A DEVELOPED HYBRID INTEGRATED FRAMEWORK WITH COMBINED ANALYTICAL APPROACHES IN MITIGATING THE FLOOD AND DROUGHT RISK ON RIVER SEVERN BASIN

A THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

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DECLARATION

I declare that no material contained in the thesis has been used in any other submission for an academic award.

I confirm that the thesis submitted is entirely my own work and based on my own research; that all sources used are appropriately acknowledged and that where the words of others are used these are clearly placed in quotation marks.

I have published material relating to this research previously, and reference is made to any such publications in the body of the thesis (please note that copies of any such publications should be submitted with the thesis included in as appendix) and referenced accordingly.

I understand that my thesis should normally be submitted at least six weeks before any anticipated date of viva examination.

Siavash Fasihi

12 July 2024

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ABSTRACT

Floods and droughts are among the most devastating natural disasters, significantly impacting environmental and socio-economic systems. With climate change exacerbating these risks, it is crucial to develop robust frameworks in assessing and mitigating the risk. This thesis aims to develop a hybrid integrated framework for flood and drought risk assessment, combining multiple methodologies and modern predictive techniques. The research employs a combination of Interpretive Structural Modelling (ISM), Causal Loop Diagrams (CLD), and network theory to build the framework. Statistical and machine learning methods are used to calculate and test the framework, ensuring a comprehensive analysis. The integrated framework effectively identifies and assesses key risk factors and their interdependencies. The spatio-temporal mapping revealed significant trends in flood and drought occurrences. Despite the presence of flooding risk partly due to more intense rainfalls, the risk of drought coexists on a river basin scale. Validation using Receiver Operating Characteristic (ROC) curves demonstrated the model's accuracy. Sensitivity analysis highlighted critical variables such as community resilience, precipitation, access to transportation networks, and reservoirs, which contribute significantly to the variance of predicted risks. Other parameters aid in the accuracy of these predictions, while factors like elevation and slope assist with the spatial distribution of the risks. The developed framework has shaped and enhanced substantial understanding of flood and drought risks, providing a robust basis for future research. Future work should focus on integrating more diverse datasets and exploring long-term climate impacts to further refine and improve the assessment process.

Keywords: Flood risk assessment, drought risk assessment, hybrid integrated framework, spatio-temporal mapping, climate change, advanced analytical techniques, sensitivity analysis, receiver operating characteristic (ROC).

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1 INTRODUCTION

"In the face of uncertainty, the only certainty is resilience. Understanding the dynamics of natural hazards such as floods and droughts is not just about predicting outcomes but about building adaptive and resilient communities."

1.1 Background and rationale

The risk of flood and drought on a river basin scale encapsulates the likelihood and potential consequences of extreme hydrological events disrupting the balance of water availability within a specific river basin (Hirabayashi et al., 2013; Trenberth et al., 2014). Flood risk refers to the potential for increase in flood level to inundate land, affecting communities, agriculture, and infrastructure, driven by factors like intense rainfall, snowmelt, or dam failures (Field, 2012; Kundzewicz et al, 2014; Paprotny et al, 2018). Conversely, drought risk characterizes periods of insufficient water supply due to prolonged below-average precipitation, or demand increase leading to water scarcity that impacts water quality, ecosystem services, and socio-economic activities (Vogel et al., 2015, Haile et al., 2020; Christian et al., 2021; Lesk and Anderson., 2021). Assessing these risks involves evaluating the vulnerability and exposure of the basin's natural and human systems to these extreme events, underpinned by climate variability and change, land use practices, and water management policies (Van Loon and Van Lanen 2013).

Flooding and drought risk are intertwined complex issues, which lie in the middle of many fields. Review of case studies that explore natural phenomena such as droughts, floods, the coexistence of droughts and floods (DFC), and urban-related aspects reveals that the interdisciplinary literature spans a broad array of fields, including earth science, climate studies, biology, hydrology, water resources, disaster research, and urban planning, among others (Hoa and Vinh, 2018).

A changing climate is intimately linked to changes in the hydrological cycle (Huang et al 2015). Therefore, considering the temporal element of change in climate, adds to the dynamic complexities of assessing and projecting these risks (Wu et al., 2017). On one hand, anticipated changes in settlement patterns and the impacts of climate change are poised to escalate the risk of floods and droughts on a global scale (Milly et al, 2002; Hirabayashi et al, 2013; Winsemius et al, 2015; Arnell & Gosling, 2016). On another hand, it signifies the importance of spatio-temporal trends of drought and flood events as analysis highlights the impact of timing and sequence of atmospheric alternations on such hydro-hazards (Zaroug et al., 2014) leading to a more in-depth investigation of the joint probabilities of continuous hydrological droughts and floods. Combination of these events in the basin scale causes extra sensitivity to the distribution of water resources and other consecutive risk factors (AghaKouchak et al., 2015; Wu et al., 2017). For instance, there are several observations that such factors affect the urban planning and regional geo-politics in a way that updated development states need to be transferred to the hydrodynamic models to inform the flood risk assessments models (Löwe et al., 2017). These multi-perspective, retrospective and regional studies need access to various large and reliable datasets to offer a foundation for uniformity across methodologies, crucial for regulators aiming to evaluate and compare different proposed plans (Hall et al., 2020).

It also requires progress of statistical modelling to infer the past and current circumstances to enhance the capacity of projecting the dynamic of flood and drought risk fluctuations in time and space (Serinaldi and Kilsby, 2014). Some of these models include extreme value perception, which is of main concern for simulating catastrophic scenarios often caused by single or a limited set of causes. Whereas, in design and implementation of water resources management scenarios, the number and frequency of less severe events are deemed to be more practical (Prosdocimi et al., 2014).

Highlighting these dimensions enhances water management in many ways. One is encouraging the integration of social aspects with hydro-climatological insights for a comprehensive understanding of flood and drought (Urquijo and De Stefano, 2016). Next would be identifying often overlooked vulnerability factors, enabling the development of user-centric strategies, which addresses the necessity of transforming scientific knowledge into actionable insights for policy-making and governance (Wheater, 2015).

Next of such enhanements could be emphasizing the importance of documenting drought and flood impacts to better characterize and manage them (Urquijo and De Stefano, 2016). When considering droughts and floods from a long-term viewpoint, it's evident that priorities vary significantly between highly developed and regulated river basins and those that are more natural and less developed finally, stressing the need for effective communication between governmental bodies and water users to improve risk response coordination (Grobicki et al., 2015). Research suggested the creation of mitigation approaches aimed at diminishing the vulnerabilities of individuals and communities to changes in hydro-meteorological patterns, heightened variability, and extreme occurrences, additionally, prioritise efforts to bridge the discrepancy between water supply and demand (Bergkamp et al 2003).

Therefore, adopting an integrated approach from the outset is crucial for mitigating long-term costs and minimizing anthropogenic impacts on the natural dynamics of river basins (Grobicki et al., 2015).

River basins are dynamic systems where water availability and risk are influenced by natural processes and human activities. The impact of flood and drought events is exacerbated by factors such as urbanization, deforestation, and agricultural practices, which alter land use and water management strategies. Furthermore, socio-economic factors, including population growth, economic development, and community resilience, play significant roles in shaping vulnerability and exposure to these hydrological hazards (Arora and Mishra, 2019).

Current methodologies for assessing flood and drought risks often rely heavily on quantitative analyses of hydrological variables, such as precipitation and river flow rates and sometimes consider the properties of the events such as the severity instead of the concept of risk. However, these approaches may not fully account for the broader socio-economic impacts and the adaptive capacities of communities. There is a pressing need for a holistic framework that integrates diverse parameters, including socio-economic factors, environmental consciousness, and community preparedness, to provide a more comprehensive assessment of flood and drought risks at the river basin scale (Adger, 2006; Merz et al., 2010a; Mechler et al., 2014).

Despite considerable advancements in hydrological modelling and risk assessment, a significant gap exists in frameworks to holistically integrate both natural and human dimensions of flood and drought risks (Pahl-Wostl, 2007; Ward et al., 2011; Withile et al., 2014). This gap is particularly pronounced in the context of climate change, where the need to understand and mitigate these risks is increasingly urgent. A comprehensive, integrative framework that encompasses a wide array of risk factors and their interconnections is critically needed (Summers et al., 2017; Jha et al., 2020).

The justification for this research lies in its potential to significantly advance our understanding of assessing flood and drought risks in the face of climate change. By incorporating a broader range of risk factors beyond traditional hydrological indicators, the proposed framework offers a more nuanced view of vulnerabilities and exposures. This comprehensive approach is crucial for developing targeted, effective mitigation and adaptation strategies that can enhance community resilience and sustainable water resource management (Allan et al., 2023). Initially, this research sought to identify the most impactful parameters and their interconnections for assessing flood and drought risks by gathering expert opinions. To achieve this, an open-ended questionnaire was distributed online, and several experts were invited to participate in interviews. However, the first round of efforts revealed significant challenges. Given the interdisciplinary nature of the research and the broad range of relevant fields, it became evident that obtaining sufficient credible insights across all targeted concepts within the time constraints of a PhD was not feasible. Furthermore, cross-verifying the interconnections between risk parameters from different disciplines proved equally challenging.

Recognizing these limitations, the experience informed a critical shift in methodology. Instead of relying on expert elicitation, the research pivoted towards conducting a systematic literature review. This approach utilized open-coded latent content analysis to systematically extract parameters across diverse disciplines. In addition to identifying key parameters, this method enabled the extraction of supplementary data, including datasets, weights, coding schemes, and insights from published studies. This adjustment allowed for a more comprehensive and rigorous foundation for assessing flood and drought risks, while addressing the challenges encountered in the initial approach.

The study aims to develop an integrative, adaptable framework accompanied by a geometric index for the simultaneous assessment of flood and drought risks in river basins. This framework is designed to capture the complexity of risk factors, including the interplay between natural hazards and socio-economic vulnerabilities, to support effective risk management, adaptation and mitigation strategies.

1.2 Aims and Objectives

Floods and droughts represent two opposing yet interconnected extremes of the hydrological cycle, with profound and often devastating impacts on ecosystems, economies, and societies. Traditionally, these phenomena have been studied in isolation, leading to fragmented and often incomplete risk management approaches. However, with the increasing variability and unpredictability of climate patterns, there is a growing and urgent need to assess these risks concurrently to address their complex interactions and compounded effects effectively.

This research directly addresses this gap by proposing a comprehensive framework designed to evaluate flood and drought risks holistically. The framework not only considers the physical and environmental factors driving these hazards but also integrates socio-economic variables that significantly influence vulnerability and resilience. By employing a diverse set of analytical methods and modeling techniques, the framework captures the multifaceted and interconnected nature of hydrological risks. The proposed approach aims to serve as a practical tool for policymakers, planners, and stakeholders engaged in river basin management, water resources modeling, and environmental service provision. It is envisioned to enhance decision-making processes, enabling a more integrated and adaptive response to the challenges posed by floods and droughts in an era of increasing climatic uncertainty.

The primary aim of this research is to develop and validate a comprehensive general framework for the simultaneous assessment of flood and drought risks at the river basin scale.

This framework seeks to integrate advanced statistical analyses, complex system modelling, and fractal mathematics to enhance the understanding of hydrological extremes and inform effective risk management strategies. By doing so, it aims to enhance the understanding of the complex interactions between flooding and drought risks, ultimately informing effective risk management strategies and sustainable water resource planning in regions susceptible to these hydrological extremes.

In order to meet the mentioned overarching aim of developing a simultaneous flood and drought risk assessment at the river basin scale, three main specific objectives were addressed.

I. To identify and elucidate deep interrelations, latent themes and data in flood and drought risk by applying advanced statistical analysis.

The goal of objective one is to systematically explore and elucidate the complex interrelationships and latent themes present in existing flood and drought risk literature. This objective employs a combination of advanced methods that fall under statistical analysis, correlation measures, similarity measures, and clustering algorithms to uncover hidden structures, generate insights, and establish a foundation for a comprehensive risk assessment framework. By using both quantitative measures such as Pearson and Spearman correlations, co-occurrence matrices, and cosine similarity as well as unsupervised clustering algorithms from machine learning and data mining, including DBSCAN and hierarchical clustering, this research aims to produce a sophisticated, multi-dimensional analysis of the latent content from literature.

II. To develop an integrative framework using Interpretive Structural Modelling (ISM), network theory, causal loop diagrams, and cross-entropy analysis to encapsulate key risk factors and their interdependencies in flood and drought risk assessment.

The second objective of this research is to develop a comprehensive framework that integrates the key risk factors identified in Objective One, focusing on understanding their interdependencies through advanced modelling and analytical approaches. This framework employs Interpretive Structural Modelling (ISM), network theory metrics, cross-entropy analysis, and causal loop diagrams (CLDs) to explore, model, and quantify the complex relationships between flood and drought risk factors. The ultimate aim is to create a dynamic model that captures these relationships and provides a structural view that informs decision-making processes for effective risk management.

The methodology used in Objective Two relies on system dynamics and network analysis, creating an integrative approach that goes beyond traditional risk assessments. By combining ISM to build structural models, network metrics to evaluate connectivity and influence, and cross-entropy analysis to rank risk factors, this objective offers a comprehensive pathway to understanding flood and drought risks.

III. To validate the developed framework, conduct sensitivity analysis, and introduce a Combined Flood and Drought Risk Index (CFDRI) for predictive risk mapping using spatial analysis, efficiency testing, and trend analysis of hydrological risks.

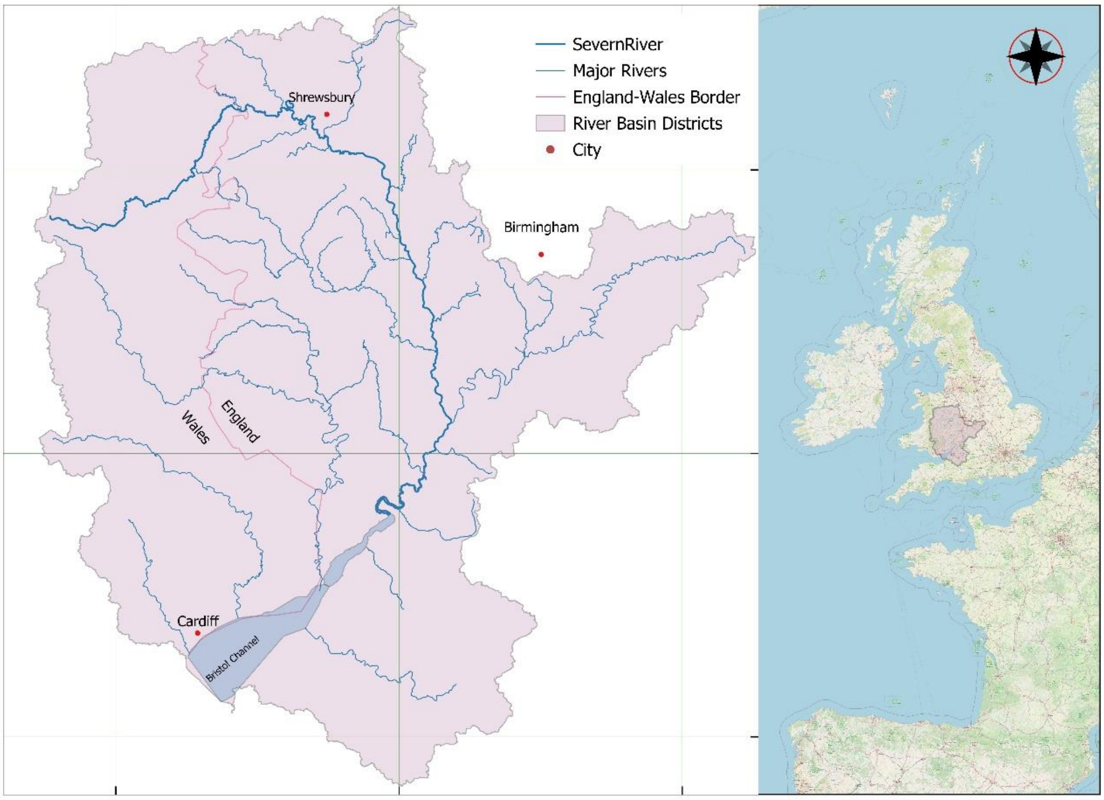
The third objective of this research focuses on validating the integrative framework developed in Objective Two, conducting sensitivity and uncertainty analyses, and introducing a novel Combined Flood and Drought Risk Index (CFDRI). This objective aims to quantify and evaluate flood and drought risks through advanced spatial analysis and to ensure the accuracy and reliability of the model by employing various validation, sensitivity, and trend analysis techniques.

The methodology for Objective Three includes spatial analysis for data classification and fuzzy modelling, validation tests using overlay methods and ROC curves, sensitivity and uncertainty analysis to understand model robustness, and trend analysis to examine changes in risk over time. Importantly, the CFDRI is developed by combining similar input variables using spatial measures such as fractal geometry to represent the spatial distribution maps. The culmination of these efforts is a predictive tool that provides monthly risk maps for the coming year, guiding stakeholders in proactive risk management.

1.3 STUDY SITE

Geographically, The third objective of this research focuses on validation, sensitivity analysis, and the development of a Combined Flood and Drought Risk Index (CFDRI), specifically applied to the River Severn Basin. The decision to focus on the River Severn Basin is justified due to its unique combination of hydrological characteristics, its geographical and socio-economic importance, and the wealth of historical data available. These factors make the River Severn an ideal case study for understanding and quantifying the risks of both flooding and droughts, providing insights that can potentially inform risk management in other similarly complex river basins.

The River Severn Basin covers over 21,000 km², including parts of both Wales and England. It encompasses not only the main river but also its numerous tributaries and a major river network, which extend its influence over a wide area of the surrounding countryside, affecting both the environment and the settlements of more than 5 million people within its reach. The river's length allows it to boast a varied geography, from its upland source through the rolling hills and fertile plains of the Midlands, to the wide tidal estuary. Its estuary is one of the largest and most important in the UK, noted for its high tidal range (Figure 1.1). The River Severn is the longest river in the United Kingdom, stretching for about 354 km. Its journey begins in the Cambrian Mountains of mid-Wales, specifically at an elevation on Plynlimon near Llanidloes, Powys. From this remote source, the river traverses the scenic landscapes of Wales and England, before reaching the Severn Estuary. This estuary then widens to form the boundary between England and South Wales, eventually merging with the Bristol Channel.



Error! Not a valid bookmark self-reference.**Figure 1.1.** Map of River Severn basin district including its major rivers.

In terms of hydrology, the average flow rate of the River Severn varies significantly along its course, influenced by rainfall, the catchment area, and water abstraction for various uses. At its mouth, the average flow rate is around 107 m^3/s, though this can vary widely with seasonal changes and upstream rainfall (Environment Agency, 2022). The River Severn plays a crucial role in the ecology, economy, and history of the regions it flows through, supporting diverse habitats, providing water for homes, agriculture, and industry, and historically enabling trade and settlement along its banks.

The River Severn Basin presents a compelling case for studying flood and drought risks due to its unique hydrological and ecological characteristics, coupled with its historical vulnerability to these extreme weather events. The basin's geographical extent, encompassing diverse landscapes across Wales and England, has historically been a hotspot for both flooding and drought conditions (Jones et al., 2019). This dichotomy is underpinned by the basin's complex climatic interactions and varied topography, which contribute to significant fluctuations in water availability and flow rates, thereby exacerbating the risk of both floods and droughts. For instance, the lower reaches of the Severn have experienced some of the UK's most severe flooding events, notably in recent decades, highlighting the basin's susceptibility to extreme rainfall and tidal surges (Smith & Davies, 2021). Conversely, the upper catchments have faced drought conditions, affecting water supply and quality (Brown & Clarke, 2020).

The transboundary nature of the Severn Basin, straddling Wales and England, adds layers of complexity to water management and conservation efforts, necessitating coordinated policy responses and interventions to mitigate these risks. Ecologically, the basin supports a rich biodiversity, including habitats of national and international importance, which are sensitive to changes in water levels, making the study of flood and drought dynamics critical for preserving the basin's ecological integrity.

Industrially, the River Severn is vital for supporting key sectors such as agriculture, manufacturing, and energy production, including the operation of hydroelectric power stations and cooling water for nuclear power plants. These industries not only contribute significantly to the regional economy but also depend on the reliable management of water resources, highlighting the economic imperatives of understanding and mitigating flood and drought risks.

Furthermore, the wealth of available hydrological and meteorological data for the Severn Basin, facilitated by a long history of monitoring and research, provides an invaluable resource for scientists and policymakers aiming to model water flow dynamics, predict future scenarios, and devise effective management strategies. This extensive data repository enables a comprehensive analysis of temporal and spatial patterns of floods and droughts, underpinning evidence-based decision-making processes. In the upcoming methods and materials chapter, a comprehensive exploration of the data and risk-related aspects of the River Severn Basin will be provided.

Given these factors, the River Severn Basin emerges as an exemplary study area for examining the coexistence of flooding and drought risks. Its significance is magnified by the need to balance ecological preservation with the demands of industrial and agricultural stakeholders, amidst the challenges posed by climate change and increasing human activity. Through targeted research and adaptive management, insights gained from the Severn Basin can inform broader strategies for enhancing resilience to water-related extremes in similar transboundary basins globally.

1.4 Chapter Summary and thesis structure

This thesis follows a traditional structure, divided into eight distinct chapters. Three chapters are specifically devoted to presenting the results and analysing the data obtained from the research. The other chapters include an introductory section that lays the groundwork for the study, a literature review that offers a critical evaluation of the current knowledge, a chapter outlining the research methodology, and another chapter providing an in-depth explanation of the methods and materials used in the research. Finally, the concluding chapter summarizes the key findings and highlights the study's contributions to the field. This structure ensures a clear, logical flow, guiding the reader smoothly from the initial stages of the research to the final conclusions.

Chapter 2 reports a thorough systematic examination of the existing literature on flood and drought risks. It accomplishes this by developing a specialized database, which is created through analysing the contents found in carefully selected peer reviewed publications. These publications include case studies as well as published opinions of the experts in the field. To minimize bias in this extensive review, the examination adopts an innovative approach using graph theory, specifically science mapping (Fasihi et al., 2021). This method is instrumental in discerning the most significant contributions from the array of publications, ensuring a focus on the most impactful insights.The primary goal of this segment of the research is to amass a comprehensive repository of reliable information. This repository is intended to facilitate further investigation into the most pertinent areas and variables that interact to influence flood and drought risks at the river basin scale. Additionally, this chapter aims to support the identification of available cutting-edge methodologies and datasets. These tools are crucial for enhancing the ability to assess and, ideally, forecast the risks associated with flooding and drought. Through this diligent inquiry, the chapter lays a solid foundation for advancing our understanding and management of these environmental challenges.

Chapter three provides a comprehensive description of the research methodology, including a detailed account of the systematic literature review and the methods employed throughout the study. It begins by outlining the procedures for accessing, screening, and selecting relevant literature, followed by the preparation of a database that fulfils the initial requirements of the research. The chapter then details the development of a framework through interpretive structural modelling (ISM), focusing on the pairwise relationships between various parameters. This section includes an analysis of the hierarchy of these parameters and their roles within the overall information flow, ultimately identifying the most significant risk factors detected by the framework. These factors are critical for assessing flood and drought risks, with the application of network theory enhancing the selection of the most influential pathways for risk assessment within the framework. The final section of the chapter explains the approach for quantifying, validating, and modelling the spatial-temporal dynamics of concurrent flood and drought risks. This includes the application of fuzzy logic and sensitivity analysis to refine the analysis and improve the accuracy of risk assessment.

The fourth chapter is dedicated to providing a detailed account of the methods and materials used in this research, offering a closer examination of the processes and tools that supported the study. This chapter also introduces the study site, offering an in-depth understanding of the geographical and environmental context where the research is applied. This chapter is critical because it establishes the foundation for replicability and transparency, allowing future researchers to understand the practical steps taken during the study and how these were aligned with the study's objectives. Moreover, understanding both the methods and the context of the study site is essential for interpreting the results and ensuring the broader applicability of the findings.

Chapter five marks the initial phase of the thesis where specific preliminary results of the study are presented. It provides an analysis of publication trends related to flooding and drought risks over the past twenty years, highlighting the principal fields contributing to the body of knowledge within a river basin context. Through the application of statistical and hierarchical analyses, the chapter delves deeper into these fields, examining their interconnections, identifying potential overlaps, and delineating the parameters that define them. Ultimately, it culminates in the creation of a comprehensive table of parameters. This table, featuring a network of directed influential links, serves as a tool for assessing the risks associated with flooding and drought.

Chapter six builds upon the work completed in the preceding chapter, utilizing the identified parameters and their connections. It begins by employing Interpretive Structural Modelling along with Causal Loop Diagrams to establish a comprehensive framework. Following this, the chapter proceeds to identify driving forces and dependencies through the use of a reachability matrix, which helps in analysing the hierarchy and significance of each parameter.

Subsequently, the chapter applies graph theory techniques to explore various characteristics of each parameter (or node) within the framework, utilizing a series of network metrics. This analysis leads to the compilation of a list of parameters that are ranked highest according to these metrics.

Finally, the chapter incorporates a cross-entropy algorithm to determine the most influential parameters overall. These parameters are significant in their contribution to the pathways within the framework designed to assess the concurrent risks of flooding and drought.

In chapter 7, by choosing specific pathways for evaluating flood and drought risks, the focus shifts to an in-depth analysis of these risks within the River Severn basin. It employs fuzzy logic functions to approximate the risks, taking into account a variety of parameters that contribute to the risk factors. The risk maps generated from this process are subsequently validated using sophisticated statistical models that draw on historical data and reports. Additionally, the chapter examines the sensitivity of results to changes in the input parameters. The complexity of the risk maps' geometry is considered as an independent metric. When this complexity is integrated with the extent of areas affected by various levels of risk, a comprehensive index for combined flood and drought risk is developed. This innovative approach offers a nuanced understanding of the risks, providing a valuable tool for assessing and mitigating flood and drought risks in the River Severn basin.

Chapter 8, encapsulates the comprehensive journey of this study on flooding and drought risks at the river basin scale. It begins with a brief overview of the research objectives, highlighting the innovative methodology adopted ranging from systematic literature review to the application of interpretive structural modelling and network theory for a nuanced understanding of the risks. Key findings from the analysis of publication trends, parameter interconnections, and risk assessment frameworks would be summarized, showcasing its contributions to the field through the development of a robust risk assessment framework. The synopsis also articulates the theoretical and practical implications of this work, underscoring how it advances existing knowledge and offers valuable insights for managing flood and drought risks. Acknowledgment of limitations and suggestions for future research directions are outlined, pointing towards areas where further investigations could yield additional significant insights. Finally, the segment concludes by reflecting on the broader significance of its findings for environmental management and policy-making, emphasizing the study's role in enhancing communities' capacity to predict and mitigate the impacts of these natural hazards.

2 Bridging Disciplines: Comprehensive Literature Review on Integrated Flood and Drought Risk Assessment: Methods, Models, and Applications

2.1 Purpose and scope of the literature review of this study

The primary aim of this literature review is to establish a comprehensive understanding of the existing body of knowledge specifically related to the assessment of flood and drought risks. This involves critically analysing previous research to identify key concepts, methodologies, and findings that are pertinent to the simultaneous evaluation of these hydrological hazards. The review seeks to highlight both theoretical advancements and practical applications in the field, thereby providing a robust foundation for the development of an integrated risk assessment framework.

Flood and drought risk assessments are critical components of effective water resource management, especially in the context of increasing climate variability and change. By systematically reviewing the literature, this chapter aims to identify the strengths and limitations of current methodologies, explore the spatial and temporal dimensions of flood and drought risks, and understand the interactions between these phenomena. This is particularly important because traditional approaches often treat flood and drought risks in isolation, failing to account for their interconnected nature and the potential for compound events. The literature review also seeks to synthesize findings from a diverse range of studies to provide a coherent narrative that underscores the importance of integrated risk assessment. By doing so, it addresses the complexity and interdependence of hydrological hazards, which demand more comprehensive and adaptive management strategies. The review will identify critical variables and methodological approaches that will inform the empirical analysis and the development of the risk assessment framework presented in this thesis.

By focusing on these specific objectives, the literature review will ensure that the research is grounded in existing knowledge while also identifying gaps and opportunities for further investigation. This will not only contextualize the research within the broader academic discourse but also justify the research questions and hypotheses posed in the study, thereby contributing to the advancement of flood and drought risk management practices.

The literature review is structured to systematically cover the breadth and depth of research pertinent to flood and drought risk assessment. It begins with a background section, which introduces fundamental concepts and theoretical frameworks that underpin the study of hydrological hazards. This includes a review of key definitions, principles, and models that have been developed over time. By grounding the review in these foundational theories, the chapter ensures a clear and consistent conceptual framework for the analysis that is delivered in subsequent chapters.

Following the theoretical background, the review delves into specific sections dedicated to flood risk assessment and drought risk assessment. These sections trace the historical evolution of risk assessment methodologies, highlighting significant advancements and current best practices. For flood risk assessment, the review covers a range of approaches from early empirical methods to modern probabilistic and deterministic models (Merz et al., 2010a; Di Baldassarre et al., 2010). Similarly, the section on drought risk assessment examines methodologies from traditional indices to sophisticated hydrological and agricultural models (Vicente-Serrano et al., 2012; Mishra & Singh, 2010). A subsequent section addresses the emerging field of combined understanding of flood and drought phenomenon and modelling. This part of the review emphasizes the need of an integrated approach, discussing some studies that have attempted to jointly assess these hydro-hazards and the challenges they encountered (Van Loon & Van Lanen, 2013; Grobicki et al., 2015; Wang et al., 2017; Leitner et al., 2020; Mai et al., 2020; Ward et al., 2020b; Eamen et al., 2021). The concluding sections of this chapter provide detailed explanations of validation, sensitivity, and uncertainty analyses to clarify their significance and rationale for inclusion. These discussions are designed to equip readers with the necessary context to comprehend the results presented in the final data chapters, emphasizing the critical role these analyses play in ensuring the accuracy, reliability, and meaningful interpretation of the findings.

2.2 Theoretical background of flood and drought risks

Flood and drought risk assessments are pivotal in managing and mitigating the impacts of these hydrological extremes. To establish a comprehensive understanding, it is essential to define and explain the key concepts and theories underpinning these assessments.

Risk is fundamentally the probability of an adverse event occurring and the potential consequences of that event. It is a concept widely used across various disciplines, including finance, health, environmental science, and disaster management. According to the International Organization for Standardization (ISO), risk is defined as the "effect of uncertainty on objectives," which can be positive or negative. Flood and drought risks are specific types of risks associated with extreme hydrological events. These risks differ from the phenomena themselves (the occurrence of floods or droughts) and their mere probability of happening. Flood and drought risks are more comprehensive than just the probability of occurrence, encompassing both the likelihood of these events occurring and the potential impacts they might have on the affected regions.

Flood risk is the likelihood of a flood event occurring and the potential adverse impacts it might cause. This encompasses the susceptibility of a region to flooding combined with the potential damage to property, infrastructure, human health, and the environment. The assessment of flood risk involves understanding flood hazards, exposure, and vulnerability (Kron, 2005; Merz et al., 2010b) whilst flood phenomenon is the actual occurrence of excess water inundating land areas, typically due to heavy rainfall, storm surges, or river overflow (Kundzewicz et al., 2014; Ward et al., 2011). For example, the risk of flooding in a coastal city might include the probability of storm surges and high tides, the city's topography and drainage capacity, and the potential damage to residential areas, businesses, and critical infrastructure.

Drought risk refers to the likelihood of a drought event and its potential impacts. This includes the susceptibility of an area to drought conditions and the potential consequences for water resources, agriculture, ecosystems, and human livelihoods. Drought risk assessment involves analysing climatic conditions, soil moisture, water demand, and the resilience of the affected systems (Wilhite, 2000; Mishra & Singh, 2010). Drought phenomenon mainly describes the actual occurrence of prolonged periods of insufficient rainfall leading to water shortages (Um et al., 2017). However, the risk of drought in an agricultural region, for instance, regardless of possible causes, might include the probability of below-average rainfall, the water retention capacity of the soil, and the potential impacts on crop yields, livestock, and local economies (Van Loon, 2015; Hao & Singh, 2015). (Van Loon, 2015; Hao & Singh, 2015).

2.2.1 Influencing components of risk

Risk i Risk is influenced by three main components: hazard, exposure, and vulnerability (IPCC, 2014). Hazard refers to the potential occurrence of a natural or human-induced physical event, such as heavy rainfall leading to floods or prolonged dry spells leading to droughts. Exposure is defined as the presence of people, livelihoods, environmental services and resources, infrastructure, or economic, social, or cultural assets in areas that may be adversely affected. For instance, urban areas located in floodplains or agricultural regions that rely on consistent rainfall are considered highly exposed. Vulnerability represents the propensity or predisposition to be adversely affected and includes various physical, social, economic, and environmental factors. Examples of vulnerability include poorly constructed buildings, a lack of emergency preparedness, or reliance on a single water source. Together, these components determine the overall risk by combining the likelihood of an event, the elements exposed to it, and the susceptibility of those elements to damage or loss.s influenced by three main components: hazard, exposure, and vulnerability (IPCC, 2014).

2.2.2 Combining susceptibility and impact in flood and drought risk assessments

The assessment of flood and drought risks goes beyond merely estimating the probability of these events. It involves a comprehensive evaluation of the region's susceptibility to these events and the potential impacts. This includes the physical characteristics of the region, the resilience of the built environment, socio-economic factors, and the capacity to respond and recover (Adger, 2006; Cutter et al., 2008). For a region prone to both floods and droughts, risk assessment might involve evaluating flood-prone areas using hydrological models and identifying drought-prone regions based on climatic data (Susceptibility Analysis). Next, estimating potential damages to infrastructure, loss of agricultural productivity, economic costs, and social disruptions (Impact Assessment). And eventually, creating a comprehensive risk map that highlights areas with the highest combined risk of floods and droughts, aiding in targeted mitigation and adaptation strategies as laid by Field et al. (2012) (Integrated Risk Map).

Flood risk assessment at the river basin scale involves evaluating the potential adverse effects of flooding on the environment, economic activities, and human health (Field et al., 2012). Understanding these impacts is essential for effective risk management and planning, helping to prioritize resources and mitigation measures to reduce vulnerabilities and improve resilience. For instance, flooding can lead to habitat destruction, disrupt local economies by damaging agricultural land and infrastructure, and pose significant health risks, including the spread of waterborne diseases and the increased burden on healthcare services. Flood risk is typically quantified as a function of hazard, exposure, and vulnerability. The hazard component encompasses the probability and magnitude of flood events, often derived from hydrological models and historical data (Smith & Ward, 1998). Exposure refers to the presence of people, property, and infrastructure in flood-prone areas, while vulnerability assesses the susceptibility of these elements to harm (UNISDR, 2009).Drought risk assessment similarly involves the evaluation of the potential adverse impacts of droughts, focusing on sectors such as agriculture, water resources, and ecosystems. Drought risk is a function of hazard, exposure, and vulnerability, where the hazard includes the frequency, duration, and intensity of drought conditions. These are typically assessed using meteorological and hydrological indices such as the Standardized Precipitation Index (SPI) and the Palmer Drought Severity Index (PDSI) (Mishra & Singh, 2010). Exposure encompasses the elements at risk within the drought-affected area, and vulnerability includes factors such as socioeconomic status, agricultural dependency, and water management practices.

Given the interconnected nature of hydrological hazards, there is an increasing recognition of the need for integrated risk assessments that simultaneously consider flood and drought risks. This integrated approach recognizes the potential for compound events, where the occurrence of one hazard influences the likelihood and impact of the other. For instance, drought conditions can reduce soil moisture and increase runoff during subsequent rainfall events, exacerbating flood risks (Van Loon et al., 2016).

2.3 Development of flood and drought risk assessment: understanding and methodology

The body of knowledge surrounding flood and drought risk assessment has undergone significant evolution over the past century, reflecting advancements in scientific understanding, technological development, and policy frameworks. Early to mid-20th century approaches to flood and drought risk assessment were predominantly empirical and qualitative, focusing on historical events and anecdotal evidence. These methods were limited by the availability of data and often lacked the precision required for effective risk management, resulting in reactive rather than proactive responses (Smith & Ward, 1998; Pender & Neelz, 2007; Wilhite, 2000).

Systematic analysis of hundreds of peer-reviewed publications provides a comprehensive overview of the themes contributing to flood and drought research over the last two decades (Fasihi et al., 2021). The horizontal axis at the bottom of Figure 1 displays the publication years, while the left vertical axis quantifies the percentage contribution of each theme to flood and drought studies.

The right vertical axis, represented by the red trend line, indicates the number of publications per year. Additionally, several key legislative acts and initiatives influencing the water sector are marked along the timeline to illustrate potential trends and shifts in research focus.

The analysis identified 13 primary themes that have shaped flood and drought research during this period. In the first decade, co-analysis of flood and drought accounted for approximately 10% of the total research publications. Over time, there has been a notable increase in publications, likely driven by key legislative developments and the enhanced availability of open-access data platforms. Initially, only a few themes contributed to the simultaneous study of floods and droughts, with "Hydrology" consistently dominating the discourse across all years. However, in recent years, the research focus has broadened significantly, incorporating themes from social sciences, such as economy, insurance, sociology, and urban planning. This shift highlights a growing interdisciplinary approach to addressing these complex challenges.

The contrast between flood and drought two extremes of the hydrological spectrum—emphasizes the dual challenge they present. Building resilience against such extreme events requires a long-term, multifaceted approach that includes comprehensive planning, adaptation, and interdisciplinary collaboration. This section discusses major legislations and frameworks that have guided water hazard management and policy development, as illustrated in Figure 1.

One of the earliest significant efforts was the Water Framework Directive (WFD), introduced in 2000, which provided guidelines for preserving both natural and artificial water bodies. In 2002, the Integrated Water Resource Management (IWRM) framework was adopted, aiming to balance economic efficiency, environmental sustainability, and social equity. Subsequently, the Hyogo Framework for Action (2005–2015) was launched under the International Strategy for Disaster Reduction, emphasizing risk reduction from natural hazards.

In 2007, the UN Convention to Combat Desertification focused on mitigating drought impacts while promoting sustainability. Two years later, the World Meteorological Organization (WMO) introduced the Global Framework for Climate Services, providing critical climate change information to improve resilience. Finally, in 2015, the United Nations endorsed the Sendai Framework, which aims to guide disaster risk reduction efforts until 2030, acknowledging the need for a more comprehensive approach to managing water-related hazards in the context of a changing climate.

Figure 2.1 portrays the evolution of the research landscape, illustrating a transition from an initial focus predominantly on hydrology to a more diverse and interdisciplinary field. This transformation underscores the increasing recognition of social, economic, and interdisciplinary approaches in understanding and addressing the impacts of floods and droughts.

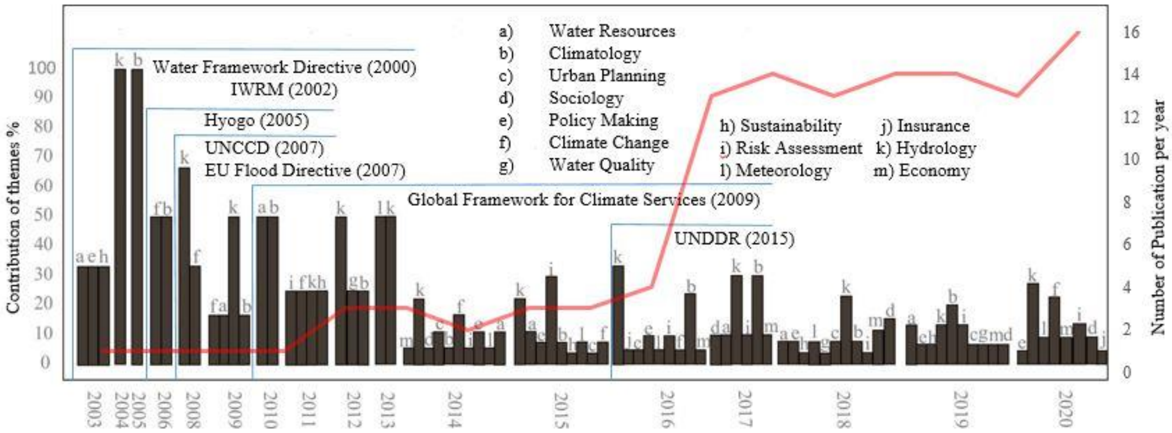


Figure 2.1. Trends in Themes and Publications on Flood and Drought Research (2003–2020), with a red line indicating the number of publications per year (Fasihi et al., 2021).

The mid-20th century marked a pivotal shift in both flood and drought risk assessments with the development of specialized models and indices. For floods, hydrological and hydraulic models enabled the simulation of river flow and floodplain dynamics, providing a more systematic and quantitative basis for risk assessment. Tools like the Hydrologic Engineering Center's River Analysis System (HEC-RAS) and two-dimensional hydraulic models such as MIKE FLOOD became possible due to advancements in computing power, allowing for detailed and accurate floodplain mapping (Brunner, 2016; DHI, 2017).

In the context of droughts, the introduction of the Palmer Drought Severity Index (PDSI) in 1965 provided a standardized method for assessing drought conditions using precipitation, temperature, and soil moisture data (Palmer, 1965). This was followed by the development of the Standardized Precipitation Index (SPI) in the late 20th century, which offered a versatile and statistically robust approach for assessing different types of droughts across various timescales (McKee et al., 1993).

The integration of Geographic Information Systems (GIS) and remote sensing technologies further revolutionized risk assessment methodologies for both floods and droughts during the late

20th century. In flood risk assessment, these tools enabled the spatial analysis of hazards, exposure, and vulnerability, resulting in the creation of detailed flood risk maps essential for urban planning and disaster management (Foody, 2003; Melesse et al., 2007). Similarly, remote sensing technologies such as the Moderate Resolution Imaging Spectroradiometer (MODIS) enhanced drought monitoring by providing global-scale data on vegetation health and soil moisture conditions (Kogan, 1997). Probabilistic approaches also gained prominence, particularly in flood risk assessment, where statistical techniques like the Gumbel distribution were used to estimate the probability and magnitude of extreme flood events, thereby informing infrastructure design and safety margins (Naghavi et al., 2020). These methods were complemented by water balance models, such as the Variable Infiltration Capacity (VIC) model and the Water Evaluation And Planning (WEAP) system, which simulated water availability under various climatic scenarios, facilitating a deeper understanding of drought mechanisms (Liang et al., 1994; Yates et al., 2005).

Contemporary methodologies for flood and drought risk assessment are characterized by the integration of advanced computational models, big data analytics, and remote sensing technologies. For floods, hydrodynamic models like HEC-RAS and MIKE FLOOD simulate water movement to predict flood extents and depths, while probabilistic models estimate the likelihood of extreme events (Brunner, 2016; DHI, 2017). Similarly, advanced meteorological and hydrological models, such as the VIC and Community Land Model (CLM), play a critical role in drought assessment by providing detailed simulations of soil moisture, evapotranspiration, and runoff (Liang et al., 1994; Oleson et al., 2010).

Remote sensing continues to be a cornerstone of both flood and drought assessments. Technologies like Synthetic Aperture Radar (SAR) and the Soil Moisture Active Passive (SMAP) satellite provide real-time data that can be integrated into GIS platforms, enabling continuous monitoring and rapid response capabilities (Anderson et al., 2011; Entekhabi et al., 2010). These advancements facilitate the spatial analysis of both floods and droughts, offering higher resolution and accuracy than ever before.

Data analytics, particularly machine learning techniques, have gained traction in recent years. Methods such as Random Forests, Support Vector Machines (SVM), and XGBoost are employed to model complex, non-linear relationships between predictors and outcomes in both flood and drought contexts. For instance, these models have been used to predict flood susceptibility and drought occurrences based on meteorological and hydrological inputs, enhancing predictive capabilities and situational awareness (Chen & Guestrin, 2016; Mosavi et al., 2018).

Flood and drought risk assessments increasingly recognize the necessity of adopting integrated frameworks that combine hydrodynamic modelling, probabilistic approaches, and socio-economic analysis. While such frameworks attempt to address the full risk management cycle—from assessment and mitigation to emergency response and recovery—significant gaps remain, underscoring the need for further research. Global initiatives like the Sendai Framework for Disaster Risk Reduction and the European Union's Floods Directive (UNISDR, 2015; European Commission, 2007) highlight a shift toward multi-disciplinary approaches but often fall short of offering practical solutions for capturing the interconnectedness of flood and drought risks within a unified model.

Despite advancements in technological tools and socio-economic integration, the current frameworks lack a cohesive approach to addressing the dynamic and interdependent nature of flood and drought risks, particularly within the context of a changing climate and socio-economic scenarios. This is where the current research becomes critical filling the gaps in understanding the feedback loops and cascading effects between these hydrological extremes. Existing methodologies often fragment the inclusion of socio-economic and environmental factors or fail to account for their interplay with hydrodynamic and probabilistic modelling.

This study aims to bridge these gaps by developing a comprehensive framework that incorporates the interconnected dynamics of flood and drought risks, while addressing their socio-economic, ecological, and infrastructural dimensions. By leveraging advanced technologies and exploring innovative methodologies, this research will not only provide deeper insights into these interdependencies but also offer scalable, adaptive solutions tailored to the specific challenges of river basin contexts. In doing so, it will contribute to advancing the field of flood and drought risk assessment, addressing limitations in current frameworks, and promoting a more integrated and forward-looking approach to managing these complex hazards.

2.4 GEOGRAPHICAL TRENDS IN FLOOD AND DROUGHT EXAMPLES: INSIGHTS, GAPS, AND REGIONAL EXAMPLES

To assess flooding and drought risk effectively, it is crucial to understand the geographical nuances and trends in the research focus (Figure 2.1). This could help identify regions with more data and guide future studies to ensure a comprehensive global understanding of these risks.

Figure 2.2 illustrates the percentage of flood and drought case studies per country or region, with 23.33% of investigated reports and peer reviewed publications not specifying any region. This could indicate a focus on broader issues, methodological papers, or global datasets that do not relate to a specific location.

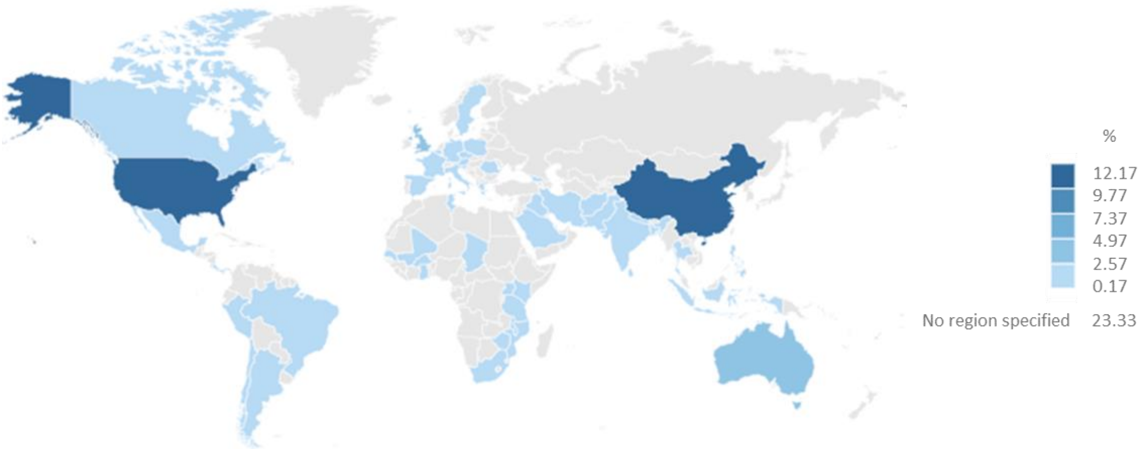


Figure 2.2. Geographical distribution of case studies investigated within the selected papers in the context of flood and drought research.

China and the USA stand out with over 12% and 11% of the case studies, respectively. This suggests a significant focus on these countries, potentially due to their large geographical areas, varied climates, and the presence of both flood and drought challenges. Global studies account for over 7%, indicating a considerable amount of research aimed at understanding floods and droughts from an international perspective. Australia and Europe also have a relatively high percentage of case studies, which may reflect their active research communities and the impacts of climate variability on these regions. Some areas with lower percentages could indicate either a lack of research focus or fewer instances of floods and droughts. However, this could also reflect a lack of reporting or data collection capabilities. Notably, sub-Saharan Africa (Africa-SS) and regions like Amazonia have percentages exceeding 1%, which could suggest a growing research interest in these areas, possibly due to their vulnerability to climate change and its impacts. Many countries have a percentage of around 0.16%, which could imply either a single study or a small number of studies relative to the dataset size. This could indicate regions where case studies are less common or possibly underrepresented in research. The distribution points to a concentration of case studies in certain areas, which could correlate with the prevalence of flood and drought events, data availability, research funding, or the presence of research institutions. The analysis also suggests potential gaps in case studies in some regions. These gaps could benefit from increased research attention, especially considering climate change's global implications on water-related hazards.

The following paragraphs present examples of regions that have recently faced flood and/or drought events, highlighting how these regions have identified, assessed, or managed their impacts. This section aims to provide a broader context for the temporal evolution of flood and drought assessment approaches, further developing the theoretical background discussed earlier and linking it to the current needs of flood and drought risk assessment modelling.

Thames Estuary 2100 (TE2100) Project, in the United Kingdom is a comprehensive flood risk management plan designed to protect London and the Thames Estuary from tidal flooding until the end of the 21st century. The project employs a combination of hydrodynamic modelling, probabilistic risk assessment, and socio-economic analysis to evaluate future flood scenarios under different climate change projections. Key outcomes include the development of adaptive flood defences and the implementation of sustainable urban drainage systems (SUDS) (Environment Agency, 2012). The International Commission for the Protection of the Rhine (ICPR) has implemented a transboundary flood risk management plan for the Rhine River, which flows through multiple European countries. The plan integrates hydrological modelling, GIS-based risk mapping, and early warning systems to enhance flood preparedness and response. The ICPR's efforts have led to significant reductions in flood risk through structural and non-structural measures, including river restoration projects and community engagement initiatives (ICPR, 2015).

In southeast Asia, the Mekong Delta faces significant flood risks due to its low-lying topography and high population density. The Vietnamese government, in collaboration with international organizations, has developed a flood risk management strategy that combines hydrodynamic modelling, land use planning, and community-based approaches. Key initiatives include the construction of flood control infrastructure, the promotion of flood-resilient agricultural practices, and the establishment of early warning systems (GSO, 2019). Additionally, the Yellow River basin is one of the most flood-prone areas in China, with a long history of catastrophic flooding. The Chinese government has implemented an integrated flood management strategy that includes structural measures, such as the construction of dams and levees, and non-structural measures, such as floodplain zoning and reforestation. Advanced hydrodynamic models and remote sensing technologies are employed to monitor and predict flood events, enhancing the effectiveness of flood mitigation efforts (Zhang et al., 2014).

Following the devastating impact of Hurricane Katrina in 2005, New Orleans, USA, has adopted a comprehensive flood risk management approach that combines hydrodynamic modelling, probabilistic risk assessment, and infrastructure improvements. The construction of the Hurricane and Storm Damage Risk Reduction System (HSDRRS) includes levees, floodwalls, and pump stations designed to withstand extreme flood events. The city's resilience strategy also emphasizes community engagement and the restoration of natural buffers such as wetlands (USACE, 2013).

California Drought, USA: California has faced severe drought conditions over the past decade, prompting the implementation of advanced drought risk assessment methodologies. The state employs a combination of remote sensing technologies, such as MODIS and Landsat, to monitor soil moisture and vegetation health. The California Drought Early Warning System integrates these data with hydrological models and socio-economic indicators to provide real-time drought assessments and inform water management policies. Key findings highlight the importance of adaptive management strategies and the integration of diverse data sources to enhance drought resilience (Lund et al., 2018).

Horn of Africa Drought: The Horn of Africa region frequently experiences severe droughts, significantly impacting food security and livelihoods. The Famine Early Warning Systems Network (FEWS NET) employs satellite data, climate models, and ground-based observations to monitor drought conditions and predict food insecurity outcomes. The integration of these data sources enables timely interventions and resource allocation, mitigating the impacts of droughts on vulnerable populations. Findings emphasize the critical role of early warning systems and international collaboration in managing drought risks (Verdin et al., 2005).

Murray-Darling Basin, Australia: In the Murray-Darling Basin has been implemented comprehensive drought risk assessment frameworks to manage its water resources effectively. The Basin Plan incorporates hydrological models, remote sensing data, and climate projections to assess drought risks and guide water allocation decisions. The use of the SPEI and other drought indices allows for the assessment of both short-term and long-term drought conditions. Key findings from this case study highlight the importance of integrated water management practices and the use of advanced modelling techniques to ensure sustainable water use in drought-prone regions (MDBA, 2012).

Iberian Peninsula, Europe: The Iberian Peninsula has experienced increasing drought frequency and severity, necessitating advanced drought risk assessment methodologies. Spain and Portugal utilize a combination of remote sensing data, meteorological models, and drought indices such as the SPEI and SPI to monitor and manage drought risks. The European Drought Observatory (EDO) plays a crucial role in providing comprehensive drought assessments and early warning information. Key findings highlight the need for coordinated water management policies and the integration of socio-economic data to enhance drought resilience in the region (Garcia-Herrera et al., 2007).

Iran's drought, Middle east: Iran faces significant drought challenges, particularly in arid and semi-arid regions. The country employs advanced hydrological models and remote sensing technologies to monitor drought conditions and manage water resources. The Iranian National Drought Warning and Monitoring System (NDWMS) integrates climatic data, drought indices, and socio-economic indicators to provide real-time drought assessments. Key findings emphasize the importance of sustainable water management practices and the need for regional cooperation to address shared water resources and mitigate drought impacts (Raziei et al., 2014).

North China Plain Drought: The North China Plain is a critical agricultural region that frequently experiences severe droughts. China employs a combination of hydrological models, remote sensing data, and drought indices such as the PDSI and SPEI to monitor drought conditions and inform water management decisions. The China Drought Monitoring and Early Warning System (CDMEWS) integrates these data sources to provide comprehensive drought assessments and early warning information. Key findings highlight the importance of modern irrigation techniques, sustainable agricultural practices, and government policies in mitigating drought impacts (Wang et al., 2012).

The missing link between these various flood and drought risk management projects as examples of common practice is the absence of an integrated, cross-disciplinary framework that holistically addresses the interdependencies between flood and drought risks within a river basin context. While many projects concentrate on either flood or drought risks, employing methodologies such as hydrodynamic modelling, GIS-based risk mapping, or remote sensing, they often fail to explore the complex interactions between these two extremes. For instance, how drought conditions might influence flood patterns through soil desiccation or reduced vegetation cover, or how floods might replenish water resources during drought periods, is rarely considered systematically. This lack of integration under changing climate and socio-economic scenarios highlights a significant knowledge gap.

Moreover, the socio-economic, ecological, and infrastructure resilience components, while included in some studies, are typically addressed in a fragmented manner. This partial approach leaves gaps in understanding the cascading hazards and feedback loops within the risk landscape. For instance, while some projects incorporate adaptive urban drainage systems or early warning frameworks, the inclusion of broader socio-economic and ecological interconnections in these models remains inconsistent.

Another critical missing link is the lack of standardization in methodologies and metrics across regions. While region-specific advancements are notable, the absence of shared frameworks and comparable metrics limits the ability to scale or transfer adaptive practices globally. This issue is further compounded in transboundary regions, where common water resources are often governed by conflicting national policies. Without a consistent, collaborative transboundary perspective, efforts to address flood and drought risks in interconnected systems remain fragmented, undermining the potential for broader, more resilient solutions.

Ultimately, these gaps underline the need for a comprehensive framework that combines flood and drought risk assessments. Such a framework would integrate socio-economic, ecological, and infrastructure dimensions into a cohesive system while encouraging cross-regional and transboundary collaboration, standardizing methodologies, and fostering adaptive risk management approaches that are scalable and globally applicable.

The results from the published outputs of these projects and similar ones have played a pivotal role in shaping the overall structure of this research by providing critical insights, guidance, and a deeper understanding of methodologies, datasets, and their limitations. These outputs served as a foundation for identifying effective approaches and adapting them to address the unique challenges of integrated flood and drought risk assessment. They highlighted the strengths and limitations of region-specific practices, offering valuable lessons that informed the development of a more cohesive and scalable framework in this study.

For instance, the use of hydrodynamic modelling and probabilistic risk assessments, as employed in the Thames Estuary 2100 Project, emphasized the importance of combining predictive tools with socio-economic analysis to evaluate future risks comprehensively. Similarly, the integration of remote sensing technologies and early warning systems in the Mekong Delta and California Drought projects demonstrated the potential of advanced data acquisition and monitoring techniques, while also exposing challenges such as data accessibility, resolution, and the need for localized calibration.

The findings from these projects also provided guidance on the benefits of multi-disciplinary approaches, such as coupling hydrological models with socio-economic indicators, as seen in the Rhine River and North China Plain studies. These insights underscored the necessity of addressing cross-sectoral interdependencies and incorporating diverse data sources, such as satellite imagery, GIS mapping, and climate projections, to create a robust risk assessment framework. However, the limitations observed in these projects, such as the fragmented inclusion of socio-economic and ecological resilience or the lack of standardization in methodologies, helped identify critical gaps that this research aimed to address. By synthesizing the benefits of existing approaches while acknowledging their shortcomings, this study was able to adopt best practices, refine methodologies, and design an integrated model tailored to the complex interplay between flood and drought risks within a river basin context.

Ultimately, the lessons learned from these outputs not only shaped the conceptual framework of this research but also informed the choice of methodologies, the design of case studies, and the interpretation of results. They provided a roadmap for leveraging strengths while addressing limitations, ensuring that this research contributes to advancing a holistic, adaptable, and globally relevant approach to flood and drought risk assessment.

2.5 Importance of integrating flood and drought risk assessment

As explained in sections 2.3 and 2.4 assessing flood and drought risks together in an integrated manner is crucial for several reasons, particularly in the context of climate change and increasing environmental variability. Traditionally, flood and drought risk assessments have been conducted in isolation, focusing on the unique characteristics and impacts of each hazard. However, this approach fails to capture the complex interactions and feedback mechanisms that exist between these two hydrological extremes.

Floods and droughts are often interconnected, with each influencing the occurrence, severity, and impacts of the other. For example, prolonged drought conditions can reduce soil moisture, increase soil compaction, and decrease vegetation cover, leading to higher runoff and more severe flooding when heavy rainfall occurs. Conversely, floods can alter groundwater recharge rates and affect the availability of water resources during subsequent dry periods (Van Loon et al., 2016). Thus, an integrated assessment provides a more holistic understanding of the hydrological cycle and the cumulative impacts of these events on the environment and society.in addition to this rationale, implications of climate change and resource management are parameters that demand attention when assessing these risks.

Climate Change Implications: Climate change exacerbates the need for integrated assessments as it intensifies both flood and drought events. Increased temperatures and altered precipitation patterns contribute to the frequency and severity of these extremes. The Intergovernmental Panel on Climate Change (IPCC) highlights that regions prone to drought may also experience flash floods, leading to complex risk scenarios that single-hazard assessments cannot adequately address (IPCC, 2014). An integrated approach enables the development of more resilient strategies that consider the multifaceted nature of climate risks.

Resource Management and Policy Development: Effective water resource management and policy development require an integrated understanding of flood and drought risks. Water scarcity during droughts and the excess of water during floods both demand comprehensive planning and management strategies. For instance, the allocation of water resources, infrastructure development, and emergency response measures must be designed to handle both extremes.

Integrated assessments provide policymakers with the necessary information to make informed decisions that optimize resource use and enhance community resilience (Wang et al., 2017).

Several regions have begun to recognize the importance of integrated assessments. Consequently, studies and frameworks have been developed to integrate flood and drought risk assessments, showcasing innovative methodologies and successful applications. For example, the Murray-Darling Basin in Australia faces both severe droughts and floods. The Basin Plan incorporates integrated risk assessment methods to manage water resources effectively, ensuring sustainable use during droughts and mitigating flood risks (MDBA, 2012). Similarly, the Rhine River Basin in Europe employs integrated flood and drought management strategies to address the cumulative impacts of these hazards on water quality, ecosystem health, and economic activities (Krysanova et al., 2008). Multi-Hazard Risk Assessment Frameworks: The Multi-Hazard Risk Assessment (MHRA) framework is one such approach that simultaneously evaluates multiple hazards, including floods and droughts. This framework employs spatial analysis and statistical methods to identify regions at high risk of both hazards. By integrating data on precipitation, soil moisture, land use, and socio-economic factors, MHRA provides a comprehensive risk profile that supports the development of targeted mitigation strategies (Kappes et al., 2012).

Integrated hydrological models, such as the VIC model and the WEAP system, are used to simulate the combined impacts of flood and drought events. However, these do not count in the concept of risk and view the problem through a single hydrologic lens. These models incorporate climatic data, hydrological processes, and human activities to predict water availability and distribution under various scenarios. For example, the WEAP system has been applied in the Sacramento-San Joaquin Basin in California to assess the combined impacts of drought and flood risks on water resources and agricultural productivity (Yates et al., 2005). Remote sensing and GIS technologies are pivotal in integrated risk assessments, providing high-resolution data on hydrological variables and land surface conditions. The integration of satellite imagery with GIS enables the continuous monitoring of flood and drought conditions, facilitating real-time decision-making. For instance, the European Space Agency's (ESA) Copernicus program employs remote sensing data to monitor soil moisture, precipitation, and vegetation health, supporting integrated flood and drought risk assessments across Europe (ESA, 2020 Chen & Guestrin, 2016; Lu et al., 2019). System dynamics and network analysis methodologies have been employed to understand the complex interactions between flood and drought risks. These approaches model the feedback loops and causal relationships between hydrological, environmental, and socio-economic factors. For example, the Causal Loop Diagram (CLD) methodology has been used to identify critical pathways and leverage points for mitigating the combined impacts of floods and droughts in the Ganges-Brahmaputra-Meghna Basin (Sterman, 2000; Gain et al., 2011).

The integrated flood and drought risk assessments in the Murray-Darling Basin, the Rhine River Basin, and the Yellow River Basin exemplify promising methodologies for addressing these dual hazards. However, they also reveal critical limitations that warrant attention. A significant shortfall lies in the lack of diverse perspectives, particularly the inadequate integration of socio-economic factors into water resource management. Socio-economic dynamics, which play a pivotal role in managing water resources impacting local communities, agriculture, industry, and broader economic activities are often insufficiently addressed. These sectors, being both prominent stakeholders and primary risk bearers, disproportionately suffer the consequences of floods and droughts. For instance, while the Murray-Darling Basin Plan emphasizes sustainable water use, it fails to fully integrate socio-economic assessments that account for the diverse vulnerabilities of key stakeholders, such as local farmers, industries, and Indigenous communities, who are heavily reliant on these water resources. This omission creates a disconnect between scientific risk assessments and the lived realities of affected populations, thereby limiting the practical application and effectiveness of risk reduction strategies.

Similarly, the Rhine River Basin's integrated strategy, which emphasizes international coordination and water quality improvements, does not adequately address the ambiguity and uncertainty surrounding the impacts on diverse water resource users. The nuanced effects of floods and droughts on various sectors agriculture, urban communities, and ecosystem services—are insufficiently articulated, resulting in a lack of clear causality. This vagueness can lead to generalized solutions that fail to address the specific needs of individual stakeholders, potentially exacerbating inequities.

In the Yellow River Basin, the application of integrated hydrological models and remote sensing data provides a solid technical foundation for managing floods and droughts. However, these efforts lack a comprehensive socio-economic analysis that bridges the gap between physical hazards and their broader human implications. The primary focus on ensuring water security and supporting sustainable agriculture overlooks the disproportionate impacts on marginalized communities and small-scale farmers, who are particularly vulnerable to hydrological variability. Moreover, the complex interdependencies between floods, droughts, and socio-economic resilience remain underexplored. This limits the understanding of how one hazard may exacerbate the other or how adaptive measures in one sector could inadvertently create vulnerabilities in another.

While these examples of integrated approaches represent progress, they fall short of addressing key gaps. The omission of a robust socio-economic perspective, the lack of clarity in causal pathways linking hazards to impacts, and the insufficient consideration of the diverse needs and vulnerabilities of all water users are significant shortcomings. To build resilience effectively, these assessments must transcend technical and environmental dimensions, incorporating a more comprehensive socio-economic framework. Additionally, addressing uncertainties, stakeholder dynamics, and the cascading effects of hydrological extremes will be critical for fostering equitable and adaptive solutions to flood and drought risks.

2.6 OVERVIEW OF METHODS, DATA AND TECHNICAL CAPACITIES UTILIZED IN FLOOD AND DROUGHT ANALYSIS

As elaborated in previous sections, researchers have explored water-related hazards from various perspectives, employing numerous methodologies and indices that often differ fundamentally. Modelling flood and drought events necessitates the use of comprehensive data and integrated approaches, which must be both unbiased and robust (Ward et al., 2020b). The first step toward achieving an unbiased integration of flood and drought modelling frameworks is to systematically review the existing literature. Such a review begins by identifying relevant publications based on predefined search terms across available databases, thus reducing potential biases that may stem from authors favoring particular subfields or methodologies.

In the next phase, the various approaches and indices used in the literature to describe flood and drought phenomena were extracted using the content analysis method. The extracted dataset was subsequently used to generate a weighted, undirected network representing the relationships among methods and indices (Figure 2.3).

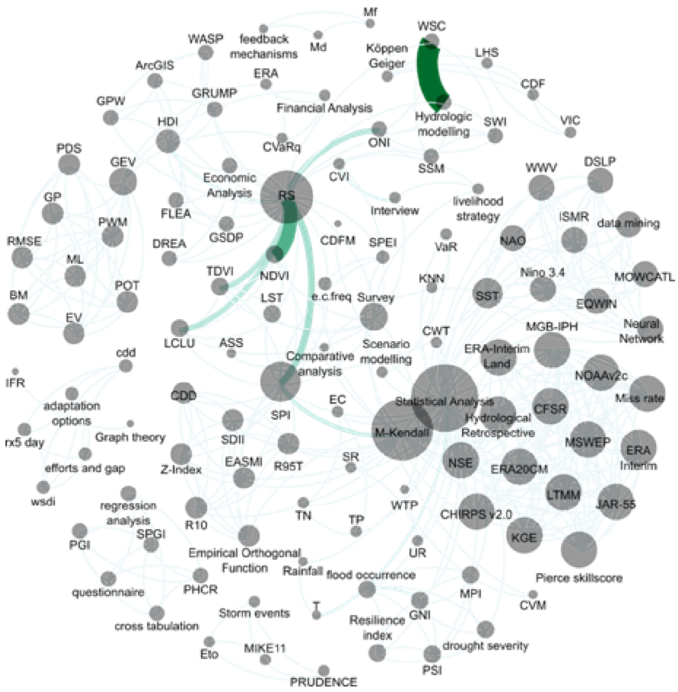


Figure 2.3. Network of Methods and Indices Utilized in Defining and Evaluating Flood and Drought-Related Topics, (Fasihi et al., 2021).

The size of each node in Figure 3 reflects its central role in communication within the science map derived from the analyzed literature. As shown in the figure, "Statistical Analysis," remote sensing (RS), and Mann-Kendall (M-Kendall) tests emerged as the most widely applied approaches for investigating both flood and drought subjects. The key index serving as the common link between these methods and thus controlling the flow of information in many of these studies—is the "Standardized Precipitation Index (SPI)." The weighted edges in Figure 3 illustrate the repetition of connections between nodes (methods and indices). Remote sensing is notably interconnected with terrestrial indices, such as Land Cover Land Use (LCLU), Normalized Difference Vegetation Index (NDVI), and Transformed Difference Vegetation Index (TDVI). Additionally, the strong link between "hydrologic modelling" and Water Storage Capacity (WSC) underscores their frequent joint application in flood and drought assessments. Key nodes within the network of methods and indices, based on their degree and betweenness centrality, include "Statistical Analysis," "M-Kendall," "RS," and "SPI". These methods and indices are among the most frequently used and function as hubs, facilitating connections across different clusters or domains.

Another noteworthy finding from this review is the diversity of subsets of indices applied in combination with specific methods and other indices. Figure 2.4 offers a different perspective of the methods and indices network, which clearly illustrates the clusters that have formed and highlights the critical nodes distinguishing these clusters.

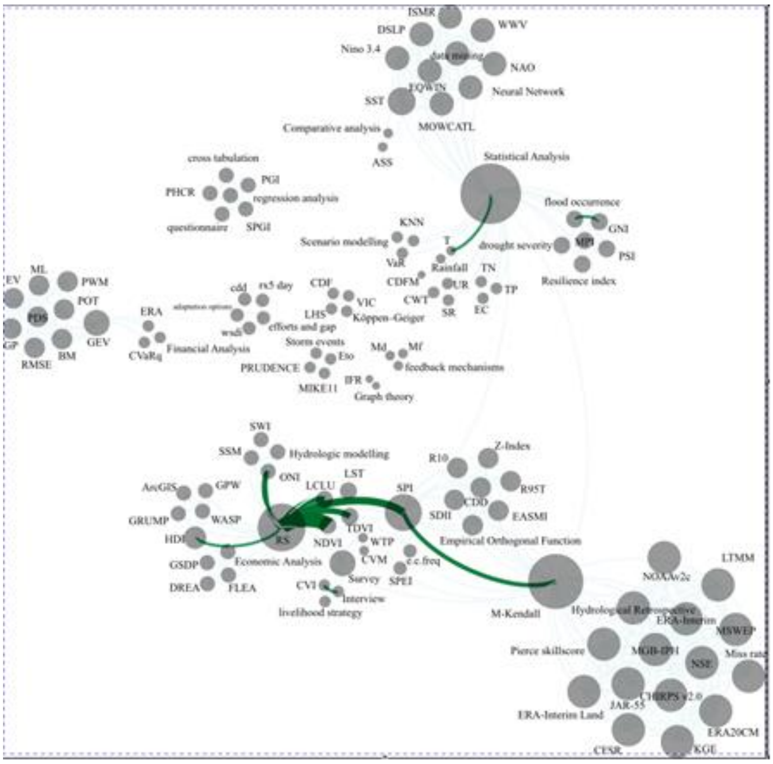


Figure 2.4. Newman-Girvan Clustered Network Visualization of Methods and Indices in Flood and Drought Research: Key Nodes, Clusters, and Interconnections.

Researchers have predominantly used meteorological and climatological subsets of indices and methods in combination with statistical analysis and the Mann-Kendall test to describe flood and drought events concurrently. This observation is particularly evident in the upper and lower right sections of the layout in Figure 2.4.

Upon analyzing Figure 4, it becomes evident that "SPI" serves as a central hub within this network, linking many of the indices used across different studies. The SPI is integral in connecting remote sensing ("RS") and Mann-Kendall methods, which are employed alongside numerous meteorological, hydrological, terrestrial, economic, and sociological indices, as illustrated in the lower right corner of Figure 4. This scientograph effectively captures the various approaches utilized by researchers and provides insight into how novel combinations of methods and indices could potentially advance the modelling of simultaneous flood and drought analysis. Such combinations can help identify particular methods and indices to form a conceptual framework for integrated risk assessment. Figure 4 suggests that a basic version of the conceptual framework sufficient for robust analysis could integrate remotely sensed terrestrial information with economic analyses, using indices such as the Gross State Domestic Product ("GSDP") and Human Development Index ("HDI"), both linked to hydrological parameters through "SPI."

Assessing risk from multiple perspectives and themes of research significantly enhances the robustness and applicability of integrated flood and drought risk assessments. Considering different perspectives, including hydrological, meteorological, environmental, and socio-economic factors, offers a holistic view of risk factors and their interconnections. For example, incorporating socio-economic data into hydrological models helps identify vulnerable populations and critical infrastructure, thereby improving risk mitigation strategies (Bouwer et al., 2010). Thematic research focusing on aspects like land use changes, urbanization, and agricultural practices provides valuable insights into how human activities impact hydrological extremes, including flood and drought risks. Understanding these interactions is essential for devising sustainable land and water management practices that mitigate vulnerability to these hazards. Research has demonstrated, for instance, that deforestation and urban sprawl can exacerbate flood risks by reducing natural water absorption and increasing runoff (Bradshaw et al., 2007).

In addition, thematic studies on climate variability and change contribute to predicting future risk scenarios, thus enabling proactive planning and adaptation measures. Research on climate models and projections supplies crucial data on anticipated changes in precipitation patterns, temperature, and extreme weather events, which is vital for mitigating future flood and drought risks (Trenberth, 2011).

The methods and concepts employed in this research, including the systematic literature review, systematic content analysis using quantitative methods, causal feedback loops integrated with interpretive structural modelling, network analysis applied to these causal loops, and geospatial and remote sensing techniques, collectively provide a robust and nuanced framework for flood and drought risk assessment. Driving from the studied literature, each of these approaches were used individually or in series to assess flood and drought related concepts. However, in this research, a combination of them are chosen to address the inherent complexities of flood and drought dynamics, ensuring comprehensive insights into their underlying mechanisms and impacts.

The systematic literature review forms the foundation of this research by capturing a wide spectrum of existing knowledge and mitigating potential biases. This method goes beyond the traditional narrative review by systematically integrating data from diverse studies, enabling a rigorous and unbiased synthesis of knowledge. By identifying critical gaps in existing frameworks and methodologies, this approach paves the way for developing innovative and effective solutions. While narrative reviews are valuable for providing context, they lack the methodological rigor to consistently synthesize diverse perspectives. The systematic review used here ensures a thorough and unbiased examination of available data, setting a reliable groundwork for the subsequent phases of the research.

The systematic content analysis using quantitative methods further strengthens the research by systematically extracting and analyzing the approaches and indices used in existing studies. Unlike qualitative approaches, which may introduce subjectivity, quantitative content analysis ensures objectivity and reproducibility. This approach not only identifies prevailing trends and patterns but also clarifies the relationships between methods and indices. Although qualitative methods are essential for exploring depth in specific contexts, they often fail to identify overarching trends across large datasets. The quantitative methods used here allow for an unbiased and systematic examination of the literature, making it possible to establish clear, data-driven connections between methods and themes.

The development of causal feedback loops integrated with interpretive structural modelling provides a dynamic perspective on how different variables interact within the flood and drought systems. This approach offers a distinct advantage over static models by addressing the cyclical and interconnected nature of hydrological, socio-economic, and environmental factors. Traditional cause-and-effect analyses, while valuable, are often inadequate for capturing the complexity of multi-layered systems where variables influence each other over time. Interpretive structural modelling adds depth by revealing hierarchies and interdependencies among these variables, enabling a comprehensive understanding of systemic interactions that static models fail to capture.

The application of network analysis to these causal loops enriches the research by illuminating the interdependencies and critical pathways within the flood and drought frameworks. Network analysis excels in identifying key nodes and connections, making it a powerful tool for analyzing system resilience and vulnerabilities. Compared to standalone regression analyses or independent variable assessments, network analysis offers a holistic view of system dynamics, identifying critical pathways and potential intervention points. This integrative approach provides insights that are crucial for effective risk mitigation, insights that simpler models may overlook.

The inclusion of geospatial and remote sensing techniques further distinguishes this research by enabling high-resolution, real-time data acquisition for monitoring and early warning systems. Unlike traditional data collection methods, which are often limited in spatial and temporal coverage, remote sensing provides comprehensive, continuous data that captures regional and global dynamics. By integrating this data into geospatial frameworks, the research enhances its ability to monitor and respond to hazard dynamics effectively. While in-situ measurements are valuable for localized assessments, they lack the broad coverage and real-time capabilities of remote sensing, which are essential for addressing large-scale hazards like floods and droughts.

This research also incorporates statistical approaches, machine learning, and sensitivity and uncertainty analyses into these geospatial methods, further enhancing their predictive accuracy and robustness. Machine learning algorithms, such as Random Forests and Support Vector Machines, are leveraged to identify complex, non-linear relationships between variables, offering superior predictive capabilities compared to conventional statistical models. Sensitivity and uncertainty analyses ensure that the outputs of the models are reliable and account for the range of possible outcomes. Unlike deterministic models, which may oversimplify risk scenarios, these advanced methods provide a more realistic and comprehensive understanding of the risks associated with floods and droughts.

When compared to other possible solutions, such as purely deterministic models, qualitative assessments, or standalone statistical approaches, the methods adopted in this research stand out for their integrative, adaptive, and resilient framework. This multi-dimensional approach captures the physical, socio-economic, and environmental aspects of flood and drought risks, bridging the gap between scientific research and practical application. By combining systematic literature reviews, quantitative content analysis, causal modelling, network analysis, and geospatial techniques enhanced with machine learning and statistical methods—this research provides a cohesive and forward-looking framework.

Ultimately, this integrated methodology provides a balanced approach that combines scientific rigor with practical relevance, offering insights that can contribute to more effective flood and drought risk management strategies in real-world scenarios. The resulting framework is uniquely positioned to mitigate the impacts of floods and droughts on both human and environmental systems, offering innovative and scalable solutions for water resource management in a rapidly changing world.

2.6.1 Systematic literature review

Integrating various research themes also facilitates interdisciplinary collaboration, leading to innovative solutions and comprehensive risk management approaches. It is essential to obtain perspective and information from various fields and sources Thus, conducting a systematic literature review (SLR) is essential for synthesizing credible and comprehensive information on complex, broad, and extensively studied subjects like flood and drought risk assessments. The systematic approach ensures that the review process is rigorous, transparent, and reproducible, thereby enhancing the reliability and validity of the findings.

An SLR helps in reaching a consensus on the relevant themes, variables, and their interconnections by systematically collecting, evaluating, and synthesizing research evidence. This method reduces the likelihood of overlooking critical studies and ensures that diverse perspectives and findings are considered. By integrating findings from multiple studies, an SLR provides a holistic view of the current state of knowledge and identifies gaps that need further exploration (Tranfield, Denyer & Smart, 2003). One of the main advantages of an SLR is its ability to minimize bias. Bias can arise from selective inclusion of studies, publication bias, or researcher bias. The systematic approach employs predefined criteria for selecting studies, which helps in reducing the subjective influence of the reviewers. Furthermore, using systematic content analysis allows for the extraction of relevant information in a structured manner, ensuring consistency and transparency in the analysis process (Petticrew & Roberts, 2006).

Systematic content analysis involves coding and categorizing qualitative data to identify patterns and themes. This method reduces bias by ensuring that the data extraction process is consistent and objective. Content analysis facilitates the identification of key variables and their interrelationships, which are critical for understanding the complex dynamics of flood and drought risks. By systematically analysing the content of the selected studies, researchers can derive meaningful insights and develop robust frameworks for risk assessment (Hsieh & Shannon, 2005).

2.6.2 Application of systematic content analysis: quantitative methods

Quantitative and statistical methods play a crucial role in synthesizing data and drawing conclusions from the extracted content. These methods include the use of co-occurrence matrices, correlation analysis, and clustering algorithms to analyse the relationships between variables and identify key themes. A co-occurrence matrix is a tool used to quantify the frequency with which pairs of themes or variables appear together in the literature. This matrix helps in identifying the most commonly associated variables, providing insights into the underlying structure of the research domain. For instance, in flood and drought risk assessment, a co-occurrence matrix can highlight the interplay between variables such as precipitation patterns, land use changes, and socio-economic factors (Beguería et al., 2009; Mourão & Nunes, 2016; Liu et al., 2017).

The Spearman correlation coefficient is a non-parametric measure of the strength and direction of the association between two ranked variables. It is particularly useful in identifying monotonic relationships between variables in the literature. By calculating Spearman correlation coefficients for pairs of variables, researchers can determine the degree of association and identify key factors that influence flood and drought risks (Mukaka, 2012; Kisi and Ay, 2014; Pingale et al., 2016).

Cosine similarity indices measure the cosine of the angle between two non-zero vectors in a multi-dimensional space, representing the similarity in the pattern of co-occurrences rather than their magnitude. This metric is valuable for comparing the similarity between different sets of variables and identifying clusters of closely related themes. In the context of risk assessment, cosine similarity can help in grouping variables that exhibit similar patterns of association, thereby facilitating a more nuanced understanding of the interconnections (Singhal, 2001; Huang et al., 2016; Ren et al., 2016).

Clustering algorithms are essential for identifying key variables and their interactions in complex datasets. These algorithms group similar data points together based on predefined criteria, revealing underlying patterns and structures. One of the highly cited of such methods is K-means clustering algorithm that partitions data into K clusters based on the distance between data points. Each cluster is defined by its centroid, and the algorithm iteratively adjusts the centroids to minimize the variance within clusters. In flood and drought risk assessment, K-means clustering can be used to group regions with similar risk profiles or to identify clusters of variables that exhibit similar behaviors (MacQueen, 1967; Dabanlı et al., 2016; Shafizadeh-Moghadam et al., 2018). Similarly, Hierarchical clustering builds a tree-like structure of nested clusters by successively merging or splitting clusters based on their similarity. This method provides a visual representation of the data hierarchy, which is useful for understanding the relationships between different variables and identifying key drivers of risk. Hierarchical clustering is particularly advantageous when the number of clusters is not known a priori (Johnson, 1967; Rahmati et al., 2016; Khalid et al., 2018). DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a density-based clustering algorithm that identifies clusters based on the density of data points. It is particularly effective in detecting clusters of varying shapes and sizes and is robust to noise and outliers. In the context of risk assessment, DBSCAN can help in identifying spatial clusters of high-risk areas and understanding the spatial distribution of flood and drought risks (Ester et al., 1996; Acharya et al, 2017; Pham et al., 2018).

2.6.3 Creating causal feedback loops integrated with Interpretive Structural Modelling

In the flood and drought literature, several key concepts underscore the importance of understanding causal pathways and network interactions. For instance, the hydrological cycle and its components, such as precipitation, evapotranspiration, and runoff, are fundamental to both flood and drought dynamics (Kundzewicz et al., 2014). Studies have shown that changes in one component can lead to cascading effects across the system, exacerbating risks (Van Loon et al., 2016).

Flood risk assessments often focus on the interplay between natural and anthropogenic factors, including land use changes, urbanization, and climate variability (Merz et al., 2010a). Similarly, drought risk assessments consider factors such as soil moisture, vegetation health, and water resource management (Wilhite, 2000). Both types of assessments benefit from identifying causal pathways that highlight how these variables interact over time and space.

Causal pathways help identify how different factors contribute to flood and drought risks, providing a clear visualization of the relationships and feedback loops within the system. For example, a causal pathway in flood risk might illustrate how heavy precipitation leads to increased runoff, which is then exacerbated by urban impermeability, resulting in flooding (Few et al., 2004).

In drought risk, a pathway might show how prolonged lack of rainfall reduces soil moisture, leading to agricultural stress and water scarcity (Mishra & Singh, 2010).

2.6.3.1 ISM Applications in Flood and Drought Studies

Interpretive Structural Modelling (ISM) has been extensively applied in various fields to understand complex systems, including flood and drought studies. ISM helps in structuring complex issues into a comprehensive model by identifying and summarizing relationships among specific variables (Warfield, 1974).

In flood risk studies, ISM has been used to analyse the interdependencies between different risk factors, such as hydrological variables, land use, and socio-economic factors (Saha et al., 2018). By creating a hierarchical structure of these factors, ISM enables researchers to identify key drivers and leverage points for effective risk management.

Similarly, in drought risk assessments, ISM has been applied to understand the interactions between climatic variables, agricultural practices, and water management strategies (Sharma & Joshi, 2018). This approach helps in identifying critical factors that influence drought resilience and guides the development of targeted mitigation strategies.

2.6.4 Introducing the network analysis into the created causal loop

The integration of network analysis into flood and drought risk assessment is rooted in the need to understand and manage the intricate interactions between various risk factors. Traditional risk assessment methods often fall short in capturing these complex interdependencies, which can significantly impact the efficacy of mitigation strategies. Causal pathways and network metrics, when applied through advanced methodologies like Interpretive Structural Modelling (ISM) and Causal Loop Diagrams (CLD), provide a robust framework for comprehensively analysing these risks.

Applying network analysis metrics to the ISM-generated framework provides additional insights into the structure and dynamics of the risk system. Metrics such as betweenness centrality, closeness centrality, authority, and hub scores help identify key variables and interactions that are critical for risk management (Freeman, 1977; Kleinberg, 1999). Several studies have demonstrated the effectiveness of integrating ISM and network analysis in flood and drought risk assessments. For instance, Saha et al. (2018) used ISM to structure the interrelationships between urbanization, climate change, and flood risks, identifying critical factors that enhance urban flood resilience. Similarly, Sharma & Joshi (2018) applied ISM to drought risk assessment in India, highlighting the key drivers of drought vulnerability and resilience. By merging ISM with network metrics, researchers can develop a comprehensive understanding of the complex interactions within flood and drought risk systems. This integrated approach enables the identification of critical pathways and influential variables, guiding the development of effective mitigation and adaptation strategies. For example, betweenness centrality can identify variables that act as bridges between different parts of the network, indicating critical points for intervention. Closeness centrality highlights variables that can quickly influence or be influenced by others, essential for understanding rapid risk escalation or mitigation. Authority and hub scores identify key sources and disseminators of influence within the network, guiding targeted risk management efforts.

After identifying the value of each node within the causal framework using the ISM-CLD approach and rating them based on various network metrics, the next step is to narrow down these variables to the main risk factors. These selected factors will then be modelled for a spatio-temporal investigation at a river basin scale.

2.6.4.1 Cross entropy Monte Carlo algorithm for variable selection

To streamline the selection process of the most critical variables, the Cross Entropy Monte Carlo algorithm is employed. This algorithm is particularly effective in optimizing complex systems and has been applied in various fields to identify top-performing parameters based on multiple criteria (Rubinstein & Kroese, 2004).

The Cross Entropy algorithm works by generating a sample of solutions, evaluating them, and then updating the sampling distribution to focus on the best solutions. This iterative process continues until convergence is achieved, resulting in the identification of the top-ranked variables based on the overall metrics of the network. This algorithm is well-suited for multi-criteria optimization problems, where multiple network metrics such as betweenness centrality, closeness centrality, authority, and hub scores need to be considered simultaneously. This ensures that the selected variables are robust and influential across various aspects of the network (Kroese et al., 2011).

By systematically evaluating a large number of potential solutions, the Cross Entropy algorithm reduces the risk of bias that might arise from subjective judgment or selective inclusion of variables. This enhances the reliability of the selection process and ensures that the most critical factors are identified (Rubinstein & Kroese, 2004). Selecting the top-ranked variables using this algorithm improves the predictive power and accuracy of the subsequent risk models. These models can then be used for detailed spatio-temporal analysis, providing valuable insights into the dynamics of flood and drought risks at the river basin scale (De Boer et al., 2005).

2.6.5 Geospatial and remote sensing techniques in flood and drought risk assessment

Flood and drought risks pose significant challenges to sustainable development and disaster management. Traditional risk assessment methods often fall short in providing timely, accurate, and spatially comprehensive data required for effective mitigation and response. This is where Geographic Information Systems (GIS) and remote sensing technologies become indispensable.

Floods and droughts are dynamic and spatially heterogeneous phenomena. They impact vast and often remote areas, making ground-based observations logistically challenging and time-consuming. Traditional methods, relying on historical records and localized measurements, lack the capability to capture real-time changes and the spatial extent of these hazards. Moreover, these conventional approaches may not integrate various types of data, such as climatic, hydrological, and socio-economic factors, essential for a holistic risk assessment. GIS and remote sensing provide the tools necessary to overcome these limitations. Remote sensing offers high-resolution, real-time data from satellite and aerial sensors, covering large and inaccessible areas. This data includes critical variables such as precipitation, soil moisture, vegetation health, and surface water bodies, essential for monitoring flood and drought conditions. GIS, on the other hand, allows for the integration and analysis of this spatial data, facilitating the creation of detailed and accurate risk maps. The ability to overlay multiple data layers enables a comprehensive assessment of vulnerability, exposure, and potential impacts. Advantages of geospatial over other techniques could be explained as follows.

Remote sensing provides a synoptic view that ground-based observations cannot match, ensuring comprehensive spatial coverage and real-time monitoring capabilities (Cracknell, 2018). GIS integrates diverse datasets, including topography, land use, hydrology, and socio-economic data, offering a multi-dimensional perspective crucial for effective risk assessment (Goodchild, 2009). Additionally, the combination of GIS and remote sensing enhances predictive accuracy through advanced spatial analysis and modelling techniques, enabling better-informed decision-making and proactive risk management (Li et al., 2019). Remote sensing data is available at various temporal scales, from daily to monthly, allowing for timely updates and continuous monitoring, which is vital for early warning systems and rapid response strategies (NASA, 2020).

Traditional methods, however, have notable limitations. These include limited spatial and temporal resolution, which makes it difficult to capture the detailed dynamics of flood and drought events. Conventional approaches may also fail to effectively integrate the diverse types of data needed for a comprehensive risk assessment, leading to incomplete or biased analyses. Furthermore, ground-based observations and manual data collection are resource-intensive and may not be feasible for large or remote areas.

In conclusion, the integration of GIS and remote sensing in flood and drought risk assessments addresses the limitations of traditional methods by providing high-resolution, real-time, and comprehensive spatial data, enhancing the overall effectiveness and efficiency of risk management strategies.

2.7 Spatial data and analysis

2.7.1 Types of spatial data used

A comprehensive understanding of flood and drought risks relies on the integration of diverse datasets, including topographical, hydrological, land use, and climatic data, each of which plays a critical role in assessing and mitigating these hazards. This research benefited from using a range of data across many disciplines as described in section 4.11.

Topographical data, typically obtained from Digital Elevation Models (DEMs), is crucial for flood risk assessment as it provides detailed information on terrain elevation and slope. DEMs are instrumental in modelling water flow, identifying flood-prone areas, and assessing the impact of terrain on flood dynamics (Gesch et al., 2002). Hydrological data, which includes information on river discharge, water levels, precipitation, and soil moisture, is essential for understanding the hydrological processes driving flood and drought events. This data is sourced from ground-based monitoring stations and satellite-based sensors like SMAP and GRACE (Entekhabi et al., 2010).

Land use and land cover (LULC) data, derived from remote sensing imagery, offers insights into the distribution of natural and human-modified landscapes. This data is critical for assessing the impact of land use changes, such as deforestation, urbanization, and agricultural practices, on flood and drought risks (Foody, 2003). Climatic data, which includes temperature, humidity, and precipitation patterns, is equally vital for drought risk assessment. Typically obtained from meteorological stations and satellite-based platforms like MODIS and TRMM, climatic data helps identify trends and anomalies that may signal the onset of drought conditions (Li et al., 2019).

2.7.2 Spatial analytical techniques employed

A range of spatial analytical techniques has been employed to deepen our understanding of flood and drought dynamics, integrating varied datasets and advancing predictive methodologies. Spatial analysis methods, including overlay analysis, buffering, and spatial interpolation, combine multiple data layers to pinpoint at-risk areas, model the extent and impact of floods and droughts, and generate visual risk maps (Longley et al., 2015). Hydrological modelling tools like HEC-RAS and SWAT use spatial data to simulate water movement within watersheds, predicting flood extents, depths, durations, and the effects of various scenarios on water availability and quality. These models are indispensable for understanding hazard dynamics and informing mitigation strategies (Neitsch et al., 2011).

Remote sensing analysis complements these techniques by extracting environmental insights from satellite imagery. Approaches such as the Normalized Difference Vegetation Index (NDVI) and Soil Moisture Index (SMI) enable monitoring of vegetation health and soil moisture, providing early drought warnings. Flood extent mapping with Synthetic Aperture Radar (SAR) imagery is another vital application, offering detailed insights into flood impacts (Jensen, 2015). Furthermore, machine learning and data mining techniques bolster these methodologies by processing large spatial datasets, uncovering patterns, and enhancing the predictive power of risk models. These advanced methods identify key risk factors and enable the development of models with high accuracy in forecasting future flood and drought events (Mosavi et al., 2018).

2.8 Spatio-temporal assessment of flood and drought risk: necessity, benefits, and limitations of fuzzy logic and machine learning techniques

2.8.1 Necessity of using advanced methods in risk assessment

The increasing frequency and severity of floods and droughts due to climate change and anthropogenic factors necessitate the use of advanced methods for spatio-temporal risk assessment. Traditional risk assessment methods often fail to capture the complex, non-linear interactions between various risk factors and do not adequately address the inherent uncertainties in environmental systems. Advanced methods like Fuzzy Logic and Machine Learning provide robust frameworks for integrating diverse datasets, handling uncertainty, and making accurate predictions, thereby enhancing the effectiveness of risk management strategies (Wang & Elhag, 2007; Beven, 2009).

2.8.2 Application of fuzzy logic and fuzzy overlay function in risk mapping

Fuzzy logic is a mathematical approach that deals with imprecision and uncertainty, making it particularly suitable for environmental risk assessments where data is often incomplete or vague. The fuzzy overlay function combines multiple criteria maps, allowing for the integration of various risk factors into a single, comprehensive risk map. This method assigns membership values to each criterion, reflecting the degree to which they belong to specific risk categories (Zadeh, 1965; Ross, 2010). It has a range of benefits such as handling uncertainty, integration of diverse data and flexibility. Fuzzy logic effectively handles the uncertainty and imprecision inherent in environmental data, providing more realistic risk assessments (Zimmermann, 2010).It allows for the integration of diverse data types, including qualitative and quantitative information, enhancing the comprehensiveness of risk assessments (Ghosh & Kar, 2018). The fuzzy overlay function is highly flexible and can be adapted to different spatial scales and study areas (Pradhan, 2011). However, it comes with some limitations. The implementation of fuzzy logic requires a deep understanding of the system and the ability to define appropriate membership functions and rules (Ross, 2010). The selection of membership functions and thresholds can be subjective, potentially introducing bias into the assessment (McBratney & Odeh, 1997). Lastly, fuzzy logic models can be computationally intensive, especially when dealing with large datasets and multiple criteria (Jiang & Eastman, 2000).

2.8.3 Machine learning algorithms for risk prediction and trend analysis

Machine learning (ML) algorithms, such as XGBoost, have gained popularity for their ability to analyse large datasets, identify patterns, and make accurate predictions. XGBoost, an optimized gradient boosting algorithm, is particularly effective for regression and classification tasks, making it suitable for predicting flood and drought risks and analysing trends (Chen & Guestrin, 2016). Benefits of applying such methods could be high predictive accuracy, scalability and automation. XGBoost and other ML algorithms provide high predictive accuracy by leveraging large datasets and learning complex patterns (Friedman, 2001). These algorithms are highly scalable and can handle large datasets efficiently, making them suitable for regional and global risk assessments (Chen & Guestrin, 2016). Machine learning models can be automated to continuously update predictions based on new data, providing real-time risk assessments (Breiman, 2001).

Limitations of these models could be grouped into data dependency, interpretability and sometimes overfitting. The accuracy of ML models heavily depends on the quality and quantity of input data. Incomplete or biased data can lead to inaccurate predictions (Domingos, 2012). ML models, especially complex ones like XGBoost, can be difficult to interpret, making it challenging to understand the underlying mechanisms driving the predictions (Rudin, 2019). There is a risk of overfitting, where the model performs well on training data but poorly on unseen data, necessitating careful model validation and tuning (Hawkins, 2004).

The integration of Fuzzy Logic and Machine Learning techniques into the spatio-temporal assessment of flood and drought risks addresses the limitations of traditional methods and enhances the accuracy and comprehensiveness of risk predictions. While each method has its benefits and limitations, their combined application provides a robust framework for managing environmental risks in a rapidly changing climate. The extensive literature underscores the necessity of these advanced techniques, highlighting their critical role in contemporary risk assessment practices.

2.9 VALIDATION TECHNIQUES FOR PREDICTED RISK MAPS

Validation of risk maps is a crucial step in ensuring their accuracy, reliability, and practical utility. Without robust validation, the predictions made by these maps can be misleading, leading to inadequate or misplaced risk management strategies. Effective validation techniques help in assessing the performance of risk models, identifying their strengths and weaknesses, and providing confidence in their use for decision-making processes (Pontius & Millones, 2011).

Receiver Operating Characteristic (ROC) curves are a widely used method for evaluating the performance of binary classifiers. In the context of risk maps, ROC curves plot the true positive rate against the false positive rate at various threshold settings, providing a comprehensive measure of the model's discriminatory power (Fawcett, 2006). The area under the ROC Curve (AUC) is particularly informative, summarizing the model's overall ability to distinguish between different risk levels. This approach provides a comprehensive evaluation without being dependant on thresholds. ROC curves provide a thorough evaluation of the model's performance across all possible thresholds, offering insights into its sensitivity and specificity (Swets, 1988). Unlike other metrics, ROC curves do not depend on a specific threshold, making them versatile and broadly applicable (Hanley & McNeil, 1982). However, these benefits come with some restrictions, such as binary limitation and data imbalance. ROC curves are primarily designed for binary classification, which may not fully capture the complexity of multi-class risk assessments (Fawcett, 2006). In cases of highly imbalanced data, ROC curves might not provide a clear indication of model performance, necessitating additional metrics (Davis & Goadrich, 2006).

Spatial Overlay and Percentage of Agreement are some other simpler validation techniques used in spatial analysis. Spatial overlay techniques involve comparing the predicted risk maps with historical data or observed events to assess their accuracy. This method visually and quantitatively evaluates the spatial congruence between predicted and actual risk areas (Goodchild, 1994). On the other note, the percentage of agreement metric calculates the proportion of correctly predicted risk areas relative to the total number of areas assessed. It provides a straightforward measure of model accuracy (Foody, 2002). Both spatial overlay and percentage of agreement are easy to interpret and communicate to stakeholders, facilitating their practical use (Goodchild, 1994). These methods allow for a direct comparison of predicted and observed risk areas, highlighting specific regions of agreement or discrepancy (Foody, 2002). However, the interpretation of spatial overlays can be subjective, depending on the visual assessment and the criteria used for comparison (Pontius & Millones, 2011). And the percentage of agreement is a simplistic metric that may not capture the nuances of model performance, especially in complex systems (Foody, 2002). Other validation techniques may involve Kappa Statistic and Cross-Validation.

The Kappa statistic measures the agreement between predicted and observed data, accounting for the agreement occurring by chance. It provides a more rigorous assessment than the percentage of agreement but can be sensitive to data imbalance (Cohen, 1960). Kappa accounts for chance agreement, providing a more accurate reflection of model performance (Landis & Koch, 1977). It is a widely accepted measure in various fields, facilitating comparisons across studies (Viera & Garrett, 2005). But Kappa can be influenced by the prevalence of classes in the data, potentially leading to misleading results in imbalanced datasets (Pontius & Millones, 2011). Additionally, the interpretation of Kappa values can be complex, particularly in the context of multiple classes or categories (Viera & Garrett, 2005).

On the other hand, cross-validation involves partitioning the data into subsets, using some for training and others for validation, to assess model performance. This method helps in estimating the model's predictive accuracy and robustness (Kohavi, 1995). It provides a robust estimate of model performance by averaging results across multiple iterations (Stone, 1974). And helps in understanding the trade-off between model bias and variance, guiding model selection and tuning (Hastie, Tibshirani & Friedman, 2009). However, it is computationally intensive, especially with large datasets or complex models (Arlot & Celisse, 2010). And the results of cross-validation can depend on how the data is partitioned, potentially leading to variability in performance estimates (Kohavi, 1995).

2.10 Sensitivity analysis and feature importance in flood and drought risk assessment

In the context of flood and drought risk assessment, understanding which variables or features most significantly impact the model's predictions is crucial for effective risk management and mitigation strategies. Sensitivity analysis and feature importance assessments help in identifying the key drivers of risk and understanding how variations in input data influence the outcomes (Saltelli et al., 2008; Pappenberger et al., 2008).

Sensitivity analysis is a method used to determine how different values of an input variable impact a particular output variable under a given set of assumptions. It is essential in risk assessment to identify which parameters most influence the model's results. Sobol's sensitivity analysis is a variance-based method that decomposes the variance of the output of a model into fractions attributed to different inputs or sets of inputs (Sobol, 2001). This method is highly effective for complex models as it considers the interaction effects between variables. Main benefits of this model are its ability in decomposition and independence to models whereas it could be computationally intense and relatively difficult to interpret (Homma & Saltelli, 1996; Saltelli, 2002; Saltelli et al., 2008; Iooss and Lemaître, 2015).

Feature importance measures the contribution of each feature to the model's predictions. It helps in understanding which variables are most influential in driving the risk assessment model. There are many approaches for assessing feature importance such as Random Forest, Permutation Importance, XGBoost and Principal Component Regression (PCR).

Random Forests provide feature importance scores based on the mean decrease in impurity (Breiman, 2001). They are effective for high-dimensional datasets and can capture non-linear relationships between variables. Slightly different, Permutation importance assesses the change in model accuracy when the values of a feature are randomly shuffled. This method provides an intuitive measure of feature importance (Breiman, 2001). XGBoost is an optimized gradient boosting algorithm that provides feature importance scores based on the contribution of each feature to the reduction in loss (Chen & Guestrin, 2016). It is particularly effective for large-scale datasets and complex models.

PCR on the other hand, combines Principal Component Analysis (PCA) with linear regression. It reduces the dimensionality of the data and then performs regression on the principal components. PCR helps in identifying the most significant features that explain the variance in the data (Jolliffe, 2002).

Methods like permutation importance and random forests provide clear, interpretable measures of feature importance (Louppe et al., 2013). Algorithms like XGBoost and random forests can capture non-linear relationships between features, offering a more nuanced understanding of feature importance (Chen & Guestrin, 2016). However, Feature importance scores can be model-specific, and different models might provide different importance rankings for the same dataset

(Strobl et al., 2007). Some methods, particularly those involving ensemble models, can be computationally intensive (Friedman, 2001).

Both sensitivity analysis and feature importance assessment are crucial in identifying the key drivers of flood and drought risks. Methods like Sobol's index provide a detailed understanding of how variations in input variables affect model outputs, while feature importance techniques such as random forests, permutation importance, XGBoost, and PCR offer insights into the significance of individual features. Uncertainty analysis, including approaches like bagging with XGBoost, is essential for quantifying and mitigating the inherent variability in risk predictions. These methods collectively enhance the robustness and reliability of flood and drought risk assessments, facilitating better decision-making and risk management strategies.

2.11 UNCERTAINTY ANALYSIS IN RISK ASSESSMENT

Uncertainty analysis is critical in risk assessment as it quantifies the degree of uncertainty in model predictions. Understanding and addressing uncertainty helps in making more robust and reliable risk management decisions (Beven & Binley, 1992). There are some limitations to progress further with uncertainty analysis in the context of this research, such as intrinsic variability in natural systems, complexity of the model and its interactions, data limitations regarding the risk values and not different properties of the phenomena.

2.11.1 Approaches for assessing uncertainty

Aleatoric uncertainty refers to the inherent variability associated with the natural randomness of the system being modelled. It is important to quantify this type of uncertainty to understand the range of possible outcomes and their likelihood. Bagging (Bootstrap Aggregating) is an ensemble technique that improves the stability and accuracy of machine learning algorithms by reducing variance. When combined with XGBoost, bagging helps in assessing and mitigating aleatoric uncertainty by generating multiple versions of the model and averaging their predictions (Breiman, 1996). Bagging helps in reducing the variance of the model, leading to more stable and reliable predictions (Breiman, 1996). Additionally, combining bagging with XGBoost leverages the strengths of both techniques, enhancing the overall predictive performance (Chen & Guestrin, 2016). However, the process of creating multiple models and aggregating their predictions can be computationally demanding (Bühlmann & Yu, 2002). And implementing bagging with XGBoost requires careful tuning and validation to ensure optimal performance (Breiman, 1996).

2.12 IDENTIFIED GAPS IN THE LITERATURE

The current body of research on flood and drought risk assessment has made significant strides, yet there remain several critical gaps and limitations that warrant further investigation. One major gap is the lack of integration between flood and drought risk assessments. While numerous studies focus on either flood risk (Merz et al., 2010a; Kundzewicz et al., 2014) or drought risk (Wilhite, 2000; Mishra & Singh, 2010) individually, integrated assessments that consider both hazards concurrently are still scarce. Such integration is particularly crucial because the occurrence of one event can often exacerbate the impacts of the other, especially in regions that are vulnerable to both phenomena. Another gap lies in the insufficient capture of spatio-temporal dynamics. Many existing studies fail to adequately incorporate changing climatic and land-use patterns over time, which are essential for accurate risk assessments. The current models often lack the sophistication to address these evolving patterns effectively (Ward et al., 2011; Van Loon, 2015).

Moreover, there is a pressing need for more comprehensive approaches to uncertainty and sensitivity analysis in flood and drought risk assessments. Although methods such as Sobol's index (Pappenberger et al., 2008) and permutation importance (Strobl et al., 2007) have been applied in some studies, these approaches are not yet universally adopted, and their applications are often limited to specific contexts or regions. The use of advanced machine learning techniques, such as XGBoost, for identifying key risk factors is relatively new in this research area. While these techniques show promise, more work is required to validate their effectiveness and establish best practices for their application (Mosavi et al., 2018; Qi et al., 2018). Model validation is another significant gap. Many studies do not adequately validate their risk models using robust techniques like ROC curves or cross-validation, which casts doubt on the reliability and generalizability of their findings (Pontius & Millones, 2011; Fawcett, 2006). Proper validation is crucial to ensure that these models can be reliably applied in real-world scenarios.

Lastly, there is a shortage of interdisciplinary approaches that integrate physical sciences, social sciences, and policy analysis to address flood and drought risks in a holistic manner. Interdisciplinary integration is vital for the development of effective mitigation and adaptation strategies (Adger, 2006; Cutter et al., 2008).Such integration is essential for developing effective mitigation and adaptation strategies (Adger, 2006; Cutter et al., 2008).

2.12.1 Future research directions

To address these gaps, several potential avenues for future research can be suggested. Firstly, the development of integrated risk models that consider both flood and drought risks, including their interactions and cumulative impacts, is essential. Such models should capture the complex interdependencies between these hazards (Wang et al., 2017).

Advances in GIS and remote sensing technologies should also be utilized to create more sophisticated spatio-temporal models that can accurately predict flood and drought risks under different climate change and land-use scenarios (Goodchild, 1994; Ghosh & Kar, 2018). Enhanced spatio-temporal modelling will improve the accuracy of predictions and support proactive risk management. There is also a need for more comprehensive uncertainty analysis frameworks. Future research should incorporate multiple methods, such as Bayesian approaches and ensemble modelling, to better quantify and manage uncertainty in risk assessments (Beven & Binley, 1992; Efron & Tibshirani, 1993). Comprehensive uncertainty analysis will make these models more reliable for decision-making. Further research should explore the application of machine learning techniques like XGBoost, random forests, and neural networks in flood and drought risk assessments. These methods have the potential to significantly improve the accuracy and robustness of predictions, enabling more reliable assessments of risk (Chen & Guestrin, 2016; Breiman, 2001). Robust model validation techniques should be employed in future studies to ensure reliability. Techniques such as ROC curves, k-fold cross-validation, and bootstrapping should be used to validate risk models, thereby enhancing the credibility and applicability of research findings (Hanley & McNeil, 1982; Kohavi, 1995).

Finally, interdisciplinary research that combines insights from hydrology, climatology, sociology, economics, and policy studies is crucial for addressing flood and drought risks comprehensively. By embracing interdisciplinary approaches, more effective and sustainable risk management strategies can be developed (Adger, 2006; Cutter et al., 2008).

2.13 SUMMARY OF KEY FINDINGS

The literature review comprehensively examined various methodologies, frameworks, and models relevant to flood and drought risk assessments. Historically, flood risk assessment methodologies have evolved from simplistic deterministic models to more sophisticated probabilistic and statistical approaches that incorporate multiple variables and uncertainties (Di Baldassarre et al., 2010; Kundzewicz et al., 2014). Current methods emphasize the integration of Geographic Information Systems (GIS) and remote sensing technologies, which facilitate the spatial analysis and visualization of risk factors (Melesse et al., 2007; Foody, 2003). Additionally, the review highlighted the increasing use of machine learning algorithms, such as XGBoost and Random Forest, in predicting flood and drought risks due to their ability to handle complex datasets and improve prediction accuracy (Chen & Guestrin, 2016; Breiman, 2001).

Similarly, drought risk assessment has transitioned from basic meteorological indices to more comprehensive hydrological and ecological models that consider a range of environmental and socio-economic factors (Mishra & Singh, 2010; Van Loon, 2015). Contemporary approaches incorporate satellite-based remote sensing data and advanced statistical methods to enhance the accuracy and timeliness of drought predictions (Anderson et al., 2011; Kogan, 1997). The review also underscored the importance of integrated risk assessments that combine flood and drought analyses, recognizing the interconnected nature of these hazards and the need for holistic management strategies (Krysanova et al., 2008; Kappes et al., 2012).

The reviewed literature provides a robust foundation for the current study, which aims to develop an integrated framework for assessing flood and drought risks in river basin contexts. The historical evolution and advancements in flood and drought risk methodologies underscore the necessity of employing sophisticated tools and technologies, such as GIS, remote sensing, and machine learning algorithms, in contemporary risk assessments. These tools will be instrumental in collecting, analysing, and synthesizing spatial and temporal data, thereby enhancing the accuracy and reliability of risk predictions.

Furthermore, the insights gained from existing integrated approaches highlight the benefits of combining flood and drought risk assessments to develop a more comprehensive understanding of these interrelated hazards. By leveraging the strengths of various models and frameworks discussed in the literature, the current study aims to address identified gaps, such as the need for more detailed spatiotemporal analyses and the integration of diverse data sources. This integrated assessment approach will facilitate the identification of critical risk factors and the development of effective mitigation and adaptation strategies, ultimately contributing to more resilient water resource management in the face of climate change and increasing environmental variability (Kundzewicz et al., 2014; Merz et al., 2010b).

The following points conclude the gaps derived from reviewing the literature. *Integration of Feedback Loops in Risk Assessment:* Many existing studies on flood and drought risk assessments fail to capture dynamic feedback mechanisms that influence both hazards. The approach of using causal feedback loops integrated with interpretive structural modeling addresses this gap by providing a more holistic and interactive understanding of the interdependencies between flood and drought events.

Lack of Combined Network and Structural Analysis: Current flood and drought risk assessments often utilize network analysis or structural modeling independently. There is a gap in integrating these two approaches to better represent and quantify the relationships and influence of variables within the system. This research's introduction of network analysis into causal feedback loops addresses this limitation, offering a deeper understanding of key nodes and connections.

Limited Use of Advanced Geospatial Techniques: While many studies use basic remote sensing and GIS approaches, they often lack the integration of advanced machine learning and sensitivity analysis to improve accuracy. Conducted research fills this gap by combining remote sensing with statistical approaches and machine learning techniques, providing enhanced spatial and temporal risk predictions.

Underrepresentation of Socio-Economic Factors in Hydrological Models: The inclusion of socio-economic data in risk models remains underdeveloped, particularly in capturing the influence of human activities on hydrological extremes. This research emphasizes the integration of socio-economic indices, which adds depth to the assessment and links physical hazards to their broader societal implications, addressing this underrepresentation.

Scalable Framework for Diverse Regional Contexts: Existing methodologies often fail to provide a scalable and adaptable framework applicable across different geographical regions. This research approach, which leverages systematic literature review to identify universally applicable methods and indices, aims to create a flexible framework capable of being tailored to diverse regional and socio-economic contexts.

3 Overview of the Research Methodology

3.1 CHAPTER INTRODUCTION

The methodologies employed to investigate complex environmental challenges, such as flood and drought risks, are indispensable for crafting effective strategies to manage these hydrological extremes, especially in the context of a changing climate. Floods and droughts represent inherently intricate phenomena, shaped by a confluence of physical, socio-economic, and environmental factors that interact across varying scales and timeframes. Addressing these challenges requires a methodological framework that integrates diverse data sources, accounts for temporal dynamics, and generates insights that are both actionable and adaptable for stakeholders. A holistic and structured research approach not only enhances our understanding of these risks but also lays the foundation for strategies that mitigate their impacts on both human communities and natural ecosystems.

Aligned with the Research Onion Framework (Saunders et al., 2009), this study adopts a pragmatist research philosophy, combining both quantitative and qualitative methods to comprehensively address flood and drought risks. The abductive research approach allows for an iterative process of moving between theoretical frameworks and empirical data, continuously refining insights. The research strategies employed include statistical analysis, interpretive structural modelling (ISM), and system dynamics modelling via causal loop diagrams (CLDs), aimed at constructing a robust and integrative framework. The study utilizes a mixed-methods design, blending quantitative data analysis with qualitative modelling techniques to enrich the research outcomes. With a longitudinal time horizon, the research captures the temporal evolution and variations of risk factors, ensuring dynamic adaptability of the framework. Data collection and analysis are carried out using advanced statistical tools for literature synthesis, specialized modelling software for ISM and CLD, and fractal geometry to develop a unified flood and drought risk indicator, enhancing the study's capacity for predictive and applied insights.

3.2 OVERVIEW OF THE RESEARCH APPROACH

This detailed overview of the research approach sets the stage for the subsequent discussion, which focuses on the specific methodologies employed for data collection and analysis. These techniques form the backbone of the framework designed to address flood and drought risk assessments. The next section will offer an in-depth exploration of how these data-driven methods are utilized to achieve the study's objectives, providing critical insights into their application and significance.

The structured steps in this research are represented in the following diagram (Figure 3.1), illustrating the hierarchical interactions necessary to achieve the overarching aim of developing a simultaneous flood and drought risk assessment at the river basin scale. Each box in the diagram corresponds to specific objectives and reflects the sequential processes essential for constructing a robust and integrative framework.

The first box is directly linked to Objective I, which focuses on identifying and elucidating the deep interrelations, latent themes, and critical data involved in flood and drought risks. This is achieved through advanced statistical analysis, laying the groundwork for the study by uncovering key parameters that influence these hydrological extremes.

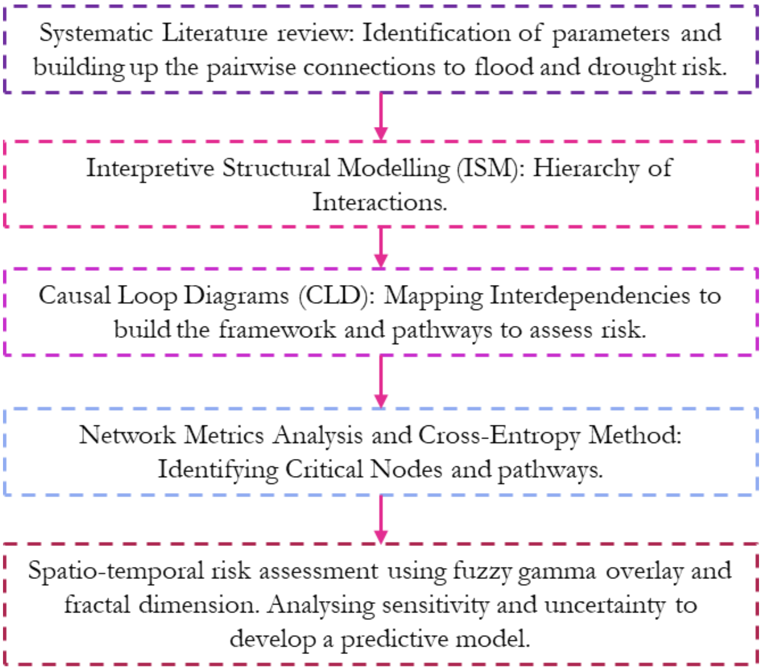


Figure 3.1. Hierarchical Framework for Simultaneous Flood and Drought Risk Assessment: Objectives and Methodological Flow.

The subsequent three boxes (boxes 2-4) align with Objective II, which emphasizes the development of an integrative framework. Using Interpretive Structural Modelling (ISM), network theory, causal loop diagrams, and cross-entropy analysis, these steps progressively capture the interdependencies and dynamics among key risk factors. Together, they highlight the framework's ability to encapsulate complex relationships and provide a comprehensive understanding of flood and drought risks. The final box corresponds to Objective III, focusing on the validation of the developed framework. This step includes conducting sensitivity analyses and introducing the Combined Flood and Drought Risk Index (CFDRI), which plays a pivotal role in predictive risk mapping. This process ensures the framework's accuracy and adaptability by leveraging spatial analysis, efficiency testing, and trend evaluations of hydrological risks. Together, the steps outlined in the diagram support the broader aim of simultaneous flood and drought risk assessment. Each stage builds upon the previous one, contributing to the framework's development and validation. These processes are elaborated further in the following sections, offering detailed insights into the methodologies and analytical approaches employed in this research.

The presented hierarchical framework, particularly from the fourth step onward, offers practical utility for catchment planning services and environmental service providers by providing a structured, data-driven approach to assess flood and drought risks over space and time. This methodology offers flexibility and a comprehensive perspective, making it a valuable tool for stakeholders engaged in water resource management and hazard mitigation. The development of the Combined Flood and Drought Risk Index (CFDRI) enables environmental service providers to quantify risks through a unified metric. This approach effectively captures the dual threats of floods and droughts, offering insights into how these risks evolve together within a catchment. For catchment planning, this step identifies critical hotspots where these hazards are most significant, guiding resource allocation efforts, such as flood defences or improvements in water storage systems.

Predictive mapping capabilities allow stakeholders to visualize how flood and drought risks vary across time and space under different climatic and land-use scenarios. This is especially useful for informing decisions about zoning, land-use planning, and locating critical infrastructure. The availability of spatio-temporal data also helps anticipate ecological impacts, such as shifts in wetland ecosystems or changes in agricultural water availability. This, in turn, supports proactive strategies like floodplain restoration or the implementation of sustainable irrigation systems. The framework's validation and sensitivity analysis ensure that it remains robust and adaptable to various catchment conditions. By examining how risk factors respond to changes such as increased rainfall, urbanization, or vegetation loss, stakeholders can develop adaptive strategies to mitigate risks under uncertain future conditions. This process also provides tools for climate adaptation planning, including nature-based solutions like reforestation or enhancing existing flood control measures to cope with extreme events. This approach is inherently scalable, making it applicable to catchments of different sizes and complexities. Whether used in small urban watersheds or large transboundary basins, the framework accounts for both localized and system-wide risks. Environmental service providers can leverage this methodology to design strategies that address both hydrological extremes while promoting sustainable natural resource use. For example, managing reservoirs to mitigate flood peaks while maintaining adequate storage for droughts becomes feasible with such tools. The framework is not restricted to technical assessments but bridges the gap between scientific analysis and actionable insights. By integrating socio-economic factors and spatial trends, it addresses the needs of diverse stakeholders, including policymakers, local communities, and industries reliant on stable water supplies. This ensures that solutions are inclusive, economically viable, and environmentally sustainable.

Overall, adopting this framework equips catchment planners and environmental service providers with an effective tool to assess and manage flood and drought risks. Its focus on spatio-temporal dynamics and predictive modelling supports better resource allocation and strategic planning, enhancing resilience against these hydrological challenges.

3.3 Methodological steps to find the pairwise connections

The methodological approach adopted to achieve the first objective is systematically presented in Figure 3.2. The flowchart outlines a step-by-step process that begins with a systematic review of peer-reviewed literature, progresses through systematic content analysis using open-coded texts, and culminates in information extraction and data synthesis using quantitative techniques. These techniques include constructing a co-occurrence matrix and applying statistical tools such as the Spearman correlation coefficient, Cosine similarity index, and clustering algorithms. Together, these methods identify critical variables influencing flood and drought risks and analyse their interconnections at the river basin scale.

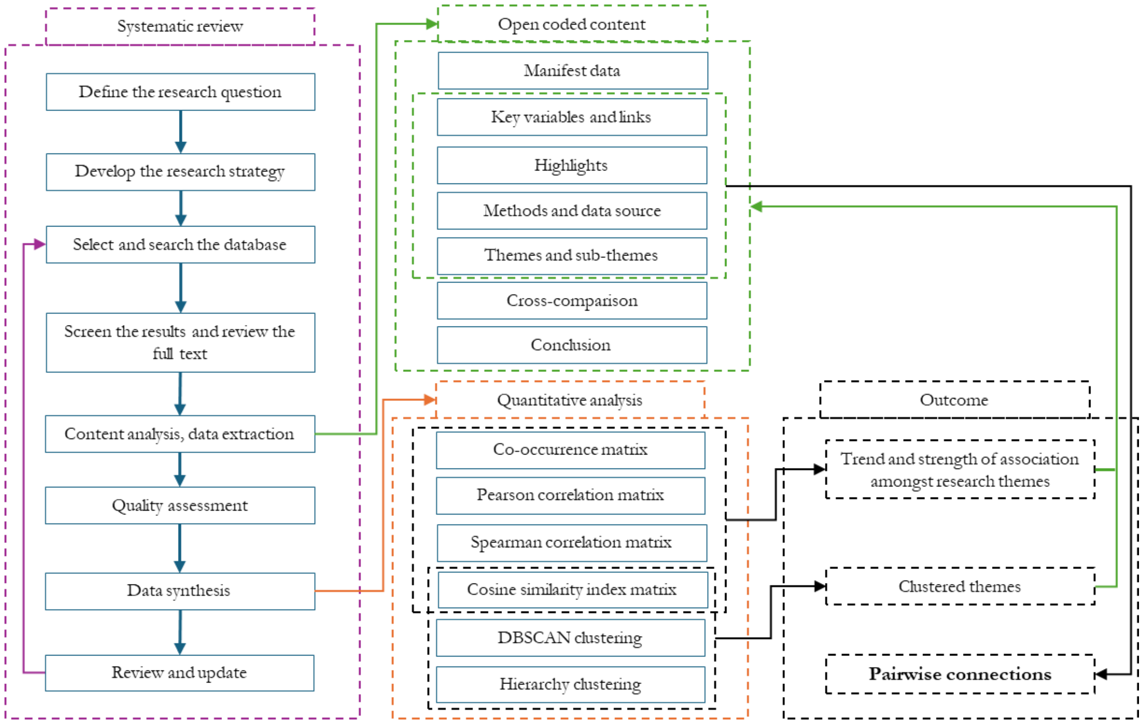


Figure 3.2. Methodological flowchart of data synthesis from systematic review and quantitative analysis.

As outlined in Section 1.1, this research utilized a systematic literature review as its foundational methodology, both to critically appraise existing studies and to systematically gather relevant data. Unlike traditional literature reviews, which are often narrative in nature and may be influenced by the subjective choices of the reviewer, a systematic literature review follows a rigorous and transparent process. This approach involves the application of clearly defined inclusion and exclusion criteria, comprehensive search strategies, and reproducible coding processes, ensuring that the resulting analysis is both unbiased and methodologically robust.

By adopting a systematic approach, this research was able to extract not only key themes and methodologies but also interrelated risk parameters and their connections across diverse disciplines. This level of detail and precision far exceeds the capabilities of traditional reviews, which often focus on providing a general overview of the literature without delving into nuanced interdependencies. Moreover, the systematic process reduces the potential for author bias, enabling a broader, more comprehensive synthesis of knowledge.

The resulting analysis provides a solid foundation for constructing an integrative framework to assess flood and drought risks. This framework benefits from the systematic approach's ability to incorporate diverse perspectives and methodologies, ensuring that the knowledge base is expansive, interdisciplinary, and methodologically sound critical qualities for addressing the complex and multifaceted nature of hydrological risks.

The systematic review initiated an exhaustive exploration of literature related to flood and drought concepts, with a particular emphasis on associated risk factors. Comprehensive searches were conducted using databases like Scopus and Web of Science, guided by keywords refined during the background research phase. The publications were then screened based on specific inclusion criteria, such as publication date, language, and relevance to the central research question. This process focused on developing an integrated framework capable of concurrently assessing flood and drought risks by identifying the parameters driving these phenomena.

Table 3.1 outlines the systematic steps undertaken to locate and extract relevant information from the reviewed publications. This structured and meticulous approach ensured comprehensive and unbiased literature coverage, forming a strong foundation for the subsequent stages of the research.

Table 3.1. Steps taken in the systematic literature review to find and extract information from publications.

Step	Definition	Performed	Remarks
Define the research question	Articulate the research question or hypothesis to identify relevant keywords and search terms	What are the causes of flood and drought risk at a river basin scale?	
Develop a search strategy	Identify keywords and phrases plus using Boolean operators	"flood" AND "drought," combined with one or more of the following root words: "risk," "framework," "cause," and "analysis."	Used “*” to include various types of the words such as “flooded”, “flooding” and “droughts”
Select databases	Choose appropriate academic databases and search engines.	Web of Science and Scopus	extensive coverage of scientific and environmental literature
Search the databases	Enter the developed search terms and apply filters	Language and publication date filters were applied	
Screen the results	Review titles and abstracts for relevance. Exclude clearly irrelevant papers and apply predefined inclusion and exclusion criteria.	2000 onwards, in English, focusing on flood and drought risks.	Study type, quality rigor, duplicate publication, outdated methodologies were also some of other exclusion criteria.

Retrieve full texts	Obtain the full-text versions of selected studies for a detailed review.	Full text downloaded whenever possible.	Tried alternative paths such as direct request from the authors if the publication was not provided through library resources.
Content analysis and data extraction	Develop a standardized form or use software tools to systematically extract relevant information from the studies.	Combined excel and word document to record and manifest the extracted data and open code the latent content of publications.	Quantitative methods used to analyse some correlation and clustering of thematised content.
Quality assessment	Evaluate the quality of the studies using established criteria or checklists relevant to the field of study.	A combination of publication metrics and peer review assessments of papers were applied.	
Data synthesis	Summarize and synthesize the extracted data, identifying common themes and patterns.	Matrices, charts and narratives used to summarise the acquired information.	
Document the process	Maintain a detailed record of the search strategy, databases used, keywords, and filtering criteria. Document the number of articles identified, screened, and included in the review.	A separate account was created to maintain records. A review paper was published from this systematic research early results.	
Review and update	Periodically review and update the search strategy and results to include the latest research developments.	The database was updated and included in the research.	

The research question, "What are the causes of flood and drought risk at a river basin scale?" directed the systematic review, ensuring a targeted and precise approach. a Boolean keyword search strategy specifically designed to conduct a structured and comprehensive search on flood and drought risk assessments (Figure 3.3). This approach ensures that the systematic literature review captures a broad collection of publications addressing key aspects such as integrated frameworks, modeling techniques, and socio-economic considerations. By combining hazard-specific terms (e.g., "flood" and "drought") with keywords related to risk evaluation and methodologies such as "risk," "framework," "cause," and "analysis", this search framework facilitates the identification of relevant interdisciplinary literature. The strategy aims to encompass diverse factors influencing flood and drought phenomena, particularly at the river basin scale, ensuring a holistic and inclusive foundation for the research. Filters were applied to refine the search, restricting the results to studies published in English after the year 2000 and categorized as peer-reviewed articles or institutional/governmental reports.

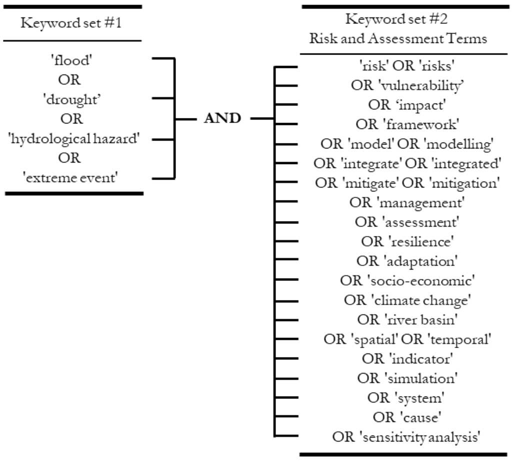


Figure 3.3. Boolean keyword search strategy for systematic literature review on flood and drought risk assessments.

The inclusion criteria for the systematic literature review were carefully chosen to ensure relevance, credibility, and alignment with the research objectives. These criteria include the relevance of studies to the research objectives, peer-reviewed publication status, publication date, language, and the geographical and thematic scope. Specifically, studies were required to directly address flood and/or drought risks at the river basin scale or related concepts, such as hydrological modelling, risk assessment frameworks, socio-economic impacts, or mitigation strategies. This ensured alignment with the overarching research aim. Only peer-reviewed articles or institutional/governmental reports were included to maintain the credibility and scientific rigor of the selected sources (Table 3.2). The review focused on studies published from the year 2000 onwards to capture recent advancements, methodologies, and technologies, ensuring the relevance of the findings to contemporary climate and hydrological challenges. To maintain consistency and accessibility during the review process, only studies published in English were considered, unless critical works in other languages were available with translations. Additionally, studies had to explicitly address parameters, methods, or case studies related to river basins or hydrological extremes, such as floods and droughts, to provide meaningful insights into spatial and temporal dynamics relevant to the research question. Titles and abstracts were carefully reviewed to exclude irrelevant works, with additional criteria such as quality rigor and methodological relevance applied to ensure the inclusion of impactful studies.

Table 3.2. Distribution and types of sources included in the study.

Publication Type	**The quantity of sources**	
Peer reviewed	Journal papers	707
	Book chapters	18
Grey literature	Institutional reports	38
	Datasets	6
	Conference papers	217
	Institutional reports	38
Total		981

The project's Excel database was prepared for analysis using the open-source software KNIME, enabling the cleaning of inevitable human-induced data entry errors and separating cells containing multiple values into distinct fields. Following this preparation, the cleaned data were imported into a Tableau dashboard to facilitate the visualization of data trends and analytical querying, including relational data analyses. In alignment with the study's specific research questions, the analysis examined the relational connections among the four themes of inquiry. Each variable was assessed both individually (as independent variables) and in relation to other variables (as dependent variables) (Table 3.3). The results of this analysis are elaborated further in the Results and Discussion sections.

Table 3.3. Analysis matrix for interpreting the manifest and latent data.

		Discipline (M)	Terminology (L)	Case Studies (L)	Definition (L)
Independent variable	Overview (frequency) (L/M)	X	X	X	X
	Temporal frequency (i.e., time) (M)	X	X	X	X
	Publication type (M)	N/A	X	X	X
	Publication origin (M)	X	X	X	X
Dependent variable	Discipline (M)	X	X	X	X

Subsequently, these annotations were coded and integrated with the manifest data recorded in Excel, enabling a relational analysis that identified and grouped similar and dissimilar headings.

This process facilitated the identification of sub-themes and their relationships. Sections 5.2 and 5.3 present the qualitative findings from this analysis, while the datasets were further merged (section 5.3 onwards) to enable a quantitative exploration such as co-occurance, Spearman and cosine similarity martices. This integration transformed qualitative insights into quantifiable metrics, enhancing methodological rigor and supporting a more detailed thematic and relational analysis (Elo & Kyngäs, 2008; Khirfan et al., 2020). The quantitative outcomes are further discussed in Sections 5.3 onward.

literature represents a diverse disciplinary and sub-disciplinary contexts through which flood and drought risks are studied and addressed, as categorized by the SCImago Journal Rank (SJR) (Table 3.4). By outlining the broad range of disciplines and their corresponding sub-disciplines, the table provides an important backdrop to the process of latent content extraction and subsequent content analysis, underscoring the multidisciplinary nature of flood and drought research.

Incorporating these classifications into the research ensures that the latent content extraction process captures a wide spectrum of perspectives and methodologies. For example, fields like Environmental Science and Engineering contribute foundational hydrological and structural insights, while Economics and Business or Social Sciences provide the socio-economic and policy dimensions essential for comprehensive risk assessment. Similarly, disciplines like Geospatial Science and Computer Science enrich the research with advanced analytical tools such as GIS, remote sensing, and machine learning. This classification system highlights the diverse methodologies and thematic focus areas across disciplines, aiding in identifying relevant themes, datasets, and risk factors for analysis. It rationalizes the inclusion of specific parameters during content analysis, ensuring a balanced representation of both natural and human dimensions of flood and drought risks. For example, integrating contributions from Natural Hazards and Disaster Science helps assess vulnerabilities, while insights from Psychology and Behavioural Science contribute to understanding risk perception and decision-making under uncertainty.

Table 3.4, is used between latent content extraction and content analysis, to serve as a bridge that links the data extraction process with the analytical phase. It ensures that the extracted latent content is systematically categorized, evaluated, and contextualized, aligning with the multidimensional objectives of this research. This approach further ensures that the developed framework reflects the interconnectivity of these disciplines, facilitating an integrated flood and drought risk assessment.

Table 3.4. Flood and drought risk discipline classifications and their corresponding sub-disciplines, as designated by SJR.

Flood and/or drought disciplines tackled by source	The sub-disciplines (discussed under each of disciplines)
Agricultural, Irrigation and Biological Sciences	Soil Science; Agronomy and Crop Science; Forestry; Ecology; Irrigation Systems and Water Management; Crop Water Use Efficiency; Drought-Resilient Agricultural (e.g., Kumar et al., 2017)
Climatology	Climate Modelling and Scenarios; Extreme Weather Events; Climate Variability and Trends; Regional and Global Climatology (e.g., Cerveny et al., 2011)
Computer Science and Mathematics	Artificial Intelligence (AI) and Machine Learning; Data Mining; Computational Mechanics; Modelling and Simulation (e.g., Walker et al., 2013)
Earth and Planetary Sciences	Hydrology; Geophysics; Meteorology and Atmospheric Science; Geochemistry and Geophysics; Geology (e.g., Camacho Guerreiro et al., 2021)
Economics and Business	Cost-Benefit Analysis of Risk Management; Water Pricing and Economics of Water Scarcity; Risk Financing and Insurance for Water-Related Disasters; Economic Valuation of Ecosystem Services; Environmental Economics; Risk Management; Sustainable Development; Resource Economics (e.g., Van Dijk et al., 2013)
Environmental Science	Environmental Management; Environmental Monitoring; Water Science and Technology; Climate Change; Ecological Modelling; Pollution and Remediation (e.g., Doody et al., 2014)
Ecology and Biodiversity Conservation	Wetland Ecology; Riparian Buffer Zones; Biodiversity Conservation and Floodplain Ecosystems; Habitat Restoration and Conservation Planning (e.g., Johnson et al., 2020)
Engineering	Civil and Structural Engineering; Water Resources Engineering; Environmental Engineering; Hydraulic Engineering; River Basin Management; Hydraulic Structures (e.g.; dams; levees); Sediment Transport and Erosion Control; Floodplain Hydraulics
Geospatial Science	Geographic Information Systems (GIS); Remote Sensing; Spatial Analysis and Cartography; Land Use and Spatial Planning (e.g., Wang & Xie 2018)
Health Sciences	Environmental Health; Public Health and Epidemiology; Waterborne Diseases; Occupational Safety and Health; Health Risk Assessment (e.g., De Alwis & Noy, 2019)
Law and Governance	Environmental Law and Policy; Water Rights and Allocation; International Water Law (Transboundary Management); Disaster Governance (e.g., Haer et al., 2019)
Natural Hazards and Disaster Science	Disaster Risk Reduction; Vulnerability and Resilience Studies; Hazard Modelling; Emergency Preparedness and Response (e.g., Yang & Liu, 2020)
Natural Resources Management	Watershed Management; Sustainable Forestry; Water Allocation for Competing Uses; Integrated Resource Management (e.g., Shuster et al., 2005)
Psychology and Behavioural Science	Risk Perception and Behavioural Change; Community Engagement and Public Awareness; Decision-Making under Uncertainty; Psychological Impacts of Disasters (e.g., Paat & Schroter., 2008)
Social Sciences, Humanitarian Studies and Development	Geography; Planning and Development; Urban Studies; Public Administration; Risk Assessment; Policy and Administration; Social Vulnerability and Risk Perception; Community Resilience; Human Geography; Cultural Adaptation and Coping Mechanisms; Livelihoods and Food Security; Migration and Displacement due to Water-Related Hazards; Community Development under Hydrological Stress (e.g., Wong-Parodi et al., 2016)
Telecommunications and Information Systems	Early Warning Systems; Data Communication for Emergency Services; Decision Support Systems; Sensor Networks for Environmental Monitoring (e.g., McNutt et al., 2017)
Urban and Regional Planning	Sustainable Urban Development; Green Infrastructure and Nature-Based Solutions; Land Use Planning for Risk Reduction; Critical Infrastructure Protection (e.g., Kalantari et al., 2018)

A rigorous content analysis of selected papers followed, extracting key information on research themes, geographical coverage, parameters, and the interconnections between these factors. This step was essential in understanding the diverse methodologies employed in existing studies and revealing complex relationships influencing flood and drought hazards. Data extraction and organization were performed using a dual approach. Explicit characteristics of each source, such as title, year, type, and geographical scope, were recorded in an Excel file (Table 3.5), while latent content was annotated and open-coded in a Word document. The Word document captured nuanced insights in an annotated bibliography format, categorized under specific headings to minimize subjectivity. Headings included but not limited to data, process, methods and modelling, case study, research comparison, subjects and statistics and study compliance.

Table 3.5. A sample from the produced database of the most cited papers in the literature on flood and drought.

Author(s)	Publication year	Title	Publication type	Details	Citations	Keywords
Manuela I. Brunner, Louise J. Slater, Lena M. Tallaksen, Martyn P. Clark	2021	Challenges in modeling and predicting floods and droughts: A review	Journal Paper (Peer reviewed)	Highly detailed	220	droughts, floods, forecasting, hydrologic extremes, prediction

The compiled resources were systematically classified, enabling the derivation of numerous insights. By analyzing the content, keywords, and methodologies across disciplines, and incorporating network theory, a series of scientographs were created to visualize the relationships between key topics and parameters, as detailed in Section 2.5 (Fasihi et al., 2021). These scientographs illustrate the interconnections between themes and disciplines, shedding light on how flood and drought risk assessments are interconnected across various fields of study. Geographical and temporal trends of projects, along with global agreements and expert opinions on flood and drought risk issues, were also extracted. This analysis, highlighted in Sections 2.5 and 5.2, captures the interrelationships between the disciplines involved and identifies the major parameters representing each field. These findings provide a comprehensive view of how different disciplines contribute to understanding the risks of floods and droughts over time and across regions.

Beyond qualitative analysis, quantitative assessments were performed to identify the most influential collaborations among disciplines. This analysis concluded with the identification of the most significant and mutual pairwise connections between the causes of flood and drought risks, offering valuable insights into the shared drivers and interdependencies of these hydrological extremes.

3.4 FROM PAIRWISE CONNECTIONS TO CAUSAL PATHWAYS OF FLOOD AND DROUGHT RISK

The methodological processes fulfilling the second objective of the research, which is to develop an integrative framework using interpretive structural modelling, network theory, causal loop diagrams, and cross-entropy analysis to encapsulate key risk factors and their interdependencies in flood and drought risk assessment is illustrated in the following diagram (Figure 3.4). These processes correspond directly to Boxes 2, 3, and 4 presented in the methodology overview (Figure 3.1).

The first diagram demonstrates the use of network metrics to uncover and quantify the relationships and interdependencies between variables identified during earlier stages of the research. Metrics such as betweenness and closeness, authority and hub scores, eigenvector centrality, indegree and outdegree, as well as eccentricity and connected components allow for a structured analysis of how variables interact within the broader system. These metrics enable the identification of critical nodes and connections within the network, which inform the causal relationships required for building a robust flood and drought risk framework.

This approach aligns with Box 2 of the methodology overview by showcasing the detailed analytical process of using network metrics to establish and quantify the relationships between the key variables. The metrics help prioritize factors and dependencies, ensuring that the integrative framework accurately captures the most influential elements of the flood and drought system. The second diagram represents the hierarchical structuring of these relationships using interpretive structural modelling. This process organizes the identified variables into a hierarchy of interactions, allowing the study to distinguish between foundational factors and more dependent variables. This step is critical for constructing a clear, actionable structure that lays the groundwork for causal loop diagrams. The hierarchical structuring directly feeds into the creation of causal loop diagrams as outlined in Box 4 (Figure 3.1). These loops visually represent feedback mechanisms and interdependencies identified through interpretive structural modelling and network metrics. Together, these steps ensure a comprehensive understanding of how variables influence each other dynamically. By integrating these analytical steps, the diagrams demonstrate how the study moves beyond static or fragmented analyses to capture the complex and interdependent nature of flood and drought risks. This iterative and structured approach lays the foundation for achieving the study's overarching aim of constructing a simultaneous risk assessment framework for flood and drought at the river basin scale.

The methodology begins with constructing a Structural Self-Interaction Matrix (SSIM) to detail pairwise interactions (explained through previous sections of this chapter) among various parameters through pairwise comparisons. This SSIM (symbols explained in section 4.6) then serves as the foundation for creating an initial reachability matrix by translating the VAXO matrix into binary form, facilitating the identification of direct and indirect parameter interactions. Subsequently, the Final Reachability Matrix is developed to examine transitive relationships, enabling the assessment of the framework's hierarchical structure through Level Partitioning. Finally, “Matrice d'Impacts Croisés Multiplication Appliquée à un Classement” MICMAC Analysis is applied, emphasizing the importance of understanding the hierarchical organization of elements and their interconnections, a key aspect in effective risk management planning and control. The subsequent step involves developing and interpreting the causal paths (Eshun and Chan, 2021).

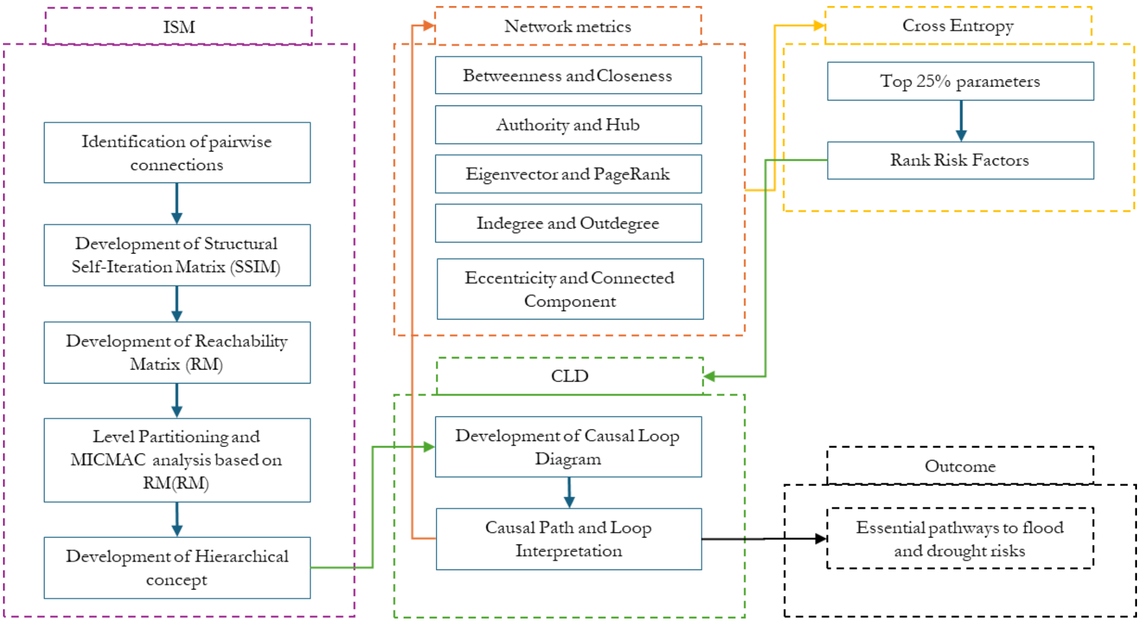


Figure 3.4. Flowchart of methodologies and processes used to identify the essential causal pathways to assess flood and drought risk.

These causal paths and parameters are treated as network edges and analysed using various metrics such as betweenness and closeness centrality, authority, and hub scores. Parameters are then ordered based on their performance across 11 network metrics. The top 25% of parameters in each metric are selected for input into the Cross Entropy algorithm, which identifies the final 30 parameters with the most influential interactions in assessing flood and drought risk. Finally, these parameters are reintegrated into Causal Loop Diagrams (CLDs) to extract the essential pathways for flood and drought risk assessment. These steps provide the framework mentioned in second objective and partially the overall aim of the research (Figure 3.4).

3.5 METHODS USED TO CREATE AND ANALYSING RISK MAPS FROM CAUSAL PATHWAYS

In the final section of this study, corresponding to the third objective of this research, a prominent river basin (River Severn Basin District) is selected for spatiotemporal analysis of the essential causal pathways identified in earlier steps.

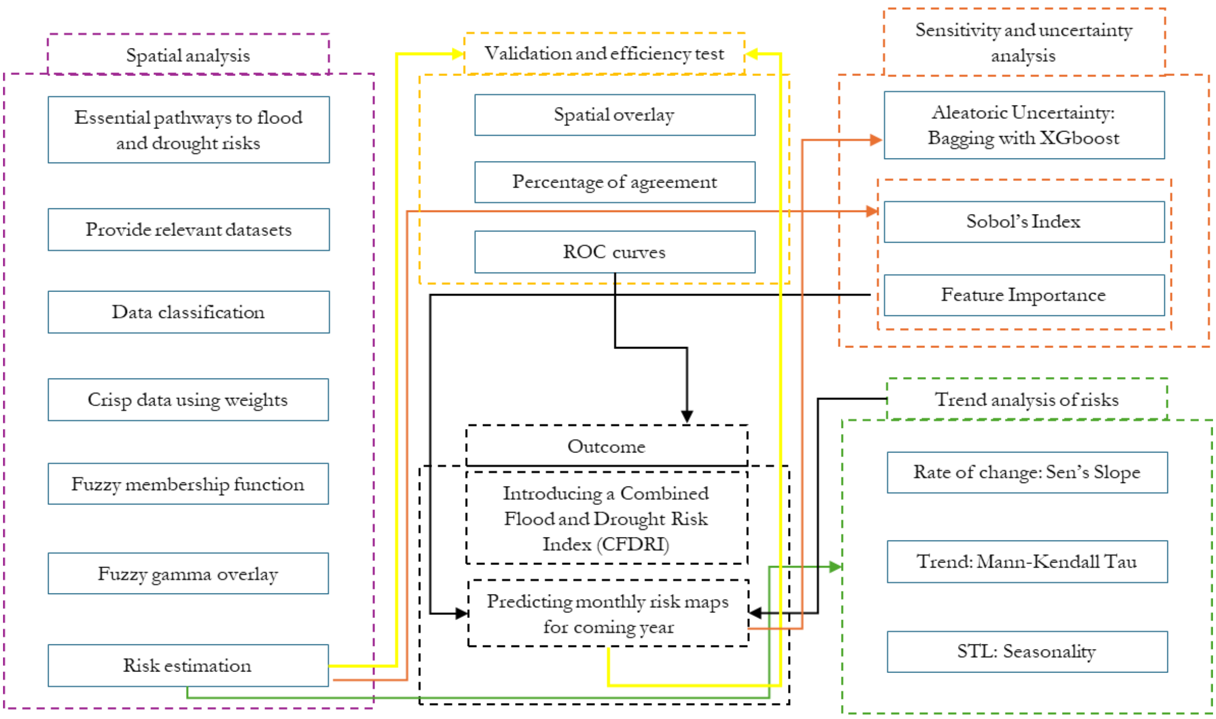


Figure 3.5. Methodological approach used to estimate flood and drought risk at the river basin scale.

This process begins with the collection of spatial data for various basin parameters, followed by the application of the fuzzy overlay function to estimate monthly risk maps for flood and drought.

These maps are then validated and tested for efficiency using Receiver Operating Characteristic (ROC) curves.

The temporality of risk and the sensitivity of these maps to input variables are assessed. Subsequently, an XGBoost algorithm, combined with trend analysis, is used to predict risks for the coming year. Finally, these risk maps are tested for efficiency against observed flood events, and an aleatoric uncertainty analysis is performed. The overall methodology of this section is provided in Figure 3.5.

4 Methods, Analytical Techniques and datasets

4.1 Introduction to methods chapter

The primary goal of this thesis is to develop a framework for simultaneously assessing flood and drought risks at a river basin scale. To achieve this goal, three specific objectives were pursued. The methods used to address each of these objectives are thoroughly explained in separate sections.

To perform a statistical analysis of thematic co-occurrence matrices of research and practice in flood and drought risk literature to elucidate major variables in play and their interrelations (Section 4.2).

To develop an integrative framework that encapsulates key risk factors and their interdependencies (Section 4.5).

To validate the framework and create a mutual flood and drought risk indicator for river basins (Section 4.10).

4.2 Quantitative analysis of co-occurrence themes in flood and drought research

The methodology behind acquiring qualitative understanding of themes responsible to analyse flood and drought risk was explained in section 3.2. In this section, mhe methodology used to analyse thematic co-occurrence in flood and drought research involved a combination of several analytical techniques and applications. These methods were aimed at grouping fields and subfields, identifying parameters, and exploring interconnections within the research (Mourão and Nunes, 2016). The primary methods used include co-occurrence matrix analysis, distribution analysis of pairwise theme co-occurrence, linear and non-linear correlation assessments, and clustering techniques. Each method provided unique insights into the relationships between research themes, ultimately contributing to a robust framework for flood and drought risk assessment. By combining these methodologies, the analysis provides a comprehensive view of how different research themes are interconnected, identifies emerging fields, and guides the selection of parameters for flood and drought risk assessment frameworks. This holistic approach enhances the understanding of thematic dynamics and informs strategic research planning.

4.2.1 Co-Occurrence Matrix: Description and Equation

A co-occurrence matrix is a fundamental tool used in data analysis to study the frequency with which pairs of items (such as words, themes, or categories) appear together in a dataset. In the context of research, a co-occurrence matrix helps identify and quantify the relationships between different themes or fields by counting how often they appear together in the same documents. This matrix provides insights into the interconnectedness and associations among various research areas, which can be crucial for identifying trends, gaps, and potential areas for interdisciplinary research.

Structurally, the co-occurrence matrix is a square matrix where rows and columns represent the different themes or categories being studied and each cell (i,j) contains a value that indicates the number of times theme i and theme j co-occur in the dataset. To enhance interpretation, the matrix is often visualized using a heatmap, where colours represent the frequency of co-occurrence, suggesting strength of associations. The co-occurrence matrix can be formally defined using the following steps.

Let D be a collection of documents, and $T=\{t1,t2,\ldots,tn\}$ be the set of themes. Next a binary matrix B (m rows and n columns) where each row represents a document, and each column represents a theme. The element b_{ij} is 1 if theme t_j appears in document d_i and 0 otherwise.

The co-occurrence matrix C is computed by multiplying the binary matrix B with its transpose B^T (Equation 4.1). The element C_{ij} of the co-occurrence matrix represents the number of documents in which themes t_i and t_j co-occur (Equation 3.2).

$$C = B^T . B \qquad \text{Eq. 4.1}$$

$$C_{ij} = \sum_{k=1}^{m} b_{ki} \cdot b_{kj} \qquad \text{Eq. 4.2}$$

Consider a simplified example with three themes *(T1, T2, T3)* and four documents *(D1, D2, D3, D4).* So, document-Theme Matrix B and co-occurrence matrix C could be like equation 4.3 and 4.4, respectively.

$$B = \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \end{pmatrix} \quad \text{Eq. 4.3}$$

$$C = B^T.B = \begin{pmatrix} 3 & 2 & 2 \\ 2 & 3 & 2 \\ 2 & 2 & 3 \end{pmatrix} \quad \text{Eq. 4.4}$$

Some of the initial applications of this matrix can be concluded as the following.

- Complementarity and Interdisciplinary Research: Co-occurrences indicate that specific thematic pairings are consistently considered together, suggesting complementarity in flood and drought research. Combining insights from diverse themes leads to a more holistic understanding of environmental studies due to their interdisciplinary nature.
- Identifying Research Gaps: Less frequently associated topics may offer opportunities for innovative perspectives and solutions that are not typically associated with each other.
- Trends and Evolution: Emerging themes may indicate shifts in focus due to environmental challenges or technological advances, perhaps reflecting temporal trends.
- Strategic Planning for Future Research: By understanding the current landscape of research themes, institutions and policymakers can strategically fund and promote studies in areas that bridge well-established and emerging fields, fostering innovation and comprehensive knowledge development.

4.2.2 Correlation matrix: Description and Equation

A correlation matrix is a table showing correlation coefficients between sets of variables. Each random variable *(RV)* in the table is correlated with each of the other values in the table. This matrix is symmetric because the correlation between *X* and *Y* is the same as *Y* and *X*. The purpose of a correlation matrix is to summarize data, as an input into a more advanced analysis, and as a diagnostic for advanced analyses. A common use is to assess relationships between numerical variables.

4.2.2.1 Pearson correlation coefficient

The Pearson correlation coefficient, often used in these matrices, is defined for two variables X and Y as: the ratio between their covariance and standard deviation of each of them (Equation 4.5) (Lee Rodgers and Nicewander, 1988).

$$\rho_{X,Y} = \frac{\sum(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum(X_i-\bar{X})^2 \sum(Y_i-\bar{Y})^2}} \qquad \text{Eq. 4.5}$$

where X_i and Y_i are individual observations of variables X and Y. $\bar{X}$ and $\bar{Y}$ are the means of X and Y.

4.2.2.2 Spearman correlation coefficient

The Spearman correlation coefficient, also known as Spearman's rank correlation coefficient or Spearman's rho (ρ), is a non-parametric measure of rank correlation. It assesses how well the relationship between two variables can be described using a monotonic function. Unlike the Pearson correlation, which measures linear relationships and assumes that the data are normally distributed, Spearman's correlation does not require a normal distribution and is less sensitive to outliers and skewed distributions (Myers and Sirois, 2004).

Spearman's correlation evaluates the monotonic relationship between two variables based on the ranks of the data rather than the raw data itself. This means it assesses whether the data in one variable increase or decrease consistently in relation to the data in the other variable. It's particularly useful when the data do not meet the assumptions necessary for Pearson correlation and for ordinal data where ranking is more appropriate than using actual values.

Spearman's correlation coefficient can be calculated using the following steps. Firstly, assign ranks to the data for each variable. If there are ties, assign to each tied value the average of the ranks that they would have otherwise occupied. Next, compute the difference between the ranks of corresponding values (Equation 4.6).

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \qquad \text{Eq. 4.6}$$

Where d_i is the difference between the ranks of corresponding values of the two variables, and n is the number of observations. A Spearman correlation of *+1/-1* implies a perfect positive/negative monotonic relationship, meaning as one variable increases, the other variable consistently increases/decreases. A Spearman correlation of 0 implies no monotonic relationship.

4.2.2.3 Cosine similarity index

Cosine similarity index (Equation 4.7), on the other hand, measures the cosine of the angle between two non-zero vectors in a multi-dimensional space, which in the context of co-occurrence data, represents the similarity in the pattern of co-occurrences rather than the magnitude (Salton & McGill, 1983). A value of 1 indicates that the two vectors are in the same direction (high similarity), while 0 indicates orthogonality (no similarity). When interpreting these metrics together in the context of co-occurrence of research themes, it's crucial to consider that Pearson and Spearman coefficients reveal the direction and type of relationship (linear or monotonic), whereas cosine similarity focuses on the degree of overlap in the presence of themes. Together, they can provide a comprehensive understanding of the relationships between themes, revealing not only which themes tend to co-occur but also the nature of their co-occurrence patterns, be they consistent, linear, or merely frequent.

$$cos(\theta) = \frac{\boldsymbol{A} \cdot \boldsymbol{B}}{|\boldsymbol{A}||\boldsymbol{B}|} \qquad \text{Eq. 4.7}$$

Where $\boldsymbol{A} \cdot \boldsymbol{B}$ is the dot product of vectors $\boldsymbol{A}$ *and* $\boldsymbol{B}$. $|\boldsymbol{A}|$ *and* $|\boldsymbol{B}|$ are the Euclidean norms (or magnitudes) of the vectors $\boldsymbol{A}$ *and* $\boldsymbol{B}$, respectively.

The dot product of two vectors $\boldsymbol{A} = [a_1, a_2, \ldots, a_n]$ *and* $\boldsymbol{B} = [b_1, b_2, \ldots, b_n]$ is calculated as equation 4.8.

$$\boldsymbol{A} \cdot \boldsymbol{B} = a_1 b_1 + a_2 b_2 + \cdots + a_n b_n \qquad \text{Eq. 4.8}$$

The norm (or magnitude) of a vector $\boldsymbol{A}$ (and *B* similarly) is calculated as equation 3.9.

$$|\boldsymbol{A}| = \sqrt{a_1^2 + a_2^2 + \cdots + a_n^2} \qquad \text{Eq. 4.9}$$

Plugging these into the cosine similarity formula gives equation 4.10.

$$cos(\theta) = \frac{a_1b_1 + a_2b_2 + \cdots + a_nb_n}{\sqrt{a_1^2 + a_2^2 + \cdots + a_n^2}\sqrt{b_1^2 + b_2^2 + \cdots + b_n^2}} \quad \text{Eq. 4.10}$$

Some of the possible combinations of the characteristics of these three matrices are explained below.

- Consistent Findings: Themes that show similar correlation or similarity patterns across all three measures indicate robust relationships worth exploring further, as they suggest that the themes are related regardless of the statistical method used.
- Differences Between Pearson and Spearman: A significant difference between Pearson and Spearman correlations could indicate that the relationship between the two themes is nonlinear. For instance, themes with a higher Spearman correlation compared to Pearson may be related nonlinearly but consistently.
- High Cosine Similarity with Low Correlation: If two themes have a high cosine similarity but low Pearson or Spearman correlation, this might suggest that the themes co-occur frequently but not necessarily in a way that is linearly or monotonically consistent. It could also indicate a few studies with very high co-occurrence counts affecting the cosine similarity.
- Contradictory Signs: If Pearson and Spearman's correlations have opposite signs, this could warrant a closer look. A nonlinear relationship may be present, or outliers or data distribution characteristics are affecting the Pearson correlation.
- Outliers and Distribution: Since Pearson is sensitive to outliers, while Spearman is not, comparing the two can provide insights into the influence of extreme values. If Spearman's correlation is significantly higher than Pearson's, it might suggest that outliers are present and affecting the Pearson calculation.

4.3 DBSCAN Clustering Approach in the Context of Co-Occurrence Matrix

4.3.1 DBSCAN Clustering Approach

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a popular clustering algorithm used to identify clusters in large spatial datasets by looking for areas of high density separated by areas of low density. It is particularly well-suited for datasets with noise and outliers. The DBSCAN algorithm requires two parameters: the radius ϵ (eps) and the minimum number of points $(minPts)$required to form a dense region (Ester et al., 1996). In the context of the co-occurrence matrix prepared in this research, the DBSCAN clustering approach and the knee method can be used to identify clusters of themes that frequently co-occur. Steps of DBSCAN could be summarized as follows:

- Initialization: Choose an arbitrary starting point that has not been visited.
- Density Reachability: Retrieve all points density-reachable from the starting point with respect to ϵ and $minPts$. A point p is directly density-reachable from a point q if p is within the ϵ-neighbourhood of q and q is a core point (contains at least $minPts$ points within its ϵ -neighbourhood).
- Cluster Formation: If p is a core point, a cluster is formed. If p is a border point (reachable from a core point but less than $minPts$), it is added to the cluster.
- Iteration: This process continues until all points have been visited.
- Noise Identification: Points that are not reachable from any core point are classified as noise.

Determining the optimal ϵ value is crucial for the effectiveness of DBSCAN. The knee method (or elbow method) is commonly used to find this optimal value (Equation 4.12).

There are 6 general steps to cluster themes which are as follows:

First, it is needed to calculate cosine similarity (Equation 4.10), next subtract it from 1 to produce cosine dissimilarity. Next step is to calculate k-distance for each point (Equation 4.11)

$$d_{i,k} = \textit{k-th smallest distance from point } i \qquad \text{Eq. 4.11}$$

Step 4 is to plot k-distance and find the optimal Knee point curvature using concept of derivative (Equation 4.12).

$$\kappa = \frac{|f''(x)|}{\left(1+\left(f'(x)\right)^2\right)^{3/2}} \qquad \text{Eq. 4.12}$$

The fifth step is defining neighbourhood for DBSCAN (Equation 4.13).

$$N_\epsilon(p) = \{q \in D \mid \textit{dist}(p,q) \leq \epsilon\} \qquad \text{Eq. 4.13}$$

And the final step is to check core point condition for DBSCAN (Equation 4.14)

$$|N_{\epsilon}(p)| \geq minPts \qquad \text{Eq. 4.14}$$

4.4 Applying hierarchical clustering to co-occurrence data

Hierarchical clustering is a method of cluster analysis which seeks to build a hierarchy of clusters. It can be divided into two main types. Agglomerative (Bottom-Up) clustering, which is the most common type. It starts with each observation as its own cluster and iteratively merges the most similar clusters until all observations are in one single cluster. Second type is Divisive (Top-Down) Clustering (Murtagh and Legendre, 2014). This method starts with all observations in a single cluster and iteratively splits the least similar clusters until each observation is in its own cluster. This research benefited from Agglomerative Hierarchical Clustering. Firstly, this method computes the distance matrix for two points $\boldsymbol{A}$ and $\boldsymbol{B}$ in Euclidean space (Equation 4.15).

$$Distance(\boldsymbol{A}, \boldsymbol{B}) = \sqrt{\sum_{i=1}^{n} (a_i - b_i)^2} \qquad \text{Eq. 4.15}$$

Next is finding distance between clusters. Different linkage criteria can be used to determine the distance between clusters. Equation (4.16) calculates the minimum linkage.

$$d(A, B) = min\{Distance(a, b) : a \in A, b \in B\} \qquad \text{Eq. 4.16}$$

In this segment, complete linkage also called as maximum linkage would be calculated (Equation 4.17).

$$d(A, B) = max\{Distance(a, b) : a \in A, b \in B\} \qquad \text{Eq. 4.17}$$

The applicational linkage, (mean linkage) is derived using the following equation (Equation 4.18).

$$d(A, B) = \frac{1}{|A||B|} \sum_{a \in A} \sum_{b \in B} Distance(a, b) \qquad \text{Eq. 4.18}$$

After completing these sections for each point as a separate cluster, it is needed to compute initial distance matrix for all points. All these steps should be iterated to find two clusters that are closest, merge them and update the distance matrix by calculating the distance between the new cluster and all other clusters using the chosen linkage criteria. Final step is to update the dendrogram to include this new cluster.

Now that there is enough analysis to find relevant research themes, their interactions, trends and clusters, it is time to retrieve the common sub-themes, their mutual parameters and respective pairwise connections to help identify the causes to produce a framework to assess the risk of flood and drought in a river basin scale.

With sufficient analysis identifying relevant research themes, their interactions, trends, and clusters, the next step is to extract common sub-themes, their shared parameters, and respective pairwise connections. This extraction will aid in identifying the underlying causes and developing a framework to assess the risk of floods and droughts on a river basin scale.

4.5 Assessment of the hierarchical structure of risk parameters as a basis for creating the causal loop feedback

4.5.1 Describing the development of Structural Self-Interaction Matrix (SSIM)

The *SSIM*, which is a square matrix of n parameters *(P1…Pn)* defines the interactions among various parameters using a pairwise comparison, where the columns and rows are represented by i and j, respectively. Symbols *V, A, X,* and *O* are used to describe the nature of relationships between these parameters. The parameters are arranged in a matrix and plotted on an x and y-axis pane, such that a cell P_{ij} in the matrix illustrates the interaction between P_i and P_j along the x and y-axis, respectively. The meanings of *VAXO* are as follows:

V = P_i influences P_j, but P_j does not influence P_i;

A = P_j influences P_i, but P_i does not influence P_j;

X = Both P_i influences P_j and P_j influences P_i;

O = There is no direct relationship between P_i and P_j.

The matrix appears symmetric, with all possible connections denoted using *VAXO* symbols on one side of the diagonal.

4.5.2 Development of Reachability Matrix (RM): Producing initial reachability matrix

The formation of the initial reachability matrix originates from the *SSIM* by converting the *VAXO* matrix into a binary format. This conversion is based on specific conditional rules that interpret the *VAXO* notations into binary values of 1 or 0 along both the x and y axes. The rules for this transformation are applied based on the *VAXO* symbol present in each "*ij*" cell of the *SSIM* as follows:

V, the *ij* cell becomes 1 and the *ji* cell becomes 0;

A, the *ij* cell becomes 0 and the *ji* cell becomes 1;

X, the *ij* cell becomes 1 and the *ji* cell becomes 1;

O, the *ij* cell becomes 0 and the *ji* cell becomes 0.

4.5.3 Final Reachability Matrix (RM)

The focus of this study is to assess risks through a system thinking approach, where the initial matrix outlines the immediate connections among parameters. To uncover both direct and indirect relationships, a transitivity examination is employed. Transitivity examination operates on the logic that if Parameter 1 (*P1*) is linked to Parameter 2 (*P2*), and *P2* is linked to Parameter 3 (*P3*), then *P1* also has an indirect connection with *P3*. Performing this check for transitive relationships, especially in a large matrix, can be complex and necessitates an automated process for accuracy and efficiency. To facilitate this, an *R* function was developed to produce the final reachability matrix. This matrix then informs level partitioning (section 5.2.4) and the *MICMAC* analysis, which evaluates the parameters based on their driving and dependency characteristics, as detailed later in section 5.2.5.

Transitivity is a fundamental concept in mathematics. It describes a property where if an element a is related to b and b is related to c, then a is also related to c. This concept can be checked using a matrix representation of a relation. Eventually, driving and dependence power of each parameter will be calculated as the sum of the rows and columns of final reachability matrix, respectively. mathematical background of transitivity check has following steps.

- Binary Relation and Adjacency Matrix:

Consider a set S with elements $\{s_1, s_2, \dots, s_n\}$. A binary relation RRR on S can be represented by an $n \times n$ adjacency matrix A, where $A[i][j] = 1\ if (si, sj) \in R$ and $A[i][j] = 0$ otherwise.

- Transitivity Definition:

A relation R on a set S is transitive if whenever$(a, b) \in R$ and $(b, c) \in R$, then $(a, c) \in R$.

In terms of the adjacency matrix A, the relation R is transitive if, for all i, j, k:

$$A[i][j] = 1\ and\ A[j][k] = 1 \implies A[i][k] = 1A[i][j] = 1 \quad \text{Eq. 4.19}$$

- Transitivity Check Using Matrix Multiplication:

To check for transitivity, matrix multiplication can be used. Specifically, to check if $A^2 \subseteq A$, where A^2 is the matrix product of A with itself.

First, compute A^2:

$$A^2[i][k] = \sum_{j=1}^{n} A[i][j] \cdot A[j][k] \quad \text{Eq. 4.20}$$

Here, $A^2[i][k]$ indicates whether there is a path of length 2 from Si to Sk.

In Transitivity Condition, Check if $A^2[i][k] \leq A[i][k]$ for all i, k. If this condition holds, the relation is transitive.

First, computing A^2 by multiply the adjacency matrix A by itself to obtain A^2. Next, comparing A^2 with A to verify that for all i and k, if $A^2[i][k] > 0$, then $A[i][k] = 1$.

4.5.4 Level partitioning of risk parameters

At this stage, the hierarchical structure and the directional nature of the relationships amongst parameters including risk components are determined through a detailed analysis. This process involves calculating three key sets: the reachability set (Rs), the antecedent set (As), and the intersection set (Is). The reachability set is composed of elements that have a value of 1 in their corresponding row in the final reachability matrix, including the risk factor itself. Conversely, the antecedent set consists of risk factors that have a value of 1 in their respective column. The intersection set is then defined as the set of risk factors that are common to both the reachability and antecedent sets.

According to the hierarchical partitioning rule, elements are assigned to the same level if their reachability set is a proper subset of their intersection set. This leads to a systematic and iterative process for classifying them into distinct levels. This process includes: (i) identifying elements that have identical members in both their reachability and intersection columns, and (ii) removing these risk factors from consideration and revisiting the first step. This iterative method continues until all risk parameters are appropriately categorized and allocated into their respective hierarchical levels. A schematic table is presented to help illustrating the outcome of the level partitioning step (Table 4.1)

Table 4.1. Schematic representation of a level partitioning table.

Parameter	Reachability Set (Rs)	Antecedent Set (As)	Intersection Set (Is)	Level
P1	n1	all but m1, m2, ..., mk	n1	1
P2	all but nx	all but m1, m2, ..., mk	all but m1, m2, ..., mk	1
P3	n3	m1, m2, ..., mk	n3	1
...	...	...	...	...
P{n1}	all but nx	all but n1, m1, m2, ..., mk	all but n1, m1, m2, ..., mk	2
P{n2}	all but nx	all but n1, m1, m2, ..., mk	all but n1, m1, m2, ..., mk	2
P{n3}	all but nx	all but n1, m1, m2, ..., mk	all but n1, m1, m2, ..., mk	2
Px	nx	all but nx	nx	3

4.5.5 MICMAC analysis visualisation

The method categorizes elements into four quadrants based on their driving and dependency powers that are extracted from level partitioning. These quadrants represent different characteristics of the elements within a system (Figure 4.1).

First quadrant contains autonomous elements with low driving power, low dependency power. These elements have minimal interaction within the system. They neither influence other elements significantly nor are they significantly influenced by others.

Second quadrant includes dependent elements with low driving power, high dependency power. These elements are heavily influenced by other factors in the system but do not have a significant impact on other elements.

Third quadrant filled up with independent elements, which possess high driving power, low dependency power. These elements have a significant influence on other elements but are not heavily influenced by others.

Finally, the fourth quadrant belongs to linkage elements with high driving power, high dependency power. These elements have significant interactions within the system, influencing many elements and being influenced by many elements.

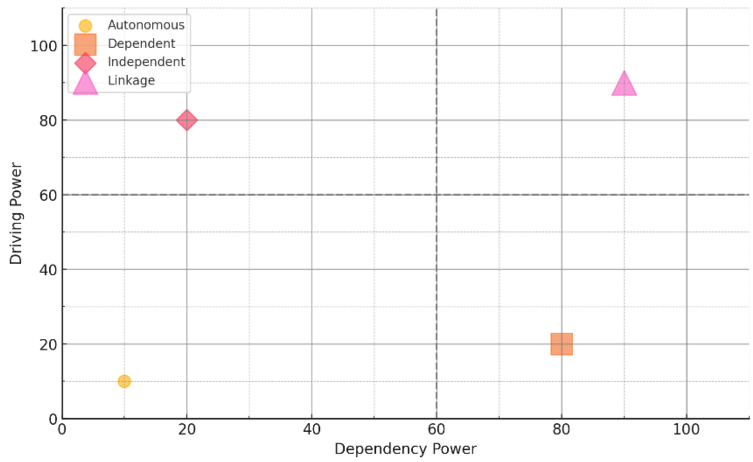


Figure 4.1. Categorization of elements into quadrant based on their individual driving and dependence power.

4.6 Developing causal loop diagram (CLD) to capture various perspectives in risk assessment

Causal Loop Diagrams (CLDs) are a visual tool used in system dynamics to represent the feedback loops within a system. These loops can be positive (reinforcing) or negative (balancing), and each type of loop has distinct mathematical characteristics (Sterman, 2000).

As illustrated in Figure 3.4, the CLD maps out the network of interactions within the system. The ISM analysis, which establishes the relationship density among parameters (as observed in the final Reachability Matrix), lays the groundwork for the CLD to spotlight risk factors with significant feedback properties. Within the diagram, the arrows represent the influence dynamics: a parameter at the tail of an arrow exerts an influence on the parameter at the arrowhead. Section 6.3 is totally devoted to this notion and completely illustrates and describes the produced feedback loops.

Positive feedback loop (reinforcing loop) usually shown as $+ve$ or R describes a situation in which a change in one element causes changes that amplify the original effect, leading to exponential growth or decline. On the other hand, negative feedback loop (Balancing Loop) with signs like $-ve$ or B reveals that a change in one element causes changes that counteract the original effect, leading to stability or equilibrium (Figure 4.2). Combined feedback loop happens when the system has both positive and negative feedback, balancing each other to some extent.

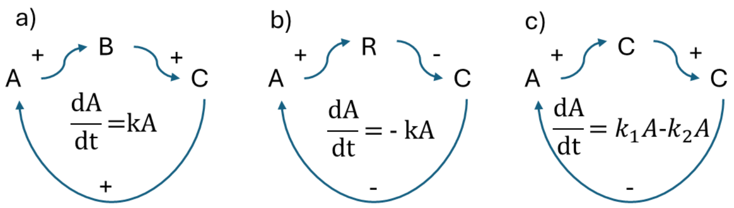


Figure 4.2. Generic Causal Loop Diagrams representing a) positive, b) negative, and c) combined feedback loops.

4.7 Enhancing flood and drought risk assessment framework through application of network theory in CLD modelling

Managing flood and drought risks in dynamic environmental systems requires a robust analytical approach. In this context, applying graph theory to a Causal Loop Diagram (CLD) with 116 diverse elements proves to be an effective method. This approach goes beyond conventional analysis by mapping and quantifying the complex interactions that define flood and drought risks. Using network theory, each element and its interconnections within the CLD are identified and evaluated in terms of their relational strength and strategic significance. This detailed analysis enhances the understanding of the systemic structure and behaviour, thereby improving the model's predictive and explanatory capabilities.

4.7.1 Explanation of Girvan-Newman clustering Algorithm

The Girvan-Newman algorithm is a method used in network theory to detect communities or clusters within a graph. Communities are groups of nodes that are more densely connected internally than with the rest of the network. The algorithm works by iteratively removing edges from the network to reveal these communities (Girvan and Newman, 2002). It identifies the edges most likely to be "between" communities by calculating edge betweenness centrality, which measures the number of shortest paths passing through each edge. By successively removing edges with the highest betweenness centrality, the network gradually breaks down into smaller, more densely connected components, revealing the underlying community structure.

For an edge e between nodes i and j, the edge betweenness centrality $C(e)$ is defined as (Equation 4.21):

$$C(e) = \sum_{s \neq t \in V} \frac{\sigma_{st}(e)}{\sigma_{st}} \qquad \text{Eq. 4.21}$$

Where σ_{st} is the total number of shortest paths from node s to node t. And $\sigma_{st}(e)$ is the number of those paths that pass-through edge e.

The algorithm starts with computing the edge betweenness centrality for all edges in the graph. Next, removing the edge with the highest betweenness centrality and recalculate the betweenness centrality. This process should be iterated until no edges remain.

Edge removal affects the connectivity of the graph, which eventually creates communities (clusters). To evaluate the quality of the detected communities, the algorithm used a measure called modularity Q.

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \qquad \text{Eq. 4.22}$$

Where, (A_{ij}) is the adjacency matrix of the graph. $(k_i) and (k_j)$ are the degrees of nodes (i) and (j), respectively. (m) is the total number of edges in the graph. $(\delta(c_i, c_j))$ is 1 if nodes (i) and (j) are in the same community and 0 otherwise.

4.7.2 Describing network metrics: betweenness centrality and closeness centrality

Betweenness Centrality measures the importance of a node within a network based on the number of shortest paths that pass through it. Nodes with high betweenness centrality play a critical role in information flow within the network as they act as bridges between different parts of the network (Equation 4.21) (Freeman, 1977).

Closeness Centrality quantifies how quickly information can spread from a given node to all other nodes in the network. Nodes with high closeness centrality have shorter average path lengths to all other nodes, indicating they are centrally located within the network (Equation 4.23) (Sabidussi, 1966).

For a node v, closeness centrality $C_c(v)$ is defined as:

$$C_C(v) = \frac{1}{\sum_t d(v,t)} \qquad \text{Eq. 4.23}$$

Where, $d(v,t)$ is the shortest path distance between node v and node t. The sum is taken over all nodes t in the network.

4.7.3 Describing network metrics: Eigenvector and PageRank

Eigenvector Centrality measures the influence of a node in a network based not only on the number of connections it has (degree) but also on the quality of those connections. A node is considered important if it is connected to other important nodes. Eigenvector centrality assigns relative scores to all nodes in the network based on this principle (Bonacich, 1972).

For a node i, the eigenvector centrality x_i is given by the principal eigenvector of the adjacency matrix A. The eigenvector centrality x_i can be defined as (Equation 4.24).

$$x_i = \frac{1}{\lambda} \sum_j A_{ij} x_j \qquad \text{Eq. 4.24}$$

Where, A_{ij} is the adjacency matrix of the network. λ is the largest eigenvalue of the adjacency matrix A. x_j is the eigenvector centrality of node j.

PageRank, which is an algorithm originally used by Google to rank web pages in their search engine results, measures the importance of each node (web page) in a network based on the number and quality of links to it. A node with a high PageRank score is one that is linked to by many nodes with high PageRank scores (Page et al., 1999).

The PageRank of a node i, denoted as $PR(i)$, can be defined as (Equation 4.25):

$$PR(i) = \frac{1-d}{N} + d \sum_{j \in M(i)} \frac{PR(j)}{L(j)} \qquad \text{Eq. 4.25}$$

Where, d is the damping factor (typically set to 0.85). N is the total number of nodes in the network. $M(i)$ is the set of nodes that link to node i. $L(j)$ is the number of outbound links on node j. $\frac{1-d}{N}$ represents the probability of randomly jumping to any node in the network.

4.7.4 Explaining network metrics: Authority and Hub

Authority and Hub Scores are components of the HITS (Hyperlink-Induced Topic Search) algorithm, which is used to rank web pages (Kleinberg, 1999). In a network, hubs and authorities exhibit a mutually reinforcing relationship: good hubs point to many good authorities, and good authorities are pointed to by many good hubs. An authority score measures the value of a node based on the number and quality of incoming links from hub nodes. A node is considered a good authority if it is linked to by many good hubs. Whereas a hub score measures the value of a node based on the number and quality of outgoing links to authority nodes. A node is considered a good hub if it links to many good authorities.

Authority Score a_i of a node i is proportional to the sum of the hub scores of nodes that point to it (Equation 4.26).

$$a_i = \sum_{j \in In(i)} h_j \qquad \text{Eq. 4.26}$$

Where $In(i)$ is the set of nodes that link to node i.

The hub score of a node i is proportional to the sum of the authority scores of nodes it points to (Equation 4.27).

$$h_i = \sum_{j \in Out(i)} a_j \qquad \text{Eq. 4.27}$$

Where $Out(i)$ is the set of nodes that node i links to. However, the notable point in this analysis is that The HITS algorithm updates authority and hub scores iteratively (Equations 4.28 & 4.29).

$$a_i^{(k+1)} = \sum_{j \in In(i)} h_j^{(k)} \qquad \text{Eq. 4.28}$$

$$h_i^{(k+1)} = \sum_{j \in Out(i)} a_j^{(k)} \qquad \text{Eq. 4.29}$$

4.8 Description of Cross-Entropy Monte Carlo Algorithm (CE) in the context of this research's framework

In the comprehensive analysis of a network with 116 distinct parameters, the Cross-Entropy Monte Carlo algorithm (CE) was employed to synthesize and aggregate the rankings derived from 11 different network metrics. This method provided a robust framework for identifying the most significant parameters by considering their performance across multiple metrics. The CE algorithm is particularly effective in optimizing complex, multi-metric landscapes, allowing for a systematic and probabilistic determination of the key parameters (Rubinstein & Kroese, 2004). The Cross-Entropy Monte Carlo algorithm is a versatile method used for rare-event probability estimation, combinatorial optimization, and other applications. Here, it is applied for ranking aggregation. The steps and mathematical foundations of the CE algorithm are as follows:

- Initialize the probability distribution $P(\theta)$ over the space of potential solutions. For ranking aggregation, this involves setting an initial distribution over possible ranking.
- Generate N sample of solutions $X_1, X_2, \dots, X_N$ from the current probability distribution $P(\theta)$.
- Evaluate the performance of each sampled solution based on a predefined objective function.

In the context of ranking aggregation, this function could be the sum of the ranks or another metric that captures the consistency of a parameter's ranking across different lists. Compute the performance score $S(X_i)$ for each sample X_i.

Select the top-performing samples (elite samples) based on their evaluation scores. Select the top ρ proportion of samples as elite samples $\{X_1^*, X_2^*, \dots, X_\rho^*\}$.

Update the parameters of the probability distribution to increase the likelihood of generating elite samples (Equation 4.30). This involves adjusting the distribution based on the elite samples.

$$\theta_{t+1} = arg\,\min_{\theta} \frac{1}{\rho} \sum_{i=1}^{\rho} log\, P\,(X_i^*; \theta) \qquad \text{Eq. 4.30}$$

Repeat the sampling, evaluation, selection, and update steps until convergence criteria are met (e.g., a fixed number of iterations or a threshold in performance improvement). The final probability distribution is used to determine the most likely optimal solution, which, in this context, identifies the key parameters within the network. These high ranked parameters are considered risk factors for both flood and drought risk. These risk factors were used to identify the most critical pathways for assessing and modelling the risks of flooding and drought, utilizing similar parameters as input. The second criterion for inclusion is that the factor should not be part of a delay causal loop, particularly those resulting from the flood and drought risks themselves. In other words, factors directly or indirectly influenced by flood and drought risks were excluded from the analysis to avoid feedback effects that could skew the assessment.

4.9 DESCRIPTION OF STUDY AREA FOR FURTHER APPLICATION OF THE PRODUCED RISK ASSESSMENT FRAMEWORK

The proposed flood and drought risk assessment method was applied in the River Severn Basin District, which is a notably flood and drought-prone area located in the United Kingdom (Figure 4.3). The geographical extent of this region spans from approximately 51.4° to 53.1° N latitude and 2.4° to 3.2° W longitude. The River Severn Basin was selected due to its frequent flooding and drought events that significantly impact the region. This area is one of the most extreme riverine flood-prone and drought-vulnerable districts in the UK. Flooding primarily occurs due to flows from upstream catchments conveyed by the River Severn and its tributaries, such as the

Teme, Avon, and Vyrnwy, which flow through the heart of this study area. Notable flood events include those in 2000, 2007, and 2014, which caused widespread inundation and damage. Conversely, the region has also experienced significant drought events, with notable droughts occurring in 1976, 1995, and 2018, leading to water shortages and agricultural impacts. The average elevation of the study area, depending on distance from open waters, ranges between 5 meters and 150 meters with heights reaching above 700 meters (Figure 4.3). Human lives, households, and various infrastructures are highly susceptible due to the presence of large and small rivers and inadequate mitigation measures for both floods and droughts. The River Severn Basin covers an area of approximately 21,000 km² with a population density of about 150 people per km². The region falls into a temperate maritime climate zone with mean annual precipitation of around 750 mm, most of which occurs during the autumn and winter months. However, prolonged dry spells during the summer can lead to drought conditions. In this region, the severity and consequences of floods are exceptionally high from October to March, corresponding to the rainy season in the UK. Meanwhile, drought risks are particularly acute during the summer months from June to August. The flat geographical location, inadequate flood and drought management strategies, vulnerable populations, intense precipitation in the river origins, and rapid river discharge all contribute to the heightened risk of flooding and drought impacts in this area. Comprehensive risk assessments and improved mitigation measures are essential to manage these dual hazards effectively.

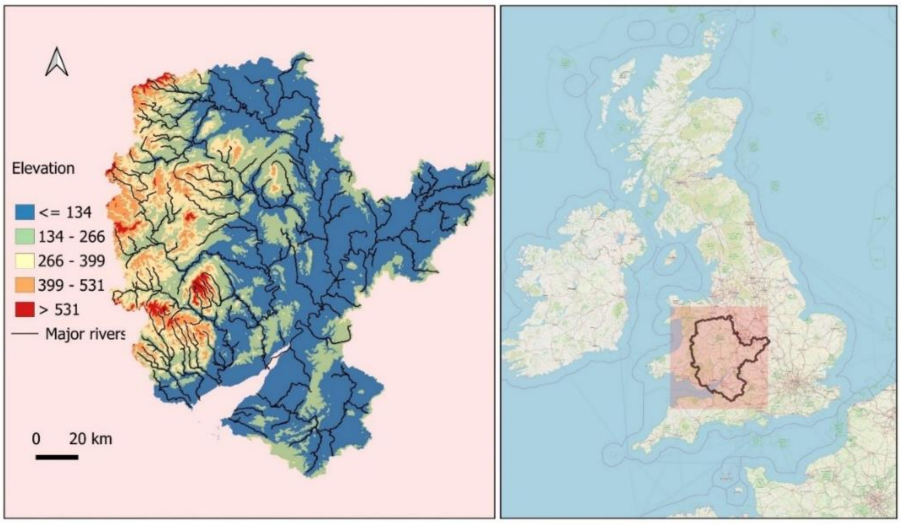


Figure 4.3. Study area, River Severn basin district, presenting elevation map, major rivers and overall location of study site within the UK.

4.10 Methodological overview of the flood and drought risk assessment models

This research adopted a Fuzzy Logic-based geospatial approach to assess both flood and drought risks in the River Severn district of the United Kingdom (Figure 3.6). The Fuzzy Logic method is widely recognized and suitable for addressing complex problems such as risk assessments for natural hazards. Its simplicity, flexibility in combining multiple map layers, and ease of implementation in geographic information systems (GIS) make it an ideal choice for such studies (Pradhan, 2011). The method standardizes spatial objects of various measurement units to values between 0 and 1 (Espada Jr et al., 2013). Various risk equations incorporating different risk components are available for assessing hazard risks. However, well-established and comprehensive risk formulas yield the most accurate results. Considering these factors and based on an extensive literature review, the following risk equations have been selected for this study to identify the optimal technique for flood and drought risk assessments:

$$Risk = Impact \times \mathrm{H}azard \qquad \text{Eq. 4.31}$$

$$Risk = \frac{Impact \times hazard}{mitigation} \qquad \text{Eq. 4.32}$$

These formulas allow for a comprehensive assessment of both flood and drought risks by considering the impact of vulnerability, exposure, hazard, and the mitigating effects of interventions.

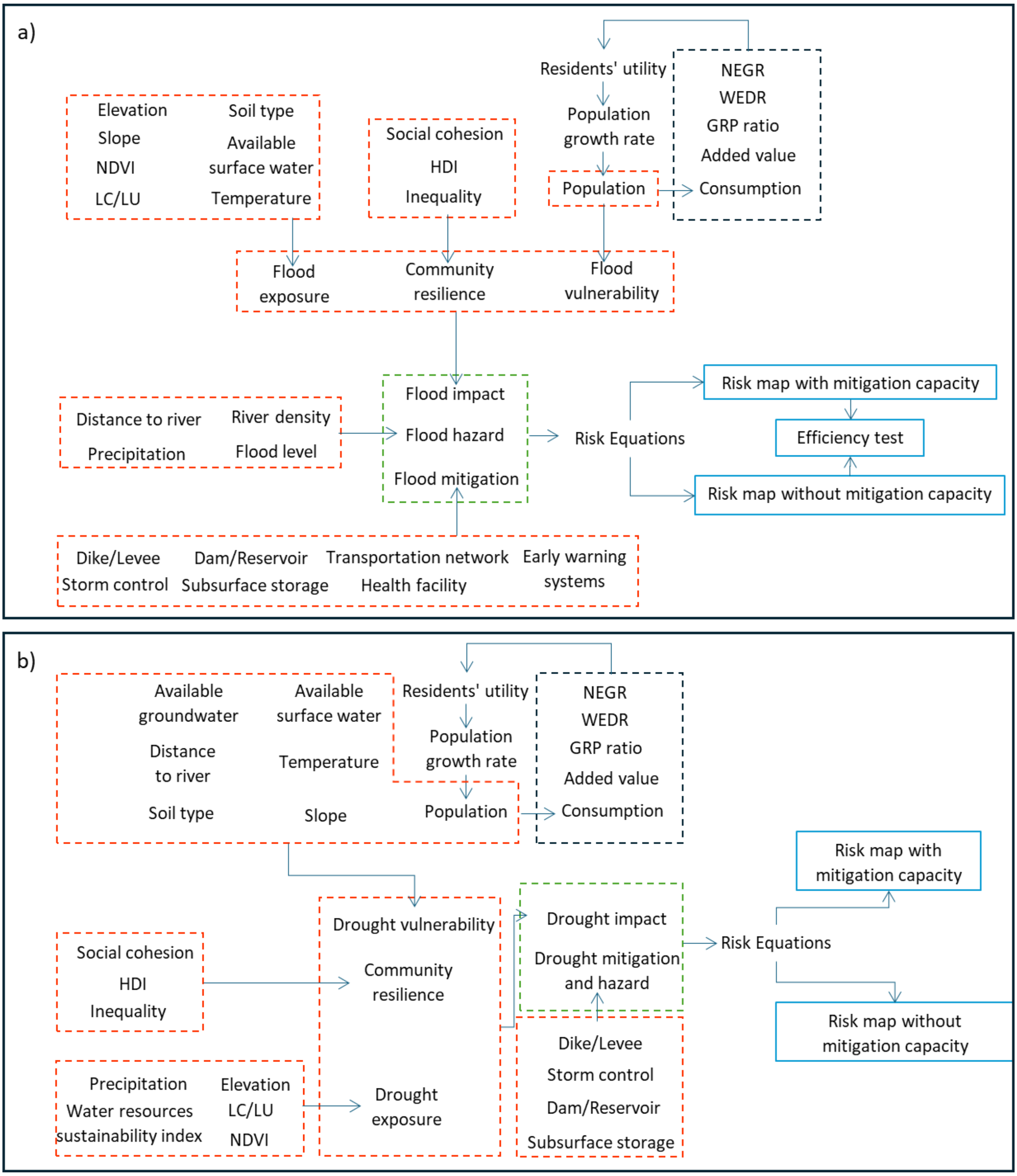


Figure 4.4. Methodological flowchart of the risk assessment approach followed in this study a) flood risk and b) drought risk. Red dashed line indicates application of fuzzy membership and fuzzy overlay functions. Black dashed line indicates application of geometric mean. Green dashed line represents risk components and blue boxes are the final products. NEGR (National Economic Growth Rate), WEDR (Watershed Economic Development Rate), GRP ration (the ratio of basin's GRP to neighbouring basins, Consumption (per capita water consumption), NDVI (Normalised Difference Vegetation Index), LCLU (Land cover Land use)

4.11 DATA

The selected parameters were analysed using advanced geospatial techniques and aggregated from a variety of data sources, ensuring a comprehensive and multi-dimensional approach to data collection (Table 4.3). The integration of diverse data sets facilitated a robust analysis, encompassing both large-scale and region-specific factors critical to the assessment of flood and drought risks.

The importance of modelling flood and drought risk assessment lies in achieving both spatial and temporal resolution. At the same time, computing resources, uncertainty levels, and the capacity of algorithms play crucial roles. Some datasets had moderate spatial scales, such as groundwater data at slightly over 27 km, while others like LCLU (Land Cover and Land Use) reached a resolution of 25 meters in recent updates. Additionally, certain datasets, such as those used for estimating community resilience (e.g., inequality data), were available at a territorial level, differing significantly from geographically distributed parameters like rainfall.

Overall, it was decided to use a 30-meter resolution, consistent with the elevation model, and a monthly temporal scale. This decision aligns with the temporal scale of most changing datasets, such as temperature and NDVI. Besides the substantial computing resources required, the nature of flood and drought phenomena differs, with floods being relatively short-lived compared to droughts. Thus, a monthly temporal scale offers a meaningful and practical trade-off.

Table 4.2. Data type and sources used for modelling flood and drought risk assessment.

Criteria	Type	Source	Period
Precipitation intensity	mm/hr - (Monthly)	GPM mission - GEE	2000-2020
Groundwater	Storage-mm (Monthly)	GLDAS 2.2 - GEE	2003-2020
NDVI	Monthly	MOD13Q1 V6.1 - GEE	2000-2020
LCLU	Land Cover Map series	UKCEH	2000-2020
Temperature	Celsius (Monthly)	MOD11A2 V6.1	2000-2020
Elevation & Slope	Digital Elevation Model (DEM)	NASA SRTM - GEE	2000
Population	Gridded population of world Revision 11	GPWv4 - GEE	2000-2020
Soil type	Soil texture class (USDA System)	EnvironmetriX Ltd - GEE	2000-2018
River density & Distance to river	Self-digitised from the source	Water Framework Directive cycle 3 project	2000-2020
Inequality	S80/S20 income quintile ratio	UK-SSPs	2020
Social cohesion	% of population reporting neighbours willing to help)	UK-SSPs	2020

Human Development Index & GRP ratio	Gridded global datasets	DRYAD	2000-2015
NEGR & WEDR & Added value	International Territorial Level (ITL) regions	Office for National Statistics	2000-2020
Early Warning System (EWS) - Flooding	Polygon - Shapefile	DEFRA data portal Natural Resources Wales	2006-2020
Dike/Epee	Flood defence mechanisms	DEFRA data portal Natural Resources Wales	2000-2020
Reservoirs	Dam, Subsurface water storage	DEFRA data portal Natural Resources Wales	2000-2020
Transportation network	Open street map Department for Transport	OSM-QGIS plugin+dft website	2000-2020
Health facilities	Humanitarian open street map team	humandata.org	2000-2020
Available surface water	Overall temporal resolution-shapefile	EA - SurfaceWaterAvailabilityfor WaterResourceCharging	2000-2020
Water resources sustainability index	Overall temporal resolution-shapefile	EA - WaterResourceAvailabilityAnd AbstractionReliabilityCycle2	2000-2020
Per capita water consumption	Global gridded monthly sectoral water use dataset	zendoo.org	2000-2010
Flood Level	DEM+Recorded flood outline	NASA SRTM - GEE DEFRA data portal	2000-2020

4.12 UTILIZING FUZZY MEMBERSHIP FUNCTIONS FOR WEIGHT ASSIGNMENT IN GEOSPATIAL ANALYSIS

To begin fuzzy overlay modelling, several critical steps must be taken following data selection. First, each dataset must be classified using an appropriate method. Next, all datasets should be normalized to ensure mutual reference compatibility. It is essential to determine the relationship of each dataset with flood and drought risk, including the weight of each data class and its ranking relative to the risks. Finally, the type of fuzzy membership function to be used must be selected (Table 4.4 and 4.5). This process ensures that the fuzzy overlay model accurately reflects the relative importance and influence of each dataset on flood and drought risk assessments.

Initially, all data must be prepared in Boolean logic format to facilitate the assignment of weights using fuzzy membership functions. The data is then classified into specific classes using one of three classification techniques: manual, equal interval, quantile interval, natural break (Jenks), and standard deviation classification. Boolean weights, ranging from 1 to 10, are assigned based on the criteria's importance, following the information acquired as the result of the performed systematic literature review and content analysis (Table 4.4).

Subsequently, fuzzy membership functions were utilized (Dayal et al. 2018). These are mathematical tools used to convert crisp input data into fuzzy values, representing degrees of truth for various variables. Here, the Fuzzy Large, Fuzzy Small, Fuzzy Linear membership functions, and the Fuzzy Gamma overlay.

If a variable is inversely related to the risk, meaning that higher values of the variable correspond to lower risk levels, the Fuzzy Small algorithm is used. For instance, in this context, a variable like elevation, where higher elevations are less prone to flooding, would be assigned using the Fuzzy Small algorithm (Equation 4.33). Here, higher weights indicate lower risk, thereby reflecting the inverse relationship.

$$\mu_{\text{Small}}(x) = \frac{1}{1+\left(\frac{x}{f_2}\right)^{f_1}} \qquad \text{Eq. 4.33}$$

Where, $\mu Small(x)$ is the membership degree of x. f_1 is the spread and f_2 is the midpoint.

Conversely, if a variable is directly related to the risk, meaning that higher values of the variable correspond to higher risk levels, the Fuzzy Large algorithm is applied (Equation 4.34). An example of this could be river density in flood-prone areas, where higher river densities correlate with higher risk. In this scenario, higher weights indicate higher risk, accurately representing the direct relationship between the variable and the risk.

$$\mu_{\text{Large}}(x) = \frac{1}{1+\left(\frac{f_2}{x}\right)^{f_1}} \qquad \text{Eq. 4.34}$$

Where, $\mu Large(x)$ is the membership degree of x. f_1 is the spread and f_2 is the midpoint.

In addition, the population density criterion is assigned using the Fuzzy Linear algorithm (Equation 4.35). This approach is appropriate when there is a linear relationship between the user-specified maximum and minimum values, ensuring a proportional and balanced assignment of risk levels based on population density.

$$\mu_{\text{Linear}}(x) = \frac{x-a}{b-a} \qquad \text{Eq. 4.35}$$

Where, $\mu Linear(x)$ is the membership degree of x. a and b are the minimum and maximum values, respectively.

Fuzzy Gamma overlay is a technique used to combine multiple fuzzy membership functions into a single composite score. This approach allows for flexible aggregation of different criteria, accounting for both multiplicative and additive effects. Combining the fuzzy sum and fuzzy product, the fuzzy gamma overlay can be expressed as (Equation 4.36).

$$\mu_{\text{Gamma}}(x) = \left(\mu_{\text{Sum}}(x)\right)^{\gamma} \cdot \left(\mu_{\text{Product}}(x)\right)^{1-\gamma} \qquad \text{Eq. 4.36}$$

Where, $\mu_{Gamma}(x)$ is the gamma overlay membership degree. $\mu_{\text{Sum}}(x)$ is the result of the fuzzy sum operation (Equation 4.37). $\mu_{Product}(x)$ is the result of the fuzzy product operation (Equation 4.38). γ is the gamma parameter ($0 \leq \gamma \leq 1$), balancing the importance of the fuzzy sum and fuzzy product operations.

$$\mu_{\text{Sum}}(x) = 1 - \prod_{i=1}^{n}\left(1 - \mu_i(x)\right) \qquad \text{Eq. 4.37}$$

$$\mu_{\text{Product}}(x) = \prod_{i=1}^{n} \mu_i(x) \qquad \text{Eq. 4.38}$$

Where, $\mu_i(x)$ are the individual membership degrees of the criteria and n is the number of criteria.

Table 4.3. Data preparation criteria for flood risk assessment.

Flood risk component	Parameter	Data classification technique	Weight assigned	Rating	Fuzzy membership function	Assumption
Exposure	Elevation (m)	Natural breaks	2 to 10	very high-very low	Fuzzy small	Inversely related
	Slope (degree)	Natural breaks	2 to 10	very high-very low	Fuzzy small	Inversely related
	NDVI	Standard deviation	10 to 2	very high-very low	Fuzzy large	Directly related
	LCLU	Defined interval	2 to 10	very low-very high	Fuzzy large	Directly related
	Soil type	Defined interval	9 to 3	high-low	Fuzzy large	Directly related
	Available surface water (defined classes)	Defined interval	2 to 10	very low-very high	Fuzzy large	Directly related
	Temperature (°C)	Standard deviation	9 to 3	high-low	Fuzzy large	Directly related
Vulnerability	Population density (count/km2)	Quantile interval	2 to 10	very low-very high	Fuzzy linear	Directly related

Community resilience	HDI	Manual	2 to 10	very high-very low	Fuzzy small	Inversely related
	Inequality	Manual	2 to 10	very low-very high	Fuzzy large	Directly related
	Social cohesion	Manual	2 to 10	very high-very low	Fuzzy small	Inversely related
Mitigation capacity	Early warning systems	Defined interval	2 to 10	very low-very high	Fuzzy large	Directly related
	Flood defence mechanisms	Manual	2 to 10	very low-very high	Fuzzy large	Directly related
	Drought control mechanisms	Manual	2 to 6	very low-medium	Fuzzy large	Directly related
	Distance to transportation network (m)	Manual	2 to 10	very low-very high	Fuzzy large	Directly related
	Distance to health facilities (m)	Manual	2 to 10	very low-very high	Fuzzy large	Directly related
Hazard	River density (km/km2)	Quantile interval	1 to 9	very low-very high	Fuzzy large	Directly related
	Precipitation intensity (mm/hr)	Standard deviation	2 to 10	very low-very high	Fuzzy large	Directly related
	Distance to river (m)	Manual	2 to 10	very high-very low	Fuzzy small	Inversely related
	Flood level (m)	Natural breaks	1 to 9	very low-very high	Fuzzy large	Directly related

Table4.4. Data preparation criteria for flood drought assessment.

Drought risk component	Parameter	Data classification technique	Weight assigned	Rating	Fuzzy member ship function	Assumption
exposure	Elevation (m)	Natural breaks	2 to 10	very low-very high	Fuzzy large	Directly related
	NDVI	Standard deviation	10 to 2	very high-very low	Fuzzy large	Directly related
	LCLU	Defined interval	2 to 10	very low-very high	Fuzzy large	Directly related
	Precipitation intensity (mm/hr)	Standard deviation	2 to 10	very high-very low	Fuzzy small	Inversely related
	Water resources sustainability index (defined classes)	Defined interval	2 to 10	very high-very low	Fuzzy small	Inversely related
vulnerability	Slope (degree)	Natural breaks	2 to 10	very low-very high	Fuzzy large	Directly related
	Distance to river (m)	Manual	2 to 10	very low-very high	Fuzzy large	Directly related
	Soil type	Defined interval	9 to 3	high-low	Fuzzy large	Directly related
	Available surface water (defined classes)	Defined interval	2 to 10	very high-very low	Fuzzy small	Inversely related
	Available groundwater (mm)	Quantile interval	2 to 10	very high-very low	Fuzzy small	Inversely related
	Population density (count/km2)	Quantile interval	2 to 10	very low-very high	Fuzzy linear	Directly related

	Temperature (°C)	Standard deviation	2 to 10	very low-very high	Fuzzy large	Directly related
Community resilience	HDI	Manual	2 to 10	very high-very low	Fuzzy small	Inversely related
	Inequality	Manual	2 to 10	very low-very high	Fuzzy large	Directly related
	Social cohesion	Manual	2 to 10	very high-very low	Fuzzy small	Inversely related
mitigation capacity and hazard	Flood defence mechanisms	Manual	2 to 10	very low-very high	Fuzzy large	Directly related
	Drought control mechanisms	Manual	2 to 6	very low-medium	Fuzzy large	Directly related

The flood level criterion is directly associated with flood incidence, as established by Bhuiyan and Al Baky (2014) and Rahman et al. (2019). The spatial flood level criteria were developed using historical flood data and Digital Elevation Model (DEM) data. The process of preparing the flood level criteria involved several steps.

Initially, historical flood level data were acquired from Sentinel-1 and Sentinel-2 images up to 2020. In the second step, the Gumbel distribution was applied to estimate the maximum flood height for a 50-year return period. Finally, a flood level map was prepared using the bathtub approach, as described by Bhuiyan and Al Baky (2014). Hereafter, all the calculations are performed using python coding in the python environment of QGIS platform. The Raster Calculator tool in QGIS was used to implicate risk maps using equations 4.31 and 4.32.

4.13 EXPLANATION OF TRENDS IN THE DATA

Trend analysis is crucial for understanding the temporal dynamics of basin behaviour concerning flood and drought risk components and parameters. By identifying these trends, we can enhance further analyses and improve predictive models, ultimately aiding in better management and mitigation strategies for flood and drought risks (Cleveland et al., 1990).

STL (Seasonal-Trend decomposition using Loess) is a robust and versatile method for decomposing time series data into three main components: seasonal, trend, and residual (or noise). The seasonal component captures the repeating patterns or cycles in the data (e.g., daily, weekly, yearly). The trend component represents the long-term progression of the series (e.g., increasing or decreasing over time). The residual component accounts for the random variation that is not explained by the seasonal or trend components.

The STL decomposition method uses locally weighted regression (Loess) to estimate the seasonal and trend components, making it highly adaptable to various types of time series data, including those with complex seasonal patterns and non-linear trends. The method is particularly effective because it iteratively applies Loess smoothing to isolate and remove the seasonal and trend effects, allowing for a clearer analysis of the underlying structure of the data.

The STL decomposition can be expressed mathematically as follows (Equation 4.39):

$$y_t = T_t + S_t + R_t \qquad \text{Eq. 4.39}$$

Where, y_t the observed time series at time t. T_t is the trend component at time t. S_t is the seasonal component at time t. And R_t is the residual component at time t.

The seasonal component captures periodic patterns that repeat over a specific period P. Loess smoothing is applied within each cycle to isolate the seasonal effect. The procedure can be summarized as (Equation 4.40):

$$S_t = Loess_{seasonal}(y_{t-kP}) \qquad \text{Eq. 4.40}$$

Here, the seasonal component at time t, S_t, is obtained by applying Loess smoothing to the series y_t across different cycles, indexed by k. For instance, if P is 12 (e.g., monthly data with an annual cycle), Loess smoothing is applied to each set of observations corresponding to each month across different years.

The trend component captures the long-term progression of the series. After removing the seasonal effect from the original series, Loess smoothing is applied to the detrended series to estimate the trend (Equation 4.41):

$$T_t = Loess_{trend}(y_t - S_t) \qquad \text{Eq. 4.41}$$

Here, T_t is the trend component at time t, obtained by applying Loess smoothing to the series $y_t - S_t$, which is the original series minus the estimated seasonal component.

For a given point t, the smoothed value $\hat{y_t}$ using Loess can be described as (Equation 4.42):

$$\hat{y_t} = \sum_{i=t-w}^{t+w} w_i y_i \quad \text{Eq. 4.42}$$

where (w_i) are the weights assigned to each point (y_i) within the window of size $(\ 2w+1\ )$ cantered at $(\ t\ )$. The weights (w_i) are calculated using a kernel function, typically the tricube weight function (Equation 4.43):

$$w_i = \left(1 - \left|\frac{i-t}{d}\right|^3\right)^3 \quad \text{Eq. 4.43}$$

where $(\ d\ )$ is the distance to the furthest point in the local neighbourhood.

To explore spatio-temporal trend within the flood and drought risk time series further, a combination of Mann-Kendall tau and Sen's Slope is applied. The Mann-Kendall test is a non-parametric statistical test used to identify trends in time series data. It is widely used in environmental science, hydrology, and climate research to detect monotonic trends (increasing or decreasing) in data over time. The test does not assume any particular distribution of the data and is robust against missing values and outliers (Kundu et al., 2015).

The Mann-Kendall test evaluates whether a dataset exhibits a statistically significant trend by comparing the ranks of the data rather than their actual values. The test statistic, S, is computed based on the difference between data points, and the significance of the trend is determined using the Z statistic.

For a dataset with n data points $x_1, x_2, \ldots, x_n$, the test statistic S is calculated as (Equation 4.44)

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \quad \text{Eq. 4.44}$$

where the sign function sgn is defined as +1 for positive values, zero for zero and -1 for negative values. Next, the variance of S under the null hypothesis of no trend is given by (Equation 4.45):

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_t t_i(t_i-1)(2t_i+5)}{18} \quad \text{Eq. 4.45}$$

where t_i is the number of ties of extent i.

The standardized test statistic Z is computed as (Equation 4.46):

$$S > 0, Z = \frac{S-1}{\sqrt{Var(S)}} \qquad S = 0,\ Z = 0 \qquad S < 0, Z = \frac{S+1}{\sqrt{Var(S)}} \tag{Eq. 4.46}$$

The significance of the trend is then determined by comparing Z to the standard normal distribution.

Sen's Slope estimator, also known as the Theil-Sen estimator, is a non-parametric method used to estimate the slope of a trend in time series data. It is particularly useful when the data contain outliers or are not normally distributed. Sen's Slope provides a robust estimate of the rate of change over time. Sen's Slope calculates the median of the slopes of all possible pairs of points in the dataset. This method is less sensitive to outliers than simple linear regression and provides a reliable estimate of the trend (Sen, 1968).

For each pair of data points (x_i, y_i) and (x_j, y_j) where $i < j$, the slope β_{ij} is calculated as (Equation 4.47)

$$\beta_{ij} = \frac{y_j - y_i}{x_j - x_i} \tag{Eq. 4.47}$$

The Sen's Slope estimator β is the median of all β_{ij} values (Equation 4.48):

$$\beta = median(\beta_{ij}) \tag{Eq. 4.48}$$

By applying these statistical methods, this research strived to detect and quantify trends in environmental and climatic data, providing valuable insights into changes over time and potential application of inclusion in inner functions of upcoming predictive models.

4.14 VALIDATION OF RESULTS AND EFFICIENCY TEST

Having calculated the risk components and obtained temporal trend analyses for predictors and responses in the basin, the next crucial step is to validate these results. Validation ensures the accuracy and reliability of the findings and involves several techniques. First, it is proposed using an overlay map to visually compare predicted and observed values. Second, an agreement map is generated and percentage of agreement between predicted and observed values is calculated. Lastly, the model's performance using the Receiver Operating Characteristic (ROC) curve against historic data and previously assessed risk by the Environment Agency (EA) is evaluated in order to quantify its predictive capability (Swets, 1988; Pontius & Millones, 2011).

An overlay map visually compares the spatial distribution of predicted values (e.g., flood risk) with observed values. It helps in identifying areas where the model predictions match or deviate from actual observations.

An agreement map identifies areas where the predicted values agree with the observed values. The percentage of agreement quantifies the proportion of the study area where the predictions match the observations.

The agreement map is generated by calculating the pixel-wise or grid-cell-wise agreement between predicted (P_i) and observed (O_i) values (Equation 4.49):

$$A_i = 1 if P_i = O_i, 0 otherwise \qquad \text{Eq. 4.49}$$

The percentage of agreement $(A\%)$ is then calculated as (Equation 4.50):

$$A\% = \left(\frac{\sum_{i=1}^{N} A_i}{N}\right) \times 100 \qquad \text{Eq. 4.50}$$

where N is the total number of pixels or grid cells.

The ROC curve is a graphical representation of the model's diagnostic ability. It plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings, allowing for the assessment of the model's discriminatory power. Mathematics behind the ROC curve involves calculating TPR and FPR for different threshold values:

$$TPR = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

$$FPR = \frac{False\ Positives}{False\ Positives + True\ Negatives}$$

The Area Under the ROC Curve *(AUC)* quantifies the overall ability of the model to discriminate between positive and negative classes. An *AUC* of 1 indicates perfect prediction, while an *AUC* of 0.5 suggests no discriminatory power.

4.15 Understanding the complexity of spatial distributions of flood and drought risk categories

Fractal dimensions provide a quantitative measure of the complexity of a fractal pattern. Unlike traditional geometric shapes, fractals exhibit self-similarity across different scales, meaning they look similar regardless of the level of magnification. Fractal dimensions help describe how the detail or complexity of a fractal pattern changes with the scale at which it is measured. Mathematically, the fractal dimension D can be defined using various methods, one of which is the box-counting method. The fractal dimension is not necessarily an integer and can take non-integer values, which reflects the complexity of the fractal structure (Mandelbrot, 1983; Falconer, 2003).

In this research, the geometric concept of fractal dimensions is employed as a quantitative measure to assess the severity of both flood and drought risk spatial distributions across various categories. These categories, as described earlier, range from very low to low, moderate, high, and very high.

The box-counting method is a common technique to compute the fractal dimension of a pattern. This method involves covering the fractal with a grid of boxes (or cells) and counting the number of boxes that contain a part of the fractal. The process is repeated for different box sizes, and the relationship between the box size and the number of boxes required to cover the fractal is used to estimate the fractal dimension.

Steps of the Box-Counting Method are as follows:

1. Overlay a Grid: Place a grid of boxes of size ϵ over the fractal.
2. Count Boxes: Count the number of boxes $N(\epsilon)$ that contain part of the fractal.
3. Vary Box Size: Repeat the process for different box sizes ϵ.
4. Log-Log Plot: Plot $l\log\big(N(\epsilon)\big)$ against $log(1/\epsilon)$.

5. Compute Slope: The fractal dimension D is estimated as the slope of the line in the log-log plot (Equation 4.51).

$$log\big(N(\epsilon)\big) = D\, log\left(\frac{1}{\epsilon}\right) \qquad \text{Eq. 4.51}$$

4.16 SENSITIVITY ANALYSIS OF THE RISK PRODUCTS TO THEIR PREDICTORS

The Sobol sensitivity index is a global sensitivity analysis method used to quantify the contribution of each input variable to the variance of the output of a mathematical model. This method is particularly useful for models with multiple inputs and non-linear interactions. It decomposes the variance of the model output into fractions attributable to inputs or sets of inputs, providing insights into which variables are most influential (Saltelli et al., 2010).

Sobol sensitivity analysis provides a comprehensive measure of sensitivity by considering not only the individual effect of each input variable but also the interactions between them. The main sensitivity indices used in Sobol analysis are:

First-order index S_i, which measures the effect of an input variable alone, excluding interactions with other variables. Second-order index S_{ij}, measures the effect of the interaction between two input variables. And eventually, Total-order index S_{T_i} that measures the total effect of an input variable, including both its individual effect and all its interactions with other variables.

Let $f(X)$ be the model output where $X = (X_1, X_2, \dots, X_k)$ are the input variables. The variance of $f(X)$, $Var\big(f(X)\big)$, can be decomposed as (Equation 4.52):

$$Var\big(f(X)\big) = \sum_{i=1}^{k} V_i + \sum_{1\le i<j\le k} V_{ij} + \cdots + V_{1,2,\dots,k} \qquad \text{Eq. 4.52}$$

where V_i is the contribution to the variance from X_i, V_{ij} is the contribution from the interaction between X_i and X_j, and so on.

The first-order sensitivity index S_i measures the main effect of X_i on $f(X)$ (Equation 4.53).

$$S_{ij} = \frac{V_{ij}}{Var\big(f(X)\big)} \qquad \text{Eq. 4.53}$$

The second-order sensitivity index S_{ij} measures the interaction effect between X_i and X_j (Equation 4.54):

$$S_{ij} = \frac{V_{ij}}{Var(f(X))} \quad \text{Eq. 4.54}$$

The total-order sensitivity index S_{T_i} measures the total contribution of X_i to the variance, including all interactions (Equation 4.55):

$$S_{T_i} = 1 - \frac{V_{\sim i}}{Var(f(X))} \quad \text{Eq. 4.55}$$

Where, $V_{\sim i}$ is the variance of $f(X)$ excluding X_i. The main criteria for a successful Sobol index computation are the convergence of S_i based on number of samples The accuracy of the Sobol sensitivity indices depends on the number of samples used in the analysis. As the number of samples increases, the estimates of S_i, S_{ij} , and S_{T_i} converge to their true values. The convergence can be evaluated by plotting the sensitivity indices against the number of samples and observing whether they stabilize.

Convergence criteria are first, stability which is that the indices should become stable as the number of samples increases and second, reproducibility which states that repeated calculations with different random samples should yield similar indices.

4.16.1 Feature importance as a measure of sensitivity analysis

Feature importance analysis helps to identify which input variables have the most influence on the model's predictions. Here, we describe four different methods used for feature importance analysis: Random Forest, Permutation Importance, XGBoost, and Principal Component Regression (PCR).

Random Forest is an ensemble learning method that builds multiple decision trees and merges them to get a more accurate and stable prediction. Feature importance in Random Forest is typically measured by the decrease in impurity (Gini impurity or entropy) across all trees in the forest (Equation 4.56) (Breiman, 2001).

$$Gini = 1 - \sum_{i=1}^{n}(p_i)^2 \qquad \text{Eq. 4.56}$$

where P_i is the probability of class i in a node. And the importance of a feature X_i is computed as the total decrease in node impurity, averaged over all trees in the forest (Equation 4.57):

$$Importance(x_j) = \frac{1}{T}\sum_{t=1}^{T}\sum_{k\in nodes}\Delta I_k \mathbf{1}(k \textit{ splits on } x_j) \qquad \text{Eq. 4.57}$$

where T is the total number of trees, ΔI_k is the decrease in impurity at node k, and $\mathbf{1}(k$ *splits on* $x_j)$ is an indicator function that is 1 if node k splits on feature X_j.

Permutation Importance is a model-agnostic method that measures the increase in prediction error when the values of a single feature are randomly shuffled, breaking the relationship between the feature and the target variable. Mathematics behind Permutation Importance has a few steps. First, train the model on the original dataset and obtain the baseline accuracy.

Next, for each feature X_j, shuffle its values and measure the accuracy of the model on this perturbed dataset. Lastly, the importance of X_j is the decrease in accuracy after shuffling (Equation 4.58)

$$Importance(x_j) = Accuracy_{original} - Accuracy_{shuffled\ x_j} \qquad \text{Eq. 4.58}$$

XGBoost (Extreme Gradient Boosting) is a scalable and efficient implementation of gradient boosting. It builds trees sequentially, with each tree attempting to correct the errors of the previous one. Feature importance in XGBoost is based on the frequency and quality of interactions a feature has within the model (Chen and Guestrin, 2016).

Firstly, the parameter Gain is defined as the average gain of splits that use the feature (Equation 4.59)

$$Gain(x_j) = \frac{1}{T}\sum_{t=1}^{T}\sum_{k\in nodes}\Delta G_k \mathbf{1}(k \textit{ splits on } x_j) \qquad \text{Eq. 4.59}$$

where ΔG_k is the gain in loss reduction at node k. Finally, frequency, which is the number of times a feature is used to split the data across all trees (Equation 4.60).

$$Frequency(x_j) = \sum_{t=1}^{T} \sum_{k \in nodes} \mathbf{1}(k \text{ splits on } x_j) \quad \text{Eq. 4.60}$$

The last but not least method performed in this section is Principal Component Regression that combines Principal Component Analysis (PCA) with linear regression. PCA reduces the dimensionality of the data by transforming it into a set of orthogonal (uncorrelated) components that capture the maximum variance. Linear regression is then performed on these components (Jolliffe, 2002).

After standardising the dataset X, the covariance matrix of X should be computed (Equation 4.61).

$$Cov(X) = \frac{1}{n-1} X^T X \quad \text{Eq. 4.61}$$

Next steps comprise of performing eigenvalue decomposition on the covariance matrix to obtain eigenvalues and eigenvectors. And transforming the original data into principal components Z (Equation 4.62)

$$Z = X W \quad \text{Eq. 4.62}$$

where W is the matrix of eigenvectors. Fit a linear regression model on the transformed dataset Z (Equation 4.63) and the feature importance is derived from the contribution of each principal component to the explained variance.

$$y = Z\beta + \epsilon \quad \text{Eq. 4.63}$$

4.17 Quantifying the Aleatoric Uncertainty to enhance the accuracy of quantified risks

Aleatoric uncertainty, also known as statistical or inherent uncertainty, refers to the variability or randomness in the data that cannot be reduced by collecting more data. This type of uncertainty is inherent to the process being studied and is due to natural variability (Kendall and Gal, 2017).

In the context of machine learning and predictive modelling, aleatoric uncertainty can be captured and quantified using ensemble methods like bagging with XGBoost. Bagging (Bootstrap

Aggregating) involves training multiple models on different bootstrap samples of the training data and aggregating their predictions (Breiman, 1996).

By training multiple XGBoost models on different bootstrap samples, the variability in predictions can be captured. This variability reflects the aleatoric uncertainty.

First, multiple bootstrap samples from the training data are created. Next, an XGBoost model on each bootstrap sample is trained. Make predictions using each model and aggregate them to capture variability. Aleatoric uncertainty can be quantified using various statistical measures derived from the distribution of predictions made by the ensemble of models such as standard deviation, interquartile range and prediction range. To evaluate the accuracy of the model's predictions Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are calculated between actual and predicted values (Chen and Guestrin, 2016).

4.18 CHAPTER CONCLUSION

This research aimed to develop a comprehensive framework for simultaneously assessing flood and drought risks at a river basin scale. The process began with a systematic review of peer-reviewed publications, followed by a systematic content analysis using open-coded texts. Information extraction and data synthesis involved constructing a co-occurrence matrix and applying statistical measures such as the Spearman correlation coefficient, cosine similarity index, and clustering algorithms to identify key variables and their pairwise connections.

A Structural Self-Interaction Matrix (SSIM) was created to detail interactions among various parameters through pairwise comparisons, leading to the development of an initial reachability matrix. This matrix facilitated the identification of direct and indirect parameter interactions. The final reachability matrix was used to examine transitive relationships, enabling hierarchical assessment through Level Partitioning.

The application of MICMAC Analysis highlighted the importance of understanding the hierarchical organization of elements and their interconnections for effective risk management planning. Causal paths and parameters were then analysed using network metrics such as betweenness and closeness centrality, authority, and hub scores. Parameters were ranked based on their performance across 11 network metrics, with the top 25% selected for further analysis using the Cross Entropy algorithm. This process identified the final 30 most influential parameters, which were reintegrated into Causal Loop Diagrams (CLDs) to extract essential pathways for risk assessment.

Finally, a spatiotemporal analysis was conducted in the River Severn Basin District. Spatial data for various basin parameters were collected and processed using the fuzzy overlay function to estimate monthly risk maps for flood and drought. These maps were validated using Receiver Operating Characteristic (ROC) curves, and their temporality and sensitivity to input variables were assessed. An XGBoost algorithm combined with trend analysis was employed to predict risks for the coming year, and the resulting risk maps were tested against observed flood events. An aleatoric uncertainty analysis was also performed to ensure robustness.

In the following chapters, the results and discussions will utilize the methodologies outlined in this chapter. Chapter Four focuses on a quantitative analysis of influential parameters and the linkage between research fields in flood and drought studies, utilizing a co-occurrence matrix. Chapter Five employs the ISM-CLD method to construct a comprehensive framework, which is then analysed using network theory metrics and the cross-entropy algorithm to identify the most significant pathways within the produced framework for modelling flood and drought risks. The final results chapter assesses these risks for the River Severn basin using fuzzy logic and machine learning algorithms. It also includes an analysis of the sensitivity of the final results to input variables and quantifies aleatoric uncertainty.

5 Results and disscussion comprehensive insight: risk of flooding and drought at river basin scale

5.1 CHAPTER INTRODUCTION

The interplay of natural and anthropogenic factors at a river basin scale significantly influences the occurrence and risk of flooding and drought events. The extensive ramifications of these hydrological extremes necessitate a multidisciplinary approach to understand, mitigate, and adapt to the associated risks. This chapter unfolds the intricate tapestry of themes and sub-themes dedicated to the scientific understanding of flooding and drought risks, shedding light on the contributions from diverse fields ranging from hydrology to tourism. The collective insight offers a robust framework for fostering resilient river basin communities amid a changing climate and evolving societal demands. The peer reviewd sources of extracted data comprises a comprehensive list of 981 publication items categorized into journal papers, book chapters, and conference papers. Specifically, there are 707 journal papers, 18 book chapters, 6 datasets, 38 reports and 217 conference papers (described in the Appendices section under titles: "Bibliography_of_all_papers" and "Sample_of_reviewd_papers"). On average, journal papers have received 48.5 citations, while book chapters have garnered an average of 14 citations. Conference papers have an average of 22 citations. These figures provide an overview of the distribution and citation impact of the publications within each category.

5.2 FLOOD AND DROUGHT RESEARCH: TRENDS, FOCUS AREAS, AND POTENTIAL GAPS.

5.2.1 Analysis of auxiliary research themes in flood and drought studies: frequency, variability, and interdisciplinary trends

As visualized in Figure 5.1, the distribution and frequency of various research themes as auxiliary focuses in research papers. Based on the graph an overview of the themes could be deducted as follows.

Hydrology is frequently featured as an auxiliary focus, with a high median and a wide range, indicating substantial variation in how often it's mentioned. Climate Science also appears frequently as an auxiliary focus, with a high median but lower than that of Hydrology. The spread and outliers indicate that while it is consistently a focus, there can be significant fluctuations in its emphasis as auxiliary theme of research across different themes.

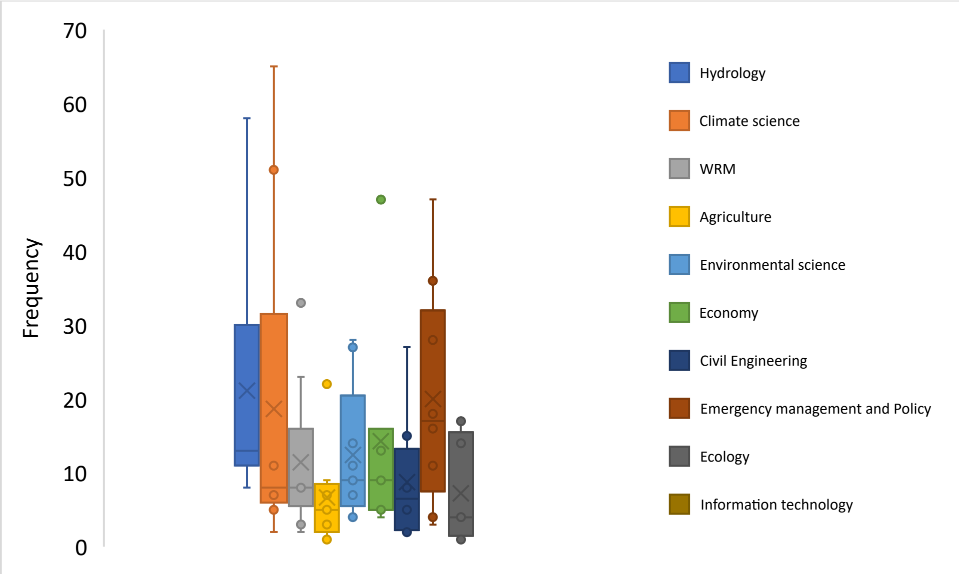


Figure 5.1. Number of times that each theme has reoccurred as an auxiliary theme of research, WRM (Water Resources Management).

Water Resources Management (WRM) has a moderately high median frequency with less considerable variation comparing to the first two themes, as indicated by the short whiskers. The theme is a common auxiliary focus but with less consistency than Hydrology or Climate Science. However, Agriculture is less frequently an auxiliary focus, with the second lowest median. The compact interquartile range (IQR) could suggest that it appears with consistent frequency across papers. Outliers might be a sign that there are occasions where studies have a higher emphasis on Agriculture as the lateral theme of research in the context of flood and drought.

Environmental Science as a research theme on flood and drought risk has a moderate median frequency, with a comparatively good range suggesting variability in its frequency as an auxiliary focus of the research. However, Outliers indicate that this theme can sometimes be a more significant second focus when certain themes are the main focus of studies. But, Economy shows a relatively low median frequency (close to those of WRM, Climate science, Environmental science, and IT) with a narrow IQR. Additionally, no outliers could suggest that it's not often an auxiliary focus, and when it is, the frequency is fairly consistent.

Civil Engineering theme has a low to moderate median frequency distribution and a low to moderate median smaller than Economy and closer to Agriculture and Ecology. The large whiskers and presence of outliers could indicate variability in this theme as the auxiliary theme of research for various main focus areas. Emergency Management and Policy theme frequently appears as an auxiliary focus, as suggested by the highest median among all the themes. It also has a wide range and outliers, which point to significant variability in emphasis of using it as an auxiliary theme to help describe flood and drought issues across different papers.

Ecology is the least frequently used as an auxiliary focus compared to the other themes. Its low median might be a sign that it is not commonly emphasized in flood and drought research. However, the compact IQR range (IQR) could imply that when Ecology is mentioned, the frequency is relatively consistent. The outliers, on the other hand could suggest some papers with certain main areas of focus have combined their understanding with ecological insights.

Information Technology (IT) has a relatively moderate median frequency among the themes, with long whiskers and outliers near the top of its range. It could suggest that in some cases, it is used infrequently as an auxiliary focus. However, for some themes IT has co-occurred very often.

In summary, themes like "Hydrology", "Climate Science" and "Emergency management and policy" are often auxiliary focuses in research papers, with considerable emphasis and variability in their frequency. Themes such as Agriculture, Civil Engineering, and Ecology are less frequently consulted as auxiliary focuses, typically appearing with a consistent level of emphasis. The box plot indicates that while some themes are central to research across many papers, others are given attention occasionally, which may reflect the specific nature of the research questions or the evolving interests and trends in flood and drought studies, which is covered to some degrees in upcoming sections of this chapter.

Overall, the distribution and median frequency of these themes suggest a diverse range of auxiliary focuses on flood and drought research, with Ecology being the least emphasized among them. This can help identify which themes have been more central to the discourse over time and which might require more attention or have been underexplored in the context of flood and drought studies. The analyse offered by the co-occurrence matrix further investigates this notion.

Flood and drought research is becoming increasingly relevant in our changing climate. This could be because climate change causes extreme weather patterns, such as relatively more frequent flooding and drought. This has increased the need for research in these areas. Additionally, more interdisciplinary research may be conducted to better understand climate change's complex effects.

The line chart (Figure 5.2) shows two different trends related to research on flood and drought. Namely Themes per Paper and Cumulative Number of Papers from the year 2000 to around 2020.

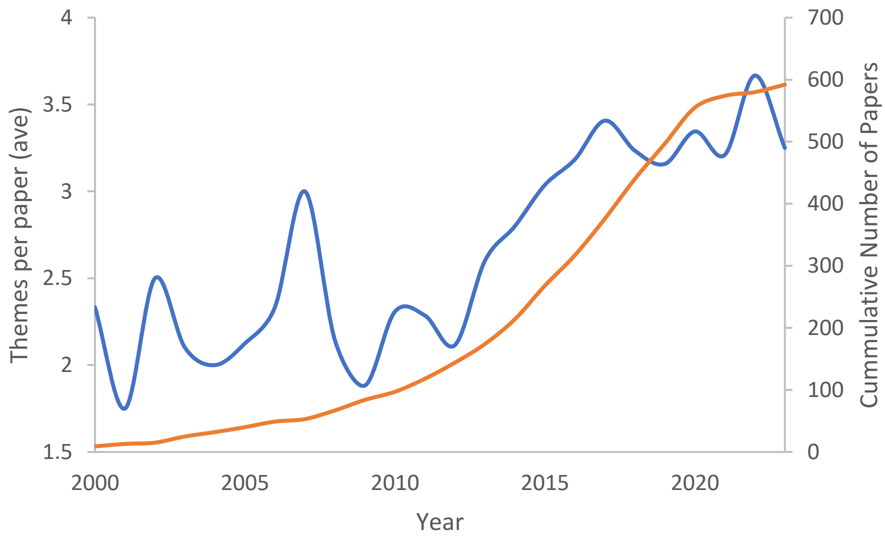


Figure 5.2. Average of yearly theme per paper and cumulative number of publications.

5.2.2 Evolving trends in flood and drought research: a dual analysis of thematic diversity and research volume (2000-2020)

In Figure 5.2. The blue line represents the average number of flood and drought themes explored in research papers each year. It appears that thematic diversity within individual publications varies over time as the line exhibits a wavy pattern with peaks and troughs. A general upward trend indicates that, on average, papers cover more themes as time progresses. There were noticeable peaks around 2005, 2010, and just before 2020. During those periods, interdisciplinary research may have been more focused. There is a peak just after 2020, which indicates the maximum average number of themes per paper.

An orange line shows the cumulative number of research papers published on floods and droughts since 2000. Research in this area has demonstrated a steady and consistent upward trend over time. Research output appears to have remained constant without any significant drops or plateaus.

After putting together both of these trends, some observations can be made. Flood and drought research has become increasingly complex, with papers addressing multiple aspects or themes simultaneously. This might indicate a growth in our understanding of flooding and drought issues, leading to a rising demand for a more comprehensive and collaborative framework to assess flood and drought risk.

According to the steady upward trend of the cumulative number of papers, flood and drought research is becoming increasingly important. This is possibly due to global factors such as climate change, extreme weather events, or heightened awareness of environmental concerns and partially, the overall growth of publications. More papers published over time suggests a broader scope and potential for multidisciplinary approaches.

In 2020, there may be a slight decrease in "Themes per Paper" due to several factors, including a shift in research focus to more specialized topics within the flood and drought domain, or perhaps a temporary shift in research priorities as a result of global events such as COVID-19. Nonetheless, flood and drought research is a vibrant and expanding field, with a tendency to become more interdisciplinary over time.

5.2.3 Dynamic evolution of research themes in flood and drought studies: a 20-year perspective

It would be even more beneficial if we could see the trend of the presence of individual themes in the body of research over time (Figure 5.3). This line chart shows trends in the percentage of themes investigated in the context of flood and drought research from 2000 onwards. Each line represents a different research theme, and the y-axis measures the percentage of times each theme has occurred as the main or auxiliary focus of studies.

Hydrology over the entire period, has been investigated the most frequently. Although it fluctuates, it tends downward toward 2020, suggesting a slight decline in focus within this field.

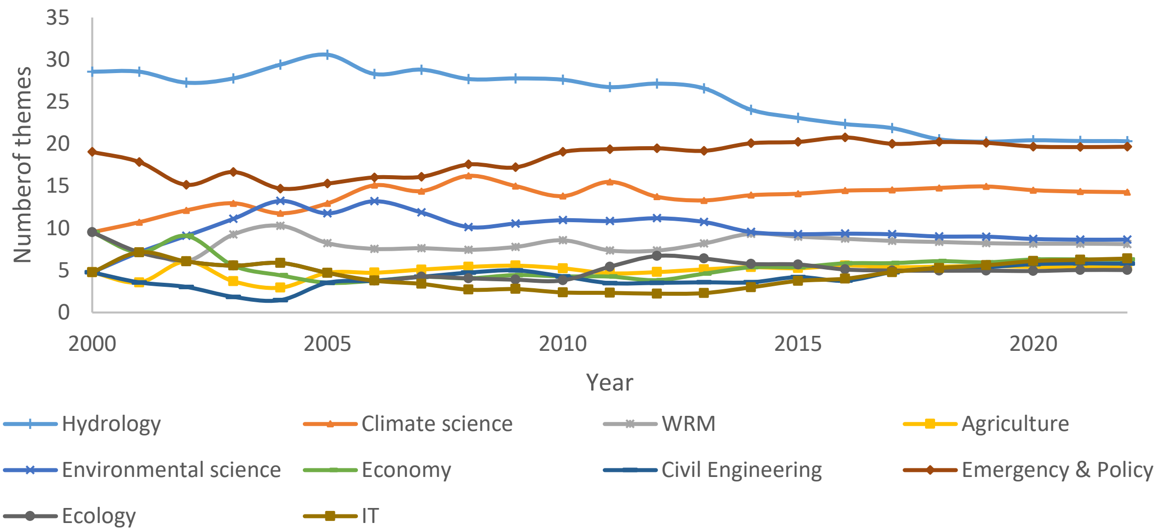


Figure 5.3. trends in the number of themes investigated in the context of flood and drought research.

Climate Science starting with a lower frequency in 2000, a notable increase peak around 2005. Afterwards, it slightly declines but remains one of the more frequently investigated themes. The frequency of Environmental science theme starts low, peaks around 2007, and then sees a decline. It suggests that Environmental-related research had a moment of increased focus, which has since waned to eventually groups up with the WRM themes.

Emergency management & Policy starting with a moderate to high frequency, there's a slight downward trend just before 2005, followed by a period of stability and then a subtle increase, getting closer to Hydrology, indicating a relatively stable interest in this type of research aspects.

Water resources management exhibiting a wave-like pattern, WRM research appears to peak around the years 2005 and 2015. The overall trend suggests that the focus on WRM within flood and drought research has waves of increased interest. Civil Engineering, IT, Economy, Ecology and Agriculture start at lower frequencies. They all fluctuate more or less in the same bandwidth but with different patterns, but later bundled up together to an approximate percentage of six.

Despite varying degrees of focus over the past two decades, hydrology remains a central theme in flood and drought research. New technologies and methodologies in this field are likely influencing the increase in IT-related research. The data suggests that while some areas have seen peaks and troughs of interest, others have remained constant. Researchers, policymakers, and funding bodies can use this chart to learn about historical trends and potential areas of flood and drought research.

On the graph, several themes have clustered together with flattened trends from 2017 onward, suggesting that flood and drought research has stabilized the number of times these themes were investigated.

In around 2017, we witnessed a convergence of research themes such as Civil Engineering, Agriculture, Economy, Ecology, and IT, which formed a cluster. This indicates that these research areas were being investigated with relatively similar frequency during that time. The proximity of these lines could suggest that these themes may be increasingly interrelated in the context of flood and drought research, or it could indicate a shared level of attention and resources directed toward these areas. There appears to be a shift from the fluctuations and distinct trends of the earlier years to more stable lines post-2017. Possibly, this is related to the maturation of these research fields, where significant fluctuations are less common as they consolidate. Additionally, it may indicate an established research scope and direction that has continued steadily.

While "Hydrology" and "Emergency management and policy" remain the most frequently studied themes, their trends also flatten, suggesting that they have reached a plateau. This could indicate that the amount of new research being initiated in these areas is balanced by the research being concluded, or it could reflect a saturation point in research focus within the available data. Generally, the clustering and flattening trends observed may suggest a period of equilibrium in research focus. This could be due to a variety of factors, including but not limited to the achievement of research goals, a shift in funding priorities, or the emergence of new, not-yet-represented themes that are drawing attention away from the established ones. The convergence and flattening of trends in this period may also reflect a broader interdisciplinary approach to flood and drought research, where the distinctions between themes become less pronounced as they are increasingly studied in conjunction with one another. This interdisciplinary approach can lead to more comprehensive understanding and solutions to the complex problems associated with flood and drought.

5.3 COMPREHENSIVE ANALYSIS OF THEMATIC CO-OCCURRENCE IN FLOOD AND DROUGHT RESEARCH

The co-occurrence matrix is a foundational tool in data analysis (Figure 5.4), especially when exploring relationships between different categories or themes. In the context of this research, it represents how often each pair of fields (like "Hydrology," "Climate Science," etc.) appears together in the same set of papers. This matrix serves as a quantitative representation of the interconnectedness of different research areas. Higher numbers indicate a greater degree of co-occurrence, suggesting stronger or more frequent associations between the fields in the research literature. The diagonal cells, distinctively emphasized, denote the proportion each theme contributes to the overall body of knowledge on flood and drought issues, respectively. For instance, when research is focused on WRM, 47% of publications investigate flood issues. These values are pivotal as they signify the amount of research focused on flood or drought and underscore its prominence within the field.

Fields	Hydrology	Emergency management and policy	Climate science	Water resources management	Economy	Environmental science	Agriculture	Civil Engineering	Ecology	Information Technology
Hydrology	55 / 45	58.00	43.00	13.00	9.00	13.00	13.00	16.00	17.00	8.00
Emergency management and policy	47.00	61 / 39	36.00	28.00	17.00	11.00	18.00	16.00	4.00	3.00
Climate science	51.00	65.00	44 / 56	11.00	5.00	7.00	12.00	8.00	7.00	2.00
Water resources management	23.00	33.00	8.00	47 / 53	3.00	9.00	9.00	8.00	8.00	2.00
Economy	16.00	47.00	13.00	5.00	66 / 34	4.00	9.00	6.00	0.00	0.00
Environmental science	28.00	27.00	11.00	8.00	4.00	50 / 50	9.00	7.00	14.00	4.00
Agriculture	9.00	22.00	5.00	8.00	4.00	7.00	40 / 60	3.00	1.00	1.00
Civil Engineering	15.00	27.00	8.00	8.00	3.00	5.00	2.00	66 / 34	2.00	0.00
Ecology	14.00	17.00	4.00	1.00	2.00	17.00	5.00	4.00	40 / 60	1.00
Information Technology	35.00	26.00	13.00	10.00	3.00	2.00	3.00	9.00	2.00	50 / 50

Emerging Fields — Highly cited fields

Relative contribution of the field to F/D (%) — 50 / 50

Figure 5.4. Co-occurrence matrix of investigated papers in the context of flood and drought research.

On the other hand, the off-diagonal cells show how frequently two themes have been researched simultaneously. These values offer insights into the interconnections between different themes, highlighting how researchers have navigated the complexities of flood and drought issues by integrating multiple thematic areas. A higher frequency, denoted by a warmer colour on the heat map, suggests a strong association and a tendency for themes to be studied together (Highly cited fields), indicating interdisciplinary focus areas. Conversely, the cooler colours represent fewer simultaneous intersections in (Emerging Fields) which may be potential frontiers for novel research.

Theme combinations classified as 'Emerging Fields' represent developing study areas with potential for growth and increased focus. On the other hand, 'Highly cited fields' have already established a solid foundation within academic discourse, often serving as cornerstones for further research and development.

5.3.1 Understanding pairwise theme co-occurrence through distribution analysis

Analysing the data accumulated by combining a histogram and a box plot comprising of only the counts of the pairwise co-occurrences between themes, provides different perspectives on the

data's distribution as shown in Figure 5.5 helps finding the main pairs of themes that are studied together to address flood and drought issues.

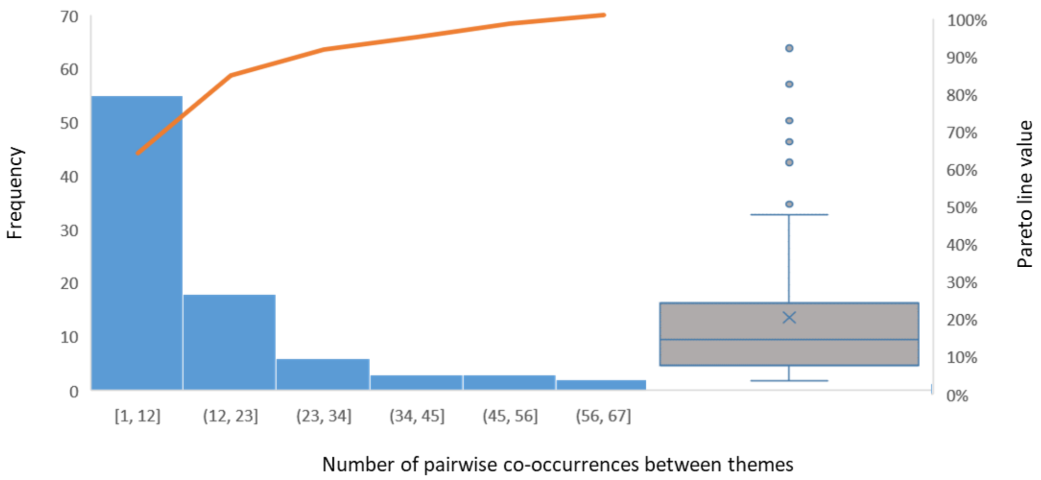


Figure 5.5. Distribution of pairwise count of thematic co-occurrence within investigated papers in the context of flood and drought research. Box plot represents the numerical distribution of pairwise co-occurrences between themes and right axis shows the percentage values of the orange Pareto line.

The histogram suggests that most research themes tend to have a lower count of co-occurrences (as shown by the first bin with the highest frequency). This might indicate that there are a few commonly associated pairs of themes that are frequently studied together, while most pairs of themes co-occur less often.

The distribution is right-skewed, with a gradual decrease in frequency as the co-occurrence count increases. This implies that as we look at higher co-occurrence counts, fewer theme pairs reach these levels. A right-skewed distribution is typical for count data where the absence or low occurrence of an event is more common than high occurrences.

The tail of the histogram extending to the right suggests the possible presence of outliers or theme pairs that co-occur with unusually high frequency. These could represent particularly hot topics within flood and drought research that warrant further investigation.

The median (the line inside the box) appears to be on the lower end of the scale, which aligns with the histogram's indication that most theme pairs do not co-occur frequently. In this distribution, mean (the 'X' inside the box) is above the median, and this could suggest that the mean is higher due to the influence of outliers, which is common in skewed distributions. The IQR is relatively small, indicating that the middle 50% of the data points are clustered within a narrow range of lower co-occurrence counts. The individual points above the upper whisker represent outliers, which are theme pairs with co-occurrence counts significantly higher than the rest. These points merit special attention to understand why these particular pairs of themes are so frequently associated in the literature.

The combined histogram and box plot in Figure 4.6 suggest a distribution typical of count data where many theme co-occurrences are rare, but a few occur much more frequently. This pattern could reflect the nature of research where specific themes are more commonly studied together due to their relevance or importance in flood and drought.

The outliers could indicate areas incredibly fertile for research or that have received much attention, possibly due to recent developments, funding availability, or particular demand from communities to investigate certain fields.

Understanding this distribution is critical for researchers, as it helps identify which themes are most often studied in tandem and which are less explored. This knowledge can guide selection parameters for the assessment framework from the intersection of research themes and suggest potential areas for interdisciplinary links. The following conclusions can be drawn from these observations: Complementarity and Interdisciplinary Research: Co-occurrences indicate that specific thematic pairings are consistently considered together, suggesting complementarity in flood and drought research. Combining insights from diverse themes leads to a more holistic understanding of environmental studies due to their interdisciplinary nature.

Identifying Research Gaps: Less frequently associated topics may offer opportunities for innovative perspectives and solutions that are not typically associated with each other.

Trends and Evolution: Emerging themes may indicate shifts in focus due to environmental challenges or technological advances, perhaps reflecting temporal trends.

Strategic Planning for Future Research: By understanding the current landscape of research themes, institutions and policymakers can strategically fund and promote studies in areas that bridge well-established and emerging fields, fostering innovation and comprehensive knowledge development.

5.4 Linear and non-linear correlation assessments

Overall, this co-occurrence matrix maps out the current state of flood and drought research and serves as a navigational chart for steering intersections where possible parameters could be considered for inclusion in the flood and drought risk assessment framework. It illustrates the interconnectedness of environmental research. Exploring these intersections will improve global water management strategies and advance knowledge. However, co-occurrence information in combination with insights driven from the correlation coefficients (Figures 5.6 and 5.7) and cosine similarity matrices (Figure 4.9) could further analyse the interactions amongst various themes. It leads to a more robust selection of parameters and their links within the risk assessment framework.

5.5 Integrating insights from multiple matrices: A holistic view of research theme dynamics.

The three matrices provided below represent different statistical measures applied to the co-occurrence matrix of research themes related to flood and drought. When analysing these combined results, the aim is to look for consistent patterns across all three measures and any notable differences that could suggest further lines of inquiry.

Examining these three matrices together, would help synthesis a comprehensive view of how themes are interrelated in the body of research on floods and drought. This can result in identifying which themes are commonly studied together, which are inversely related, and which have complex relationships that vary depending on the measure used. Such insights can guide future research directions, suggest a potential for interdisciplinary studies, or reveal gaps in the literature. Alternatively, it opens a way for insights suggesting the overlap between parameters, which exist in various themes simultaneously.

5.5.1 Analysing linear relationships between research themes.

As illustrated in Figure 5.6, which essentially is a linear correlation investigation of the co-occurrence matrix, the diagonal represents the density distribution of individual themes.

The Pearson correlation coefficient (Figure 5.6) measures the linear relationship between two variables, indicating the strength and direction of this relationship. A value of 1 represents a perfect positive linear correlation, -1 represents a perfect negative linear correlation, and 0 indicates no linear correlation. It assumes that the variables are normally distributed and is sensitive to outliers.

The fact that the correlations between Hydrology and most of the themes are negative suggest that it is often the primary focus and not studied in conjunction with themes like Economy or Environmental Science. However, the positive correlation with Climate Science could be due to the natural overlap between water-related issues and climate studies. Emergency Management and Policy has a positive correlation with Economy that could be because emergency management often involves economic analysis of disasters' costs or resource allocation for emergency response.

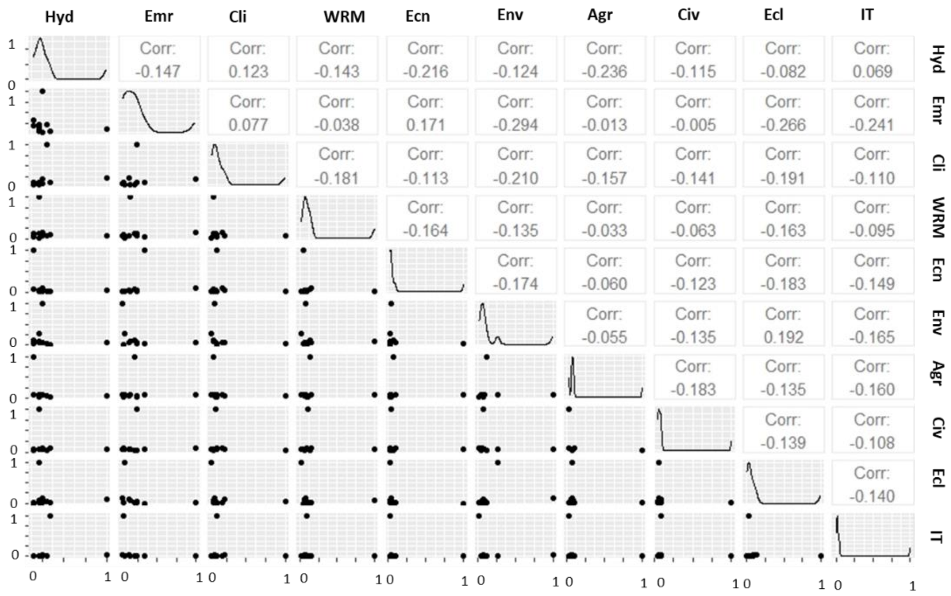


Figure 5.6. Co-occurrence Pearson correlation coefficient and data distribution matrices, Hyd (Hydrology), Emr (Emergency management and policy), Cli (Climate change), WRM (Water resources management), Ecn (Economy), Env (Environmental science), Agr (Agriculture), Civ (Civil engineering), Ecl (Ecology) and IT (Information technology).

5.5.2 Analysing monotonic relationships between research themes.

In contrast with Pearson coefficient, the Spearman correlation coefficient (Figure 5.7) assesses the monotonic relationship between two variables. This rank-based measure does not assume normality and is less affected by outliers and skewed distributions. It can detect any consistent relationship, whether linear or not. Values are interpreted similarly to the Pearson correlation, with 1 indicating a perfect positive monotonic relationship, -1 a perfect negative monotonic relationship, and 0 no monotonic relationship.

The strong positive monotonic relationship with hydrology and Information Technology might imply that hydrological studies increasingly incorporate technological tools or data analysis methods.

Emergency Management and Policy had a strong negative correlation with Information Technology, which might suggest that as emergency management becomes more policy-focused, it becomes less associated with technological aspects. Similarly, Climate Science, had a strong negative correlation with Environmental Science is intriguing, as it suggests that when studies focus deeply on climate science, they may do so to the exclusion of broader environmental considerations.

Fields	Hydrology	Emergency management and policy	Climate science	Water resources management	Economy	Environmental science	Agriculture	Civil Engineering	Ecology	Information Technology
Hydrology	N/A	-0.273	0.576	-0.055	-0.395	-0.370	-0.479	0.297	0.345	0.634
Emergency management and policy	-0.273	N/A	0.467	0.152	0.571	-0.442	0.370	-0.055	-0.564	-0.677
Climate science	0.576	0.467	N/A	-0.176	0.274	-0.709	-0.212	0.042	-0.273	-0.037
Water resources management	-0.055	0.152	-0.176	N/A	-0.067	0.091	0.273	0.467	-0.248	0.287
Economy	-0.395	0.571	0.274	-0.067	N/A	-0.055	0.498	-0.018	-0.444	-0.385
Environmental science	-0.370	-0.442	-0.709	0.091	-0.055	N/A	0.224	-0.127	0.624	0.055
Agriculture	-0.479	0.370	-0.212	0.273	0.498	0.224	N/A	-0.418	-0.321	-0.104
Civil Engineering	0.297	-0.055	0.042	0.467	-0.018	-0.127	-0.418	N/A	0.042	0.262
Ecology	0.345	-0.564	-0.273	-0.248	-0.444	0.624	-0.321	0.042	N/A	0.250
Information Technology	0.634	-0.677	-0.037	0.287	-0.385	0.055	-0.104	0.262	0.250	N/A

Figure 5.7. Spearman non-linear correlation coefficient matrix.

Water Resources Management lacked strong correlations suggests that the relationships with other themes may not be consistent or may be non-monotonic.

Economy had a strong positive relationship with Emergency Management. It could suggest a consistent trend of incorporating economic analyses into policymaking for emergencies. Similarly, Agriculture was positively correlated with Economy could indicate a consistent consideration of economic factors in agricultural research, possibly related to the economic impacts of floods and droughts on agriculture. At the same time, Civil Engineering showed a positive correlation with Hydrology and Water Resources Management that could reflect the practical need to consider water-related issues in civil engineering projects.

Environmental Science's strong negative correlation with Climate Science might suggest that studies focusing on immediate environmental impacts may not simultaneously address long-term climate trends. The results showing the negative correlations between Ecology and Emergency Management and Policy could indicate that ecological research is less prevalent in studies that are primarily policy oriented. Information Technology, similar to the linear analysis, had a strong positive relationship with Hydrology and strong negative with Emergency Management. It suggests that IT's role in hydrology is more consistent and perhaps technical, whereas in emergency management, it may be less integrated or more varied.

5.5.3 Assessing the similarity of co-occurrence patterns

Cosine similarity index (Figure 5.8) measures the cosine of the angle between two non-zero vectors in a multi-dimensional space, which in the context of co-occurrence data, represents the similarity in the pattern of co-occurrences rather than the magnitude. A value of 1 indicates that the two vectors are in the same direction (high similarity), while 0 indicates orthogonality (no similarity). When interpreting these metrics together in the context of co-occurrence of research themes, it's crucial to consider that Pearson and Spearman coefficients reveal the direction and type of relationship (linear or monotonic), whereas cosine similarity focuses on the degree of overlap in the presence of themes. Together, they can provide a comprehensive understanding of the relationships between themes, revealing not only which themes tend to co-occur but also the nature of their co-occurrence patterns, be they consistent, linear, or merely frequent. Moderate to high similarity between Emergency Management and policy with most of the other fields such as Hydrology, Climate Science, WRM and Economy indicates that these themes are often considered in the context of disaster management and response planning. Considering the risk components of analysis is mainly composed of a range of parameters described in them. Environmental Science's high similarity with Ecology (and vice versa) is consistent with the strong interrelation between environmental and ecological studies.

Fields	Hydrology	Emergency management and policy	Climate science	Water resources management	Economy	Environmental science	Agriculture	Civil Engineering	Ecology	Information Technology
Hydrology	N/A	0.593	0.527	0.329	0.221	0.296	0.373	0.385	0.367	0.255
Emergency management and policy	0.593	N/A	0.567	0.468	0.414	0.295	0.504	0.450	0.270	0.181
Climate science	0.527	0.567	N/A	0.236	0.180	0.177	0.323	0.261	0.207	0.119
Water resources management	0.329	0.468	0.236	N/A	0.141	0.200	0.323	0.281	0.191	0.131
Economy	0.221	0.414	0.180	0.141	N/A	0.110	0.249	0.176	0.068	0.044
Environmental science	0.296	0.295	0.177	0.200	0.110	N/A	0.270	0.203	0.383	0.071
Agriculture	0.373	0.504	0.323	0.323	0.249	0.270	N/A	0.226	0.207	0.088
Civil Engineering	0.385	0.450	0.261	0.281	0.176	0.203	0.226	N/A	0.185	0.149
Ecology	0.367	0.270	0.207	0.191	0.068	0.383	0.207	0.185	N/A	0.070
Information Technology	0.255	0.181	0.119	0.131	0.044	0.071	0.088	0.149	0.070	N/A

Figure 5.8. Cosine similarity matrix of thematic co-occurrence.

Agriculture had a moderate similarity with Emergency Management, which may reflect studies on agricultural resilience and recovery in the face of natural disasters. Civil Engineering showed some similarity with Hydrology and Water Resources Management that is likely due to the intersection of these fields in the design and management of water infrastructure. Finally, Information

Technology had a low similarity across the board might indicate that IT is a tool used within these fields rather than a central focus of research.

These detailed analyses across the matrices can help to identify not just how frequently themes co-occur, but also the nature of their relationships, whether they're linear, non-linear, consistent, or varying. In summary, the combined analysis across the three matrices suggests distinct patterns of research focus and interconnection among the themes. Some themes like Hydrology, Climate Science, and Environmental Science show expected connections based on the subject matter. In contrast, themes like Information Technology and Economy exhibit more complex relationships with other research areas, potentially indicative of evolving interdisciplinary trends or emerging research domains.

5.6 ADVANCED ANALYTICAL APPROACHES IN FLOOD AND DROUGHT RESEARCH: CO-OCCURRENCE, CLUSTERING, AND FIELD CONTRIBUTIONS.

When analysing a co-occurrence matrix, clustering can be useful in revealing the underlying structure and relationships among the themes. Based on their co-occurrence pattern similarity, this grouping themes technique makes it easier to identify clusters of themes.

5.6.1 Determining optimal parameters with the knee method: "selecting eps value for DBSCAN clustering.

The Knee method, also known as the "elbow" method, is a technique used to determine an optimal value for the "eps" parameter in clustering algorithms, particularly in Density-Based Spatial Clustering of Applications with Noise (DBSCAN) method (Figure 10). "eps" stands for epsilon, which defines the maximum distance between two points for them to be considered as in the same neighbourhood. While popular with DBSCAN, the Knee method can also be useful in other clustering methods or situations where a critical threshold needs to be determined from a curve.

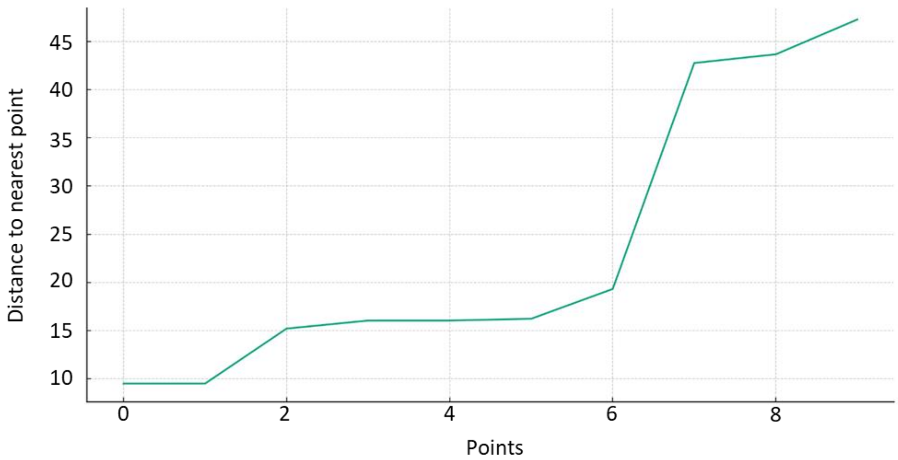


Figure 5.9. Determining the optimum "eps" for clustering the themes using the Knee method.

Choosing the right eps is crucial for the effectiveness of DBSCAN (Figure 5.9). Using DBSCAN clustering with eps approximately equal to 16.03 and minimum of samples set to 2 (both are optimised values), the research themes have been clustered as follows (Table 5.1).

These clusters suggest that "Water resources management" and "Environmental science" share a close co-occurrence pattern, as do "Agriculture", "Civil Engineering", and "Ecology".

Table 5.1. Clusters of research themes based on DBSCAN method.

Clusters	Theme
Cluster 0	Water resources management, Environmental science
Cluster 1	Agriculture, Civil Engineering, Ecology
Noise	Hydrology, Climate science, Emergency management and policy, Economy, IT

The remaining themes did not group tightly enough to form clusters with the given parameters. The 'Noise' label in DBSCAN indicates themes that did not fit well into a cluster with others, potentially due to less frequent or inconsistent co-occurrence with other themes. Clustering themes as noise could be a result of considering them as outliers, which could be due to a relatively large difference in the higher average of their co-occurrence compared to that of the other themes. Therefore, it could be more efficient to apply the same outcome of the "eps" to hierarchical clustering. In this context, it is a method to organize and interpret the relationships between different research themes based on how often they co-occur in the literature. It offers insights into how these themes are interconnected and can guide researchers in identifying closely related areas or potential new avenues for interdisciplinary links.

5.6.1 Applying hierarchical clustering to co-occurrence data: "grouping themes based on similarity.

In hierarchical clustering, the distance between any two themes is calculated without considering directionality, and the resulting dendrogram groups themes based on the similarity of their co-occurrence patterns with all other themes. Similarly, spectral clustering and DBSCAN do not take the direction of the relationship into account.

This approach is typical when the order of co-occurrence does not carry additional meaning, which is often the case in co-occurrence matrices unless the matrix was specifically constructed to reflect a directional relationship, such as citation direction in bibliometric data or the flow of processes in a system.

Themes that merge at lower heights of the dendrogram are more similar to each other (Figure 5.10). The height at which two themes or clusters merge represents the distance or dissimilarity between them. The dendrogram can be used to interpret both the relationships within clusters (intra-cluster) and between different clusters (inter-cluster). Themes within the same cluster should have more in common with each other than with themes in different clusters. Similar to results derived from DBSCAN method, “Agriculture” and “Civil Engineering” are linked together at the lowest distance, which at a higher distance are coupled with “Ecology” to form the part one. On the other hand, with a slightly higher distance, “Water resources management” and “Environmental science” are joined together. This combination is grown by “Information technology” being added to the team. These three themes at the distance of about 30 are joined with “economy” to form the second part. All the themes mentioned so far are joined by “Climate science” at distance 66, then by “Hydrology” at 73 and finally by “Emergency management and policy” at distance 78. This classification will later help identify areas of higher importance in studying flood and drought and find the parameters with valuable links to define and assess the risk of flood and drought. The following sections are devoted to explaining the most cited themes and sub-themes that contribute to defining these risks. These estimates are based on peer reviewed published research, derived from a systematic literature review and further content analysis (partly described in previous sections), and there may be some overlap and variability in their assessments. The overall process of this systematic review is outlined in chapter two.

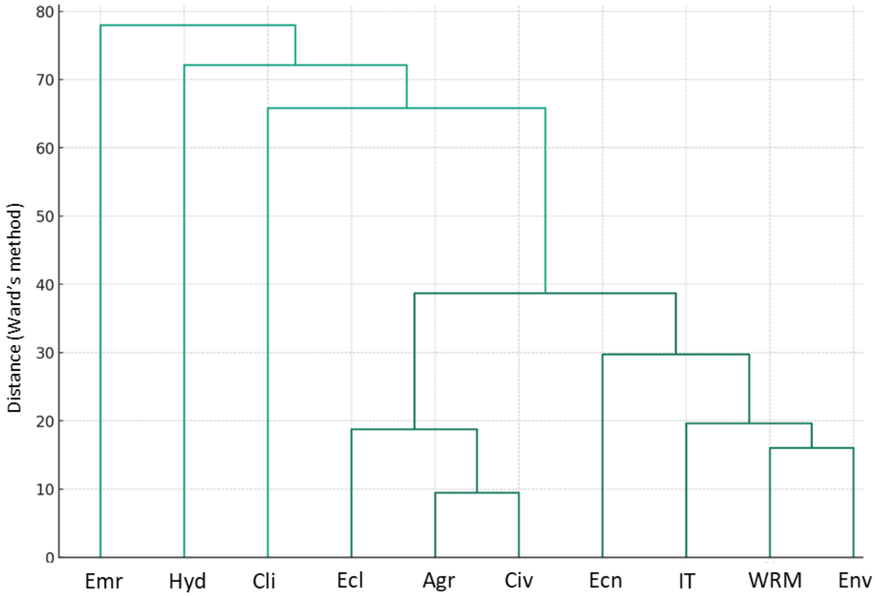


Figure 5.10. Hierarchical clustering dendrogram of the research themes.

5.7 MAPPING KEY RESEARCH FIELDS IN FLOOD AND DROUGHT STUDIES: "TOP CONTRIBUTING FIELDS AND THEIR SUBFIELDS.

Results from analysing the context of the literature and categorizing them into sub-fields led to formation of the following breakdown (Table 5.2), which represents the top twenty fields that contribute to current understanding of both flooding and drought risk. As described in Table 5.2, many fields actively research flooding and drought from various perspectives. In some cases, the study focuses primarily on the physical factors contributing to the risk of flooding and drought, such as hydrological and terrestrial factors. Other fields are working towards adapting and risk-mitigating schemes. A wide range of recently published efforts is in line with realising and addressing the aftermath impacts of hydro hazards. For instance, the research focuses on the social and economic impacts of flooding and drought, such as the effects on agriculture, infrastructure, and public health. Additionally, some studies focus on the psychological effects of flooding and drought, such as the impact on individuals and communities. However, this research focuses on the fields that, based on the systematic literature review, together contribute to 75% of our understanding of flooding and drought risk. These fields and their sub-fields are illustrated in Figure 5.11.

Table 5.2. Fields and their subfield that contribute to the risk of F&D.

Field	Subfield	Field Contribution %		Field	Subfield
Hydrology	Geology Geomorphology Hydrogeology	15	3	Public health	Waterborne diseases Vector-borne diseases Environmental health
Climate science	Meteorology Climatology Atmospheric science	10.5	3	Energy	Renewable energy Energy efficiency Energy policy
Water resources management	Water supply management Irrigation engineering Water treatment technology	9	3	Policy studies	Environmental policy Water policy Climate policy
Environmental science	Environmental engineering Environmental policy Natural resource management	8	3	Anthropology	Cultural anthropology Disaster anthropology Human ecology
Civil engineering	Coastal engineering Transportation engineering Structural engineering	7	2	History	Environmental history Water history Disaster history
Agriculture	Crop science Soil science Agroforestry	6.5	2	Philosophy	Environmental ethics Sustainability ethics Disaster ethics
Emergency management	Disaster response planning Crisis management Risk assessment	6	2	Education	Environmental education Disaster education Water education
Economics	Natural resource economics Agricultural economics Water economics	6	2	Psychology	Risk perception Coping strategies Trauma response
Information technology	Remote sensing GIS Computer modelling	4	2	Communications	Risk communication Crisis communication Public relations
Ecology	Restoration ecology Ecosystem services Biodiversity conservation	4	2	Tourism	Sustainable tourism Disaster tourism

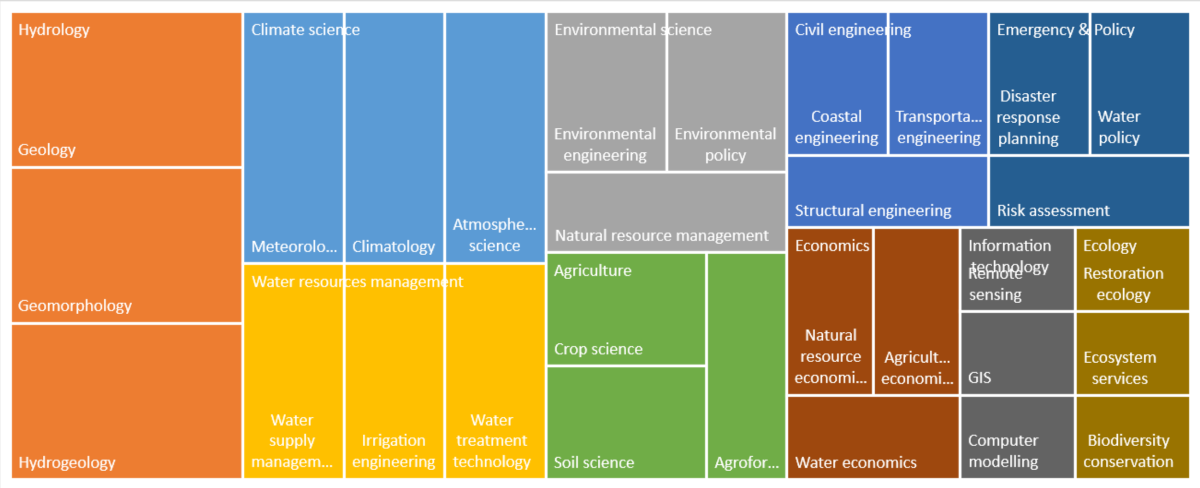


Figure 5.11. Fields that contribute to 75% of our understanding of flooding and drought risk.

5.8 Thematic analysis of main contributing fields in flood and drought research.

5.8.1 Hydrology: understanding water dynamics in river basins.

Hydrology lays the foundation for understanding the dynamics of water movement and storage within a river basin. Key sub-themes include hydrological modelling, flood forecasting, drought monitoring, and groundwater-surface water interactions. Unravelling the hydrological processes and their interactions with climatic variables is pivotal for risk assessment and management. The outcome of thematic content analysis led to articulating the main sub-themes of hydrology related to flooding and drought risks at a river basin scale into three categories. Firstly, Hydrological modelling and forecasting including physiographical factors, such as precipitation, evaporation affect water flow (surface and subsurface) and storage within river basins (Doswell, 2015; Pavur and Lakshmi, 2023). These models can be utilised to forecast flooding and drought events, aiding in early warning and preparedness. This sub-field has a direct connection with some of other themes such as Water Resources Management. Recent progress in Information technology has made the way smoother for the collection of hydrological data from satellite-based Earth observations (NDVI, LCLU), which can be instrumental in comparing flood and drought events over time and across different regions (Pavur and Lakshmi, 2023).

The analysis of hydrological extremes such as floods and droughts include analysing the severity, frequency, and variability of these events. Understanding the impacts of climate change and anthropogenic stressors on water resources (Population growth, Migration) and assessing the risks posed to communities and infrastructure are integral components of this sub-theme (Gebrechorkos et al., 2022; Satoh et al., 2022, Fasihi et al., 2021).

These sub-themes encompass a span of methodologies and technologies that contribute to the comprehensive understanding and management of flooding and drought risks at a river basin scale. Through hydrological modelling and forecasting, enhanced data acquisition via remote sensing, and meticulous investigation of hydrological extremes, stakeholders can better prepare for, respond to, and mitigate the adverse impacts of these hydrological events. The parameters that contribute to understanding the risk of flooding and drought that are extracted from this theme are tabulated here (Table 5.3).

Table 5.3. Hydrological parameters that affect risk of flooding and drought.

Hydrology				
Elevation	Slope	Distance to river	Percolation	Land cover/use
Soil moisture	Soil type	River Density	Flood level	Precipitation
Evapotranspiration	Runoff	Seepage from groundwater to surface water	Evaporation	Snowmelt pattern

5.8.2 Climate science: impact on hydrology and water events

Climate science enhances our understanding of how atmospheric phenomena influence water availability and hydrological events. Specifically, climate change projections, extreme weather events, and their implications for flooding and drought are discussed.

At the river basin scale, Meteorology, Climatology, and Atmospheric Science provide a comprehensive understanding of flood and drought risks.

To forecast and understand immediate hydrological responses in river basins, it is imperative to have a thorough understanding of weather patterns, such as precipitation, temperature, humidity, and wind. Meteorological models can be helpful in forecasting heavy rainfall events within a river basin (Li et al., 2023). Studies underlines the significance of using large-scale climate models to simulate future climate conditions and their potential impact on water resources at a river basin level (Talsma et al., 2023; Wu et al., 2022). For example, higher levels of atmospheric humidity can increase the intensity of precipitation and contribute to hydrological extremes (Payne et al., 2020).

The way meteorological, climatological, and atmospheric phenomena interact with each other has a significant impact on how water behaves in river basins (Table 4.4). This knowledge can help in making more informed decisions and developing effective risk management strategies at the river basin level.

Table 5.4. Climatic parameters that affect risk of flooding and drought.

Climate science				
Change factor	Wind speed	Temperature	Air humidity	Precipitation

5.8.3 Strategic water resources management for flood and drought resilience

The sustainable utilization and protection of water resources within a river basin constitute the water resources management field that demands effective management. This field entails sub-themes such as water allocation, reservoir management, and integrated water resources management (IWRM), employed to create a balance between water supply and demand across different regions (Transferred inflow) (Dirwai et al., 2021). A comprehensive approach to water resources management in a river basin guarantees the careful allocation of water resources, the careful management of water reservoirs, and the effective implementation of IWRM strategies. With careful planning and implementation, it is possible to balance the competing demands while minimizing the risks associated with flood and drought (Water resources sustainability index). Three main sub-themes of WRM are Water supply management Irrigation engineering and Water treatment technology. Irrigation engineering focuses on designing, constructing, and operating irrigation systems to provide water to agricultural lands, thereby enhancing food security. Well-designed and managed irrigation systems are vital to maintaining agricultural productivity during drought conditions. Moreover, irrigation engineering also encompasses flood management to prevent waterlogging and soil erosion during heavy rainfall or flooding events. (Singh et al., 2019) . Market allocation and tradeable water rights are among the mechanisms that can facilitate efficient water use and allocation in different sectors (Deng et al., 2022). The combination of these sub-themes works together to create a more durable and sustainable framework for managing water resources. This framework can effectively handle the challenges posed by flooding and drought on a river basin scale. By practicing careful water supply management, utilizing effective irrigation engineering, and implementing fair water allocation practices and parameters (Table 5.5), we can mitigate the negative impacts of extreme hydrological events and promote the sustainable use of water resources in river basins (Singh et al., 2019; Deng et al., 2022).

Table 5.5. Water resources management parameters that affect risk of flooding and drought.

Water resources management				
Water consumption	Water demand	Water supply	Returned flow	Water inflow/outflow
Water abstraction	Transferred inflow	Irrigation water requirement	Per capita water consumption	Water resources sustainability index

5.8.4 Environmental science approaches to flood and drought

Environmental science studies the connection between natural processes and human activities. It focuses on topics such as managing watersheds, controlling erosion, changing land use, and ensuring the ecological well-being of river systems. Environmental science is vital to understanding and mitigating flooding and drought risks, especially on a river basin scale (Table 5.6). Environmental Engineering (Kiedrzyńska et al., 2015), Environmental Policy, and Natural Resource Management (NRM) (Poff et al., 2016; Tan et al., 2022) are three sub-disciplines of Environmental Science that play a significant role in managing these risks (Wang et al., 2022; Crespo et al., 2022). The NRM policy measures could include flood risk management strategies, drought preparedness plans, and climate change adaptation initiatives (Wang et al., 2022; Crespo et al., 2022). Understanding the environmental aspects of flooding and drought risks at a river basin level involves exploring various sub-themes.

These sub-themes form a holistic understanding and can assist in devising robust strategies to mitigate the adverse effects of hydrological extremes. An interdisciplinary approach that includes engineering solutions, policy frameworks, and sustainable resource management practices is necessary to promote environmental sustainability in river basins (Wang et al., 2022; Crespo et al., 2022).

Table 5.6. Environmental Science parameters that affect risk of flooding and drought.

Environmental science				
Soil Erosion	Environmental flow	Land cover/use	Surface water inflow	Returned flow

5.8.5 Agricultural strategies for managing flood and drought risks

Agriculture is a crucial sector that is highly susceptible to the negative impacts of flooding and drought, particularly at a river basin level (Table 5.7). It deals with examining the vulnerability and adaptive capacity of food production systems. The sub-themes of Crop Science, Soil Science, and Agroforestry are essential in devising strategies that help in fighting against these hydrological challenges. These strategies include irrigation management, crop diversification, and soil conservation practices that enhance the resilience of food production systems against water-related shocks. In the context of flooding and drought risks, there are sub-themes such as Crop science (Quandt et al., 2023), Soil science (Acevedo et al., 2020) and Agroforestry (Brown et al., 2018) that conclude the role of Agriculture field.

Through the interplay of these sub-themes, it is possible to build a more resilient agricultural sector capable of withstanding the adversities of flooding and drought at a river basin scale. These sub-themes, through their distinct yet interconnected focus areas, contribute significantly to the overall sustainability and resilience of agricultural systems in the face of hydrological extremes (Wilson and Lovell, 2016).

Table 5.7. Agriculture parameters that affect risk of flooding and drought.

Agriculture				
Land cover/use	Actual land area for crop	Expected land area	Crop pattern	Soil moisture
Irrigation Efficiency	Cultivation cost	Irrigation water requirement	Precipitation	NDVI
Delivery rate	Production of crops	Benefit from crops	Surface water inflow	Expected agricultural water requirement

5.8.6 Economic perspectives on flood and drought mitigation

Evaluating the costs and benefits of flood and drought mitigation measures requires economic analyses. This involves assessing water resources value, conducting economic impact evaluations, and creating financial instruments like insurance schemes (Table 5.8).

When it comes to flood and drought risks at a river basin scale, economics plays a crucial role in analysing the financial and resource allocation implications of these hydrological extremities. The main sub-themes of economics in this context are Natural Resource Economics, Agricultural Economics, and Water Economics, each highlighting different aspects of the economic interaction involved. Here's a closer look at these sub-themes in the context specified. Natural resources, Agricultural and water economics are the main sub-themes of the Economics which deal with the risk of flood and drought more directly.

The aim of Natural resource economics and sustainable resource management is to understand the significance of natural resources in the economy, which is crucial for developing sustainable management strategies in fluctuating hydrological conditions (Martin, 2019). Emerging from the amalgam of farm economics and management, Agricultural Economics has broadened to encompass the entire food supply chain, natural resources, and development. The focus extends to analysing the economic viability and impact of various agricultural practices aimed at mitigating the risks associated with these hydrological extremities (Tietenberg, 2018).

5.8.6.1 Water economics: analysing scarcity and management impacts

Water Economics delves into the economic implications of water scarcity, allocation, and management, especially in the face of flooding and drought. The sub-theme explores how water scarcity can have a ripple effect on the economy at both the basin and global levels. Studies indicates that higher physical water scarcity can result in both positive and negative economic impacts, depending on various factors such as the basin's adaptive capacity and global land-use policies (Dolan et al., 2021). By exploring the sub-themes, which are intricately interlinked, we can gain a comprehensive understanding of the economic dynamics that are associated with the risks of flooding and drought at a river basin scale. This exploration can enable stakeholders to better formulate policies and strategies that can mitigate the adverse economic impacts of such hydrological challenges, ensuring sustainable resource management and economic resilience (Eamen et al., 2021).

Table 5.8. Economic parameters that affect risk of flooding and drought.

Economy				
National economic growth rate	Added value	Net benefit	Benefit from crops	Flood premium
Watershed economic development rate	Cultivation cost	Flood alleviation investment	Access to insurance	Required insurance
Disaster alleviation investment	Drought alleviation investment	Drought premium	Drought relief	Flood relief

5.8.7 Emergency management and policy in flood and drought contexts

Effective preparedness, response, and recovery strategies are crucial in minimizing the adverse impacts of flooding and drought. These strategies encompass disaster risk reduction, early warning systems, and community-based disaster management (Table 5.9).

Emergency management plays a pivotal role in mitigating the risks and addressing the challenges posed by flooding and drought, especially at a river basin scale. The three sub-themes of emergency management - Risk Assessment, Crisis Management, and Disaster Response Planning - are essential in orchestrating a well-rounded approach to handling these hydrological adversities. Policy studies evaluate the governance frameworks, policies, and institutional arrangements necessary for an effective flood and drought risk management. Sub-themes include policy analysis, regulatory frameworks, and multi-level governance. Following is a detailed breakdown of these sub-themes in the context of flooding and drought risks at a river basin scale.

Risk assessment is crucial to emergency management. It involves identifying, analysing, and evaluating potential hazards and the risks they pose. This process enables us to understand the vulnerabilities and potential impact of flooding and drought on communities and ecosystems within a river basin. By conducting a systematic risk assessment, emergency managers can prioritize actions and allocate resources more effectively to mitigate the identified risks. Overall, risk assessment is the foundation of effective emergency management (Department of Homeland

Security, U.S., 2008). Effective crisis management ensures that the necessary measures are taken in a timely and organized manner. This is to protect lives, property, and the environment during and after a crisis event.

These sub-themes offer a structured approach to managing flooding and drought risks at the river basin level. By conducting meticulous risk assessments, implementing robust crisis management, and developing well-thought-out disaster response plans, it is possible to mitigate the adverse effects of hydrological extremes and increase river basins' resilience (Federal Emergency Management Agency, 2010; Lindell, 2020).

Table 5.9. Emergency management and policy parameters that affect risk of flooding and drought.

Emergency management and policy				
Flood Risk	Migration	Early warning systems	Health facility	Residents' utility
Population growth rate	Population	The ratio of basin's GRP to neighbouring basins	Drought Risk	Public demand for mitigation
Flood premium	Required insurance	Access to insurance	Flood relief	Dependence on flood relief
Community resilience	Drought relief	Drought premium	Dependence on drought relief	Risk perception
Flood impact	Drought impact	Flood Vulnerability	Drought Vulnerability	Flood Exposure
Drought Exposure	Flood hazard	Drought hazard	Flood awareness	Drought awareness

5.8.8 Civil engineering's role in flood and drought risk management

Civil engineering is essential in the design and maintenance of infrastructure that can withstand, manage, and mitigate the impacts of flooding and drought. Hydraulic engineering, floodplain management, dam and reservoir design, and the construction of water-retention and drainage systems are key sub-themes of civil engineering (Table 5.10). At a river basin scale, civil engineering plays a vital role in mitigating the risks associated with flooding and drought. The sub-themes of civil engineering, namely structural engineering, transportation engineering, and coastal engineering, contribute to this endeavour in various ways (Ding et al., 2020; Trinh and Molkenthin, 2021).

Structural engineering plays a crucial role in designing sturdy structures that can withstand the impact of natural disasters such as floods and droughts. It involves developing structural designs and implementing measures such as dams, levees, and reservoirs that aid in flood prevention, water storage, and drought management. Transportation engineering is a field that aims to facilitate the safe and efficient movement of people and goods, especially in adverse weather conditions. In the event of flooding or drought, it is essential to have resilient infrastructure such as roads, bridges, and ports that can continue to function. That's where transportation engineering comes in, providing the expertise needed to design and build infrastructure that can withstand these extreme conditions (Liu et al., 2020).

Coastal engineering is crucial for managing the risks associated with flooding in coastal and river basin areas. This sub-theme involves designing structures like sea walls, bulkheads, and revetments to protect against coastal flooding. Additionally, coastal engineers work on flood hazard mapping and the development of flood control structures. This is to reduce inundation areas, flood stages, and flooding duration in coastal river basins (Wolanski et al., 2011; Jha et al., 2020).

Together, these sub-themes of Civil Engineering contribute to a comprehensive approach to managing the risks of flooding and drought at a river basin scale. This ensures the resilience and sustainability of infrastructure systems amidst hydrological adversities.

Table 5.10. Civil Engineering parameters that affect risk of flooding and drought.

Civil Engineering				
Flood shelter	Urbanization	Transportation network	Irrigation efficiency	Flood level
Precipitation	Dam/Reservoir	Subsurface storage	Storm control	Dike/Levee

5.8.9 Ecological perspectives in flood and drought risk management.

Ecology studies the relationships between living things and their environment in river basins. Its sub-themes include the study of aquatic and riparian ecosystems, biodiversity, habitat restoration, and the ecological impacts of hydrological extremes (Table 5.11).

As a field, ecology plays a significant role in understanding and addressing the risks of flooding and drought, especially at a river basin level. Restoration Ecology, Ecosystem Services, and Biodiversity Conservation are three sub-themes that are particularly relevant to this scenario. Restoration projects across the globe have demonstrated positive impacts on both biodiversity and ecosystem services, underscoring the significance of ecological restoration as a means of mitigating the adverse effects of hydrological extremes (Benayas et al., 2009; Bullock et al., 2011). Ecosystems possess a natural ability to regulate floods and droughts to some extent. It is crucial to recognize the provision of ecosystem services such as water regulation, water quality, and disease regulation, among others, in the context of flooding and drought. In fact, the natural capacity of ecosystems can decrease both the severity and frequency of floods. Furthermore, it is essential to evaluate the implications of drought on freshwater provisioning and food provisioning services, as drought is a widespread extreme climate event with the potential to alter freshwater availability and related ecosystem services (Li et al., 2017; Hua et al., 2022).

Preserving the variety of life in all its forms is the main concern of biodiversity conservation. This is significant as biodiversity plays a crucial role in making ecosystems resilient to flooding and drought (Vári et al., 2022). Considering the management of risks associated with flooding and drought at a river basin scale, the sub-themes of ecology play a vital role in devising a comprehensive approach. Restoration ecology helps to restore ecosystem health and function. Meanwhile, understanding the benefits that humans derive from ecosystems is made possible through the lens of ecosystem services. On the other hand, biodiversity conservation aims to maintain the ecological balance and resilience of these ecosystems against hydrological adversities.

Table 5.11. Main parameters of Ecology discipline that affect risk of flooding and drought.

Ecology		
Biodiversity	Environmental flow	Surface water inflow

5.8.10 Leveraging information technology in flood and drought risk management

Information Technology (IT) plays a crucial role in enhancing data acquisition, modelling, and decision-making in managing flood and drought risks (Table 5.12). The sub-themes under this umbrella term, which are Remote Sensing, Geographic Information Systems (GIS), real-time monitoring systems, and the development of decision support systems, are noteworthy. These sub-themes, especially Remote Sensing, GIS, and Computer Modelling, have significantly improved the understanding and management of flood and drought risks at a river basin scale. Below, I've explained how each of these sub-themes contributes.

Remote Sensing technologies play a crucial role in monitoring hydrological variables and detecting flood and drought events. Multispectral imaging, LIDAR, and radar technologies enable the collection of essential data for flood prediction and monitoring of drought impacts. Similarly, the use of Geographic Information Systems (GIS) has brought about a significant change in the way spatial data is managed. With the help of computer modelling, GIS enables the processing of vast amounts of spatial data to extract valuable insights, which is especially useful in assessing and monitoring the risk of drought and flood. This technology has proven to be a game-changer in flood and drought risk management.

IT encompasses several sub-themes that work together seamlessly to provide a strong foundation for obtaining, analysing, and comprehending data that is crucial for comprehending and mitigating the dangers linked with floods and droughts at a river basin level. By constantly improving these areas, IT allows for a more accurate, timely, and efficient response to the obstacles presented by hydrological extremes.

Table 5.12. Main parameters of Ecology discipline that affect risk of flooding and drought.

Information Technology					
NDVI	Precipitation	Temperature	Early warning systems	Land cover/use	Elevation

5.9 Complementary fields in flood and drought risk assessment

These themes are all utilized in assessing the risk of flooding and drought because they influence how people respond to these risks and how they can be managed, compared to the main themes are less considered.

5.9.1 Public health: addressing health impacts of hydrological extremes

Public Health: Public health investigates the health implications of flooding and drought, focusing on waterborne diseases, mental health stressors, and the provision of safe drinking water and sanitation facilities during crises.

5.9.2 Interdisciplinary perspectives: energy, anthropology, and policy studies

Energy: The energy sector explores the interlinkages between water and energy, scrutinizing the impacts of hydrological extremes on energy production, particularly hydropower, and the energy requirements for water treatment and distribution.

Anthropology: Anthropology examines the cultural, social, and human dimensions of flood and drought risks, including community resilience, traditional knowledge systems, and the socio-cultural impacts of water scarcity and excess.

Policy Studies: Policy studies evaluate the governance frameworks, policies, and institutional arrangements essential for effective flood and drought risk management. Sub-themes include policy analysis, regulatory frameworks, and multi-level governance.

5.9.3 Communication, education, and historical lessons in risk management

Communications: Effective communication strategies are pivotal for risk awareness, disaster preparedness, and community engagement. This field emphasizes public awareness campaigns, risk communication, and media relations in the context of hydrological extremes.

Education: Education fosters a culture of understanding, preparedness, and action against flood and drought risks. It embraces curriculum development, public education, and professional training to enhance societal resilience.

History: Historical analyses provide insights into past flooding and drought events, societal responses, and the evolution of risk management strategies over time. This field underscores the importance of historical lessons in shaping contemporary and future approaches.

5.9.4 Integrating philosophy, psychology, and tourism into risk management

Philosophy explores the ethical, moral, and value-based considerations inherent in flood and drought risk management, provoking reflection on human-nature interactions, justice, and sustainability.

Psychology investigates the human behavioural and mental health aspects, including stress, trauma, and the psychological factors influencing risk perception and decision-making during hydrological extremes.

Finally, Tourism examines the vulnerability and adaptability of the sector to flooding and drought, exploring the economic implications, disaster preparedness, and the promotion of sustainable tourism practices within river basins.

5.10 Assessing Flood and Drought Risks: The Role of Interdisciplinary Parameters

By considering the various fields related to flood and drought risk factors at the river basin level, we can gain a more comprehensive understanding of these hydrological extremes. An interdisciplinary approach is crucial in developing effective and sustainable solutions to mitigate their negative impacts. By adopting an integrative perspective, we can identify a simpler pathway towards building resilient river basins. This emphasizes the importance of collective responsibility and action to tackle the complex water-related challenges of the 21st century.

As described earlier, the concept of risk has two main components, namely hazard and impact, which in turn impact breaks down to exposure and vulnerability. Investigating the literature revealed that 25% of parameters within the context of both flooding and drought risk correspond to hazards whereas the remaining contribution is reserved for vulnerability and exposure. However, this ratio varies spatially and between the risk of flood and drought individually. So far, many fields' contribution has been spotted, results from the thematic analysis gathered and scaled show that which fields are the most influential to understanding of the mentioned risks and are interconnected at the same time (Figure 5.12).

As it is illustrated, Emergency Management and Policy is the only field that is well connected to all the fields whilst IT is more linked with Economics, Civil Engineering, WRM and Environmental Science.

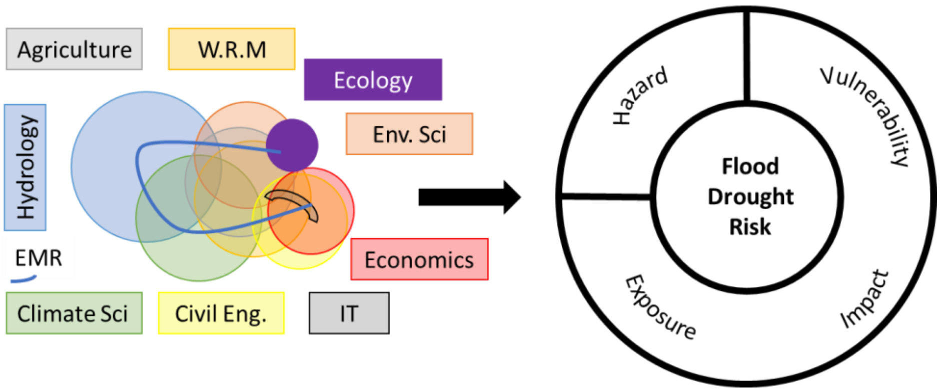


Figure 5.12. Scaled Thematic analysis of contributor fields. (W.R.M) Water Resources Management, (Env. Sci) Environmental Science, (EMR man) Emergency Management, (Civil Eng.) Civil Engineering. (Climate Sci) Climate Science, (IT) Information Technology.

A total number of 116 parameters and some of their prominent interactions were extracted that rationally and based on the literature were directly or indirectly contributed to the risk of flood and drought (Table 5.13). So far, fields, sub-fields, and parameters that are involved in describing of our understanding of the flood and drought risks are systematically extracted from the literature.

Table 5.13. Parameters involved in understanding the risk of flood and drought.

Parameter name	Num.	Parameter name	Num.
Change Factor	p1	Industrial added value	p59
Flood Risk	p2	Domestic added value	p60
Flood shelter	p3	Agricultural added value	p61
Urbanization	p4	Per capita water consumption	p62
Migration	p5	Population growth rate	p63
Elevation	p6	Population	p64
Slope	p7	Per capita domestic water demand	p65
Transportation network	p8	Per capita domestic water demand growth rate	p66
Early warning systems	p9	Per capita industrial water demand	p67
Health facility	p10	Per capita industrial water demand growth rate	p68
Distance to river	p11	The ratio of basin's GRP to neighbouring basins	p69
NDVI	p12	Per capita agricultural water demand	p70
Snowmelt pattern	p13	Per capita agricultural water demand growth rate	p71
Biodiversity	p14	Water resources sustainability index	p72
LC/LU	p15	Watershed water consumption	p73
Soil moisture	p16	Watershed economic development rate	p74
Soil type	p17	Drought Risk	p75
Wind speed	p18	Irrigation efficiency	p76
River density	p19	Net agricultural water use	p77
Flood level	p20	Delivery rate	p78
Soil erosion	p21	Actual land area for crop	p79
Precipitation	p22	Expected agricultural water requirement	p80
Temperature	p23	Cultivation cost	p81
Evapotranspiration	p24	Net benefit	p82
Available surface water	p25	Production of crops	p83
Available groundwater	p26	Expected land area	p84
Returned flow	p27	Irrigation water requirement	p85
Water supply	p28	Benefit from crops	p86
Water use	p29	Crop pattern	p87
Water demand	p30	Expected water requirement	p88
Surface water inflow	p31	Public demand for mitigation	p89
Domestic demand	p32	Flood alleviation investment	p90
Industrial demand	p33	Flood premium	p91
Agricultural demand	p34	Required insurance	p92
Domestic water use	p35	Access to insurance	p93
Agricultural water use	p36	Flood relief	p94
Industrial water use	p37	Dependance on flood relief	p95
Agricultural returned flow	p38	Community resilience	p96
Industrial returned flow	p39	Drought relief	p97
Domestic returned flow	p40	Drought premium	p98
Groundwater withdrawal	p41	Dependance on drought relief	p99
Groundwater outflow	p42	Drought alleviation investment	p100
Groundwater returned flow	p43	Risk perception	p101
Groundwater inflow	p44	Dike/Levee	p102
Natural groundwater inflow	p45	Storm control	p103
Surface water returned flow	p46	Subsurface storage	p104
Transferred inflow	p47	Dam/Reservoir	p105
Natural surface water inflow	p48	Flood impact	p106
Surface water outflow	p49	Drought impact	p107
Percolation	p50	Flood Vulnerability	p108
Surface water withdrawal	p51	Drought Vulnerability	p109
Seepage from groundwater to surface water	p52	Flood Exposure	p110
Evaporation	p53	Derought Exposure	p111
Runoff	p54	Flood hazard	p112
Environmental flow	p55	Drought hazard	p113
Residents' utility	p56	Flood awareness	p114
National economic growth rate	p57	Drought awareness	p115
Added value	p58	Air humidity	p116

6 Results and discussion: Advanced causal framework construction for flood and drought risk assessment: an integration of ISM-CLD and network theory

6.1 CHAPTER INTRODUCTION

This chapter delineates the development of an advanced causal framework for assessing the risk of flooding and drought, a crucial component in understanding and managing these complex hydrological events. The framework's construction is rooted in the integration of Interpretive Structural Modelling (ISM) and Causal Loop Diagrams (CLD), methodologies renowned for their effectiveness in analysing and visualizing complex systems and their interrelated components (Eshun and Chan, 2021).

The essence of this research lies in identifying and meticulously selecting a set of parameters that significantly influence flood and drought risks. These parameters are derived from a thorough review of existing literature and empirical studies, encompassing a diverse range of factors such as environmental conditions, climatic variability, socio-economic factors, and infrastructural aspects. Such a comprehensive selection reflects the multifaceted nature of flood and drought risks within river basins. Central to the framework's development is the establishment of causal relationships between these selected parameters. The ISM methodology facilitates a structured approach to understanding these interactions, allowing for the hierarchical arrangement of variables and elucidating their direct and indirect influences within the system. Complementing this, CLD provides a dynamic perspective by illustrating feedback mechanisms and recurring patterns that could amplify or mitigate the risks.

A significant challenge in flood and drought risk assessment is managing the extensive array of possible risk pathways. To streamline this complexity, principles of graph theory are applied. This mathematical approach aids in reducing the number of pathways, focusing the framework on more targeted and relevant modelling scenarios. The application of graph theory ensures that the framework remains both comprehensive and manageable, enhancing its practical utility in risk analysis.

The framework presented in this chapter is not merely theoretical; it is designed to be a pragmatic tool for various stakeholders, including policymakers, urban planners, and environmental researchers. It offers a detailed understanding of the causal factors driving flood and drought risks and their interdependencies, facilitating informed decision-making and effective policy formulation.

Subsequent sections of this chapter will expound on the methodologies employed in constructing the framework, and the integration of ISM-CLD with graph theory. The chapter aims to underscore the scientific and practical implications of this framework in flood and drought risk management, contributing valuable insights to the field of sustainable water resource management in an era marked by increasing climatic uncertainties.

6.2 Analysing risk management through hierarchical structuring and MICMAC analysis

The procedure begins with constructing a Structural Self-Interaction Matrix (SSIM) to detail interactions among various parameters through pairwise comparisons. This SSIM then serves as the foundation for creating an initial reachability matrix by translating the VAXO (Symbols explained in section 4.5 and Figure 4.1) matrix into binary form, facilitating the identification of direct and indirect parameter interactions. Subsequently, the Final Reachability Matrix is developed to examine transitive relationships, enabling the assessment of the framework's hierarchical structure through Level Partitioning. Finally, "Matrice d'Impacts Croisés Multiplication Appliquée à un Classement" MICMAC Analysis is applied, emphasizing the importance of understanding the hierarchical organization of elements and their interconnections, a key aspect in effective risk management planning and control.

6.2.1 Structural Self-Interaction Matrix (SSIM)

The SSIM defines the interactions among various parameters using a pairwise comparison, where the interpretative logic and direct relationships among the parameters are depicted in Table 6.1. In presenting the results of this study, it's important to note that the comprehensive tables generated are too extensive to be fully included within the main body of the text. To ensure clarity and maintain the readability of the document, only a representative sample of each table is displayed in the main sections. The complete tables, in their entirety, are meticulously catalogued and provided in the Appendix (Supplementary_material_ISM). This approach allows for a detailed examination of the full data sets while preserving the flow and coherence of the main text. Readers interested in a deeper exploration of the complete data can refer to the supplementary spreadsheet.

Table 6.1. Structural Self-Interaction Matrix (SSIM).

	P1	P2	P3	P4	P5	P6	P7	P8	P9
P1	X								
P2		X							
P3			X						
P4				X					
P5				X	X				
P6						X			
P7							X		
P8				V				X	
P9									X

• • •

	P108	P109	P110	P111	P112	P113	P114	P115	P116
P108	X								
P109		X							
P110			X						
P111				X					
P112					X				
P113						X			
P114							X		
P115							X	X	
P116									X

6.2.2 Initial Reachability Matrix

The formation of the initial reachability matrix originates from the SSIM by converting the VAXO matrix into a binary format. For instance, cell P4P8 is V. The binary conversion for this cell is 1 and 0 for P8P4. The outcome of the 116 × 116 binary matrix of risk relationships is presented in Table 6.2.

Table 6.2. Initial Reachability Matrix

	P1	P2	P3	P4	P5	P6	P7	P8	P9
P1	1	0	0	0	0	0	0	0	0
P2	0	1	0	0	0	0	0	0	0
P3	0	0	1	0	0	0	0	0	0
P4	0	0	0	1	1	0	0	0	0
P5	0	0	0	1	1	0	0	0	0
P6	0	0	0	0	0	1	0	0	0
P7	0	0	0	0	0	0	1	0	0
P8	0	0	0	1	0	0	0	1	0
P9	0	0	0	0	0	0	0	0	1

• • •

	P108	P109	P110	P111	P112	P113	P114	P115	P116
P108	1	0	0	0	0	0	0	0	0
P109	0	1	0	0	0	0	0	0	0
P110	0	0	1	0	0	0	0	0	0
P111	0	0	0	1	0	0	0	0	0
P112	0	0	0	0	1	0	0	0	0
P113	0	0	0	0	0	1	0	0	0
P114	0	0	0	0	0	0	1	1	0
P115	0	0	0	0	0	0	1	1	0
P116	0	0	0	0	0	0	0	0	1

6.2.3 Final Reachability Matrix (RM)

The initial reachability matrix was subjected to an iterative transitivity check process to yield the final reachability matrix (Table 6.3). This matrix then informs the MICMAC analysis, which evaluates the parameters based on their driving and dependency characteristics, as detailed later in Table 6.5 and Figure 6.1 (Section 6.2.5).

Table 6.3. Final Reachability Matrix

											P108	P109	P110	P111	P112	P113	P114	P115	P116	Driving
P108	1	1	1	1	1	1	1	1	1	. . .	0	0	0	0	0	0	0	0	0	1
P109	1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1	115
P110	1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1	115
P111	1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1	115
P112	1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1	115
P113	1	1	1	1	1	1	1	1	1		0	0	0	0	0	0	0	0	0	1
P114	1	1	1	1	1	1	1	1	1		0	0	0	0	0	0	0	0	0	1
P115	1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1	115
P116	1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1	115
Dependance	100	99	99	99	99	100	100	99	99											

The results indicate that the driving power for the parameters discussed in the final reachability matrix exhibit three distinct values: 1, 115, and 116. In contrast, the dependence values were calculated as 1, 99, and 100.

6.2.4 Level Partitioning

According to the methodology described in Section 3.6.4, a level partitioning table was created to delineate the connections between the parameters (Table 6.4). This iterative method continues until all parameters are appropriately categorized and allocated into their respective hierarchical levels.

Table 6.4. Level partitioning.

	Reachability set	Antecedent Set	Intersection Set	Level
P1	1	all but 6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,74,76,87,	1	1
P2	all but 73	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,74,76,87,	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,73,74,76,87,	
P3	all but 73	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,74,76,87,	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,73,74,76,87,	
P4	all but 73	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,74,76,87,	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,73,74,76,87,	
P5	all but 73	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,74,76,87,	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,73,74,76,87,	
P6	6	all but 1,7,10,11,14,17,18,19,20,47,55,57,69,70,71,74,76,87,	6	1
⋮				
P114	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,73,74,76,87,	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,74,76,87,	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,73,74,76,87,	2
P115	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,73,74,76,87,	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,74,76,87,	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,73,74,76,87,	2
P116	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,73,74,76,87,	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,74,76,87,	all but 1,6,7,10,11,14,17,18,19,20,47,55,57,69,70,71,73,74,76,87,	2
		Level 3		
P73	73	73	73	3

The hierarchical structure derived from the results reveals a three-tiered framework based on the interconnectedness among various elements (Table 6.5).

At the foundational level, level one, a total of 17 elements are identified, forming the initial layer of the structure. Progressing to the next layer, level two encompasses a significantly larger group, with 98 elements included indicative of a more complex and intertwined set of relationships. Finally, the structure culminates at level three, which is characterized by a singular element. This distinct arrangement highlights the varying degrees of influence and connection among the elements, including parameters, risk components and risk factors, with each level representing a specific tier of interrelation and impact in the overall hierarchical model.

Elements in the first level of the hierarchy require a range of parameters to effectively convey their impact throughout the system. In contrast, elements in the second category primarily establish links between themselves and other hierarchical levels. The top level of the hierarchy, represented by water conflict, dictates that if it occurs, many other elements and their interconnections are already functioning to address this element.

Table 6.5. Hierarchical ISM.

Level 1	Level 2				Level 3
	Flood Risk	Domestic returned flow	Drought Risk	Flood impact	
	Flood shelter	Groundwater withdrawal	Net agricultural water use	Drought impact	
	Urbanization	Groundwater outflow	Delivery rate	Flood Vulnerability	
	Migration	Groundwater returned flow	Actual land area for crop	Drought Vulnerability	
Change Factor	Transportation network	Groundwater inflow	Expected agricultural water requirement	Flood Exposure	
Elevation	Early warning systems	Natural groundwater inflow	Production of crops	Derought Exposure	
Slope	NDVI	Surface water returned flow	Expected land area	Flood hazard	
Health facility	Snowmelt pattern	Natural surface water inflow	Irrigation water requirement	Drought hazard	
Distance to river	LC/LU	Surface water outflow	Benefit from crops	Flood awareness	
Biodiversity	Soil moisture	Percolation	Expected water requirement	Drought awareness	
Soil type	Soil erosion	Surface water withdrawal	Public demand for mitigation	Air humidity	Water conflict
Wind speed	Precipitation	Seepage from groundwater to surface water	Flood alleviation investment	Industrial water use	
River density	Temperature	Industrial added value	Flood premium	Agricultural returned flow	
Flood level	Evapotranspiration	Domestic added value	Required insurance	Evaporation	
Transferred inflow	Returned flow	Agricultural added value	Access to insurance	Runoff	
Environmental flow	Water supply	Per capita water consumption	Community resilience	Cultivation cost	
National economic growth rate	Water use	Population growth rate	Drought relief	Net benefit	
The ratio of basin's GRP to neighbouring basins	Water demand	Population	Drought premium	Available surface water	
Watershed economic development rate	Surface water inflow	Per capita domestic water demand	Dependance on drought relief	Available groundwater	
Irrigation efficiency	Domestic demand	Per capita domestic water demand growth rate	Drought alleviation investment	Residents' utility	
Crop pattern	Industrial demand	Per capita industrial water demand	Risk perception	Added value	
	Agricultural demand	Per capita industrial water demand growth rate	Dike/Levee	Flood relief	
	Domestic water use	Per capita agricultural water demand	Storm control	Dependance on flood relief	
	Agricultural water use	Per capita agricultural water demand growth rate	Subsurface storage		
	Industrial returned flow	Water resources sustainability index	Dam/Reservoir		

6.2.5 Analysing driving and dependence power of parameters using MICMAC

The results of the MICMAC analysis, crucial for effective planning and control in risk management, are focused here on the hierarchical structure of elements and their interrelationships. Table 5.4 illustrates the driving and dependency powers of these elements, essential for understanding their roles in the system.

Key insights from the analysis are highlighted by the categorization of elements into four quadrants in Figure 6.1, each representing different characteristics: autonomous, dependent, independent, or linkage elements. Autonomous elements, identified with low driving and dependency powers, exhibit minimal interaction within the system. In contrast, dependent elements are characterized by high dependency and low driving powers, indicating their occurrences are significantly influenced by other factors.

Independent elements, on the other hand, have high driving power with low dependency, marking them as highly influential within the system. The most dynamic quadrant is the linkage category, where elements demonstrate both high dependency and driving powers, denoting their unstable nature as they significantly influence and are influenced by other factors in the system.

This analysis, particularly the graphical plotting in Figure 6.1, is instrumental in identifying leverage points for managing these elements. The driving power, represented on the y-axis, is calculated as the sum of rows in the final reachability matrix (RM), while the dependency power on the x-axis is derived from the sum of individual columns. These insights offer a comprehensive view of the elements, guiding strategic planning and decision-making in risk management.

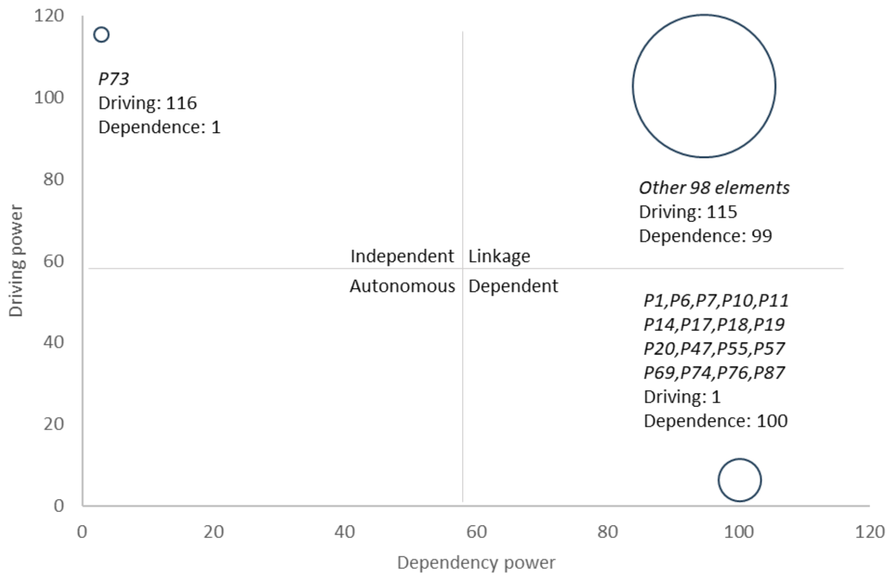


Figure 6.1. MICMAC analysis of parameters.

The results from the MICMAC analysis of this framework, involving a total of 116 elements with their respective connections, present a compelling narrative about the dynamics within the system. These results are particularly insightful when analysed in the context of driving and dependency powers, as defined in the analysis.

The first group of parameters including 98 elements with high driving (115) and moderate dependency (99) is within the linkage quadrant of the plot (Figure 6.1). These elements are significantly influenced by a large portion of the network, as indicated by their high driving power of 115. This suggests that a majority of the other elements in the system directly or indirectly affect these 98 elements. On the other hand, their moderate dependency power of 99 indicates that these elements, while being highly influenced, also have a substantial impact on other elements in the network. They are not the most influential, but they play a significant role in the network dynamics. Thus, given their balanced position between being influenced and influencing others, these elements could act as stabilizers in the network, transmitting and moderating the effects of changes across the system.

The second group containing 17 elements with low driving (1) and high dependency (100) is in the dependent quadrant of the graph (Figure 6.1). These elements are minimally influenced by others in the system (low driving power) but have a high capacity to influence (high dependency power). They are less reactive to the system's changes but significantly impact many other elements. These elements could be seen as critical leverage points. Their ability to affect a large portion of the network, despite being less influenced, positions them as critical leverage points in strategic planning. They could be key to initiating changes or maintaining stability in the network.

One last element (P73: Water conflict) with extremely high driving (116) and low dependency (1) is within the independent quadrant of the plot (Figure 6.1).

According to the flow of information through this network of parameters, this element is unique in that it is influenced by every other element in the network (highest driving power) but has almost no influence over others (lowest dependency power). Its position makes it highly vulnerable and central to the network. Being affected by all other elements, any change in the network converges on this element, making it a critical point for monitoring and understanding the overall system health. Due to its high sensitivity to the network, changes in this element's behaviour or state could be indicative of broader systemic shifts or emerging issues. In summary, the majority of elements in this network are both significantly influenced by and influential to others, suggesting a complex web of interdependencies. The 17 elements with low driving but high dependency power emerge as strategic points for influencing the network. In contrast, the single element with extremely high driving power and low dependency is a unique indicator, highly sensitive to the system's changes and potentially a focal point for monitoring the overall network health and dynamics.

6.3 Utilizing causal loop diagrams for effective flood and drought risk assessment in river basin

The utilization of Causal Loop Diagrams (CLDs) in graphically conveying the cause-and-effect relationships among risk factors significantly facilitates the development of targeted measures and mitigation strategies. These strategies are crucial for enhancing system performance, particularly in the context of feedback and behavioural changes of the risk factors. The core objective of the CLD is to reveal and comprehend the intricate feedback and causal dynamics that underlie key flood and drought risks, particularly in the realm of river basin management infrastructure. This understanding is vital for achieving optimal and equitable resource distribution.

Further enriching this narrative, the structural analysis and findings derived from the Interpretive Structural Modelling (ISM) and the (MICMAC) evaluation uncover the existence of dynamic relationships and feedback loops (Section 6.3). These findings warrant deeper exploration, modelling, and interpretation, roles adeptly fulfilled by the CLD. The CLD goes beyond mere identification of relationships; it precisely deciphers these connections to ascertain the most effective mitigation strategies for ensuring the success of project implementation. This approach is instrumental in navigating the complexities of system dynamics.

As illustrated in Figure 6.2, the CLD maps out the network of interactions within the system. The ISM analysis, which establishes the relationship density among parameters (as observed in the final Reachability Matrix), lays the groundwork for the CLD to spotlight risk factors with significant feedback properties. Within the diagram, the arrows represent the influence dynamics: a parameter at the tail of an arrow exerts an influence on the parameter at the arrowhead.

The nature of regulation within CLDs is delineated as either a self-reinforcing or a self-balancing system, discerned through the direction of the arrows and the accompanying positive (+) or negative (-) and delay (\\) symbols. A self-reinforcing system is characterized by growth or escalating effects, fuelled by mutual influences among system elements. Conversely, in a self-balancing system, there exists a moderating element that imposes constraints or limits on growth, ensuring stability and equilibrium within the system. This dualistic nature of CLDs offers a comprehensive lens through which the dynamics of system elements can be effectively analysed and managed.

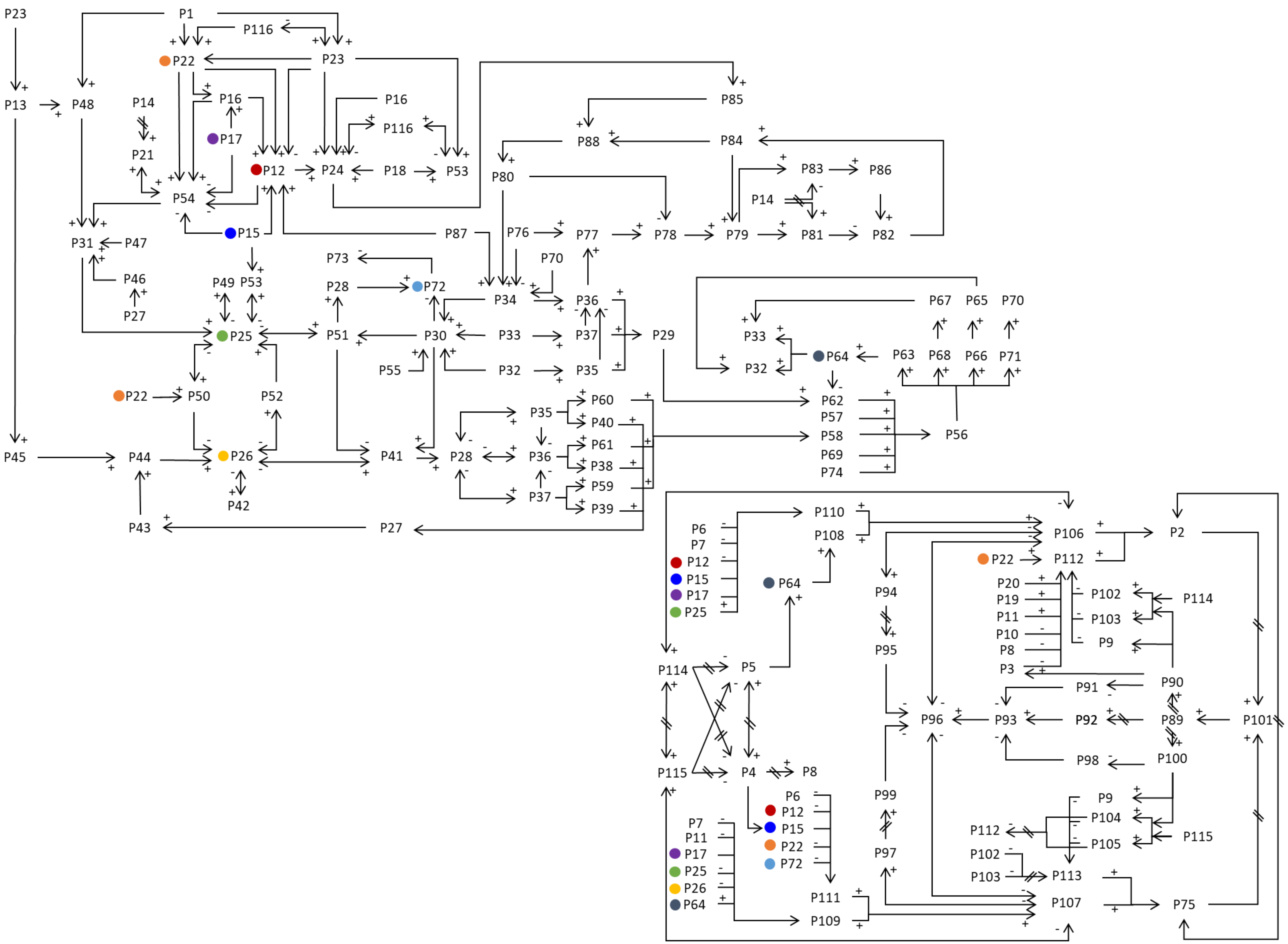


Figure 6.2. Causal loop diagram (CLD) of all parameters – links which were further apart are connected using a colour-coded mechanism.

This diagram represents the complete framework used in this research, capturing the intricate causal relationships among diverse parameters influencing flood and drought risks at the river basin scale (Figure 6.3). The Causal Loop Diagram (CLD) effectively maps the system's complexity by visually showcasing cause-and-effect dynamics, feedback loops, and interdependencies among risk factors. These connections play a critical role in identifying targeted measures and mitigation strategies, especially for managing behavioural changes and feedback effects in hydrological systems. The core objective of this comprehensive framework is to provide a robust basis for river basin management by addressing resource distribution challenges in an optimal and equitable manner.

The framework integrates findings from the quantitative analysis presented in section 5.3 and Interpretive Structural Modelling (ISM) performed on the pairwise connections between various parameters contributing to the causes of flood and drought risk, which establishes the foundational relationships amongst all of the parameters. Through ISM and MICMAC analysis, the density of relationships is systematically uncovered, setting the stage for the CLD to identify parameters with strong feedback properties. Each parameter and its interactions in this network have been validated through multiple peer-reviewed publications and real-world case studies, ensuring credibility and practical relevance.

As illustrated in the figure, clusters of interconnected parameters form distinct sub-models, each corresponding to specific disciplines such as hydrology, climate science, and water resource management. These clusters are color-coded to enhance readability and distinguish their roles within the system. For example, the Risk Perception sub-model connects parameters such as 89-101 with others like 2, 75, 106, and 107, forming a focused interaction group that directly informs risk management strategies. These sub-models are further elaborated in the following sections to provide a clear understanding of their contributions to the overall framework.

To reduce complexity and improve clarity, the diagram uses parameter IDs instead of detailed names. However, upcoming subsections will explore these IDs in detail, describing the role and importance of each parameter within its respective sub-model and across the broader framework. Additionally, the framework's flexibility allows for modifications based on specific basin requirements or unique circumstances. For instance, influences like deforestation or restoration projects can be incorporated by adjusting indices such as the Normalised Difference Vegetation

Index (NDVI) or Land Cover Land Use (LCLU).The framework serves as the foundation for subsequent refinement processes, such as using cross-entropy analysis to condense the full model into a generalized pathway. This simplified pathway provides a globally adaptable framework suitable for computation and risk mapping in any river basin. Stakeholders can further tailor the general pathway by adding specific feedback loops or parameters to assess the resulting impacts on risk maps. By presenting the full framework first, followed by a general model, the study ensures both comprehensive coverage and practical applicability, making it a versatile tool for flood and drought risk assessment.

6.3.1 Hydro physical sub-model

This sub-model (Figure 6.3) primarily integrates hydrological and climatic parameters (Ionita et al., 2017), their internal connections, and intersections with agricultural, water resource management (WRM) (Van Dijk et al., 2013; Bagley et al., 2014), and risk factors sub-models. The Change factor, representing climate transient projections under various emission scenarios, significantly impacts parameters like Precipitation, Temperature, and Natural surface water inflow (Braun et al., 2014; Miao et al., 2017; Vogel et al., 2017; Briffa et al., 2009; Martius et al., 2016). Not all connections apply universally to every basin; for instance, snowmelt's role in water inflow is specific to certain regions. In the context of this sub-model, the dynamics between soil moisture, precipitation, and runoff are critical (Huning and Aghakouchak, 2018).

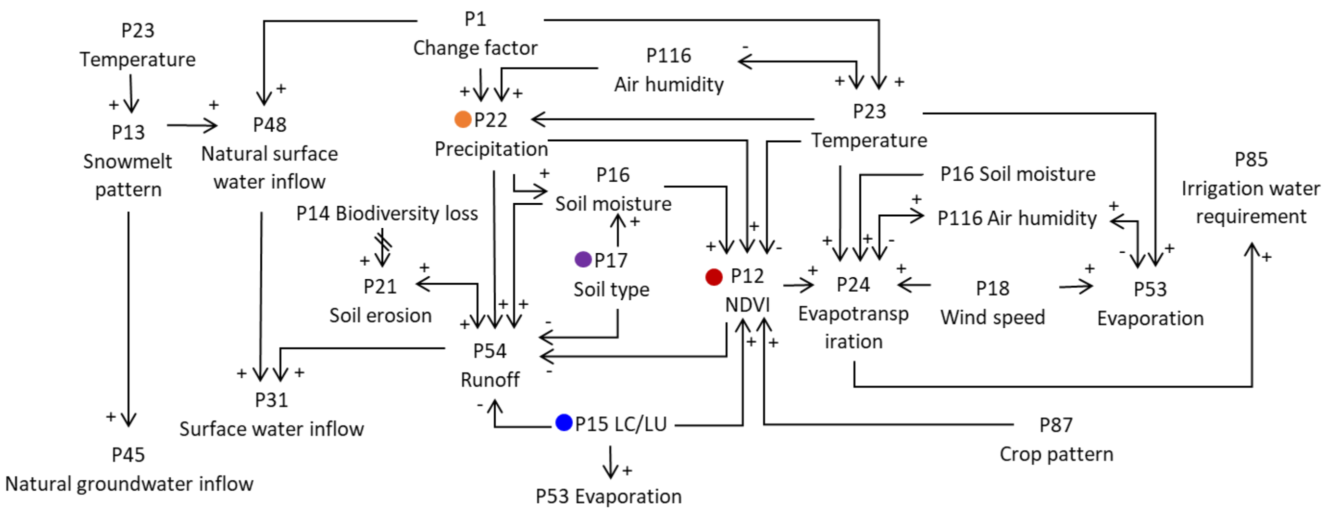


Figure 6.3. CLD of hydro physical parameters of river basin.

There are two primary pathways from precipitation to runoff. One is a direct connection where precipitation immediately impacts runoff, applicable in regions with established correlations between these two factors (Berghuijs et al., 2019; Aldridge et al., 2020). The other pathway involves soil moisture, influenced by soil type, which then indirectly affects runoff. High soil moisture levels can independently contribute to runoff, alongside other parameters (Kalantari et al., 2019; Trnka et al., 2016; Lima et al., 2011). This dual-pathway approach accommodates different regional characteristics and relationships, ensuring the model's adaptability to various hydrological scenarios. Because in the sub-model, runoff is not inherently a risk factor for flooding or drought. Its impact as a contributing parameter is contingent upon how it influences the available surface water through surface water inflow. This aspect underscores the importance of considering the interconnectedness of hydrological processes when assessing flood and drought risk components. The interactions between various parameters, such as air humidity, wind speed, and evaporation, may exhibit both short-term, near-real-time effects and longer seasonal trends.

Ultimately, the interactions within this sub-model have far-reaching implications. They influence crucial aspects such as irrigation water requirements in agriculture, water flow dynamics into the basin for water resource management (WRM), and various risk components including flood hazard, flood exposure, as well as drought vulnerability and exposure. This interconnectedness underscores the model's holistic approach in assessing and managing these key environmental and resource management factors.

6.3.2 Basin’s agricultural sub-model

The significance of the agriculture sub-model (Figure 6.4) in this framework, especially in the context of drought risk assessment, is emphasized by its prominent role in water resource allocation (Du et al., 2023). Agriculture is often the primary consumer of water resources, even in regions with developed water infrastructure. In numerous case studies focusing on drought risks, a significant portion, often exceeding 70% of water supplied to a basin is allocated for agricultural use (Yang et al., 2020). This reality underscores the critical importance of agriculture in both drought and flood risk management, spanning socio-economic and technical dimensions (Tsao et al., 2021).

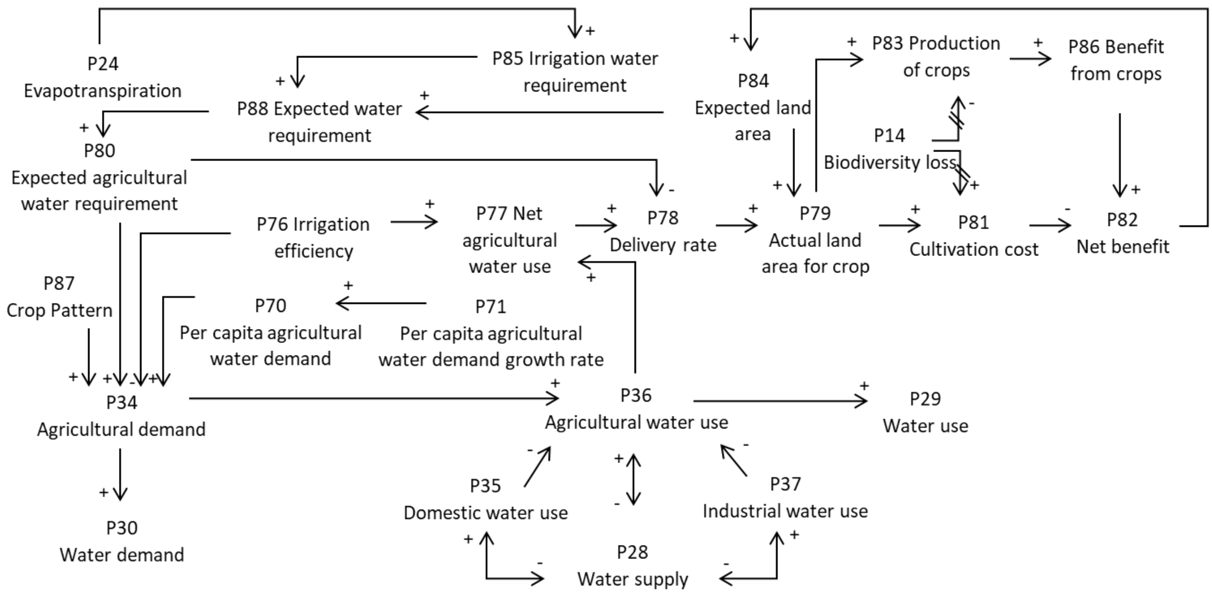


Figure 6.4. CLD of Agriculture parameters of river basin.

In this research, the Agricultural sub-system's CLD incorporates various irrigated crops in a basin, reflecting the diversity in irrigation water demands of different agricultural practices (Madani and Mariño, 2009; Mirchi et al., 2012; Bussmann et al., 2016; Anderson et al., 2019; Khazaei et al., 2019). By including crop pattern in the analysis, the model caters to specific crop interests or the overall crop pattern of a region (Madani, 2014; Maghrebi er al., 2020; McCarthy et al., 2021). Figure 5.4 illustrates the agricultural sub-system for a hypothetical crop pattern. It's predicated on the assumption that farming decisions are driven by maximizing income, influencing land allocation for crops based on their previous year's net economic benefits (Mesgaran et al., 2017; Reiter et al., 2018). Expected land area and irrigation water requirements of each crop are directly related to its anticipated water needs (Klaus et al., 2016). The basin's total agricultural water requirement is an aggregate of all crops' water needs, influencing the net agricultural water demand. Agricultural water demand inversely correlates with irrigation efficiency and is often only partially met due to limited water availability (Deryng et al., 2014; Watanabe et al., 2018).

In this context, "delivery rate" refers to the ratio of agricultural water demand that is met by the available irrigation water supply (Gohari et al., 2013, Gohari et al., 2017). Both agricultural water demand and supply are positively linked to actual water usage. High agricultural water usage combined with efficient irrigation can minimize water loss and increase net consumption. The actual land area dedicated to each crop is determined by adjusting the expected land area according to the delivery rate, which has a positive relationship with the actual land area utilized for crops.

If a basin already has a simulated the economic model to estimate the net benefit for each crop, then an established relationship between the chosen crop pattern and agricultural water demand can be utilized. This approach could effectively replace the need for the loop initially described, by using the link between crop pattern and agricultural water demand (Dile et al., 2013). In such a scenario, the production of each crop would be directly influenced by these market simulations, aligning more closely with actual economic behaviours and demands within the agricultural sector of the basin. In the basin's agricultural model, the production of each crop is influenced by the actual land area allocated to it. An increase in this allocated area typically leads to higher crop production. However, there is a delayed causal process at play, particularly from an environmental management perspective, where a loss in biodiversity can eventually increase cultivation costs and potentially reduce crop yields. This delayed effect highlights the interconnectedness of agricultural practices and environmental health, underscoring the importance of sustainable management in agricultural systems. In the agricultural model, crop price is inversely related to its production level within the same year, indicating that higher production could lead to lower prices due to supply and demand dynamics. The net benefit derived from each crop, positively linked to its production, encompasses the total gains from both the crop itself and its by-products. Additionally, the cultivation cost for each crop escalates with the increase in actual land area used and biodiversity loss, incorporating expenses related to energy, water, seeds, labour, fertilizer, and pesticide, underscoring the multifaceted nature of agricultural economics.

It's crucial to recognize that the costs and benefits of agricultural activities significantly fluctuate under different political, economic, and societal contexts. These causal relationships display a dynamic pattern, necessitating further investigations. Special focus should be on the local parameters that influence the markets relevant to agricultural activities within specific river basins.

6.3.3 Water resources sub-model in a river basin

The Water Resource Management (WRM) sub-system's CLD captures the interplay between elements of the hydrologic cycle and WRM, including the indirect effects of population and water consumption patterns from societal sub-models. It highlights water supply and demand as key factors influencing water conflict (Figure 6.5).

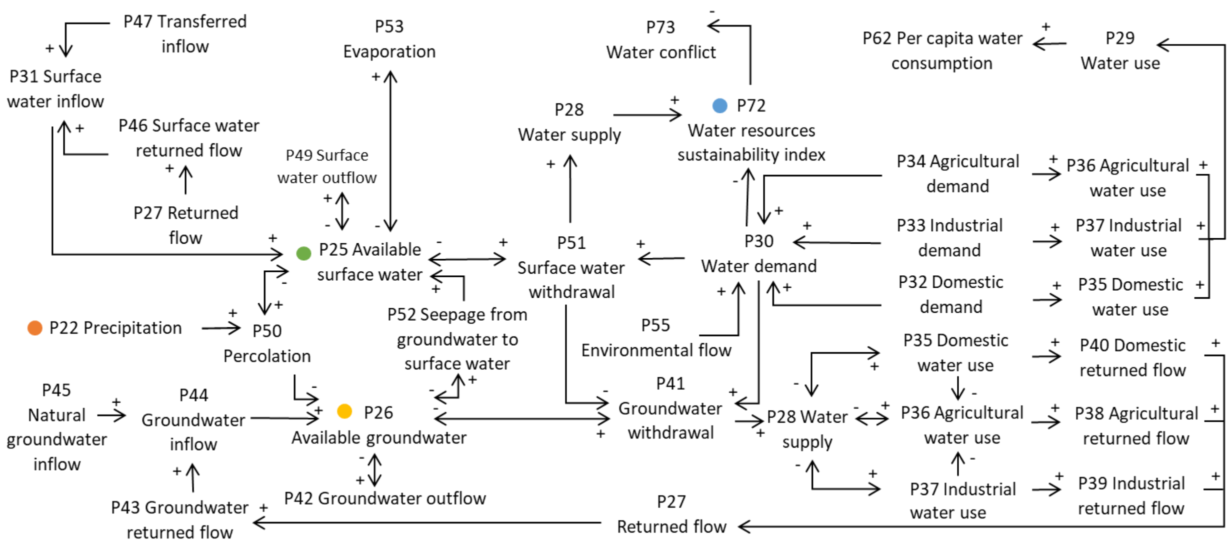


Figure 6.5. CLD of Hydrological and WRM parameters of river basin.

The Water Resource Management (WRM) sub-system's CLD captures the interplay between elements of the hydrologic cycle and WRM, including the indirect effects of population and water consumption patterns from societal sub-models (Gohari et al., 2013; Gohari et al., 2017; Liu et al., 2019; Coletta et al., 2021). It highlights water supply and demand as key factors influencing water conflict. The diagram also reflects how inter-basin water transfer projects and the interaction between groundwater and surface water affect water availability, posing risks for both flooding and drought (Jiménez and Chávez, 2004; McMartin et al., 2018; Hedrick et al., 2020). Figure 5.5 emphasizes the role of regional climatic and hydrological attributes—temperature, precipitation, evapotranspiration, runoff, natural flows, and groundwater recharge—in determining the natural water balance of the basin (Jun et al., 2011; Wang and Xie, 2018).

The CLD illustrates the interactions between various components, using arrows to indicate positive or negative causal relationships. It highlights how supply-oriented human interventions, like inter-basin water transfers, increase water availability to meet rising demand (Kallis, 2010; Hall et al., 2019). Water allocation within the basin prioritizes domestic, industrial, agricultural, and environmental needs in that order, with surface water being the primary source. When surface water is insufficient, groundwater is utilized (Di Baldassarre et al., 2018). Additionally, the return flow from the non-consumptive use of water across sectors is reintegrated into the system, enhancing both surface and groundwater recharge. This in turn can show the capability of different drainage systems within the basin (Richts and Vrba, 2016).

6.3.4 Socio-economic sub-model

The socioeconomic sub-system's CLD, depicted in Figure 6.6, integrates with Water Resource Management (WRM), agriculture, and Emergency management and policy sectors. Socioeconomic development influences water demand in the basin, affecting resident utility and prompting in-migration from adjacent basins. Additionally, the basin's GRP (Gross Regional Product) ratio to neighbouring basins, the Watershed economic development rate, and the National economic growth rate are exogenous factors impacting resident utility, highlighting the complex interplay between economic indicators and water management strategies (Delalay et al., 2020; Zhai et al., 2020; Dottori et al., 2023). National economic growth rate is in essence, GDP, or Gross Domestic Product, measures a country's total economic output in goods and services for a specific period. It serves as a key indicator of the dynamic of national economic performance (Gohari et al., 2013; Gohari et al., 2017).

Comparing the ratio of the basin's economic performance with neighbouring basins, which in this CLD is captured by GRP could be an influential factor in attracting in-migration. GRP represents the total economic output of goods and services within a specific region or locality over a certain period. It functions similarly to GDP but focuses on a regional or local level, offering insights into a region's economic health and activity.

The Watershed Economic Development Rate, unlike GDP, lacks a standardized unit and is measured using indicators such as employment rates, business growth, and sector-specific trends. Assessments of living standards, including income, access to services, and infrastructure improvements, contribute to understanding economic health in watershed management. These combined indicators offer a holistic view of economic progress within a watershed (Lemoine and Kapnick, 2016).

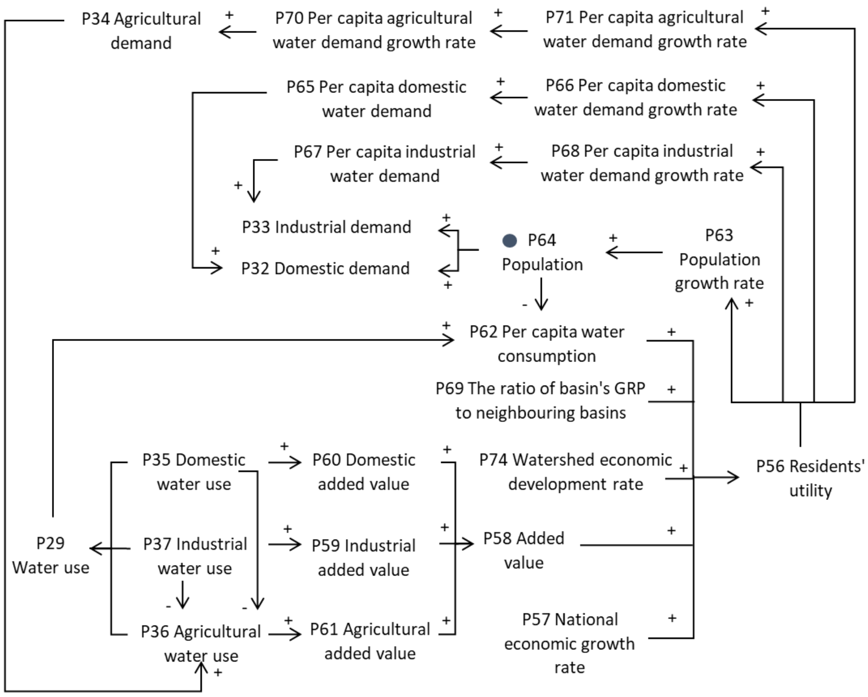


Figure 6.6. CLD of Socio-economy and WRM parameters of river basin.

The national economic growth rate significantly influences the desirability of living conditions across the country, impacting basins of interest. Factors such as per capita water use, water's added value, national economic growth, and the watershed's GRP compared to nearby areas shape residents' utility. This parameter is indicative of economic progress and satisfaction with local job opportunities, services, and goods, can spur in-migration from surrounding basins, highlighting the interconnectedness of economic factors and demographic shifts within a watershed.

Economic growth in a basin, especially when it outpaces that of neighbouring regions, fuels rapid development, enhancing job prospects and prompting in-migration. This growth escalates water consumption across sectors, thus increasing residents' utility and socio-economic development, which, in turn, raises per capita water use. The resultant growth in sector-specific water demand boosts the basin's overall water needs (Van Dijk et al., 2013; Johnson et al., 2020). With economic gains varying across industrial, domestic, and agricultural sectors, the aggregate economic productivity from water use elevates the basin's attractiveness, further driving up water demand in a self-reinforcing cycle (Ward et al., 2017).

6.3.5 Flood and drought impact sub-model

In this segment of the model (Figure 6.7), various factors are intricately linked, impacting both vulnerability and exposure to flood and drought risks (McCarthy et al., 2021; Merz et al., 2021).

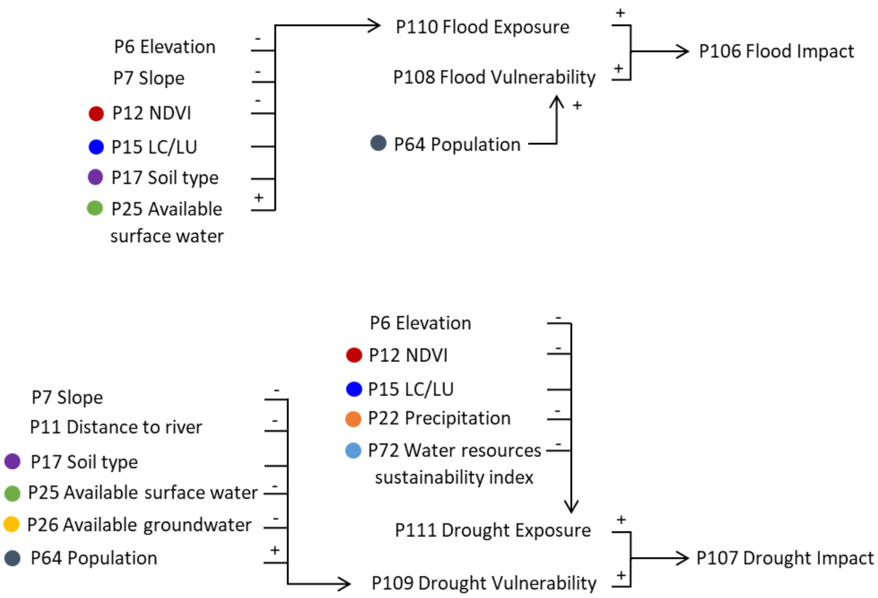


Figure 6.7. CLD of flood and drought impact in a river basin.

While certain interactions directly or indirectly influence these components, others exhibit both effects simultaneously, underscoring the complexity of these relationships. For example, land use significantly affects risk: natural areas like forests and wetlands decrease both drought and flood exposure through enhanced moisture retention and buffering capacity, respectively. In contrast, urbanization increases risk by reducing water absorption. Similarly, soil types with high infiltration rates decrease flood risk, whereas low-infiltration soils increase it, demonstrating the dual impact of these parameters on risk components. Impact refers to the overlap of areas where either vulnerability or exposure exceeds the average levels found in the dataset (Cammalleri et al., 2020; Ahmed et al., 2022).

6.3.6 Sub-model of hazard contributors in a river basin

Within this segment of the CLD (Figure 6.8), the focus is on the interaction between Civil Engineering, Emergency Management and Policy, Hydrology, and the physical characteristics of the basin (Leitner et al., 2020; Dash and Sar, 2020; Ahmed et al., 2022).

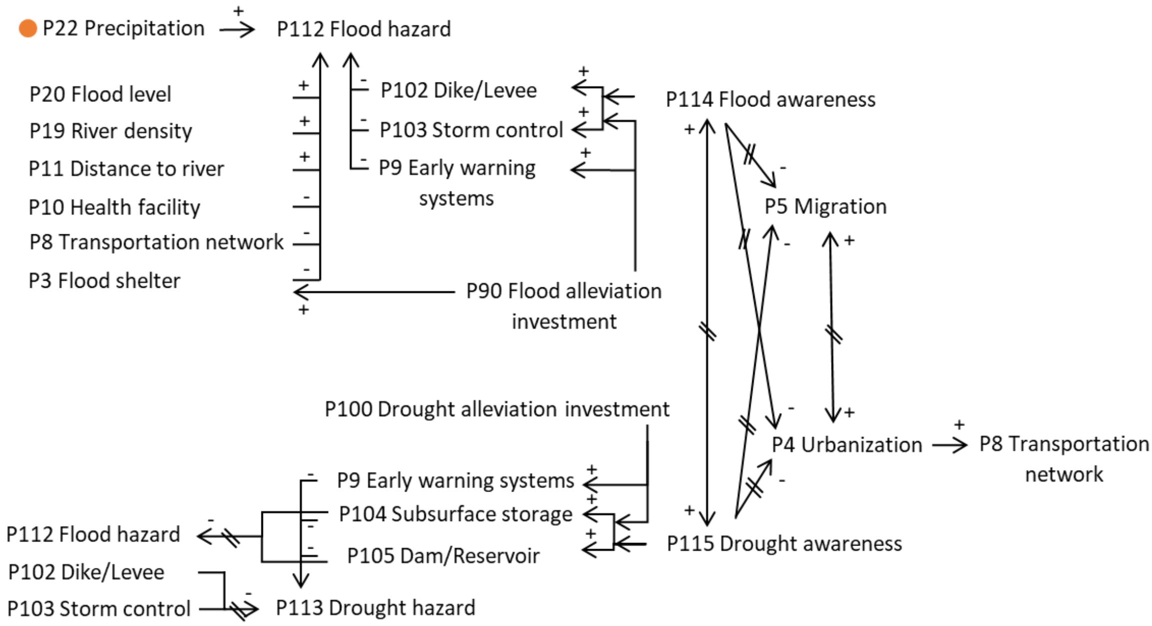


Figure 6.8. CLD of flood and drought hazard contributors in a river basin.

Mitigation measures are seen to inversely affect flood and drought hazards. For example, traditional structural defences like dikes and dams aim to lessen potential risks whilst subsurface storage acts as a buffer. However, interestingly, the failure of such structures can, paradoxically, increase drought hazards, highlighting the complex, delayed effects these flood mitigation strategies may have on drought conditions.

With increasing urbanization usually, some growth in health facilities and transportation network happens which directly mitigate the flood hazard, unless reported otherwise locally due to improper design (Ward et al., 2020a).

Urbanization often brings transportation network expansion, which can mitigate flood hazards, assuming proper design. Flood and drought awareness share a bidirectional relationship, varying in strength across basins and influencing societal factors like migration and population. Enhanced alleviation efforts mitigate hazards, but evidence shows that measures benefiting one risk (e.g., flooding) might adversely affect the other (e.g., drought), demonstrating the complexity of managing these risks (Lal et al., 2020; Ward et al., 2020b; Zhai et al., 2021). This necessitates further localized research to identify any potential dual effects of these mitigation measures, emphasizing the importance of tailored approaches in addressing flood and drought risks.

6.3.7 Perception of risk and community resilience sub-model

There's an increasing understanding that to avert future flood damages (Sörensen et al., 2017; Schrieks et al., 2021), enhancing community flood resilience is key (Mai et al., 2020). This entails the community's capacity to diminish, avert, and manage flood risks, a concept underscored by the Sendai Framework for Disaster Risk Reduction 2015–2030.

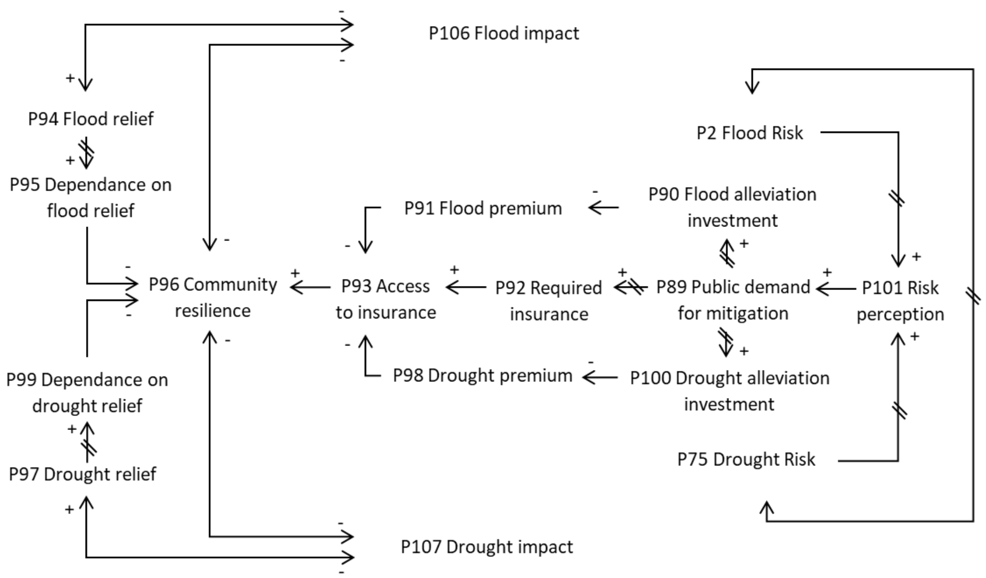


Figure 6.9. Perception of risk and contributors to community resilience in a river basin.

The presented sub-model diagram combined with the following discussion highlights the critical role that risk perception plays in shaping community resilience after flood and drought events. Risk perception is not static; it evolves in response to lived experiences of disasters, influencing how communities and institutions plan for and mitigate future risks (Figure 6.9). In a river basin, where diverse socio-economic and political factors converge, the complexities of risk perception and its influence on resilience are magnified.

Access to insurance is a particularly significant factor in shaping community resilience, especially in basin-wide regions characterized by varied governance and socio-economic conditions. In transboundary basins, some areas may fall under different national jurisdictions, leading to disparate access to insurance and risk management resources. Similarly, within the same basin, certain regions may operate under unique contractual agreements, such as international conservation funds or special governmental protection schemes. These variations affect how different communities perceive and respond to risks, thereby influencing their capacity to recover and adapt.

The cyclical nature of risk perception and its relationship with insurance dynamics is vividly captured in Figure 5.10. Following major flood or drought events, insurance premiums often rise significantly, making coverage unaffordable for many communities. This reduced access to insurance weakens resilience, creating a feedback loop that exacerbates vulnerability. However, targeted awareness campaigns and proactive mitigation strategies can help break this cycle by fostering a culture of preparedness and reducing the impact of subsequent events (Sörensen et al., 2017; Schrieks et al., 2021).

Investments in mitigation measures, including structural defences, early warning systems, and adaptive insurance schemes, are essential for bolstering resilience. These efforts are particularly relevant in regions with uneven access to resources, where risk perception may vary based on socio-economic conditions and historical experiences of disasters. The reinforcing loop observed in relief efforts underscores a paradox: while external aid alleviates immediate suffering, it can inadvertently diminish risk awareness and incentivize settlements in high-risk areas. This dynamic necessitates a balanced approach that combines immediate relief with long-term strategies to build sustainable resilience (Rosenzweig et al., 2018).

Ultimately, this section emphasizes the need for a nuanced understanding of how risk perception, insurance access, and socio-economic diversity intersect within a river basin. These insights are crucial for designing policies and interventions that address the specific challenges of transboundary basins and heterogeneous governance structures, ensuring equitable and effective risk management across all regions. The subsequent sections will delve deeper into how these dynamics are integrated into the broader framework for flood and drought risk assessment, providing actionable pathways for enhancing resilience.

6.3.8 Sub-model of flood and drought risks components in a river basin

In this framework segment (Figure 6.10), the core components of risk assessment—hazard, impact, exposure, and vulnerability—are interconnected directly, with numerous parameters within the framework affecting these components either singularly or collectively. The relationship between flood and drought risks includes a delayed effect, stemming from natural events or human interventions like disaster risk reduction measures. Spatially, regions with significant overlap of vulnerability and exposure face greater flood or drought impacts, emphasizing the need for targeted risk reduction strategies in these areas.

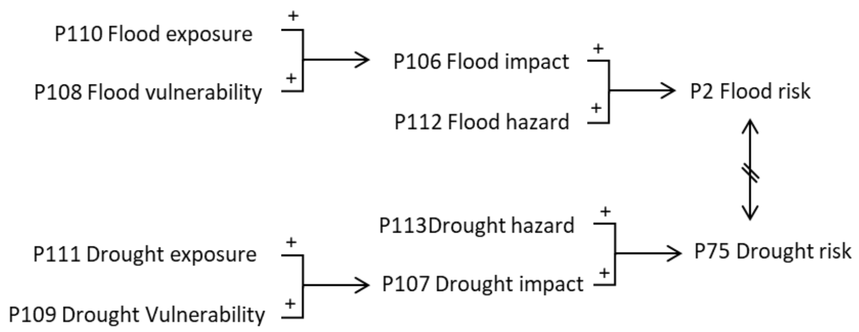


Figure 6.10. Components of flood and drought risks in a river basin.

6.4 Enhancing Flood and Drought Risk Assessment through Graph Theory in CLD Modelling

The intricate task of necessitated managing flood and drought risks in dynamic environmental systems necessitates a robust analytical approach. In this context, the application of graph theory to a Causal Loop Diagram (CLD) consisting of 116 diverse elements emerges as a particularly potent method. This approach transcends conventional analysis by intricately mapping and quantifying the complex web of interactions that define flood and drought risks. Through the lens of graph theory, each element and its interconnections within the CLD are not merely identified but are also evaluated in terms of their relational strength and strategic significance. This nuanced analysis facilitates a deeper understanding of the systemic structure and behaviour, thereby enhancing the model's predictive and explanatory power.

By integrating graph theory into the CLD framework, we unlock several transformative outcomes:

I. Prioritization of Risk Factors: The ability to discern and prioritize key risk factors and pathways, based on their centrality and influence within the network, empowers decision-makers with targeted insights for risk mitigation.

II. Identification of Critical Pathways: Understanding the most influential pathways aids in pinpointing where interventions might yield the most significant impact, thereby optimizing resource allocation and efforts.

III. Enhanced Predictive Accuracy: By quantifying the strength of connections and the role of individual elements, the model's accuracy in predicting the onset and progression of flood and drought conditions is markedly improved.

IV. Dynamic Risk Management: The dynamic nature of graph theory analysis aligns seamlessly with the evolving nature of environmental risks, enabling a more adaptive and responsive risk management strategy.

V. Holistic System Understanding: This approach fosters a comprehensive understanding of the system, highlighting not just the direct but also the indirect interactions and feedback loops that govern flood and drought dynamics.

Incorporating graph theory into CLD modelling for flood and drought risk assessment is more than an analytical enhancement; it is a paradigm shift towards a more refined, insightful, and actionable understanding of complex environmental systems. This integration paves the way for more effective, efficient, and proactive management of environmental risks, ultimately contributing to the sustainability and resilience of our ecosystems and communities.

6.4.1 Advancing Strategy Formulation in Flood and Drought Mitigation with Girvan-Newman Analysis

In the pursuit of uncovering the intricate structure of this network, a clustering algorithm (Girvan-Newman) has been employed that capitalizes on the rich information provided by edge weights, acknowledging the varied strength and significance of each connection. In the context of this framework, which assesses the risks of flood and drought, the Girvan-Newman method could be especially beneficial for identifying clusters of elements that are closely related to each other in terms of risk management. By pinpointing these clusters, the method allows for targeted interventions, enabling more efficient allocation of resources and tailored risk mitigation strategies. It essentially deconstructs the complex web of relationships into more manageable sub-networks, each with its distinctive dynamics and influence patterns, which can be addressed with specific, localized strategies. The benefit of this approach in this framework lies in its ability to reveal not just the most influential individual elements, but also the most significant relationships and the structure of the network at a larger scale. More information regarding the normalisation of these metrics and produced interim results are available at Appendix_A.

With randomization activated to ensure a comprehensive exploration of potential community structures, the resolution parameter was tuned to 1.0, striking a balance between the granularity of clusters and the overarching network architecture. The algorithm's adeptness is reflected in a high modularity score of 0.652, affirming the presence of well-defined communities within our network. This modularity persists even when the resolution is factored in, underscoring the robustness of the community divisions unearthed by our approach. The algorithm has successfully partitioned the network into 8 distinct communities, each representing a cohesive subgroup with intra-connections of various densities (Table 6.6). as compared to inter-connections with other groups (Figure 6.11). This subdivision into communities not only enhances our understanding of the network's topology but also offers a framework for targeted analysis and intervention in the context of flood and drought risk management.

Table 6.6. Network metrics for each of the produced cluster of parameters.

			Graph Metrics									
Group	Colour	Shape	Vertices	Unique Edges	Total Edges	Reciprocated Vertex Pair Ratio	Reciprocated Edge Ratio	Max Vertices in a Connected Component	Max Edges in a Connected Component	Max Geodesic Distance (Diameter)	Average Geodesic Distance	Graph Density
G1		Circle	23	43	43	0.049	0.093	23	43	5	2.431	0.085
G2		Disk	21	34	34	0.097	0.176	21	34	7	2.753	0.081
G3		Sphere	19	41	41	0.079	0.146	19	41	5	2.161	0.120
G4		Square	16	18	18	0.000	0.000	16	18	5	2.383	0.075
G5		Solid Square	12	15	15	0.000	0.000	12	15	6	2.250	0.114
G6		Diamond	11	16	16	0.333	0.500	11	16	5	2.116	0.145
G7		Solid Diamonc	10	18	18	0.385	0.556	10	18	4	1.920	0.200
G8		Triangle	4	3	3	0.000	0.000	4	3	3	1.250	0.250

Based on the analysed network metrics for each group, interpretation of the clusters is as follows.

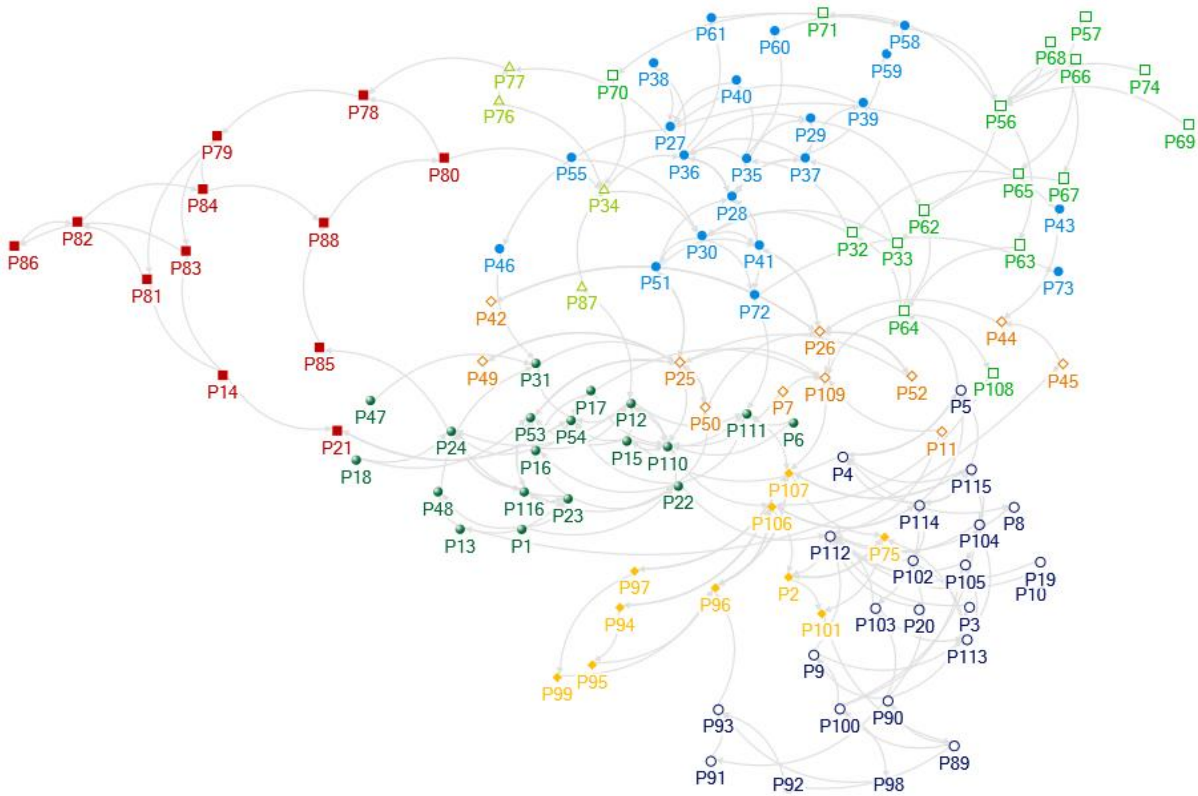


Figure 6.11. Schematic representation of produced clusters of the framework parameters G1 (dark blue), G2 (light blue), G3 (dark green), G4 (light green with squares), G5 (Red), G6 (orange), G7 (yellow), G8 (light green with triangles).

G1 is a large and moderately connected cluster. With the most vertices and edges, G1 is the largest group, indicating a broad and moderately dense network. The low reciprocated vertex pair ratio and edge ratio suggest that while there is some reciprocity, many connections are one-way, which may indicate a hierarchical structure. A max diameter of 5 and an average geodesic distance of 2.431 show that the elements are relatively close to each other, facilitating communication or influence across the group (Table 6.7).

Table 6.7. Cluster G1, ID represents parameters and G1 represents the first clustering group.

ID	G1	ID	G1	ID	G1
P3	Flood shelter	P89	Public demand for mitigation	P103	Storm control
P4	Urbanization	P90	Flood alleviation investment	P104	Subsurface storage
P5	Migration	P91	Flood premium	P105	Dam/Reservoir
P8	Transportation network	P92	Required insurance	P112	Flood hazard
P9	Early warning systems	P93	Access to insurance	P113	Drought hazard
P10	Health facility	P98	Drought premium	P114	Flood awareness
P19	River density	P100	Drought alleviation investment	P115	Drought awareness
P20	Flood level	P102	Dike/Levee		

G2 with High Diameter and Reciprocity, has a high max geodesic distance (diameter) of 7, which suggests a longer path length between some vertices. A higher reciprocated vertex pair and edge ratios than G1 indicate more mutual interactions, which could imply collaborative or interdependent relationships. Despite its smaller size compared to G1, its slightly less average geodesic distance shows that it's still quite interconnected (Table 6.8).

Table 6.8. Cluster G2, ID represents parameters and G2 represents the second clustering group.

ID	G2	ID	G2	ID	G2
P1	Change Factor	P37	Industrial water use	P55	Environmental flow
P22	Precipitation	P38	Agricultural returned flow	P58	Added value
P27	Returned flow	P39	Industrial returned flow	P59	Industrial added value
P28	Water supply	P40	Domestic returned flow	P60	Domestic added value
P29	Water use	P41	Groundwater withdrawal	P61	Agricultural added value
P30	Water demand	P43	Groundwater returned flow	P72	Water resources sustainability index
P35	Domestic water use	P46	Surface water returned flow	P73	Water conflict
P36	Agricultural water use	P51	Surface water withdrawal		

G3 is compact with moderate Reciprocity. It has a moderate number of vertices and edges but shows a higher graph density compared to G1 and G2, signifying closer ties between nodes. The average geodesic distance is the lowest, and the reciprocated ratios are moderate, indicating a balance between directed and mutual interactions (Table 6.9).

Table 6.9. Cluster G3, ID represents parameters and G3 represents the third clustering group.

ID	G3	ID	G3
P6	Elevation	P31	Surface water inflow
P12	NDVI	P47	Transferred inflow
P13	Snowmelt pattern	P48	Natural surface water inflow
P15	LC/LU	P53	Evaporation
P16	Soil moisture	P54	Runoff
P17	Soil type	P110	Flood Exposure
P18	Wind speed	P111	Derought Exposure
P23	Temperature	P116	Air humidity
P24	Evapotranspiration		

G4 is sparse and unidirectional. It is characterized by a lack of reciprocated connections, suggesting a unidirectional flow of influence or information.

Table 6.10. Cluster G4, ID represents parameters and G4 represents the fourth clustering group.

ID	G4	ID	G4
P32	Domestic demand	P66	Per capita domestic water demand growth rate
P33	Industrial demand	P67	Per capita industrial water demand
P56	Residents' utility	P68	Per capita industrial water demand growth rate
P57	National economic growth rate	P69	The ratio of basin's GRP to neighbouring basins
P62	Per capita water consumption	P70	Per capita agricultural water demand
P63	Population growth rate	P71	Per capita agricultural water demand growth rate
P64	Population	P74	Watershed economic development rate
P65	Per capita domestic water demand	P108	Flood Vulnerability

The network is sparser, with fewer edges relative to the number of vertices, and a lower graph density, meaning it is less interconnected (Table 6.10).

G5 is sparse with longer reach. Similar to G4, G5 shows no reciprocity and has a low number of edges and graph density. The max geodesic distance of 6 indicates that some nodes can be quite far apart, which may hinder quick communication or influence (Table 6.11).

Table 6.11. Cluster G5, ID represents parameters and G5 represents the fifth clustering group.

ID	G5	ID	G5
P14	Biodiversity	P82	Net benefit
P21	Soil erosion	P83	Production of crops
P78	Delivery rate	P84	Expected land area
P79	Actual land area for crop	P85	Irrigation water requirement
P80	Expected agricultural water requirement	P86	Benefit from crops
P81	Cultivation cost	P88	Expected water requirement

G6 is small with high reciprocity. Despite its small size, G6 has high reciprocated ratios, indicating a strong tendency towards mutual interactions. This group could represent a tightly-knit community with significant bilateral relationships. The graph density is also higher, reinforcing its cohesiveness (Table 6.12).

Table 6.12. Cluster G6, ID represents parameters and G6 represents the sixth clustering group.

ID	G6	ID	G6
P7	Slope	P45	Natural groundwater inflow
P11	Distance to river	P49	Surface water outflow
P25	Available surface water	P50	Percolation
P26	Available groundwater	P52	Seepage from groundwater to surface water
P42	Groundwater outflow	P109	Drought Vulnerability
P44	Groundwater inflow		

G7 is a highly interconnected small group. G7, while small, shows the highest reciprocated ratios and graph density, suggesting a very interconnected network with many mutual relationships. The lower max geodesic distance implies that all nodes are relatively close to each other (Table 6.13).

Table 6.13. Cluster G7, ID represents parameters and G7 represents the seventh clustering group.

ID	G7	ID	G7
P2	Flood Risk	P99	Dependance on drought relief
P75	Drought Risk	P101	Risk perception
P94	Flood relief	P106	Flood impact
P95	Dependance on flood relief	P107	Drought impact
P96	Community resilience		
P97	Drought relief		

G8 is very small and least dense. The smallest group, G8, also has no reciprocity and the least edges, indicating a very simple and direct structure, possibly linear. Its high graph density is due to its small size, and the low max geodesic distance suggests that all nodes are directly connected without intermediaries (Table 6.14).

Table 6.14. Cluster G8, ID represents parameters and G8 represents the eighths clustering group.

ID	G8
P34	Agricultural demand
P76	Irrigation efficiency
P77	Net agricultural water use
P87	Crop pattern

The network clusters show a range of characteristics from large and hierarchical to small and highly interconnected groups. Larger clusters like G1 tend to have more complex structures with a mix of one-way and reciprocal connections, whereas smaller groups like G6 and G7 exhibit high levels of mutual interactions, indicative of strong interdependencies. The variation in max geodesic distances across groups suggests that the spread of influence or information may be more efficient in some clusters than others. Groups with higher diameters might contain key influencer nodes that bridge distant parts of the network, while those with lower diameters likely have more rapid dissemination within the cluster.

Reciprocity is a critical factor in determining the nature of the interactions within the groups. High reciprocated vertex pair and edge ratios, as seen in G6 and G7, are typical of collaborative environments, whereas low ratios indicate more hierarchical or linear communication pathways.

In summary, the network analysis reveals a rich tapestry of interconnections with varying degrees of complexity and interaction styles. This diversity must be considered when formulating strategies for flood and drought risk management, as different clusters will have unique roles and influence within the broader network. The nuanced understanding of each group's structure and dynamics is paramount for effective intervention and risk mitigation efforts.

6.4.2 Analysing betweenness centrality and closeness centrality

In the intricate web of hydrological and climatic systems, such as the developed framework in this research, understanding the pivotal points of influence is essential for both prediction and management. Betweenness centrality serves as a crucial metric in this endeavour, spotlighting the nodes that frequently act as bridges along the shortest paths between others within the network. These key nodes can be likened to vital conduits through which water, information, or resources flow, potentially regulating the system's dynamics. On the other hand, closeness centrality sheds light on the proximity or reachability of each node, offering insight into how quickly and efficiently a node can communicate or be affected by changes across the network. Together, these centrality measures provide a profound understanding of the network's topology (Figure 6.12) revealing both the influential nodes that shape pathways of interaction and the nodes that are central to the network's rapid response capability. In the context of hydrology and water resource management, such insights are invaluable for developing robust strategies for risk mitigation, resource allocation, and infrastructure development.

Analysing the provided network metrics, one can derive an understanding of the dynamics and behaviour of the network. Betweenness centrality measures the frequency at which a node appears on the shortest paths between other nodes, while closeness centrality represents the average length of the shortest path from the node to all other nodes in the network. These centrality measures provide insights into the importance and connectivity of nodes within the network.

There are some nodes with High Betweenness Centrality (e.g., Population – P64, Flood hazards – P112, Precipitation – P22, Drought vulnerability – P109) are likely to be crucial connectors or bridges within the network, controlling the flow of information or resources. Having high betweenness centrality indicates these nodes are critical for maintaining the network's connectivity; their removal could potentially fragment the network or significantly disrupt communication.

Some nodes with high closeness centrality (Drought vulnerability - P109, Flood exposure - P110, Available surface water – P25, and NDVI – P12) are well-placed to quickly interact with all other nodes and may be well-suited for spreading information or mobilizing resources across the network due to their shorter paths to all other nodes.

Nodes with Low Betweenness and Closeness Centrality (Benefit from crops – P86, Flood level – P10 and Health facility – P20) might be relatively peripheral within the network, with limited influence or control over the network's flow. They are neither significant connectors nor are they central in terms of information flow or accessibility.

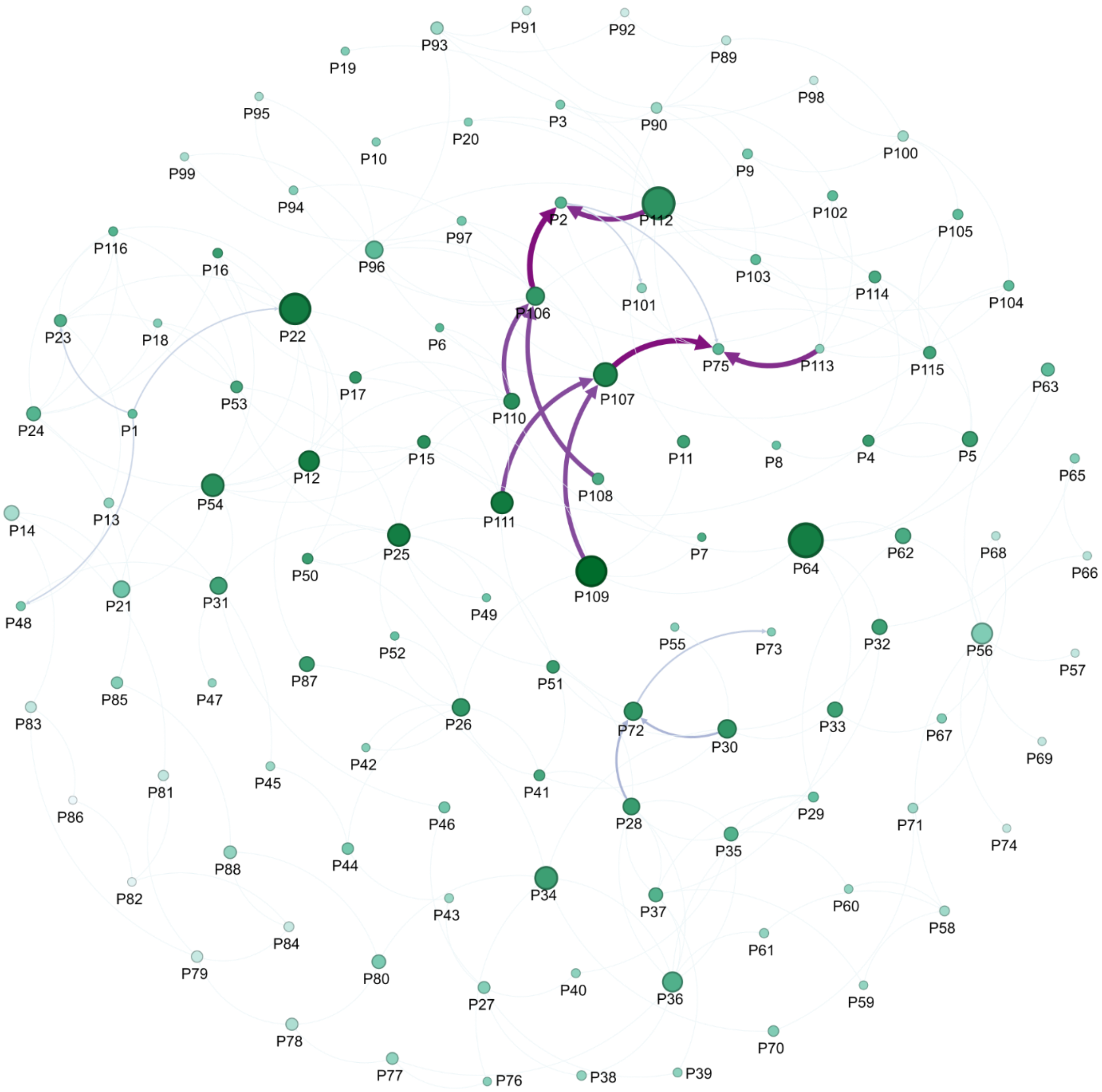


Figure 6.12. Visualization of Betweenness centrality (size of circles) and Closeness centrality (colour intensity of circles) network metrics for the overall framework.

A few nodes have zero betweenness but varying degrees of closeness centrality. These nodes such as "Watershed economic development rate – P74" and "Environmental flow - P55" do not act as bridges on any shortest path between other nodes, suggesting they may serve in more specialized or local roles within their immediate community or cluster rather than the network at large.

The combination of betweenness and closeness centrality measures suggests this framework consists of distinct hubs of influence and pathways of interaction. The nodes with both high betweenness and closeness centrality are likely to be the network's most influential members, with the capability to quickly and efficiently connect various parts of the network. These hubs or central nodes could potentially be influential leaders or critical communication points that hold the network together. Their strategic position allows them to access and disseminate information across the network effectively.

Conversely, nodes with low betweenness centrality but higher closeness centrality may indicate localized influencers that are not critical for the network's connectivity but are still efficient in interacting within their immediate vicinity. These nodes can be seen as local leaders or specialists that are important within their specific clusters or communities.

The overall dynamic of the network seems to be characterized by a few highly central and influential nodes that ensure connectivity and flow, surrounded by nodes with varying degrees of local influence and reachability. Understanding the roles of these different types of nodes is crucial for network management, especially in the context of risk and information propagation. For instance, in a flood or drought risk management scenario, the nodes with high betweenness centrality would be critical for spreading alerts and coordinating responses, while those with high closeness centrality could be instrumental in local community engagement and support.

Furthermore, the network exhibits a gradient of centrality values, which suggests there's a diversity in the function and importance of nodes. This can be advantageous for resilience, as it implies that the network is not overly reliant on a single point of failure but rather has multiple key nodes that ensure its functionality.

6.4.3 Exploring the impact of eigenvector centrality and PageRank on network analysis

Eigenvector centrality measures the influence of a node in a network. Unlike other centrality measures that consider only the immediate connections of a node, eigenvector centrality considers the centrality of a node's neighbours as well, providing a view of the influence over the entire network. PageRank on the other hand, assigns a higher score to nodes with a greater number of incoming links, and considers the importance of the nodes that provide these links. It's a measure of node influence that incorporates the concept of link quality, not just quantity. Interpreting the data (Figure 6.13), following observations can be made.

As a standout parameter with top scores in both metrics, parameters such as “Drought impact - P107” is likely a crucial node within the network. Its high eigenvector centrality suggests it is connected to other influential nodes, playing a significant role in the network's integrity. The high PageRank score indicates it is a trusted node, receiving many incoming links from other important nodes. P107 may represent a key hydrological or climatic factor that warrants close attention in flood and drought management.

Nodes with a high eigenvector centrality and moderate PageRank such as “Surface water availability - P25” is connected to other influential nodes, suggesting it has a role in core processes related to flood and drought risks. However, its moderate PageRank score indicates it's not a primary source of information flow in the network, which could mean it's not a starting point for most processes, but it plays a supportive role among other central nodes.

Nodes that have a strong PageRank and moderate Eigenvector centrality, such as “Risk perception – P101”, “Community resilience – P96” which suggest key nodes in terms of the flow of information or influence, receiving endorsements from other significant nodes. Its moderate eigenvector centrality indicates it's somewhat influential, but perhaps its influence is more due to the network's directed structure rather than its position within the entire network's connectivity.

The parameters “Evaporation – P53” or “Drought vulnerability – P109” may not be central in the overall network structure but are still relatively important in the directed aspects of the network flow. This could imply they are secondary nodes, possibly acting as intermediate steps in the transmission of effects or information related to flood and drought risks.

Parameters with moderate Eigenvector Centrality and PageRank like “Flood hazard - P112” have moderate influence and connectivity. It may be a factor that is involved in several pathways or processes but not central to any primary ones. It's still an important node, but interventions here might have a less systemic impact compared to nodes with higher scores.

There are parameters such as (drought awareness - p115, urbanization - p4, and migration - p5) with low eigenvector centrality and moderate PageRank. These nodes are not central in terms of the overall network structure, but their moderate PageRank scores suggest they have some influence on the network's directed flow, perhaps as specialized nodes that come into play under specific conditions or in certain pathways related to flood and drought scenarios.

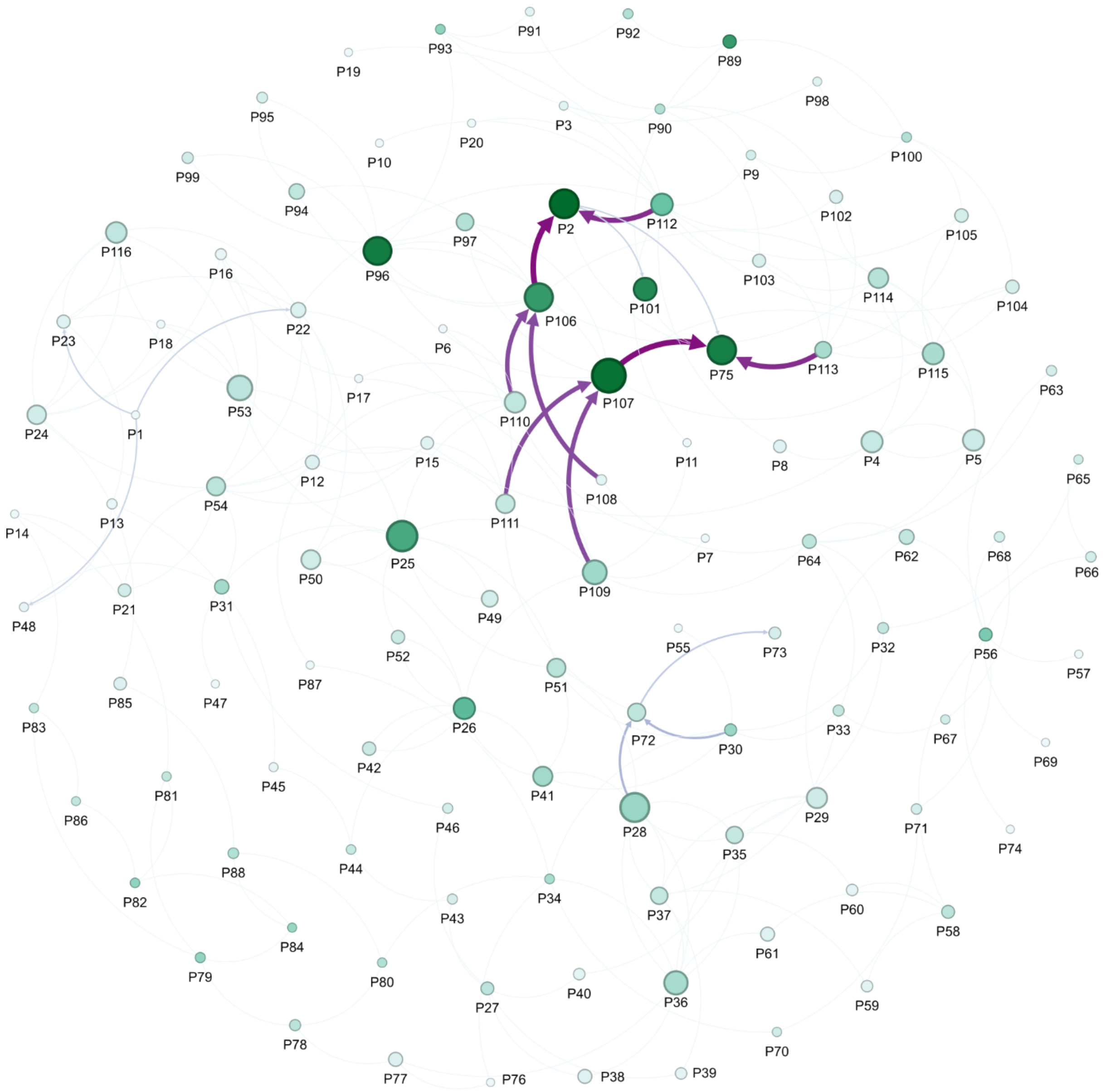


Figure 6.13. Visualization of Eigenvector (size of circles) and PageRank (colour intensity of circles) network metrics for the overall framework.

A few parameters like (Available groundwater - P26 and Water resources sustainability index - P72 have moderate eigenvector centrality and low PageRank. These parameters are somewhat central in the network's structure, indicated by their eigenvector centrality, but they are not key drivers of information flow within the network, as reflected by their low PageRank scores. They might represent underlying factors or conditions that have a stable influence over time but are not often directly acted upon in management decisions or immediate responses to flood and drought events.

Parameters with low scores in both metrics such as (Change factor - P1, Elevation – P6 and Slope – P7) are peripheral to both the overall structure and the directed flows of the network. They might be less influential or less active nodes, possibly only coming into play under specific circumstances or representing localized issues that don't broadly impact the river basin's flood and drought dynamics. In the broader context of the network, we see a hierarchy of nodes where Drought impact - P107, Available surface water - P25, Flood risk - P2, Drought risk - P75, and Community resilience - P96 emerge as particularly significant due to their high centrality measures. Their roles may differ, with some like (Drought Impact - P107 and Drought risk - P75) being central in both the undirected and directed aspects of the network, and others like (Flood risk - P2 and Community resilience - P96) possibly acting more as influential hubs within directed flows. The analysis of these parameters with respect to their centrality measures should be integral to the design of any interventions. For example, measures to improve resilience to flooding and drought should consider the impact on these key parameters due to their potential to affect the overall system. It also highlights the importance of understanding not just the presence of connections in a network, but the nature and direction of those connections, as well as the context in which the nodes operate.

In conclusion, the combined analysis of eigenvector centrality and PageRank provides a nuanced understanding of each parameter's role. High-scoring parameters in both measures are critical to the network and should be primary focuses for any intervention strategies. Parameters with disparities between their eigenvector centrality and PageRank scores may have more complex roles and might require more contextual investigation to fully understand their position and function within the network. This understanding is crucial for developing effective flood and drought management policies and for prioritizing research and monitoring efforts.

6.4.4 Exploring the impact of Authority and Hub on network analysis

In network analysis, Authority and Hub scores stem from algorithms like Kleinberg's HITS algorithm, which identifies the most authoritative sources of information and the best aggregators of that information within a network.

Authority Scores indicate the value of the information contained at a node. A high authority score suggests that a node is a trusted source of information and is frequently referenced by other nodes in the network. In the visualization (Figure 6.14), the colour of a node corresponds to its Authority score. This means that nodes with a similar colour intensity would have similar levels of valuable information, with darker or more intense colours typically representing higher Authority scores.

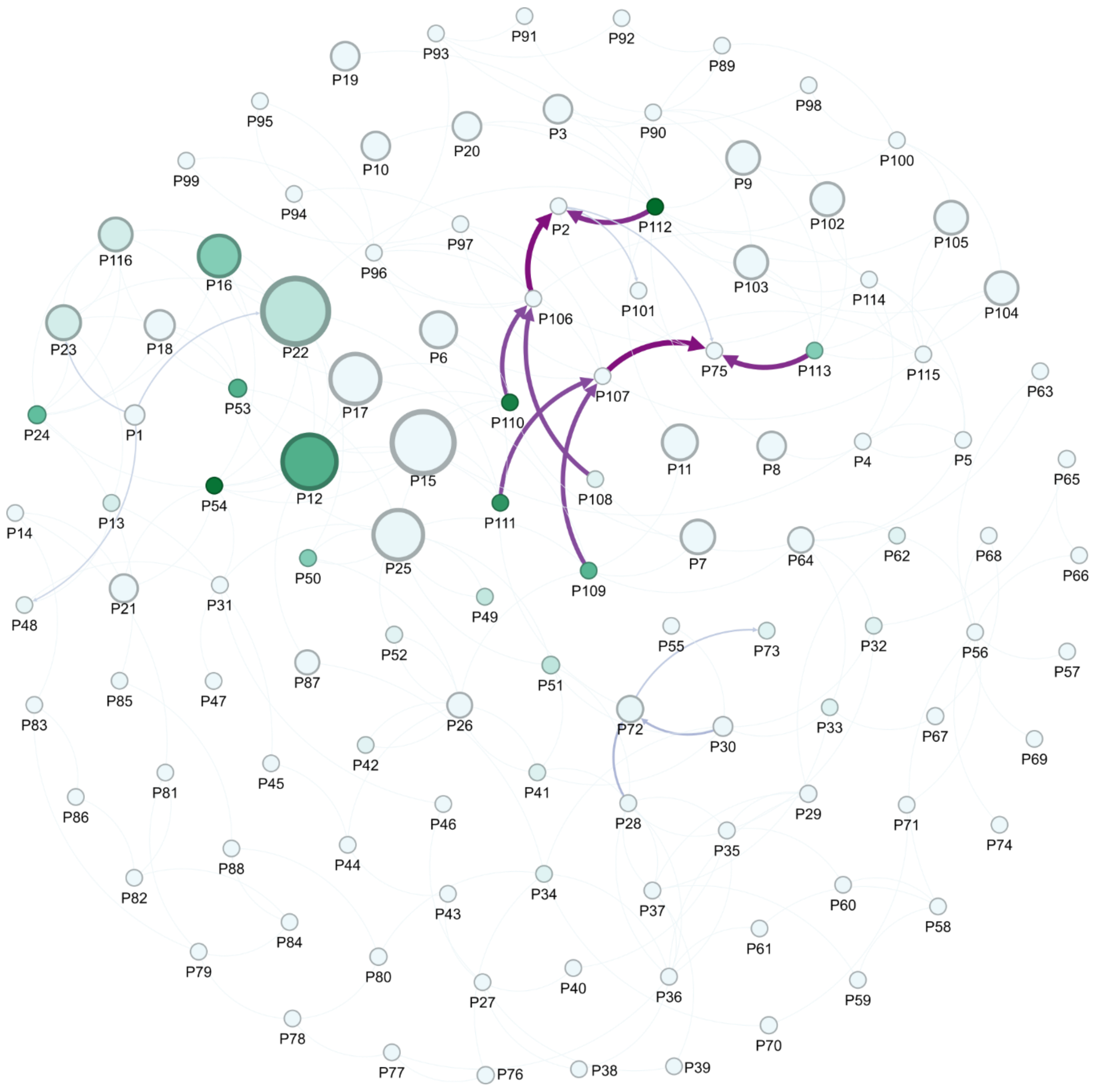


Figure 6.14. Visualization of Hub (size of circles) and Authority (colour intensity of circles) network metrics for the overall framework.

Hub Scores reflect the quality of a node's links to other nodes, particularly to authoritative nodes. A high Hub score means the node points to many high-quality sources of information. In this visualization, the size of a node represents its Hub score. Larger nodes are those that act as superior connectors or 'hubs' in the network, directing users to valuable information.

Nodes that are large and intensely coloured are both high-quality hubs and contain valuable information, making them central to the network's function and influence. Large nodes with less intense colour might be great at pointing to other valuable sources, but they do not necessarily hold high-value information themselves. Small, intensely coloured nodes are valuable sources of information but may not connect well to other nodes. Small, lightly coloured nodes might neither hold valuable information nor connect well to valuable sources, indicating they are peripheral to the network's main flow of information (Figure 6.14). Understanding the balance between these two metrics can help identify which nodes are crucial for disseminating information (hubs) and which are important for containing it (authorities). In practical terms, enhancing the visibility and connectivity of high-authority nodes can improve the network's overall value, while strengthening the links of high-hub nodes can enhance the flow of information. This interpretation can guide strategic decisions in network design, content placement, and the targeting of interventions for network optimization or control. For instance, in an online social network, high-authority nodes might be key opinion leaders, while high-hub nodes could represent influential content curators or aggregators. Addressing the connectivity and content of these nodes can significantly impact the spread and quality of information across the network.

6.5 CONSOLIDATED RISK FACTORS USING CROSS-ENTROPY MONTE CARLO ALGORITHM (CE).

In the comprehensive analysis of a network consisting of 116 distinct parameters, each was evaluated based on 11 different network metrics to determine their significance and influence within the network's structure. This meticulous ranking process revealed that approximately 80 percent of the total parameters managed to secure a position in at least one of the top-ranking lists for the network metrics (Table 6.15), indicating a wide dispersion of importance and influence among the parameters.

Table 6.15. Top 30 parameters from 11 network metrics.

Weighted indegree	Weighted outdegree	Weighted Degree	Eccentricity	Closeness centrality	Betweenness centrality	Authority	Hub	PageRanks	Connected component	Eigen centrality
P75	P107	P107	P104	P25	P107	P112	P22	P2	P87	P107
P2	P106	P106	P105	P64	P64	P54	P15	P107	P76	P25
P107	P112	P2	P102	P115	P25	P110	P12	P96	P74	P28
P106	P113	P75	P103	P114	P115	P111	P17	P75	P69	P2
P112	P109	P112	P9	P51	P101	P12	P25	P101	P57	P75
P72	P110	P113	P8	P87	P89	P53	P16	P106	P55	P106
P25	P111	P109	P3	P5	P106	P109	P6	P89	P47	P96
P109	P108	P110	P20	P4	P96	P24	P11	P25	P20	P53
P110	P1	P111	P19	P22	P5	P113	P23	P26	P19	P109
P54	P28	P25	P10	P15	P30	P16	P7	P112	P18	P36
P28	P25	P28	P112	P26	P56	P50	P116	P56	P17	P101
P96	P22	P72	P113	P23	P93	P22	P104	P93	P14	P112
P53	P30	P22	P2	P53	P114	P51	P105	P82	P11	P26
P26	P115	P30	P75	P116	P36	P49	P102	P79	P10	P115
P24	P114	P108	P101	P12	P34	P116	P103	P84	P7	P5
P111	P2	P36	P77	P41	P53	P23	P9	P28	P6	P4
P113	P36	P26	P90	P34	P92	P13	P18	P30	P1	P116
P56	P23	P56	P100	P30	P51	P41	P8	P109	P2	P110
P22	P35	P23	P89	P107	P28	P73	P3	P41	P107	P29
P36	P37	P114	P78	P106	P4	P32	P20	P31	P96	P114
P31	P64	P115	P79	P32	P2	P33	P19	P36	P75	P41
P12	P15	P12	P83	P33	P116	P62	P10	P34	P101	P50
P30	P90	P54	P92	P17	P111	P34	P21	P113	P106	P24
P34	P72	P1	P98	P1	P88	P108	P72	P115	P89	P111
P101	P26	P35	P91	P50	P80	P52	P64	P88	P25	P54
P23	P56	P37	P72	P52	P32	P42	P26	P92	P26	P51
P48	P12	P116	P29	P36	P33	P48	P87	P90	P112	P72
P5	P116	P64	P93	P31	P15	P72	P1	P100	P56	P97
P4	P100	P24	P81	P49	P31	P25	P30	P80	P93	P35
P116	P17	P53	P11	P35	P75	P28	P53	P97	P82	P37

Remarkably, none of the parameters consistently appeared in the top 25 percent across all 11 measures, underscoring the diversity in their roles and impacts within the network. However, the parameter "Available surface water" distinguished itself by securing a high rank in ten out of the eleven lists, showcasing its critical significance in the network's dynamics. To synthesize these findings and identify the most overall important factors within this complex multi-metric landscape, the Cross-Entropy Monte Carlo algorithm (CE) was employed (Figure 5.15). This sophisticated approach allowed for an effective aggregation of rankings across all eleven lists, enabling the identification of key parameters that hold the greatest overall importance in the network, with "Available surface water" likely emerging as a pivotal element due to its consistent high rankings. This methodological approach not only highlights the crucial factors within the network but also demonstrates the nuanced interplay of various parameters, facilitated by an advanced algorithmic treatment to discern overarching patterns of influence. Visualisation resulted from optimisation process using CE method which are presented in Figure 6.15 contains a set of three plots. The first plot at the top illustrates the trajectory of the objective function's minimum values over time, with the global minimum highlighted in the top right corner. A histogram representing the objective function scores at the final iteration is presented in the adjacent plot, providing insights into the convergence rate and the distribution of candidate lists at this stage. The third plot below displays individual lists and the final solution, along with an optional average ranking, offering a comprehensive view of the outcomes and methodology applied.

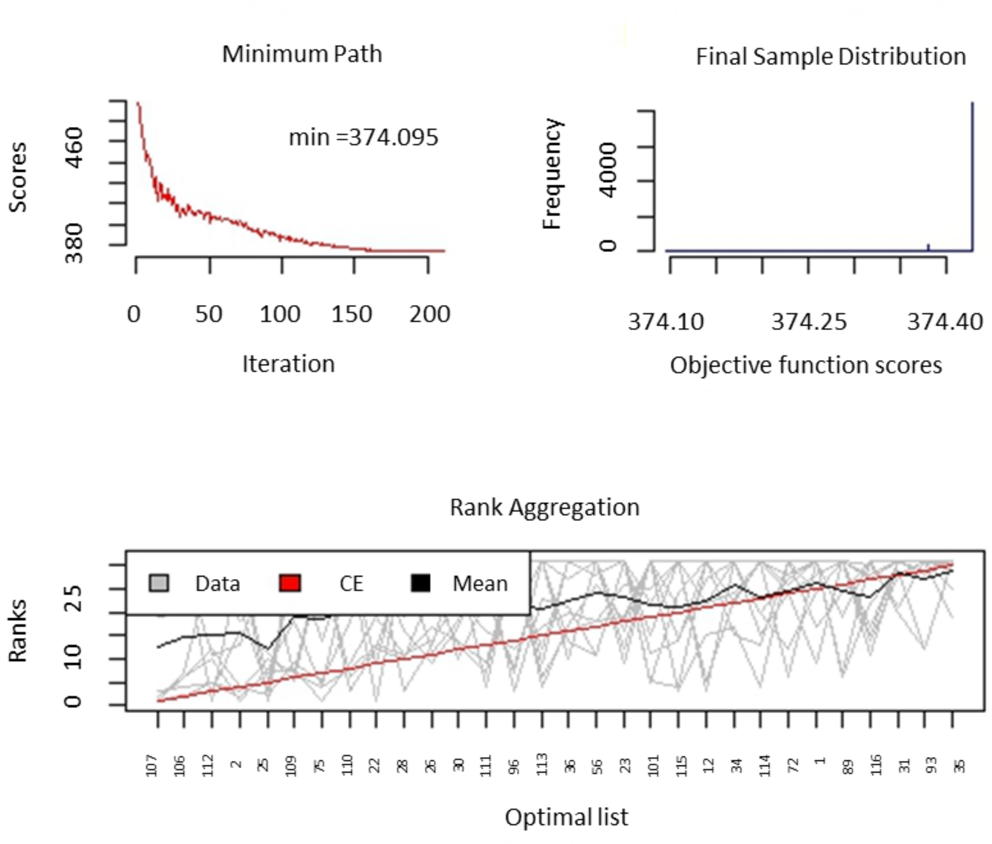


Figure 6.15. Visual representation of the rank aggregation results indicating the optimal list of parameters.

In an endeavour to identify the most influential parameters within a complex network, a sophisticated approach was employed, utilizing the Cross-Entropy (CE) Monte Carlo algorithm to reach a consensus among various network metrics, including diverse centrality measures, Authority, Hub, and others (Table 6.16). This method allowed for the integration and comparison of rankings across different metrics, highlighting the paramount significance of certain parameters amidst a multitude of network dynamics. The culmination of this rigorous analysis is concisely encapsulated in the Table 5.16, presented in alphabetical order, which summarizes the investigation's results in terms of risk factors. By distilling the essence of multiple network metrics into a unified ranking, this approach offers a nuanced understanding of the parameters that play pivotal roles in the network's structure and functionality, thereby providing a valuable tool for further exploration and decision-making in network analysis.

Table 6.16. Consolidated ranking of network parameters as risk factors.

Rank	Risk Factors	Rank	Risk Factors	Rank	Risk Factors	Rank	Risk Factors
1	Drought impact	9	Flood Exposure	17	Agricultural water use	25	Change factor
2	Flood impact	10	Precipitation	18	Residents' utility	26	Public demand for mitigation
3	Flood risk	11	Water supply	19	Temperature	27	Air humidity
4	Flood hazard	12	Available groundwater	20	Risk perception	28	Surface water inflow
5	Available surface water	13	Water demand	21	Drought awareness	29	Access to insurance
6	Drought Vulnerability	14	Drought Exposure	22	NDVI	30	Domestic water use
7	Flood awareness	15	Community resilience	23	Agricultural demand		
8	Drought risk	16	Drought hazard	24	Water resources sustainability index		

The information derived from the comprehensive analysis, which culminated in the creation of a table of risk factors (Table 6.16), will be instrumental in identifying the most influential pathways for conducting an integrated assessment of flood and drought risks at the river basin scale. This strategic selection process aims to pinpoint key areas for focused evaluation, leveraging the synthesized data to enhance the accuracy and efficacy of risk assessment models in addressing the complexities of water-related challenges within a specific geographical context. The selection of pathways for the integrated assessment of flood and drought risks is informed by the culminated results from the identification of risk factors, achieved through the application of the Cross-Entropy (CE) approach. These pathways are meticulously crafted to encompass as many relevant links as possible that exhibit close centrality to the identified risk factors, deliberately sidestepping connections characterized by delay or secondary influence to maintain analytical precision. For both flood and drought risk assessments, two distinct sets of causal interrelationships have been delineated (Figure 6.16 and Figure 6.17), underscoring the nuanced dynamics inherent to each risk type. In consideration of the spatio-temporal resolution of these links, certain less pervasive connections have been deliberately omitted. This strategic simplification is intended to eliminate potential confusion or redundancy, all the while ensuring that the requisite degree of complexity is retained in our risk assessment methodology.

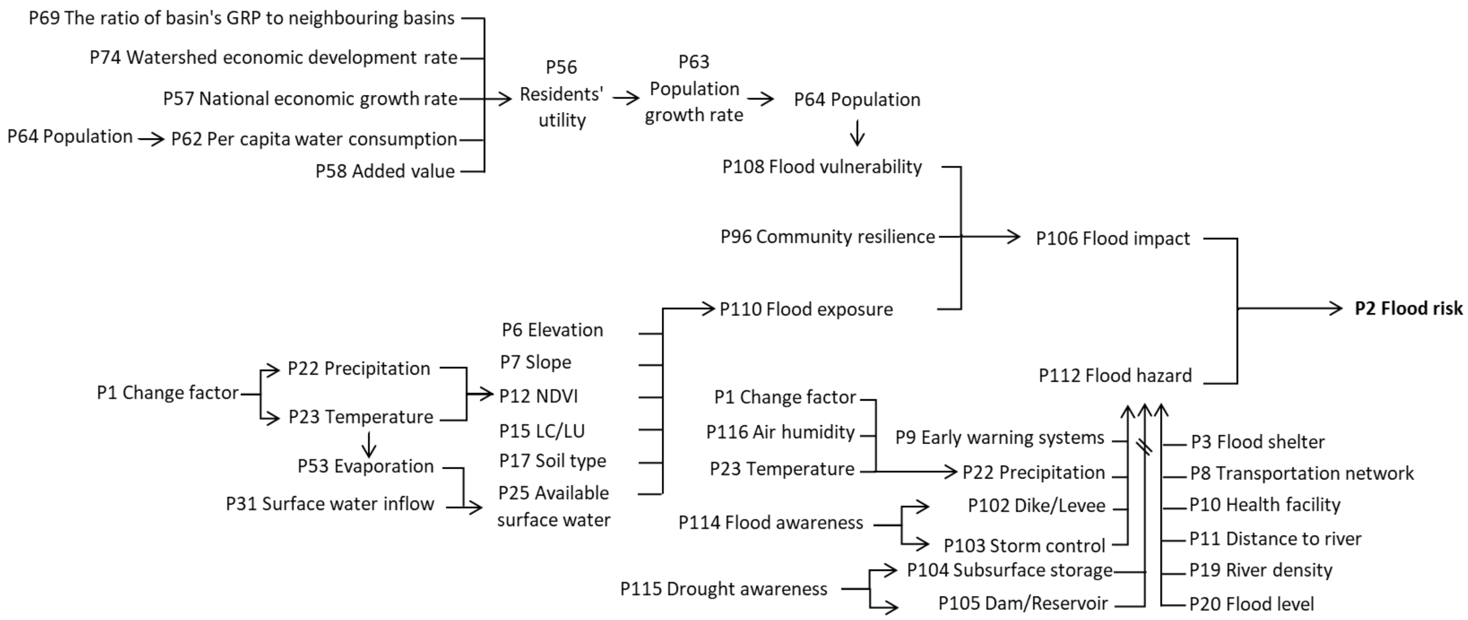


Figure 6.16. Causal relationship network identifying flood risk at a river basin scale.

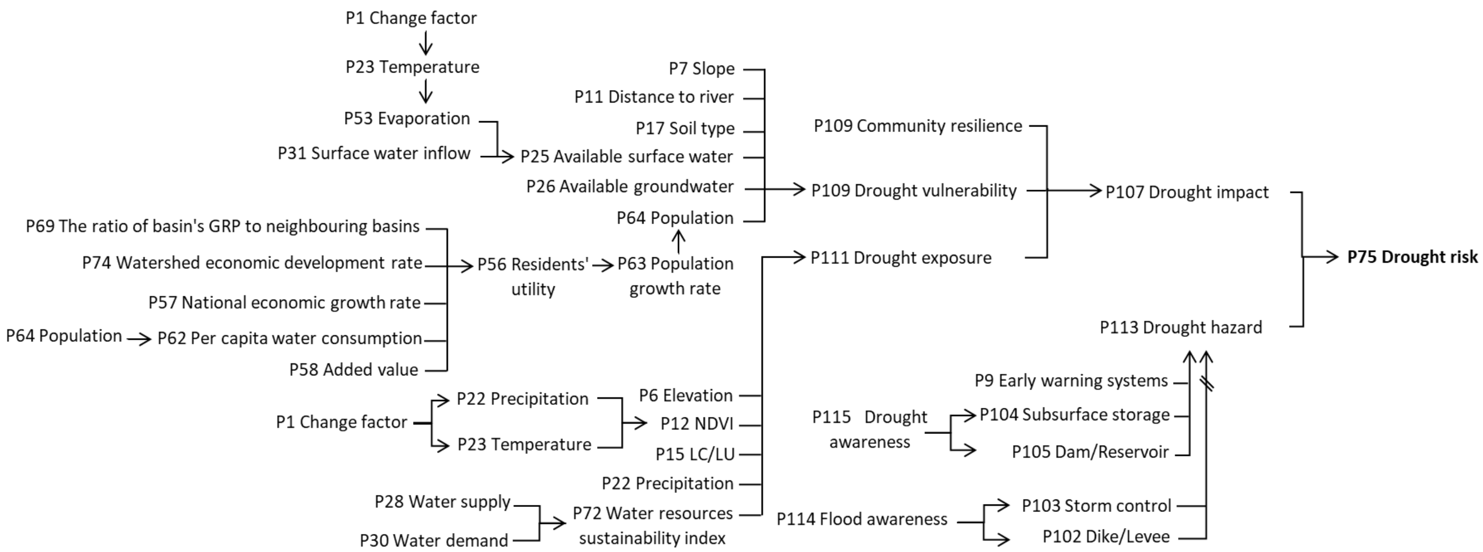


Figure 6.17. Causal relationship network identifying drought risk at a river basin scale.

This chapter presented the construction of an advanced causal framework for flood and drought risk assessment, integrating Interpretive Structural Modelling (ISM), Causal Loop Diagrams

(CLD), and Graph Theory. The framework's robustness lies in its comprehensive approach to selecting and analysing parameters influencing flood and drought risks, derived from extensive literature and empirical studies.

The ISM methodology structured these parameters hierarchically, revealing direct and indirect influences, while CLDs offered a dynamic perspective on feedback mechanisms. Graph Theory streamlined the complexity of risk pathways, ensuring the framework's practical utility by focusing on relevant modelling scenarios.

The results highlighted the hierarchical structure of risk parameters, categorized through Level Partitioning and analysed using MICMAC to understand driving and dependency characteristics. The three-tiered hierarchy underscored the varying degrees of influence among elements, emphasizing water conflict as a pivotal factor at the top level.

Utilizing CLDs, the study effectively mapped interactions within the system, illustrating both self-reinforcing and self-balancing dynamics. This duality is crucial for targeted risk mitigation strategies, ensuring optimal resource allocation and management.

Network analysis, employing Girvan-Newman clustering, betweenness, and closeness centrality measures, revealed the intricate interdependencies within the system. High centrality nodes were identified as critical leverage points for strategic interventions in risk management.

Finally, the application of the Cross-Entropy Monte Carlo algorithm provided a consolidated ranking of risk factors, facilitating the selection of key pathways for integrated flood and drought risk assessments. This methodological advancement offers a sophisticated tool for policymakers, urban planners, and environmental researchers, contributing significantly to sustainable water resource management in the face of increasing climatic uncertainties.

This conclusion synthesized the key findings and methodologies of this chapter, emphasizing the framework's scientific and practical implications in flood and drought risk management.

Looking ahead, the subsequent chapter is poised to undertake a comprehensive evaluation of flooding and drought risks within the River Severn Basin District over the past two decades. Leveraging the methodologies delineated in Chapter 3, a novel combined flood and drought risk index will be proposed. This forward-looking analysis aims to provide a robust framework for understanding and mitigating the impacts of these intertwined environmental challenges, reflecting a sophisticated integration of theoretical insights and practical implications drawn from the preceding analytical endeavours.

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7 Results and discussion: Integrated assessment and uncertainty analysis of flood and drought risk: a case study of River Severn basin

7.1 CHAPTER INTRODUCTION

The chapter provides a comprehensive analysis of flood and drought risk within the River Severn basin, utilizing integrated assessment methodologies to evaluate spatial and temporal variations in risk components. It aligns with the third research objective: to validate the framework through sensitivity analysis and combine it with fractal geometric indices, ultimately creating a mutual flood and drought risk indicator for river basins. By incorporating information and selected pathways from the previous chapters, this chapter aims to model the risks associated with flood and drought more comprehensively. Following the initial mapping, the chapter delves into the validation of these risk assessments. This involves a meticulous comparison of predicted risk areas with observed flood events and established risk zones, employing Receiver Operating Characteristic (ROC) curves to quantify the accuracy of the predictions. This validation process ensures that the models are not only theoretically sound but also practically applicable.

The chapter proceeds with a thorough sensitivity and uncertainty analysis, identifying the key parameters that influence risk predictions and assessing their impact on the overall model performance. By understanding these variables, the study refines the models, making them more robust and less prone to error. Modern statistical techniques play a pivotal role in this chapter, as they are employed to predict future flood and drought risks. The efficiency of these predictions is critically evaluated, ensuring that the models can provide reliable forecasts that stakeholders can use for effective planning and mitigation strategies.

Finally, the chapter concludes with a synthesis of the findings, highlighting the implications of the results for flood and drought risk management in the River Severn basin. This section underscores the value of the validated models in informing policy decisions, enhancing community resilience, and contributing to the broader field of risk assessment research. The methodologies and results presented in this chapter serve as a crucial link to the overarching goals of the thesis, demonstrating how scientific rigor and innovative techniques can address complex environmental challenges.

7.2 Spatial and temporal analysis of flood risk components

7.2.1 Flood exposure, vulnerability and impact

The spatial variation of the flood exposure of the study area along with its temporal trend analysis for the data period (2000-2020) are presented in Figure 7.1(a) and (d) respectively. The result shows that 68% (13986 km^2) of the exposure map is exposed to a moderate category (Table 7.1), followed by 29% (5984 km^2) classified as highly exposed to flooding. In urbanized landscapes, areas characterized by low vegetation cover, fine-textured soils, and lowland topography, which are predominantly influenced by geographical features and land cover land use (LCLU) patterns, exhibit higher susceptibility to flood exposure.

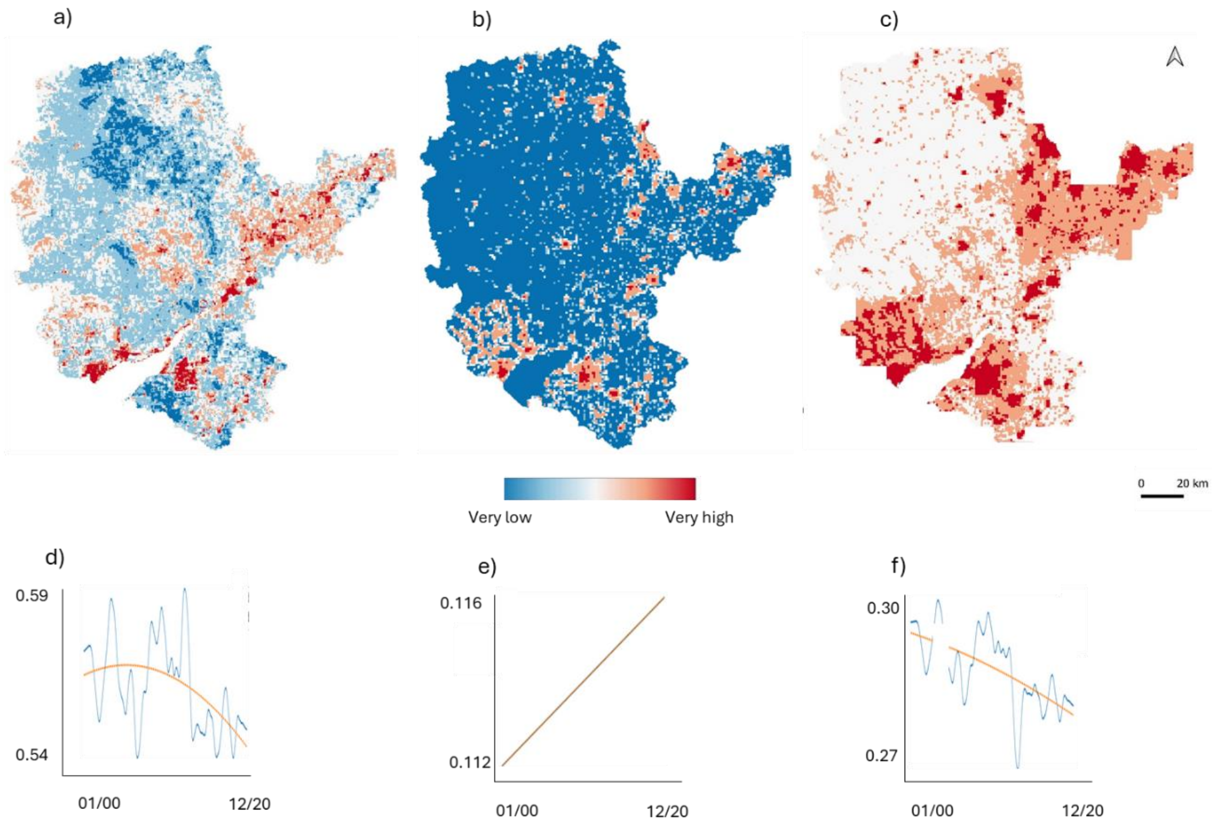


Figure 7.1. Maps of flood risk assessment components of the study area: a) exposure, b) vulnerability and c) impact, d) exposure temporal trend, e) vulnerability temporal trend, f) Impact temporal trend.

Notable observation is a total 4 percent drop to the flood exposure of the basin over the period of study, which could be attributed to enhancements in vegetation cover and LCLU management. On the other hand, a not much condensed distribution of population density, faced the flood vulnerability of 85% (17212 km^2) of the basin to low and very low category. However, in regions (15%) where redistribution communities' assets based on economic prosperity and consequently water infrastructure and consumption increase, vulnerability to flood falls under the category of moderate to very high (Figure 7.1(b)). This risk component has not changed significantly since year 2000 (Figure 7.1(e)).

Table 7.1. Area coverage of flood risk components, exposure, vulnerability and impact.

	Exposure		Vulnerability		Impact	
Class	**Area (km^2)**	**%**	**Area (km^2)**	**%**	**Area (km^2)**	**%**
Very high	246.13	1.2	128.19	0.64	1673.34	8.55
High	5984.85	29.15	1285.37	6.43	6223.68	31.8
Moderate	13986.74	68.12	1349.61	6.76	11668.49	59.62
Low	313.63	1.53	1489.92	7.46	1.96	0.01
Very low	0	0	15723.91	78.71	3.85	0.02

Results for flood impact, which is a combination of exposure, vulnerability and community resilience represented in Figure 7.1(c), reveals that 59% (11668 km^2) of this basin is classified as moderate whilst around 31% (6223 km^2) could experience a high impact. Generally, these areas are geographically lowlands with low vegetation cover and denser populations highly involved in more socio-economic activities. This feature has shown an overall 3% drop in its temporal trend since year 2000 (Figure 6.1 (f)).

7.2.2 Flood hazard, mitigation capacity and risk

Figure 7.2(a) exhibits the overall mitigation capacity of the River Severn basin district against the flood. A particular region with effective mitigation measures indicates the ability to reduce consequences and consists of a better adaptive capacity against natural hazards. According to the prepared mitigation capacity map, eastern and southwestern, parts of the study site are covered with areas were marked as very high to high mitigation measures. The very high (1.2%) and high (29.1%) mitigation capacity classes combinedly cover (6230 km2) of the study area (Table 7.2). These areas consist of proper mitigation capacity, such as major roads, health institution, access to Early Warning Systems (EWS) and a vast range of natural and built defence mechanisms and reservoirs. In contrast, the better part of the basin (68%-13986 km2) mainly in west of River Severn, central regions of the basin moving up to north, and west the ratio of areas that are classified as having very low and low mitigation capacity increases. Moreover, low and very low mitigation capacity areas are witnessed in only 1.5% (313 km2) of the area. Relatively in contrast to mitigation class spatial distribution, around a third (33% - 7029 km2) of the areas fall within the class of high hazard active rivers, high flood levels, and extensive rainfall are mainly responsible for intense flood hazards in those regions. Almost 34.5% (7272 km2) of regions under the category of moderate corelate with slightly higher river density and much less distance to rivers (Figure 7.2 (b)). Mapping the results from flood hazard computational assessments reveals that the hazards associated with flood in this basin have a visible overlay with areas of moderate towards high mitigation capacity.

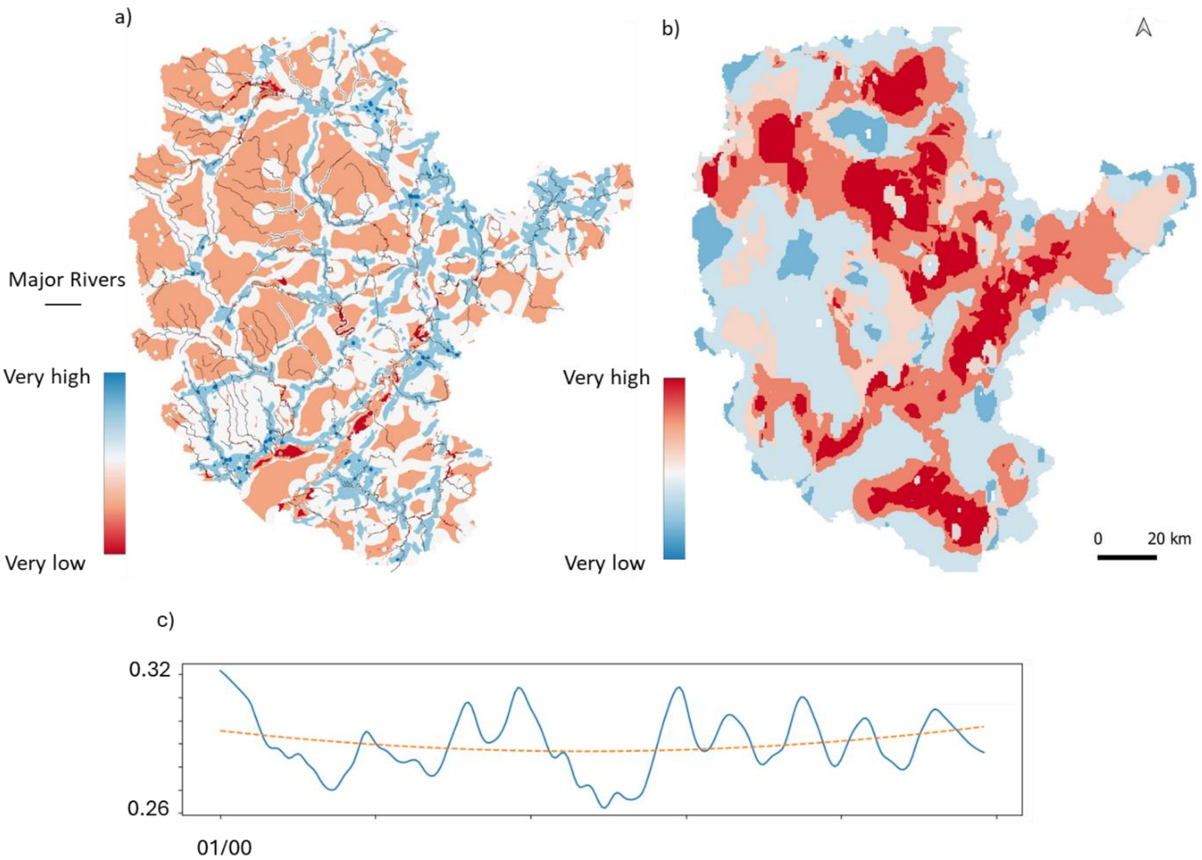


Figure 7.2. Maps of flood risk assessment components of the study area: a) Mitigation capacity, b) flood hazard and c) flood hazard temporal trend.

A relatively small upward trend is observed in the general trend of flood hazard in the overall basin involving more picks with less intervals in average (Figure 7.2(c)).

Table 7.2. Area coverage of risk components, flood hazard and mitigation capacity.

	Hazard		Mitigation capacity	
Class	**Area (km²)**	**%**	**Area (km²)**	**%**
Very high	1707.71	8.11	246.13	1.2
High	7029.22	33.4	5984.85	29.15
Moderate	7272.18	34.56	13986.74	68.12
Low	4731.74	22.48	313.63	1.53
Very low	303.93	1.44	0	0

Flood risk mapping approach of the study area without integrating mitigation capacity was generated using results from flood impact and hazard (Figure 7.2(a)). The spatial distribution of this risk map indicates around 16% of the study area (3080 km^2) were classified as very high and high flood risk, while almost 35% of the study area belongs to the moderate flood risk class. Notable information is that around 43% (8053 km^2) of the basin potentially experience below moderate risk of flooding (Table 7.3).

Table 7.3. Area coverage of flood risk with and without mitigation capacity according to the defined classes.

	Risk without mitigation capacity		Risk with mitigation capacity	
Class	**Area (km²)**	**%**	**Area (km²)**	**%**
Very high	348.32	1.88	11.6	0.06
High	2739.15	14.77	335.19	1.73
Moderate	6559.1	35.91	5840.69	30.08
Low	8053.98	43.44	11625.87	59.88
Very low	740.87	4	1602.15	8.25

Eventually, the flood risk scenario of this district integrating mitigation capacity is represented in Figure 7.3(b). The spatial analysis of this map demonstrates that around 1.8% (346 km^2) of the study area is under a high or very high-risk class, whereas 30% (5840 km^2) of the target area belongs to the moderate risk zone (Table 7.3).

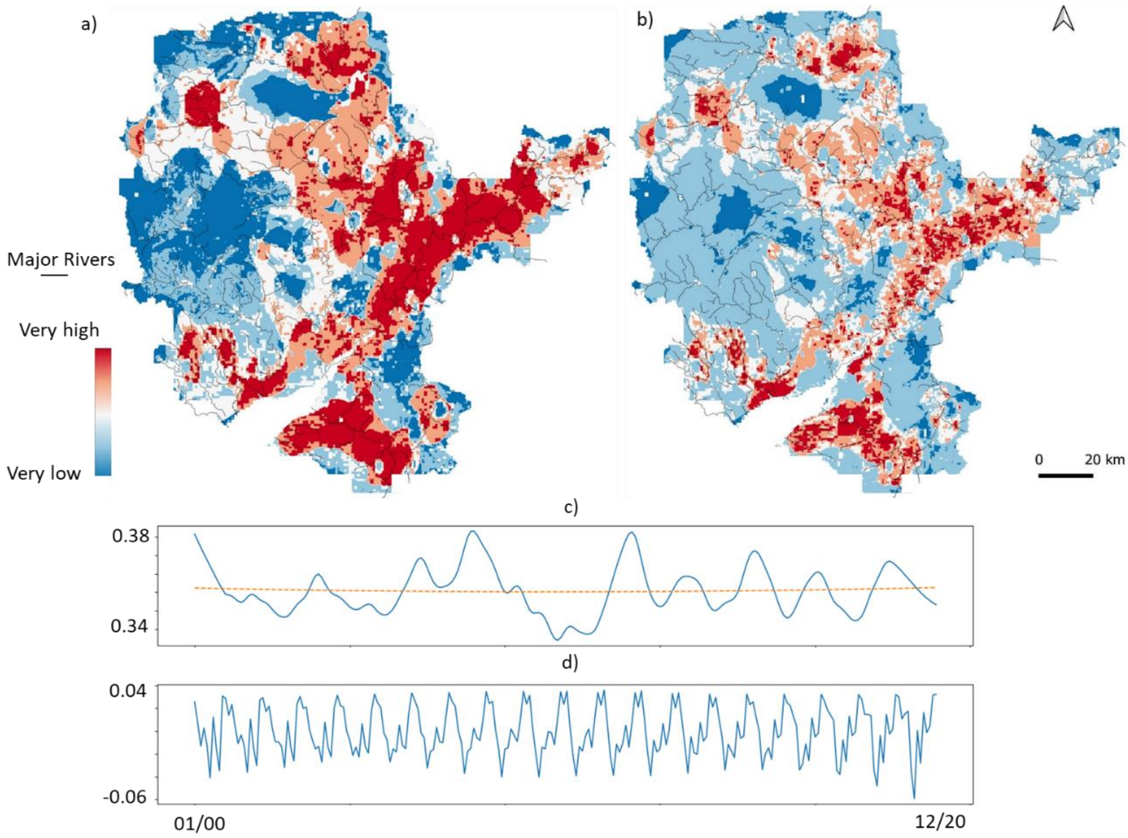


Figure 7.3. Maps of flood risk assessment components of the study area: a) without mitigation capacity, b) with mitigation capacity, c) temporal trend of flood risk and d) seasonal trend of flood risk (x axis in panels c and d is time, whilst the y axis represents risk).

Results from mapping the areas affected by higher than moderate risk of flooding indicates that City of Bristol, Bath and northeast Somerset, north Somerset and south Gloucestershire, west Gloucestershire, parts of Worcester, Warwickshire, Telford and Wrekin, and Shropshire are much more affected than the rest of the basin (Figure 7.3 (a)). Western parts of the basin have experienced comparably lower risk of flooding compared to the eastern side of the River Severn. As the risk map is the final production of the risk components, therefore, the final risk is comparatively lower after including the effect of mitigation (Figure 7.3(b)). In other words, because of the integration of mitigation capacity, the high flood risk subsided in some areas, for instance, central regions and northeaster part of the basin transformed into moderate to the low-risk class, which was high to very-high flood risk initially. The temporal trend of monthly time series of flood risk has remained fairly constant over the course of this study (Figure 7.3 (c)). However, difference in seasonal trend has been constantly increasing from 6 percent to a little over 10 percent (Figure 7.3(d)).

7.2.3 Validation of flood risk assessment with historical observed floods

Using GIS packages a spatial analysis was carried out, to overlay the flood risk map and the historically flooded regions map (Figure 7.4 (a) and (b)). The results show that areas already affected by flooding have been captured well within the predicted high-risk regions. Temporal extent of historic flood dataset extends from 1946 to 2020. However, the risk reduction measures such as some of flood defence schemes and early warning systems have not been put in place before year 2006. Additionally, sources of vulnerability such as population, as well as resilience factors concerning social cohesion and human development index were not as high standard as they are today. Thus, regions with higher risk could be more vastly distributed.

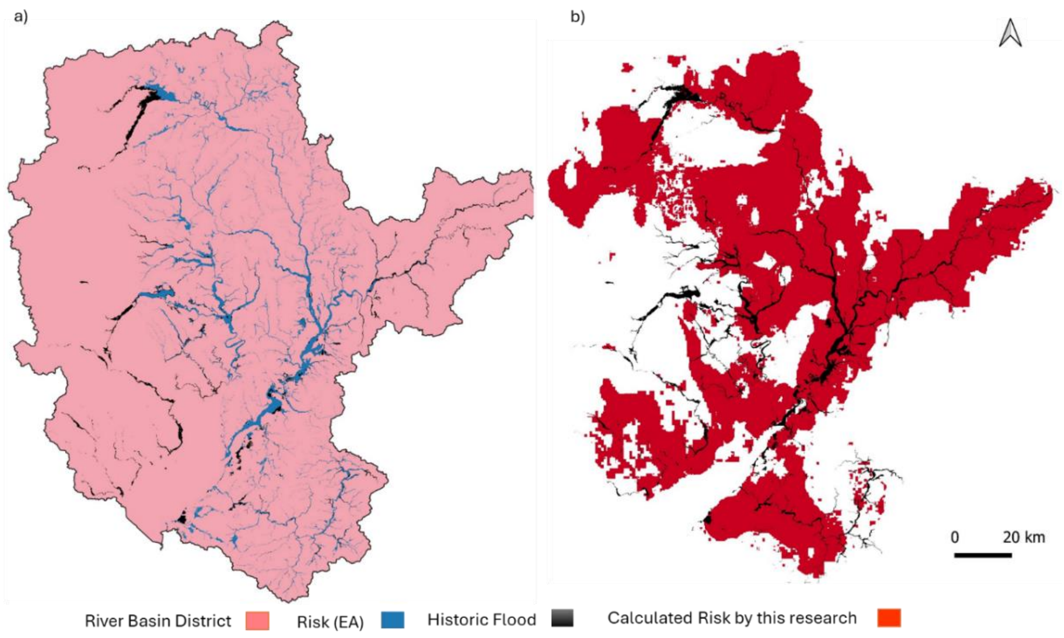


Figure 7.4. Maps of observed flood overlaid on predicted flood risk: a) risk calculated by environment agency and b) risk calculated by this research.

The areas of agreement and disagreement between results from this research versus historic flooding extent were identified and mapped (Figure 7.5). Areas with agreement between flooded events and estimated as high risk by this research is around 70.25 % (Figure 7.5 (a)) for the whole temporal extent of historic dataset (1946-2020) and 84.87% (Figure 7.5 (b)) for floods that have occurred within the time frame of data utilised in this research (2000-2020). It is notable to mention that not necessarily only the areas that are not affected by flood can experience a higher flood risk as flooding is an event. Events can sometimes happen as a result of a chain of less likely scenarios. However, areas that are historically flooded could be considered as zones of higher risk.

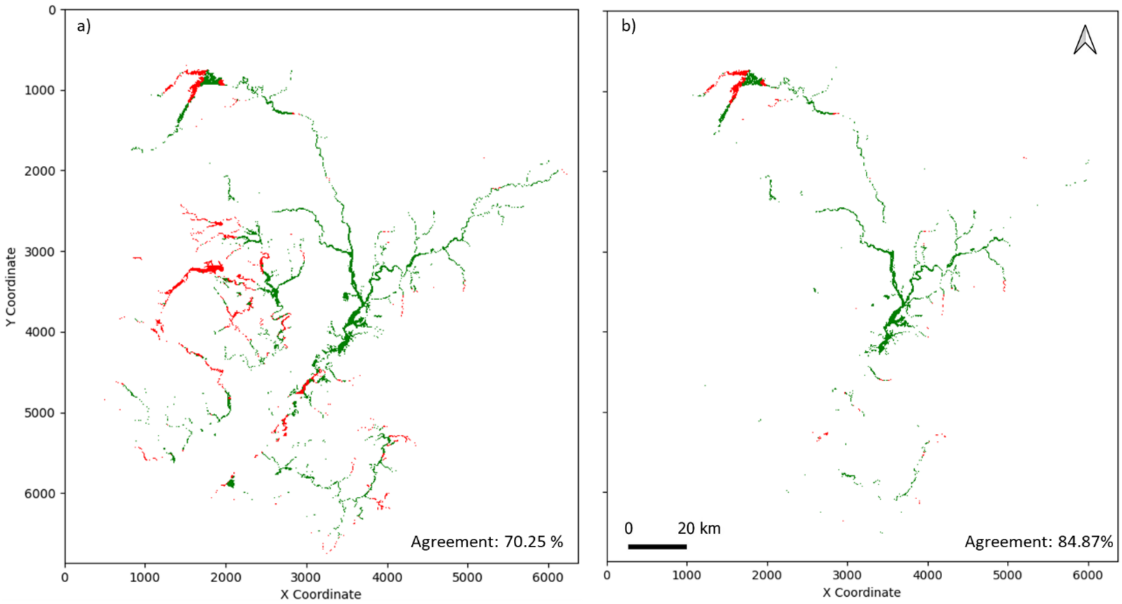
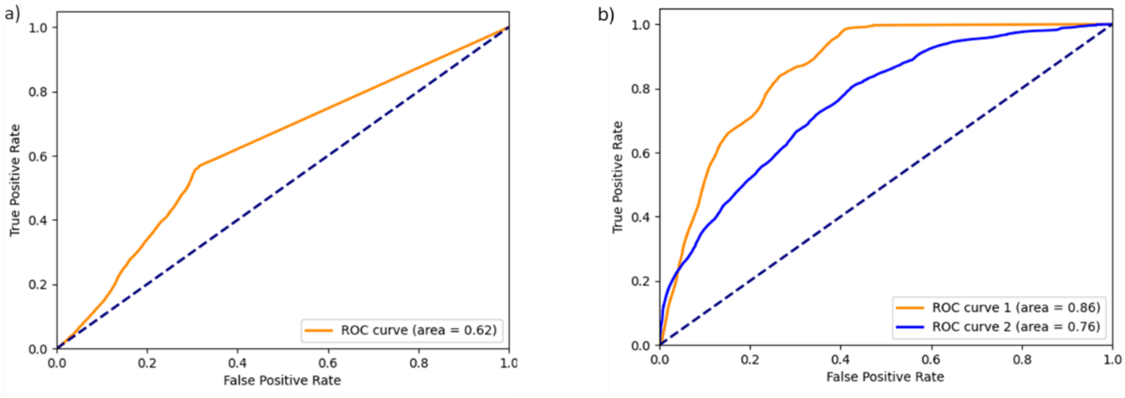
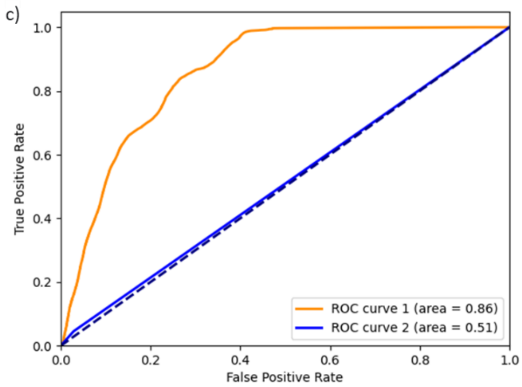


Figure 7.5. Spatial visualisation of agreement between assessed flood risk and flood observations: a) flood dataset since 1946, b) flood dataset since 2000.

To further validate the results for flood risk estimation, an investigation was conducted using Receiver Operating Characteristic (ROC) curves. This involved comparing observed flooded regions and existing published risky areas for river, sea, and runoff floods. Firstly, the result from this study is compared against the previously assessed risk models' results published by the Environment Agency and then against observed floods considering scenarios with and without mitigation. In Figure 7.6 (a), the ROC curve compares the risk published by the Environment Agency against the risk assessment based on the results from this research. The curve shows a moderate area under the curve (AUC) of 0.62, indicating a moderate performance of the research model compared to the official assessment. This ROC in figure 7.6 (b) curve compares areas marked as high risk by the research estimation against observed flooding events with and without mitigation. The graph shows two ROC curves, one with an AUC of 0.86 and the other with an AUC of 0.76, indicating good predictive performance of the research model, especially in the context of mitigated scenarios.





Historic	Predicted	Chi-square
Historic Flood	Risk by EA	6614
Risk by EA	Risk by this research (without mitigation)	76614
Historic Flood	Risk without mitigation	713468
Historic Flood	Risk with mitigation	567995

- P value for all tests was zero -

Figure 7.6. Validation of flood risk assessment using Receiver Operating Characteristic (ROC): a) risk by this research vs risk by EA, b) risk by this research with/without mitigation capacity vs historic floods and c) risk by this research and risk by EA vs historic floods.

This ROC curve evaluates how the research risk assessment model performs against flooding events compared to the official estimation by the Environment Agency. The graph presents two ROC curves with AUCs of 0.86 (research model) and 0.51 (official estimation), indicating that the research model has a higher predictive accuracy than the official estimation (Figure 7.6 (c)). The chi-square table assesses the performance of different models, showing the chi-square statistics for the comparisons. The results indicate statistically significant differences between the models, with the research model showing better alignment with the observed flooding events. Overall, the visual comparison through ROC curves and statistical validation via the chi-square collectively suggest that the research model provides a reasonable and statistically significant prediction of flood risk areas compared to the official dataset published by the Environment Agency and observed flooding extents.

7.3 Spatial and Temporal Analysis of drought risk components

7.3.1 Drought exposure, vulnerability and impact

The spatio-temporal variation of exposure to drought within the River Severn basin is illustrated in Figure 7.7 (panels a and d). Areas benefiting from the utilization of water resource assets experience less severe drought conditions compared to upstream regions, where elevation and dependence on land and vegetation resource management are crucial factors.

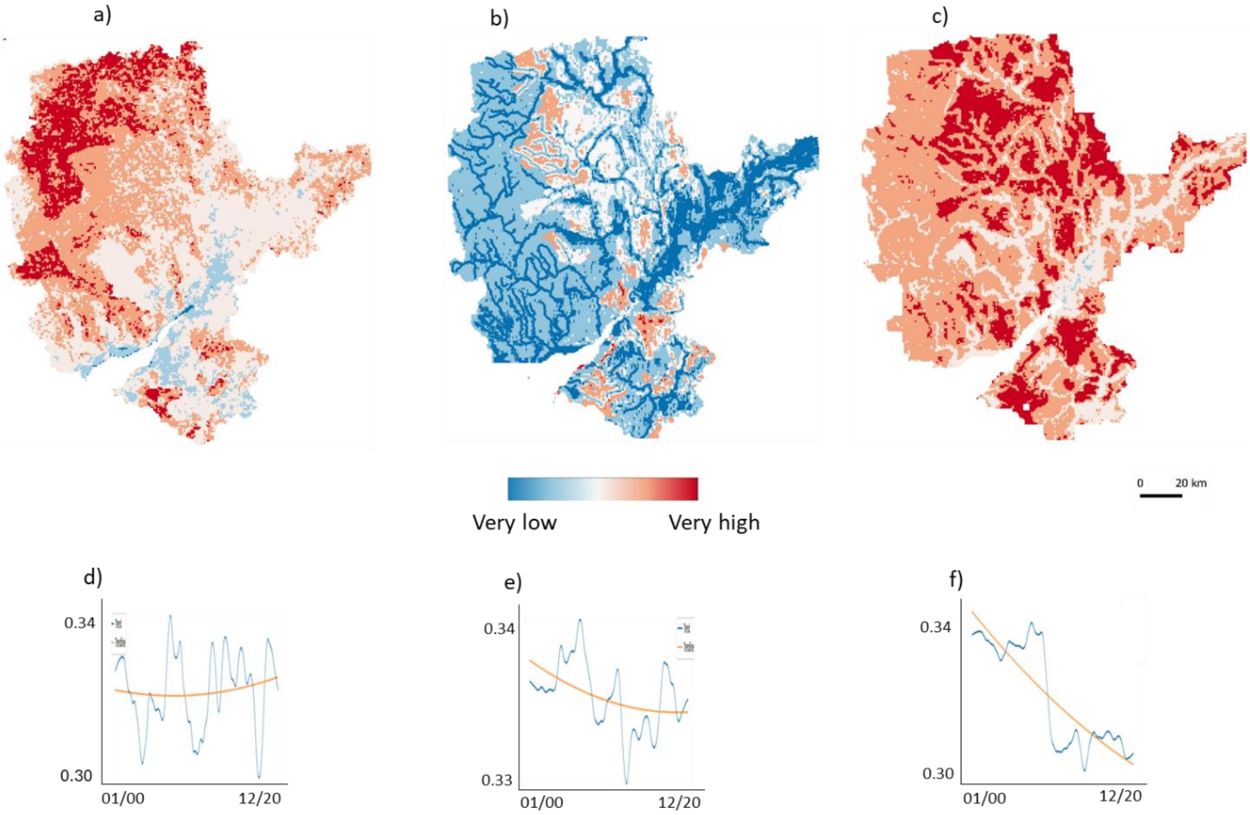


Figure 7.7. Maps of drought risk assessment components of the study area: a) exposure, b) vulnerability and c) impact, d) exposure temporal trend, e) vulnerability temporal trend and f) Impact temporal trend.

Notably, most of the basin, approximately 80% (16830 km²), is subject to moderate and high exposure in drought risk (Table 7.4). This heightened exposure is largely attributable to the prevalent agricultural and related land uses, coupled with an over-reliance on water resources and precipitation patterns. Overall trend of exposure to drought is observed to be slightly upward during the study period. Vulnerability to drought risk in the study area, influenced primarily by population and water resource assets through the redistribution of socio-economic capacities, is depicted in Figure 7.7 (panels b and e). The results indicate that approximately 70% (14780 km²) of the basin exhibits below moderate vulnerability to drought (Table 7.4).

Table 7.4. Area coverage of drought risk components, exposure, vulnerability and impact.

	Exposure		Vulnerability		Impact	
Class	**Area (km²)**	**%**	**Area (km²)**	**%**	**Area (km²)**	**%**
Very high	2753.77	13.27	54.25	0.26	4377.26	22.86
High	8050.94	38.80	1678.61	8.08	11198.95	58.48
Moderate	8780.48	42.32	4251.03	20.46	3543.34	18.50
Low	1132.98	5.46	10087.6	48.56	31.91	0.17
Very low	29.20	0.14	4701.36	22.63	0	0

Areas in the centre of the basin and slightly towards both the north and south experience a moderate level of vulnerability to drought. This moderate vulnerability appears to be driven by a combination of population density and the relatively limited availability of managed water resources. The overall trend in vulnerability to drought is slightly decreasing, potentially due to changes in surface and groundwater patterns or shifts in water resource allocation. Almost all of the basin experiences above moderate drought impact, particularly in areas with high concentrations of population and water infrastructure-related assets (Figure 7.7, panels c and f). This elevated risk is likely due to the combination of the basin's physiological properties and the distribution of socio-economic capacities, which act as potential countermeasures to hydro-hazard risks. However, based on the temporal analysis conducted in this study, the overall trend in drought impact has decreased by approximately 4% over the past two decades.

7.3.2 Drought, mitigation capacity and risk

Figure 7.8a presents the map of mitigation capacity, which includes water resources management assets and flood defence mechanisms that can influence drought risk, both positively and negatively. Approximately 39% of the mitigation capacity falls under the category of very high, indicating substantial infrastructure and resources dedicated to mitigating drought risk. Conversely, almost no part of the region has very low mitigation capacity (Table 7.5). However, a significant portion of the basin, totalling 9279.75 km² (43.66%), still suffers from low mitigation capacity, highlighting areas where additional resources and efforts are needed to improve drought resilience.

Figure 7.8. Maps of drought risk assessment components of the study area: a) Mitigation capacity, b) drought risk, c) temporal trend of drought risk and d) seasonal trend of drought risk (x axis in panels c and d is time, whilst the y axis represents risk).

The spatio-temporal distribution of drought risk for the River Severn basin is illustrated in Figure 7.8 (panels b, c, and d). Regions with either very high or very low drought risk constitute less than 10% each of the total area. Notably, there are two peaks in the frequency of pixels indicating either high or low risk. This distribution reflects the impact of mitigation measures, which have effectively reduced areas where drought risk was historically higher. These measures have been particularly effective in regions where it was feasible to implement water resources management and enhance resource allocation quality. Overall, the trend in drought risk across the basin has declined by approximately 3%. The seasonality of drought risk appears minimal, and its variance has decreased over this period, indicating a more stable risk profile.

Table 7.5. Area coverage of drought and mitigation capacity according to the defined classes.

	Mitigation capacity		Drought risk	
Class	**Area (km²)**	**%**	**Area (km²)**	**%**
Very high	8370.36	39.39	1300.63	6.79
High	0	0	6442.05	33.63
Moderate	3597.91	16.93	3192.36	16.67
Low	9279.75	43.66	6586.98	34.40
Very low	0.4	0.02	1628.90	8.51

7.4 Fractal dimension analysis of flood and drought risk dispersion

Fractal dimension is a mathematical descriptor used to quantify the self-similarity and complexity of shapes. In this research, it measures the spatial dispersion of regions affected by various flood and drought risk categories. Applying this criterion provides a comprehensive understanding of the variability in dispersion and the severity of concurrent flood and drought risks across the river basin. The analysis involves a 5x5 matrix, where rows represent different levels of drought risk, and columns represent flood risk levels (five classes, ranging from very low to very high). For instance, the number in column 2, row 4 denotes the fractal dimension of areas where flood risk is low, and drought risk is high (Figure 7.9 panel a). This matrix facilitates a detailed assessment of risk variability across the basin.

The matrix of fractal dimensions, representing regions with various combinations of flood and drought risk, is illustrated in Figure 7.9 (panels a and b). The results of this dimension analysis range from 1.275 to 1.625. Higher fractal dimension values indicate greater dispersion of affected areas, implying more significant challenges in addressing the risks associated with flooding and drought. This increased dispersion complicates the management of these hydro-hazards on a river basin scale. When multiplied by the area of the affected region, this measure becomes more robust, helping decision-makers understand both the size of the risk-affected areas and the severity of the spatial distribution that needs to be addressed.

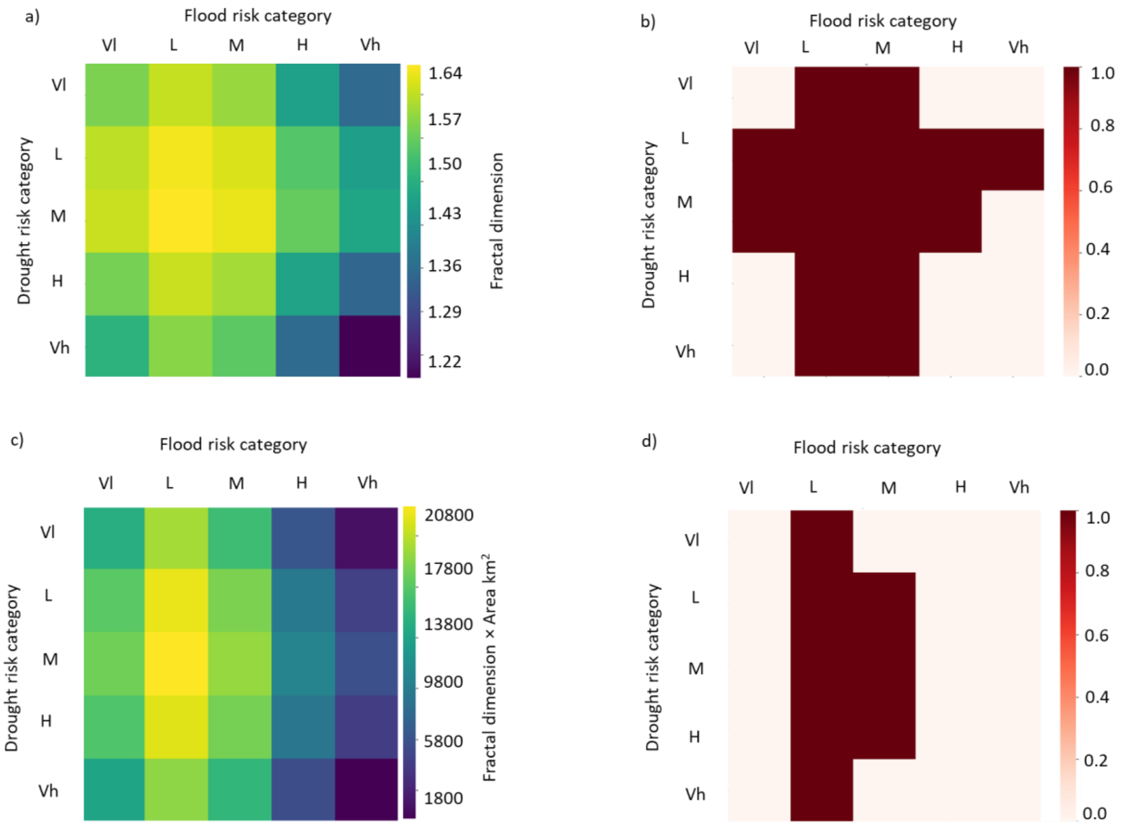


Figure 7.9. Visualisation of combined flood and drought risk categories (Vl: Very low; L: Low; M: Moderate; Vh: Veri high; H: High): a) fractal dimension matrix, b) high risk categories based only on fractal dimension of the shape of spatial distribution of the categorical risk regions (reference from panel a), c) matrix of combined effect of fractal dimension and area of the spatial risk distribution and d) statistically significant categories of the combined effect depicted in panel c.

Higher values (Close to 1.625) are typically associated with areas where both flood and drought risks are present at medium levels. This suggests that regions with moderate risks in both categories exhibit complex and fragmented patterns, making risk management more challenging. Lower values (Close to 1.275) occur in areas with high flood risk, regardless of the severity of drought risk. This indicates that regions with higher flood risk have more straightforward, less fragmented patterns, possibly due to the dominance of flood risk factors over the spatial complexity.

A combined measure of risk is estimated using multiplying fractal dimension by Area (Figure 7.9 panels c and d). To provide a more robust measure for decision-makers, multiplying the fractal dimension by the area of the affected region offers a better understanding of the size of the risk-affected areas and the severity of the spatial distribution. This combined metric helps highlight regions that are not only large but also spatially complex, requiring more sophisticated management approaches.

To determine which levels of fractal dimensions and the combined measure of risk are more important or significant, an analysis was implemented. First, the range, standard deviation, mean, skewness, and kurtosis of the data within the metrics were calculated. With low kurtosis (0.3) and slightly negative skewness, it was realized that the tails are not very extreme compared to a normal distribution. Additionally, focusing on the tail with higher than mean values was both rational (due to an increase in the concept of dispersion) and statistically meaningful. A threshold was introduced and normalized, above which the values of either fractal dimension or combined measure of risk were considered more significant. The threshold was set at mean + standard deviation. Figures 7.9 (panels b and d) represent the heatmap for this analysis with darker values being above this threshold, considered as of higher statistical and applicational significance.

Dispersion has management challenges. Regions with high fractal dimensions signify a highly dispersed pattern of risk, indicating that these areas are more difficult to manage due to their fragmented nature. These regions require more nuanced and extensive management strategies to address the dispersed risks effectively. Conversely, areas with lower fractal dimensions, particularly those with high flood risk, suggest less spatial complexity. These areas, while still at significant risk, may be easier to manage due to their more coherent spatial patterns.

The maximum combined measure values are found around cells representing moderate levels of both flood and drought risks. These are highly dispersed, fragmented and vast areas posing significant challenges for hydro-hazard management.

By moving towards regions where the flood risk is higher, the fractal dimension decreases, indicating a reduction in spatial complexity. This trend suggests that flood risk tends to dominate the spatial structure, leading to more homogeneous patterns irrespective of the drought risk level. This analysis suggests that combining strategies at different spatial scales for flood and drought risk management could be highly effective. Specifically, implementing localized treatments for flood risk reduction, along with broader spatial scale solutions such as adaptive measures for drought risk, can provide a comprehensive approach to managing these hydro-hazards. By addressing flood risks with targeted local interventions and applying expansive, adaptive strategies for drought risks, a more resilient and effective management framework can be established.

In conclusion, the fractal dimension analysis reveals that regions with medium flood and drought risks are the most complex and challenging to manage due to their high dispersion. In contrast, areas with high flood risk, regardless of drought severity, tend to have lower fractal dimensions, indicating less spatial complexity and potentially a more localised management. By combining fractal dimension values with the area of affected regions, decision-makers can gain a more comprehensive understanding of both the size and severity of risk-affected areas, enabling more effective strategies to mitigate flood and drought risks at the river basin scale.

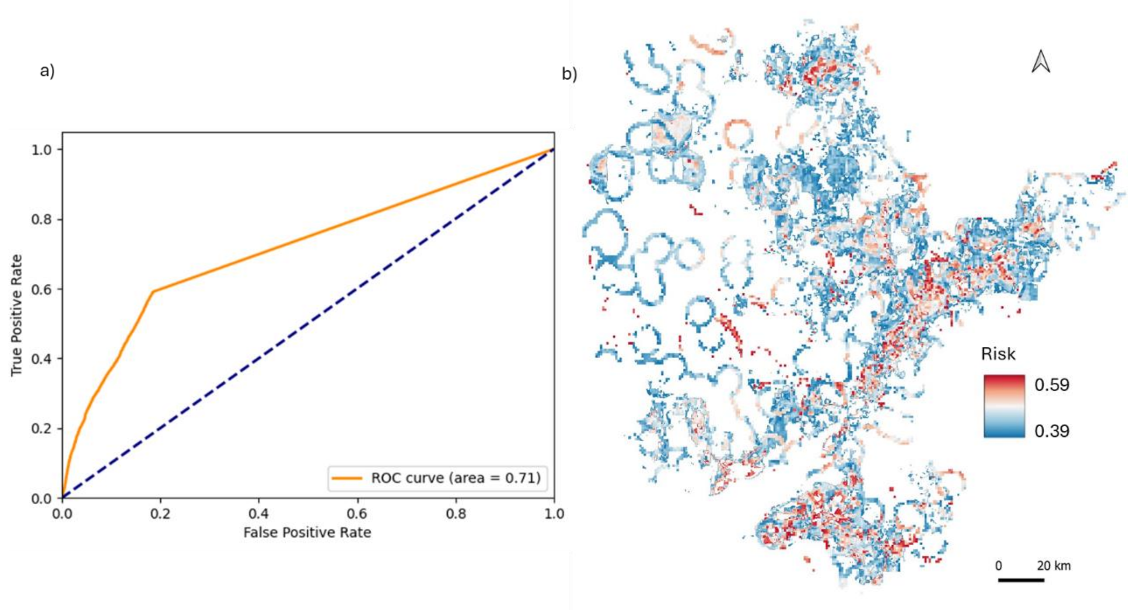


Figure 7.10. Map of combined flood and drought risk of the study area: a) ROC curve of risk showed in this map vs observed flood, b) spatial distribution of selected combination of flood and drought map based on fractal dimension analysis.

Figure 7.10 illustrates the map of regions where both flooding and drought risks are classified as medium. This map highlights areas with a combined higher fractal dimension and area, indicating greater dispersion and the vastness of the affected regions. Although the risk class for both flood and drought is medium, a legend is included to clarify and provide further insight into the calculated fractal dimension values. This enhances understanding of the spatial distribution and complexity of the areas at risk. The good AUC=0.71 for the areas of moderate combined flood and drought risk versus the observed flood (Figure 7.10 b) indicates considering region presented in this map as a baseline for mitigation and adaptation policies for a combination of flood and drought risk would be advantageous and possibly less costly. Another representation of this result, based on the analysis of pixel frequency within the combination of flood and drought risks, is illustrated as follows. The indices in this matrix (Figure 7.9 c) can be normalized and classified into six categories. Category "I" includes indices where flood risk is predominantly high. Category "II" encompasses areas where both flood and drought risks exist, but flood risk is more dominant. Category "III" represents regions where both risks are present but low. Category "IV" includes areas where both risks are high. Category "V" consists of regions where both risks exist, with drought risk being more significant. Finally, Category "VI" covers areas where drought risk is predominantly high. All these classes are described in detail in Figure 7.11 (a).

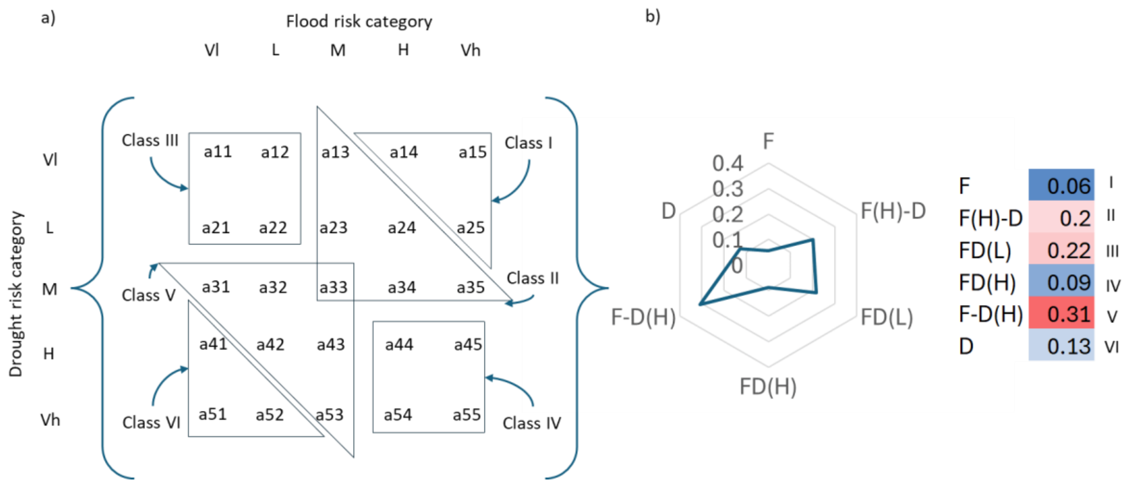


Figure 7.11. Classification of combined flood and drought risks of river Sever Basin, a) schematic matrix of combined risk categories (Vl: Very low; L: Low; M: Moderate; Vh: Veri high; H: High) and b) diagram of flood-drought risk spectrum (F: Flood risk prominent; F(H)-D; Flood risk dominant and drought risk considerable; FD(L): coexistence of low flood and drought risks; FD(H): coexistence of high flood and drought risks; F-D(H): Drought risk dominant and flood risk considerable; D: Flood risk prominent).

The matrix indices are normalized and classified into six categories, with index a33, which is mutual between classes II and V, divided equally between both classes. Panel b in Figure 7.11 presents the results for the study basin, showing the normalized combined measure for flood and drought risk. This measure reflects the spatial distribution and intensity of these risks within the basin. The radar chart highlights that the highest combined risk value, 0.31, is observed in the F-D(H) category, which corresponds to Class V. This class includes regions where both flood and drought risks exist, with drought risk being more significant. The second highest value, 0.22, is found in the

FD(L) category, indicating moderate combined risk where both flood and drought risks are low. Other categories, such as high flood risk (F) and high drought risk (D), exhibit lower combined risk values of 0.06 and 0.13 respectively. These results underscore the intricate spatial and risk-related interplay between flood and drought, with regions experiencing significant drought risk showing higher combined risk measures. This analysis provides a comprehensive understanding of how different combinations of flood and drought risks manifest across the river basin, aiding in targeted risk management and mitigation strategies.

7.5 Trend analysis using Mann Kendall test and Sen's slope

The Mann-Kendall test and Sen's Slope are statistical methods used to detect and quantify trends in time-series data. The Mann-Kendall test measures the significance and direction of trends, represented by Kendall's tau (τ). A positive τ indicates an increasing trend, a negative τ indicates a decreasing trend, and $\tau = 0$ suggests no trend. Sen's Slope calculates the rate of change over time, where a positive slope signifies an increasing trend, a negative slope indicates a decreasing trend, and a slope of zero denotes no change. These metrics help in understanding the spatio-temporal variations in flood and drought risks. Interpretation of possible combinations of Mann-Kendall τ τ and Sen's Slope is as follows.

Class 1: Both Mann-Kendall τ and Sen's Slope are Positive: Meaning: There is a significant increasing trend over time. The positive Sen's Slope quantifies the rate of increase.

Class 2: Both Mann-Kendall τ and Sen's Slope are Negative: Meaning: There is a significant decreasing trend over time. The negative Sen's Slope quantifies the rate of decrease.

Class 3: Mann-Kendall τ is Positive and Sen's Slope is Near Zero: Meaning: There is a significant increasing trend detected, but the rate of change is very small.

Class 4: Mann-Kendall τ is Negative and Sen's Slope is Near Zero: Meaning: There is a significant decreasing trend detected, but the rate of change is very small.

Class 5: Mann-Kendall τ is Near Zero and Sen's Slope is Positive: Meaning: There is no significant trend detected, but the rate of change is positive. This might indicate fluctuations without a clear trend.

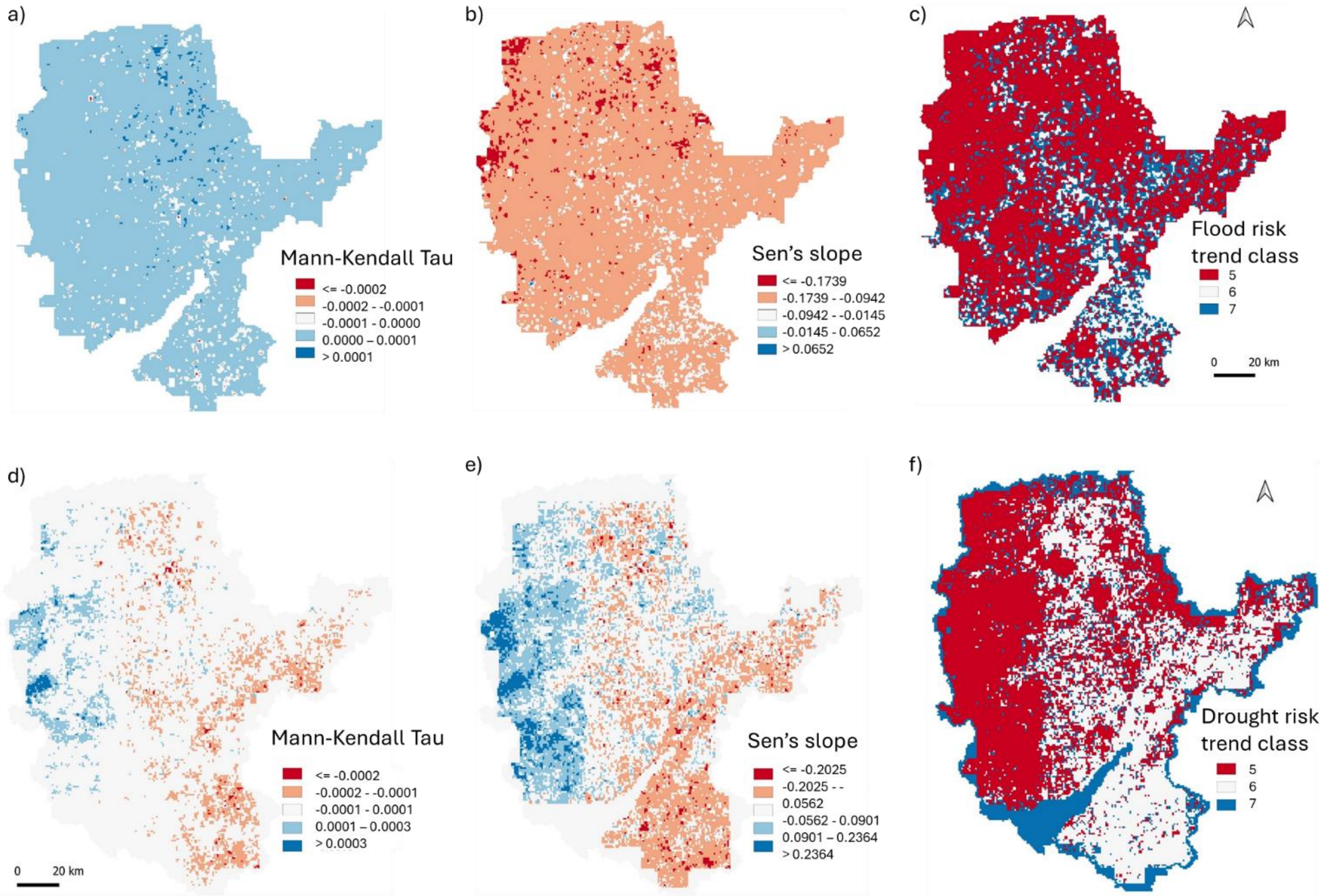


Figure 7.12. Spatial distribution of trend detection indices of flood and drought risk: a) Mann-Kendal Tau (flood risk), b) Sen's Slope (flood risk), c) trend classification (flood risk), d) Mann-Kendal Tau (drought risk), e) Sen's Slope (drought risk), f) trend classification (drought risk).

Class 6: Mann-Kendall τ is Near Zero and Sen's Slope is Negative: Meaning: There is no significant trend detected, but the rate of change is negative. This might indicate fluctuations without a clear trend.

Class 7: Both Mann-Kendall τ and Sen's Slope are Zero: Meaning: There is no trend in the data over time. The parameter remains relatively constant.

The results indicate that while flood risk in the River Severn basin has been slightly increasing, the overall rate of change over time has been declining (Figure 7.12 panels a and b). The basin predominantly experienced flood risk classified under categories 5, 6, and 7 according to the combined Mann-Kendall tau and Sen's Slope analysis (Figure 7.12 c). This suggests that, for most of the region, there may be fluctuations in flood risk without a clear, consistent trend.

Conversely, the trend in drought risk intensity was slightly stronger than that of flood risk, displaying a more diverse spatial distribution across the basin. The rates of both increasing and decreasing changes over time for drought risk were also more pronounced (Figure 7.12, panels d and e). Despite this spatial diversity, the trend classes for drought risk were similar to those for flood risk, indicating potential fluctuations without a definitive trend (Figure 7.12 f).

Understanding the spatio-temporal dynamics of flood and drought risks, as elucidated by the combined Mann-Kendall tau and Sen's Slope analysis, provides several benefits for river basin management and the enhancement of predictive models, which are discussed later in this chapter.

7.6 Unveiling sensitivity of flood and drought risks to their key drivers in the River Severn basin

The Sobol sensitivity index is a powerful tool used to quantify the contribution of each input variable to the output variance in a model. In the context of this research, it is employed to identify and rank the importance of various environmental and socio-economic predictors in influencing flood and drought risks. This method not only provides first-order sensitivity indices (S1), which measure the direct effect of each predictor, but also total-order indices (St), capturing the overall contribution including interactions with other predictors. Moreover, second-order interaction effects between primary drivers, such as precipitation and surface water availability, can be analysed to understand their combined impact on drought risk. To ensure robustness, a convergence map will be presented, indicating the stability and reliability of the sensitivity indices across varying sample sizes. This comprehensive analysis offers a deeper insight into the underlying dynamics, aiding in more effective risk management and mitigation strategies for the River Severn basin.

Combined Sobol sensitivity indices for flood risk, showcasing the contributions of various predictors are presented in Figure 7.13 (a). The bar chart illustrates the total-order sensitivity indices (ST) in purple, representing the overall contribution of each predictor, including interactions with other predictors. The black dots denote the first-order sensitivity indices (S1), which measure the direct effect of each predictor. The orange dots indicate the total-order sensitivity indices (ST) with their 95% confidence intervals shown as whiskers. The plot effectively illustrates the relative importance and uncertainty associated with each predictor, highlighting key factors influencing flood risk in the study area.

Road and Community Resilience (ComRes) have the highest total-order sensitivity indices, indicating they have the most significant overall influence on flood risk, including interactions with other predictors. Their first-order indices also show substantial direct effects. The whiskers for Road and ComRes are relatively long, indicating some uncertainty in their sensitivity estimates. Flood Level follows, with a notable total-order index, suggesting it significantly impacts flood risk directly and through interactions.

Early Warning Systems (EWS), Land Cover/Land Use (Lclu), Precipitation (Pr), Normalized Difference Vegetation Index (NDVI), and Reservoir have moderate sensitivity indices, implying they moderately affect flood risk. Their whiskers indicate varying degrees of uncertainty, with some being quite narrow, suggesting precise estimates.

Surface Water (SurfWat), Population (Pop), Elevation (Elv), Slope, Distance to River (Distance), Defence Mechanisms (Def), Groundwater (GW), Health, Soil Class, and Sustainable Water Management (Sustain) exhibit lower sensitivity indices, indicating a lesser impact on flood risk. Their whiskers are also short, showing low uncertainty in these estimates. River Density has the smallest total-order sensitivity index, suggesting minimal influence on flood risk in this river basin.

The convergence plot presented in Figure 7.13 (panels b and d) depicts the first-order sensitivity indices (S1) for various predictors influencing flood and drought risk, plotted against the number of samples used in the Sobol sensitivity analysis. The x-axis represents the number of samples used in the sensitivity analysis, ranging from 50 to 1000 samples. And the y-axis represents the value of the first-order sensitivity index (S1) for each predictor. The plot indicates that the sensitivity indices for most predictors stabilize as the number of samples increases. This suggests that the results are reliable and not highly sensitive to the sample size beyond a certain point.

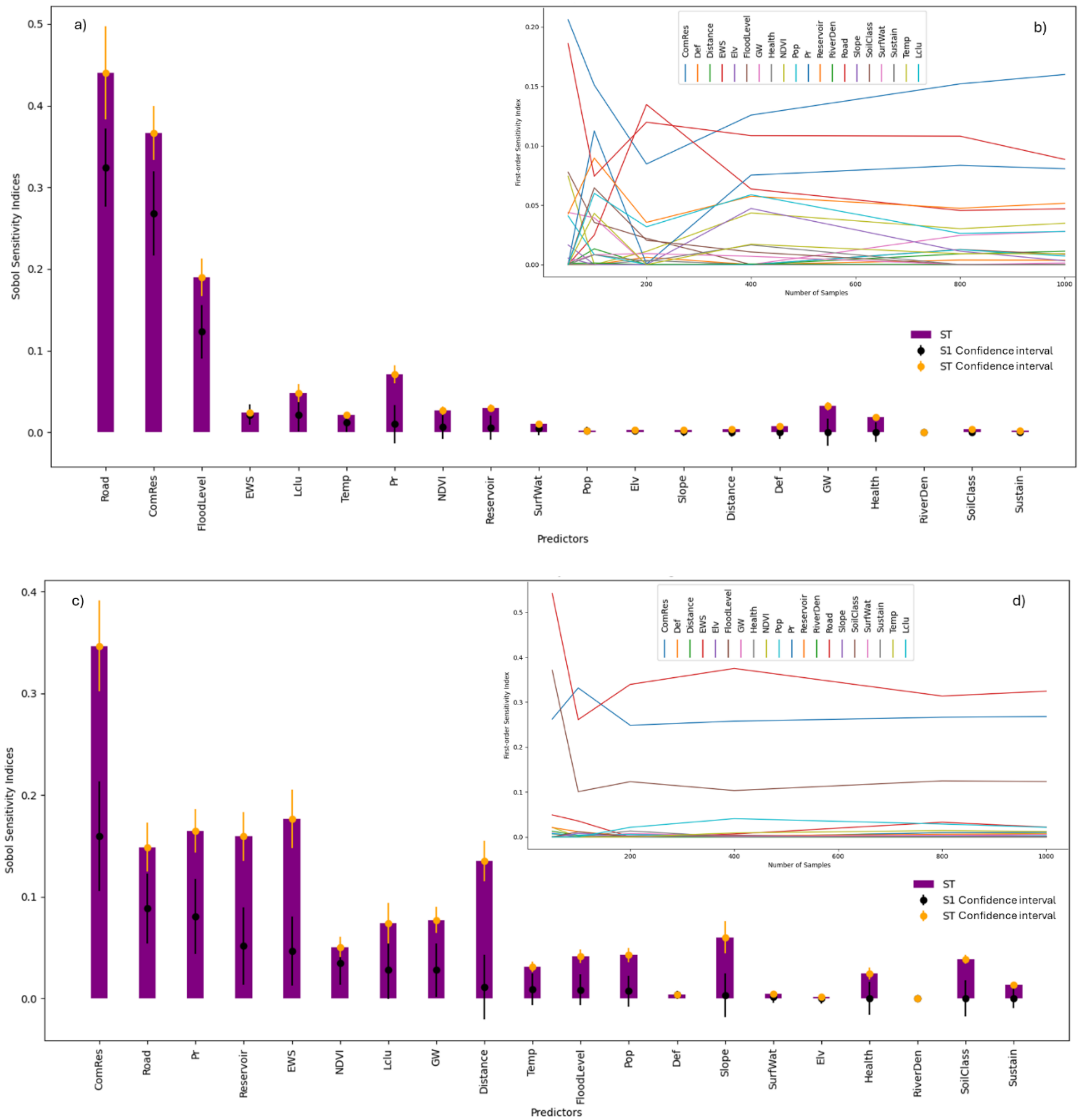

a)
b)
Sobol Sensitivity Indices
0.5
0.4
0.3
0.2
0.1
0.0
First-order Sensitivity Index
Number of Samples
ComRes
Def
Distance
EWS
Elv
FloodLevel
GW
Health
NDVI
Pop
Pr
Reservoir
RiverDen
Road
Slope
SoilClass
SurfWat
Sustain
Temp
Lclu
ST
S1 Confidence interval
ST Confidence interval
Road
ComRes
FloodLevel
EWS
Lclu
Temp
Pr
NDVI
Reservoir
SurfWat
Pop
Elv
Slope
Distance
Def
GW
Health
RiverDen
SoilClass
Sustain
Predictors
c)
d)
Sobol Sensitivity Indices
0.4
0.3
0.2
0.1
0.0
First-order Sensitivity Index
Number of Samples
ST
S1 Confidence interval
ST Confidence interval
ComRes
Road
Pr
Reservoir
EWS
NDVI
Lclu
GW
Distance
Temp
FloodLevel
Pop
Def
Slope
SurfWat
Elv
Health
RiverDen
SoilClass
Sustain
Predictors

Figure 7.13. Sensitivity analysis of flood and drought risk to the input parameters: a) Sobol's sensitivity index (flood risk), b) first order sensitivity convergence graph (flood risk) c) Sobol's sensitivity index (drought risk), d) first order sensitivity convergence graph (drought risk).

Similarly, the combined Sobol sensitivity indices (S1 and ST) for various predictors impacting drought risk are presented in Figure 6.13 (c). The bars represent the total order sensitivity indices (ST), while the whiskers show the first-order sensitivity indices (S1) along with their confidence intervals. High influence predictors are ComRes (Community Resilience): Highest ST value (~0.35) and S1 value (~0.3). Road and Pr (Precipitation): High ST values (~0.2) with lower but significant S1 values. Moderate influence predictors include Reservoir, EWS (Early Warning Systems), NDVI (Normalized Difference Vegetation Index), and Distance: Moderate ST and S1 values. FloodLevel, Pop (Population), Slope, and others: Low ST and S1 values, indicating minimal impact on drought risk.

Confidence intervals for most predictors are narrow, suggesting high confidence in the sensitivity indices. ComRes, Road, and Pr show slightly wider confidence intervals, indicating some uncertainty. The stability of sensitivity indices with increasing sample size suggests that the results are robust and reliable. The high initial fluctuation for some predictors indicates the need for sufficient sample sizes to ensure accurate sensitivity estimates. Consistent results across different sample sizes enhance confidence in the importance of the identified key predictors.

This combined analysis using Sobol sensitivity indices provides a comprehensive understanding of the key factors influencing both flood and drought risk. For drought risk, Community Resilience (ComRes), Road infrastructure, and Precipitation (Pr) emerge as the most significant predictors, highlighting areas for targeted risk mitigation. For flood risk, the most influential predictors are also Community Resilience (ComRes), Road infrastructure, and Flood Level. These findings suggest that improving community resilience, enhancing road infrastructure, and managing precipitation and flood levels are critical for effective risk reduction. The convergence plots further validate the robustness of these findings, ensuring that the sensitivity indices are reliable and independent of the sample size used in the analysis. This integrated approach provides a solid foundation for developing comprehensive risk management strategies that address both flood and drought risks in a balanced and informed manner. Figure 7.14 illustrates the second-order interaction effects between pairs of predictors on flood and drought risk, derived from the Sobol sensitivity analysis. Each cell in the heatmap represents the interaction effect between two predictors, with colours indicating the magnitude and direction of the interaction. Positive values in all the cells denote positive interactions, where the combined effect of the two predictors on flood and drought risk is greater than their individual effects.

The heatmap for flood risk indicates key interactions (Figure 7.14 a). The interaction between distance to major roads and several other predictors like River Density (RiverDen), Reservoir, and Pr (Precipitation) shows higher sensitivity indices. This indicates that the combination of infrastructure and these environmental factors significantly influences flood risk. Flood Level and Reservoir, this interaction has a noticeable sensitivity index, indicating that the interplay between flood levels and reservoir storage is crucial for understanding flood risk. EWS and several other predictors, like the drought risk, EWS interacts with various other predictors but to a lesser extent than seen in the drought risk heatmap (Figure 7.14 b). Key Interactions between pairs of predictors on the response variable (drought risk) revealed that EWS (Early Warning Systems) and Distance shows a relatively high sensitivity index, suggesting that the combination of early warning systems and distance from river significantly affects drought risk. Reservoir and Pr (Precipitation), there is a notable interaction between reservoir and precipitation, indicating that the interplay between these factors has a significant impact on drought risk. Sustainable water resources interact with a range of other factors, but these interactions show moderate sensitivity indices.

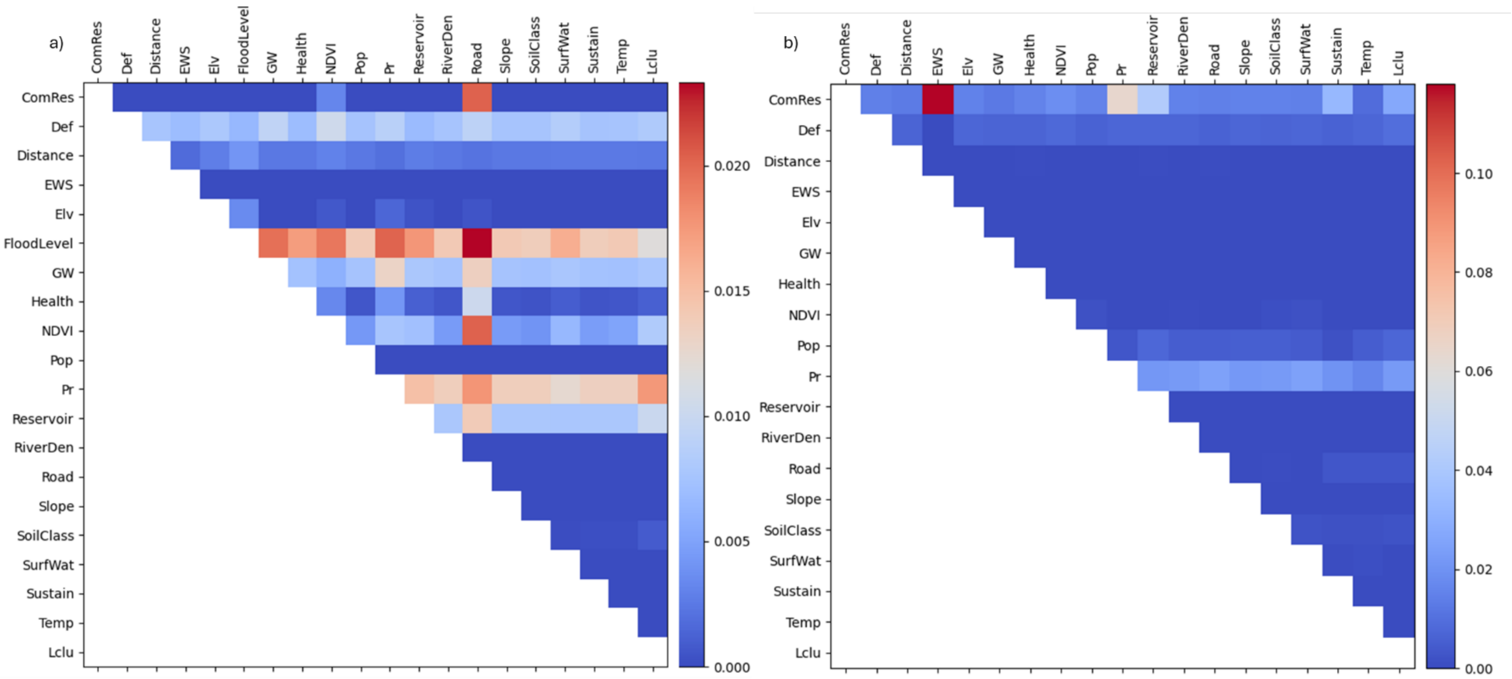


Figure 7.14. Second-order interaction effects between different parameters for a) flood risk and b) drought risk.

The key interactions affecting drought risk are between EWS and Distance, as well as Reservoir and Pr. These findings suggest focusing on improving early warning systems and managing reservoirs in conjunction with precipitation patterns to mitigate drought risk effectively. Individual predictors primarily drive drought risk, with limited significant interactions between predictors. Flood risk is influenced by a broader range of interactions, especially those involving infrastructure (e.g., roads) and environmental factors (e.g., River Density, Reservoirs, Precipitation). Managing flood risk requires a comprehensive approach that considers the complex interplay between various factors, emphasizing the importance of integrated flood management strategies.

Overall, these heatmaps highlight the importance of considering both individual and interaction effects of predictors in risk assessment models for drought and flood. The significant interactions identified should be prioritized in developing mitigation strategies and policies in the Severn basin.

7.6.1 Analysis of feature importance for flood and drought risks

Analysing the results illustrated in Figure 7.15 provides feature importance for Flood (black line) and Drought risk (Orange line), derived from four different methods: Random Forest (feature importance based on decreases in impurity), Permutation Importance (feature importance based on increase the accuracy), XGBoost (feature importance based on frequency of quality interaction within the predictor and response spaces), and Principal Component Regression (PCR) (feature importance based on the contributing variance in high dimensional and colinear data). Common findings across methods indicated that Reservoir and Population consistently show high importance for both flood and drought risk. Pr (Precipitation) and Def (Defence mechanism) are highly important for flood risk in most methods. Ground Water (GW), Community resilience ComRes, Sustainable water resources (Sustain), and distance to Health facilities and shelters are also frequently highlighted. Other important features are Temperature (Temp), Soil class, Early Warning System (EWS), Surface Water (SurfWat) and flood level. There are some differences across methods and risks. In terms of flood risk, Random Forest emphasizes Pr and Def. Permutation Importance ranks Pop and GW higher. XGBoost and PCR show a more diverse set of important features, though Pr and Def remain significant. In case of drought risk: Reservoir and Pop dominate the importance in all methods. NDVI and Sustainable water resources are also critical, though their importance varies across methods.

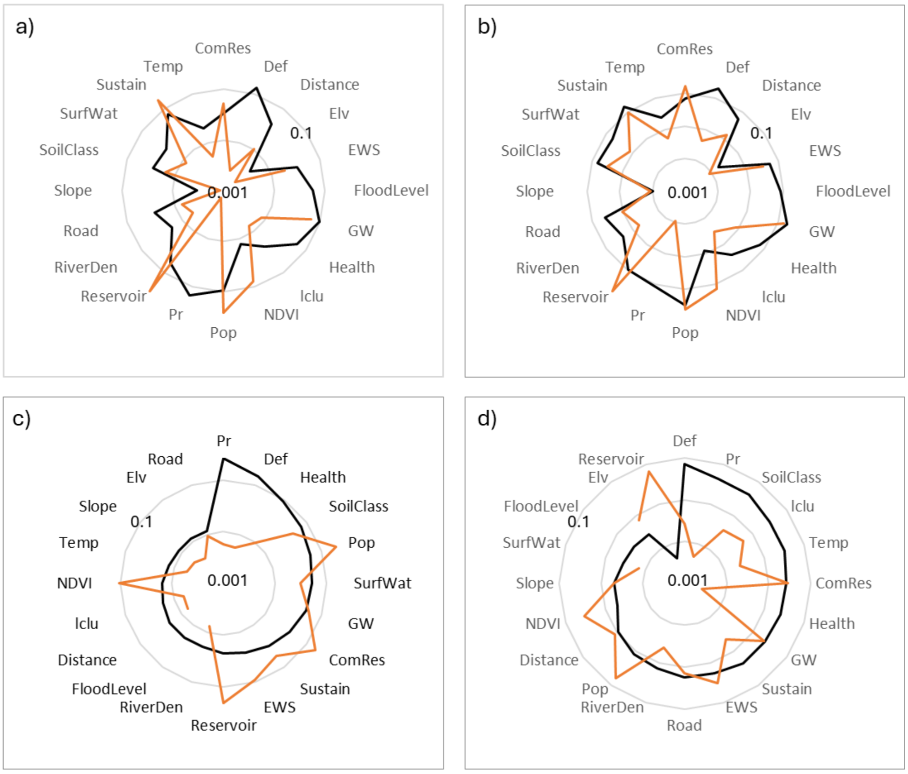


Figure 7.15. Diagram of Feature Importance analysis for flood risk (black line) and drought risk (orange line) – a) Random Forest, b) Permutation Importance, c) XGboost and d) Principal Component Regression (PCR) - (Def: Defence mechanism; Pr: Precipitation; SoilClass :Soil class; lclu: Land cover Land use; Temp: Temperature; ComRes: Community Resilience; Health: distance to health and shelter facilities; GW: Groundwater; Sustain: sustainable water resources; EWS: early warning systems; Road: distance to major roads; RiverDen: river density; Pop: Population; Distance: distance to rivers; NDVI: Normalised difference vegetation index; Slope: Slope; SurfWat: Available surface water; FloodLevel: Flood level; Elv: Elevation; Reservoir: distance to reservoirs).

7.7 Aleatoric Uncertainty Analysis in Flood and Drought Risk Predictions

The aleatoric uncertainty analysis refers to the inherent variability or randomness in the data, which cannot be reduced even with more data. In this context, the use of bagging with XGBoost captures the variability in predictions by training multiple models on different bootstrap samples of the training data. The variability among these multiple predictions reflects the aleatoric uncertainty, which is then quantified using measures such as the standard deviation, interquartile range, and prediction range (Figure 7.16 and 7.17). It also calculates RMSE and MAE between the ground truth and mean predictions. In this context, the ground truth is the original response layers representing flood and drought risk maps. These response layers serve as the reference against which the predictions made by the current models are compared. The Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) are calculated between these original response layers (ground truth) and the mean of the predictions generated through the bagging process (6.16 (e), 6.17 (e)). This comparison helps evaluate the accuracy of the predictions against the known (original) data.

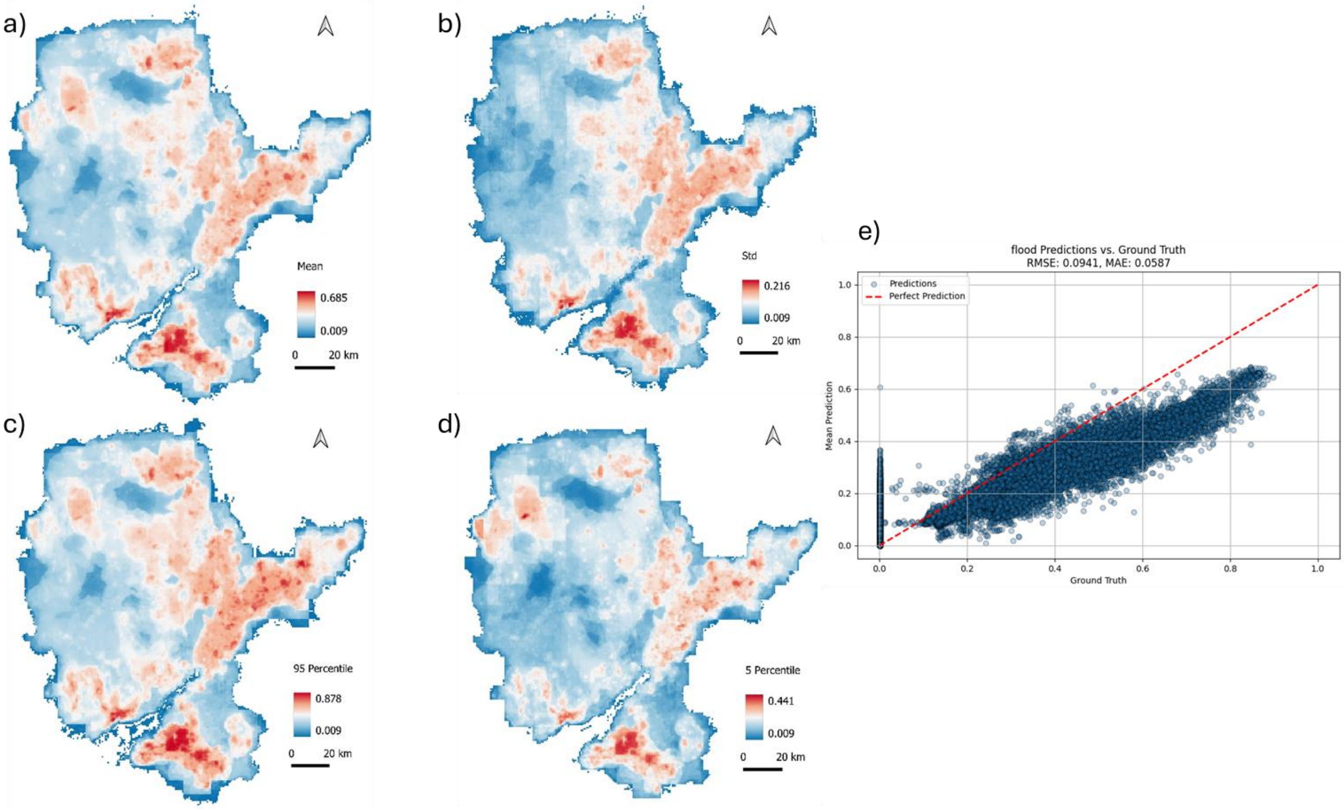


Figure 7.16. Visualizations of the uncertainty in flood risk predictions of the study area: a) mean of flood predictions, b) standard deviation of flood predictions, c) 95th percentile of flood predictions, d) 5 percentiles of the flood predictions and e) quantitative measures of the model's prediction accuracy (flood risk).

Results show the mean predicted flood risk values across the region, aggregated from the monthly predictions (6.16 a). This map provides a central estimate of flood risk across the region, representing the average risk (0.009-0.685) over the analysed period. Areas with a higher standard deviation (red) indicate greater variability in the flood risk predictions over time, suggesting higher uncertainty in those regions. Conversely, areas with lower standard deviation (blue) have more consistent predictions, indicating lower uncertainty (Figure 7.16 b). The 95th percentile represents the value below which 95% of the predicted flood risks fall. It provides an upper bound estimate of flood risk, highlighting regions that could experience the highest flood risk under extreme conditions, which is useful for identifying potential worst-case scenarios (Figure 7.16 c). Conversely, results depicted in Figure 7.16 (panel d) map helps to identify areas with consistently low flood risk. Scatter Plot: Assesses the accuracy of mean predictions against ground truth, with RMSE (0.0941) and MAE (0.0587) quantifying prediction errors (Figure 6.16 e). In general, southeastern and central towards northeast experienced higher flood risks with the aleatoric uncertainty slightly higher than other regions of the River Severn basin district.

Outcome provides in Figure 7.17 tries to analyse the uncertainties in drought risk prediction. Average of drought risk depicts a central estimate of it over the analysed period (Figure 7.17 a). the spatial focus of the drought risk, comparing to risk of flood is more central and widely scattered. Standard deviation map, however, indicates the variability and uncertainty in predictions over time illustrated in figure 7.17 (panel b), which seems to be less diverse both spatially and in comparison, with flood risk. This could indicate that mitigative strategies against this risk could spatially be generalised relatively easier. 5th and 95th Percentile maps showing the lower and upper bound of drought risk under extreme conditions, highlighting potential worst-case scenarios and identifying areas with consistently low risk. Scatter plot assesses the accuracy of mean predictions against ground truth, with RMSE (0.1038) and MAE (0.0585) quantifying prediction errors (Figure 7.17 e). Regarding the variability and uncertainty, flood risk predictions exhibit higher variability (greater maximum standard deviation) compared to drought risk predictions. This suggests more uncertainty in flood risk predictions over time. The lower bound of flood risk (5th percentile) is significantly lower than that of drought risk, indicating that the minimum predicted flood risk is much lower than the minimum predicted drought risk. Upper bound risk for both flood and drought risks has similar predictions (95th percentile), indicating comparable levels of extreme risk in both scenarios. These comparisons provide insights into the nature of flood and drought risks in the analysed region. The higher variability and lower minimum predictions for flood risk suggest that flood events are more sporadic and can range from very low to high risk. In contrast, drought risk is more consistently higher, even in the least likely scenarios, but both risks reach similar severity under extreme conditions.

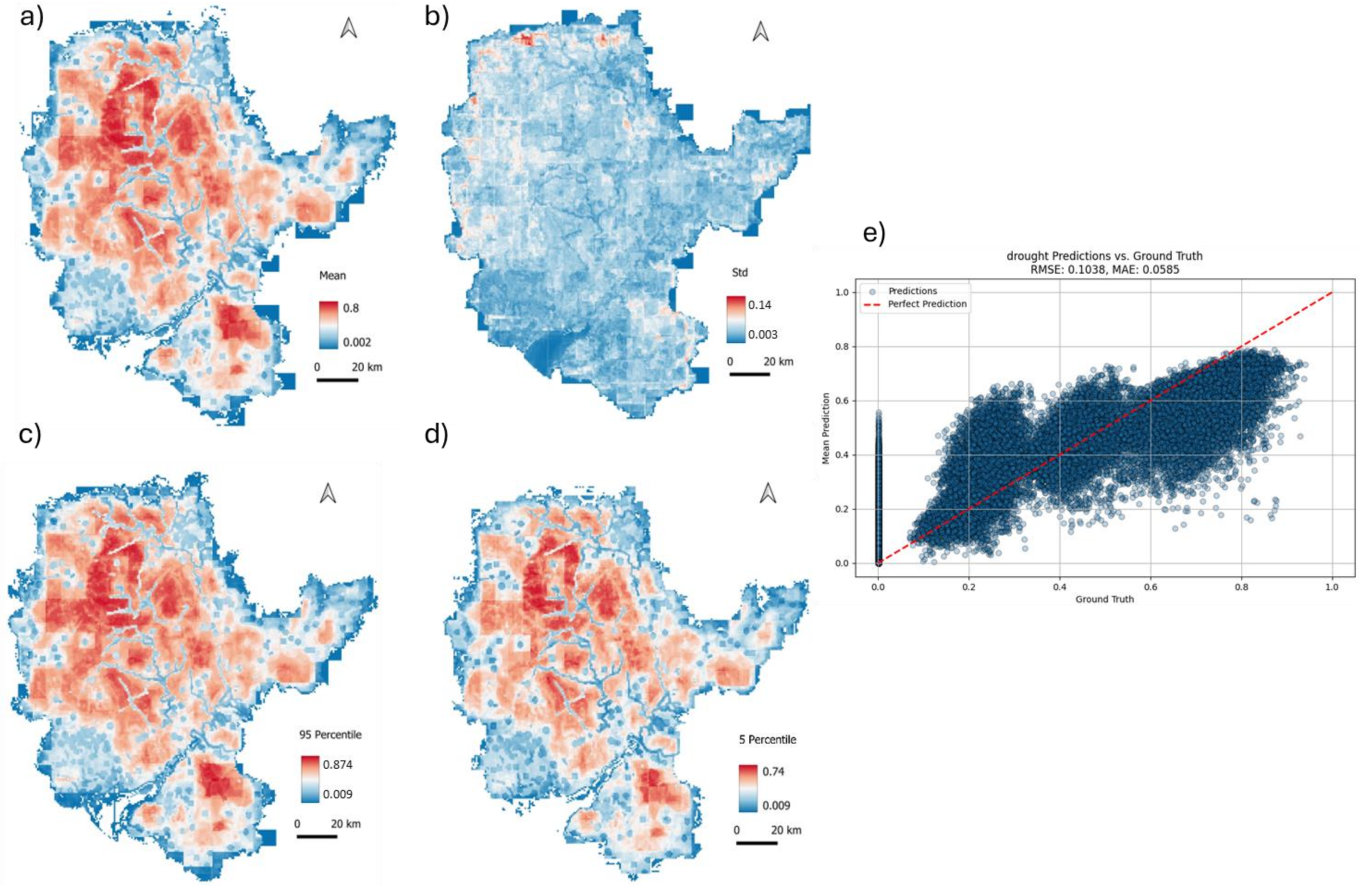


Figure 7.17. Visualizations of the uncertainty in drought risk predictions of the study area: a) mean of drought predictions, b) standard deviation of drought predictions, c) 95th percentile of drought predictions, d) 5th percentiles of the drought predictions and e) quantitative measures of the model's prediction accuracy (drought risk).

7.8 Predicting monthly flood and drought risks using advanced machine learning and trend analysis techniques

In this section of study, a combination of machine learning, statistical decomposition, and trend analysis methods was employed to predict monthly flood and drought risk maps for the River Severn basin. The primary machine learning method used was an optimised XGBoost regression model. Additionally, STL (Seasonal-Trend decomposition using LOESS) was used to decompose predictor data into trend and seasonal components, providing insights into temporal patterns. The Mann-Kendall trend test and Sen's slope analysis were applied to further adjust the predictor data for future months based on historical trends. As a result, monthly flood and drought risk maps for the next 12 months were produced. The average of the monthly predicted flood and drought risks, along with their respective standard deviations, are presented in Figure 7.17 (panels a to d).

Spatial distribution of predicted flood risk and standard deviation is presented in Figure 7.18 (panels a and b) respectively. The mean predicted flood risk map (Panel a) illustrates the spatial distribution of flood risk across the River Severn basin. The map categorizes the flood risk into various levels, The central and eastern and south easter parts of the basin exhibit very high flood risk, as indicated by the dense red areas. This suggests that these regions are more prone to flooding, likely due to factors such as low elevation, high precipitation, and proximity to rivers. Surrounding the high-risk areas, there are regions with moderate flood risk, represented by lighter shades of red and pink. The western and southern parts of the basin show very low flood risk.

The standard deviation map (Panel b) depicts the variability in flood risk predictions. The red areas in this map indicate regions with the highest standard deviation, suggesting significant variability in flood risk predictions. These areas are primarily located in the central and eastern parts of the basin, coinciding with high flood risk areas from Panel a. This indicates that while these regions are at high risk, there is considerable uncertainty in the exact extent and severity of the risk. Areas with moderate standard deviation indicate some level of uncertainty but not as pronounced as the high variability areas. Regions, primarily located in the western and southwestern parts of the basin, align with the low flood risk regions in Panel a, suggesting that predictions in these areas are more reliable and stable. The mean predicted drought risk map (Panel c) illustrates the spatial distribution of drought risk across the River Severn basin. The map categorizes the drought risk into various levels. The central and northern parts of the basin exhibit very high drought risk These regions are more susceptible to drought conditions, possibly due to precipitation patterns, areas actively engaged in and rely on agroforestry. Surrounding the high-risk areas, there are regions with moderate drought risk. The western and southern parts of the basin show very low drought risk. The standard deviation map (Panel d) depicts the variability in drought risk predictions. Areas with higher standard deviation are primarily located in the central and northern parts of the basin, coinciding with high drought risk areas from Panel c. Regions where the variability is lower are mainly located in western and southern parts of the basin, align with the low drought risk regions in Panel c.

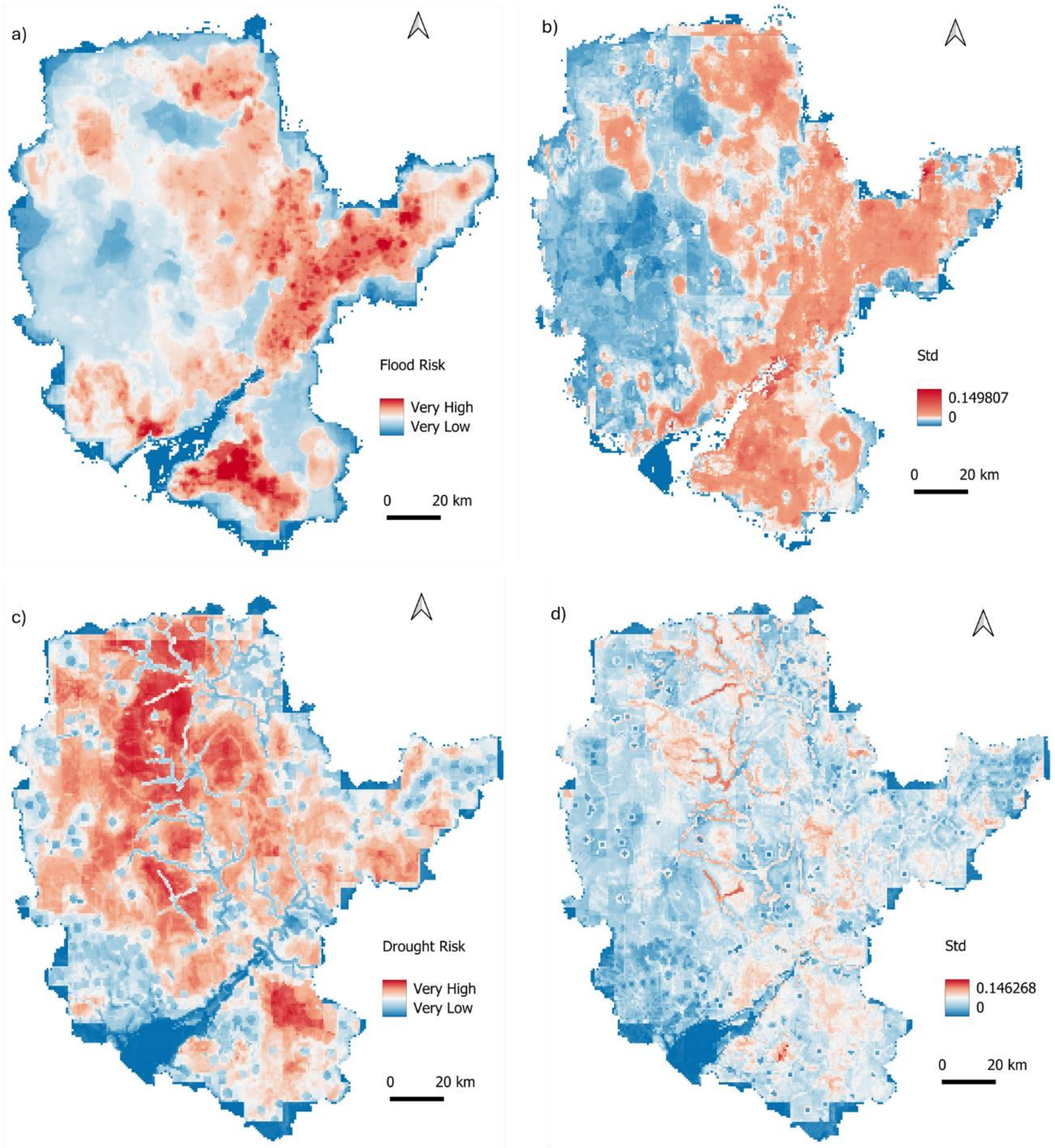


Figure 7.18. Spatial visualisation of predicted flood and drought risk for coming year: a) mean prediction of flood risk, b) standard deviation of monthly flood risk prediction, c) mean prediction of drought risk and d) standard deviation of monthly flood risk prediction.

Comparison between estimated areas within each flood and drought risk category with the predicted areas for the coming year is presented in Table 7.6.

Table 7.6. Comparison area coverage of predicted flood and drought risk for coming year with that of the existing conditions.

	Flood risk		**Drought risk**	
Class	**estimated**	**predicted**	**estimated**	**predicted**

	Area (km²)	%	Area (km²)	%	Area (km²)	%	Area (km²)	%
Very high	11.6	0.06	119.95	0.61	1300.63	6.79	530.53	2.49
High	335.19	1.73	2335.06	11.78	6442.05	33.63	5185.22	24.35
Moderate	5840.69	30.08	7539.71	38.05	3192.36	16.67	6773.02	31.80
Low	11625.87	59.88	8045.31	40.60	6586.98	34.40	6828.72	32.07
Very low	1602.15	8.25	1774.20	8.95	1628.90	8.51	1978.80	9.29

The predicted area for very low flood risk (1774.20 km², 8.95%) is marginally larger than the estimated area (1602.15 km², 8.25%). The same margin exists for very high-risk regions. The main shift is observed where the areas already experiencing low flood risk were shifted towards moderate, and some areas with moderate risk are more or less likely to observe high flood risks.

Regarding the risk of drought, the predicted area (530.53 km², 2.49%) is significantly smaller than the estimated area (1300.63 km², 6.79%), suggesting a decrease in very high-risk areas. Similarly, for high drought risk regions, prediction (5185.22 km², 24.35%) is slightly smaller than the estimated area (6442.05 km², 33.63%), indicating a reduction in high-risk areas. Comparing moderate drought risk, however, indicated that the predicted area (6773.02 km², 31.80%) shows a significant increase compared to the estimated area (3192.36 km², 16.67%), suggesting a broader moderate drought risk region. Range of change in areas with below moderate drought risk was marginal.

The comparison of estimated and predicted areas for both flood and drought risk categories reveals significant changes. For flood risk, there is a substantial increase in very high and high-risk areas, underscoring the need for enhanced flood management strategies. For drought risk, the notable shift towards moderate and low-risk categories indicates changes in drought vulnerability across the basin. The ROC (Receiver Operating Characteristic) curve presented illustrates the performance of flood risk prediction models under two different conditions (Figure 7.19).

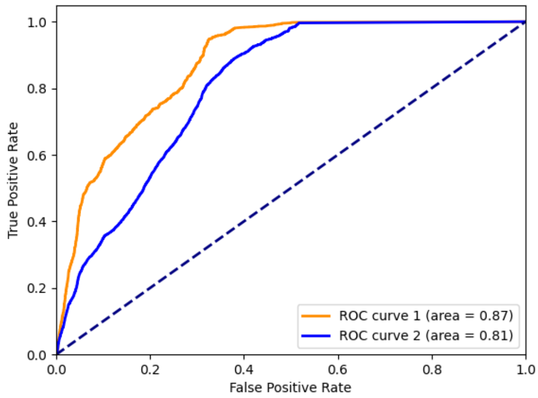


Figure 7.19. Validation of flood risk prediction using Receiver Operating Characteristic (ROC): blue line – flood risk predicted by this research vs observed floods since 1946, orange line - flood risk predicted by this research vs observed floods since 2000.

On the other hand, the blue curve (ROC curve 2) with an AUC of 0.81 represents the model's performance when evaluated against all recorded flood observations since 1946. The slightly lower AUC value suggests that the model's predictive accuracy decreases when considering a broader historical context, which includes floods outside the training data's timeframe. This drop in performance can be attributed to changes in environmental and climatic conditions over the extended period, which may not be fully captured by the training data. The results highlight the importance of context-specific evaluation and the challenges of extending predictive models to longer historical periods without incorporating additional data or adjusting for historical variability.

In this stage of the research, SHAP (SHapley Additive exPlanations) is applied to unravel the contribution and interaction of various input parameters in assessing the predicted flood and drought risks. By leveraging SHAP values, we gain insights into the importance and influence of each predictor variable on the model's output. This enables a detailed understanding of how factors such as rainfall, temperature, groundwater levels, and NDVI impact the risk of flood and drought events. The application of SHAP enhances the interpretability of complex machine learning models, providing a transparent mechanism to quantify predictor contributions and facilitating informed decision-making for risk management and mitigation strategies. Diagrams concerning SHAP values for flood and drought risk of predicted model outouts are presented and followed by a discussion outlining possible interpretations in the real world scenarios (Figure 7.20 and 7.21). This diagram illustrates the SHAP values for flood risk predictions, indicating the impact of various features on the model's output. Features on the y-axis are sorted by their importance, with the most influential features at the top. The x-axis represents the SHAP value, showing the impact on the model output, where values to the right increase flood risk, and values to the left decrease it. The color gradient from blue to red indicates the feature value from low to high.

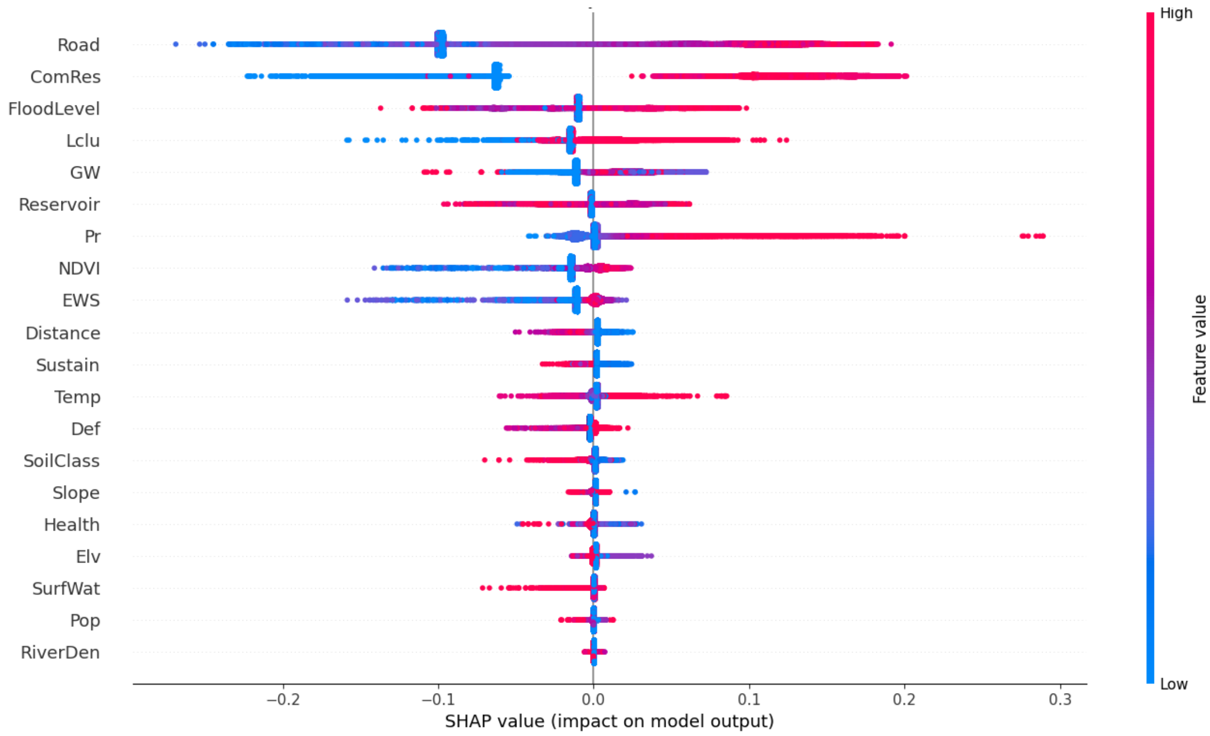


Figure 7.20. SHAP summary plot for predicting flood risk using multiple environmental and socio-economic factors - (Def: Defence mechanism; Pr: Precipitation; SoilClass :Soil class; lclu: Land cover Land use; Temp: Temperature; ComRes: Community Resilience; Health: distance to health and shelter facilities; GW: Groundwater; Sustain: sustainable water resources; EWS: early warning systems; Road: distance to major roads; RiverDen: river density; Pop: Population; Distance: distance to rivers; NDVI: Normalised difference vegetation index; Slope: Slope; SurfWat: Available surface water; FloodLevel: Flood level; Elv: Elevation; Reservoir: distance to reservoirs).

The behavior of precipitation indicates that high values contribute to medium to high increases in flood risk. Additionally, extreme values (relative to the existing data) significantly elevate the risk of flooding in this region. For temperature, higher values are associated with both increases and decreases in flood risk, suggesting seasonal impacts and early signs of climate change on flood risk. High values of available surface water correlate with relatively lower flood risks, which may indicate the effectiveness of surface water collection schemes and natural flood management. This observation aligns with lower values of land cover and land use (LCLU) representing water-related land covers. Although minor, the proximity to early warning systems and defense mechanisms has been noted to reduce the risk of flooding. Furthermore, the distance to transportation networks and community resilience factors, as part of the mitigation capacity, show a significant effect on reducing the flood risk predicted by this model.

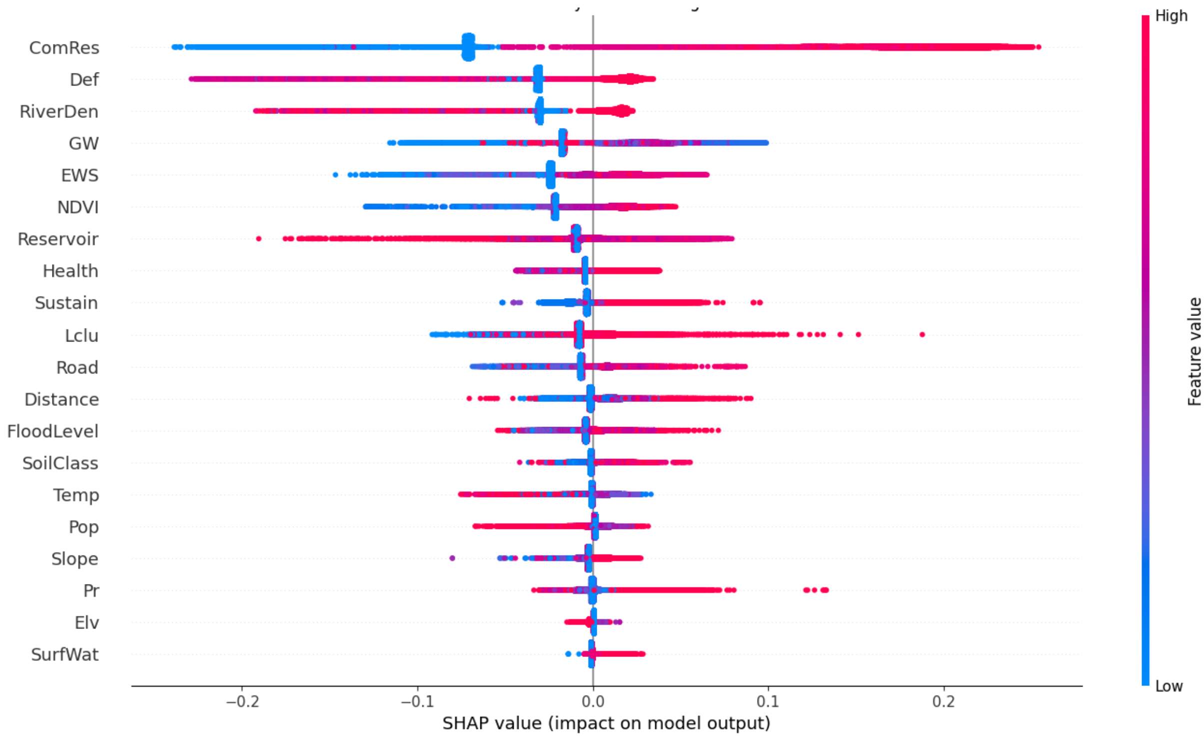


Figure 7.21. SHAP summary plot for predicting drought risk using multiple environmental and socio-economic factors - (Def: Defence mechanism; Pr: Precipitation; SoilClass :Soil class; lclu: Land cover Land use; Temp: Temperature; ComRes: Community Resilience; Health: distance to health and shelter facilities; GW: Groundwater; Sustain: sustainable water resources; EWS: early warning systems; Road: distance to major roads; RiverDen: river density; Pop: Population; Distance: distance to rivers; NDVI: Normalised difference vegetation index; Slope: Slope; SurfWat: Available surface water; FloodLevel: Flood level; Elv: Elevation; Reservoir: distance to reservoirs).

This diagram illustrates the impact of various mitigation capacities on drought risk. Specifically, it highlights the role of community resilience (indirect impact on flood risk), defense mechanisms, and early warning systems in reducing drought risk. However, the basin's heavy reliance on reservoirs and available surface water is concerning in terms of drought risk. Additionally, higher NDVI values, correlating with high land cover and land use (LCLU), along with the unequal distribution of sustainable water resources, population, and economic assets between urban and rural areas, have collectively increased the overall risk of drought.

7.9 Chapter conclusion

The findings from this study underscore the critical importance of integrated risk assessment in managing flood and drought hazards within the River Severn basin. Key observations include:

Flood Risk Components:

- Exposure: Approximately 68% of the study area falls under moderate flood exposure, with 29% highly exposed. Urbanized areas with low vegetation cover and fine-textured soils are more susceptible.

- Vulnerability: 85% of the basin exhibits low to very low flood vulnerability, with 15% facing moderate to very high vulnerability, primarily due to economic factors and water infrastructure.

- Impact: Around 59% of the basin experiences moderate flood impact, with 31% at high impact, highlighting the need for effective mitigation measures.

- Mitigation Capacity and Hazard:

- Regions with high mitigation capacity, such as those with major roads and health institutions, exhibit better resilience against floods.

- Approximately 33% of the basin faces high flood hazards due to active rivers and extensive rainfall.

- Validation and ROC Analysis:

- The flood risk assessment model shows good predictive performance with an AUC of 0.86 when validated against historical flood data, indicating its reliability in predicting high-risk areas.

Drought Risk Components:

- Exposure: Most of the basin (80%) is subject to moderate and high drought exposure due to agricultural land use and water resource dependency.

- Vulnerability: 70% of the basin has below-moderate vulnerability to drought, influenced by population and water resource management.

- Impact: Above-moderate drought impact is observed in areas with high population and water infrastructure.

Mitigation Capacity and Risk:

- Approximately 39% of the basin exhibits very high mitigation capacity against drought, while 43.66% still suffers from low mitigation capacity.

- The overall trend in drought risk has declined by 3% over the study period.

Fractal Dimension Analysis:

- Regions with moderate flood and drought risks are the most dispersed and challenging to manage.

- Areas with high flood risk show less spatial complexity, suggesting more localized management.

7.9.1 Implications for Stakeholders, Community and contribution to research

The outcomes of this research provide valuable insights for stakeholders, including policymakers, urban planners, and community leaders, in developing targeted risk management strategies. The detailed spatial and temporal analysis of flood and drought risks enables better planning and allocation of resources to mitigate these hazards. For the community, understanding the areas most at risk can inform emergency preparedness and response strategies, enhancing resilience against future hydro-hazard events.

This chapter contributes to the existing body of knowledge by integrating advanced analytical techniques to assess and predict flood and drought risks comprehensively. The innovative use of fractal dimension analysis and ROC validation enhances the robustness of the risk assessment model. These contributions are pivotal in advancing flood and drought risk management practices, providing a framework that can be applied to other river basins globally.

The integration of mitigation capacities into risk assessment highlights the importance of infrastructure and community resilience in reducing hydro-hazard impacts. These findings will aid in the development of more effective and sustainable risk management policies, ensuring long-term safety and resilience of the River Severn basin and similar regions.

The results and discussions presented in this chapter lay the groundwork for the conclusion chapter, where the overall implications of the study will be synthesized. The conclusion will draw together the key findings, emphasizing their significance for future research and practical applications in hydro-hazard risk management. This integrated approach ensures a coherent flow of information, reinforcing the study's contributions to enhancing flood and drought resilience.

8 Synthesis, conclusion and directions for future research

8.1 Synopsis

This chapter synthesizes the findings of the research presented in the preceding chapters, offering a comprehensive overview of the methodologies employed, the results obtained, and the implications for flood and drought risk management. The reportage of this research was structured around six primary objectives (including the main aim and objectives of the research), each contributing to a holistic understanding of flood and drought risks in a river basin scale.

- Introduction to Flood and Drought Risks: The first chapter laid the foundation by exploring the concepts of flood and drought risks, highlighting their significance and the need for comprehensive risk assessment frameworks. This section provided the context for the entire study, emphasizing the growing importance of understanding and mitigating these risks in light of climate change and increased human activities.

- Literature Review: The second chapter provided a detailed review of existing literature on flood and drought risk assessment methodologies. It identified gaps in current research, particularly the need for integrative frameworks that combine multiple risk factors and advanced modelling techniques. This review informed the development of the methodological approach used in subsequent chapters.

- Spatio-Temporal Risk Mapping: Chapter three focused on mapping the spatio-temporal distribution of flood and drought risks in the River Severn basin. Utilizing historical data and advanced geospatial analysis techniques, this chapter provided a detailed understanding of the spatial and temporal patterns of flood and drought occurrences, identifying high-risk areas that require targeted management interventions.

- Validation of Risk Models: The fourth chapter validated the risk assessment models by comparing predicted flood and drought zones with observed events and published risk areas. This validation was achieved using Receiver Operating Characteristic (ROC) curves and other statistical measures, ensuring the reliability and accuracy of the models.

- Sensitivity and Uncertainty Analysis: Chapter five examined the sensitivity and uncertainty of the risk models. This analysis identified key parameters that influence model predictions and assessed the robustness of the models under different scenarios. The findings highlighted the importance of certain variables, such as land use changes and precipitation patterns, in driving flood and drought risks.

- Modern Predictive Techniques: The sixth chapter applied modern statistical and machine learning techniques to predict future flood and drought risks. These methods included Random Forests, Gradient Boosting Machines, and Neural Networks, which were evaluated for their efficiency and accuracy. The results demonstrated the potential of these techniques to enhance predictive capabilities and provide more timely and accurate forecasts.

This chapter synthesizes these findings, emphasizing the practical implications for stakeholders, the contributions to the field, and the potential for future research.

8.2 Conclusions on Contributions to Knowledge and Stakeholder Impact

The integrated assessment of flood and drought risks in the River Severn basin, as presented in this research, demonstrates the efficacy of combining traditional risk assessment methods with modern statistical and geospatial techniques. The spatio-temporal mapping of risks provides a detailed understanding of vulnerable areas, which is crucial for targeted risk management and mitigation efforts. The objectives of this study (section 1.2) have been achieved. Objective I is addressed in chapter 5 with links to the data extraction resulted from the performed on meta-analysis of the literature. Objective II is achieved in chapter 6 where the framework integrated flood and drought risks with 114 more parameters to encapsulate most relevant interdependencies. Objective III is covered in the last data chapter (chapter 7) where the risks were validated for a UK prominent river basin and a mutual indicato fpr flood and drought risks was proposed.

The contributions made by this research are multifaceted, addressing significant gaps in the existing body of knowledge regarding integrated flood and drought risk assessments at the river basin scale. Specifically, this study has established a holistic and multidisciplinary framework that enhances the simultaneous understanding of flood and drought phenomena by incorporating hydrological, socio-economic, and environmental dimensions. The importance of integrating diverse domains, such as water resource management, socio-economic vulnerability, and environmental feedback, cannot be overstated, as these factors are all critical components in predicting and managing hydrological risks in a changing climate. This contribution is particularly significant for river basins that are subject to increasingly variable climatic conditions.

In addition to this integrated framework, key contributions of this research include the creation of a novel Combined Flood and Drought Risk Index (CFDRI), which offers a unified metric for assessing risk that captures the dual threats of flooding and drought concurrently. The formulation of such an index is a critical step towards providing a comprehensive tool that stakeholders can use to assess the interplay of these two hydrological extremes effectively. The integration of advanced methodologies, such as Interpretive Structural Modelling (ISM) and Causal Loop Diagrams (CLDs), further advances the ability to identify and visualize complex relationships and feedback loops among the various risk factors, making the framework adaptable and insightful for different contexts.

This research also contributes to the practical and theoretical understanding of hydrological risks by providing enhanced insights into the spatio-temporal dynamics of flooding and drought. Through an in-depth exploration of how these risks evolve over time and across regions, the study provides the tools needed for stakeholders including environmental agencies, water companies, and local authorities to make informed, proactive decisions. The stakeholder-focused approach ensures that the outcomes of this research are not merely theoretical but are directly applicable for planning and implementing water resource management strategies aimed at reducing risk and enhancing resilience. By advancing both theoretical understanding and practical applications, this study stands as a pivotal contribution to the field of flood and drought risk management at the river basin scale.

One of the principal contributions to knowledge lies in the development and validation of the Combined Flood and Drought Risk Index (CFDRI). This index serves as an innovative tool for assessing hydrological risks in a unified manner, capturing the dynamics of both flood and drought events within a single metric. Unlike existing frameworks that often treat floods and droughts as separate entities, CFDRI integrates their assessment to reflect their interdependencies and cumulative impacts more accurately. By doing so, it provides a more comprehensive picture of the risks faced by a river basin, which is especially pertinent in regions where both flood and drought hazards co-exist. This integrative approach can be instrumental in reshaping the way water resource managers understand and mitigate hydrological extremes, offering them a practical and robust tool for decision-making.

The study's use of Interpretive Structural Modelling (ISM), network theory, and causal loop diagrams (CLDs) has further contributed to a nuanced understanding of the relationships between various risk factors. By identifying the deep interrelations and latent themes among different parameters, this research offers new insights into how risk factors influence each other and propagate across the system. This is particularly valuable for stakeholders such as environmental agencies, water companies, and city councils in high-risk areas. These stakeholders are often tasked with managing multiple, interlinked risks under resource constraints, and understanding these connections can guide them in prioritizing mitigation efforts more effectively. For instance, the identification of feedback loops that exacerbate either flood or drought impacts provides practical knowledge that can be used to intervene strategically, mitigating one risk without inadvertently amplifying another.

Another major contribution of this research is the systematic exploration of geographical and temporal trends in flood and drought risks. By applying advanced statistical analysis and utilizing geospatial datasets, the research has uncovered distinct spatio-temporal patterns in flood and drought occurrences across the studied river basin. These findings offer a granular understanding of how hydrological risks evolve over time and space, providing actionable insights for policymakers and practitioners. The detailed geographical and temporal analysis presented here highlights regions within the basin that are particularly vulnerable to simultaneous flood and drought risks, which can inform zoning regulations and infrastructure development. Stakeholders such as city councils can use this information to direct investments towards adaptive infrastructure, such as resilient flood defences or improved water storage systems, based on specific vulnerability profiles.

Moreover, this research contributes to the understanding of the socio-economic dimensions of flood and drought risk. The integration of socio-economic factors into hydrological risk assessments is still limited in current practices, often due to a lack of suitable models or comprehensive datasets. By incorporating socio-economic data such as demographic information, economic dependency on water resources, and access to adaptive capacity tools like insurance the research has illustrated how community resilience is shaped by both environmental and social factors. The CFDRI explicitly accounts for these socio-economic influences, providing a more holistic assessment that goes beyond the physical characteristics of flood and drought events. This has critical implications for stakeholders such as insurance companies, municipal planners, and government agencies that deal with the aftermath of hydrological disasters. By understanding how socio-economic conditions affect vulnerability, these stakeholders can craft more targeted policies and programs that address not only the environmental but also the human aspects of hydrological risk.

The research also introduces methodological innovations that have potential applications beyond the immediate scope of flood and drought risk assessment. The use of cross-entropy analysis, combined with network theory, to refine the general pathway of risk interactions represents a novel approach in this field. This method allows for the identification of a simpler, generalized framework that could serve as a basis for risk assessment across different river basins globally. This general framework is adaptable, allowing users to modify or add specific feedback loops based on local conditions, thereby ensuring both applicability and flexibility. This adaptability is crucial for various stakeholders, including international development agencies and regional water management authorities, who require standardized yet flexible tools that can be adapted to diverse geographical and socio-economic contexts.

Another key area of contribution is the validation of the proposed framework through sensitivity analysis and the introduction of a unified risk indicator for predictive risk mapping. By validating the CFDRI against historical events and conducting rigorous sensitivity analyses, the research provides evidence for the robustness and reliability of the developed framework. This is particularly significant for stakeholders who need confidence in the tools they use for planning and investment decisions. The ability to predict potential risk hotspots and quantify the likely impacts of different risk factors can help agencies like the Environment Agency or local water boards allocate resources more effectively and prioritize interventions that have the highest potential to reduce overall risk.

In addition to methodological contributions, the research also addresses the limitations of current flood and drought risk management practices by proposing a framework that incorporates multi-scale and multi-temporal assessments. The identification of simultaneous flood and drought risks alongside an understanding of their spatial co-occurrence is a critical advancement. It suggests that risk management practices need to evolve to consider the compounded effects of these hazards rather than addressing them in isolation. This contribution is particularly important for stakeholders involved in long-term infrastructure planning and resource allocation, such as city councils and water companies operating in high-risk areas. By providing a framework that can simultaneously evaluate both risks, the study helps these stakeholders move towards more integrated and resilient planning approaches.

Furthermore, this research emphasizes the practical implications of feedback loops and system dynamics in hydrological risk management. The causal loop diagrams developed in this study highlight the reinforcing and balancing mechanisms that govern the dynamics of flood and drought risks within a river basin. This understanding of systemic behaviour is vital for stakeholders to develop adaptive and proactive strategies for risk mitigation. For example, the identification of self-reinforcing loops that may escalate flood impacts can lead to targeted interventions that focus on breaking these loops, thereby preventing cascading failures. For environmental agencies and policymakers, this provides a scientific basis for designing policies that are not only reactive but also preventative in nature, ultimately reducing long-term vulnerability.

Overall, the contributions of this research extend beyond the academic realm and have practical implications for a range of stakeholders involved in hydrological risk management. By providing a comprehensive, integrated, and adaptable framework for flood and drought risk assessment, this study offers valuable tools and insights that can support more effective decision-making and resource allocation. The incorporation of socio-economic, environmental, and hydrological factors ensures that the developed framework is both holistic and grounded in real-world complexities, ultimately enhancing the resilience of communities and ecosystems to the challenges posed by climate variability and water-related hazards.

Key Findings:

- Policy and Planning: The detailed risk maps and validated models can inform policy-making and planning, helping authorities to allocate resources effectively and implement targeted mitigation strategies.

- Community Resilience: By identifying high-risk areas, the research supports efforts to enhance community resilience through improved preparedness and adaptive measures.

- Scientific Contribution: The integration of modern predictive techniques with mutual flood and drought assessment indicator contributes to the advancement of the field, offering a framework that can be adapted and applied to other regions.

The findings underscore the critical role of accurate and timely risk assessments in managing flood and drought risks. The validated models and advanced predictive techniques developed in this study provide robust tools for decision-makers, enabling more effective risk management and mitigation strategies.

8.3 Replicability of Findings

The replicability of this study's findings is one of its most significant strengths, as it offers a structured and comprehensive approach to assessing flood and drought risks that can be applied to different river basins worldwide. The methodologies employed, including systematic literature review, content analysis, Interpretive Structural Modelling (ISM), Causal Loop Diagrams (CLDs), and the development of the Combined Flood and Drought Risk Index (CFDRI), have been designed with adaptability and scalability in mind. Each of these techniques contributes to a robust framework that can be tailored to the unique characteristics of different hydrological contexts while maintaining consistency in the process of data gathering, analysis, and risk assessment.

The systematic literature review and content analysis form the backbone of the methodological approach, enabling a replicable foundation for identifying key variables and risk factors. The systematic approach ensures that all relevant and high-quality sources are captured, creating a baseline dataset that can be reproduced with minimal subjectivity. This approach allows future researchers to replicate the review process for other geographical regions, effectively updating the body of knowledge and adapting the risk framework to specific local contexts. Moreover, by utilizing Boolean keyword searches and explicit inclusion and exclusion criteria, the review process reduces author bias and ensures consistency across iterations.

Another key aspect of the replicability of this study lies in the methodological rigor of the ISM and CLD processes. Interpretive Structural Modelling provides a clear pathway for determining the hierarchy and interdependencies of the different parameters that contribute to flood and drought risks. The step-by-step structure of ISM including reachability matrix generation, level partitioning, and model formulation ensures that future studies can replicate the analysis and create similar hierarchical representations for other river basins. This feature is particularly beneficial for understanding the contextual importance of various risk factors and how they interact to affect hydrological risks. Similarly, CLDs offer an adaptable mechanism for understanding feedback dynamics. The integration of feedback loops in risk modelling is instrumental for replicability, as it allows researchers to understand how different factors influence each other and how interventions in one area may affect other interconnected elements of the system.

The CFDRI developed in this research is another core element of replicability. The CFDRI offers a unified metric that integrates various parameters, including hydrological, socio-economic, and environmental factors, to evaluate flood and drought risks in a cohesive manner. This index can be recalculated for different basins using data specific to those regions, allowing for adaptation without changing the core structure of the model. The CFDRI's flexibility ensures that the findings of this research can be replicated in different contexts by adjusting input data to reflect local realities, thus making it a valuable tool for regional planners, policymakers, and water resource managers around the globe.

Moreover, the methodology for calculating the CFDRI including data normalization, weighting parameters, and employing advanced statistical measures like cross-entropy analysis is transparent and systematically documented. This level of detail ensures that any researcher or practitioner wishing to use the CFDRI in other contexts can follow the same steps and understand the rationale behind each decision. This aspect of transparency is fundamental to the replicability of the study, as it allows for easy comparison between results obtained in different basins and facilitates a standardized approach to risk assessment.

The inclusion of spatio-temporal analysis also enhances the replicability of this research. By employing geospatial analysis, such as Geographic Information Systems (GIS) and remote sensing techniques, the study provides a means of mapping the evolution of flood and drought risks over time. This spatio-temporal perspective is critical for understanding how risks change in response to environmental, climatic, or socio-economic factors. The use of open-source geospatial tools ensures that other researchers can apply similar analyses to their own regions of interest without needing access to proprietary software. Moreover, the data layers used in this research, such as topography, land use, hydrology, and socio-economic datasets, are commonly available or accessible through similar data sources worldwide, further facilitating the replicability of these analyses.

This research also emphasizes the need to incorporate socio-economic dimensions and environmental feedback mechanisms, ensuring that risk assessments are not limited to purely physical or hydrological factors. The integration of socio-economic data into the hydrological framework ensures that the risk assessments are holistic and contextually relevant. This multi-dimensional approach is designed to be adaptable to various socio-economic settings, which means that the framework developed in this study can be replicated in different regions, each with its own socio-economic realities. Whether it is assessing risks for a developed country with advanced infrastructure or a developing region with limited resources, the adaptability of the socio-economic component ensures that the findings of this research can be extended and applied universally.

Lastly, the transparency of data sources, methodological assumptions, and parameter selection further enhances the replicability of this research. Throughout this study, every step of the methodology has been carefully documented, including the rationale for selecting specific parameters, the choice of statistical models, and the validation techniques used. This documentation ensures that future researchers can replicate the analysis under similar or modified conditions and compare their findings to those presented in this research. Furthermore, the study openly acknowledges the limitations inherent in the datasets used such as temporal gaps, spatial resolution issues, and quality variations thus allowing others to understand the constraints within which the findings should be interpreted. This acknowledgment of limitations is crucial for ensuring that the methodology can be refined and improved in future applications, thereby further enhancing replicability.

In summary, the replicability of the findings from this research is ensured by the methodological rigor, adaptability, and transparency embedded in each stage of the study. From the systematic literature review to the use of ISM, CLDs, and the development of the CFDRI, every aspect has been carefully designed to be applicable in different contexts and adaptable to local conditions. The integration of socio-economic, hydrological, and environmental data, combined with the use of open-source tools, ensures that the findings are not only replicable but also relevant to a wide range of stakeholders across different river basins. By providing a detailed, step-by-step approach to risk assessment, this research has established a replicable framework that can be used to understand and manage the dual threats of flood and drought in diverse settings around the world.

8.4 CHALLENGES AND LIMITATIONS OF THIS RESEARCH

While this research makes significant contributions to the field of flood and drought risk assessment, several limitations must be acknowledged. One of the primary limitations is related to data availability and quality. The reliance on publicly available datasets, while ensuring replicability, also means that the quality of the data used may vary, potentially affecting the accuracy of the model outcomes. In some regions, hydrological and socio-economic data may be sparse, outdated, or inconsistent, which poses challenges for accurately assessing risk factors and their interrelationships. The lack of comprehensive data also limits the capacity for high-resolution analysis, which could provide a more nuanced understanding of risk at finer spatial scales.

Another limitation of this research lies in the calibration of fuzzy overlay coefficients used to integrate different risk factors. While the use of fuzzy logic provides a flexible method for combining variables, the calibration of these coefficients remains inherently subjective. Different normalization criteria and parameter weightings can lead to different outcomes, introducing uncertainty into the model results. Future research should explore the calibration of these coefficients in greater depth, potentially involving local stakeholders to ensure that the chosen values are contextually appropriate.

The use of causal loop diagrams and interpretive structural modelling, while providing valuable insights into the interrelationships between risk factors, also has limitations related to the subjectivity of expert input. The development of these models relies on the knowledge and perspectives of experts, which can vary depending on their background and experience. This introduces a degree of subjectivity into the modelling process, potentially affecting the generalizability of the findings. Efforts were made to mitigate this limitation by triangulating expert input with empirical data, but the potential for bias cannot be entirely eliminated.

The complexity of the model developed in this research also poses challenges for its application in practice. The need for detailed input data, combined with the computational requirements of the cross-entropy and network analysis, may limit the accessibility of the model to stakeholders with limited technical expertise or resources. Simplified versions of the model, such as the general pathway identified through cross-entropy analysis, may be more suitable for practical applications, but this simplification comes at the cost of reduced accuracy and comprehensiveness.

Another key limitation relates to the epistemological basis of the study. The reliance on existing literature and expert opinion means that the findings are inherently shaped by the current state of knowledge in the field. The evolving nature of flood and drought science, particularly in the context of climate change, means that some of the assumptions underlying the model may need to be revisited as new information becomes available. The analogy between the current research and existing practices may also limit the extent to which the findings can be generalized to novel contexts, particularly in regions experiencing unique hydrological conditions or socio-political challenges.

Furthermore, the model's ability to account for transboundary issues is limited. In many river basins, flood and drought risks are influenced by factors that cross political boundaries, such as differences in water management practices, access to insurance, and legal frameworks governing water rights. The current model does not fully account for these transboundary complexities, which are particularly relevant in large river basins shared by multiple countries or jurisdictions. Future research should seek to address this limitation by incorporating transboundary considerations into the risk assessment framework.

8.4.1 Data Availability and Quality

One of the most significant limitations of this research is the availability and quality of data. While efforts were made to source data from credible databases, such as Scopus and Web of Science, the reliance on secondary data presents inherent challenges, particularly in ensuring the consistency and reliability of datasets. Many of the parameters related to flood and drought risk such as soil moisture, socio-economic vulnerability, and environmental indicators are spatially and temporally variable. The lack of high-resolution data for some of these parameters, especially in developing regions or transboundary basins, impacted the precision of the analysis. Additionally, missing data and inconsistent reporting practices across different regions and institutions posed significant challenges for building comprehensive and comparable datasets. In the future, more collaborative data collection efforts involving stakeholders such as the Environment Agency, local councils, and water companies are needed to overcome these limitations.

8.4.2 Methodological Constraints and Assumptions

This study employed a systematic literature review and a mixed-methods approach that integrated both qualitative and quantitative analyses, including Interpretive Structural Modelling (ISM), Causal Loop Diagrams (CLDs), and spatial analyses. Each of these methodologies comes with its own set of limitations:

- The systematic literature review, while rigorous, is inherently limited by the subjectivity involved in setting inclusion and exclusion criteria. Despite the use of open coding for latent content extraction, bias in selecting publications and assigning thematic categories can never be entirely eliminated, potentially affecting the comprehensiveness of the thematic analysis.

- Fuzzy overlay and cross-entropy methods used for normalization and risk mapping, although powerful, have limitations in terms of calibration. The choice of fuzzy overlay coefficients, for instance, can significantly impact the results, and the current study lacked a detailed calibration phase for these coefficients. This issue directly affects the generalizability of the results to other basins, as the chosen calibration might not accurately represent all hydrological and socio-economic conditions.

- Interpretive Structural Modelling (ISM) assumes a hierarchical structure among variables, which may not always hold true in real-world settings where the interactions are far more complex. The simplification necessary to create an ISM model, while useful for understanding relationships, inevitably leaves out some of the nuance and overlapping interactions between variables.

8.4.3 Modelling Limitations

The modelling approach in this research aimed to integrate flood and drought risks using ISM, CLDs, and network analysis. However, the limitations inherent in the modelling process impacted the depth and applicability of the findings:

- The Causal Loop Diagram (CLD) approach is highly effective for visualizing feedbacks but is limited when it comes to quantifying these relationships. The use of CLDs was mainly qualitative, and while the relationships identified provide useful insights, they lack the numerical precision required for predictive modelling. The absence of quantitative calibration or validation restricts the applicability of the findings for real-time decision-making by stakeholders.

- Cross-Entropy Analysis, used to deduce the general model from the entire network, introduces challenges related to computational intensity and the interpretation of results. Cross-entropy is effective for reducing uncertainty, but it is a complex method that can be computationally burdensome, requiring significant resources for processing and analysis. Additionally, this complexity might limit the replicability of the findings by other researchers who may not have access to similar computational resources.

- The Combined Flood and Drought Risk Index (CFDRI) was introduced to offer a unified metric for assessing risks; however, its reliance on historical data and specific coefficients reduces its adaptability to future climate scenarios or basins with significantly different hydrological dynamics. The lack of calibration of CFDRI across diverse basins is a significant limitation that affects its generalizability beyond the study area.

8.4.4 Epistemological and Conceptual Weaknesses

The epistemological basis of this research rests on the integration of socio-economic, hydrological, and environmental dimensions to provide a holistic understanding of flood and drought risks. However, this integrative approach is limited by the differences in epistemological traditions across these fields:

- Hydrology relies heavily on deterministic models and empirical data, whereas socio-economic vulnerability is assessed through more interpretive and qualitative approaches. The differing epistemologies posed challenges in creating an integrated framework where both quantitative precision and qualitative nuances were appropriately balanced. There is a lack of a standardized protocol for integrating these diverse dimensions, leading to potential inconsistencies in how risks are assessed and weighted within the framework.

- Analogy Limitations: Another conceptual limitation lies in the analogy used to represent the interactions between variables. The network analysis and feedback loops, while effective in demonstrating relationships, may oversimplify the complex interdependencies in flood and drought risk scenarios. Such analogies may not fully capture the non-linear dynamics and emergent properties inherent in socio-hydrological systems.

8.4.5 Scale and Scope Limitations

The spatial and temporal scope of this research also presents limitations:

- The research was conducted at the river basin scale, which, while appropriate for understanding regional dynamics, might overlook smaller-scale phenomena that are critical for local community resilience. Localized factors, such as micro-topography or specific socio-economic dynamics at a neighborhood level, could significantly influence flood and drought impacts but were not captured in this basin-wide analysis.

- The temporal resolution of the data used for risk analysis was also limited. The study considered monthly averages and seasonal trends, which are effective for capturing long-term dynamics but may miss critical short-term events that could significantly affect the outcomes of flood or drought risks, especially in rapidly changing climate conditions.

8.4.6 Stakeholder Engagement Limitations

Although the research aimed to develop a framework applicable to stakeholders, such as the Environment Agency, water companies, and city councils in high-risk areas, there were limitations in stakeholder engagement during the research process:

- Stakeholder input, which could have provided valuable insights into the real-world applicability of the framework, was limited due to time and resource constraints. Direct consultations with local councils or agencies might have helped refine the risk parameters and calibration methods, but these interactions were largely absent.

- Additionally, the differences in socio-political structures within transboundary river basins were not fully explored. For instance, the study acknowledged that access to insurance could vary across borders, but the implications of these variations were not extensively modeled. In basins shared between different countries, such as those with varying management or protection schemes, this could lead to significant differences in resilience, which were not fully captured in the analysis.

8.4.7 Calibration and Sensitivity Analysis

The research also faced limitations in calibration and sensitivity analysis:

- The fuzzy overlay coefficients used in the spatial analysis were not rigorously calibrated, which limits the robustness of the findings. The coefficients were set based on expert judgment and literature, but a more systematic calibration could enhance the precision of the results.

- Sensitivity analysis was performed, but its scope was limited to selected parameters due to computational constraints. A broader sensitivity analysis could provide deeper insights into which parameters most influence the overall risk, thus improving the reliability of the model for policy application.

8.5 Suggestions for Future Research

The limitations identified in this research open several promising avenues for future investigations, each of which can contribute to improving the robustness, applicability, and generalizability of integrated flood and drought risk assessments. Addressing these limitations through dedicated research efforts will enable the development of more resilient, adaptive, and effective management strategies for hydrological extremes.

8.5.1 Enhancing Data Quality and Accessibility

Future research should prioritize efforts to improve data quality and accessibility, especially in regions where data availability is limited or inconsistent. This can be achieved through several initiatives:

- Collaborative Data Collection: Establishing collaborations between research institutions, government agencies, and international bodies could enhance data collection efforts. A unified data repository could allow for consistent updates, improved data quality, and easier access for researchers and stakeholders, including water companies and local authorities. Such collaborations are particularly crucial for transboundary basins, where different political jurisdictions may have different data reporting and collection standards.

- Remote Sensing and Real-Time Monitoring: Leveraging advanced remote sensing technologies and real-time monitoring systems would significantly enhance the spatial and temporal resolution of the data. Using satellite-based techniques like Synthetic Aperture Radar (SAR) and the Soil Moisture Active Passive (SMAP) satellite can improve monitoring accuracy and provide data for poorly monitored areas. Future studies could also utilize sensor networks and Internet of Things (IoT) technologies for continuous, real-time data collection at high resolutions.

8.5.2 Calibration and Validation of Framework Components

The calibration of fuzzy overlay coefficients and other parameters used in the integrated risk assessment framework is an area that requires further attention. The following actions are suggested:

- Detailed Calibration of Fuzzy Overlay Coefficients: Future work should incorporate rigorous calibration protocols for fuzzy overlay coefficients to better reflect the actual dynamics within different basins. By collecting empirical data for calibration, researchers could establish more reliable coefficients that can be used to quantify risks more accurately.

- Validation Across Diverse Regions: The framework developed in this study should be applied and validated across multiple basins with different hydrological, climatic, and socio-economic characteristics. Comparative analysis would help determine the generalizability of the framework and identify specific regional adjustments required. In particular, there is an opportunity to test the Combined Flood and Drought Risk Index (CFDRI) across diverse environments, including urban and rural basins, transboundary regions, and basins facing significant climatic pressures. Validation efforts should also consider basins with varying degrees of access to resources, institutional structures, and political boundaries to understand the adaptability of the framework across diverse socio-political settings.

8.5.3 Expanding Stakeholder Engagement

Future research must address the gap in stakeholder engagement, which limits the real-world applicability of the risk assessment framework:

- Stakeholder Consultation and Participatory Research: Incorporating stakeholder perspectives especially from vulnerable communities, local governments, and private companies would improve the applicability of the risk model. Future studies could use participatory research approaches to involve stakeholders in defining risk priorities, setting calibration coefficients, and validating model outputs. Engaging stakeholders from the Environment Agency, water utilities, and city councils would allow researchers to better align their models with real-world needs and conditions.

- Socio-Political Dynamics in Transboundary Basins: A more comprehensive understanding of the socio-political context within transboundary basins is also warranted. These basins are governed by multiple jurisdictions, each with different risk management approaches, which directly impact the allocation of resources and access to risk-reducing mechanisms such as insurance. Future research could explore the implications of socio-political variability for risk resilience, particularly with a focus on equitable water rights, cross-border insurance coverage, and coordination challenges.

8.5.4 Refining and Expanding Modelling Approaches

To enhance the robustness and applicability of flood and drought risk assessments, the following modelling improvements are recommended:

- Incorporating Quantitative Feedback Mechanisms: The Causal Loop Diagrams (CLDs) used in this research provide qualitative insights into feedback relationships between risk factors. Future research should extend this approach to incorporate quantitative simulations of feedback loops using tools like System Dynamics (SD) modelling. Quantitative models can provide more precise assessments of the impact of feedback mechanisms and allow for scenario-based risk predictions.

- Integration with Machine Learning: Machine learning offers substantial potential for enhancing predictive capability in flood and drought risk assessment. Future studies could integrate ML techniques, such as Random Forests or Neural Networks, with the existing framework to enhance the detection of relationships between variables, predict high-risk scenarios, and calibrate the risk indices based on a larger dataset. The inclusion of ML-based approaches in calibration could also help refine the fuzzy overlay coefficients and improve the accuracy of risk classification and mapping.

- Scenario Testing with Multiple Models: Another area for future exploration is the use of multiple models to evaluate the same river basin or extend the general framework by including alternative modelling approaches, such as Agent-Based Models (ABM). These approaches allow for the representation of autonomous entities, like farmers or municipalities, which make decisions based on changing conditions, thus providing a more nuanced understanding of individual or collective behavior under flood and drought risk scenarios. Comparing the results of multiple models could further enhance the understanding of risk dynamics and validate model outputs.

8.5.5 Broader Integration of Socio-Economic Parameters

The socio-economic component of the framework could benefit from further development, particularly regarding how socio-economic factors directly influence vulnerability and resilience:

- Assessing Socio-Economic Dimensions at a Finer Scale: Future studies could incorporate socio-economic data at a finer scale, including metrics such as income distribution, employment type, and educational levels. These variables could provide a more granular understanding of how socio-economic vulnerabilities vary within the basin. The inclusion of these detailed metrics would enable the development of targeted strategies to reduce risks for the most vulnerable populations.

- Exploring Willingness to Pay for Insurance: Given that insurance is a critical mechanism for enhancing community resilience, future research should investigate factors influencing the willingness to pay for flood and drought insurance. This investigation should consider variables such as cultural attitudes, risk perception, and past experience with insurance. Understanding these factors can help policymakers and insurance providers develop more affordable and accessible insurance schemes tailored to specific communities.

8.5.6 Cross-Disciplinary Epistemological Integration

The integration of diverse disciplines hydrology, socio-economics, ecology requires a more robust epistemological framework. Future research could:

- Develop an Integrated Epistemological Approach: This research encountered difficulties in reconciling the empirical approaches of hydrological sciences with the interpretive methods used in socio-economic studies. Future efforts should aim to establish an integrated epistemological framework that provides a standardized method for integrating these diverse data sources. Such an approach could lead to a more holistic understanding of hydrological risks, fostering a stronger theoretical foundation for interdisciplinary studies.

- Exploring Interdependencies in Greater Detail: Future research could also expand on the use of network analysis to investigate interdependencies between parameters in greater detail. The current study identified broad categories of relationships, but a deeper exploration of the specific nature of these interactions could provide insights into emergent properties, thresholds, or tipping points within the hydrological and socio-economic systems. This type of analysis could help in identifying the conditions under which minor perturbations could lead to significant changes in risk, thus allowing for more proactive management of flood and drought hazards.

8.5.7 Addressing Temporal and Spatial Scale Challenges

The issue of temporal and spatial scales, which affected the granularity of the risk analysis, should be addressed in future work:

- Temporal Expansion: Incorporating finer temporal resolutions, such as daily or weekly data, could allow researchers to capture the immediate impacts of extreme events. Future studies should aim to integrate high-frequency monitoring data to assess short-term risk fluctuations and assess the impact of individual flood or drought events on basin-scale dynamics.

- Multi-Scale Spatial Analysis: Developing a multi-scale spatial analysis approach could also help to address the limitation of the river basin-wide focus of the current research. By integrating micro-scale analyses such as the impacts on individual communities, farms, or neighborhoods researchers could identify local factors that influence risk within the broader river basin context. This approach would support the development of more customized risk mitigation strategies that address both local and regional needs.

8.5.8 Expanded Validation and Application of Findings

Future research should also focus on validating the findings and expanding the framework's application:

- Field Validation and Empirical Testing: The findings should be validated through fieldwork and empirical testing in a variety of basin contexts. By comparing the framework outputs to real-world observations—such as historical flood and drought events—researchers can assess the accuracy and reliability of the framework and refine it accordingly.

- Application Across Diverse Hydrological Systems: Applying the framework across a range of hydrological systems with different climatic, topographic, and socio-economic conditions will test its replicability and robustness. Future studies should include basins with different levels of water regulation, varying precipitation patterns, and distinct land use practices to evaluate the versatility of the model and adapt it to specific regional contexts.

By addressing these areas, future research can build on the findings of this study to develop more comprehensive and effective strategies for managing flood and drought risks in the River Severn basin and other similar regions.

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APPENDICES

A section of early results from this research is published open access via the following link and cited accordingly:

https://www.mdpi.com/2073-4441/13/19/2788/pdf

Fasihi, S., Lim, W.Z., Wu, W. and Proverbs, D., 2021. Systematic review of flood and drought literature based on science mapping and content analysis. Water, 13(19), p.2788.

Given the extensive amount of information in each category of supplementary materials, each section has been categorized and titled in a separate file. A comprehensive list of all these sections is provided here for reference, should further information be needed.

- Appendix_A

This document contains some more general information about the performed systematic literature review (Chapter 4). Next, this file contains the code written for transivity check of the final reachability matrix utilised in the ISM approach (Section 5.2). Additionally, more explanation and normalised equations for network metrics analysis along with more figures and tables are provided here.

- Supplementary_material_ISM

The spreadsheet contains the actual large tables of reachability matrices, level partitioning and driving and dependency power produced by the ISM method in section 5.2.

- Sample_of_reviewd_papers

This document includes a sample of the reports created for each paper used in the systematic literature review process

- Bibliography_of_all_papers

This document contains the bibliographic list of all the papers used in the systematic literature review, which served as the basis for extracting the informative data used in the statistical analysis presented in Chapter 4.