, and sensitivity analysis is essential to ensure data comparability and enhance the reliability of flood risk models (Moel et al., 2015; UNDRR, 2015).

Chapter 2 presented an in-depth analysis of variables through a detailed literature review to identify the main factors influencing flood risk. The analysis focused on variables that define each sub-district's sensitivity to flooding, including flood frequency, flood return periods, and other hydrological parameters, as well as factors contributing to uncertainty, such as population density, building density, and socio-economic conditions. The study also evaluated potential sources of uncertainty arising from data inconsistency, temporal discrepancies, and variations in data collection procedures, which could influence the accuracy and interpretation of model outcomes. Here, this was extended to the specific conditions of data availability in Thailand.

The initial data analysis indicated notable differences in data structures and collection units between the pilot and full-scale projects. These discrepancies arose from the distinct geographic, socio-economic, and administrative characteristics of the two study areas, necessitating refinement of the data framework to align with each country's context. For instance, in the United Kingdom, building density was calculated using the total building area within each Lower Layer Super Output Area (LSOA). In contrast, Thailand's analysis relied on representative center-point data, where building density was measured by counting the number of structures per square kilometer. These methodological adjustments were essential to ensure comparability and maintain analytical consistency across both study sites. A detailed comparison of the variable characteristics adapted to the Thai context is presented in Table 6.1.

Table 6.1. Comparison of the characteristics of transferred variables

Component/ Variables	Pilot project (UK)		The project (Thailand)	
	Criteria	Unit	Criteria	Unit
Hazard				
H1 Hazard zone by frequency of flood	Added variables	-	Thailand Flood Monitoring System (Flood data years 2005-2024)	Weighting of Flood (20 years 2005-2024)
H2 Hazard zone by return period	Flood Map for Planning (Rivers and Sea)	Flood recurrence rate: • 3 High Zone 3 (1 in 100 chances of flooding) • 2 Medium Zone 2 (1 in 100 chances of flooding) • 1 Low Outside zone 2 and zone 3 (Outside mapped floodplain)	Flood hazard 100 years and Flood hazard 1,000 years	Flood recurrence rate: • 3 High (1 in 100 chances of flooding) • 2 Medium (1 in 100 chances of flooding) • 1 Low (Outside mapped floodplain)
Exposure				
E1 Building density	Build-up area per LSOA	%of building density	Number of buildings per km^2	Building density per km^2
E2 Population density	Number of Population per LSOA	%of population density	Number of Population per km^2	Population density per km^2
E3 Size of household	Added variables	-	Number of Population per household	Population number per household
Vulnerability				
V1 AGE	Children under 4 years and elder over 75 years	% people age in the population	Children under 5 years and elder over 60 years	Population number of children ≤5 and elderly ≥60
V2 Gender	Added variables	-	Women in the population	Population number of woman

Component/ Variables	Pilot project (UK)		The project (Thailand)	
	Criteria	Unit	Criteria	Unit
V3 No Education	Added variables	-	No qualification or No Education	Population number of No qualification or No Education
V4 Less hi school	Level of qualification; no or level 1 qualification	%people with no or level 1 qualification	Level of qualification with primary school	Population number of primary school
V5 Un Employed	Unemployed ratio of all economically active	% Unemployed	Unemployed ratio of all economically active	Population number of Unemployed
V6 Income	People with low income	%people deprived in terms of their income	Household with income less than 40,000 bath/years	Household number of income less than 40,000 bath/years
V7 LowSaving	Added variables	-	Household with low saving less than 10,000 bath	Household number of low saving less than 10,000 bath
Diversity	not British ethnic group	%not British ethnic group	No data is stored, only religious information is available and there is a lot of zero data.	-
Health problem	Long-term health problem or disability; Day-to-day activities limited a lot	% people whose health was not good	Only data on the number of disabled people is available. Data will begin in 2024. Data for 2025 is not yet complete.	-
Renter	households rented from private landlords	%tenant	No similar data is stored in this section.	-

The data characterization analysis identified the need to incorporate five additional variables to ensure comprehensive coverage of all dimensions of flood risk assessment, including hazard zone by flood frequency, household size, gender, no education, and low savings. Each variable was selected for its significance in representing the social, economic, and physical aspects of vulnerability and resilience. Flood frequency provides an essential measure of hazard intensity, allowing comparison of flood severity across different return periods and spatial scales. Household size reflects a community's adaptive capacity, as larger families often face constraints in resource allocation, decision-making, and post-disaster recovery. Gender composition highlights potential inequalities, as a higher proportion of women in certain areas may indicate greater exposure to risks due to caregiving responsibilities, limited access to resources, and social vulnerability. Educational attainment, represented by the percentage of people with no formal education, is used as a proxy for awareness and preparedness, influencing the ability to interpret warnings and follow evacuation measures. Low savings indicates reduced financial resilience, demonstrating how economic insecurity limits recovery potential. Together, these variables strengthen the model by capturing complex interconnections among hazard, exposure, and vulnerability dimensions within flood-prone areas.

In contrast, three variables, diversity, health problems, and renter status, were excluded due to contextual and data-related limitations in Thailand. The diversity variable was removed because Thailand lacks detailed ethnic classification systems, and national data primarily record religious affiliation rather than ethnicity. Since more than 90 percent of the population identifies as Buddhist, regional variation is minimal, reducing the variable's relevance to flood risk differentiation. The health problem variable was excluded because the available datasets remain incomplete and inconsistently managed across agencies. Although some information exists, the 2024 public dataset lacks sufficient spatial detail and integration for reliable analysis. The renter status variable was also omitted due to the absence of systematic records within national census data, as most rental arrangements are informal and privately managed. Given these limitations, low savings was adopted as a more reliable proxy for financial vulnerability, effectively reflecting households' capacity to manage repairs, temporary relocation, and recovery costs after flooding. This adjustment ensures that the model remains both contextually appropriate and data-driven, enhancing its relevance for Thai conditions and data structures.

Building on these refinements, this preliminary analysis integrates a detailed literature review, variable definitions, data collection, data availability assessment, and public service datasets to establish a robust foundation for the study. The process supports the selection of variables at appropriate spatial and temporal scales, ensuring alignment with the study's objectives and analytical framework. It also enhances understanding of data characteristics, such as resolution, completeness, and reliability, which are essential for producing consistent and accurate results. Emphasis on publicly accessible data, particularly those related to population, infrastructure, and public services, promotes transparency and reproducibility, enabling other researchers and policymakers to replicate or extend the methodology. Moreover, systematic evaluation of data compatibility across multiple sources ensures smooth integration within the GIS environment, facilitating accurate spatial representation and subsequent analysis. Overall, this stage of research provides efficient data preparation for advanced statistical and spatial analyses, serving as a critical step toward developing a robust, adaptable, and transferable GIS-based flood risk assessment model suitable for use in diverse geographic and socio-economic settings.

6.2 Statistics analysis

6.2.1 General statistical analysis

The statistical analysis section presents the general statistical results used to describe and interpret the main characteristics of the data employed in this study. The purpose of this analysis is to provide an overview of the data distribution, central tendencies, and variability among the selected variables related to flood risk. General statistical measures, including mean, median, range, and standard deviation, were used to summarize and compare the characteristics of each variable.

These measures help to identify typical patterns, detect extreme values, and ensure that the data are suitable for further spatial and quantitative analysis. The analysis also supports the evaluation of data consistency and reliability, which are essential for building a robust and interpretable flood risk model. By examining the statistical behavior of hazard, exposure, and vulnerability variables, this stage establishes a clear understanding of the dataset and provides a foundation for more detailed analyses in subsequent sections. See details of general statistics of the variables used in this research in Table 6.2.

The general statistical analysis provides an overview of the descriptive characteristics of hazard, exposure, and vulnerability variables for the years 2023 and 2024. The results reveal the variation, distribution, and year-to-year dynamics of data across sub-districts, reflecting differences in physical, demographic, and socio-economic conditions influencing flood risk. These basic statistics form the foundation for evaluating the internal consistency of the dataset and identifying key changes that may affect the model's spatial performance and sensitivity. Overall, the analysis demonstrates that while some variables remained stable, others showed clear fluctuations due to changes in land use, population distribution, and socio-economic status, all of which contribute to evolving flood risk conditions.

For hazard variables, data were available only for 2024. The hazard zone by flood frequency (H1) recorded an average of 1.67 with a standard deviation of 0.84, suggesting moderate variability in flood occurrence intensity across sub-districts.

Higher maximum values (3.72) represent areas with more frequent flooding, possibly corresponding to low-lying or river-adjacent zones. Similarly, the hazard zone by return period (H2) had a mean value of 0.69 and a standard deviation of 0.82, indicating relatively fewer but significant flood events concentrated in specific locations.

Table 6.2. Statistical characteristics of Thai hazard, exposure and vulnerability variables

Component/Variables	2023				2024			
	Max	Min	Avg.	Std.	Max	Min	Avg.	Std.
Hazard								
H1 Hazard zone by frequency of flood	-	-	-	-	3.72	0	1.67	0.84
H2 Hazard zone by return period	-	-	-	-	2.98	0	0.69	0.82
Exposure								
E1 Building density	-	-	-	-	779	19	95	99
E2 Population density	2,161	33	211	243	2,120	33	207	235
E3 Size of household	4	1	3	1	3	1	3	0
Vulnerability								
V1 AGE	3,317	271	1,072	528	3,531	299	1,126	552
V2 Gender	5,139	354	1,719	828	5,088	371	1,705	813
V3 No Education	194	1	46	41	204	0	45	41
V4 Less Hi School	4,385	92	1,353	789	4,303	183	1,343	776
V5 Un Employed	1,162	0	37	92	268	0	53	44
V6 Low Income	111	0	10	15	26	0	4	5
V7 LowSaving	1,525	12	644	319	2,190	76	673	368

The presence of zero values in both indicators reflects flood-free areas, while higher values highlight recurrent flood zones. This pattern confirms the spatial heterogeneity of flood hazards and underscores the importance of integrating both flood frequency and return period to capture the full range of hazard intensity in the model.

For exposure variables, the results indicate both stability and spatial diversity between 2023 and 2024. Building density (E1) in 2024 exhibited wide variability, with a maximum of 779 and an average of 95 buildings per square kilometer, indicating a strong contrast between densely urbanized centers and sparsely populated rural areas. This variability reflects the rapid pace of urban expansion and land-use transformation in certain sub-districts. Population density (E2) remained consistent across the two years, with means of 211 and 207 persons per square kilometer, respectively, suggesting demographic stability at the sub-district level. However, the relatively high standard deviations (243 and 235) show that population distribution remains uneven, with concentrated settlements in specific urban areas. The size of household (E3) remained unchanged, averaging three persons per household, indicating demographic consistency and limited short-term migration effects. Collectively, these patterns imply that exposure is relatively stable but still influenced by localized development trends that may heighten risk in high-density areas.

For vulnerability variables, the analysis shows nuanced socio-economic changes between 2023 and 2024. The average population age (V1) increased slightly from 1,072 to 1,126, with corresponding increases in standard deviation, suggesting an aging population and growing variation among sub-districts. Gender (V2) values remained relatively stable, indicating a consistent demographic composition across both years. The no education variable (V3) increased marginally from 46 to 45 on average, showing persistent challenges in educational attainment in certain areas, while those with less than high school education (V4) showed a slight decline in average values, which may indicate gradual improvement in access to education. Unemployment (V5) showed a decline in mean from 37 to 53 but with a smaller standard deviation, implying reduced but more spatially concentrated unemployment. Low income (V6) dropped notably from an average of 10 to 4, reflecting possible improvements in economic conditions or refined data accuracy. Conversely, low savings (V7) increased slightly from 644 to 673 with higher variability, suggesting that despite income improvements, financial resilience remains weak in several regions. This pattern highlights the complexity of socio-economic vulnerability, where increased income does not always translate into improved financial preparedness for flood recovery.

Overall, the statistical results indicate moderate yet meaningful shifts across hazard, exposure and vulnerability conditions between 2023 and 2024. While many physical and demographic indicators remained relatively stable, more pronounced changes emerged in economic and financial variables, signaling evolving patterns of vulnerability within communities. These shifts are particularly important in the Thai context, where flood impacts are closely linked to structural inequalities, fluctuating local economies and household-level financial resilience. Variations in indicators such as low income, savings levels and unemployment suggest that communities possess differing capacities to prepare for, withstand and recover from flooding. At the same time, the observed increase in hazard intensity, alongside persistent socio-economic disparities, highlights how climate pressures can intensify existing vulnerabilities.

These findings demonstrate that flood risk in Thailand is shaped not only by physical exposure but also by dynamic socio-economic drivers, including labour-market instability, migration, household indebtedness and uneven access to state support mechanisms. Such conditions can shift quickly from year to year, influencing both community resilience and the stability of model outputs. However, at the moment the statistical analysis does not yet achieve the level of diagnostic precision required, and the descriptions of the data and interpretations drawn from it remain too imprecise. This reflects both limitations in current data quality and the need for more detailed analytical work to fully understand the drivers of flood vulnerability across sub-district contexts.

Recognizing these dynamics is therefore crucial for designing targeted mitigation strategies, strengthening local governance and informing integrated planning that accounts for both environmental and social determinants of risk. The statistical patterns identified here provide an initial foundation for more advanced correlation and spatial analyses, supporting a deeper and more contextually grounded understanding of flood-risk behavior across Thailand.

6.2.2 Model diagnostics with OLS analysis

This section presents the results of the Ordinary Least Squares (OLS) analysis, which was undertaken to examine the statistical relationships between the flood risk index and its explanatory variables across the study area. OLS was applied as a global regression technique to quantify the strength, direction, and significance of variables representing hazard, exposure, and vulnerability components. The analysis provides an initial overview of how physical and socio-economic factors jointly influence spatial patterns of flood risk and identifies which predictors exert the strongest influence.

The OLS results are interpreted in terms of both overall model performance and individual variable behaviour. Model diagnostics, including Adjusted R^2, Akaike's Information Criterion (AIC), Jarque–Bera, and Koenker (BP) statistics, are used to assess goodness of fit, normality, and heteroscedasticity. At the same time, Variance Inflation Factor (VIF) and P-values support the evaluation of multicollinearity and statistical significance. These findings form a baseline for subsequent spatially explicit analysis using GWR. Therefore, the OLS analysis in this research will be analyzed in two steps: model diagnosis (see tables 6.3, 6.4) and variable diagnosis (see table 6.5).

Table 6.3. Model diagnostics with OLS

Scenario/ Statistical variables	Adjusted R^2	AIC	Koenker (BP)	Jarque–Bera
Raw				
HFrequency 2023	0.205	396.096	10.831	6.307
HFrequency 2024	0.194	398.447	10.710	7.448
HReturnP 2023	0.003	428.824	7.661	25.247
HReturnP 2024	0.003	428.824	7.661	25.247
Grouping				
HFrequency 2023	0.148	521.680	14.107	5.556
HFrequency 2024	0.133	524.514	11.579	4.812
HReturnP 2023	0.034	593.432	9.311	17.109
HReturnP 2024	0.019	596.027	8.743	17.816
Average				
HFrequency_Avg	0.200	397.180	9.878	6.994
HReturnP_Avg	0.031	423.977	7.874	26.246

The OLS diagnostic results demonstrate how different hazard data-processing strategies influence model robustness, statistical behavior, and suitability for subsequent spatial analysis. In the raw scenario, the flood-frequency variables show the strongest modelling performance among all hazard indicators. The 2023 model achieves the highest Adjusted R^2 at 0.205, indicating that approximately 20 percent of the spatial variation in flood risk is explained by this variable alone. The relatively low AIC value of 396.096 confirms that the information loss in the model is limited and that the parameter estimates are efficient. Moderately elevated Koenker (BP) statistics (10.831) suggest some heteroscedasticity, implying that relationships between flood frequency and risk vary across locations. The Jarque–Bera statistic (6.307) indicates slight non-normality but remains within an acceptable range for OLS. Comparatively, the 2024 flood-frequency model follows a similar pattern, confirming stability across two consecutive years of census-aligned hazard input data. In contrast, hazard models based on return-period rasters in the raw scenario show almost no explanatory ability, with Adjusted R^2 values of 0.003, demonstrating that this variable does not capture sufficient spatial variability to predict localized flood risk. The high Jarque–Bera values (>25) further indicate strong deviations from normality, reducing the reliability of this variable.

In the Grouping scenario, model performance declines sharply across all hazard indicators, showing that grouping hazard data into five classes reduces statistical sensitivity. For grouped flood-frequency models, the Adjusted R^2 values fall to 0.148 (2023) and 0.133 (2024), demonstrating a clear reduction in explanatory power. The substantial increase in AIC values, such as 521.680 for the 2023 model, indicates greater information loss and poorer overall model efficiency. The Koenker (BP) statistics become more pronounced, particularly the value of 14.107, suggesting stronger heteroscedasticity. This implies that grouping reduces the continuous variability of the hazard raster, creating artificial thresholds that distort the relationship between the hazard variable and the dependent risk index. Grouped return-period variables show similar instability. Their low Adjusted R^2 values (<0.04) highlight their limited predictive potential, while elevated Jarque–Bera statistics (17–18) confirm persistent non-normality. These patterns show that grouping introduces additional noise and weakens any potential linear relationship in the model.

In the Averaged scenario, flood-frequency variables show improved performance compared to the grouped version. With an Adjusted R^2 of 0.200, the averaged flood-frequency model retains much of the explanatory strength observed in the raw scenario. The AIC value (397.180) closely aligns with the raw models, indicating that averaging does not compromise information efficiency. The Koenker statistic (9.878) is slightly lower than in the grouped scenario, suggesting more stable residual variance. These results imply that averaging across the 2023–2024 layers preserve the continuous range of hazard intensity without introducing artificial breaks, thereby producing more consistent model behavior. However, the average return-period indicator continues to perform poorly, with an Adjusted R^2 of 0.031 and a very high

Jarque–Bera value (26.246). This confirms that the return-period dataset contains structural limitations that are not resolved by temporal averaging.

Overall, the diagnostic patterns demonstrate that flood-frequency variables consistently outperform flood-return-period indicators across all scenarios. The raw and average datasets provide the most stable results, showing higher Adjusted R^2 values and lower AIC scores, which indicates stronger explanatory power and more efficient model performance. In contrast, the Grouping scenario substantially weakens model quality by reducing the continuous variability of the hazard data, resulting in lower model fit and higher information loss. The elevated Koenker (BP) statistics across most models reveal the presence of spatial non-stationarity, meaning that the relationship between hazard intensity and the dependent variable varies across locations. This supports the use of spatially adaptive techniques such as Geographically Weighted Regression (GWR) to capture local variations more effectively. The consistently poor performance of return-period variables, reflected in very low Adjusted R^2 values and high Jarque–Bera statistics, suggests structural limitations within these datasets. Their reduced sensitivity and weak statistical behavior indicate that they add little value to hazard representation at the sub district scale and should therefore be used cautiously or considered for exclusion from more advanced modelling stages.

Table 6.4. Summary of the best model options using OLS diagnostics

Model option	Scenario	Hazard Variable	Census Year	Description
Selected as the Best Overall Model	Raw Scenario	Flood-Frequency	2023	This model provides the strongest overall diagnostic performance. It shows the highest Adjusted R^2 (0.205), the lowest AIC (396.096), and acceptable levels of normality and heteroscedasticity. It captures the natural variability of flood frequency without distortion from grouping or averaging, while remaining stable across census datasets. Its diagnostic strength indicates that the raw flood-frequency information in 2023 explains spatial flood risk patterns most effectively.
Alternative Strong Model (Very Close in Quality)	Raw Scenario	Flood-Frequency	2024	Although slightly weaker than the 2023 model, the 2024 version shows very similar performance with an Adjusted R^2 of 0.194 and low AIC (398.447). Its behavior is consistent with the 2023 model, confirming reliability over time. This makes it a strong alternative but still slightly less optimal than the 2023 model.
Second-Best Scenario Choice	Averaged Scenario	Flood-Frequency (Averaged 2023–2024)	Combined	The averaged model closely matches Raw model performance with an Adjusted R^2 of 0.200 and AIC of 397.180. Averaging reduces noise and maintains continuity in hazard intensity, producing stable residuals. However, it performs marginally below the Raw 2023 model and therefore ranks second.

6.2.3 Variable diagnostics with OLS analysis

The diagnostic evaluation of exposure and vulnerability variables was conducted using a combined set of criteria designed to ensure that selected predictors demonstrate either statistical independence or statistical significance. A variable was included in the model when it achieved a Variance Inflation Factor below 7.5, which indicates an acceptable level of multicollinearity, or a p-value below 0.01, which reflects a strong statistical relationship with the dependent variable. This approach allows the model to retain variables that are either structurally reliable or statistically meaningful. It also acknowledges that some variables remain valuable due to their stable behavior even when their immediate influence is modest. Applying these criteria across the three hazard processing scenarios allows for a consistent assessment of how each variable performs under different data conditions. This method ensures both methodological transparency and flexibility, while supporting the identification of variables that meaningfully contribute to the modelling framework.

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Table 6.6. Variable diagnostics with OLS

Scenario/ variables	Statistical	PopDen	BuildDen	HouseS	Age	Gender	No Edu	LessHiSc	UnEmp	LowInc	LowSav
Raw											
HFrequency 2023	VIF	0.358	3.557	1.585	32.130	38.829	2.247	5.773	1.094	1.158	3.110
	p-value	0.290	0.004	0.121	0.429	0.919	0.001	0.060	0.001	0.20	0.156
HFrequency 2024	VIF	2.955	3.284	1.583	30.700	42.257	2.686	12.828	1.384	1.321	3.012
	p-value	0.333	0.001	0.117	0.700	0.651	0.0002	0.018	0.436	0.079	0.415
HReturnP 2023	VIF	2.955	3.285	1.583	30.700	42.257	2.686	12.828	1.384	1.321	3.012
	p-value	0.318	0.004	0.974	0.195	0.402	0.465	0.986	0.789	0.742	0.558
HReturnP 2024	VIF	2.955	3.285	1.583	30.70	42.257	2.686	12.828	1.384	1.321	3.012
	p-value	0.318	0.004	0.974	0.195	0.402	0.465	0.986	0.789	0.742	0.558
Grouping											
HFrequency 2023	VIF	4.33	4.534	1.583	8.200	9.602	2.868	5.832	2.075	1.234	2.855
	p-value	0.600	0.070	0.388	0.455	0.368	0.007	0.022	0.564	0.048	0.278
HFrequency 2024	VIF	3.906	4.526	1.388	8.469	10.383	2.494	7.645	1.402	1.169	2.321
	p-value	0.563	0.100	0.211	0.455	0.545	0.0001	0.069	0.362	0.012	0.832
HReturnP 2023	VIF	4.331	4.535	1..583	8.120	9.602	2.868	5.832	2.075	1.234	2.855
	p-value	0.367	0.586	0.623	0.906	0.936	0.003	0.058	0.168	0.125	0.567
HReturnP 2024	VIF	3.906	4.526	1.388	8.469	10.383	2.494	7.645	1.402	1.169	2.322
	p-value	0.568	0.336	0.921	0.102	0.158	0.038	0.402	0.0232	0.163	0.792
Average											
HFrequency_Avg	VIF	3.220	3.450	1.596	31.833	40.618	2.491	8.505	1.248	1.249	3.905
	p-value	0.355	0.0005	0.122	0.680	0.667	0.0001	0.0417	0.744	0.008	0.866
HReturnP_Avg	VIF	3.220	3.450	1.596	31.833	40.618	2.491	8.505	1.248	1.250	3.905
	p-value	0.440	0.003	0.783	0.270	0.339	0.142	0.401	0.001	0.045	0.674

Under the Raw scenario, most exposure and socioeconomic variables perform well when evaluated using the combined criteria. Many variables achieve a Variance Inflation Factor below 7.5, indicating that they are not affected by problematic multicollinearity and can be retained even when their statistical significance is limited. Variables such as Population Density, Household Size, Low Savings and Low Income meet this requirement and therefore remain suitable for modelling. At the same time, several variables demonstrate strong statistical significance, including Building Density, No Education, Less High School and Unemployment. These indicators achieve p-values below 0.01 and therefore qualify for selection regardless of their Variance Inflation Factor. The only variables that fail to meet either criterion are Age and Gender. These variables have extremely high Variance Inflation Factor values that exceed acceptable limits and their high p-values indicate weak explanatory influence. The combined results show that exposure characteristics and education related indicators provide strong predictive value in the raw scenario, while demographic variables make little meaningful contribution to the model.

The Grouping scenario modifies the hazard data by classifying it into discrete intervals, which reduces natural variation and influences the behavior of the explanatory variables. This adjustment decreases multicollinearity for most predictors, allowing nearly all variables to satisfy the Variance Inflation Factor threshold of 7.5. As a result, many variables qualify for inclusion based solely on their low multicollinearity, even when their statistical significance is limited. Despite the smoothing effect of grouped hazard data, several variables continue to demonstrate strong significance, including No Education, Less High School and Low Income. These variables maintain p-values below 0.01 and therefore remain important contributors. Although Age and Gender show lower multicollinearity in this scenario compared with the raw scenario, they do not achieve significant p-values and remain excluded from selection. Other variables such as Population Density, Household Size, Low Savings and Unemployment are retained due to their acceptable Variance Inflation Factor. Overall, the Grouping scenario broadens the set of retained variables but also reduces their individual explanatory strength because the grouped hazard values provide less contrast across the study area.

The Averaged scenario uses temporally smoothed hazard inputs that provide a more stable representation of flood-related conditions. Most exposure and vulnerability variables meet the Variance Inflation Factor threshold and therefore remain suitable for modelling. Variables such as Population Density, Household Size and Low Savings maintain acceptable levels of multicollinearity and are included despite weaker statistical significance. Several variables qualify based on their strong p-values, particularly Building Density, No Education, Less High School and Low Income. These variables consistently achieve p-values below 0.01, indicating stable explanatory importance across averaged hazard conditions. As observed in the previous scenarios, Age and Gender remain unsuitable because they continue to show extremely high Variance Inflation Factor values and lack statistical significance. Unemployment meets the multicollinearity requirement but does not present strong significance, reducing its relative influence in this scenario. Overall, the Averaged scenario supports a similar set of selected variables to the raw scenario and underscores the consistent importance of education, economic status and structural exposure indicators.

Across all scenarios, the combined criteria produce a consistent set of variables that demonstrate either acceptable multicollinearity or strong statistical significance. The most reliable predictors are those that meet both criteria across multiple scenarios, particularly Building Density, No Education, Less High School and Low Income. These variables show stable behavior and strong explanatory value and therefore serve as important components in the modelling framework. Several additional variables, including Population Density, Household Size, Low Savings and Unemployment, qualify because they consistently meet the Variance Inflation Factor requirement, even when their p-values do not indicate strong statistical effects. This suggests that these variables can be retained without compromising model stability. In contrast, Age and Gender are excluded across all scenarios because they fail to meet either selection criterion. Their very high Variance Inflation Factor values indicate severe redundancy within the vulnerability component, while their high p-values demonstrate limited predictive value. The overall results emphasize that indicators related to education, income and structural exposure are the strongest and most consistent contributors within the model.

However, Less High School is selected because it meets the required criteria of VIF below 7.5 or p-value below 0.01 in multiple scenarios, demonstrating that it contributes meaningful information to the model without causing problematic multicollinearity. In the Raw 2023 model its VIF is comfortably below the threshold, indicating structural independence, while in the Grouping and Averaged scenarios it shows stronger statistical relevance with p-values that reflect a meaningful relationship with the dependent variable. Even when its VIF rises in some models, its statistical behavior remains stable enough to justify inclusion. Overall, the variable consistently satisfies at least one selection requirement across scenarios, confirming its value as an important educational vulnerability indicator within the modelling framework.

Table 6.7. Summary variable selection using OLS diagnostics

Scenario	**Selected Variables** (VIF < 7.5 or p < 0.01)	**Unselected Variables**
Raw	Population Density; Building Density; Household Size; No Education; Less High School; Unemployment; Low Income; Low Savings	Age; Gender
Grouping	Population Density; Building Density; Household Size; No Education; Less High School; Unemployment; Low Income; Low Savings	Age; Gender
Averaged	Population Density; Building Density; Household Size; No Education; Less High School; Unemployment; Low Income; Low Savings	Age; Gender
Overall Across Scenarios	Population Density; Building Density; Household Size; No Education; Less High School; Unemployment; Low Income; Low Savings	Age; Gender

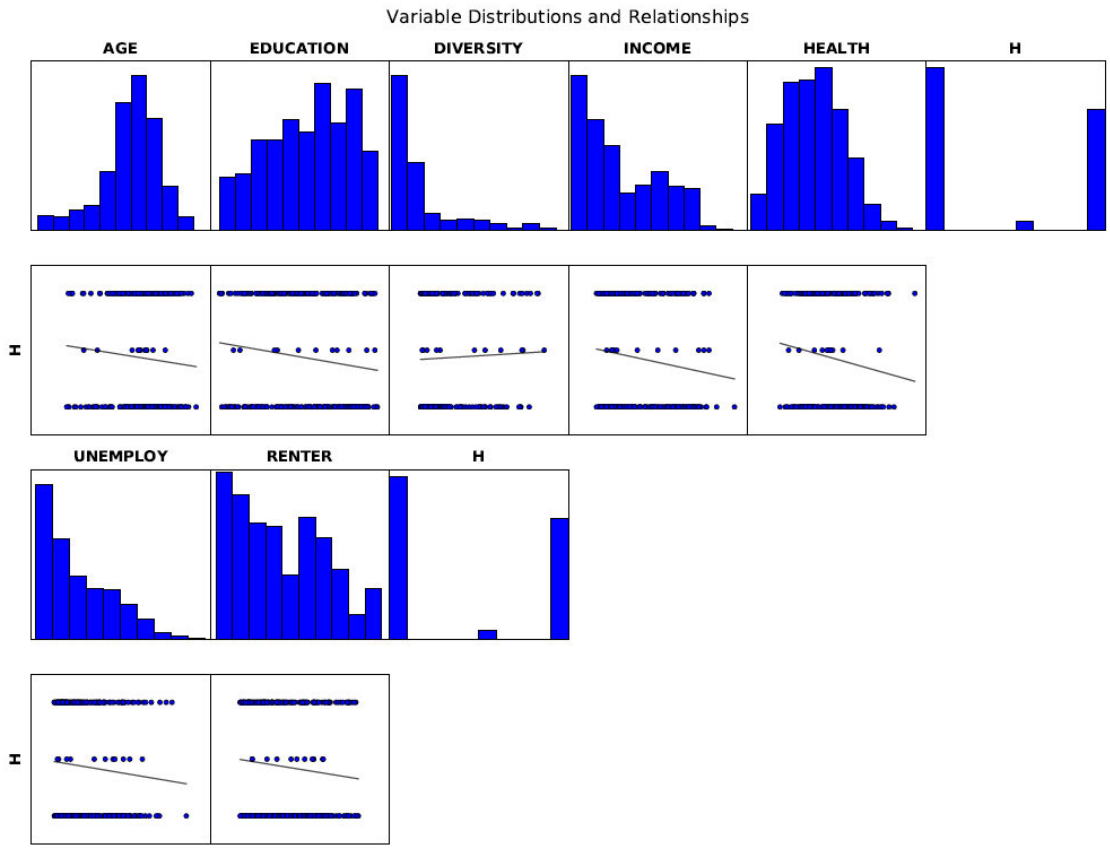
6.2.4 PCA analysis

Principal Component Analysis (PCA) is applied in this study to reduce the dimensionality of the exposure and vulnerability dataset and to identify the underlying factors that influence flood-risk patterns across the study area. Many socioeconomic indicators are correlated, and PCA provides an objective way to transform these correlated variables into a smaller set of uncorrelated components that retain most of the original variance. This process reduces redundancy, minimizes multicollinearity and supports clearer interpretation in later modelling stages such as OLS and GWR. By extracting the dominant structures within the data, PCA helps ensure that only the most meaningful variables are retained for spatial analysis and contributes to an evidence-based understanding of how socio-economic and physical factors combine to shape flood vulnerability across the three provinces.

Although PCA is a valuable method for simplifying complex datasets, it also has important limitations. The technique assumes the presence of linear relationships, which means it may overlook non-linear patterns that often arise in socio-economic and environmental contexts. PCA also depends on variance as a measure of importance, which can cause conceptually relevant variables with low variance to be down weighted or excluded. The resulting components can be difficult to interpret because they represent mathematical combinations of variables that do not always correspond neatly to real-world processes or policy domains. PCA is also sensitive to differences in measurement scales, and if variables are not standardized appropriately, the component loadings may be distorted. Furthermore, PCA outcomes depend heavily on the characteristics of the dataset used, which limits the transferability of components across different years or scenarios.

A key issue in this study relates to the suitability of applying PCA to the Thai dataset. The exposure and vulnerability variables in the Thai case do not exhibit sufficiently balanced or continuous distributions. Several variables show extreme skewness, clustered values or very limited variation, creating an unstable covariance structure that prevents PCA from extracting meaningful components. These characteristics differ from the pilot project dataset, which displayed more uniform distributions and therefore allowed PCA to operate more effectively. Because the Thai dataset does not meet the essential statistical conditions for PCA, the method could not be applied reliably during data processing. For this reason, Ordinary Least Squares regression was chosen as the primary diagnostic tool for variable selection. OLS is more robust when dealing with uneven or skewed variables and provides clearer statistical criteria, such as p-values and variance inflation factors, which support the identification of significant predictors and the detection of multicollinearity. This approach ensured a more dependable basis for selecting variables for the subsequent stages of the flood-risk modelling.

Figure 6.1 and Figure 6.2 present the OLS diagnostic results used to evaluate the suitability of applying Principal Component Analysis (PCA) to the UK pilot dataset and the Thailand dataset, respectively. In both figures, subfigure (a) displays histograms and scatterplots, where the x-axis and y-axis represent the values of the candidate variables. These plots were used to examine variable distributions, variance and linear relationships among variables. Subfigure (b) presents the Variance Inflation Factor (VIF) diagnostics, where the x-axis represents the candidate variables and the y-axis represents the corresponding VIF values used to assess multicollinearity. Together, these diagnostics provide evidence of whether the datasets satisfy the statistical assumptions required for PCA and support the selection of appropriate variables for subsequent flood-risk modelling.



(a)

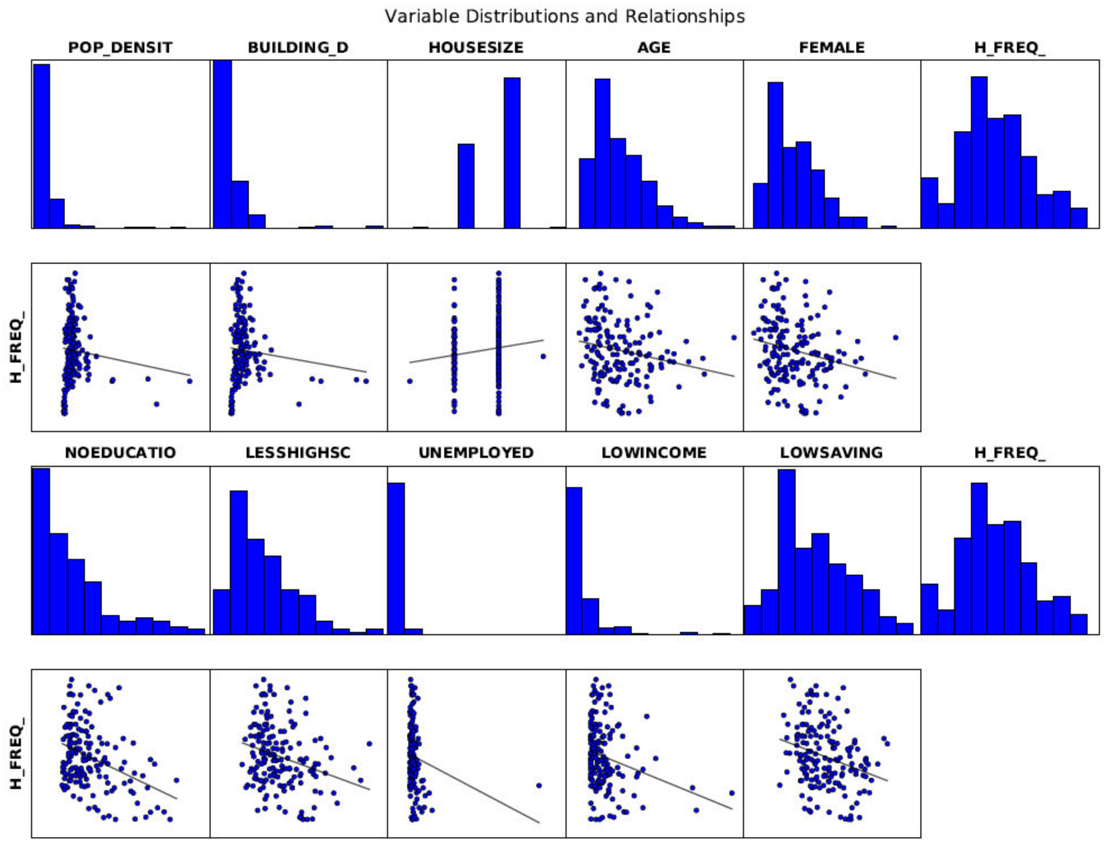
Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	2.424943	0.375068	6.465342	0.000000*	0.374423	6.476488	0.000000*	--------
AGE	-0.019895	0.023111	-0.860842	0.389925	0.022932	-0.867538	0.386252	3.300386
EDUCATION	-0.008047	0.009679	-0.831422	0.406312	0.009743	-0.825965	0.409397	8.896856
DIVERSITY	0.005212	0.004287	1.215686	0.224957	0.003906	1.334349	0.182999	2.077745
INCOME	-0.434610	1.551571	-0.280110	0.779572	1.543394	-0.281594	0.778434	14.310704
HEALTH	0.019235	0.030708	0.626380	0.531491	0.030860	0.623283	0.533521	5.797773
UNEMPLOY	0.036591	0.045461	0.804900	0.421434	0.045167	0.810133	0.418424	5.534188
RENTER	-0.007601	0.004607	-1.649779	0.099931	0.004621	-1.644815	0.100951	4.768340

(b)

Figure 6.1. OLS diagnostic for PCA analysis (UK dataset)

Figure 6.1 shows the pilot dataset satisfies the statistical conditions required for PCA, which explains why PCA could be applied successfully during the UK pilot study. First, the variable distributions in the histograms on Figure 6.1a show smoother, more continuous and more balanced patterns compared with the Thai dataset. Variables such as Age, Education, Diversity, Income, Health, Unemployment and Renter all display wide and evenly spread distributions, with no extreme clustering or near-constant values. This ensures sufficient variance for PCA to extract meaningful components. The pilot dataset also has larger sample size (345 observations), which stabilises the correlation matrix and supports reliable eigenvalue computation. In addition, multicollinearity levels (Figure 6.1b) are moderate: although a few variables have higher VIF values (e.g., Education VIF ≈ 8.9, Income VIF ≈ 14.3), these levels are still manageable for PCA because they indicate shared structure among variables rather than instability in the covariance matrix. The scatterplots on Figure 6.1 (a) also show clearer linear patterns compared with the Thai dataset, which PCA requires because it is a linear transformation method. Overall, the pilot data exhibit continuous distributions, adequate variance, moderate multicollinearity and consistent scaling, all of which create the stable covariance structure necessary for PCA to function. These characteristics contrast sharply with the Thai dataset, where skewed variables, low variance, and extreme multicollinearity made PCA unsuitable.



(a)

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	1.819678	0.436742	4.166481	0.000055*	0.400044	4.548699	0.000013*	--------
POP_DENSIT	-0.000195	0.000433	-0.448740	0.654244	0.000183	-1.060816	0.290386	3.357888
BUILDING_D	-0.001636	0.001101	-1.485925	0.139302	0.000553	-2.956076	0.003598*	3.557644
HOUSESIZE	0.204053	0.143625	1.420742	0.157371	0.130963	1.558099	0.121221	1.584612
AGE	0.000454	0.000617	0.735407	0.463176	0.000573	0.793168	0.428861	32.129614
FEMALE	0.000040	0.000433	0.091379	0.927298	0.000389	0.101681	0.919129	38.828667
NOEDUCATIO	-0.006356	0.002085	-3.047853	0.002709*	0.001818	-3.496338	0.000622*	2.247046
LESSHIGHSC	-0.000297	0.000175	-1.697854	0.091512	0.000157	-1.897807	0.059546	5.773288
UNEMPLOYED	-0.000610	0.000652	-0.935612	0.350891	0.000175	-3.486874	0.000643*	1.093572
LOWINCOME	-0.006437	0.004187	-1.537113	0.126276	0.002737	-2.351826	0.019905*	1.157551
LOWSAVING	-0.000407	0.000319	-1.277310	0.203371	0.000285	-1.425499	0.155995	3.109573

(b)

Figure 6.2. OLS diagnostic for PCA analysis (Thailand dataset)

The PCA method was not applied in this study because the characteristics of the full Thai dataset did not meet the statistical requirements necessary for stable component extraction. As shown in the variable histograms and scatterplots in the OLS diagnostics (Figure 6.2a), several variables display extreme skewness, limited value ranges, or near-constant distributions, particularly unemployment, household size, and population density. These issues reduce variance to levels too low for meaningful component formation. In addition, the VIF results (Figure 6.2b) indicate severe multicollinearity, especially for AGE and FEMALE, which exceed values of 30 and 38 respectively, creating an unstable covariance matrix that violates PCA assumptions. The data also contain non-linear and weak relationships, uneven scaling across variables, and imbalanced distribution patterns compared with the pilot study, where PCA had been successful. Together, these conditions prevent PCA from identifying reliable underlying components, making the method unsuitable for this dataset. For these reasons, OLS was selected as the diagnostic tool, as it can accommodate irregular distributions more effectively and provides clearer statistical indicators for variable selection.

6.3 GWR analysis

Geographically Weighted Regression (GWR) analysis was conducted to explore how the relationship between flood risk and the selected socioeconomic and exposure variables varies across the study area. Unlike OLS models, which assume uniform statistical behavior across all locations, GWR captures spatial differences in these relationships, revealing patterns that would otherwise remain hidden in global analyses. This capability is particularly relevant for flood risk assessment, where physical environments, demographic structures and development patterns differ substantially between sub-districts. The GWR results show clear spatial variation in both the magnitude and direction of key predictors, demonstrating that factors such as population density, building density and socioeconomic vulnerability influence flood risk differently across locations. Overall, GWR provides a more context-sensitive and realistic understanding of the factors shaping flood risk, emphasizing the importance of incorporating spatial variation into hazard–exposure–vulnerability evaluations.

Building on the OLS screening and variable diagnostics, three models were selected for spatial analysis using the 2023 census data, the 2024 census data and the averaged dataset, all employing the flood-frequency hazard layer as the dependent variable. From the initial indicator set, eight variables were retained: three exposure related variables (population density, building density and household size) and five vulnerability related variables (no education, less than high school education, unemployment, low income and low savings). Age and gender were removed because they did not meet the statistical criteria for inclusion and exhibited weak or inconsistent associations with flood risk. These refined variables were then incorporated into the GWR models to analyze how their influence changes across the study area, reinforcing the finding that local demographic, economic and settlement characteristics strongly shape hazard–exposure–vulnerability interactions.

To ensure robust model performance, an adaptive kernel with AICc-based bandwidth optimisation was applied. The adaptive kernel was selected due to the considerable variation in the size, density and spatial distribution of Thai sub-districts, enabling the model to adjust to local feature density and maintain stable coefficient estimation even in sparsely populated or geographically large areas. AICc-based bandwidth selection was used to identify the most statistically efficient bandwidth for each model, minimizing information loss and improving the reliability of local parameter estimates across the different census years and socioeconomic scenarios. A fixed bandwidth was not chosen because it cannot accommodate the uneven geographic and demographic characteristics of the study area. The results of the GWR models are summarized in Table 6.8.

Table 6.8. GWR result

Model/ Variable	Census 2023		Census 2024		Average 2023-2024	
	Exposure	**Vulnerability**	**Exposure**	**Vulnerability**	**Exposure**	**Vulnerability**
Neighbors	63	54	59	64	40	70
Residual Squares	52.052	41.815	49.463	47.454	37.438	51.199
Effective Number	26.211	50.115	28.352	43.570	42.745	38.084
Sigma	0.604	0.593	0.593	0.615	0.544	0.625
AICc	330.694	349.662	326.379	353.332	311.436	353.492
R^2	0.560	0.646	0.582	0.599	0.683	0.567
R^2 Adjusted	0.482	0.500	0.500	0.462	0.579	0.444

The GWR performance metrics reveal substantial differences between the exposure-based and vulnerability-based models across the three census datasets, demonstrating how the spatial drivers of flood risk shift from year to year. In the 2023 model, vulnerability variables show a noticeably stronger relationship with flood risk than exposure indicators. This is reflected in the higher R^2 (0.646) and lower sigma (0.593), indicating that areas with lower education levels, reduced income, limited savings and larger household structures were more closely aligned with higher flood risk. Although the exposure model for 2023 uses slightly more neighbors, its explanatory strength remains weaker, suggesting that physical exposure patterns alone could not fully capture the spatial variation of flood risk in that year. The strength of the 2023 vulnerability model lies in its ability to reflect local socioeconomic sensitivity; however, its limitation is that it may be influenced by short-term or year-specific demographic and economic fluctuations.

In contrast, the 2024 model reveals a clear shift in which exposure variables exert a stronger spatial influence on flood risk. The exposure-based GWR achieves higher adjusted R^2 (0.500), lower AICc (326.379) and lower residual variance compared to the vulnerability model. This indicates that population density, building density and settlement concentration were more dominant predictors of risk in 2024. Despite the vulnerability model using a larger number of neighbors, its higher sigma and residual squares suggest that socioeconomic sensitivity was less spatially consistent that year. This shift may reflect changes in flood conditions, population movement or development patterns that intensified the role of exposure relative to vulnerability.

The averaged 2023–2024 dataset produces the most statistically reliable and internally consistent results. The exposure-based model shows the highest overall performance, with the strongest R^2 (0.683), highest adjusted R^2 (0.579), lowest sigma (0.544) and lowest AICc (311.436). These results demonstrate that smoothing the census data across two years reduces noise, filters out annual anomalies and strengthens the underlying spatial structure of exposure-related indicators. This stability is beneficial for long-term risk modelling, as it captures persistent spatial patterns in population concentration and built development. The vulnerability model for the averaged dataset performs less effectively, showing higher sigma and lower adjusted R^2, reflecting the inherently variable and context-dependent nature of socioeconomic vulnerability, which fluctuates more rapidly from year to year.

Overall, the three models collectively reveal how flood risk emerges from the dynamic interaction between hazard intensity, spatial exposure and evolving vulnerability conditions. The results highlight that exposure tends to be more spatially stable and structurally consistent over time, making it a strong predictor in multi-year or averaged datasets. Vulnerability, in contrast, is more dynamic, sensitive to temporal change and reflective of year-specific socioeconomic contexts. The averaged model therefore provides the clearest representation of long-term spatial patterns, while the individual yearly models capture short-term variability and provide insights into how annual socioeconomic differences influence flood risk.

In addition to generating spatially varying coefficients for each independent variable, the GWR analysis also produces predictive surface maps that highlight areas with comparatively higher or lower flood risk. In this study, these results are presented in descending order of model performance based on the preceding OLS diagnostics. Only the three highest-performing models are reported, and their corresponding maps are organized according to the three core components of the flood risk framework. These outputs are illustrated in Figures 6.3-6.5.

Figure 6.3 shows the spatial distribution of flood hazard based on flood frequency across Chainat, Sing Buri, and Ang Thong from 2005 to 2024. Flood frequency is classified into five levels, with green indicating low hazard and red indicating very high hazard. The highest hazard levels occur along the Chao Phraya River, particularly in eastern Chainat, central and eastern Sing Buri, and northern to eastern Ang Thong, where repeated flooding has historically taken place. In contrast, the western part of Chainat shows predominantly low hazard values, reflecting minimal flood occurrence. The pattern demonstrates a strong relationship between proximity to the river and increased flood hazard, while areas farther from major waterways generally fall within the low to moderate categories. The map highlights where flooding has occurred most frequently over the past two decades and provides a foundational understanding of hazard distribution for further flood risk analysis.

Figure 6.4 shows the predicted influence of exposure-related factors on flood risk across Chainat, Sing Buri, and Ang Thong using GWR with 2023 census data. Exposure reflects population density, building density, and other settlement characteristics that increase the potential impact of flooding. The highest predicted exposure values are concentrated in Ang Thong, especially in the southern and southeastern sub districts where urban and built-up areas are more prominent. Central Sing Buri also contains several pockets of elevated exposure linked to clustered population centers. In contrast, Chainat shows mostly low to moderate predicted exposure due to its more rural settlement pattern. Unlike the hazard map, which follows the natural floodplain pattern, this distribution reflects the spatial characteristics of the socio-economic and demographic data.

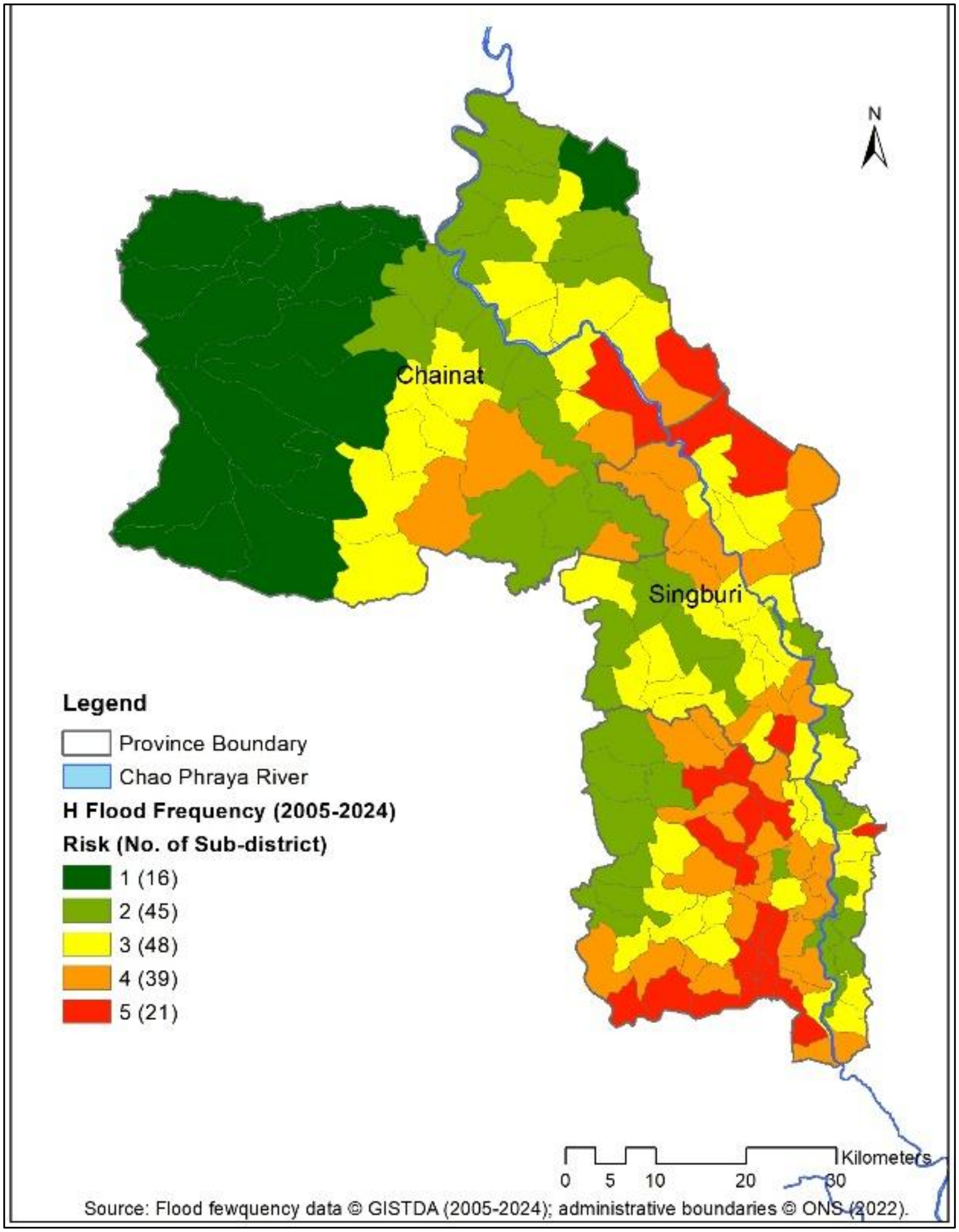


Figure 6.3. Hazard (H_Flood Frequency), 2023 census data

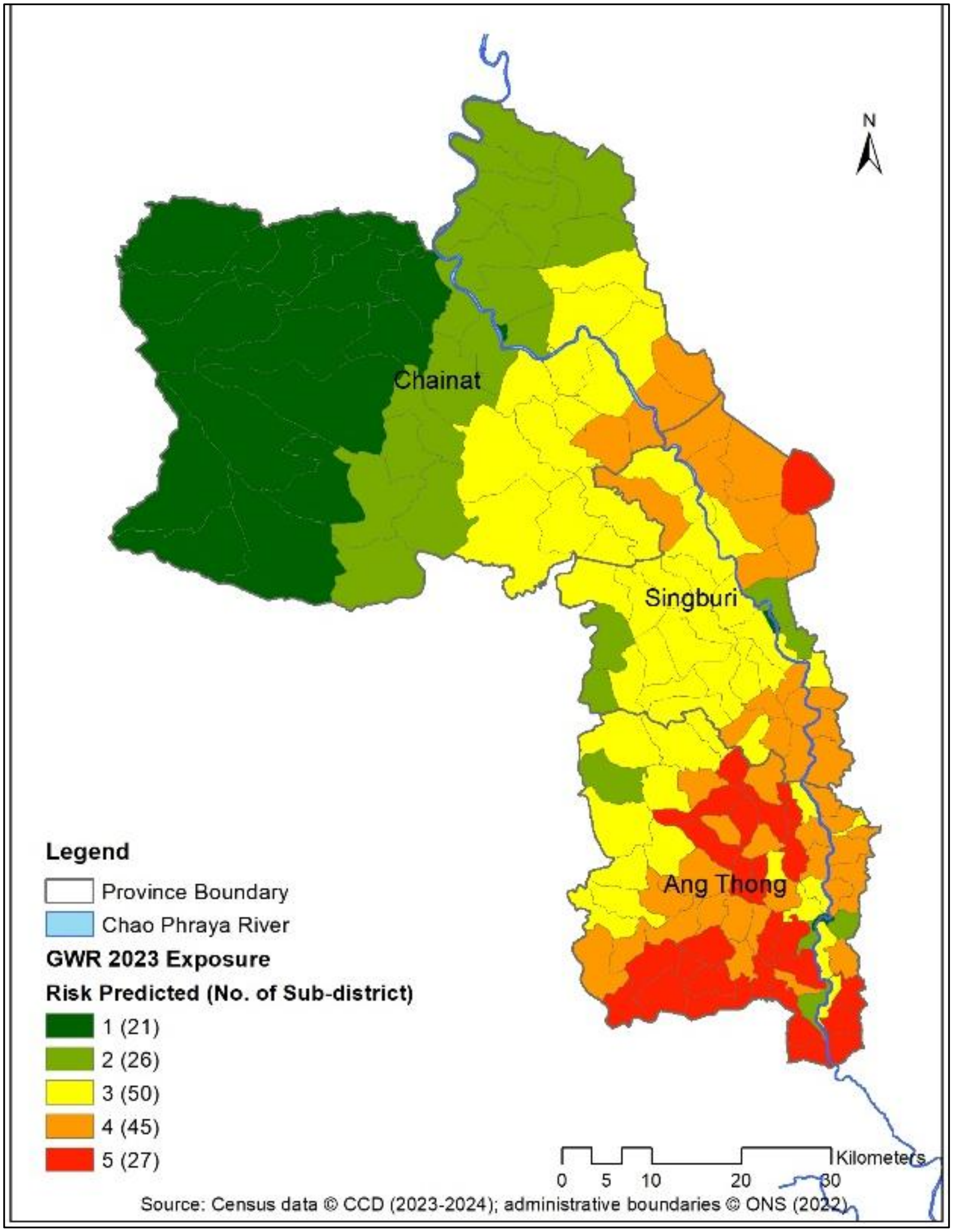


Figure 6.4. Exposure, 2023 census data

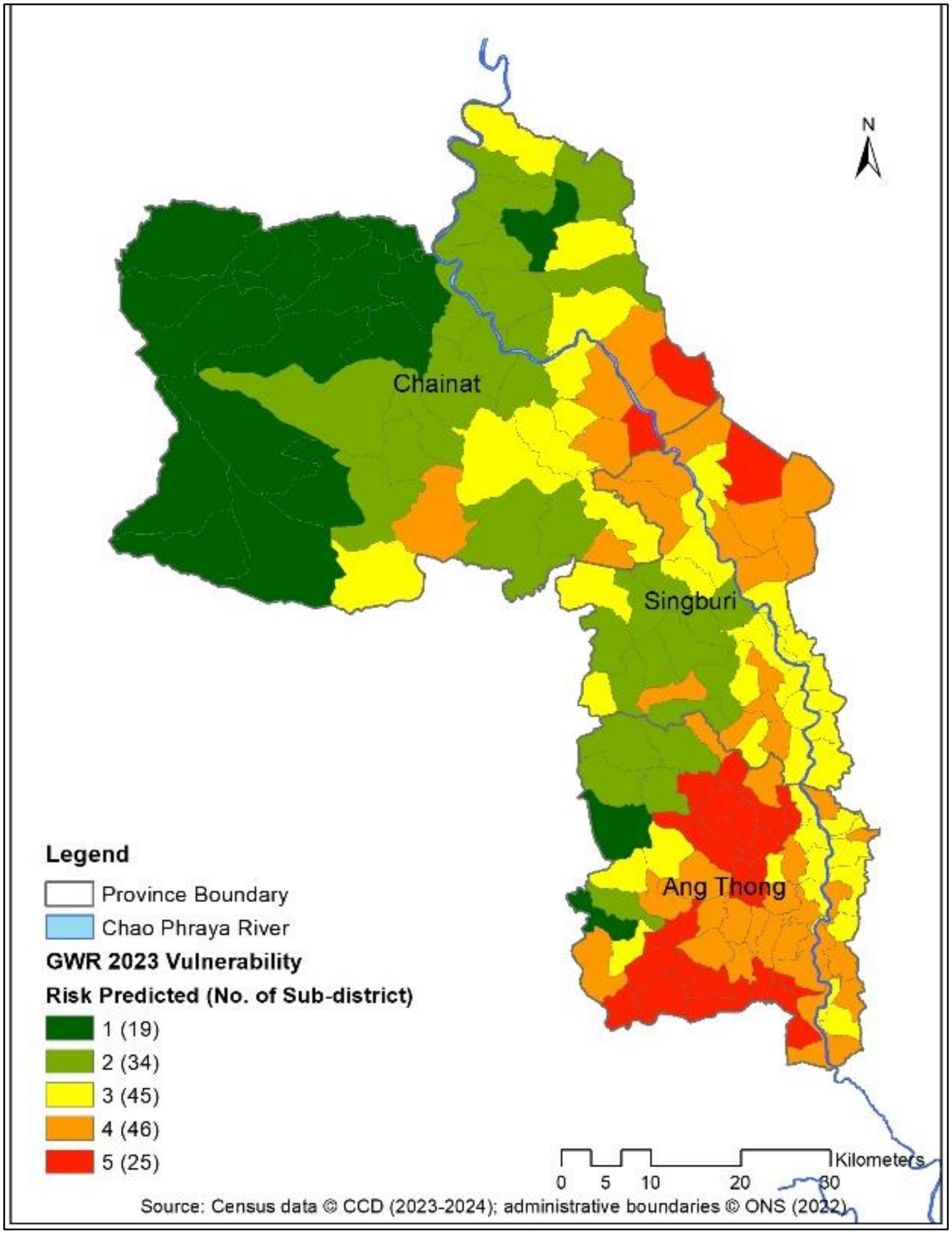


Figure 6.5. Vulnerability, 2023 census data

Figure 6.5 shows the predicted contribution of vulnerability-related socioeconomic factors to flood risk in Chainat, Sing Buri, and Ang Thong using GWR with 2023 census data. High predicted vulnerability is mainly concentrated in Ang Thong, where lower income, lower education levels, and limited savings increase sensitivity to flooding. Sing Buri also contains several sub districts with moderate to high vulnerability, particularly in rural and peri-urban areas. Chainat, in contrast, displays mostly low to moderate values, indicating comparatively lower socioeconomic sensitivity. The spatial pattern differs from hazard-based maps because vulnerability reflects social and economic conditions rather than physical flood processes. Overall, the map highlights where socioeconomic characteristics most strongly amplify flood risk within the three-province study area.

The three maps Figure 6.3-6.5, showing hazard, exposure, and vulnerability, together illustrate how different components of flood risk vary across Chainat, Sing Buri, and Ang Thong. All three display a similar pattern in which higher values cluster along the Chao Phraya River, indicating that river proximity consistently influences flood risk. Despite this shared pattern, each map highlights different drivers. The hazard map reflects physical flood processes, with high values concentrated in areas that have experienced repeated inundation between 2005 and 2024. The exposure map follows human settlement patterns, showing higher predicted values in densely populated and built-up areas, particularly in Ang Thong and central Sing Buri. The vulnerability map shows the widest spread of elevated values, representing socioeconomic sensitivity in communities with lower education levels, lower income, and limited savings, mostly in rural and peri-urban areas of Sing Buri and Ang Thong. Although the hazard map is shaped by natural hydrology, the exposure and vulnerability maps are driven by population concentration and social conditions. Together, the three maps show how flood risk is influenced by the combined effects of physical hazard, human settlement, and socioeconomic capacity.

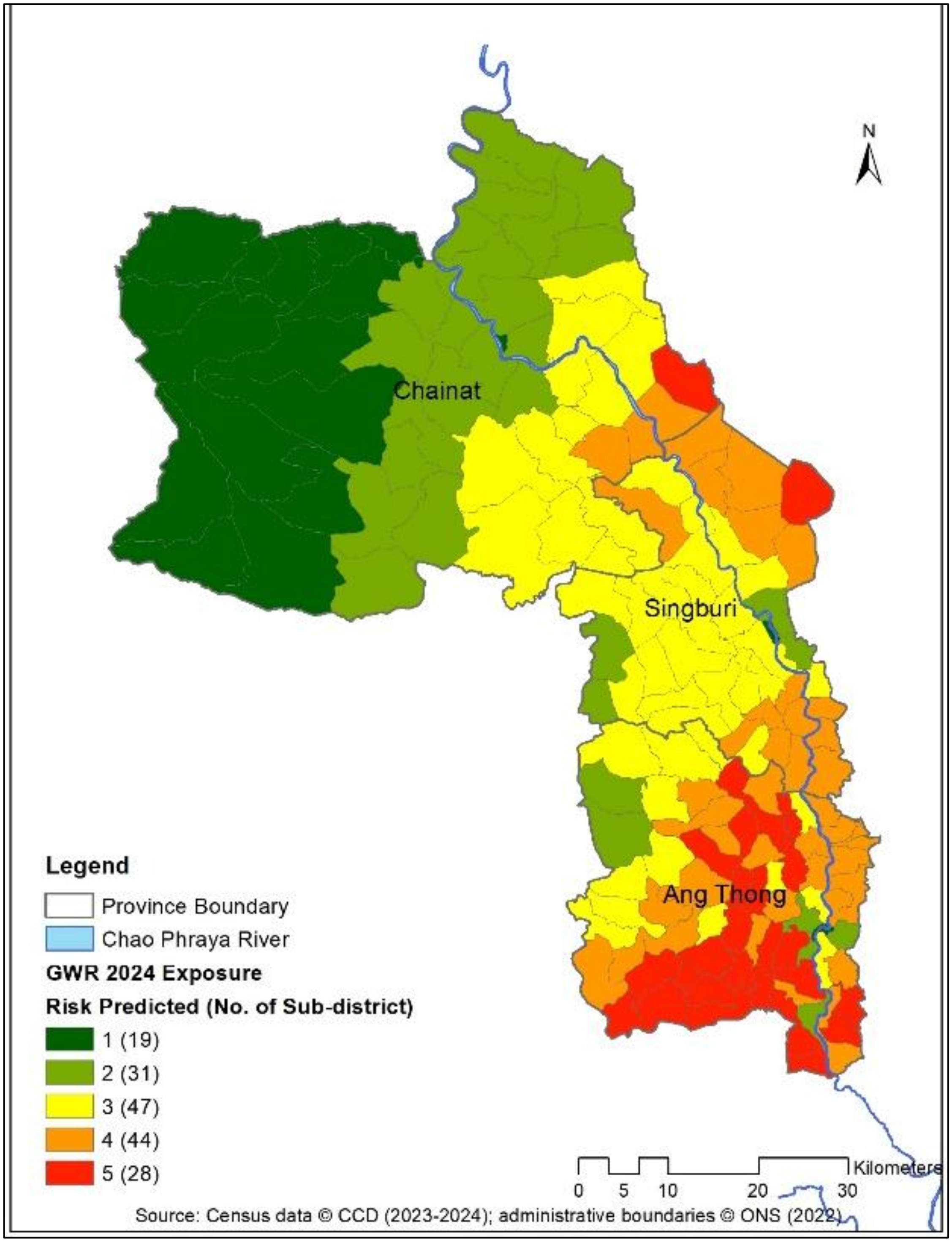


Figure 6.6. Exposure, 2024 census data

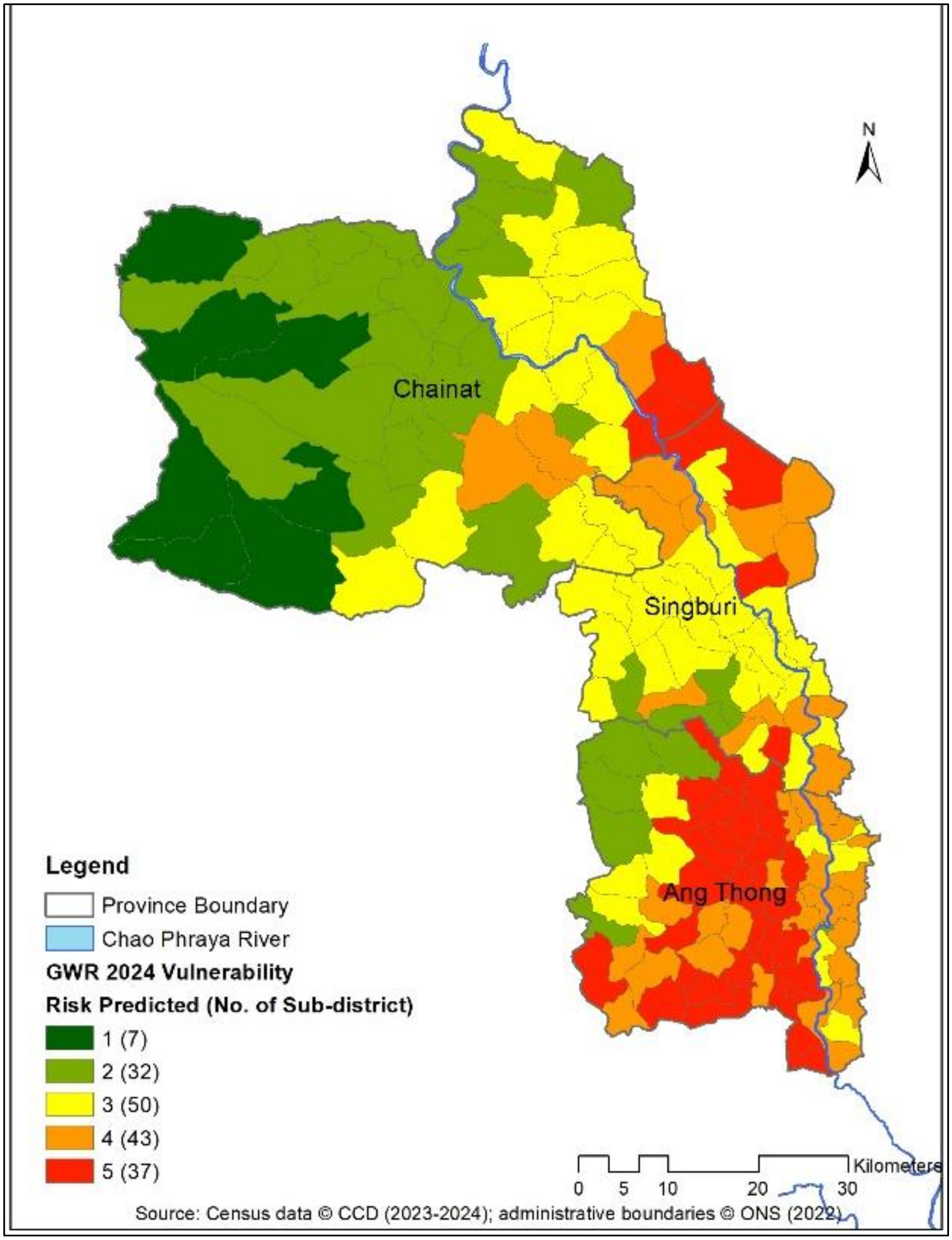


Figure 6.7. Vulnerability, 2024 census data

Figures 6.6 and 6.7 show Exposure and Vulnerability maps based on the 2024 Census data for comparison with Figures 6.4 and 6.5. When comparing the exposure maps between the results of the GWR of the census data of 2023 (Figure 6.4) and 2024 (Fig 6.6) years, it was found that both maps display a similar overall pattern, with the highest exposure values concentrated in Ang Thong and moderate levels extending into Sing Buri, while Chainat remains mostly low to moderate. The main difference is that the 2024 map shows a slightly stronger and more widespread concentration of high exposure values. A few sub districts in Ang Thong and Sing Buri shift into higher classes, and the highest-risk category increases slightly from 27 sub-districts in 2023 to 28 in 2024. These changes reflect small year-to-year variations in population density and building expansion, which slightly increase the predicted influence of exposure on flood risk. The spatial pattern remains consistent, but the 2024 results indicate a marginal intensification of exposure-driven risk.

The two maps (Fig 6.5 and Fig 6.7) compare the predicted influence of vulnerability-related socioeconomic factors on flood risk using GWR based on 2023 and 2024 census data, and although the overall spatial pattern remains similar, the 2024 map shows a stronger and more widespread vulnerability effect. In both years, the highest predicted vulnerability appears in southern and eastern Ang Thong, with moderate levels in Sing Buri and mostly low to moderate values in Chainat. However, the 2024 map shows a clear shift in class distribution, with the lowest vulnerability class decreasing sharply from 19 sub-districts in 2023 to 7 in 2024, while the highest categories expand significantly, indicating that more areas fall into high and very high vulnerability. These changes reflect year-to-year differences in socioeconomic conditions captured in the census, such as income, education, and savings, which slightly increase the predicted sensitivity of communities to flood impacts. Overall, both maps share a consistent spatial pattern, but the 2024 results depict a broader and more intense distribution of vulnerability-driven flood risk across the study area.

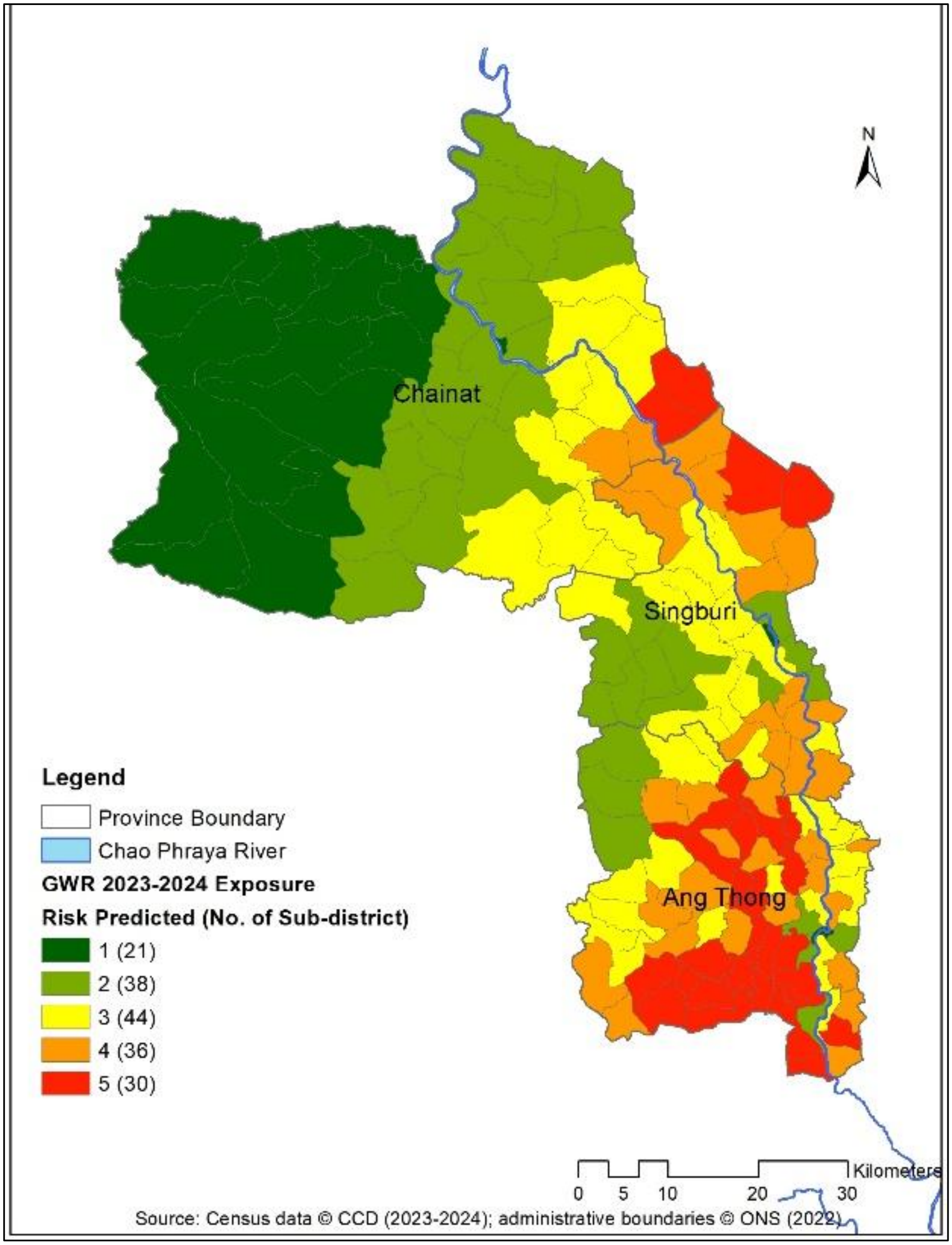


Figure 6.8. Exposure, combined (mean) 2023-2024 census data

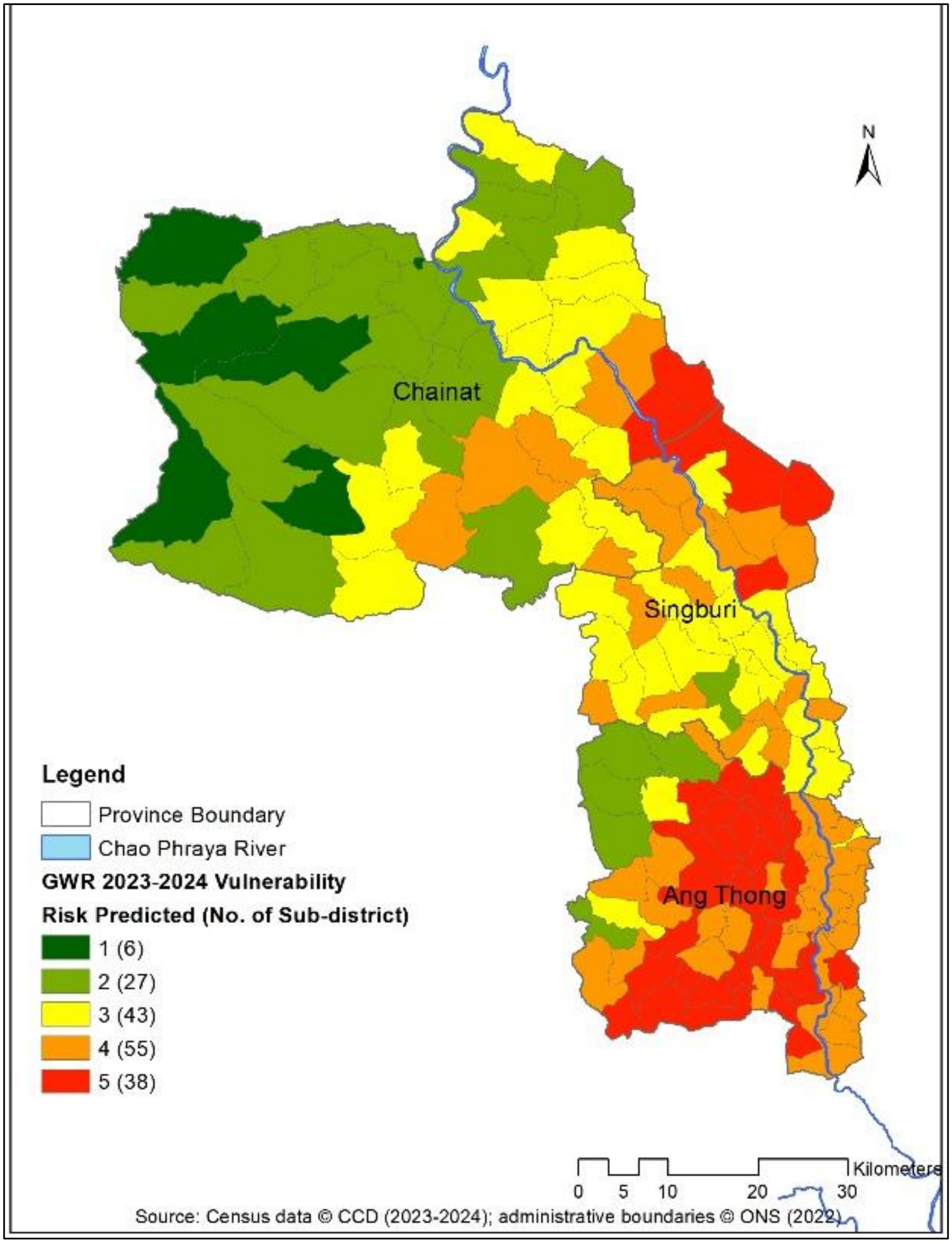


Figure 6.9. Vulnerability, combined (mean) 2023 and 2024 census data

Focusing on Exposure component of flood risk, the three maps (Figures 6.4, 6.6, 6.8) compare the predicted influence of exposure-related factors on flood risk using GWR, based on Census 2023 data, Census 2024 data, and a combined 2023–2024 dataset. Although all three maps share a similar overall spatial structure, with the highest exposure-driven risk consistently concentrated in Ang Thong and moderate levels in Sing Buri while Chainat remains largely low to moderate, there are clear differences in the intensity and distribution of exposure across the maps. The 2023 map shows high and very high predicted exposure mainly in southern and southeastern Ang Thong, with scattered moderate values across Sing Buri. Chainat displays mostly low exposure, reflecting its more rural and less densely settled character. In the 2024 map, the areas of high exposure become slightly more widespread, with several sub districts in Ang Thong and central Sing Buri shifting to higher exposure classes. The highest class increases slightly in count, which indicates subtle demographic or settlement growth between the two census years, such as an increase in population density or expansion of built-up areas.

The combined 2023–2024 map represents an average of both years and smooths out short-term fluctuations. While it still highlights Ang Thong as the most exposure-sensitive province, it reduces some of the extremes seen in individual years. Areas that appear very high in only one of the yearly maps tend to shift to moderately high in the combined version, giving a more stable representation of long-term exposure conditions. Sing Buri continues to show moderate exposure, and Chainat remains predominantly low, consistent with its lower building density and smaller population concentrations. Overall, the three maps demonstrate that exposure-driven flood risk is persistent in the same general areas, but year-to-year census variations slightly influence the intensity of predicted risk. The combined map provides the most balanced view by reducing annual noise and representing more stable exposure conditions across the study area.

Focusing on Vulnerability, the three maps (Figures 6.5, 6.7, 6.9) compare the predicted influence of vulnerability-related socioeconomic factors on flood risk using GWR based on Census 2023, Census 2024, and the combined 2023–2024 dataset. All three maps show a similar overall pattern, with the highest predicted vulnerability concentrated in Ang Thong, moderate values in Sing Buri, and mostly low to moderate values in Chainat. However, the intensity and distribution of vulnerability change clearly between the three versions. The 2023 map shows a relatively balanced spread across the five classes, with 19 sub-districts in the lowest category and 25 in the highest, indicating moderate but uneven vulnerability across the study area. In the 2024 map, vulnerability intensifies, with the lowest category dropping sharply to only 7 sub-districts and the highest category increasing to 37, showing that more areas have shifted into higher vulnerability classes due to year-to-year changes in socioeconomic indicators such as income, education, and household savings. The combined 2023–2024 map smooths these annual variations and provides a more stable representation of long-term vulnerability conditions. Although Ang Thong still shows the strongest vulnerability, the combined map reduces some of the extreme highs seen in the 2024 data and redistributes several sub-districts into moderate or moderately high categories. This averaging effect highlights consistent patterns of socioeconomic sensitivity while filtering out short-term fluctuations. The three maps show that vulnerability-driven flood risk is persistent in similar geographic areas, but its intensity varies between years, and the combined dataset produces the most balanced and stable spatial pattern.

6.4 Mapping of Flood risk assessment

This research employs the Crichton and Cutter risk triangle to develop a comprehensive spatial understanding of flood risk across Chainat, Sing Buri, and Ang Thong. The model integrates the three core dimensions of flood risk: the physical flood hazard, the level of exposure of people and built structures, and the underlying socioeconomic vulnerability of communities. By combining these dimensions, the assessment provides a more complete interpretation of flood risk than relying on hazard information alone. This framework also allows the research to capture how physical and social factors interact across different landscapes and settlement patterns. As a result, the study produces a more realistic understanding of which areas are likely to experience higher impacts during flood events and why these areas possess greater sensitivity or reduced capacity to respond.

To transform these components into spatially meaningful outputs, a detailed GIS-based workflow was carried out. The first stage involved processing the results produced by the GWR analysis, which identifies how strongly each factor explains flood patterns at the local scale. The GWR outputs were then reclassified using the Natural Breaks method, which separates the data into five classes that reflect natural groupings rather than arbitrary thresholds. Class 1 indicates the lowest influence on risk, while class 5 indicates the highest influence. This procedure ensures compatibility between the three components, allowing them to be analysed and visualised together within a single integrated spatial framework.

Once standardized, the three reclassified layers were combined through a GIS overlay procedure guided by the risk triangle concept. This method calculates a composite flood risk index by adding the hazard, exposure, and vulnerability values for each sub-district. The resulting index ranges from 3 to 15, where higher values represent locations with strong contributions from all components. Areas with scores near 15 mark locations where flood hazard is intense, where buildings and population are highly concentrated, and where socioeconomic vulnerability is substantial. These locations represent the most at-risk communities within the study provinces. The final flood risk maps provide a clear and spatially detailed representation of flood risk patterns across the three provinces.

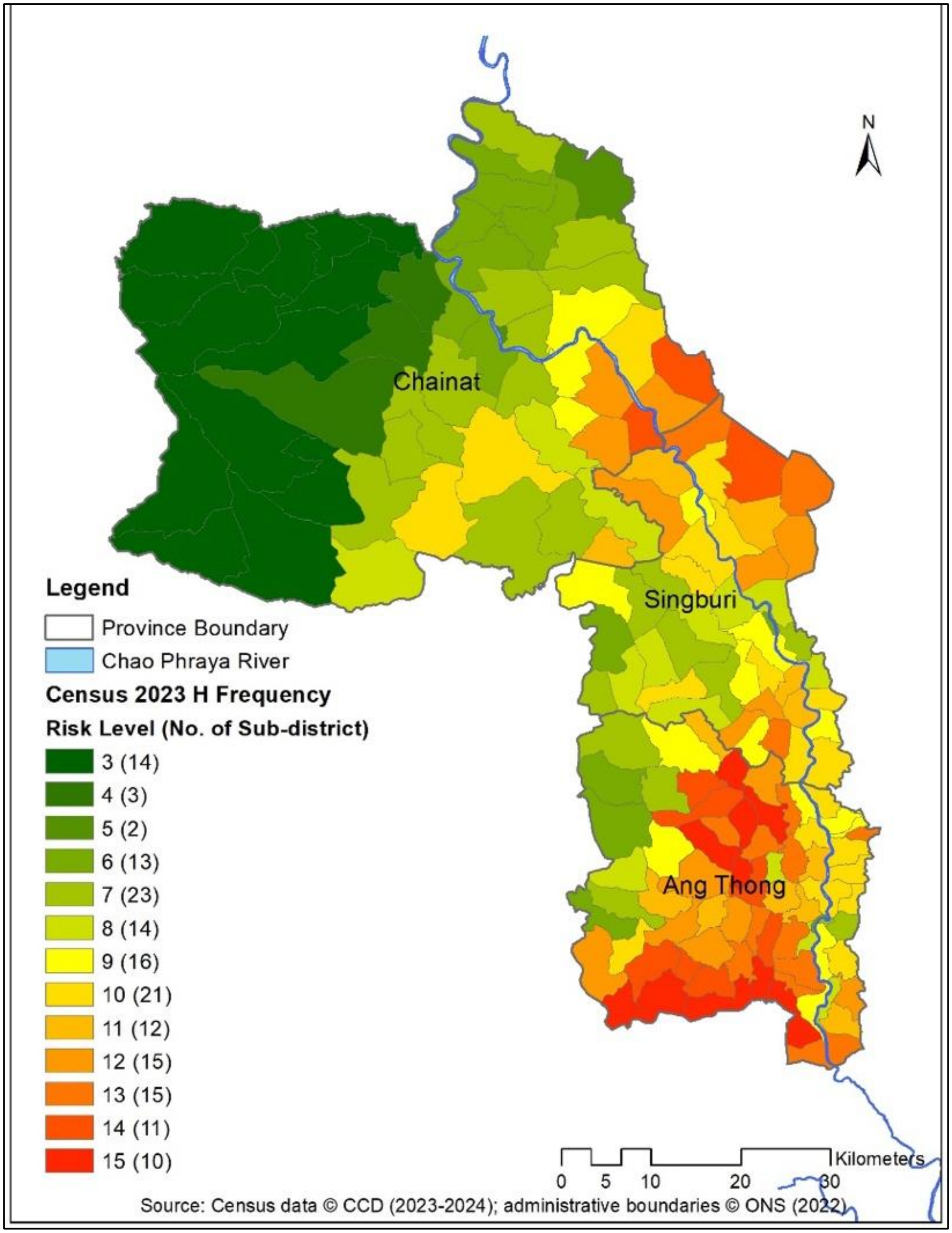


Figure 6.10. Modelled Flood Risk, 2023 Census data, H_frequency hazard

Table 6.9. Characteristics of the variable data for the flood risk index 15 (Census 2023, H-frequency)

No	ID	Subdistrict	District	Province	Hazard	Exposure			Vulnerability				
						Pop Density	Building Den	House Size	No Education	Less HighSc	Unemployed	Low income	Low Saving
Flood risk index					5	5			5				
1	150603	Phai Dam Patthana	Wiset Chaicharn	Ang Thong	3.72	230	92	3	17	817	7	4	162
2	150614	Lak Kaeo	Wiset Chaicharn	Ang Thong	3.12	185	63	3	66	1737	35	3	435
3	150607	Bang Chak	Wiset Chaicharn	Ang Thong	3.50	219	82	3	97	1612	46	9	905
4	150610	Phai Wong	Wiset Chaicharn	Ang Thong	3.43	152	50	3	56	1034	20	3	449
5	150307	Ekkarat	Pa Mok	Ang Thong	2.77	119	46	3	14	910	5	0	67
6	150507	Chamlong	Saweangha	Ang Thong	3.34	178	69	3	15	815	16	5	458
7	150414	Bang Chao Cha	Pho Thong	Ang Thong	3.07	192	73	3	27	871	22	12	284
8	150409	Khok Phutsa	Pho Thong	Ang Thong	3.32	157	72	2	13	756	23	15	667
9	150415	Kham Yat	Pho Thong	Ang Thong	2.74	140	60	3	18	1064	27	44	649
10	150411	Bo Rae	Pho Thong	Ang Thong	2.98	199	66	3	4	573	4	16	358

6.4.1 Modelled flood risk (2023 Census data, Flood Frequency Hazard)

Figure 6.10 illustrates a clear and well-defined spatial pattern in which the highest levels of flood risk are heavily concentrated within Ang Thong Province. Ten sub-districts, all located in Ang Thong, achieved the maximum composite risk score of 15, indicating that these areas represent the most critical hotspots within the study region (Table 6.9). These high-risk zones are clustered mainly in the southern and eastern portions of the province, where severe and recurrent flood hazards align with densely settled areas and communities exhibiting heightened socioeconomic vulnerability. This combination of physical and social factors strengthens the overall risk and explains why Ang Thong consistently emerges as the most flood-sensitive province in the model.

Moreover, Sing Buri Province also displays a substantial number of moderately to highly vulnerable sub-districts. These areas are largely situated along the Chao Phraya River basin, which has a long history of seasonal flooding and contains several urban and suburban centers with concentrated residential populations. The interaction between riverine flood processes and human settlement patterns contributes to elevated risk levels in these locations. By contrast, the spatial distribution of risk in Chainat Province is more dispersed, with most sub-districts classified within the low to moderate categories. The western and central regions of Chainat, in particular, show lower risk scores because these areas experience fewer flood events and contain more rural, widely spaced settlements. As a result, the combined influence of hazard, exposure, and vulnerability is less pronounced.

The map demonstrates the important role of hydrological conditions, settlement density, and socioeconomic characteristics in shaping the intensity and distribution of flood risk. It reinforces the need for targeted risk reduction strategies that consider both environmental and community-level factors.

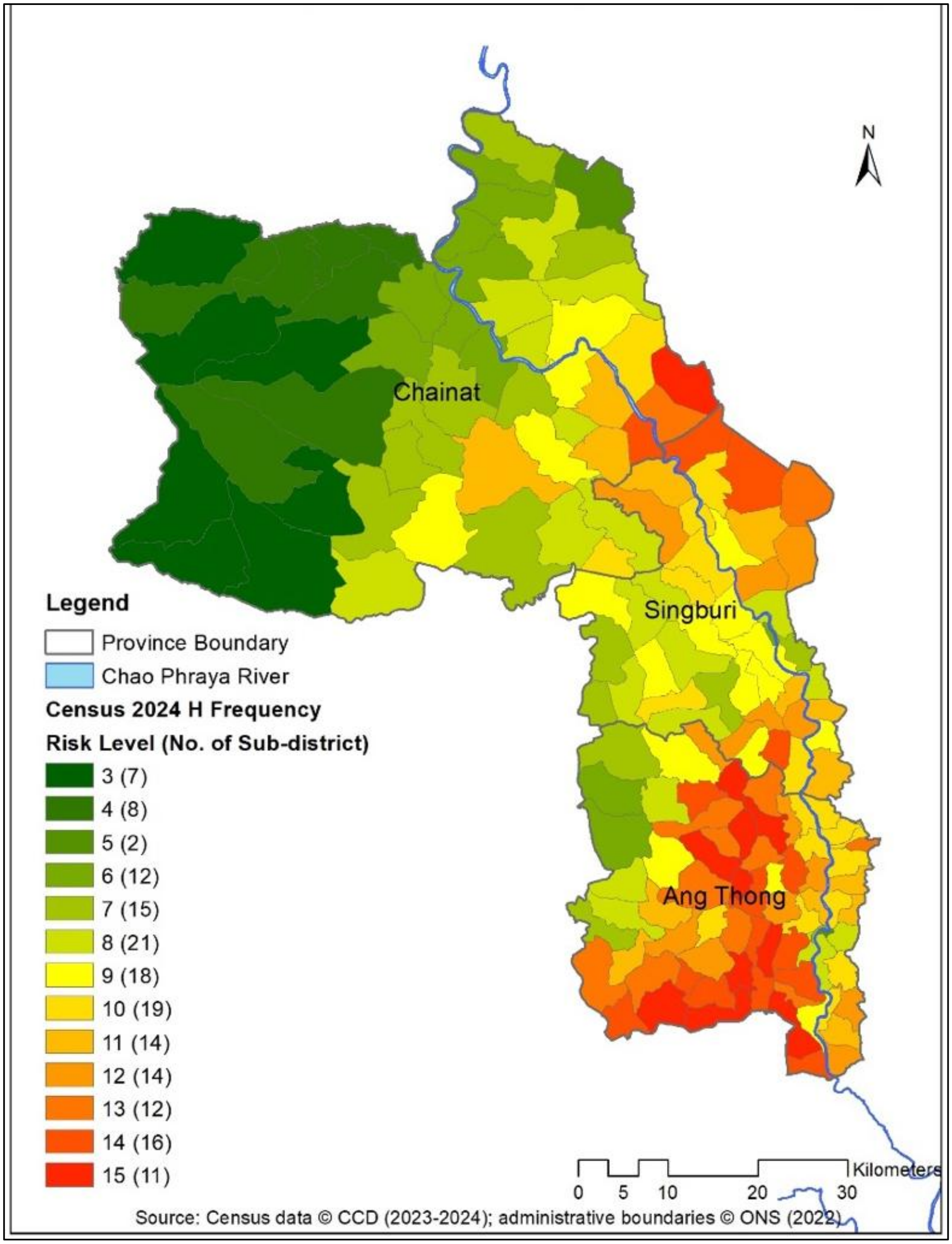


Figure 6.11. Modelled Flood Risk, 2024 Census data, H_frequency hazard

Table 6.10. Characteristics of the variable data for the flood risk index 15 (Census 2024, H_Flood Frequency)

No	ID	Subdistrict	District	Province	Pop Densit	Building Den	House Size	No Education	Less HighSc	Unemployed	Low income	Low Saving
1	150614	Lak Kaeo	Wiset Chaicharn	Ang Thong	181	63	3	58	1727	20	1	713
2	150607	Bang Chak	Wiset Chaicharn	Ang Thong	211	82	3	93	1557	89	3	1278
3	150307	Ekkarat	Pa Mok	Ang Thong	109	46	2	7	824	14	1	480
4	150507	Chamlong	Saweangha	Ang Thong	176	69	3	19	789	43	6	294
5	150414	Bang Chao Cha	Pho Thong	Ang Thong	199	73	3	28	906	145	1	663
6	150409	Khok Phutsa	Pho Thong	Ang Thong	157	72	2	12	749	20	3	696
7	150415	Kham Yat	Pho Thong	Ang Thong	133	60	2	16	1018	49	4	791
8	150411	Bo Rae	Pho Thong	Ang Thong	196	66	3	8	556	78	9	462
9	150107	Mahatthai	Muang Ang Thong	Ang Thong	117	59	3	12	557	10	0	362
10	150611	Si Roi	Wiset Chaicharn	Ang Thong	190	127	2	15	899	27	3	569
11	180403	Khao Kaeo	Sanphaya	Chainat	66	31	3	68	1150	31	1	290

6.4.2 Modelled flood risk (2024 Census data, Flood Frequency Hazard)

When compared with the 2023 flood risk map, the 2024 spatial pattern (Figure 6.11) shows both strong similarities and important differences across the three provinces. Ang Thong Province continues to display the highest concentration of flood risk in both years, indicating a stable pattern of severe hazard exposure, dense settlements, and persistent socioeconomic vulnerability. In both maps, the southern and eastern sub-districts of Ang Thong fall within the highest risk classes. However, in 2024 the number of areas receiving the maximum score of 15 increases from 10 to 11 sub-districts, demonstrating a measurable intensification of risk in the province. This change reinforces the finding that Ang Thong remains the most flood-sensitive province, and that its vulnerability may be increasing over time.

The maps of Sing Buri also show a similar overall pattern of moderate to high risk, especially in sub-districts located along the Chao Phraya River. Nevertheless, the 2024 results reveal slightly expanded clusters of elevated risk levels, indicating that annual variations in settlement density or socioeconomic factors may have increased exposure and vulnerability in certain river-adjacent areas. Chainat Province remains predominantly within the low to moderate risk categories in both years, reflecting its lower flood frequency, more rural settlement structure, and comparatively stronger socioeconomic conditions. The differences between years are minor, though the 2024 map shows a small decline in the number of lowest-risk areas, suggesting slight increases in risk in some locations.

The 2024 map retains the main spatial characteristics observed in 2023 but shows a broader and more intensified distribution of high-risk zones, especially in Ang Thong. The increase to 11 sub-districts scoring the maximum risk value highlights emerging pressures on local communities and emphasizes the need for strengthened flood management and resilience strategies.

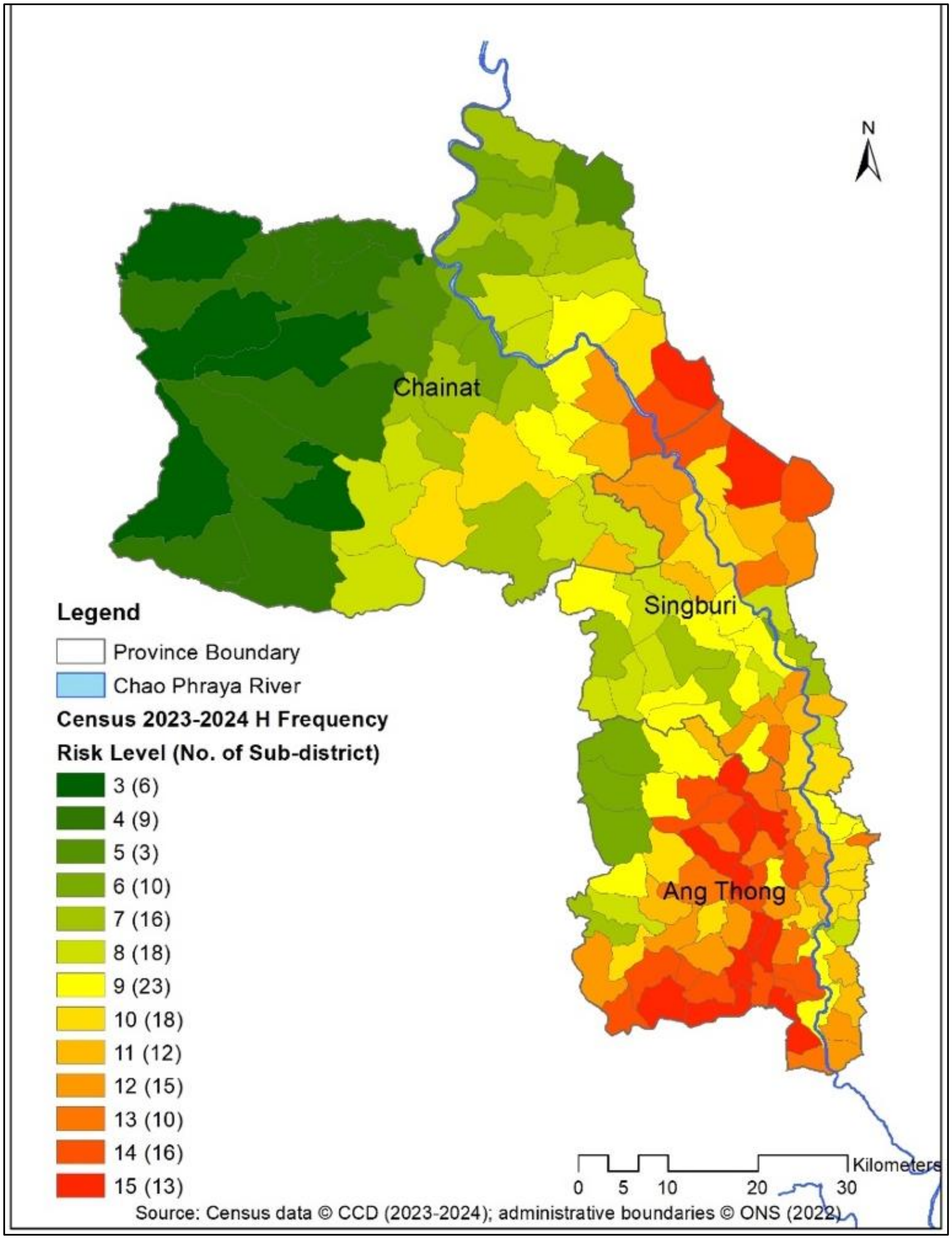


Figure 6.12. Modelled Flood Risk, combined (mean) 2023-2024 Census data, H_frequency

Table 6.11. Characteristics of the variable data for the flood risk index 15 (Average Census 2023-2024)

No	ID	Subdistrict	District	Province	Pop Density	Building Density	House Size	No Educatio	Less HighSc	Un employed	Low income	LowSaving
1	150614	Lak Kaeo	Wiset Chaicharn	Ang Thong	183	63	3	62	1732	28	2	574
2	150607	Bang Chak	Wiset Chaicharn	Ang Thong	215	82	3	95	1584	68	6	1092
3	150307	Ekkarat	Pa Mok	Ang Thong	114	46	2	10	867	10	0	274
4	150507	Chamlong	Saweangha	Ang Thong	177	69	3	17	802	30	6	376
5	150414	Bang Chao Cha	Pho Thong	Ang Thong	196	73	3	28	888	84	6	474
6	150409	Khok Phutsa	Pho Thong	Ang Thong	157	72	2	12	752	22	9	682
7	150415	Kham Yat	Pho Thong	Ang Thong	136	60	2	17	1041	38	24	720
8	150411	Bo Rae	Pho Thong	Ang Thong	198	66	3	6	564	41	12	410
9	150613	Hua Taphan	Wiset Chaicharn	Ang Thong	284	125	3	18	946	16	2	601
10	150107	Mahatthai	Muang Ang Thong	Ang Thong	118	59	3	13	558	10	1	284
11	150611	Si Roi	Wiset Chaicharn	Ang Thong	187	127	2	17	890	28	6	550
12	180403	Khao Kaeo	Sanphaya	Chainat	66	31	3	73	1160	34	1	346
13	170608	Thong En	Inburi	Singburi	121	57	3	82	2187	78	5	816

6.4.3 Modelled flood risk (combined 2023-2024 Census data, Flood Frequency Hazard)

Figure 6.12 illustrates the composite flood risk distribution for the combined (mean) 2023–2024 dataset, integrating flood hazard frequency with exposure and vulnerability indicators across Chainat, Sing Buri, and Ang Thong. By averaging census data from both years, this map provides a more stable representation of flood risk patterns, reducing the influence of year-to-year fluctuations in population, building density, and socioeconomic conditions. The risk index ranges from 3 to 15, where higher values indicate greater combined influence of flood hazard, exposure, and vulnerability.

The spatial pattern shows that Ang Thong Province continues to exhibit the highest overall concentration of flood risk. The southern and eastern sub-districts of Ang Thong display the most critical scores, including 13 areas reaching the maximum risk value of 15. These sub-districts lie within low-lying floodplain environments adjacent to the Chao Phraya River, where repeated flooding, dense settlements, and elevated socioeconomic vulnerability overlap. The clustering of high-risk zones in Ang Thong demonstrates persistent and compounded flood sensitivity across both years.

Sing Buri displays a widespread pattern of moderate to high risk, especially in sub-districts located along the Chao Phraya River corridor. These areas experience recurring inundation and contain significant residential and agricultural activity, contributing to higher composite risk scores. Furthermore, Chainat Province remains predominantly low to moderate in flood risk, especially in the western and central regions. These areas have fewer high-risk characteristics due to lower flood frequency, more dispersed settlement patterns, and comparatively stronger socioeconomic conditions.

The combined 2023–2024 flood risk map highlights consistent risk hotspots across the two years, offering a more robust understanding of long-term flood vulnerability. It reinforces the importance of prioritizing Ang Thong and river-adjacent areas of Sing Buri for targeted mitigation, preparedness, and resilience planning.

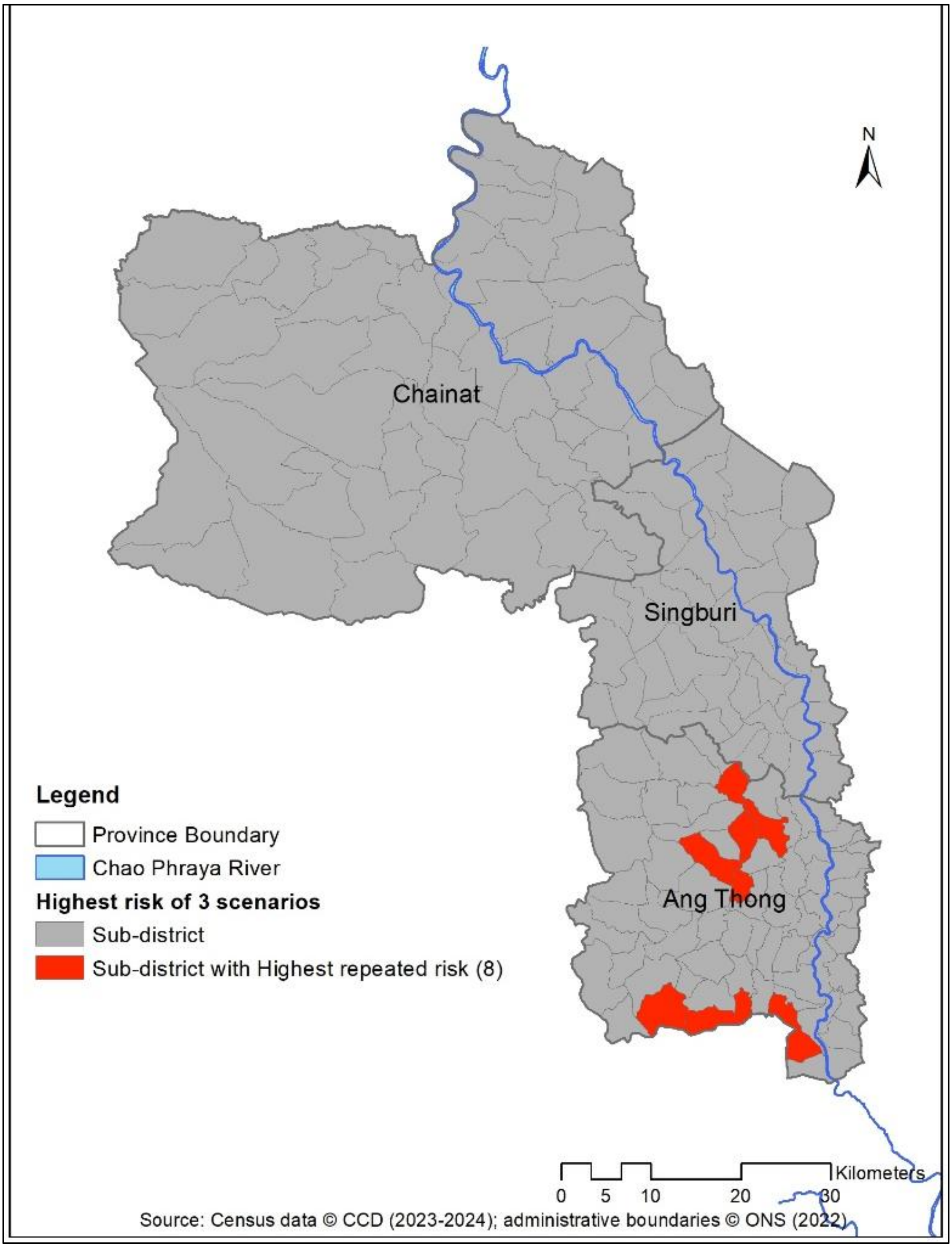


Figure 6.13. Flood risk map of the highest risk across the 3 scenarios

6.5 Sensitivity of variables

Figure 6.13 highlights the sub-districts that consistently appear in the highest flood-risk category across the three scenarios based on Census 2023, Census 2024, and the two-year average. Most sub-districts in Chainat, Singburi and Ang Thong are shown in grey, indicating that they do not repeatedly fall into the highest risk class. In contrast, eight sub-districts in Ang Thong are shown in red, representing areas that appear in the highest risk category across all three scenarios. These red sub-districts form a clear cluster along the Chao Phraya River and its surrounding floodplain, particularly in central and southern Ang Thong. Their repeated classification as highest risk suggests that these locations share persistent characteristics that elevate flood vulnerability, including river proximity, concentrated settlement patterns and lower socioeconomic resilience. The map therefore demonstrates that while risk levels vary across most of the study area, a core group of sub-districts in Ang Thong consistently remains highly exposed under all modelling conditions.

The sensitivity analysis provided a detailed understanding of how individual hazard, exposure, and vulnerability variables influence the final flood-risk outcomes across the study area. By examining changes in model performance under different data scenarios and variable configurations, the analysis reveals which indicators consistently drive spatial variations in risk and which contribute minimal or unstable effects. These results are essential for validating the robustness of the model because they highlight the relative importance of each variable, confirm the appropriateness of the selected predictors, and identify variables that introduce noise, redundancy, or instability. The findings also show how alternative data treatments such as raw census inputs, grouped classifications, and averaged datasets affect model responsiveness, demonstrating the implications of data-processing choices for risk estimation.

Following the findings in Section 6.2.2, the model derived from the 2023 census data, using flood frequency as the dependent variable, demonstrated the highest overall performance. The 2024 model and the two-year average model showed slightly lower effectiveness. Accordingly, this section uses the 2023 model as the primary benchmark and compares its results with the other years to assess shifts in flood-risk patterns and identify areas exhibiting the most substantial changes.

The analysis also investigates the specific variables that drive elevated risk across different locations, considering both physical characteristics and socioeconomic conditions.

Figure 6.14 illustrates the spatial variability of flood-risk classifications between the 2023 and 2024 census datasets across the three provinces of Chainat, Singburi, and Ang Thong. Sub-districts are symbolized using three colors that indicate the degree of change in flood-risk category: green represents areas with no change in risk level, yellow indicates a moderate change of one class, and red highlights sub-districts where risk shifted by two risk levels. The distribution shows that most sub-districts across the study area remained stable (92 in total), while a substantial number experienced single-level changes (71). Only a small group of sub-districts (6) exhibited more substantial variability, shown in red, and these are concentrated particularly along the Chao Phraya River corridor in Chainat and Ang Thong. Provincial boundaries and the course of the Chao Phraya River are clearly marked, helping to contextualize where risk variability is more pronounced. This pattern suggests that year-to-year fluctuations in risk are localized rather than widespread, with the most dynamic areas situated in river-adjacent zones.

As presented in table 6.12 and figure 6.15, the observed changes in variable values are closely associated with corresponding changes in flood risk levels. These relationships can be explained as follows.

- Bang Pla Kot shows an overall improvement in socioeconomic stability. Low income and low savings decreased notably, and the number of individuals with no education and those with lower educational attainment also declined. These changes indicate moderate strengthening in financial and social resilience.
- Bang Kaeo experienced a marked rise in financial vulnerability. The most significant change was a large increase in low savings, which signals a reduction in household financial buffers. Other variables remained relatively stable, placing financial insecurity as the primary area of concern.

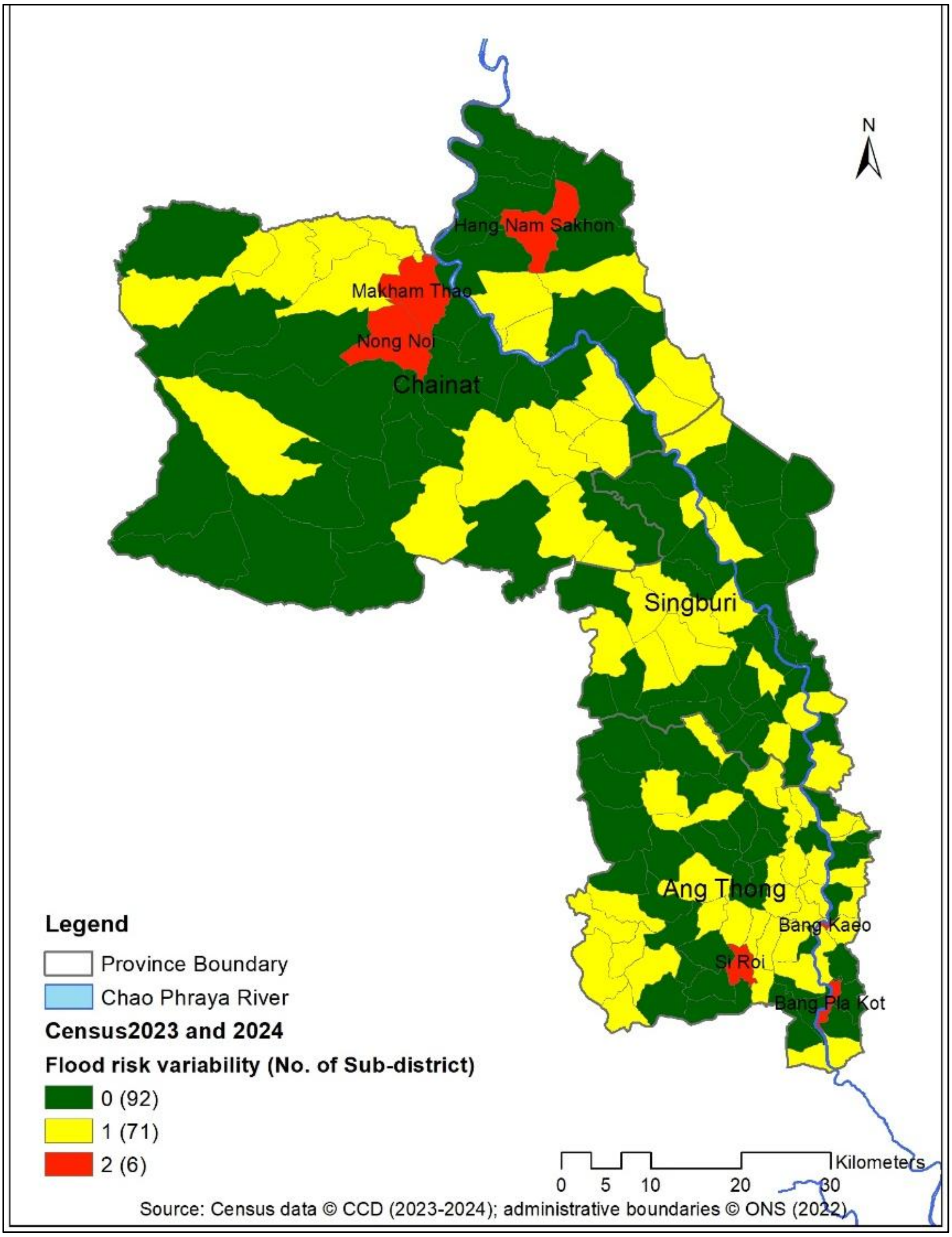


Figure 6.14. Flood risk variability of Census 2023 and 2024

Table 6.12. Changes in variables affecting risk change (2023 and 2024).

No	Sub-district	Exposure						Vulnerability									
		2023 Pop D	2024 Pop D	2023 Build D	2024 Build D	2023 House S	2024 House S	2023 No Edu	2024 No Edu	2023 Less HighSc	2024 Less HighSc	2023 Unemploy	2024 Unemploy	2023 Lowi nc	2024 Low inc	2023 Low Sav	2024 Low Sav
1	Bang Pla Kot	303	296	173	173	3	2	11	8	548	522	9	9	14	3	388	345
2	Bang Kaeo	1458	1446	476	476	2	2	1	0	274	263	0	0	15	16	12	76
3	Si Roi	184	190	127	127	3	2	19	15	882	899	28	27	8	3	532	569
4	Nong Noi	58	60	29	29	2	3	44	48	1368	1330	1162	66	3	8	627	580
5	Hang Nam Sakhon	105	104	52	52	2	2	47	38	1922	1902	31	34	41	11	1208	692
6	Makham Thao	88	88	43	43	2	2	85	104	1509	1481	80	101	25	1	699	1008

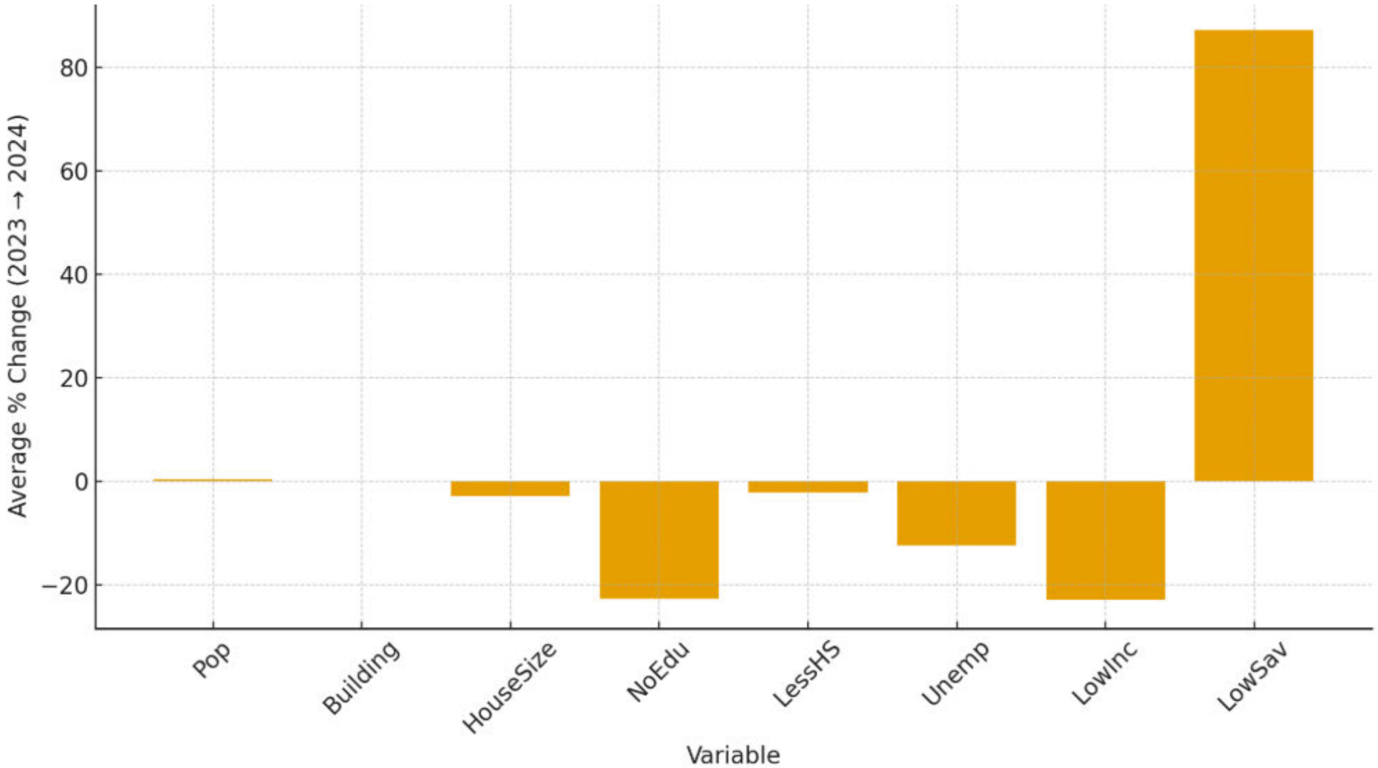


Figure 6.15. Chart of Percentage change in variable value to risk change

- Si Roi exhibited mixed changes. Household size and the number of individuals with no education decreased modestly, suggesting slight social improvements. However, low savings increased, indicating a growing financial vulnerability that may offset gains in other areas.
- Nong Noi experienced the most dramatic improvement among all subdistricts, with unemployment decreasing sharply from very high levels. Despite minor increases in low income and no education, the significant reduction in unemployment strongly enhances overall socioeconomic stability.
- Hang Nam Sakhon showed substantial improvements in economic conditions. Low savings, low income and no education decreased considerably, indicating stronger financial stability and improved social conditions. This subdistrict recorded some of the strongest positive changes across the dataset.
- Makham Thao displayed the most complex and contrasting changes. While low income declined sharply suggesting improved short-term economic conditions low savings increased substantially, indicating rising financial vulnerability. Increases in unemployment and no education also point to weakening social conditions. This combination reflects growing socioeconomic stress despite isolated improvements.

Overall, financial vulnerability demonstrated the widest variation across the study area. The contrasting movements in low savings and low income reveal that while some sub-districts experienced improvements in economic stability, others faced worsening conditions. This uneven spatial pattern underscores the dynamic nature of socioeconomic change and reinforces the importance of incorporating time-sensitive indicators into flood-risk assessments.

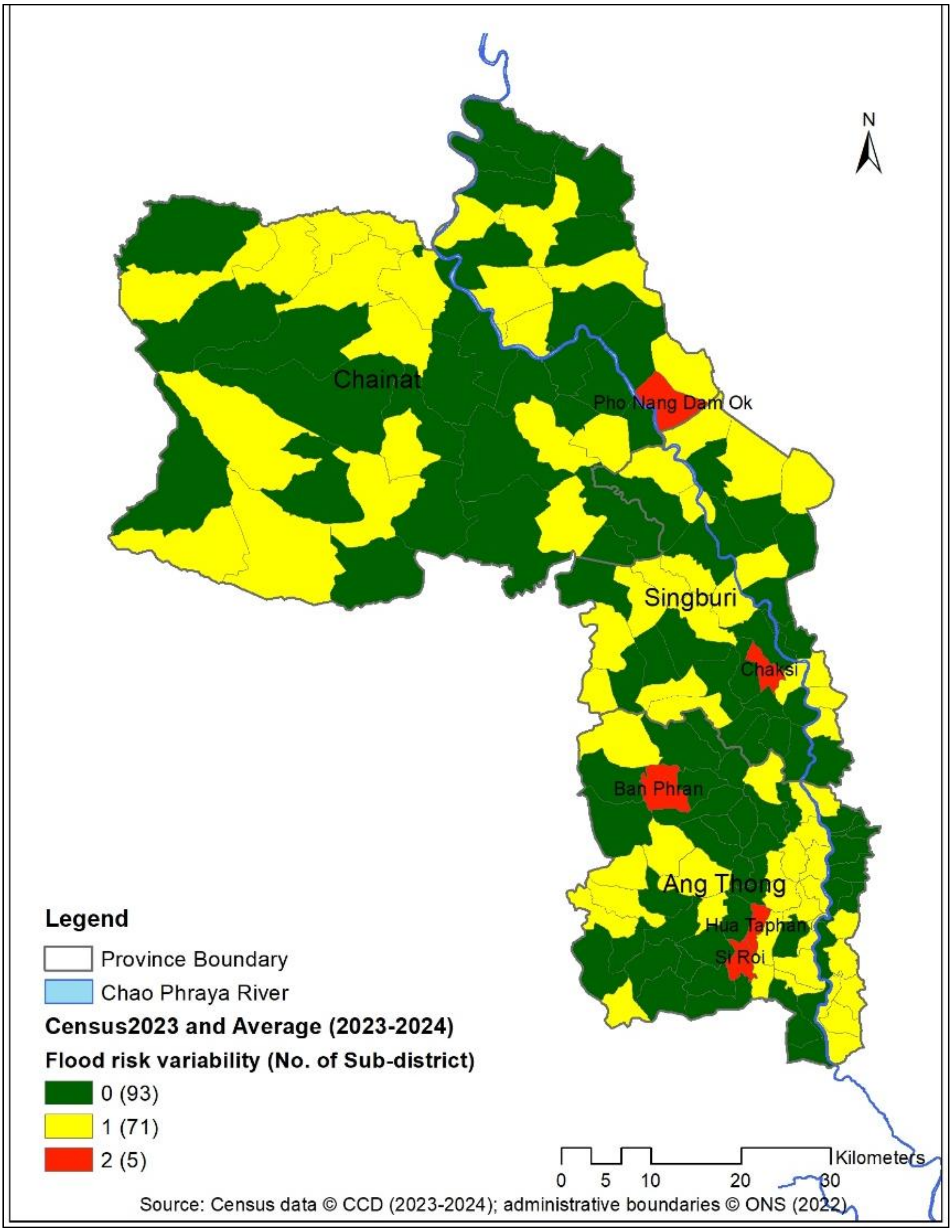


Figure 6.16. Flood risk variability of Census 2023 and Average (2023-2024)

Figure 6.16 displays the spatial variability of flood-risk classifications between the 2023 census dataset and the two-year averaged dataset (2023–2024) across Chainat, Singburi, and Ang Thong provinces. The majority of sub-districts (93 in total) remain stable, suggesting strong consistency between the 2023 and averaged datasets. A substantial number of areas (71 sub-districts) show a moderate, single-level shift, while only five sub-districts experience a more notable, two-level change. These higher variability areas, marked in red, appear predominantly along the Chao Phraya River corridor, particularly in parts of northern Chainat, central Singburi, and southeastern Ang Thong. The inclusion of province boundaries and the river network helps contextualize where variability is concentrated. This map indicates that the averaged dataset largely aligns with the 2023 distribution, with variability occurring mainly in river-adjacent zones where socioeconomic and exposure conditions are more dynamic.

Table 6.13. Changes in variables affecting risk change (2023 and Average)

No	Sub-distric	Exposure						Vulnerability									
		2023 Pop D	Avg Pop D	2023 Build D	Avg Build D	2023 House S	Avg House S	2023 No Edu	Avg No Edu	2023 Less HighSc	Avg Less HighSc	2023 Unemploy	Avg Unemploy	2023 Low inc	Avg Low inc	2023 Low Sav	Avg Low Sav
1	Chaksi	247	248	120	120	3	3	24	22	891	896	23	22	0	0	249	424
2	Ban Phran	149	148	70	70	3	3	106	106	1676	1658	37	62	7	5	834	858
3	Hua Taphan	285	284	125	125	3	3	20	18	955	946	19	16	2	2	592	601
4	Si Roi	184	187	127	127	3	2	19	17	882	890	28	28	8	6	532	550
5	Pho Nang Dam Ok	180	175	54	54	3	3	42	42	1748	1716	21	34	0	0	696	570

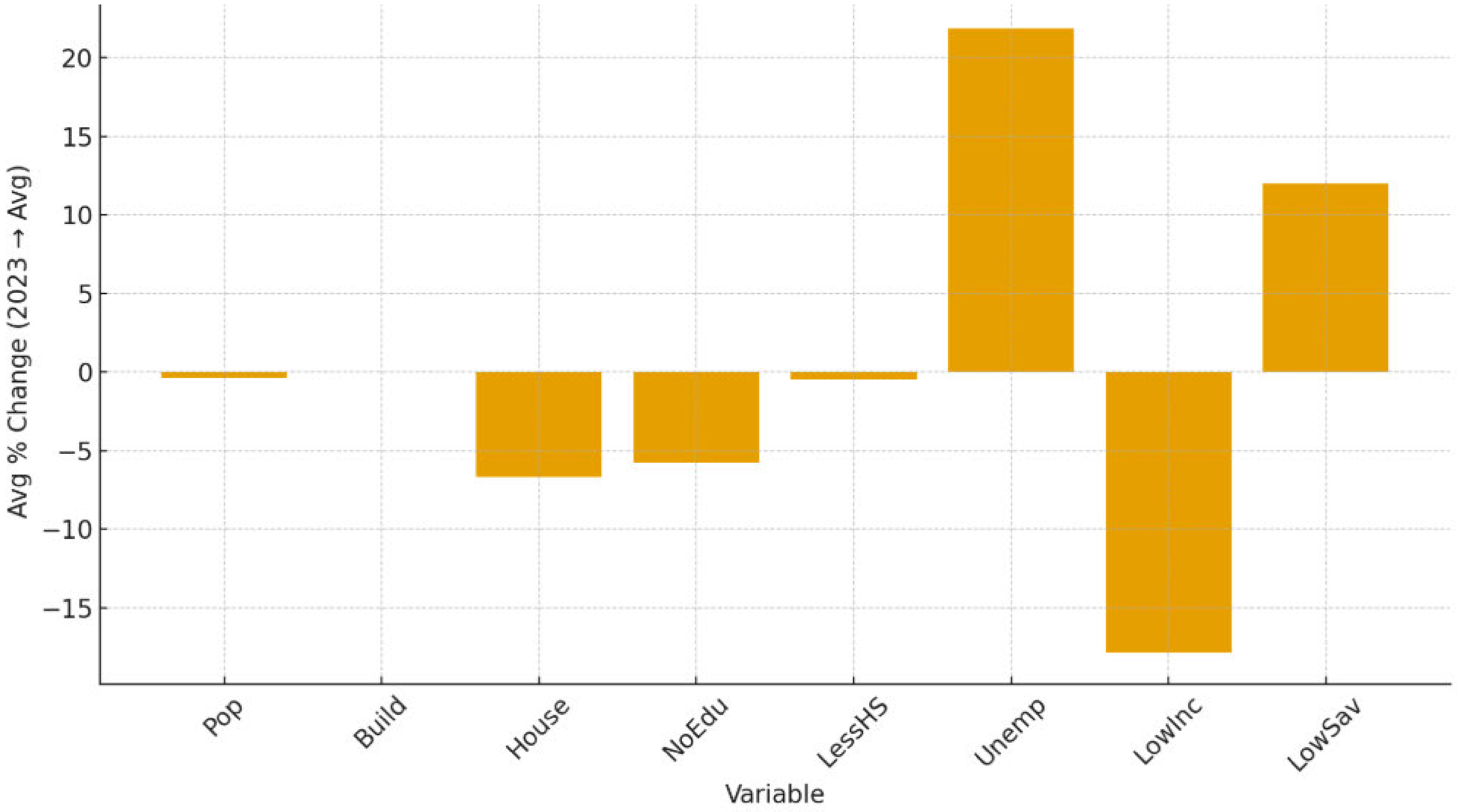


Figure 6.17. Chart of Percentage change in variable value to risk change (2023 and Average).

As presented in table 6.13 and figure 6.17, the observed changes in variable values are closely associated with corresponding changes in flood risk levels. These relationships can be explained as follows.

- Chaksi displays a generally stable pattern across most exposure and vulnerability indicators. Population density, building density and household size show negligible changes. Educational vulnerability exhibits a slight improvement, with small decreases in both no-education and lower-education groups. However, unemployment rises modestly, and low savings increases considerably from its 2023 level. This combination suggests that while social conditions improved slightly, household financial security weakened, signalling an emerging vulnerability in economic resilience.
- Ban Phran shows a more mixed and uneven pattern. Most exposure indicators remain unchanged, and educational measures remain stable. However, unemployment increases noticeably, indicating growing labour-market stress. Low savings also rises, implying that households face reduced financial cushions. Although low-income values improve, the concurrent rise in unemployment and declining savings suggest that the subdistrict is experiencing financial instability and shifting vulnerability dynamics.
- Hua Taphan experiences moderate improvements in educational indicators, as both no-education and lower-education categories decrease. Exposure indicators remain almost entirely stable. Unemployment shows a slight reduction, while low savings increases only minimally, suggesting households are experiencing both mild social improvements and stable financial conditions. Overall, Hua Taphan appears to be the most stable subdistrict, with only marginal vulnerabilities emerging.
- Si Roi presents a combination of improvements and emerging risks. Household size decreases slightly, suggesting small demographic shifts within households. Both educational indicators show moderate reductions, reflecting improved educational attainment. However, unemployment remains unchanged on average, and low savings increases moderately. These changes indicate that while educational vulnerability has improved, financial

resilience is weakening, potentially increasing sensitivity to future economic or environmental shocks.

- Pho Nang Dam Ok shows the most pronounced reduction in low-income households, indicating substantial short-term economic improvement. Educational and exposure indicators remain stable, and unemployment increases slightly. However, low savings decreases in this subdistrict, marking it as the only area not experiencing a worsening savings trend. Nevertheless, the contrast between improved income levels and fluctuating savings patterns highlights persistent financial instability that may affect households' ability to cope with future disaster impacts.

The analysis shows that vulnerability across the subdistricts is changing in uneven ways. While some areas demonstrate improvements in social indicators such as education levels and the share of low-income households, other areas show rising unemployment and increasing levels of low savings. These changes indicate that financial resilience is weakening in several locations, even where other aspects of vulnerability have improved. Overall, the results reveal that vulnerability is neither uniform nor static across the study area. Instead, it shifts differently from one subdistrict to another, underscoring the importance of treating vulnerability as a dynamic and spatially variable component within flood-risk assessment.

6.6 Conclusion

- The assessment of data availability and quality shows that Thailand's hazard, exposure and vulnerability datasets vary significantly in structure, completeness and reliability, creating important sources of uncertainty in the GIS-based flood risk model. These limitations, identified across the statistical, OLS and GWR analyses, highlight the need for careful data harmonization and indicator refinement before full model implementation. This directly prepares the groundwork for the next chapter, where the refined inputs are applied to create the integrated flood-risk maps.
- The comparison between UK and Thai datasets demonstrates that variables behave differently across national contexts due to contrasts in census design,

data collection practices and socio-economic conditions. These findings clarify which indicators can be transferred, which require adaptation and which must be excluded, informing the construction of the unified modelling framework used in the next chapter to produce composite flood risk outputs.

- The statistical diagnostics confirm the strong performance of flood-frequency hazard layers and reveal the instability of return-period data, showing which variables provide the most reliable predictive value for Thai conditions. These insights justify the selection of variables and modelling decisions carried forward into the next chapter, where the refined hazard, exposure and vulnerability components are combined to generate the final provincial-scale flood-risk assessment.

Chapter 7: Optimisation of flood risk modelling in the Chao Praya River Basin through incorporation of expert judgement

This chapter builds upon the analytical progression developed in the earlier stages of this research. Chapter 5 investigated the sensitivity of the flood risk model to inter annual variation in input data within a data-rich environment in Sheffield, United Kingdom. This analysis demonstrated how year-to-year differences in socioeconomic and hazard variables influence regression performance, coefficient stability and the consistency of spatial risk outputs. Chapter 6 then examined the transferability of the modelling framework to Thailand and identified the adjustments required to account for variations in data availability, data quality and dataset specifications across the Thai study provinces. In both chapters, the scaling, weighting and optimization of variables were guided by global academic literature and by statistical diagnostics generated through Ordinary Least Squares and Geographically Weighted Regression.

In this chapter, the optimization process is extended through the formal integration of expert knowledge from Thai practitioners who have direct experience with local flood behavior, socioeconomic vulnerability and regional governance in Ang Thong, Sing Buri and Chainat. This approach recognizes that expert judgement forms an essential part of environmental modelling. Krueger et al. explain that expert opinion is inherently embedded in modelling decisions and should therefore be elicited and documented systematically to improve transparency and reduce hidden subjectivity (Krueger et al., 2012). Their work supports the need for structured engagement with experts when defining model parameters, especially in contexts where formal data may be incomplete or uncertain.

7.1 Introduction

The chapter also draws on insights from participatory flood risk research. The value of local and situated knowledge lies in its ability to strengthen the quality and legitimacy of flood risk assessments, particularly in contexts where scientific modelling alone may not fully capture local hazard conditions, socio-economic realities, or community priorities (Maskrey et al., 2022). Their analysis demonstrates that involving practitioners and stakeholders in model development can enhance accessibility, contextual accuracy and the usefulness of resulting outputs for decision-making.

Using these foundations, Thai experts were interviewed and asked to evaluate the relevance of hazard, exposure and vulnerability variables, and to propose weighting schemes based on their practical experience. These expert-informed weightings were then incorporated into the established GWR modelling framework, allowing direct comparison with the statistically optimized scenarios from earlier chapters. The resulting outputs are analyzed to determine how expert-led parameterization reshapes spatial patterns of flood risk and how these differences relate to previously identified sources of uncertainty, including temporal variation, data transformation effects and sensitivity to hazard scenarios.

By combining expert perspectives with quantitative methods, this chapter demonstrates the practical value of local knowledge for refining variable selection and guiding future data collection. The integration of Thai expert judgement ultimately enhances the contextual relevance and decision-making utility of the flood risk model at the sub-district scale, reinforcing the importance of locally grounded parameterization within flood risk assessment frameworks for Thailand.

7.2 Expert Interview Methodology

7.2.1 Expert selection

The selection of experts is a critical methodological element that underpins the credibility and contextual relevance of this flood-risk assessment. Because flood risk is shaped by the combined influence of hydrological behavior, landscape characteristics, built-environment conditions, and socio-economic vulnerabilities, it is essential to involve individuals whose expertise spans these interconnected domains. In this study, experts were purposively selected based on demonstrated professional experience in hydrology, flood modelling, GIS-based spatial analysis, disaster management, Census dataset, and local government planning in Thailand. Purposive expert selection is widely recommended in multi-criteria and environmental decision-making frameworks to enhance relevance, reduce subjective bias, and strengthen the reliability of judgement-based procedures (Mendoza & Martins, 2006). The following presents a brief methodological overview of considerations in selection and interpretation of expert opinion.

Stages of modelling. The development of an expert-informed flood-risk assessment typically progresses through three interconnected stages: the parameterization of its components, and the evaluation of its performance and relevance. Each stage requires a distinct configuration of expert knowledge and methodological decision-making that collectively ensures scientific coherence, transparency, and practical applicability.

1. <u>Parameterization</u> translates the conceptual model into measurable, operational variables that can be used analytically. This process involves selecting appropriate datasets, defining variable thresholds, developing data normalization procedures, and assigning weights when required. Parameterization relies on expertise in GIS, data analytics, and socio-economic interpretation to determine the most suitable data transformations and classification schemes. In flood-risk studies, parameterization also includes designing scenario structures, selecting statistical models such as OLS or GWR, and ensuring that variables reflect both regional flood characteristics and local socio-economic conditions. Effective parameterization is essential for maintaining methodological consistency and reducing uncertainty in model outputs.
2. <u>Evaluation</u> assesses whether the conceptual structure and parameterized model perform effectively in representing spatial patterns of flood risk. This stage involves reviewing diagnostic indicators, testing model stability, comparing

predictions with known risk conditions, and validating the realism of outputs. Evaluation requires the combined input of hydrologists, spatial-analytics experts, and local disaster-management practitioners. Their judgments help determine whether the model accurately captures hazard–vulnerability interactions, whether statistical assumptions have been satisfied, and whether the outputs are meaningful and actionable for sub-district planning contexts. Rigorous evaluation enhances the credibility and usability of the model and supports continuous refinement.

Together, these two stages ensure that the flood-risk assessment framework is scientifically robust, methodologically transparent, and practically aligned with local decision-making needs. Their application reflects established best practices in environmental modelling, where conceptual clarity, rigorous parameterization, and systematic evaluation form the core of high-quality analytical design (Refsgaard et al., 2007).

Number of experts. Determining the number of experts for a study is guided by principles of expert elicitation, which priorities achieving an appropriate balance between disciplinary diversity and practical manageability. Although there is no fixed formula for calculating expert numbers, most approaches rely on three key considerations: the complexity of the problem, the range of disciplines involved, and the nature of the judgement required (Ayyub, 2001). Complex, multi-dimensional problems typically require broader representation, whereas tasks involving highly specialized reasoning are better supported by small, focused expert panels.

Literature on expert elicitation and environmental modelling also distinguishes between conceptual tasks, which rely on deep expertise from a few specialists, and parameterization or weighting tasks, which benefit from larger numbers to reduce individual biases and increase the reliability of aggregated judgement (Rowe & Wright, 1999). As a result, many environmental modelling studies adopt recommended ranges such as 3–5 experts for conceptualization, 10–20 experts for variable weighting, and 3–5 experts for technical evaluation (Ayyub, 2001; Rowe &

Wright, 1999). These principles ensure that expert input remains methodologically defensible and well aligned with the demands of each analytical stage.

Following these principles, this research adopts a two-stage expert-engagement framework commonly used in environmental and hazard-modelling studies. In a full modelling workflow, experts may contribute at three points. The first is the Parameterization Stage, which usually involves a larger panel of 10–15 experts whose role is to support variable selection, threshold setting, data interpretation, and evaluation of alternative modelling choices. A larger group is recommended here because parameterization is sensitive to disciplinary bias; drawing from multiple practitioners reduces subjectivity and strengthens the credibility of selected indicators. The second is the Evaluation Stage, which again normally engages a small group of 1–5 experts to perform detailed technical scrutiny, review diagnostic outputs, and validate the realism and operational relevance of the model (Refsgaard et al., 2007). This stage benefits from focused expert judgement grounded in modelling experience rather than broad participation.

In this research, experts were involved only in the parameterization stage, not in conceptual model construction or post-hoc evaluation. The conceptual structure of the hazard–exposure–vulnerability framework was already defined through the literature review, the pilot study in Sheffield, and the diagnostic work completed in earlier chapters. Similarly, model evaluation was carried out through statistical and spatial diagnostics rather than expert review. Therefore, expert engagement was deliberately limited to the stage where it would add the greatest value: providing insight on variable relevance, local data behavior, and the practical significance of different parameters within the Thai context. This enabled the study to assess how expert-informed parameter choices influence model outputs and to compare expert-weighted results with the data-driven GWR models. By focusing expert involvement at this stage, the research ensured that local knowledge was incorporated where it would have the strongest methodological impact, while maintaining consistency with established modelling principles.

Knowledge and Specialization of Experts. The experts engaged in this study possessed specialized knowledge that supported the multidisciplinary requirements of the flood-risk assessment. Their expertise covered hydrology and flood modelling, GIS and spatial analysis, disaster management, local planning, and community-based understanding. Hydrology and flood-modelling experts contributed detailed knowledge of flood frequency behavior, return periods and river dynamics, which informed the development of the hazard component. GIS and spatial-analysis specialists ensured methodological rigour in the preparation, classification and modelling of spatial datasets, including the application of OLS and GWR. Practitioners in disaster management and local planning provided operational insights into institutional capacities and development conditions at the provincial and sub-district levels. Equally important, local people and community representatives contributed experiential knowledge that was especially valuable for interpreting census-based socio-economic datasets. Their familiarity with local income patterns, household characteristics, employment conditions and educational differences provided essential contextual validation that national census data alone cannot fully capture. Integrating this community knowledge is widely recognized as a critical element of disaster-risk research because it enhances the accuracy, relevance and social legitimacy of vulnerability assessments and strengthens the link between scientific modelling and real-world lived conditions (Gaillard & Mercer, 2013; Mccall, 2008).

Defining 'expert'. In this study, an expert is defined as an individual who possesses specialized knowledge, substantial professional experience and proven competence in areas directly relevant to flood-risk assessment. This definition follows the perspective of Burgman (2016) who argues that expertise arises from both formal scientific training and long-term professional practice, rather than solely academic credentials (Burgman, 2016). Three forms of expertise are recognized. The first form includes scientific and technical specialists such as hydrologists, flood-modelling professionals and GIS analysts who contribute analytical and methodological knowledge. The second form includes practitioners in disaster management and local planning whose operational experience supports the alignment of model outputs with real decision-making processes. The third form includes community representatives whose situated knowledge of local socio-economic conditions enhances the interpretation of census datasets, reflecting the view of Gaillard and Mercer who emphasize that community-based knowledge is essential for capturing lived vulnerability patterns that formal data may overlook (Burgman, 2016; Gaillard & Mercer, 2013). Together, these expert types ensure that the assessment integrates scientific evidence, technical practice and local realities in line with established principles of expert elicitation.

Based on the literature reviewed, this study defined both the types of experts and the specific expertise characteristics required to support each stage of the assessment. The selection criteria were informed by established principles of expert elicitation, which emphasize aligning expert knowledge with the analytical tasks they are expected to inform. For this research, a total 12 experts were chosen not only for their disciplinary backgrounds but also for their ability to provide contextually grounded information, methodological insight and experiential explanations that directly address the research questions. This included the expectation that experts could interpret hydrological behavior, clarify the operational relevance of socio-economic variables, validate the suitability of census data at the sub-district level and assess whether the model outputs reflect real flood conditions. The resulting structure of expert types, along with their areas of specialization and anticipated contributions, is presented in Table 7.1.

Table 7.1. Types and specialization of experts

Types of experts	No. of Participant	Description of specialization
1. Parameterization		
Professional experts		
○ Academic - Thammasat university ○ Government - Community Development Department - Office for Prevention and Mitigation ○ Private - TEAM Consulting Engineering and Management PCL ○ Local authorities - Office for Prevention and Mitigation Sing Buri	P1, P2, P3, P9, P10, P11, P12	Academic • Support variable selection, interpretation of flood-related indicators and validation of socio-economic datasets • Advise on data transformations, threshold classification and justification of parameter choices Government • Explain the operational significance of variables such as local exposure, and socio-economic vulnerability • Contribute practical understanding of how variables behave during real flood events Private • Offer technical guidance on data preparation, model configuration and engineering-oriented variable significance Local authorities • Provide ground-level perspectives on variable relevance based on actual flood responses • Explain sub-district characteristics that influence exposure and vulnerability

Types of experts	No. of Participant	Description of specialization
Non-professional experts		
○ People with experience in flood area	P7, P8	• Provide lived knowledge of flood severity, temporal patterns and socio-economic impacts • Validate how census variables such as income, employment, household size and education translate into on-the-ground vulnerability • Offer insight into flood behaviors not fully captured in formal datasets
2. Evaluation		
Professional experts		
○ Local authorities - Office for Prevention and Mitigation Sing Buri	P4, P5, P6	Local authorities • Assess whether model outputs match actual flood conditions and administrative experience • Provide recommendations regarding causes, consequences and spatial patterns of risk
Non-professional experts		
○ People with experience in flood area	P7, P8	• Offer community interpretation of high-risk areas based on repeated flood experiences • Explain local drivers of vulnerability and confirm whether model predictions reflect real conditions

7.2.2 Interview and questionnaire design

The interview and questionnaire design in this study was developed to systematically collect expert judgement, professional experience and local knowledge needed to support the conceptual modelling, parameterization and evaluation stages of the flood-risk assessment. The design process followed formal institutional procedures to ensure ethical integrity, clarity of communication and methodological consistency.

The interviews were conducted online through telephone and mobile communication applications to accommodate participants' schedules and geographical constraints. All interviews were conducted in Thai to ensure that respondents could communicate comfortably and precisely, especially when discussing technical terminology related to flood risk assessment. At the beginning of each session, the interviewer introduced the purpose of the study, clarified the expected contributions from the interviewee, and outlined the structure of the questionnaire and discussion. A detailed explanation of the overall research process was provided, including how the data would be collected, how expert scores would be processed, and how the final results would be integrated into the spatial analysis to produce flood-risk maps. This introduction helped participants understand how their input would influence the weighting of variables and the development of the final risk assessment model. The interviewer also described the rationale behind using expert elicitation as a methodological step and its importance for model optimization and validation.

The explanation of the interview form covered all relevant components. This included clarifying the definitions of each variable, providing contextual information about how the indicators relate to hazard, exposure, or vulnerability, and discussing how these variables were previously used in the pilot study. Participants were encouraged to share their professional perspectives, discuss practical experiences from their agencies, and explain the reasoning behind their scoring decisions. This process helped capture not only numerical ratings but also qualitative insights that could guide interpretation of the results. Before beginning formal questioning, participants were asked for consent to record the interview. It was emphasized that recordings would be stored securely, used solely for research purposes, and would not be released publicly, in accordance with the approved ethical guidelines. Interviewees were reassured that their identities would remain confidential in the reporting of results. The last, participants were informed that they might be contacted again if clarification was required particularly in instances where their assigned scores differed from patterns emerging in the statistical analyses or from the flood-risk maps produced using OLS or GWR. This potential follow-up ensured the accuracy and iterative refinement of the expert weighting process, supporting both transparency and methodological rigour.

The questionnaire was structured into two comprehensive sections to ensure both the reliability of expert input and the clarity of variable evaluation. Section 1, “Expert Knowledge and Experience,” focused on gathering key background information necessary for interpreting the expert responses. This section requested the respondent’s name and contact details, professional affiliation, specific areas of expertise related to Model, Variable, Evaluation, Local flood officer, Others, and their primary responsibilities within their organization (e.g., Policy making, Operation Academic, Stakeholder). It also captured the number of years of experience in relevant fields to contextualize the level of authority and depth of knowledge behind each evaluation. This information was essential for validating the credibility of expert contributions and for distinguishing insights across different professional domains (Morgan, 2014).

Section 2, “Rating of Variables,” was designed with two structured tables to guide the evaluation process and minimize ambiguity. The first table presented the full list of 14 variables selected from the literature review and refined through insights gained during the UK pilot study. To ensure consistent interpretation across respondents, each variable was accompanied by clearly written rating criteria that explained what constitutes agreement or disagreement. Experts were asked to rate the importance or relevance of each variable using a five-level Likert scale: Strongly Disagree (–2), Disagree (–1), Neutral (0), Agree (1), and Strongly Agree (2). This scale enabled the identification of both consensus and divergence in expert judgment (Likert, 1932). The second table provided detailed definitions, contextual notes, and examples for each variable to support accurate evaluation. These explanations clarified how each indicator contributes to the hazard, exposure, or vulnerability dimensions of flood risk. For example, indicators such as population density, building density, and household size were described in terms of how they represent physical exposure, while variables such as levels of education, income, savings, and unemployment were contextualized as components of socioeconomic vulnerability. This supporting information ensured that respondents understood not only the variables themselves but also their role within the broader flood-risk assessment framework, thereby enhancing the reliability and interpretability of the expert-derived weights. The research questionnaire form shown in Appendix 2.

To enhance transparency, the interview materials is included a project workflow illustrating how the collected information would feed into the conceptual model, inform parameterization decisions and contribute to model evaluation. Providing this workflow ensured that participants understood how their insights would be integrated into the research, supporting informed, accurate and contextually grounded responses. Through this comprehensive design, the interview and questionnaire process contributed high-quality qualitative and semi-quantitative data essential for strengthening the scientific and practical validity of the overall flood-risk assessment, is presented in Appendix 2.

Ethics approval for this research was granted by the university following a formal review of the study's objectives, procedures and data collection methods. The approval confirms that the interview and questionnaire processes comply with institutional standards for confidentiality, informed consent and the responsible handling of participant information. The official ethics documentation is included in the appendix 2 for reference.

7.2.3 Data collection

Formal permission was required before conducting any interviews. For government agencies, approval documents were submitted from the interviewer's parent institution to the interviewee's parent agency in accordance with official administrative procedures. For private companies, respondents were contacted directly after receiving a clear explanation of the study's purpose and scope. In the case of local residents, coordination was carried out through local authorities to ensure appropriate participant selection, respectful engagement and accurate communication of the interview objectives.

Interviews were conducted online via telephone, and informed consent was obtained for audio recording in every session. Some government agencies preferred group interviews; in these cases, a hard-copy version of the interview form was later provided to confirm the accuracy of the discussion. For interviews involving local residents, local authorities assisted by clarifying questions, supporting communication and helping verify responses to ensure correct interpretation of local conditions and lived experience.

All appointments were arranged in advance by the project coordinator (Co-workers at GISTDA) in Thailand. Because Thailand is currently affected by widespread telephone fraud, many individuals are reluctant to answer calls from unfamiliar numbers. To avoid misunderstanding and ensure full cooperation, respondents or their agencies were contacted only at pre-agreed times through the coordinator. In several cases, respondents were officially designated by their organizations, meaning that direct personal contact information was not accessible to the research team. This agency-based coordination approach ensured institutional transparency, reduced participant concern and maintained adherence to organizational protocol.

The interviews followed a structured and carefully sequenced procedure designed to uphold ethical standards, maintain comparability across agencies and ensure high data quality. At the beginning of each session, the interviewer provided a clear introduction outlining the purpose of the study, explaining all variables used in the model and emphasizing voluntary participation and confidentiality in line with the university's ethics approval. Recording began only after explicit verbal consent.

The step-by-step procedure was as follows:

1) Submission of a formal permission request through the parent agency, accompanied by the questionnaire and an explanation of the research objectives.
2) Receipt of official approval and a list of designated respondents assigned to represent their organization.
3) Coordination of interview schedules by a Thai official (Participant No. 4), who confirmed suitable dates and times with each participant.
4) Conducting the interview at the agreed appointment time, including project introduction, explanation of all variables, clarification of instructions and request for permission to record.
5) Systematic documentation of responses, including variable weightings, qualitative explanations and participant comments, which were entered into Excel for processing.
6) Integration of expert-provided weights and explanations into the analytical workflow, supporting the production of expert-informed flood-risk maps for the study area.

This structured protocol ensured that data were collected consistently, ethically and with sensitivity to institutional constraints and cultural considerations, thereby reinforcing the reliability and validity of the expert-elicitation process. See interview dates in Appendix 2.

7.3 Data Analysis and Incorporation into Modelling

The data obtained from expert interviews, questionnaires and secondary datasets were processed through a structured, multi-stage analytical workflow designed to ensure accuracy, transparency and methodological consistency. This workflow brought together qualitative insights, expert-derived weights and statistical model outputs into an integrated framework for flood-risk assessment. The procedure ensured that both empirical behavior and practitioner knowledge informed the final modelling outcomes.

Data Preparation and Cleaning. All quantitative ratings, qualitative explanations and variable-specific comments collected from interview recordings and questionnaire forms were systematically entered into a structured Excel database. Each response was reviewed for completeness, internal consistency and clarity. This review included checking for missing entries, identifying unusually high or low values and ensuring that qualitative statements aligned with numerical ratings. When clarification was required, the coordinating agency contacted participants to verify or elaborate on their responses. The cleaned dataset was then cross-checked with the predefined definitions of hazard, exposure and vulnerability variables to ensure full alignment with the conceptual framework. This preparation provided a reliable foundation for the modelling stages that followed.

Transformation of Expert Scores into Variable Weights. Expert ratings were converted into numerical values based on the predefined five-point scale, which ranged from negative two (strongly disagree) to positive two (strongly agree). Weighted averages were calculated for each variable across all expert groups, capturing the collective judgement while limiting individual bias. These averages were then normalized to a 0 – 1 scale through a linear transformation, ensuring compatibility with the spatial multi-criteria evaluation framework. The normalized weights enabled direct comparison across variables and supported integration into the GIS modelling environment. Through this process, qualitative expert assessments were transformed into a structured set of quantitative weights suitable for spatial analysis.

Integration with Statistical Outputs. The expert-derived weights were compared with the results produced by the OLS analyses to examine the degree of alignment between expert judgement and empirical evidence. Variables showing strong statistical significance or spatial influence, including education level, income, savings and flood-frequency hazard, were reviewed alongside expert ratings to identify areas of agreement. Instances of divergence were examined in relation to local socio-economic conditions, institutional practices and historical flood experiences. This integrative assessment strengthened the modelling framework by combining objective statistical behavior with context-specific professional understanding.

Spatial Standardization and Reclassification. All hazard; exposure and vulnerability variables were prepared as GIS-compatible vector layers using a consistent sub-district boundary framework. Continuous variables were normalized using a min–max scaling approach that enabled indicators with different units and magnitudes to be directly compared. Reclassification procedures were applied to support interpretability within the multi-criteria environment. Flood-frequency hazard values were categorized using the Natural Breaks method to reflect the statistical distribution of the dataset. Socio-economic variables were reclassified based on expert-informed criteria that represented their influence on vulnerability. This spatial standardization ensured that all input layers were expressed in consistent forms appropriate for integration into the modelling workflow.

Geographically Weighted Regression (GWR) for Composite Index Generation. The final weighting scheme, developed from expert judgement and supported by statistical diagnostics, was integrated into a Geographically Weighted Regression framework to generate the composite Flood Risk Index for each sub-district. In contrast to global weighting techniques, GWR allows the coefficients of hazard, exposure and vulnerability variables to vary across space, capturing local differences in how these factors influence flood risk. Each predictor surface was calibrated using its locally estimated GWR coefficient, producing spatially explicit layers that represent context-specific importance rather than uniform, province-wide weights. These locally weighted hazard, exposure and vulnerability outputs were combined to produce a continuous flood-risk surface. This method provides a more realistic representation of sub-district variability, increases the sensitivity of the final index to local socio-environmental conditions and supports more precise identification of high-risk areas across the three provinces.

Map Production and Interpretation. The composite Flood Risk Index values were grouped into five categories using the Natural Breaks method to produce the final flood-risk maps. These maps illustrated spatial patterns of risk, highlighting sub-districts requiring prioritized planning and mitigation. Interpretation of the maps was supported through cross-referencing expert insights, statistical findings and known local flood conditions. This triangulated approach ensured that the final mapped outputs reflected both quantitative evidence and practitioner understanding, strengthening the credibility of the results.

Validation and Sensitivity Analysis. Validation was achieved by comparing the expert-informed flood-risk map with the map generated solely through statistical modelling. Differences in spatial patterns were identified and analyzed to determine which variables were responsible for the observed variations. Each indicator was assessed to evaluate how changes in its weighting or classification influenced the final risk outcomes. Variables that produced notable changes were interpreted as sensitive and influential components of the model, while those with limited impact were considered stable contributors. This sensitivity assessment enhanced the transparency and robustness of the final flood-risk model.

7.4 Results

7.4.1 Expert opinion on selection of variables

Expert opinion forms a crucial component of this study by providing context-specific insights that complement and enhance the quantitative modelling results. Although the statistical analyses offer an objective assessment of variable behavior and spatial patterns, experts contribute nuanced interpretations informed by their institutional responsibilities, operational experience and understanding of local socio-economic dynamics. Their perspectives are especially valuable in areas where data alone may be insufficient to capture complex or evolving flood-risk conditions.

Importantly, the expert feedback collected during interviews and questionnaire evaluations revealed not only areas of strong consensus but also clear points of divergence in how different practitioners assess the relevance and behavior of certain variables. These differences are particularly instructive, as they highlight limitations in the current variable definitions, gaps in available datasets, and variations in local context across the study area and differences in how agencies perceive or priorities flood-risk drivers. Rather than treating these discrepancies as inconsistencies, they are used in this study as a basis for refining the variable set, improving the weighting structure and guiding revisions for future model iterations.

Emphasizing these points of difference allows the modelling framework to evolve in a more informed and realistic manner. Diverging opinions indicate were additional clarification, restructuring or reclassification of variables may be necessary. They also reveal where certain indicators require improved definition, more context-sensitive thresholds or a more nuanced representation within the spatial database. As a result, the expert recommendations not only strengthen the interpretive validity of the current model but also provide a roadmap for enhancing the conditions, weighting and operationalization of variables in subsequent versions of the flood-risk assessment framework.

Table 7.2 presents a summary of the recommendations made by experts during the elicitation interviews.

Table 7.2. Summary expert recommendation

Variables	No. Participant	Recommendation
Hazard		
H1 Hazard zone	P1, P2	• When considering the overall picture, if an area has a high flood frequency, there is a chance that it will flood again in the future because it is a physical factor of the area. • The elevation may also need to be considered. • Consideration may need to be given to building flood defenses.
Exposure		
E1 Density of Buildings	P6, P7, P8	• Particular consideration may be given to densely packed buildings near rivers as they may overflow. • Some dense areas are high-rise buildings, so people living on high floors may not be affected.
E2 Population density	P5, P6	• Materials and strength in building construction may also be considered. • It may depend on the survival skills of the residents.
E3 Landuse	P1, P9	• Drainage of the area may also need to be considered.
E4 Size of household	P3, P5, P6, P9	• Building preparedness for flooding and evacuation routes may need to be considered. • It may not affect all families with good jobs. • It may depend on the survival skills of the residents.
Vulnerability		
V1 Children	P2, P4, P11, P12	• May be considered at 9 years of age because they are still unable to read and understand signs. • It is recommended to use the age 5 criterion because children are already entering nursery school, which is where the census collects this information.

Variables	No. Participant	Recommendation
V2 Elder	P4, P11, P12	• Those over 60 years old are classified as elderly.
V3 Gender	P2, P5, P6, P9, P10, P11, P12	• The reason is that women have less power than men, which makes it difficult to move. • There is concern that there may be issues of equal rights involved. • In some families, only the woman is the main breadwinner of the family.
V4 Education	P1, P2, P3, P6, P9, P10, P11, P12	• Able to use demographic data for people aged 15-59 years to read, write Thai and do simple math. • Education is not a barrier to mobility. • Providing training related to frequent flooding may enhance understanding of evacuation and survival.
V5 Employed	P3, P9, P10	• Having a job is not a barrier to moving or making repairs to your home, like a person without a job may have an income. • A person without a job may be someone who has an income, such as an elderly person who receives a grant or pension. • Occupation is not a barrier to mobility.
V6 Income	P3, P9, P10, P11, P12	• Calculated from the average income of the entire household. If a household has many people but there is only one income earner, the income will be divided by the average of the total number of people in the household. • Income is not a barrier to mobility.
V7 Older_care		No recommendation
V8 Disabled		No recommendation
V9 Illness		No recommendation

Based on the expert feedback summarized in Table 7.2, the key recommendations can be outlined as follows:

- **Hazard:** Experts agreed that areas with high historical flood frequency are likely to flood again, reflecting inherent physical characteristics of the landscape. They suggested that elevation and the presence or absence of flood-defense structures should also be considered when assessing hazard.
- **Exposure:** Experts emphasized that densely built areas near rivers are particularly vulnerable, although high-rise buildings may reduce risk for residents on upper floors. Additional factors such as construction quality, drainage conditions and preparedness (including evacuation routes) may influence exposure. Household size may not always increase risk if families have stable incomes or strong coping skills.
- **Vulnerability:** Experts recommended defining children as under age 5–9 due to limited ability to read warnings, and classifying elderly as those over 60. Views on gender and employment varied, with some noting that gender may affect mobility while others highlighted issues of equality and diverse household roles. Education was widely seen as important for understanding warnings, and income should be assessed at the household level. No specific recommendations were provided for variables relating to care of older persons, disability or illness.

7.4.2 Expert weighting

The expert-weighting results provide valuable insight into how practitioners, government officials, academics and local stakeholders understand the relative importance of the variables included in the flood-risk assessment model. Whereas the statistical analyses establish an empirical picture of how each indicator behaves within the study area, the expert input adds a complementary layer of contextualized knowledge grounded in practical experience, institutional responsibilities and local flood-management practice. Integrating these perspectives enhances the interpretability, realism and policy relevance of the final outputs, reflecting broader recommendations in the literature that expert judgement should supplement quantitative modelling in complex environmental systems, as noted by Birkholz et al. (2014) and Jakeman et al. (2006).

The results summarized in Table 7.3 present the collective evaluations of the participating experts, including raw rating distributions, normalized weights and areas of convergence or divergence between respondent groups. These patterns show which variables are perceived as most influential in shaping flood risk and which indicators hold lower practical priority. They also highlight differences between professional sectors, supporting findings from earlier studies showing that risk perception varies with institutional roles, experience of past events and operational responsibilities. This trend mirrors the work of Kellens et al. (2013) and Wachinger et al. (2013), who similarly report that experts with emergency-response or engineering roles priorities physical hazards, while those in social or community-based roles emphasize vulnerability and coping capacity.

The expert priorities show strong alignment with existing research on flood vulnerability, particularly studies by Cutter et al. (2003) and Rufat et al. (2015), which emphasize disability, age and socio-economic fragility as key drivers of risk. In contrast, the mixed expert views on exposure variables mirror wider debates in the literature about the dual role of urban density and household structure, which can either heighten or lessen flood impacts depending on local infrastructure and social organization, as noted by Baldassarre et al. (2013). These parallels indicate that the variations observed in this study reflect broader, cross-context challenges in interpreting exposure rather than isolated inconsistencies.

Overall, the expert-derived weights provide an important interpretive lens that enriches the quantitative modelling; while also identifying were clearer conceptualization, improved data definitions or further stakeholder engagement may be required to refine future iterations of the flood-risk assessment model.

Table 7.3. Expert scores and weighting

Variable	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	Average (Likert)	Stdev	Weighting factor (0-1)
Hazard															
H1 Hazard	2	2	1	2	1	2	1	1	2	2	1	1	1.5	0.5	0.88
Exposure															
E1 Building density	1	2	1	1	1	-2	-2	-2	0	0	1	1	0.17	1.34	0.54
E2Population density	1	2	1	2	-1	-1	1	1	1	1	1	1	0.83	0.9	0.71
E3 Land use	2	1	1	2	1	2	1	1	-1	-1	1	1	0.92	0.95	0.73
E4 Size household	0	1	0	2	-1	-1	1	1	-1	-1	1	1	0.25	1.01	0.56
Vulnerability															
V1 Children	1	-1	2	2	1	1	1	1	1	1	1	1	1	0.71	0.75
V2 Elderly	1	1	2	2	1	1	1	1	1	1	1	1	1.17	0.37	0.79
V3 Gender	-1	-1	1	1	-2	-2	1	1	-1	-1	1	1	-0.17	1.21	0.46
V4 Education	-2	-1	-1	1	1	0	1	1	-1	-1	1	1	0	1.08	0.50

Variable	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	Average (Likert)	Stdev	Weighting factor (0-1)
V5 Employment	0	1	-1	2	1	0	1	1	0	0	1	1	0.58	0.76	0.65
V6 Income	1	1	-1	2	1	0	1	1	0	0	1	1	0.67	0.75	0.67
V7 Older care	2	2	1	2	1	1	1	1	2	2	2	2	1.58	0.49	0.90
V8 Disabled	2	2	1	2	2	2	1	1	2	2	2	2	1.75	0.43	0.94
V9 Illness	2	2	1	2	2	1	1	1	2	2	2	2	1.67	0.47	0.92

Following Table 7.3, the expert-weighting results demonstrate distinct patterns in how practitioners across government agencies, academic institutions, private organizations and local authorities understand the drivers of flood risk. Overall, experts consistently prioritized hazard intensity and socio-economic vulnerability, while exposure-related indicators received more varied evaluations. This distribution of perspectives provides important insight into local interpretations of risk and highlights areas where variables may require refinement in future modelling.

Hazard received uniformly high ratings, indicating that practitioners across all sectors regard flood frequency and intensity as the most critical determinants of risk. The high average and low variability confirm that hazard remains the central component of flood-risk assessment in the study area, aligning closely with the results from the statistical analyses.

Vulnerability indicators exhibited the strongest consensus. Variables such as disability, severe illness, and elderly care needs achieved the highest mean values and the lowest standard deviations, showing near-universal agreement that these groups are significantly less able to respond to, cope with, or recover from flood events. Other socio-economic indicators like income and employment status also received broadly positive assessments, reflecting an understanding of financial capacity as a major determinant of household resilience.

In contrast, exposure variables showed the greatest variability in expert judgement. Building density and household size produced highly divergent ratings, suggesting differences in interpretation between agencies. Some experts viewed dense built environments as high-risk areas due to concentration of people and assets, while others associated them with better infrastructure, flood protection or emergency response capability. Similarly, household size elicited both positive and negative assessments, indicating uncertainty around its conceptualization as an exposure or vulnerability factor.

Two variables, gender and education, produced particularly mixed responses. Their near-zero mean values and high standard deviations reflect a lack of shared understanding of their roles in local flood risk. These results suggest that both indicators require clearer definition, improved operationalization or contextual adjustment in the next iteration of the model.

Taken together, the expert-weighting outcomes show that practitioners place the greatest emphasis on hazard and vulnerability, while exposure-related variables generate more interpretive differences. These results not only guide the prioritization of variables in the modelling process but also highlight where conceptual clarification, data refinement or stakeholder engagement may be needed to improve the accuracy and relevance of future flood-risk assessments.

7.4.3 Integrating expert weighting with statistics

The expert-assigned weights were subsequently evaluated through statistical analysis using Ordinary Least Squares to ensure consistency with the model's variable-selection framework. Two diagnostic parameters were used to assess the reliability of each expert-weighted variable: the Variance Inflation Factor, which detects multicollinearity, and the p-value, which indicates statistical significance. The same inclusion thresholds applied in the main modelling process were adopted here, specifically a VIF threshold of 7.5 and a significance level of $p < 0.01$. This procedure allowed the expert-derived weights to be cross-checked against objective statistical behavior, ensuring that the selected variables were both conceptually justified and empirically supported. The outcomes of this assessment are presented in Table 7.4.

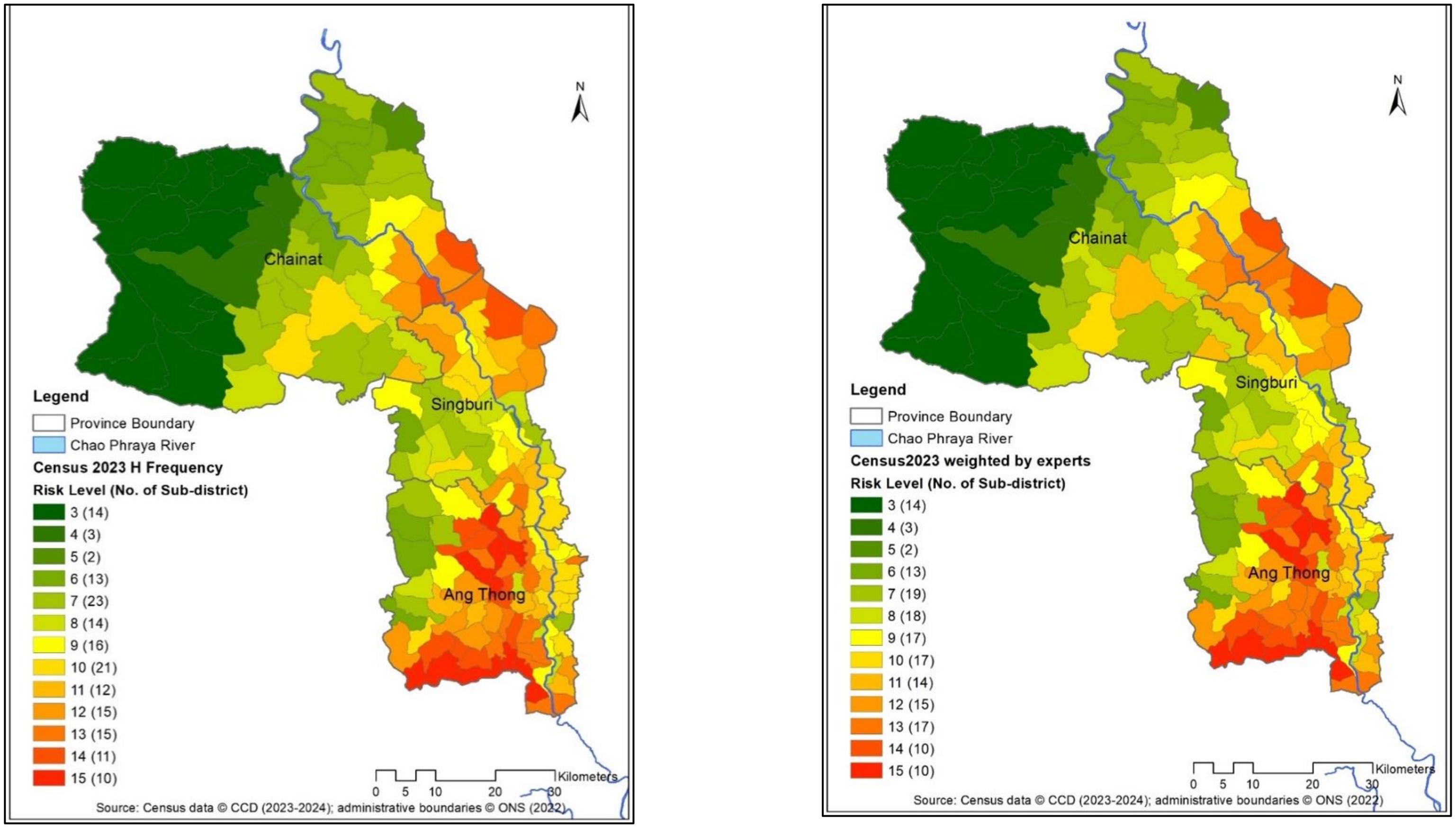
Table 7.4. Expert weighted variable diagnosis with OLS

Variable	Census 2023		Census 2024		Census Avg (2023-2024)	
	VIF	p-value	VIF	p-value	VIF	p-value
Hazard						
H1 Hazard	-	-	-	-	-	-
Exposure						
E1 Building density	3.55	0.004	3.27	0.15	3.45	0.0005
E2 Population density	3.35	0.33	2.89	0.71	3.22	0.36
E3 Size of household	1.51	0.09	1.35	0.53	1.60	0.12
Vulnerability						
V1 AGE	22.81	0.18	>1,000	1	31.83	0.68
V2 Gender	29.57	0.82	>1,000	1	40.62	0.67
V3 No Education	2.22	0.0009	7.45	1	2.49	0.0002
V4 Less Hi School	5.76	0.06	7.29	0.12	8.50	0.04
V5 Un Employed	1.09	0.0006	1.25	0.95	1.25	0.74
V6 Low Income	1.16	0.02	1.24	0.78	1.25	0.008
V7 LowSaving	3.11	0.16	2.84	0.86	3.90	0.87

Following Table 7.4, the OLS evaluation indicates that only a limited number of variables meet the statistical selection thresholds. Building Density is the strongest and most consistent exposure variable, satisfying the criteria across all census datasets. Within the vulnerability group, No Education and Unemployment meet the criteria in the 2023 dataset, while No Education and Low Income qualify in the averaged dataset. Several variables do not meet either statistical condition, most notably Age and Gender, which show extremely high VIF values and non-significant p-values throughout. As a result, Age and Gender are not selected for inclusion in subsequent analysis due to multicollinearity and lack of statistical significance. Overall, the variables that qualify for selection are Building Density, No Education, Unemployment and Low Income, depending on the dataset, while Age, Gender, Population Density, Household Size and Low Saving remain unselected.

7.4.4 Flood risk mapping using expert-weighted variables

The expert-derived weights, together with the variables confirmed through statistical selection, were incorporated into the GWR framework to generate an expert-informed flood risk map. This map was then compared against the model-driven GWR outputs to evaluate the consistency, spatial behavior and sensitivity of risk patterns produced under each approach. This comparison enables an assessment of how expert judgement aligns with, supports or diverges from statistically derived relationships, offering insight into the strengths and limitations of both perspectives. The key findings from this comparative analysis are presented below for models based on 2023 census data, 2024 census data, and the combined (mean 2023 and 2024) census data.



(a) Flood Risk Maps by Models (b) Flood Risk Maps by Experts

Figure 7.1. Comparison of Flood Risk Maps Models and Weighted by Experts (Census 2023)

2023 Census data. Figure 7.1 shows a detailed comparison between the 2023 GWR-based flood risk map and the expert-weighted flood risk map reveals substantial areas of agreement as well as noteworthy differences that reflect contrasting perspectives between data-driven modelling and practitioner-informed judgement.

Both maps consistently identify the eastern floodplain along the Chao Phraya River, covering large parts of Ang Thong and Singburi, as the most flood-prone region. These sub-districts experience recurrent inundation in the historical flood-frequency data and exhibit socio-economic characteristics that heighten vulnerability. This combination explains why both the statistical model and the expert assessments converge in classifying these areas as high risk. In contrast, the western and north-western parts of Chainat, located farther from the main river corridor and characterized by lower population density, appear persistently in the lowest-risk categories across both maps.

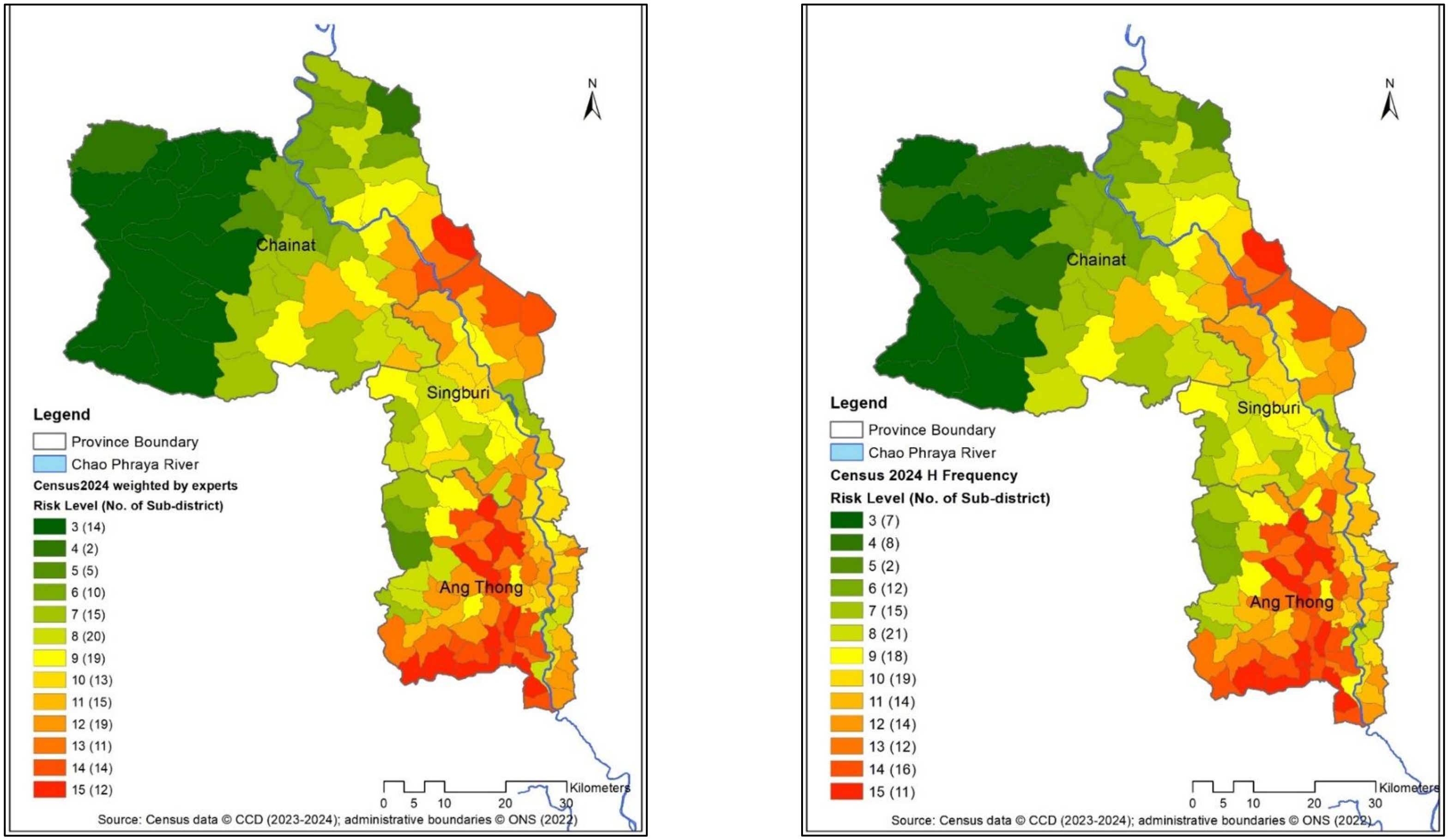
Although the two approaches align in their identification of the broad spatial pattern, they diverge in how they distribute moderate and high-risk classes internally. The expert-weighted map presents a more continuous spread of elevated risk, particularly in the central portion of the study area. This suggests that experts assign greater importance to underlying socio-economic vulnerabilities such as limited education, unstable income, or local exposure conditions. As a result, a wider band of communities is classified as moderately or highly at risk. This tendency reflects expert awareness of subtle, contextual factors that may not be fully captured through statistical relationships alone.

The GWR-based map, by comparison, produces sharper and more localized clusters of risk. In eastern Ang Thong, several sub-districts along the Chao Phraya River, especially south of Pa Mok and around Chaiyo, shift quickly from moderate (yellow–orange) to very high risk (red). These abrupt contrasts reflect locations where GWR identifies strong local interactions between flood frequency, settlement patterns, and socio-economic characteristics. A similar pattern is evident in southern Singburi, where the model highlights pronounced increases in risk around Bang Rachan and In Buri due to pockets of dense population and concentrated economic activity.

Northern Chainat also displays isolated high-risk sub-districts along the river, despite being surrounded by predominantly low-risk agricultural areas. These fine-scale variations show how GWR captures spatial dependencies and localized hotspots that the expert-weighted map smooths into broader, more continuous patterns.

Another key difference lies in the treatment of mid-range risk levels. The expert-weighted map places a larger number of sub-districts in intermediate categories (risk levels 8–11), indicating a more conservative and precautionary interpretation of flood risk. In contrast, the GWR model produces more extreme values at both ends of the scale, distinguishing more clearly between low- and high-risk areas based strictly on statistical evidence and spatial parameter variation.

Overall, the comparison demonstrates that while both approaches consistently identify the same high-risk core zones, they diverge in the granularity and distribution of risk across the region. The expert-weighted map reflects broader contextual judgement and produces smoother spatial transitions, whereas the GWR model provides sharper, more data-sensitive distinctions. Together, these perspectives highlight the complementary value of expert insight and spatial modelling for understanding flood risk across the three provinces.



(a) Flood Risk Maps by Models (b) Flood Risk Maps by Experts

Figure 7.2. Comparison of Flood Risk Maps Models and Weighted by Experts (Census 2024)

2024 Census data. Figure 7.2 shows the comparison between the expert-weighted 2024 flood-risk map and the GWR-based flood-frequency map reveals strong agreement in identifying the principal high-risk zones, while also highlighting important differences in the spatial extent, risk intensity and class distribution across the study area.

Both maps clearly identify eastern Ang Thong, the southern flood corridor and the river-adjacent portions of Singburi as the most critical high-risk zones. These areas experience repeated inundation and possess higher levels of socio-economic vulnerability, explaining their consistent appearance in the upper risk classes. In contrast, the western side of Chainat continues to show predominantly low-risk conditions due to limited exposure and reduced flood frequency.

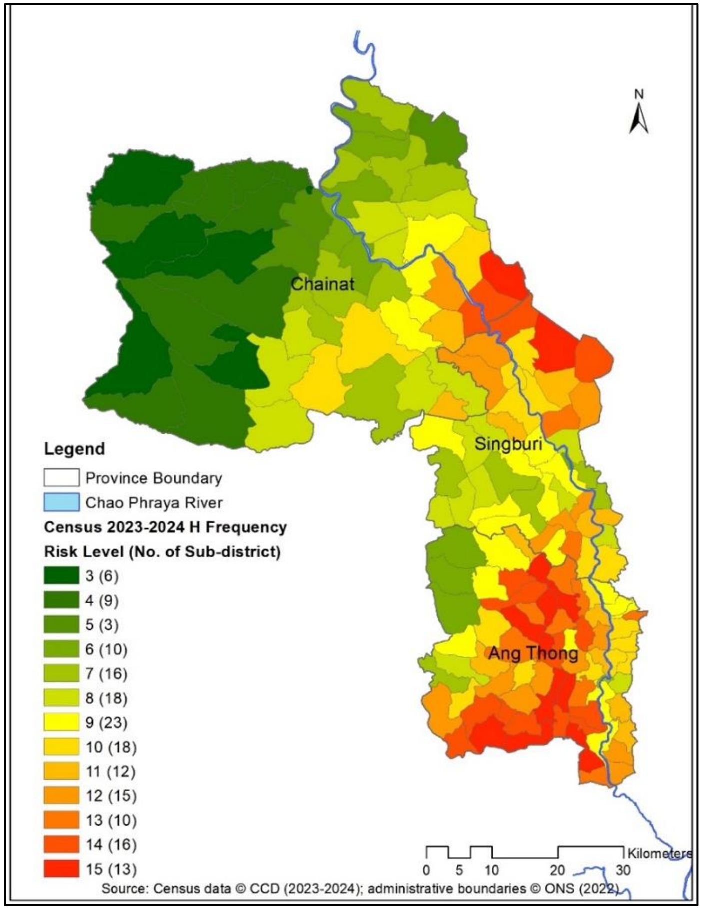
Despite this broad alignment, the spatial patterns diverge in how moderate and high-risk zones expand across the provinces. The expert-weighted map shows a wider spread of elevated risk in central Ang Thong, southern Chainat and parts of Singburi, reflecting expert perceptions that socio-economic pressures and community vulnerabilities extend risk beyond the core floodplain.

The GWR-based map presents sharper spatial contrasts and more localised clusters of risk. This reflects GWR's ability to assign unique coefficients to each sub-district, producing a more detailed representation of how hazard frequency, exposure and vulnerability interact on a fine spatial scale.

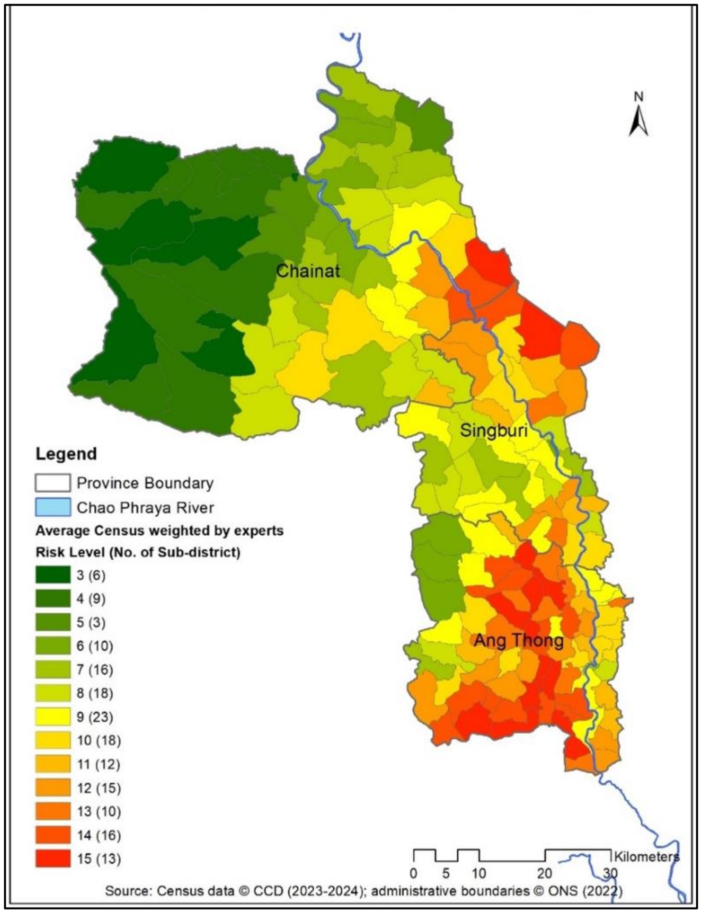
Another point of difference lies in the ranking distribution. The expert-weighted map places a greater number of sub-districts into intermediate-to-high risk level (levels 9–14), while the GWR map produces a more balanced distribution across the full range of classes. This indicates that experts perceive the region as having a generally higher baseline vulnerability, likely due to experience with chronic flooding, local knowledge of community resilience limitations and recognition of non-quantifiable risks. The model, in contrast, is strictly anchored to the measured data relationships.

Additional differences are evident at the extremes of the classification scale, particularly in risk levels 3 and 15. In the expert-weighted map, risk level 3, representing the lowest level of risk, contains a similar number of sub-districts to the model output but is slightly more concentrated in western Chainat, where experts emphasize stable topography and lower socio-economic sensitivity. The GWR map distributes risk level 3 more selectively, identifying only those areas with consistently low hazard coefficients and minimal vulnerability signals, resulting in sharper delineation of the safest zones. At the high end, risk level 15 shows a marked contrast: the expert-weighted map includes a larger cluster of sub-districts in southern Ang Thong and parts of eastern Singburi, reflecting expert judgement that these areas remain critically vulnerable even when annual census fluctuations are modest. The GWR map assigns risk levels 15 more selectively to specific sub-districts where hazard frequency and vulnerability variables align strongly in 2024, producing a smaller but more statistically defined high-risk cluster.

Overall, while both maps identify the same core areas of concern, the expert-weighted map presents a broader and more precautionary interpretation of risk, whereas the GWR model emphasizes spatial precision and data sensitivity. Together, these perspectives provide a more comprehensive understanding of flood risk across the three provinces.



(a) Flood Risk Maps by Models



(b) Flood Risk Maps by Experts

Figure 7.3. Comparison of Flood Risk Maps Models and Weighted by Experts (Average Census 2023-2024)

Combined Census Data. Figure 7.3 shows the close similarity between the GWR-based map and the expert-weighted map indicates that the underlying data are sufficiently robust to produce stable and consistent flood-risk patterns across methods. Both approaches independently highlight the same core high-risk zones in eastern Ang Thong and river-adjacent parts of Singburi, as well as the same low-risk areas in western Chainat. This convergence suggests that the hazard, exposure and vulnerability variables used in the analysis are capturing real and persistent spatial characteristics of the region's flood-risk environment.

The fact that different weighting strategies produce nearly identical spatial outcomes implies that the dataset is not overly sensitive to minor variations in weighting or method, which strengthens confidence in the reliability of the data and the model structure. It also indicates that the risk patterns are strongly driven by consistent signals in the flood-frequency and socio-economic indicators rather than by methodological artefacts.

Although the expert-weighted map tends to assign slightly higher risk across a broader area, and the GWR model shows sharper local variations, the overall agreement between the two confirms that the information contained in the 2023–2024 census data and hazard layers is of good quality and well aligned with on-the-ground flood realities. This consistency reinforces the validity of using these datasets for flood-risk assessment and suggests that both expert judgement and statistical modelling are responding to the same underlying spatial drivers.

7.5 Discussion and recommendation

Impact of the Expert Weightings on the Flood Risk Model Output. The comparison between the expert-weighted outputs and the GWR model indicates that the model-based assessment provides a more precise, internally consistent and evidence-driven representation of flood risk. Although the expert weightings produced broadly similar spatial patterns, particularly in the high-risk zones of eastern Ang Thong and the lower Chao Phraya River corridor, the GWR model generated sharper spatial distinctions that aligned more closely with the underlying hazard and socio-economic datasets. This outcome is consistent with findings in the modelling literature showing that spatially adaptive statistical methods typically yield stronger explanatory power and clearer internal logic than subjective assessments (Fotheringham & Charlton, 2002; Beven, 2009). The expert-weighted approach tended to generalize elevated risk across wider areas, while the model results highlighted localized gradients shaped directly by data behavior. These observations demonstrate that although expert judgement adds contextual sensitivity, the model-based assessment offers stronger analytical reliability and should serve as the primary reference for interpreting flood-risk patterns (Refsgaard et al., 2007).

Critical Review of the Suggestions Made by the Experts. The expert suggestions provided important contextual insight, especially regarding the chronic vulnerabilities faced by communities with limited adaptive capacity. However, several recommendations emphasised variables such as age or gender that did not meet statistical significance thresholds and showed high multicollinearity within the dataset. Similar tensions between expert perception and empirical evidence have been widely reported in the risk-perception literature, where subjective beliefs do not always align with observed risk relationships (Birkholz et al., 2014; Wachinger et al., 2013). In this study, the GWR model retained only those predictors that demonstrated meaningful statistical relationships with hazard intensity, ensuring that the final outputs remained grounded in measurable conditions. The inconsistencies between expert recommendations and statistically validated variables therefore highlight the need to priorities model-based findings to avoid misclassification or overestimation in areas where data-driven evidence does not support expert expectations.

Limitations of the Method and the Approach. Both approaches are affected by limitations related to data availability and spatial resolution, yet the constraints associated with the expert-based method are more substantial. Census-derived socio-economic data introduce uncertainty for both techniques, but expert weighting is additionally shaped by personal experience, institutional background and varying degrees of exposure to past flood events. These influences are known to affect professional risk interpretation and lead to divergent views on the significance of particular indicators (Kellens et al., 2013). Although GWR is sensitive to bandwidth selection and local data variability, it remains grounded in a transparent and reproducible statistical process that avoids cognitive bias. The prioritization of variables by experts that are not supported empirically further illustrates the possibility of misalignment. These limitations show that while expert insights offer interpretive value, the model-based assessment provides a more defensible analytical foundation for identifying spatial patterns of flood risk.

Implications for Use of the Model. The strong correspondence between the expert-weighted and model-based outputs confirms that the modelling framework effectively captures the principal spatial drivers of flood risk across the study area. Nevertheless, the superior precision, objectivity and reproducibility of the GWR model indicate that it should serve as the primary decision-support tool for local and regional authorities. The expert-weighted map can be used as a complementary layer to highlight contextual or experiential considerations, but it should not override statistically validated classifications. Prioritizing the model-based assessment ensures a defensible, consistent and transparent approach to flood-risk mapping and provides a robust foundation for mitigation planning, early-warning development and resource allocation (Sayers & Rowsell, 2020).

7.6 Conclusion

- The incorporation of expert judgement added important contextual understanding of local flood behaviour and socio-economic vulnerability. However, comparison with the GWR outputs shows that the model-based assessment provides sharper spatial distinctions, stronger internal consistency and a closer match to the underlying hazard and census datasets. This confirms that GWR should serve as the principal framework for interpreting flood-risk patterns, with expert insight used as a complementary layer.
- The expert evaluations identified several variables considered influential by practitioners, but the OLS diagnostics demonstrated that only a limited subset, including building density, education, income and unemployment, met

statistical thresholds. Variables such as age and gender showed high multicollinearity and limited significance. This highlights the limitations of relying primarily on subjective assessments and reinforces the importance of statistically validated variable selection.

- Both the expert-weighted and model-based maps consistently identified the same high-risk zones along the eastern floodplain of the Chao Phraya River. This convergence indicates that the underlying datasets are robust, while the remaining differences between the two approaches reflect their unique strengths. The expert map provides broader contextual interpretation, and the GWR output delivers more spatial precision. Together, they offer a comprehensive understanding of flood risk and support the use of a model-led approach informed by expert experience.

Chapter 8: Discussion and Conclusions

This chapter presents an integrated discussion of the main findings that emerged from the development, testing and optimization of the GIS based flood risk assessment model. The analysis draws together the conceptual foundations established in the literature review, the methodological performance demonstrated in the UK pilot study, the transferability evaluation conducted for the Thai context, and the incorporation of expert knowledge from practitioners in Thailand. Together, these findings clarify how hazard, exposure and vulnerability interact across different geographical and socio-economic settings and explain the strengths, limitations and implications of the modelling framework. The chapter highlights where the model performs strongly, where contextual adaptation is necessary and how the combination of quantitative and qualitative knowledge supports robust flood risk decision making.

8.1 Key findings

8.1.1 Conceptual Insights from the Literature

The literature reviewed in Chapter 2 confirms that flood risk is shaped by the combined interaction of hazard, exposure and vulnerability. This conceptual structure is supported by internationally recognized frameworks such as the risk triangle and the European Floods Directive, which describe risk as a multidimensional and spatially variable condition rather than a single physical characteristic. Research highlights that hazard describes the probability and intensity of flood events, exposure describes the location of people and assets within potentially affected zones, and vulnerability describes the underlying social and economic sensitivity of populations to flood impacts. The literature repeatedly emphasizes that flood risk cannot be interpreted properly when only one component is examined because the interaction between physical and human factors determines actual outcomes.

The review also demonstrates that socio economic vulnerability is often the most dynamic and influential component of flood risk, especially in regions undergoing rapid socio-economic change. Studies show that income level, savings, education, age structure, household composition and employment conditions shape the ability of communities to respond, adapt and recover from floods. This broader understanding of vulnerability informed the selection of variables for the present study and provided a theoretical basis for integrating complex demographic and socio-economic characteristics into the model.

In addition, the literature strongly supports the use of quantitative methods such as PCA, OLS and GWR within GIS environments. These approaches allow the identification of significant variables, examination of statistical relationships, removal of redundant indicators and interpretation of spatial heterogeneity. The literature indicates that these methods improve objectivity compared with purely expert based multi criteria approaches and strengthen the transparency and reproducibility of flood risk models.

8.1.2 Findings from the UK Pilot Study

The pilot study undertaken in Sheffield served as an important testing stage, allowing the assessment of model behavior in a controlled, highly documented environment. The pilot confirmed that the modelling workflow is technically feasible and that it produces interpretable and spatially meaningful results. The pilot showed that PCA effectively reduced redundancy among vulnerability variables, leaving only indicators that significantly influence flood risk. This confirmed that PCA serves as a reliable screening method and that datasets containing many variables require systematic dimensionality reduction before regression modelling.

OLS and GWR applied in the pilot also demonstrated the importance of accounting for spatial heterogeneity. The pilot confirmed that GWR performs more strongly than OLS because it allows relationships between variables to differ across space. The results showed that the influence of population density, building density, age structure and income vary significantly across different neighborhoods, confirming that flood risk is not uniform across space even within a single city. The pilot therefore validated both the conceptual structure of the model and the suitability of spatially adaptive methods for dealing with complex socio environmental variation. These findings provided confidence that the model can be transferred to other settings, provided that data quality, variable selection and contextual conditions are handled carefully.

8.1.3 Transferability of Data and Model Structure to Thailand

The analysis presented in Chapter 6 revealed that transferring socio-economic datasets from the UK context to Thailand introduces several challenges that influence model performance and interpretation. Data collected under different national statistical systems differ in resolution, measurement method, administrative classification and completeness. These differences create uncertainty in variable behavior and require careful adjustment before use in regression modelling. For example, building density in the UK is derived from total building footprint area, whereas in Thailand it is measured using building counts per square kilometer. Household size, educational categories, income thresholds and age group definitions also differ between countries. These differences required recalibration to align with Thai census structures and local conditions. The transferability analysis confirmed that although the overall modelling architecture remains valid, variable definitions, criteria and units must be adapted to match national datasets. The need for this adaptation underscores the importance of context specific interpretation and the careful translation of conceptual frameworks into operational indicators.

The transferability evaluation also identified which variables were unsuitable for Thai conditions. Diversity, renter status and certain health variables were excluded because equivalent Thai datasets either did not exist or lacked sufficient resolution. At the same time, the analysis showed that new variables such as low savings, no education and household size are particularly relevant in Thailand due to their strong relationship with socio economic vulnerability. These additions improved the ability of the model to capture real variations in sensitivity to flooding. So, the transferability findings demonstrate that although flood risk modelling frameworks can be applied across countries, the data structures and variable specifications must be adapted to each national context to preserve statistical validity and practical relevance. These findings provide essential guidance for extending the model to other Thai provinces or neighboring Southeast Asian countries in future work

8.1.4 Insights from OLS and GWR Modelling in Thailand

The regression results revealed several important findings regarding the behavior of hazard, exposure and vulnerability indicators in Thai floodplains. The OLS diagnostics showed that flood frequency is a much stronger predictor of risk than return period. This is because the flood frequency dataset, which draws on nineteen years of flood records, captures the cumulative behavior of river flooding more accurately than return period datasets. Return period maps produced very low adjusted R^2 values and unstable statistical behavior, indicating that they do not adequately represent local flood risk conditions.

The GWR analysis produced even more informative results. GWR demonstrated that socio economic vulnerability is the strongest predictor of risk, surpassing both hazard and exposure in explanatory power. Variables such as education, unemployment, income and savings showed strong spatial patterns that closely align with known areas of socioeconomic stress within the three provinces. This finding is fully consistent with the literature on vulnerability and disaster risk, which describes how socio-economic conditions shape resilience, coping ability and long-term recovery potential. The GWR models also demonstrated high spatial variability in variable coefficients, confirming that the influence of vulnerability indicators is not uniform across the landscape. Certain sub districts showed strong influence from low savings and low education, while others were more affected by household size or unemployment. This reinforces the view that flood risk must be examined at fine geographical scales because broader regional analyses can obscure important local differences.

8.1.5 Expert Led Optimization and Comparison with Model Based Results

The expert interviews conducted in Chapter 7 added valuable understanding by incorporating practical, operational and experiential knowledge from individuals who have worked directly with flood conditions in Ang Thong, Sing Buri and Chainat. Experts confirmed the importance of variables such as low income, low savings, no education and building density, and they provided context that helped explain why certain variables behave as they do in the statistical models.

The comparison between expert weighted maps and model-based maps showed a high degree of agreement in identifying key high-risk areas. Both approaches highlighted similar clusters along the eastern floodplain of Ang Thong and the lower basin areas of Sing Buri. However, experts tended to assign risk more broadly, reflecting their reliance on long term memories of past flood impacts, organizational experience and precautionary reasoning. Experts emphasized multi year flood behavior, seasonal patterns and unresolved local weaknesses such as drainage problems, embankment deterioration and unregistered housing areas. These factors are often not captured within census-based datasets but strongly influence perceived risk.

Although the expert input enriched the contextual understanding of flood risk, the statistical model remained more precise and diagnostically consistent. The quantitative outputs showed clearer spatial gradients and stronger internal validity, indicating that model-based assessments should take priority when defining risk zones, while expert input should be used to interpret results, refine variable selection and enhance local applicability. This finding supports the literature which shows that expert elicitation is most effective when it complements, rather than replaces, quantitative modelling.

8.1.6 Integrated Interpretation of Findings

Taken together, the findings demonstrate that the modelling framework successfully captures the complex interaction between hazard, exposure and vulnerability. The model consistently identifies vulnerability as the most influential component of risk, confirming that socio economic inequality shapes the intensity of flood impacts more strongly than physical hazard alone. This outcome is significant because it indicates that flood risk management should not focus exclusively on structural or hydrological measures but should also address the underlying socio-economic conditions that make certain populations more at risk.

The model also revealed that although hazard patterns are relatively stable along major river corridors, vulnerability patterns change dynamically across short distances and influence risk even in areas with moderate hazard levels. Exposure variables remain important for defining where risk can occur, but they do not explain the largest differences in risk intensity across the study area. The findings confirm that public, secondary datasets provide a reliable foundation for sub district risk assessment when combined with rigorous screening, harmonization and statistical diagnostics. The modelling approach is transparent, replicable and adaptable, making it suitable for long term risk governance in data constrained settings.

The key findings of this research show that a spatially explicit, quantitative flood risk model grounded in publicly available data provides a reliable and transferable approach for assessing risk at sub district scale in Thailand. Vulnerability is the principal driver of risk, flood frequency is a more accurate hazard input than return period, and GWR is the most effective method for capturing localized patterns of risk. Expert knowledge enriches contextual interpretation but should complement rather than replace model driven analysis. Overall, the study provides a strong empirical and conceptual foundation for strengthening evidence-based flood risk governance in Thailand.

8.1.7 Positioning the Findings within the International Literature

The findings of this research are broadly consistent with international studies that conceptualize flood risk as the interaction between hazard, exposure and vulnerability within a spatially explicit framework (Crichton, 1999; Moel et al., 2015; UNDRR, 2015). Similar to studies conducted in Europe, North America and China, the results demonstrate that GIS-based approaches provide an effective mechanism for integrating physical flood characteristics with socioeconomic conditions to identify spatial patterns of flood risk (Alfieri et al., 2017; Islam & Meng, 2024; Teng et al., 2017). The present study therefore supports the growing consensus that flood risk assessment must extend beyond hazard mapping and incorporate social dimensions of vulnerability.

The findings also support previous research demonstrating that socioeconomic vulnerability often explains flood impacts more effectively than physical exposure alone. Studies by Cutter et al. (2003), Fekete (2019) and Islam and Meng (2024) found that variables related to education, income, employment and social disadvantage play a significant role in determining differential flood outcomes. The Thai case study produced similar results, with education, income and savings consistently emerging as influential variables across multiple modelling scenarios. This agreement strengthens international evidence that social vulnerability remains a critical determinant of flood risk regardless of geographical context.

However, the findings also challenge assumptions commonly found in flood risk studies developed in data-rich environments. Much of the international literature relies upon extensive socioeconomic datasets, detailed property inventories and high-resolution environmental information (Kreibich et al., 2015; Merz et al., 2007). The results of this research demonstrate that reliable flood-risk assessments can still be produced using publicly available secondary datasets and relatively simple modelling approaches. This finding contributes to the literature on flood-risk assessment in developing countries, where data scarcity remains a major constraint.

The Sheffield pilot study contributes to international discussions on model transferability. While previous studies have often developed and validated flood-risk models within a single geographical setting, this research explicitly examined the transfer of a modelling framework between a data-rich environment in the United Kingdom and a data-constrained environment in Thailand. The results demonstrate that although the conceptual structure of hazard, exposure and vulnerability can be transferred successfully, variable selection and model performance remain highly sensitive to local data characteristics. This finding supports observations by Kreibich et al. (2015) that flood-risk models are context dependent and require adaptation rather than direct replication.

The research also contributes to methodological debates regarding variable selection and model construction. While PCA is widely recommended as a dimensionality-reduction technique in flood-risk studies, the results demonstrate that PCA may not be appropriate where variables exhibit extreme skewness, low variance or severe multicollinearity. In contrast, OLS proved to be a more robust and transparent diagnostic tool for identifying suitable predictors within the Thai dataset. This finding extends existing methodological literature by demonstrating the importance of matching analytical techniques to data characteristics rather than assuming universal applicability.

Finally, the comparison between expert-informed and statistically derived models contributes to a growing body of literature on participatory and expert-supported environmental modelling. Consistent with studies by Krueger et al. (2012) and Maskrey et al. (2022), the results show that expert knowledge can improve contextual understanding and support parameter interpretation. However, the findings also demonstrate that statistically derived GWR models produced more spatially differentiated and analytically robust outputs than expert weighting alone. This suggests that expert knowledge is most valuable as a complementary component of model parameterisation rather than as a replacement for quantitative analysis. In doing so, the thesis contributes a practical framework for integrating local knowledge with data-driven modelling in flood-risk assessment.

Overall, this research extends the international literature by demonstrating how GIS-based flood-risk assessment can be adapted to data-constrained environments, by providing empirical evidence on model transferability between contrasting national contexts, and by proposing a framework that combines statistical diagnostics, spatial modelling and expert knowledge within a coherent flood-risk assessment methodology.

8.2 Summary of contribution to knowledge

This thesis makes seven key contributions to the advancement of GIS based flood risk assessment, particularly in data-constrained and socio-economically diverse contexts such as Thailand. Through the integration of empirical modelling, cross national transferability testing and systematic expert input, the research provides new insights into the design, performance and practical application of sub district flood risk models. The contributions relate to methodological development, conceptual refinement, data adaptation, and decision support for local flood governance. They also challenge several assumptions that underpin conventional flood risk modelling and thereby expand the academic understanding of hazard exposure vulnerability interactions.

1: Development of a Transferable and Data Driven GIS Based Flood Risk Model

The first major contribution of this thesis is the development of a fully transferable flood risk assessment framework that uses only publicly available datasets and quantitative techniques. Many existing flood risk models rely on specialist hydrological data and expert based multi criteria methods that are difficult to reproduce and highly sensitive to subjective interpretation. This study demonstrates that a quantitative model grounded in PCA, OLS and GWR can be developed and applied across different national contexts using only secondary datasets that are accessible to local authorities. This finding is important because it provides an evidence-based alternative to models that depend heavily on expert opinion or hydrological simulations. The approach enhances transparency, supports operational reproducibility and expands the potential for local governments to conduct flood risk assessments without the need for specialist software, proprietary datasets or large technical teams.

2: Empirical Evidence of the Dominant Role of Socio-Economic Vulnerability in Flood Risk Formation

A second key contribution is the systematic demonstration that socio economic vulnerability plays a more influential role in shaping flood risk than either hazard intensity or physical exposure. Although the risk triangle concept is widely recognized in literature, few empirical studies quantify the relative influence of each component across large and diverse regions. This thesis provides robust statistical evidence, supported by both OLS and GWR, showing that variables such as low savings, low income, no education and unemployment exert the strongest influence on spatial flood risk patterns in Thailand. These finding challenges dominant assumptions that flood hazard intensity is the primary driver of risk and instead highlights that long term socioeconomic inequality is the most important determinant of vulnerability. This insight advances academic understanding by clarifying where interventions should be focused to reduce risk at community scale.

3: Cross National Evaluation of Data Transferability and Contextual Adaptability

Another contribution lies in the detailed examination of dataset transferability between the United Kingdom and Thailand. The thesis demonstrates that even when a modelling framework is theoretically transferable, the underlying datasets require extensive adaptation due to differences in administrative classification, measurement practices, demographic structure and socioeconomic indicators. The analysis provides a structured method for identifying which variables can be transferred directly, which require recalibration and which must be replaced entirely. This represents an important advancement because it shows how international flood risk models can be operationally adapted without losing their statistical integrity. The study offers a clear methodological pathway for researchers working in other cross national or multi regional contexts where data availability and statistical definitions vary significantly.

4: Integration of Expert Knowledge into a Quantitative Framework without Sacrificing Analytical Rigour

A key contribution of this research is the development of a structured approach for integrating expert knowledge specifically within the parameterization stage while maintaining the analytical rigour of a quantitative modelling framework. Unlike traditional expert-based flood-risk assessments that depend heavily on subjective weighting, this study incorporates expert judgement only where it adds demonstrable value: in clarifying the local relevance of variables, identifying context-specific socio-economic drivers and interpreting patterns not fully captured by census data. These insights are then translated into quantitative weights and tested against OLS and GWR diagnostics to ensure that all parameter choices remain grounded in statistically validated relationships. The comparison between expert-weighted and model-based outputs demonstrates how practitioner knowledge can enrich contextual interpretation without overriding empirical evidence, thereby showing that expert insight and data-driven modelling can be systematically combined in a transparent and methodologically defensible way.

5: Advancement of Spatial Modelling Techniques for Sub District Flood Governance

The thesis also contributes to flood management practice by demonstrating that geographically weighted regression provides a more realistic representation of spatial risk patterns than global regression or indicator-based approaches. By identifying localized variations in variable influence, the model supports more targeted interventions at district and sub district levels. This finding is especially valuable in Thailand, where administrative units vary significantly in socioeconomic and physical characteristics. The study therefore provides a methodological advancement that is directly relevant to practitioners responsible for land use planning, resource allocation and community level disaster preparedness. It also clarifies how spatial heterogeneity should be incorporated into model design in order to produce actionable risk maps.

6: Evidence Based Framework for Reducing Subjectivity in Flood Risk Modelling

Existing flood risk assessment approaches in many countries, including Thailand, often rely on subjective classification schemes or expert scoring systems that lack empirical diagnostics. This thesis provides an alternative method that prioritizes statistical evidence, diagnostics and validation techniques. The use of PCA for variable screening, OLS for global diagnostics and GWR for localized interpretation establishes a coherent modelling pipeline that reduces uncertainty and increases analytical reliability. This contribution is valuable because it shows how locally available datasets can be transformed into statistically robust risk indicators, even in contexts where data quality is uneven.

7: Novel Multi Stage Evaluation Combining Pilot Validation, Data Transferability and Expert Optimization

A final distinctive contribution is the novel multi stage evaluation process used in this thesis. The model was first tested in a data rich environment in the United Kingdom, then adapted for Thailand through the transferability study and finally refined through expert engagement. This stepwise refinement process is rarely used in flood risk research, where models are typically applied to a single region or validated with limited sensitivity testing. The multi stage design used in this thesis substantially increases the credibility and robustness of the final model and provides a replicable blueprint for future research in other regions and hazards.

However, this thesis contributes new knowledge by demonstrating how quantitative GIS based modelling can be systematically developed, validated, transferred and optimized across different national contexts. It advances theoretical understanding of vulnerability, provides a reproducible methodological framework for practitioners and establishes a more transparent and data driven approach to flood risk assessment. The research strengthens the intellectual foundation for sub district level flood governance in Thailand and offers an adaptable framework that can be extended to other flood prone regions facing data limitations and socio-economic challenges.

8.3 Implications for policy and practice in Thailand

This section discusses how the findings and methodological contributions of the thesis can be translated into practical value for flood risk governance in Thailand. The results demonstrate strong potential for improving national and provincial decision making, strengthening sub district disaster preparedness and guiding future investment in socio economic resilience. The seven implications presented here follow from the contributions established in the previous section and show how the model supports more effective planning and risk reduction across multiple institutional levels.

1: Strengthening Evidence Based Flood Governance for National Agencies

The research offers important value to national agencies responsible for country wide flood risk management, including the Royal Irrigation Department, the Department of Disaster Prevention and Mitigation, the Office of the National Water Resources and the Department of Water Resources. These agencies face increasing pressure to evaluate risk consistently across provinces, yet the diversity of data structures and local conditions has made this difficult. The model developed in this thesis provides a practical framework for national level risk assessment because it uses only public datasets that are already collected by state agencies. The model therefore avoids dependence on specialist hydrological simulations that are costly to run and difficult to update regularly. National agencies can apply the model to produce harmonized risk surfaces across the entire Chao Phraya Basin or other key catchments, enabling clearer prioritization of infrastructure investment, hazard mitigation planning and watershed management strategies.

The use of flood frequency as the primary hazard input has important policy implications. It demonstrates that long term historical observations from national flood monitoring systems can be used to produce stable and realistic hazard layers. This supports national capacity for long horizon flood planning and reduces ambiguity created by return period maps, which often perform poorly in real world Thai conditions.

2: Supporting Provincial and District Authorities with Spatially Detailed Risk Mapping

Provincial agencies such as the Office for Prevention and Mitigation in Sing Buri and the Community Development Department require methods that can identify high risk communities with sufficient spatial resolution to guide resource allocation. The sub district level modelling approach presented in this study directly addresses this need. It offers a practical method for producing spatially detailed maps that align with administrative boundaries used in actual disaster response operations. Because the model incorporates socio economic vulnerability as a central component, provincial authorities can move beyond hazard centered thinking and instead adopt a more comprehensive understanding of risk. The results show that areas with moderate hazard but high vulnerability can be more at risk than areas with high hazard but stronger socio-economic resilience. This insight supports more balanced prioritization of provinces and districts that require immediate attention.

Provincial agencies can use the model to identify clusters of low-income households, areas with high numbers of residents with low educational attainment and communities with limited savings. These patterns correspond directly to conditions that provincial disaster management teams observe during flood events. The model therefore provides an analytical foundation for integrating social protection programs with flood mitigation strategies.

3: Providing sub district administrative organizations with a practical tool for local planning

Sub district administrative organizations require information that is both specific enough to support local decision making and simple enough to use without advanced technical expertise. The modelling framework provides this by integrating census based datasets with a clear analytical workflow that can be replicated by staff with basic GIS training. The findings can help sub district authorities identify households and neighborhoods that are most vulnerable to flood impacts. They can guide preparedness planning, early warning communication and the placement of community shelters. The ability of the model to highlight vulnerability drivers such as low savings and low education directly supports local planning for community-based disaster risk reduction activities. The model also promotes accountability because it uses publicly accessible datasets. Local authorities can explain how risk assessments were created and demonstrate that decisions are supported by objective evidence rather than subjective judgement. This transparency strengthens trust between authorities and communities.

4: Improving Coordination among Agencies through a shared analytical framework

Flood risk governance in Thailand involves multiple agencies that operate at different administrative levels and often use different datasets or classification systems. This fragmentation hinders coordinated planning. The modelling framework developed in this thesis provides a shared analytical foundation that can unify the activities of agencies working on hazard mitigation, land use planning, social welfare, infrastructure development and emergency response. By using the same hazard, exposure and vulnerability components, agencies can align their risk assessments and compare results across provinces. This creates a common language of risk that improves communication and facilitates cooperative planning. The ability to scale the model from pilot study to regional application also supports long term integration across institutions.

5: Guiding Investment in Socio Economic Resilience

One of the clearest findings of this thesis is that socio economic vulnerability is the strongest determinant of flood risk. This has important implications for Thai policymakers. It shows that investment in education, income stability, local employment programs and household savings can reduce flood risk even without major engineering interventions. This insight supports integration between flood governance and social welfare policies. For example, the Ministry of Social Development and Human Security can use the model outputs to priorities communities for livelihood assistance or financial inclusion programs. Community Development Department officers can use vulnerability indicators to design targeted community capacity building initiatives. The findings reinforce that physical flood control infrastructure should be complemented by social resilience strengthening, especially in communities where households lack the resources to recover quickly after repeated events.

6: Enhancing Local Early Warning and Emergency Preparedness

The spatial patterns produced by the GWR model reveal which sub districts have the highest sensitivity to future flood events. This supports improvements in early warning systems. Sub district officers can use the risk maps to refine evacuation routes, position emergency equipment and design training programs for residents. The identification of high-risk zones at precise geographic scales also enables more efficient resource placement. For instance, local authorities can locate boats, relief supplies and rescuers closer to the most vulnerable neighborhoods before the onset of the flood season.

7: Informing Long Term Land Use Planning and Development Control

The model results can be integrated into future land use plans and zoning regulations. By identifying areas where hazard and vulnerability combine to produce persistent risk, the model provides evidence to discourage inappropriate development in high-risk areas. It also supports planning decisions regarding relocation, flood proofing measures and infrastructure adaptation. Urban planners in provincial municipalities can incorporate the risk surfaces into comprehensive plans, ensuring that development decisions do not increase exposure to future floods. This is especially relevant in rapidly urbanizing areas near riverbanks and floodplains within the Chao Phraya Basin.

The implications of this research extend across national, provincial and sub district levels of governance in Thailand. The model supports evidence-based decision making, identifies socio economic inequalities that influence flood sensitivity, enables targeted resource allocation and strengthens coordination across agencies. It provides a transparent and reproducible method for assessing risk using public data and offers a practical tool that aligns with the institutional structures of Thai flood management. The findings therefore have clear relevance for improving policy and practice, enhancing community safety and supporting long term resilience in the lower Chao Phraya Basin and beyond.

8.4 Limitations and challenges

This research faced several limitations and practical challenges that influenced the pace, scope and operational complexity of the project. These challenges highlight both the constraints inherent in conducting flood risk analysis in Thailand and the importance of establishing robust, reproducible modelling approaches that can function despite such constraints.

A major limitation arose from the COVID-19 situation, which significantly affected the project's overall progress. Restrictions on movement and workplace operations limited the ability to conduct field visits, meet with stakeholders and collect primary data directly. Many government agencies operated with reduced personnel, staggered working hours or remote work arrangements. This made coordination slower and more fragmented than initially planned. Several experts and officials were unavailable for extended periods, and scheduling interviews required intermediary support and advance planning. As a result, the project relied more heavily on secondary data, digital communication and remote consultation, which constrained the depth of qualitative insight that could be gathered.

The pandemic also accelerated the shift toward online data acquisition systems across many Thai agencies. Although this shift created new opportunities for transparency, it also introduced uncertainties. Many online platforms were still undergoing development, and some remained unstable, incomplete or outdated. Datasets often appeared in changing formats or with inconsistent classifications. This required repeated rounds of data checking, cleaning and harmonization to ensure that variables were suitable for modelling. In several cases, data structures changed mid project, creating additional work for alignment and verification. These issues affected both hazard and socio-economic datasets and created substantial delays in the preparation of regression ready inputs.

Another challenge concerned the general variability and uneven quality of publicly available data in Thailand. Hazard datasets, particularly flood frequency information, are updated annually but may contain inconsistencies arising from differences in satellite acquisition, flood delineation techniques or administrative boundary updates. Socio-economic datasets also vary in completeness, especially for more sensitive variables such as income, savings, education and employment. Some indicators required careful interpretation because agencies use different measurement methods or reporting practices. This variability increases the difficulty of building a stable, replicable model and underscores the importance of rigorous data screening and statistical diagnostics.

Coordination across multiple agencies presented an additional challenge. Flood risk management in Thailand involves a wide range of institutions that maintain their own datasets, technical procedures and internal standards. During the pandemic period, communication among agencies was further constrained, and the availability of up-to-date information was sometimes limited. The project therefore required substantial effort in aligning datasets, tracking metadata and confirming definitions. These challenges highlight the fragmented nature of flood related information systems in Thailand and the need for improved data integration in future national flood governance efforts.

Despite these limitations, the challenges encountered reinforce the significance of this research. They illustrate the real-world conditions under which Thai flood analysts and local authorities operate and demonstrate why robust, transparent and data driven models are essential. The difficulties in accessing consistent data, the delays caused by system instability and the need for frequent data cleaning all emphasize that flood risk assessment in Thailand is a complex and evolving task. This research addresses these conditions by providing a model that is adaptable, reproducible and less dependent on perfect datasets, thereby offering practical value to future flood risk planning and policy development.

8.5 Suggestions for future research

This thesis establishes a robust and transferable GIS based flood risk model for Thailand, but it also opens several opportunities for further research. The limitations encountered, the insights from expert evaluations and the analytical behavior of the model highlight areas where future work can deepen understanding, expand methodological capability and enhance practical application. The following nine suggestions outline how future researchers can build upon this work, what could be improved in similar projects and what the next logical steps in advancing flood risk science in Thailand should be.

1: Improve Variable Definitions and Develop More Context Sensitive Indicators

The modelling results show that socio economic vulnerability is the most influential component of flood risk, yet several vulnerability indicators depend on broad census categories. Future research could refine these indicators by developing more precise or locally calibrated definitions. For example, the definition of “low savings” may differ between rural agricultural households and urban workers. Age related vulnerability may differ depending on access to family support, mobility constraints or local health service capacity. Similar issues arise with employment indicators that do not capture informal work, seasonal labor or hidden unemployment.

Developing more context specific variables through targeted focus groups, local administrative records or community surveys would enhance the realism of vulnerability modelling. These refined indicators could help reduce model error and improve the accuracy of GWR outputs.

2: Integrate Physical, Hydrological and Infrastructure Data More Fully

This study focused on socio economic data due to its strong statistical influence and availability. However, several experts noted the importance of local drainage systems, soil conditions, elevation and existing flood defenses. These factors are important for understanding how water moves through landscapes and why some communities face repeated flooding even under moderate rainfall.

Future studies could incorporate hydrodynamic simulation outputs, river network characteristics, drainage maintenance records, urban growth layers and detailed land elevation models. Integrating these datasets would support the creation of compound flood risk models that combine both physical processes and socioeconomic fragility. This would provide a more comprehensive understanding of why risk is higher in specific locations.

3: Develop temporal flood risk models using multiyear socio-economic data

The sensitivity analysis showed that socio economic indicators change between years and that these changes can shift flood risk profiles. Future research could use multiyear census datasets, satellite derived flood histories or long term economic surveys to explore how vulnerability evolves over time. This would allow researchers to create dynamic models that detect trends in risk progression or reduction.

Temporal analysis could also identify which vulnerability variables are most persistent, which are cyclical and which respond to economic shocks or policy interventions. Such insight would help decision makers prioritize investments that produce long term reductions in flood sensitivity.

4: Expand Testing to Larger Geographic Areas or Additional Provinces

The analytical framework developed in this thesis was applied to three core provinces of the lower Chao Phraya Basin. The model could be extended to other high risk provinces with different socio environmental contexts such as Ayutthaya, Pathum Thani, Nakhon Sawan or Phitsanulok. This would test the model's ability to adapt to different flood mechanisms, administrative structures and demographic patterns.

Scaling up the model to basin wide or national levels could also support the development of national flood risk atlases. These would provide policymakers with consistent and comparable risk maps across regions, enabling integrated planning and prioritization of budgets for flood prevention and social assistance.

5: Build an Integrated National Flood Risk Database and Automated Modelling Platform

One of the major challenges experienced in this study was the inconsistency of data formats and the instability of online data acquisition platforms. Future research could support the development of a centralized national database designed specifically for flood risk modelling. This system could integrate hazard, exposure and vulnerability datasets into a single platform with standardized metadata, automated updates and built in quality checks.

An automated modelling tool based on this database could generate annual or seasonal flood risk maps without the need for repeated manual data processing. Such a system would enhance continuity, reduce human error and make the modelling framework accessible to district and sub district authorities with limited technical capacity.

6: Explore Comparative Modelling Techniques

While GWR provided strong results in this thesis, flood risk is inherently complex and may benefit from additional modelling approaches. Future research could explore the use of machine learning methods such as random forest, gradient boosting or neural networks to detect nonlinear relationships. Spatial econometric models could also be tested to better model spatial dependence and spillover effects between neighboring sub districts.

Comparing these techniques with GWR would determine whether more advanced algorithms produce meaningful improvements in predictive performance or interpretability. A hybrid approach combining machine learning with spatial regression could provide deeper insight into the drivers of flood risk.

7: Advance Participatory and Co-Produced Flood Risk Modelling

The expert findings revealed that differences between model based and expert weighted maps often arise from local knowledge that is not fully captured in census datasets. Future research could advance this into a formal participatory modelling framework where local government officers, community leaders and residents jointly review model outputs.

The resulting maps, especially where differences between statistical results and expert weights appear, could be presented to local stakeholders to identify the reasons behind discrepancies. For example, a sub district may appear low risk in the statistical model but be marked as high risk by residents due to past experience with flash flooding, drainage failure or unrecorded riverbank erosion. Coordinated sessions with communities would help reveal such overlooked local realities.

This process would not only improve model calibration but also increase the legitimacy and acceptance of risk maps. Co-produced models can be continuously refined using local feedback, resulting in flood risk assessments that are both technically robust and socially grounded. This iterative refinement would help produce a next generation modelling framework that responds to real conditions on the ground while maintaining analytical rigour.

8: Evaluate Policy Impact and Real-World Implementation

Future studies could examine how agencies use flood risk maps generated from the model and whether this results in improved preparedness, better allocation of resources or more targeted emergency response. Real world testing could involve monitoring local government decision processes, assessing the distribution of funding or evaluating whether intervention programs reduce vulnerability in identified high risk zones.

This type of evaluation would provide evidence on how models influence policy and how modelling tools should be adapted to better support practical decision making.

9: Integrate Climate and Socio-Economic Change Scenarios

Thailand is experiencing rapid changes in land use, climate patterns and socioeconomic structure. Future research could incorporate climate change projections, urbanization simulations or socio-economic development scenarios into the flood risk model. This would enable forecasting of future vulnerability and identification of emerging risk hotspots.

Such forward looking models would help agencies prepare long term strategies for adaptation, land use planning and flood mitigation investments.

8.6 Final reflections

This thesis has shown that understanding flood risk in Thailand requires an approach that recognizes both the physical behavior of floods and the social and economic conditions that shape how communities experience them. Through the development and testing of a GIS based, data driven modelling framework, the study demonstrated that rigorous statistical methods can reveal underlying patterns of vulnerability that are often overlooked in traditional hazard focused assessments. The results consistently indicated that socio economic vulnerability is the most influential driver of flood risk, confirming that long term inequalities, limited financial resilience and uneven access to education significantly shape community exposure and sensitivity.

The research process revealed the value of combining quantitative modelling with qualitative insight. While PCA, OLS and GWR provided strong analytical structure and spatial precision, expert consultations offered practical explanations for unexpected patterns and helped ground the results in real experience. This combination highlighted that flood risk modelling is not only a technical exercise but also a dialogue between data and lived reality. A model can show where risk is highest, but local practitioners and residents can explain why these areas remain vulnerable and how conditions have evolved over time.

Working with Thai datasets also exposed important practical challenges. Frequent changes in data format, inconsistent administrative classifications, unstable online platforms and incomplete records slowed progress and required repeated data cleaning. These challenges reflected the broader difficulty of maintaining consistent national flood related datasets in Thailand. At the same time, they underscored why a transparent, publicly accessible and flexible modelling framework is essential. The experience of navigating these issues emphasized that robust flood risk analysis depends not only on methodological strength but also on the capacity of national data systems.

Reflecting on the cross-national comparison between the UK pilot study and the Thai application, the research highlighted the importance of contextual adaptation. Although the model structure was transferable, the variables and data definitions required careful modification to reflect Thai demographic patterns, local vulnerability realities and distinct institutional environments. This showed that transferring analytical tools across countries is feasible, but only when local knowledge is integrated into the adaptation process.

Overall, these reflections illustrate that flood risk assessment must remain adaptive, interdisciplinary and people centered. The model developed through this research provides a strong technical foundation, but the real value lies in its ability to support more equitable and informed decision making. By revealing how vulnerability shapes risk at sub district scale, the thesis contributes to a more holistic understanding of flood impacts and offers practical tools that can guide future planning, resource allocation and policy development in Thailand.

This project has also made clear that flood risk challenges will continue to evolve as climate change, economic transformation and urban growth reshape communities. Continued research, collaboration with local authorities and investment in data systems will therefore be essential. The reflections gained through this work reinforce that improving flood resilience in Thailand is an ongoing journey and that this thesis provides an important step toward more evidence based and community centered flood governance.

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Appendix

Appendix A: Questionnaire

Appendix B: 2023 Census data

Appendix A: Questionnaire

The research questionnaire form

This form is a part of a PhD research on the topic of "Optimisation of strategies using spatial approaches to manage flood risk in Thailand." Conducted by Ms. Karuna Pimprasan, who is a PhD student of Social and Economic Research Institute, Sheffield Hallam University, United Kingdom. She also has got a scholarship from the Royal Thai Government and is an officer of Geo-Informatics and Space Technology Development Agency (GISTDA), Ministry of Higher Education, Science, Research and Innovation. The aim of the form is to receive advice on the suitability of risk variables from experts who have expertise in flood risk assessment as well as those with experience in the area. All data will be kept confidential and not shared. For any inquiries please contact: [redacted]

Please complete the form by words or tick (✓)

Section 1: Expert knowledge and experience

1.1 Personal information

First name:..Family name:..

Email:..

Sector: ☐ Academic ☐ Government ☐ Private ☐ Others ....

Organization:...

1.2 Type of expertise: ☐ Model ☐ Variable ☐ Evaluation ☐ Local flood officer
☐ Others..

1.3 What form of activity are you involved in?

☐ Policy making ☐ Operation ☐ Academic ☐ Stakeholder

1.4 How long have you been experienced?

☐ < 5 years ☐ 5-10 years ☐ 10-20 years ☐ >20 years

Table A1. Section 2: Rating of variables

Component/ Variables	Criteria	Strongly disagree (-2)	Disagree (-1)	Neutral (0)	Agree (1)	Strongly agree (2)
Hazard						
H1 Hazard zone	High Frequency increase hazard					
Exposure						
E1 Density of Buildings	High density increase exposure					
E2 Population density	High density increase exposure					
E3 Landuse	High value increase exposure					
E4 Size of household	High density increase exposure					
Vulnerability						
V1 Children	High children increase vulnerability					
V2 Elder	High older increase vulnerability					
V3 Gender	High women increase vulnerability					
V4 Education	Low education increase vulnerability					
V5 Employed	Low employment					

Component/ Variables	Criteria	Strongly disagree (-2)	Disagree (-1)	Neutral (0)	Agree (1)	Strongly agree (2)
	increase vulnerability					
V6 Income	Low income increase vulnerability					
V7 Older_care	High older care increase vulnerability					
V8 Disabled	High disabled increase vulnerability					
V9 Illness	High illness increase vulnerability					

Table A2. Variables Description

Component/Variables	Description
Hazard	
H1 Hazard zone	Floods are natural, recurring events, so floods are often described in terms of statistical frequency. For example, plains located next to rivers and coasts are subject to frequent flooding. Therefore, the flood plain is "Area at risk of flooding" (HR Walliford, 2022). This research uses repeated flood area data from GISTDA that has been interpreted from 12 years of satellite data.
Exposure	
E1 Density of Buildings	In high-density residential areas, incident response emergency services may be overloaded (Cutter et al., 2003).
E2 Population density	Population density is often linked to low-income housing, which in overcrowded areas tends to have poor drainage and inadequate infrastructure (Rinc et al., 2018).
E3 Landuse	Land use is categorized according to the economic damage value. Whereas the industrial land use category is defined as the category with the highest economic value (Rinc et al., 2018). It also affects drainage: community areas may have more water barriers than farmlands (Kaźmierczak & Cavan, 2011).
E4 Size of household	Families with many dependents often have limited funds to care for their dependents from outside. Therefore, they are responsible for working and taking care of family members. All effect resilience and recovery from danger (Cutter et al., 2003).
Vulnerability	
V1 Children	Age affects the ability to move out of danger, which increases the burden of care and lacks flexibility because children are not yet able to help themselves. Additionally, children still do not understand signs regarding warnings and evacuation, which can create barriers to movement during flooding (Clark et al., 1998).

Component/Variables	Description
V2 Elder	An advanced age affects movement without causing harm. Therefore, older adults may have limited mobility or mobility concerns that increase the burden of care and their ability to recover (Cutter et al., 2003).
V3 Gender	Women are generally considered more vulnerable to natural hazards than men because they may have a more difficult time recovering than men, due to their mobility and family care responsibilities (Cutter et al., 2003).
V4 Education	The study was linked to socioeconomic status and ability to understand warning information and access to rescue information (Cutter et al., 2003).
V5 Employed	The loss of employment results in slower recovery from disasters, such as repairing homes and equipment in preparation for the next flood (Cutter et al., 2003).
V6 Income	The ability to recover from losses faster due to various insurance and entitlement programs to cope with flooding (Kaźmierczak & Cavan, 2011).
V7 Older_care	Elderly people needing care, which can create barriers to movement during floods and evacuations (Kaźmierczak & Cavan, 2011).
V8 Disabled	Persons with disabilities who need care, which can create barriers to movement during floods and evacuations (Kaźmierczak & Cavan, 2011).
V9 Illness	Patients with chronic illnesses requiring care, which can create barriers to movement during floods and evacuations (Kaźmierczak & Cavan, 2011).

Step of work

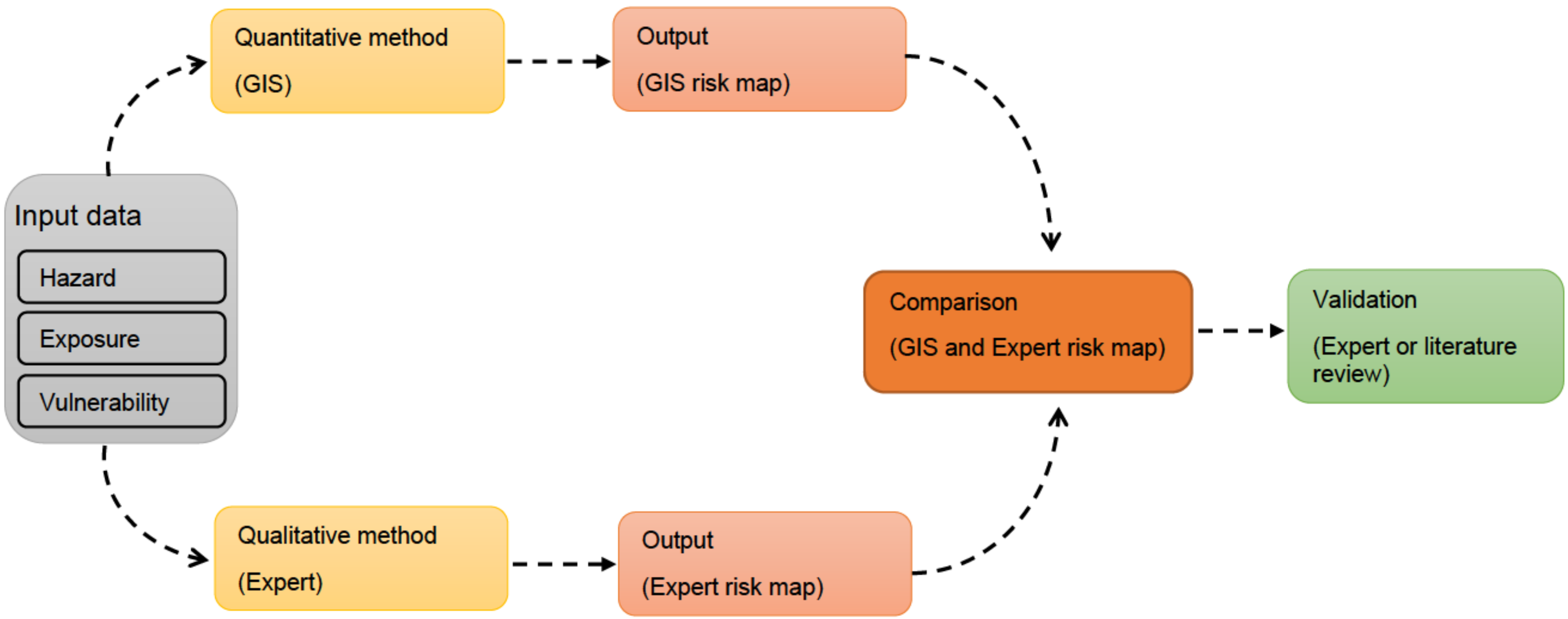

Figure A1. Workflow for expert interviews

Table A3. Description of experts and interview dates

No. of Participant	Name	Specialization	Affiliation	Organization	Date of Interview
1	P1	Academic Remote Sensing, Digital Image Processing, Disaster Management, Weather Monitoring with IoTs, Agriculture Geo-analytics, GIS Data Analytic, GIS Data Visualization	Dean, Faculty of Science and Technology	Thammasat University	10/5/2024
2	P2	Government Satellite imagery in flooding. Natural Resources, Environment and Natural Disaster Division	Specialist (Geo-Informatics) Office of Geo-Informatics Management and Solutions	Geo-Informatics and Space Technology Development Agency	10/5/2024
3	P3	Private Drought and flooding	Water resources engineering	ATT Consultants Co., Ltd.	6/5/2024
4	P4	Government Local authority	Director of the Social Welfare Division	Phra Ngam Subdistrict	5/5/2024
5	P5	Government Local authority		Phra Ngam Subdistrict	5/5/2024
6	P6	Government Local authority		Phra Ngam Subdistrict	5/5/2024
7	P7	Private Local		Phra Ngam Subdistrict	5/5/2024

No. of Participant	Name	Specialization	Affiliation	Organization	Date of Interview
8	P8	Private Local		Phra Ngam Subdistrict	5/5/2024
9	P9	Prevention and Mitigation	Assistant Head of the Office of Disaster Prevention and Mitigation	Office for Prevention and Mitigation Sing Buri	7/5/2024
10	P10	Prevention and Mitigation	Head of planning and directing disaster prevention and mitigation	Office for Prevention and Mitigation Sing Buri	7/5/2024
11	P11	Census data	Director of Community Development Information Division	Community Development Department Sing Buri	7/5/2024
12	P12	Census data	Community development specialist	Community Development Department Sing Buri	7/5/2024

Appendix B: 2023 Census data

Table B1. 2023 Census data

ID	Subdistric	Province	Pop Den	Build Den	HouseSize	Age	Female	NoEducatio	LessHighSc	Unemployed	Lowincome	LowSaving	Hfrequency	FR
1	Champa Lo	Ang Thong	193	85	3	820	1464	15	1042	12	9	587	2.19	13
2	Phai Dam Patthana	Ang Thong	230	92	3	692	1121	17	817	7	4	162	3.72	15
3	Khlong Khanak	Ang Thong	175	91	3	882	1336	32	932	27	1	778	2.69	14
4	Lak Kaeo	Ang Thong	185	63	3	1285	2092	66	1737	35	3	435	3.12	15
5	Norasing	Ang Thong	386	127	3	587	1165	12	913	6	0	339	2.53	13
6	Sai Thong	Ang Thong	223	83	3	678	1287	24	745	9	8	445	1.81	12
7	Bang Chak	Ang Thong	219	82	3	1252	2102	97	1612	46	9	905	3.50	15
8	Bang Pla Kot	Ang Thong	303	173	3	565	898	11	548	9	14	388	1.19	8
9	Phai Wong	Ang Thong	152	50	3	672	1202	56	1034	20	3	449	3.43	15
10	Ekkarat	Ang Thong	119	46	3	644	1147	14	910	5	0	67	2.77	15
11	Pa Mok	Ang Thong	352	246	2	1206	1729	16	1172	4	29	997	1.68	9
12	Rong Chang	Ang Thong	200	73	3	646	1220	15	808	4	36	760	1.90	11
13	Bang Sadet	Ang Thong	195	94	3	668	1105	20	668	9	15	269	2.26	13
14	Phong Pheng	Ang Thong	248	86	3	745	1275	17	849	5	22	387	2.52	13
15	Ban Cha	Singburi	116	51	3	816	1198	17	1018	4	15	359	1.34	8
16	Tha Kham	Singburi	202	104	3	1014	1649	19	1130	10	0	395	1.37	9
17	Chaksi	Singburi	247	120	3	880	1426	24	891	23	0	249	1.76	10
18	Pho Thale	Singburi	165	59	3	1104	1754	48	1693	30	1	530	1.34	8
19	Pho Sangkho	Singburi	213	114	3	1420	2337	32	1847	15	0	732	1.13	7
20	Phrom Buri	Singburi	227	120	3	693	1169	42	589	20	0	514	1.07	8
21	Hua Pa	Singburi	68	70	2	271	354	3	193	3	0	256	2.13	11
22	Kho Sai	Singburi	119	62	3	625	1037	47	832	29	0	413	1.63	10
23	Nong Krathum	Singburi	117	49	3	579	963	15	901	9	1	459	1.05	7
24	Wihan Khao	Singburi	141	75	2	461	663	15	495	11	4	125	2.53	12

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25	Ban Paeng	Singburi	141	81	2	553	726	4	403	4	2	325	1.35	10
26	Rong Chang	Singburi	171	88	2	636	1012	16	677	2	0	523	2.24	11
27	Bang Rachan	Singburi	223	108	3	1299	2520	150	2050	33	0	797	1.59	8
28	Bang Nam Chiao	Singburi	179	111	2	705	944	5	513	3	0	388	1.09	9
29	Pho Prachak	Singburi	216	105	2	850	1212	23	1012	12	10	749	2.03	12
30	Huai Phai	Ang Thong	169	82	3	592	1012	29	940	24	1	432	2.40	11
31	Si Bua Thong	Ang Thong	119	44	3	1440	2459	117	2554	74	4	1199	0.75	7
32	Sawaeng Ha	Ang Thong	194	85	3	1849	3211	104	2741	75	15	1477	2.15	9
33	Thon Samo	Singburi	281	155	2	1455	1944	24	1448	9	1	1106	1.87	9
34	Phikun Thong	Singburi	175	93	2	712	1016	24	743	0	4	416	2.86	13
35	Phra Ngam	Singburi	149	80	2	873	1239	13	1030	4	0	366	1.72	10
36	Ban Mo	Singburi	174	96	2	1276	1985	27	1466	19	1	1025	1.33	10
37	Chamlong	Ang Thong	178	69	3	606	998	15	815	16	5	458	3.34	15
38	Wang Nam Yen	Ang Thong	186	55	3	1597	2768	76	2736	60	14	1273	0.71	6
39	Ongkharak	Ang Thong	165	97	2	1044	1447	7	1112	12	4	849	2.46	12
40	Ban Phran	Ang Thong	149	70	3	1054	1686	106	1676	37	7	834	0.96	7
41	Si Phran	Ang Thong	129	59	3	570	1008	32	769	18	1	475	3.31	14
42	Chaiyo	Ang Thong	200	106	3	498	833	2	587	4	4	381	1.39	9
43	Chaiyaphum	Ang Thong	288	103	3	735	1386	24	823	10	5	558	0.99	10
44	Bang Rakam	Ang Thong	160	81	2	518	740	12	486	19	10	304	1.67	13
45	Bang Chao Cha	Ang Thong	192	73	3	795	1351	27	871	22	12	284	3.07	15
46	Nong Mae Kai	Ang Thong	89	56	2	572	926	13	722	14	25	682	2.21	14
47	Ram Masak	Ang Thong	175	61	3	2234	3457	121	3182	174	111	1132	0.70	6
48	Khok Phutsa	Ang Thong	157	72	2	574	969	13	756	23	15	667	3.32	15
49	Lak Fa	Ang Thong	132	68	3	321	560	2	357	1	2	112	1.26	9
50	Chawai	Ang Thong	587	121	4	414	998	3	838	0	5	343	1.51	9
51	Thang Phra	Ang Thong	235	101	3	647	1085	34	806	51	17	493	2.36	13

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52	Ratsathit	Ang Thong	211	74	3	564	1061	12	758	10	4	151	1.76	10
53	Kham Yat	Ang Thong	140	60	3	781	1307	18	1064	27	44	649	2.74	15
54	Yang Chai	Ang Thong	198	68	3	1447	2420	45	2259	42	51	1224	1.62	9
55	Ang Kaeo	Ang Thong	236	141	2	756	1276	13	656	14	21	681	2.48	13
56	Tri Narong	Ang Thong	290	75	3	360	606	20	486	19	11	329	2.85	13
57	Inthapramun	Ang Thong	200	101	2	827	1253	14	648	10	6	719	2.08	13
58	Chorakhe Rong	Ang Thong	180	85	3	653	1124	13	624	6	6	493	1.54	10
59	Thewarat	Ang Thong	154	67	3	462	767	6	380	3	0	255	2.45	11
60	Mongkhontham Nimit	Ang Thong	135	51	3	837	1424	75	1294	46	36	532	1.13	8
61	Muang Tia	Ang Thong	154	79	3	1413	2270	24	1871	16	3	606	2.53	12
62	Bang Phlap	Ang Thong	441	180	3	791	1415	26	840	9	0	368	1.22	8
63	Chaiyarit	Ang Thong	244	88	3	714	1222	7	740	8	13	510	1.47	10
64	Sam Ngam	Ang Thong	249	80	3	416	722	9	550	15	7	326	2.52	14
65	Bo Rae	Ang Thong	199	66	3	407	721	4	573	4	16	358	2.98	15
66	Ratsadon Phatthana	Ang Thong	106	50	3	633	977	56	871	55	12	385	1.59	11
67	Yan Sue	Ang Thong	283	135	3	612	1079	8	526	1	0	362	2.21	10
68	Sam Ko	Ang Thong	219	77	3	1288	2336	116	1750	106	10	698	1.02	7
69	Talat Kruat	Ang Thong	234	83	3	604	790	15	490	19	0	352	1.31	10
70	Pa Ngio	Ang Thong	291	150	2	985	1810	20	960	14	1	413	1.81	11
71	Pho Rang Nok	Ang Thong	133	99	2	436	516	12	381	19	10	328	2.22	14
72	Sala Daeng	Ang Thong	484	210	3	1145	2293	42	1238	32	2	529	2.03	11
73	Ban Ri	Ang Thong	236	96	3	434	751	18	444	2	0	103	1.77	10
74	Optom	Ang Thong	195	66	3	1003	1907	145	1786	120	80	572	0.84	6
75	Phai Chamsin	Ang Thong	267	139	2	1247	1991	45	1133	24	10	324	2.21	12
76	San Chao Rong Thong	Ang Thong	433	179	3	1645	2481	71	1257	60	8	716	1.57	11
77	Yi Lon	Ang Thong	175	80	3	1015	1494	13	1145	18	9	292	1.56	12
78	Hua Taphan	Ang Thong	285	125	3	723	1179	20	955	19	2	592	2.87	13

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79	Ban It	Ang Thong	413	202	3	1034	1810	39	1155	40	0	643	1.18	7
80	Mahatthai	Ang Thong	118	59	3	391	668	14	559	10	2	206	3.55	14
81	Talat Luang	Ang Thong	2161	525	2	937	1472	3	804	3	3	459	0.85	6
82	Khlong Wua	Ang Thong	134	95	2	499	841	14	674	14	4	455	2.44	13
83	Bang Kaeo	Ang Thong	1458	476	2	553	786	1	274	0	15	12	0.91	7
84	Pho Muang Phan	Ang Thong	269	84	3	1021	1887	101	1575	71	14	687	1.35	10
85	Ban Hae	Ang Thong	464	240	3	575	976	13	723	10	1	302	1.03	8
86	Pho Sa	Ang Thong	272	174	3	767	1451	15	732	16	6	318	1.03	9
87	Sao Rong Hai	Ang Thong	121	48	3	1071	1894	121	1467	51	6	1063	2.03	12
88	Tha Chang	Ang Thong	186	83	3	1028	1713	47	1166	35	2	303	1.72	12
89	Huai Khan Laen	Ang Thong	121	54	3	812	1320	64	1008	9	0	111	2.17	14
90	Hua Phai	Ang Thong	303	107	3	977	1788	49	1383	35	7	705	1.28	10
91	Si Roi	Ang Thong	184	127	3	670	1062	19	882	28	8	532	3.31	13
92	Talat Mai	Ang Thong	212	59	2	498	726	12	585	10	2	446	2.21	14
93	Taluk	Chainat	156	44	3	2377	3856	91	2928	54	1	1013	1.91	9
94	Nong Noi	Chainat	58	29	2	891	1364	44	1368	1162	3	627	0.90	4
95	Wang Man	Chainat	34	19	2	818	1487	173	1542	108	26	445	0.20	3
96	Ban Kluai	Chainat	293	128	2	2134	3398	41	1407	20	8	1215	1.58	7
97	Hat A Sa	Chainat	132	41	2	1898	2885	78	2557	54	0	1026	1.48	10
98	Tha Chai	Chainat	162	86	2	1678	2814	137	2048	48	12	884	1.16	6
99	Nai Mueang	Chainat	854	779	1	652	857	10	227	4	4	474	0.85	5
100	Bang Luang	Chainat	146	66	2	1395	2007	59	1437	48	0	1155	1.42	9
101	Nang Lue	Chainat	110	44	3	1879	2983	157	2663	80	11	1389	1.47	7
102	Khao Kaeo	Chainat	66	31	3	765	1149	78	1169	36	1	402	3.32	14
103	Sapphaya	Chainat	122	46	2	1618	2131	40	1682	17	1	959	2.88	12
104	Chai Nat	Chainat	177	84	3	1891	2943	37	2071	34	22	890	1.21	7
105	Nong Saeng	Chainat	50	22	3	1671	3290	128	3299	49	0	1094	0.43	4
106	Huai Ngu	Chainat	110	43	3	1449	2308	41	2083	26	5	460	1.59	7

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107	Phrai Nok Yung	Chainat	45	21	3	586	2450	124	2464	59	0	933	0.01	3
108	Kabok Tia	Chainat	41	19	3	1100	2110	183	2142	21	4	1012	0.00	3
109	Pho Nang Dam Ok	Chainat	180	54	3	1612	2509	42	1748	21	0	696	2.60	12
110	Chi Nam Rai	Singburi	95	58	2	993	1438	46	1035	15	14	521	3.55	13
111	Huai Krot	Chainat	423	163	3	2049	3233	24	2509	22	21	706	1.38	9
112	Thiang Thae	Chainat	109	62	3	1599	2238	78	2069	35	9	792	0.97	8
113	Pho Nang Dam Tok	Chainat	320	95	3	1668	2746	47	2242	37	0	711	2.82	14
114	Phraek Si Racha	Chainat	128	65	2	3317	5139	77	4385	83	4	1525	2.01	10
115	Sam Ngam Tha Bot	Chainat	112	40	3	1183	1814	37	1627	24	1	648	1.63	7
116	Thong En	Singburi	123	57	3	1810	2909	82	2238	72	6	830	3.22	14
117	Huai Krot Phatthana	Chainat	128	66	3	1215	1975	51	1806	54	13	574	2.46	12
118	Den Yai	Chainat	62	25	3	1129	1942	150	2098	31	28	706	0.19	3
119	Tha Ngam	Singburi	171	86	3	1263	1997	61	1451	23	3	986	1.81	10
120	Prasuk	Singburi	139	74	2	1521	2076	68	2016	49	11	820	2.02	11
121	Han Kha	Chainat	101	47	3	2005	3224	73	3095	39	4	860	1.64	7
122	Pho Chai	Singburi	56	21	3	574	893	25	775	25	2	253	2.23	13
123	Wang Kai Thuean	Chainat	80	35	3	1678	2522	30	2554	24	0	1067	2.10	10
124	Noen Kham	Chainat	33	21	2	1445	1969	71	2044	14	9	1132	0.05	3
125	Pho Ngam	Chainat	120	65	3	1881	2692	62	2491	44	11	1009	1.30	8
126	Huai Chan	Singburi	98	43	3	1011	1829	41	1386	21	3	414	2.34	12
127	Dong Khon	Chainat	87	40	2	2733	4114	194	4092	120	6	1300	1.04	7
128	Bang Khut	Chainat	115	60	2	1662	2555	34	2394	21	17	1083	1.29	7
129	In Buri	Singburi	448	207	2	2128	2957	33	1692	13	6	638	1.36	9
130	Ngio Rai	Singburi	141	57	3	1177	2032	46	1722	39	3	779	1.90	11
131	Namtan	Singburi	139	79	2	932	1353	37	835	29	8	545	1.56	10
132	Suk Duean Ha	Chainat	61	25	3	1242	2047	91	2287	25	7	977	0.00	3

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133	Hua Phai	Singburi	140	55	3	1212	1960	42	1512	33	7	771	2.34	12
134	Thap Ya	Singburi	179	91	3	1663	2355	30	1575	26	1	758	2.06	10
135	Don Kam	Chainat	99	59	2	681	914	17	807	19	3	341	2.04	11
136	Ban Chian	Chainat	114	45	3	2425	3781	46	3856	40	13	901	1.37	8
137	Phok Ruam	Singburi	129	83	3	919	1340	49	933	33	0	389	2.02	12
138	Mae La	Singburi	69	43	3	402	594	13	444	8	2	252	1.97	10
139	Pho Chon Kai	Singburi	134	82	2	1071	1338	25	1041	9	7	660	1.16	7
140	Phak Than	Singburi	64	42	2	831	1165	27	1138	4	2	564	1.89	9
141	Choeng Klat	Singburi	120	77	3	1127	1583	27	1233	19	13	463	1.29	7
142	Bang Krabue	Singburi	197	108	2	1372	2142	31	1278	19	6	966	1.87	8
143	Bang Man	Singburi	409	157	2	2703	3976	66	92	42	10	1255	1.46	8
144	Sing	Singburi	140	77	3	862	1443	37	1104	8	3	515	1.74	8
145	Sa Chaeng	Singburi	93	48	3	923	1401	39	1457	10	2	506	0.87	6
146	Mai Dat	Singburi	130	98	2	1393	2009	5	698	5	14	762	0.79	7
147	Ton Pho	Singburi	215	153	2	1466	2510	72	1192	21	0	826	1.56	9
148	Bang Phutsa	Singburi	867	725	2	1015	1245	7	454	6	0	443	0.89	6
149	Muang Mu	Singburi	445	182	3	1399	2421	34	1516	15	3	856	0.89	7
150	Tha Chanuan	Chainat	101	55	2	1681	2483	28	2499	13	15	1082	1.20	7
151	Sila Dan	Chainat	90	47	2	772	1125	6	1156	3	37	756	1.22	6
152	Rai Phatthana	Chainat	45	27	2	664	1163	20	1241	5	12	927	0.62	5
153	Wat Khok	Chainat	71	51	2	878	1263	17	1225	17	25	629	1.15	6
154	Hang Nam Sakhon	Chainat	105	52	2	1326	2186	47	1922	31	41	1208	1.33	6
155	Khung Samphao	Chainat	124	82	2	1159	1651	22	1159	13	9	1182	1.17	6
156	Wang Takhian	Chainat	51	27	3	1682	2571	162	2523	84	41	1027	0.31	3
157	Bo Rae	Chainat	61	26	3	640	945	31	869	64	17	434	0.54	3
158	Nong Bua	Chainat	98	43	2	634	1038	53	920	138	34	325	0.63	3
159	U Taphao	Chainat	49	31	2	686	1050	31	1110	4	8	702	1.00	7

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160	Kut Chok	Chainat	35	24	2	577	835	46	867	26	2	362	0.29	3
161	Thammamun	Chainat	146	62	3	1696	2944	123	2898	56	3	788	1.23	6
162	Nong Mamong	Chainat	56	26	3	1071	2006	80	2077	43	15	1009	0.09	3
163	Nong Khun	Chainat	45	22	2	809	1387	56	1345	130	22	539	0.32	3
164	Suea Hok	Chainat	126	37	3	1677	2731	64	2582	42	11	1219	1.14	7
165	Wat Sing	Chainat	1604	402	2	748	1174	61	615	200	83	424	0.24	3
166	Makham Thao	Chainat	88	43	2	1207	1909	85	1509	80	25	699	0.76	4
167	Hat Tha Sao	Chainat	147	68	3	1259	1907	89	1784	48	7	911	0.84	6
168	Khao Tha Phra	Chainat	129	114	2	1594	2803	106	2160	27	0	1229	1.52	7
169	Saphan Hin	Chainat	43	24	3	1059	2111	142	2047	39	18	867	0.06	3